Journal of Healthcare Engineering

# Complexity Systems for Scheduling in Healthcare

Lead Guest Editor: Saeid Jafarzadeh Ghoushchi
Guest Editors: Mohsen Ahmadi, Abbas Sharifi, and Abbas Mardani

# Complexity Systems for Scheduling in Healthcare

Journal of Healthcare Engineering

# Complexity Systems for Scheduling in Healthcare

Lead Guest Editor: Saeid Jafarzadeh Ghoushchi
Guest Editors: Mohsen Ahmadi, Abbas Sharifi, and Abbas Mardani

# Contents

Hindawi
Journal of Healthcare Engineering
Volume 2022, Article ID 1938719, 15 pages
https://doi.org/10.1155/2022/1938719

*Research Article*

# Presented a Framework of Computational Modeling to Identify the Patient Admission Scheduling Problem in the Healthcare System

**Reza Hosseini Rad,[1] Sahba Baniasadi,[2] Parisa Yousefi,[3] Hakimeh Morabbi Heravi [4] Muzhir Shaban Al-Ani,[5] and Mohsen Asghari Ilani [6]**

[1]*Department of Industrial Engineering, Amirkabir University of Technology, Tehran, Iran*
[2]*Master of Industrial Engineering, Department of Industrial Engineering, University of Houston, Houston, TX, USA*
[3]*Department of Industrial Engineering, Qazvin Islamic Azad University (QIAU), Qazvin, Iran*
[4]*Department of Statistics, University of Bojnord, Bojnord, Iran*
[5]*University of Human Development, College of Science and Technology, Department of Information Technology, Sulaymaniyah, KRG, Iraq*
[6]*School of Mechanical Engineering, College of Engineering, University of Tehran, Tehran, Iran*

Correspondence should be addressed to Mohsen Asghari Ilani; mohsenasghari1990@ut.ac.ir

Received 2 January 2022; Revised 8 March 2022; Accepted 23 March 2022; Published 29 November 2022

Academic Editor: Abbas Sharifi



Operating room scheduling is a prominent study topic due to its complexity and significance. The increasing number of technical operating room scheduling articles produced each year calls for another evaluation of the literature to enable academics to respond to new trends more quickly. The mathematical application of a model for the patient admission scheduling issue with stochastic arrivals and departures is the subject of this study. The approach for applying our model to real-world issues is discussed here. We present a solution technique for efficient computing, a numerical model analysis, and examples to demonstrate the methodology. This study looked at the challenge of assigning procedures to operate rooms in the face of ambiguity regarding surgery length and the arrival of emergency patients based on a flexible policy (capacity reservation). We demonstrate that the proposed methods derived from deterministic models are inadequate compared to the answers produced from our stochastic model using simple numerical examples. We also use heuristics to estimate the objective function to build more complicated numerical examples for large-scale issues, demonstrating that our methodology can be applied quickly to real-world situations that often include big information sets.

## 1. Introduction

Patients seeking medical treatment often turn to outpatient services, and their efficiency is critical to patient satisfaction with the healthcare system. Outpatient service operations management has faced a number of challenges in response to the growing demand for outpatient services and the changing behavioral patterns of patients. In today's healthcare system, it is widely recognized that timely and straightforward access to healthcare services must be provided to all patients. In general, there has been an increase in the demand for healthcare services over the past decade. The reasons for this include an aging population and increasing awareness of the benefits of preventative care. In contrast, the global economic crisis is forcing healthcare systems to reorganize. There is a reduction in public healthcare providers at the macro level [1]. Patients can easily access clinics through a good scheduling system [2]. Thus, long patient wait times are caused by inefficient or poorly planned schedules. As a result, there are more complaints and unhappy patients. By recognizing and appreciating the importance of effective patient scheduling, as highlighted by Suss et al., outpatient clinics can use various scheduling strategies to strike a balance between patient satisfaction and resource utilization [3].

Furthermore, outpatient clinics' use of appointment systems was praised by patients as a sign of competent service delivery [4]. Consumers perceive that scheduling appointments enhances patient accessibility and satisfaction in a significant way [4]. A study by Sprentrup et al. concluded that appointment systems' dependability, particularly in clinics, had been widely acknowledged as a means to ensure improved patient care and organizational incentives [5, 6]. The most popular methods of scheduling in healthcare are walk-ins and appointments [6–10]. Walk-in scheduling techniques are popular because they are able to maintain a continuous patient flow. According to this method, patients are treated based on a first-come, first-served basis [11]. The appointment system is unique, in that it includes certain delimited intervals or slots in a schedule that can accommodate patients on the same day they seek or apply for an appointment. Schoenfelder et al. concluded that each scheduling approach aims to improve one metric at the expense of another. Therefore, it may be difficult to achieve a balance between patient contentment and resource utilization using a single scheduling strategy [12]. Two scheduling strategies are used by HAS to increase its ability to meet both patient and clinic needs. While appointments allow patients to shorten wait times, walk-ins allow them to enter the facility without an appointment, giving them more freedom [6]. As well as reviewing numerous papers written in English and published in peer-reviewed journals, we searched databases covering a variety of disciplines, such as Scopus and Google Scholar, for relevant articles using terms such as "nurse scheduling," "nurse rostering," "patient admission scheduling," "patient to bed assignment," "operating room scheduling," and "operating theater scheduling." We conducted a forward and backward search for the publications identified to identify related papers. We only examined English-language articles published between 2010 and 2020 (see Figure 1). All articles describing the implications of metaheuristics in arranging healthcare decision-making within an optimization setting were also considered.

The scheduling of patients is the subject of several studies since it affects the length of time it takes for patients to be seen, as well as the waiting time and idle time in the system over time. Outpatient clinics employ single queues, according to Brahimi and Worthington. Depending on their arrival time, patients may have to wait in long lines. However, such a strategy is ineffective since patients' needs differ. According to Brahimi and Worthington, some people may come to the center for non-health-related consultations, but others may need immediate medical care. In order to ensure increased operating efficiency, a more efficient scheduling approach is required. In addition, each patient is assigned a specific period of time; therefore, the time slot may be squandered if a customer fails to show up. Nevertheless, Aburayya et al. noted that the health center loses money [3]. Section 2 examines the current literature on outpatient scheduling difficulties. In Section 3, we discuss essential patient planning programs by implementing flow and model thinking to better understand general service time distribution and overall performance criteria of current appointment scheduling methods. Section 4 discusses a number of healthcare application areas and methodologies. The patients' choice function, on the other hand, covers a wider range of topics. Provider selection impacts carrier fines and healthcare income, day of the week selection impacts carrier delays, and appointment time selection impacts patient convenience. Section 5 concludes with a discussion of the results and recommendations for the future. The mathematical application of a model for the patient admission scheduling issue with stochastic arrivals and departures is the subject of this study. The approach for applying our model to real-world issues is discussed here. We present a solution technique for efficient computing, a numerical model analysis, and examples to demonstrate the methodology. This study looked at the challenge of assigning procedures to operate rooms in the face of ambiguity regarding surgery length and the arrival of emergency patients based on a flexible policy (capacity reservation).

## 2. Previous Investigations

The goal of this review, as stated before, is to examine outpatient appointment scheduling approaches and compare different tactics to explain the benefits of appointment scheduling. Over the last few decades, outpatient appointment scheduling has piqued the interest of various academics and clinicians, starting with the work of Welch and Bailey [13]. In recent decades, the literature has properly covered appointment scheduling, including outpatient scheduling [14], operation room scheduling [15–24], and medical examination scheduling [25–29]. The primary issues with appointment scheduling are connected to optimizing healthcare resources through better usage of human resources and medical equipment, which results in shorter patient wait times. Numerous research studies have found that patient dissatisfaction with outpatient scheduling is typically due to long wait times and that reasonable wait times are necessarily based on clinical competency [30]. Simulation models are among the most well-known methods for examining the impact of random variables on patient wait times and idle doctor time in appointment scheduling [31]. For the issue of appointment scheduling, Granja et al. [32] presented a simulation model optimization method. The suggested simulation model demonstrates good effectiveness in the assessment of medical imaging processes. The patient appointment scheduling is optimized using a simulated annealing approach, which reduces the average service period and overall patient waiting times.

In comparison to the existing scenario, the whole service time and patient waiting time have been decreased by roughly 5% and 38%, respectively, according to the acquired results. Zonderland et al. [1] investigated an open-access policy that expanded a system and suggested an appropriate heuristic policy for patient-cancelable appointment scheduling. They showed a model that takes data from a real clinic and examines it section by section using a heuristics approach. With all of the other measures in place, many patients have above-average performance. According to Zhao

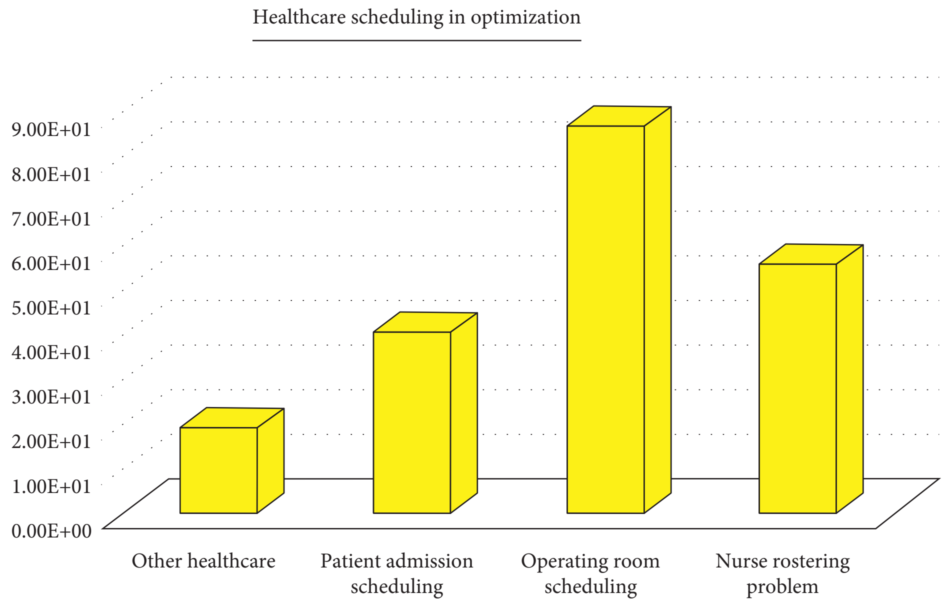



Figure 1: Number of the covered article.

et al. [33], there is a growing trend toward web-based appointment systems. They discussed the benefits of a wide range of patient outcomes from web-based scheduling that overlapped with other research. Early patient acceptance and continued use of a conventional appointment scheduling system were studied by Grain [34]; however, the usual kind of customer utilized an E-Health Service and an E-Appointment Scheduling system. The study was based on a review evaluation to gather relevant information from patients, such as their approval of the system, their thoughts on its features, and their justifications for utilizing it.

Wu et al. [35] devised scheduling principles that define a succession of review responsibilities and different services. The simulation findings assign functions to correct the service time, support the pharmaceutical task across many resources, and optimize the utilization flow. According to Harding and Bottrell [36], waiting times for outpatient physiotherapy were percent shorter in the year after implementing the triage model's specified, timely appointments [33, 34]. Rohleder and Klassen [37] presented a framework for distinguishing patients' viewpoints, reducing the number of times doctors are idle and the number of times patients are waiting. Kong et al. [38] created a robust distributional model that reduces the total cost of patient waiting time. They also provided a model that considered a service provider's idle and overtime to optimize patient arrival times. This approach is challenging because calculating the total cost of a schedule requires linear integer programming with uncertainty in both the goal characteristic and the structure of the restrictions. A new perturbation approach was developed by Liu et al. [39] to improve the dynamical stability of digital chaotic maps. Wu et al. [40] proposed a distributed architecture to permit the scalability of several association-rule-based recommendation algorithms. Wu et al. [41] studied an efficient SQL-to-MapReduce Translator (CAT) that is cost-aware. CAT stands out for two reasons. Based on digital footprint images, Sharifi et al. [42] proposed a new method to diagnose tired feet. Abadi et al. [46] combined the salp swarm algorithm with genetic algorithms to develop a novel method for scheduling nurses for the care of COVID-19 patients. Eslami et al. [44] investigated an attention-based multiscale convolutional neural network (A+MCNN) for automatically classifying frequent distress and non-distress items in pavement photographs. Zheng et al. [45] compared six state-of-the-art class rebalancing approaches against five common classification algorithms for SBR prediction. They outline eight key conclusions from their empirical investigations, which may be used to advise practitioners in selecting optimal class rebalancing strategies and classifiers for SBR prediction. In a multistage outpatient healthcare system, Diamant et al. [46] developed a unique appointment technique for assessing existing healthcare service deployments and observations. The clinic develops a unique appointment scheduling technique in which patients are assigned to a particular appointment day. However, the absence of decision-making in patients' judgments renders this technique ineffective; therefore, they attempted to overcome this restriction. They used a discrete-event simulation to compare their solutions to heuristic scheduling techniques and assess the quality of their solutions based on structural results. Chervenak et al. [47] suggested investigating the detrimental effects of malignant religion and nationalism on patients' biopsychosocial health and medical professionalism. Davoudi et al. [48] used machine learning to investigate the influence of statins taken before infection on the severe decrease of COVID-19. Jia et al. [49] investigated a probabilistic method to schedule port vehicles. Yazdani et al. [50] suggest an application of eXtended Classifier Systems (XCS) for detecting database intrusions in this research. Rezaei et al. [51] suggested a data-driven technique for segmenting the hand parts on depth maps that does not need any additional

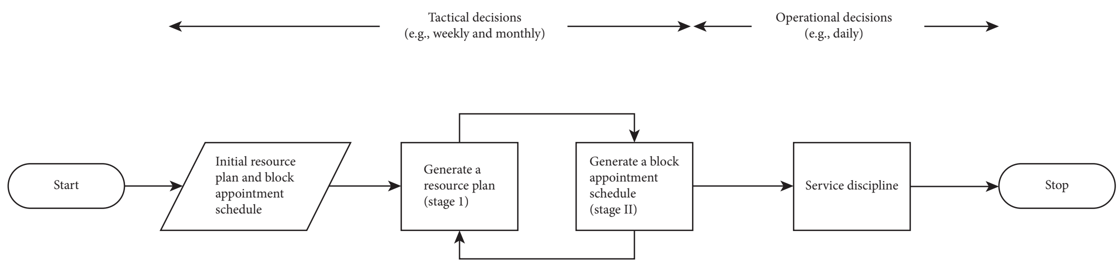



Figure 2: Scheduling appointments and allocating resources integrated [24].

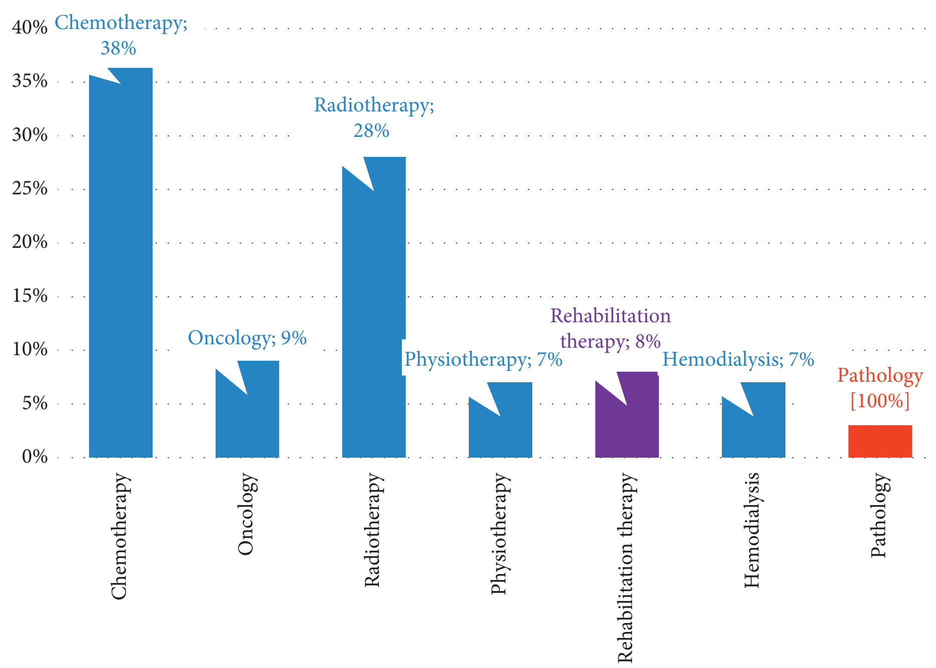



Figure 3: The pie chart for the applications to patient and outpatient scheduling problems.

work to produce segmentation labels. The proposed technique learns to predict the hand form and posture given a depth map by using the labels previously supplied by public datasets in terms of main 3D hand joint positions. Sadeghipour et al. [52] suggested an Intelligent Diabetes Diagnosis System using the XCSLA System. Ahmadi et al. [53] showed how to segment brain tumors using the FWNNet approach. The authors introduced a unique supervised segmentation approach based on the FWNNet layer in this article. Garaix et al. [54] used previously published research to create models that optimize the number of patient visits, reduce affected patient waiting time, and improve patient satisfaction.

The majority of the literature review studies such as Deng et al. [55] Moreover, Robinson and Chen focused on static modeling techniques [56]. As you can see, the quantity of recent articles has outgrown its capacity. Figure 2 depicts the proportion of application areas related to patient and outpatient scheduling issues. The majority of extant patient scheduling applications, as can be shown, are in the fields of chemotherapy and radiation. As a result, we suggest a pie chart depicting the many healthcare branches responsible for green outpatient scheduling inside a radiation department, which is defined in such a way as to illustrate various real-life scenarios. The success of the research presented is assessed using haphazardly created problems and a real-life scenario. The results are highly encouraging because the created optimization models enable us to outperform human specialists (see Figure 2).

As seen in Figures 2 and 3, many literature review topics have covered appointment scheduling. In general, the issues are based on highly aggregated data collected at various periods throughout the year. It is worth noting that over half of the contributions are from 2013 or later, demonstrating the growing number of subjects for researchers in the appointment scheduling program. We limit manuscripts to those submitted in or after 2014 and 2015 due to many submissions. Between 2014 and 2015, there were just a few publications published in English on this topic. Nevertheless, due to the collaboration between researchers and the healthcare industry, the number of articles published after 2015 has increased. They recognized that they might profit from the benefits of this approach, such as increased staff productivity and appropriate follow-up for typical chronic disease patients.

This contribution has enabled scholars in this field to pursue more exciting and new subjects. We have provided a taxonomy of outpatient scheduling concepts and methodologies in. The majority of the research, as described in Appendix, focuses on the modeling techniques discussed previously in this review article, which explored achieving equilibrium between patient waiting time and doctor usage through hospital consultation and resources. In actuality, one of the first practical variables in appointment scheduling is direct and indirect waiting time. Nevertheless, modeling a process indirectly is challenging for a variety of reasons. To begin with, unlike the direct waiting period during which the appointment is terminated, waiting-time difficulties are more accurately depicted as infinite problems. Second, in a schedule conflict, outpatients are given a good appointment time to choose among multiple preferred physicians. ASPs created on a given day for a specific doctor are also linked to various days and physicians.

*2.1. Decision Level in Production Control.* Production planning was defined by Szander et al. [25] and improved by Stamps et al. [26]. The five hierarchical phases of resource capacity management as proposed by Vissers et al. are strategy development, patient volume planning and control, resource planning and control, patient group planning and control, and patient planning and control. Each hierarchical tier is listed below:

Level I: Strategic planning: This is the most high level of the framework. This level of decision-making takes place every two to five years. In addition to being connected to the provider's top executives, they help determine the future direction of the provider.

Level 2: Plan and manage the patient volume: Each patient group has a target number of patients, service levels, and production volume. The process could take up to two years.

Level 3: Resource allocation and control: This section deals with the allocation of resources to groups of patients, such as specialties or departments. These rules determine how patients are grouped. The effects of these activities last from three months to one year.

Level 4: Patient group planning and control: We are referring to the resources required to perform the patient planning and control function. It takes between three weeks and three months for decisions to be made at this stage.

Level 5: Patient planning and control: This is the area where you arrange daily tasks relating to patient planning. The choices last between one and seven days and relate to the point at which waiting patients are approved. They determine when they will be admitted and released.

Although this approach views healthcare providers as self-contained commercial organizations, it only addresses resource capacity management and ignores online decision-making.

*2.2. Optimizing Operating Room Scheduling.* The scheduling operating room literature has a variety of techniques that apply to the optimization sector. To solve the challenge of operating room scheduling, several heuristics and metaheuristics have been used. [1] Constructing a weekly operating theater operation schedule utilizing an open scheduling method is proposed in this context. This project aims to maximize operating room utilization, reduce operating theater overtime costs, and reduce unplanned idle time among surgical patients. The solution process in this work is divided into two parts. The first step is assigning a particular date for each surgeon to each patient, and surgeons are allowed to allocate their cases to any time block. Then, the daily timetable is established to maintain the operation sequence, taking into account the available recuperation beds. A set-partitioning integer-programming paradigm is used in the suggested technique, and the solution is found via a column-generation-based heuristic procedure. The daily scheduling problem is addressed in the second phase, represented by a two-staged hybrid flow-shop model that is addressed by a hybrid genetic algorithm that employs a Tabu search technique for local search. Depending on Belgian university hospital data, the suggested approach was evaluated with several actual surgical schedules. The findings indicate that there was reduced idle time between surgical patients as a result of the operation schedules as well as more operating room utilization with little overtime. Additionally, [20] created a unique two-stage stochastic mixed-integer-programming approach to handle surgical schedules across many operating rooms under uncertainty. The major point of this study is that the availability of several operating rooms and assistance and support from other surgeons, particularly the chief staff surgeon, allows many procedures to be done concurrently. It explained why surgeons should pool their resources and share them. The following diagram depicts the summary of all optimization algorithms and data collections with categorization (see Table 1).

## 3. Methodologies

*3.1. Overlapping Appointment Scheduling Methods.* Generally, there are several approaches used in the field of healthcare study. Using appointment scheduling is one of the essential aspects. In this part, various approaches are compared to see one is more practical than the others, using their benefits as a foundation. Just the online or phone services initiate the admission procedure, which may be done with or without an appointment. The primary objective is to reduce access time by allocating specific resources to patients who phone in for an appointment the same day or within a few days [69]. A standard appointment scheduling process for a multidoctor outpatient unit may be reduced to gathering many discrete single-doctor problems [70]. In an outpatient healthcare hospital with a random service time, the overlapping appointment scheduling (OLAS) method minimizes patient awaiting time and doctor idle time while increasing doctor productivity and patient contentment [71]. The OLAS method is used to determine the best overlapping intervals between patient appointments and service hours. Given the probability distributions for patient flow and service time, OLAS is generally framed as an optimization process to reduce the overall cost of patients awaiting and idle doctor time [71, 72]. Much research has been performed to organize patient care time in hospitals utilizing innovative OLAS model techniques. It may be employed to look at a queuing system for patient satisfaction

Table 1: Healthcare scheduling in optimization context: a review.

| References | Method | Uncertain/elective |
|---|---|---|
| [56] | Programming in a stochastic manner | Uncertainty |
| [46] | Programs that use integers | — |
| [57] | Linear stochastic program | Uncertainty |
| [58] | Exact solution algorithm based on branch and price | |
| [59] | Algorithm of branching and bounding | — |
| [60] | Local search and heuristics | Elective |
| [61] | Dynamic stochastic programming | Elective |
| [62] | Light robustness approach and mixed-integer linear formulation | Elective |
| [63] | Model of integer linear programming | Elective |
| [64] | Model of stochastic dynamic programming | Elective |
| [65] | Bi-criteria heuristics discrete-event simulation model heuristics GA | Elective |
| [66] | Binary programming, local search, integer programming | Elective/emergency |
| [67] | Discrete-event model | Uncertain |
| [68] | Discrete event dynamic system | Elective |

in a hospital setting in a particular field study. Patient satisfaction is essential to any hospital's performance and the public's perception of the hospital as they stand in line for their opportunity to visit a doctor and during their time with the doctor [70]. This finding should aid in the improvement of clinic services and the assurance of the quality of service. Patients' satisfaction with the quality of treatments in outpatient clinics was examined in another research at Egypt's University Hospital, indicating that the healthcare environment requires continuous quality development and attention, notably to please patients [73].

The Monte Carlo (MC) numerical solution may be used to evaluate the findings of optimal overlapping periods provided by an OLAS model as an alternate technique. The OLAS approach may also be employed to test the elements that influence the procedure of establishing an overlap period in clinics, such as service time distribution, over time, and no-shows [74]. The development of an overlap period in clinics with various assumptions is linked to service time distribution over time and no-shows [75]. The lack of particular scheduling services, such as alerts and warnings of overlapping periods, is one of OLAS's significant benefits for appointment scheduling. Despite the cost of extra employees, OLAS enhances overall productivity and profit. In addition, specific appointment analyses place a premium on the number of operation studies. Furthermore, we can expand the MC simulation feature to figure out the number of patients to schedule an appointment with at the start of the session and the duration of a gap between the remaining appointment times using a simulation approach like MC. After this is known, the value may be noted; utilizing this results in a suitable equilibrium between the patient's waiting time and the doctor's idle time. It was observed that the shorter the mean consulting times, the faster the patient's waiting time, and the doctor's idle time decreased [76].

*3.2. Model Assumptions.* The goal of the MC simulation is to evaluate randomness to provide more accurate findings based on the patient's historical data. MC simulation provides the decision-maker with a variety of probable outcomes and the probability associated with each option. Table 1 categorizes the simulation techniques for outpatient scheduling difficulties. In the simplest optimization model, one customer is included in all modeling to determine the start time of each engaged patient where the OLAS model is particular. For each patient and service level, there are also stochastic factors. For the version, the notation explanation is as follows:

$t_i^{OLAS}$: The appointment begins at the time of patient $i$ (OLAS + doctor and patient) for $i = 1, 2, \ldots$, N. $t_j^{doc}$ The appointment begins at the appointed time for patient $j$ (doctor just patient) for $j = 1, 2, \ldots, M$.

$S_i^{OLAS}$: OLAS provides service $i$ to patients at a set time.

$W_i^{OLAS}$: Patient i's OLAS waiting time.

$I_k$: Doctor's idle time between patients $k$ and k-1, where $k = 1, 2, \ldots, N + M$.

T: Clinic closure time.

O: The clinic's extra time working. $C_w^{OLAS}$: The cost of the patients who are waiting for the OLAS.

$c_w^{doc}$: The cost of the patient's time spent waiting for the doctor.

$A_k$: Arrival time for the kth patient in the second and A($k$) is the kth order statistic for $k = 1, 2, \ldots, N + M$.

$W_k$: The time it takes for a doctor to see the kth patient, where W($k$) is the kth-order statistic for $k = 1, 2, \ldots, N + M$.

$S_k$: Kth patient visited by the doctor's appointment time, where S($k$) is the kth-order statistics for $k = 1, 2, \ldots\ldots, N + M$.

The definitions that apply are as follows:

$$\begin{aligned}
W_1^{\text{OLAS}} &= 0,\\
W_i^{\text{OLAS}} &= \max\left\{W_{i-1}^{\text{OLAS}} + S_{i-1}^{\text{OLAS}} - t_i, 0\right\}\text{for} i = 2, \ldots\ldots, N,\\
W1 &= 0\,\text{for} k = 1,\\
Wk &= \max\{Wk-1+Sk-1-Ak-1,0\}\text{for} k = 2,\ldots\ldots, N+M,\\
I1 &= 0,\\
Ik &= \max\{Ak-(Ak-1+Wk-1+Sk-1),0\}\text{for} k = 2\ldots\ldots, N+M,\\
O &= \max\{Ak\text{–}(\text{Ak}-1+\text{Wk}-1+\text{Sk}-1\,),0\}\text{–Tfork} = \text{N}+\text{M}.
\end{aligned} \tag{1}$$

Flow time of outpatient

$$i = W_i^{\text{OLAS}} + W_k + S_i^{\text{OLAS}} + S_k. \tag{2}$$

The goal of the equation is to construct an approximation timetable that minimizes the following function: total projected cost of patient wait length and service point, doctor idle time, and clinic overtime.

We can suppose that $E$ follows a uniform distribution in the case of OLAS. Outpatients are anticipated to arrive at different times $t_1, t_2, \ldots\ldots t_N$ and $t_1, t_2, \ldots\ldots t_M$ if they come up.

$$\text{Min} c_w^{\text{OLAS}} E\left[\sum_{i=1}^{n} W_i^{\text{OLAS}}\right] + c_w^{\text{doc}} E\left[\sum_{j=1}^{m} W_k\right] + cIE\left[\sum_{k=1}^{k} I_k\right] + \text{co}[o]. \tag{3}$$

$t_i$, $t_j$ subject to

$$\begin{aligned}
t_1 &\geq 0,\\
t_N &\leq T,\\
t_1^{\text{OLAS}} &\leq t_2^{\text{OLAS}} \leq \ldots \leq t_N^{\text{OLAS}},\\
t_1^{\text{doc}} &\leq t_2^{\text{doc}} \leq \ldots \leq t_M^{\text{doc}},\\
&t_i,\ t_j \text{integer}.
\end{aligned} \tag{4}$$

Given that integer values are appointment start instances, it is still accurate that the doctor's maximal work is comparable to $T - \sum_J I_j + O$ depending on the stated mathematic equations. Outpatients could be accepted earlier, late, or on time for their planned appointment. The OLAS is used to see patients. The doctor line is organized depending on their first appointment time and examination room availability. Patients are displayed in the line according to a first-come-first-served principle. An OLAS-afflicted patient, for instance, can immediately enter the physicians' queue when the OLAS is done.

If a physician-only patient with a later appointment comes before the OLAS, the health doctor will see them first. If there is a vacant examination room, a doctor-only patient will instantly join the medical doctor line. After admittance, all patients are put in exam room lines. A qualified patient is allocated to an exam room if one is accessible or waiting in line. They are in both the OLAS and doctor queues at the same time. As a result of the first appointment and examination room, the number of exam rooms is restricted. Generally, OLAS individuals in an examination room will seek medical assistance sooner than doctor-only individuals who have not yet been allocated a room. Simultaneously, with several phases, overall service examples are generally more significant. The goal is to devise schedules that reduce the accessible ready time for patients while minimizing idle time and time spent outside of the fitness care facility's control. Most OLAS modeling techniques are created for an outpatient healthcare program, and several parameter pairs are mathematically tested. The findings also touch on the topic of appointment scheduling. This approach examines some variables including service time, coefficient, variance, cost ratio, total doctor idle time and overtime, and patient waiting time. Furthermore, numerical studies show that the OLAS approach can considerably cut clinic costs. Outpatients with a long service duration, a high coefficient of variation for service time, a high-cost ratio, and a high no-show rate have the most extended overlap period and lowest cost. As a result, this technique may be studied and contrasted with other appointment scheduling strategies [64].

Furthermore, discrete-event modeling is a flexible technique designed to form the techniques necessary to alert healthcare scheduling, thanks to those simulation methods types. It provides for a wider range of tools than the Markov standard approach and the creation of procedures at a level appropriate for the task. Its risks are low and easily handled, putting our field closer to the need for strong modes that decision-makers can rely on. To manage the clock in most discrete-event simulations, AnyLogic or Arena Simulation software is used.

*3.3. Multiple Objectives.* Preoperative holding units (PHUs), multiple ORs, postanesthesia care units (PACUs), and intensive care units (ICUs) are the three components of an operating room. They are all useful in supplying effective planning and scheduling for surgical procedures. The most efficient components of the operating room, such as numerous ORs and critical care units, are evaluated in this study's operation schedule (ICUs). Other areas, on the other hand, are believed to have adequate resources. The weekly scheduling of operations for chosen patients and the problem of assigning procedures to operate rooms in the event of ambiguity about surgery duration and the coming of emergency patients depending on a flexible policy (capacity reservation) were studied in this research. We have a list of chosen patients awaiting surgery and some surgeons with various specialties who should be booked in the event of ambiguity about the length of surgery and the advent of emergency patients on their surgeon's days off. The scheduling of operating room units and intensive care units is taken into account in this research. The problem under investigation has several restrictions. These considerations comprise the intensive care unit (ICU), the restricted time accessible for work, the noninterference of procedures involving an operating room, and the noninterference of operations involving a surgeon because most multiple ORs are outfitted with specialized equipment and can accommodate a variety of operations. We approached the operating room separately, and it is also conceivable to add a restricted number of beds to the intensive care units (ICUs) in the event of a bed constraint.

The following are the assumption of the theory in question.

(i) All patients are operated, both nonpreferentially and selectively, in the many ORs available

(ii) The value of a weekly routine cannot be overstated

(iii) It is possible to schedule multiple rooms

(iv) The length of the operation varies

(v) Emergency patients are also admitted at random

(vi) The objectives of patients are taken into account while scheduling

(vii) It is feasible to do business outside of regular working hours (overtime)

(viii) Anesthesiologists, nurses, surgeons' assistants, and other human resources are available

(ix) Professionals, on the other hand, see constraints as the most valuable human resource

(x) The characteristics of operating rooms are the same

(xi) Index:

$p$: Set of all patients
$q'$: Set of all noninfectious patients
$p'$: Set of all nonemergency patients
$p'$: Set of all emergency patients
$o$: Set of all multiple ORs
$s$: A Set of all surgeons
$t$: A set of all available time blocks
$d$: Set of all available days

(xii) Parameters:

$C_{pos}$: The expense of assigning the $P$ th patient to the $O$ th operating room and assigning the $s$ th surgeon to the $P$ th patient
$D_{p'}$: The expense of altering a nonemergency patient $p'$s treatment plan
$EC_{od}$: On the $d$ th day, the expense of not utilizing the $o$ operating room
$LC_{od}$: On the $d$ th day, the expense of excessive usage of the operating room
$\delta_{p'}$: The total number of modifications made to the nonemergency patient program $p'$ to this point
$U_d$: Intensive care unit (ICU) shortfall cost per day $d$
$du_p$: When the patient's $p$ operation lasts, the number of blocks
$cl_q$: After $q$ th operation, the number of time blocks required to clean the operating area
$da_p$: The most recent time frame (day) in which we are permitted to operate on my $p$ th patient
$dI_p$: The number of days in the intensive care unit that the $p$ th patient should spend (ICUs)
$R_{po}$: If the $p$ th patient may be allocated to the $o$ th operating room, $R_{po}$ is one; otherwise, it is zero
$Q_{ps}$: If the $p$ th patient can be allocated to the $s$ surgeon, $Q_{ps}$ equals one; otherwise, it equals zero
$G$: The number of nonemergency surgical time blocks a surgeon can do each day
$HN_{od}$: The number of time blocks allotted on the $d$ th day to run the $o$ th operating room
$HS_{od}$: Max number of extra work block for chosen patients in the $o$ operating room on the $d$ th day
$HO_{od}$: The maximum number of time blocks that emergency patients can utilize the operating room after the authorized time blocks linked to the $o$ operating room on the $d$ th day
$\widetilde{HM}_{od}$: The amount of time allotted to emergency patients in the $o$ operating room on day $d$; this parameter has a usual distribution with $E(\widetilde{HM}_{od})$ as the mean and $Var(\widetilde{HM}_{od})$ as the variance
$MT_s^{max}$: The $s$ physician is max working hours on the planning
$\widetilde{WICU}_d$: The number of intensive care unit (ICU) units allotted to emergency patients; this variable has a normal distribution with $E(\widetilde{WICU}_d)$ as the mean and $Var(\widetilde{WICU}_d)$ as the variance
$\widetilde{Cicu}_d$: The number of boards accessible in the intensive care unit (ICUs); this variable has a normal distribution with $E(\widetilde{Cicu}_d)$ as the mean and $\mathrm{Var}(\widetilde{\mathrm{Cicu}}_d)$ as the variance
$x^0_{postd}$: It is one if the $p$ th patient's preoperative surgery in the operating room begins utilizing the $s$ th surgeon in the $t$ th time block on the $d$ th day; otherwise, it is zero
$\theta$: The most significant number of times a nonemergency patient's treatment schedule can be altered

(xiii) Decision variables:

$x_{postd}$: If the $p$ th patient's operation is started in the operating room by the $s$ th surgeon in the $t$ th time block on the dth day, $x_{postd}$ is one; otherwise, it is zero
$\overline{x}_{postd}$: If the $p$ th patient's operation is done in the operating room by the $s$ th surgeon in the $t$ th time block on the $d$ th day, $\overline{x}_{postd}$ equals one; otherwise, it equals zero

$y_{pd}$: If the $p$ th patient is admitted to the intensive care unit (ICU) on the dth day, $y_{pd}$ equals one; otherwise, it equals zero
$\overline{y}_{pd}$: If the $p$ patient is in the intensive care unit (ICUs) on the $d$ th day, $\overline{y}_{pd}$ is one; otherwise, it is zero
$Z_d$: The number of intensive care beds in limited supply on the $d$ th day
$\gamma_{p'}$: If the treatment plan for the $p$'th nonemergency patient is altered, $\gamma_{p'}$ equals one; otherwise, it equals zero
$\alpha_{od}$: The length of time on the $d$ th day that the operating room will not be used
$\beta_{od}$: On the $d$ th day, the amount of time to misuse the operation room

(xiv) Mathematical model.

(xv) This section contains a list of patients.

$p$: All patients, including patients, are gathered
$q$: Compile a list of all infected patients
$q'$: All noninfectious patients are gathered
$p'$: All nonemergency patients are gathered

This area does not have any emergency patients; only the capacity is set aside for them.

$$\operatorname{Min} Z = \sum_{p=1}^{P}\sum_{o=1}^{O}\sum_{s=1}^{S}\sum_{t=1}^{T}\sum_{d=1}^{D} C_{pos} \times x_{postd} + \sum_{o=1}^{O}\sum_{d=1}^{D} EC_{od} \times \alpha_{od} + \sum_{o=1}^{O}\sum_{d=1}^{D} LC_{od} \times \beta_{od} + \sum_{d=1}^{D} U_d \times Z_d, \tag{5}$$

$$\sum_{o=1}^{O}\sum_{s=1}^{S}\sum_{t=1}^{T}\sum_{d=1}^{D} x_{postd} = 1\ \forall p, \tag{6}$$

$$\overline{x}_{postd} = \sum_{t'=\max\left(t-du_p+1,1\right)}^{t} x_{post'd} \forall\ p, o, s, t, d, \tag{7}$$

$$\sum_{\substack{p=1 \\ p\neq q}}^{P}\sum_{s=1}^{S}\sum_{t=t'}^{t'+du_q+cl_q-1} x_{postd} \le 1 - \sum_{s=1}^{S} x_{qost'd} \forall\ q, o, t', d, \tag{8}$$

$$\sum_{p=1}^{P}\sum_{s=1}^{S} \overline{x}_{postd} \le 1 \forall\ o, t, d, \tag{9}$$

$$\sum_{p=1}^{P}\sum_{o=1}^{O} \overline{x}_{postd} \le 1 \forall s, t, d, \tag{10}$$

$$\sum_{p=1}^{P}\sum_{o=1}^{O}\sum_{s=1}^{S}\sum_{t=1}^{T}\sum_{d=da_p+1}^{D} x_{postd} = 0, \tag{11}$$

$$\sum_{s=1}^{S}\sum_{t=1}^{T}\sum_{d=1}^{D} x_{postd} \le R_{po} \forall p, o, \tag{12}$$

$$\sum_{o=1}^{O}\sum_{t=1}^{T}\sum_{d=1}^{D} x_{postd} \le Q_{ps} \forall p, s, \tag{13}$$

$$\sum_{p'=1}^{P'}\sum_{o=1}^{O}\sum_{t=1}^{T} \overline{x}_{p'ostd} \le G \forall s, d, \tag{14}$$

$$\sum_{p'=1}^{P'}\sum_{s=1}^{S}\sum_{t=1}^{T} \overline{x}_{p'ostd} \le HN_{od} + HS_{od} \forall\ o, d, \tag{15}$$

$$\sum_{p'=1}^{P'}\sum_{s=1}^{S}\sum_{t=1}^{T} \overline{x}_{p'ostd} + \widetilde{HM}_{od} \le HN_{od} + HO_{od} \forall\ o, d, \tag{16}$$

$$\alpha_{od} \ge HN_{od} - \sum_{p=1}^{P}\sum_{s=1}^{S}\sum_{t=1}^{T} \overline{x}_{postd} \forall o, d, \tag{17}$$

$$\beta_{od} \ge \sum_{p'=1}^{P'}\sum_{s=1}^{S}\sum_{t=1}^{T} \overline{x}_{postd} - HN_{od} \forall o, d, \tag{18}$$

$$\sum_{p'=1}^{P'}\sum_{o=1}^{O}\sum_{t=1}^{T}\sum_{d=1}^{D} \overline{x}_{p'ostd} \le MT_s^{max} \forall\ s, d, \tag{19}$$

$$\sum_{o=1}^{O}\sum_{s=1}^{S}\sum_{t=1}^{T} \overline{x}_{postd} \le M \times y_{pd} \forall p, d, \tag{20}$$

$$\overline{y}_{p\,d} = \sum_{d'=\max\left(d-dI_p+1,1\right)}^{d} y_{pd'} \forall p, d, \tag{21}$$

$$\sum_{p'=1}^{P'} \overline{y}_{p'd} + \widetilde{WICU}_d \le \widetilde{Cicu}_d + Z_d \forall\ d, \tag{22}$$

$$1 - \sum_{q'=1}^{Q'}\sum_{s=1}^{S}\sum_{t=t'+1}^{T} x_{q'ostd} \ge \sum_{s=1}^{S} x_{qost'd} \forall\ q, o, t', d. \tag{23}$$

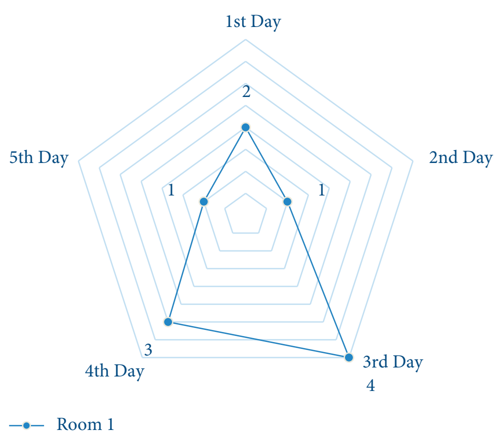



Figure 4: The amount of time allowed to work for room 1 and each day.

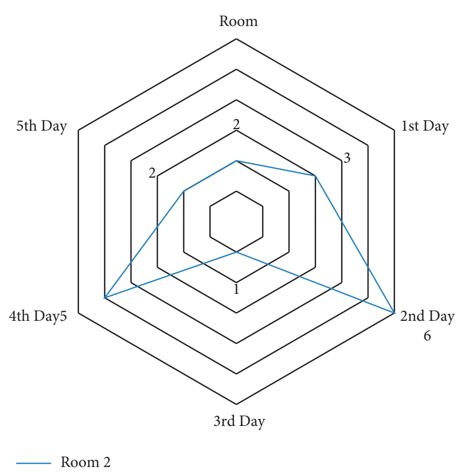



Figure 5: The amount of time allowed to work for room 2 and each day.

Equation (5)'s goal is to reduce the expense of assigning patients to many ORs and surgeons, not utilizing and overusing multiple ORs, and the cost of overusing an intensive care unit. Restriction (6) guarantees that each patient (including emergency and nonemergency) is allocated to a particular operating room and surgeon on a given day and for a specific amount of time. Restriction (7) guarantees that each patient receives the appropriate time blocks for time block surgery. Limit (8) guarantees that each operating room is cleaned after surgery for each contaminated patient for at least $cl_q$ minutes. Limit (9) indicates that each operating room can only execute one surgery during each time block in a day. Restriction (10) specifies that each surgeon can only do one surgery in one operating room during each time block in a day. Restriction (11) guarantees that each patient is allocated to a specific operating room and

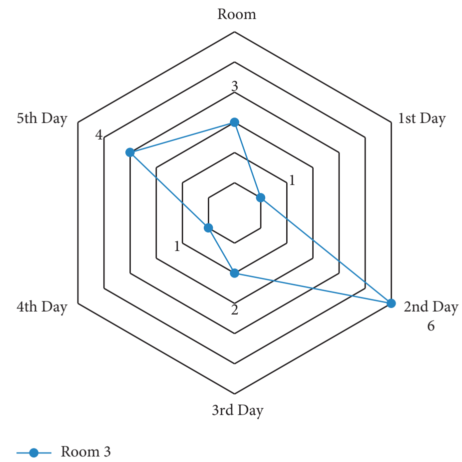



Figure 6: The amount of time allowed to work for room 3 and each day.

surgeon before a deadline. Restrictions (12) and (13) guarantee that each patient is allocated to a particular operating room and surgeon. Restriction (14) guarantees that physicians do not work more than a specific number of hours per day on nonemergency patients. Patients can utilize each operating room as much as they like in emergency and nonemergency situations, according to restrictions (15) and (16). Restrictions (17) and (18) measure the amount of time that operating rooms are overused and underutilized for nonemergency patients on various days. The restriction (19) is linked to surgeons' maximum working hours. It regulates the amount of time on nonemergency patients. Restriction (20) guarantees that each patient who has surgery is admitted to the critical care unit. The restriction above (21) guarantees that each patient receives a bed in an intensive care unit (ICU) for the number of days necessary for admission. Restriction (22) estimates the number of bed limitations for emergency and nonemergency patients based on the intensive care unit's capacity. Daily, restriction (23) guarantees that infected patients are the last patients allocated to operating rooms.

## 4. Computational Results

A small-scale instance is presented for each suggested model in this part to comprehend and verify the concepts above. In the first half of the instance, there are three operating rooms and three surgeons. Each day is separated into six time periods. Ten patients were scheduled in different operating rooms and intensive care units, comprising eight chosen patients and three infectious patients (patients 1, 2, and 3). The number of time intervals permitted to work for each room each day $HN_{od}$ is different in this case. Over time, it is deemed if the patient's room allotment exceeds this amount (see Figures 4–7).

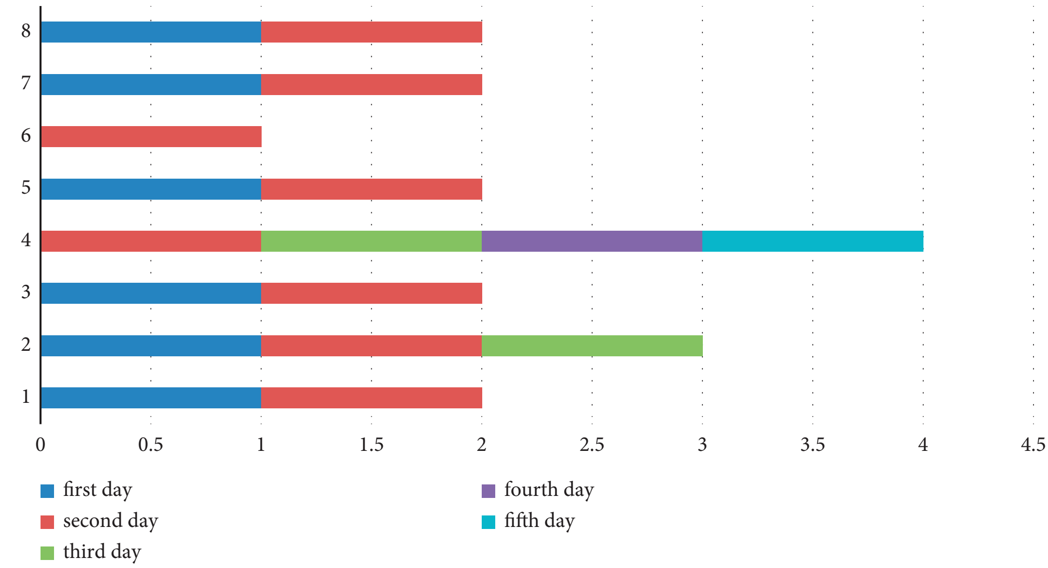



Figure 7: Intensive care schedule (part 1).

Table 2: Calculation of the objective function.

| The value of the objective function | Solving time (seconds) |
|---|---|
| 3569 | 0.0085 |

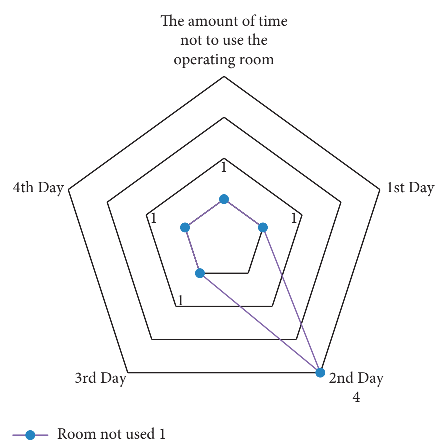



Figure 8: The amount of time not to use the operating room 1.

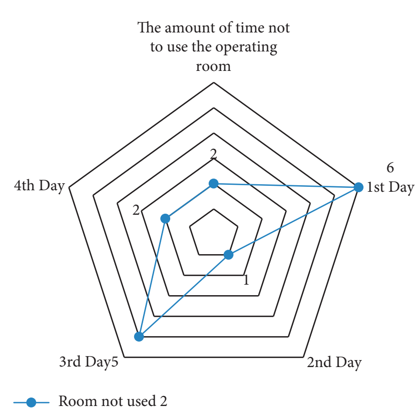



Figure 9: The amount of time not to use the operating room 2.

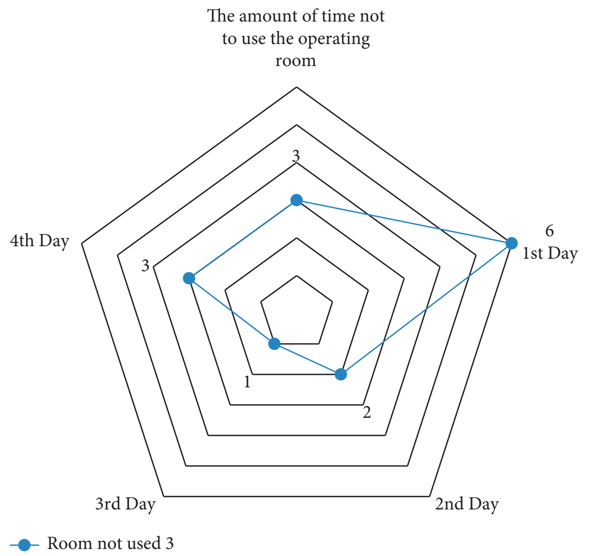



Figure 10: The amount of time not to use the operating room 3.

The results are derived from the GAMS program output (see Figures 8–10).

## 5. Discussion

Compared to other sectors, healthcare quality assessment is doubly important due to the sensitivity of the services provided in this area on the one hand due to their relationship with death and life of individuals and on the other hand due to the asymmetry of information between providers and patients. Along with reducing the length of hospital stays, improving the quality of healthcare can also reduce mortality. Healthcare system managers can identify their opportunities and weaknesses with a tool that measures patient expectations and perceptions. A manager who identifies and covers service quality gaps will likely increase customer satisfaction by increasing customer perception of service quality. From the point of view of outpatients, not all aspects of service quality were in good condition. This indicates a gap between the expectations and perceptions of clients of the quality of services provided in this center, which needs to be improved in all its dimensions. For this reason, it is suggested that managers pay more attention to patients' needs and provide appropriate services to reduce the existing quality gap. Trying to reduce the gap between patients' expectations and perceptions will lead to greater satisfaction and ultimately loyalty and return to the organization. Also, by using the SERVQUAL model (as one of the quality measurement tools), managers are able to evaluate the quality of services from the perspective of patients as the most important customers, and with proper planning and correction of existing disorders and weaknesses, ultimately improved service quality is possible. Based on the literature review described above, the performance of outpatient facilities in the different departments evaluated in the healthcare clinic has greatly improved. To improve the efficiency of outpatient care, various techniques such as scheduling, modeling, and artificial intelligence are used to create a patient-centered appointment cycle. Treatment duration varies greatly depending on the patient. The challenge is choosing which model is more effective despite the fact that we have studied several articles and shown the benefits of several models. Since many scientists in this field have conducted simulation work, we can conclude that separate event simulation offers the most advantages and a better understanding of how to overcome the restrictions. In general, discrete-event simulation is an effective method of coordinating the many scheduling techniques required for healthcare. It also has a larger scale than classical Markov chain optimization, which makes it perfect for this application. It is imperative that our industry meet the rigorous design criteria that decision-makers will accept because the dangers are minimal and straightforward.

## 6. Conclusion and Limitation

Healthcare in the United States is complicated and expensive. Therefore, there are many opportunities for researchers from a variety of disciplines to contribute to the improvement of healthcare systems. A hospital's operating room (OR) generates the most income and expense, according to healthcare analysts. In this study, we looked at existing modeling techniques for outpatient appointment scheduling in the healthcare industry. More than 200 publications are examined in this respect better to understand outpatient appointment scheduling issues in the literature. Researchers have paid great attention to the scheduling issue in the twenty-first century. Published technical OR scheduling publications have steadily increased since 2000. Rather than that, it reflects the diversity of viewpoints and healthcare contexts around the world on the issue. The reader may see an increasing trend of study interest in recent years (Figure 1) due to expanded hospital resources based on the data reports provided in this research. Despite the abundance of literature on outpatient appointment scheduling, there are several ways to enhance the current research, such as establishing planning models, performance metrics, and forecasting skills under various generalized situations. More research, for example, may be designed to focus on developing timetables that can be performed successfully on this issue.

It may be possible to create alternative healthcare access solutions by understanding scheduling systems' performance dynamics. It is necessary to have a different area of inspection in order to reduce overbooking. Healthcare access and service delivery will likely be scrutinized more closely by the general public due to their desire to improve. Mathematics can also be used to model numerous providers, such as double bookings, overtime expenses, and increasing the effectiveness time of visiting doctors. A mathematical model for the patient admission scheduling problem with stochastic arrivals and departures is the subject of this study. We discuss how we can apply our model to real-world problems. We present a solution technique for efficient computing, a numerical model analysis, and examples to demonstrate the method. In this study, we examined the challenge of assigning procedures to operating rooms in the face of ambiguity regarding surgery length and emergency arrivals based on a flexible policy (capacity reservations).

Using simple numerical examples, we demonstrate that the proposed methods derived from deterministic models are inadequate compared to the answers obtained from our stochastic model. Similarly, we use heuristics to estimate the objective function to build more complicated numerical examples for large-scale issues, showing that our methodology can be applied quickly to real-world situations. [30, 77].

*6.1. Future Work.* Researchers should examine how outpatients and walk-ins unexpectedly arrive at clinics, disrupting operations. A discrete-event simulation technique is often used in healthcare for real-time decision-making but is rarely discussed publicly. In healthcare applications, such as screening and illness management, discrete-event simulation is the most accurate modeling method. Let's use a version of healthcare optimization. In such a case, different patients must be convinced of their benefits and limitations within the healthcare industry. Further studies are needed to evaluate how walk-in outpatients affect the timeliness of scheduled arrivals in greater detail. A further area of future investigation would be the formulation of sequencing issues based on individual unpunctuality habits. A game theory approach could be used to extend current models to account for physicians, nurses, and patients' unpredictable behavior. As a research gap, scheduling difficulties during outpatient appointments might be used to simulate the multistage health process, like the initial examination, drug test, and preparation of patients, or to optimize multivisit schedules in clinics.

## Data Availability

Data are available and can be provided over the emails querying directly to the corresponding author (mohsenasghari1990@ut.ac.ir).

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## References

[1] M. E. Zonderland and R. J. Boucherie, "A survey of literature reviews on patient planning and scheduling in healthcare," *International Series in Operations Research & Management Science*, vol. 302, pp. 17–23, 2021.

[2] Z. Xie and C. Or, "Associations between waiting times, service times, and patient satisfaction in an endocrinology outpatient department: a time study and questionnaire survey," *Inquiry: The Journal of Health Care Organization, Provision, and Financing*, vol. 54, 2017.

[3] H.-J. Oh, A. Muriel, H. Balasubramanian, K. Atkinson, and T. Ptaszkiewicz, "Guidelines for scheduling in primary care under different patient types and stochastic nurse and provider service times," *IIE Transactions on Healthcare Systems Engineering*, vol. 3, no. 4, pp. 263–279, 2013.

[4] T. Cayirli, E. Veral, and H. Rosen, "Assessment of patient classification in appointment system design," *Production and Operations Management*, vol. 17, no. 3, pp. 338–353, 2008.

[5] A. J. Forster, I. Stiell, G. Wells, A. J. Lee, and C. Van Walraven, "The effect of hospital occupancy on emergency department length of stay and patient disposition," *Academic Emergency Medicine*, vol. 10, no. 2, pp. 127–133, 2003.

[6] M. Mahdavi, M. Parsaeian, E. Jaafaripooyan, and S. Ghaffari, "Recent Iranian health system reform: an operational perspective to improve health services quality," *International Journal of Health Policy and Management*, vol. 7, no. 1, pp. 70–74, 2018.

[7] S. T. T. Nguyen, E. Yamamoto, M. T. N. Nguyen et al., "Waiting time in the outpatient clinic at a national hospital in Vietnam," *Nagoya Journal of Medical Science*, vol. 80, no. 2, p. 227, 2018.

[8] V. Roshanaei, C. Luong, D. M. Aleman, and D. R. Urbach, "Reformulation, linearization, and decomposition techniques for balanced distributed operating room scheduling," *Omega*, vol. 93, p. 102043, 2020.

[9] D. J. Morrice, D. Wang, J. F. Bard, L. K. Leykum, S. Noorily, and P. Veerapaneni, "A patient-centered surgical home to improve outpatient surgical processes of care and outcomes," *IIE Transactions on Healthcare Systems Engineering*, vol. 4, no. 3, pp. 119–134, 2014.

[10] H. Zhu, Y. Chen, E. Leung, and X. Liu, "Outpatient appointment scheduling with unpunctual patients," *International Journal of Production Research*, vol. 56, no. 5, pp. 1982–2002, 2018.

[11] J. T. Blake and M. W. Carter, "Surgical process scheduling: a structured review," *Journal of the Society for Health Systems*, vol. 5, no. 3, pp. 17–30, 1997.

[12] K. S. Shehadeh and R. Padman, "Stochastic optimization approaches for elective surgery scheduling with downstream capacity constraints: models, challenges, and opportunities," *Computers & Operations Research*, p. 105523, 2021.

[13] K. A. Safdar, A. Emrouznejad, and P. K. Dey, "An optimized queue management system to improve patient flow in the absence of appointment system," *International Journal of Health Care Quality Assurance*, 2020.

[14] M. Samorani and S. Ganguly, "Optimal sequencing of unpunctual patients in high-service-level clinics," *Production and Operations Management*, vol. 25, no. 2, pp. 330–346, 2016.

[15] M. Bam, B. T. Denton, M. P. Van Oyen, and M. E. Cowen, "Surgery scheduling with recovery resources," *IISE Transactions*, vol. 49, no. 10, pp. 942–955, 2017.

[16] M. Rezaeiahari and M. T. Khasawneh, "Simulation optimization approach for patient scheduling at destination medical centers," *Expert Systems with Applications*, vol. 140, p. 112881, 2020.

[17] I. Marques, M. E. Captivo, and M. Vaz Pato, "Scheduling elective surgeries in a Portuguese hospital using a genetic heuristic," *Operations Research for Health Care*, vol. 3, no. 2, pp. 59–72, 2014.

[18] S. Nayeri, S. Ali Torabi, M. Tavakoli, and Z. Sazvar, "A multi-objective fuzzy robust stochastic model for designing a sustainable-resilient-responsive supply chain network," *Journal of Cleaner Production*, vol. 311, p. 127691, 2021.

[19] R. Guido and D. Conforti, "A hybrid genetic approach for solving an integrated multi-objective operating room planning and scheduling problem," *Computers & Operations Research*, vol. 87, pp. 270–282, 2017.

[20] E. W. Hans and P. T. Vanberkel, "Operating theatre planning and scheduling," in *Handbook of Healthcare System Scheduling*, pp. 105–130, Springer, Boston, MA, USA, 2012.

[21] N. Al Talalwah, K. H. McIltrot, and A. Al Ghamdi, "Elective surgical cancellations in a tertiary hospital in the Middle East:

quality improvement process," *Journal of PeriAnesthesia Nursing*, vol. 34, no. 2, pp. 310–321, 2019.

[22] J. M. Molina-Pariente, V. Fernandez-Viagas, and J. M. Framinan, "Integrated operating room planning and scheduling problem with assistant surgeon dependent surgery durations," *Computers & Industrial Engineering*, vol. 82, pp. 8–20, 2015.

[23] G. Latorre-Núñez, A. Lüer-Villagra, V. Marianov, C. Obreque, F. Ramis, and L. Neriz, "Scheduling operating rooms with consideration of all resources, post anesthesia beds and emergency surgeries," *Computers & Industrial Engineering*, vol. 97, pp. 248–257, 2016.

[24] C. K. Y. Lin, T. W. C. Ling, and W. K. Yeung, "Resource allocation and outpatient appointment scheduling using simulation optimization," *Journal of Healthcare Engineering*, 2017.

[25] N. Szander, L. Ros-McDonnell, M. de-la-Fuente-Aragón, and R. Vodopivec, "Sustainable urban homecare delivery with different means of transport," *Sustainability*, vol. 10, no. 2, p. 398, 2018.

[26] C. N. Stamps, *Exploring Retention of united states-based Inbound Call center Employees: A Case Study*, Grand Canyon University, ProQuest Dissertations Publishing, 2014.

[27] S. Wright, J. Barlow, and J. K. Roehrich, "Public-private partnerships for health services: construction, protection and rehabilitation of critical healthcare infrastructure in Europe," in *Public Private Partnerships*, pp. 125–151, Springer, Cham, 2019.

[28] A. G. Leeftink, I. M. H. Vliegen, and E. W. Hans, "Stochastic integer programming for multi-disciplinary outpatient clinic planning," *Health Care Management Science*, vol. 22, no. 1, pp. 53–67, 2019.

[29] X. Shang, X. Lining, W. Ling, and Z. Kai, "Comprehensive learning pigeon-inspired optimization with tabu list," *Science China Information Sciences*, vol. 62, no. 7, 2019.

[30] C. F. Chien, Y. C. Huang, and C. H. Hu, "A hybrid approach of data mining and genetic algorithms for rehabilitation scheduling," *International Journal of Manufacturing Technology and Management*, vol. 16, no. 1-2, pp. 76–100, 2009.

[31] J. Vissers, "Selecting a suitable appointment system in an outpatient setting," *Medical Care*, vol. 17, no. 12, pp. 1207–1220, 1979.

[32] C. Granja, B. Almada-Lobo, F. Janela, J. Seabra, and A. Mendes, "An optimization based on simulation approach to the patient admission scheduling problem using a linear programing algorithm," *Journal of Biomedical Informatics*, vol. 52, pp. 427–437, 2014.

[33] W. Cao, Y. Wan, H. Tu et al., "A web-based appointment system to reduce waiting for outpatients: a retrospective study," *BMC Health Services Research*, vol. 11, no. 1, 325 pages, 2011.

[34] B. A. Walters and K. Danis, "Patient online at dartmouth-hitchcock–interactive patient care web site," *AMIA Annual Symposium Proceedings*, vol. 2003, p. 1044, 2003.

[35] X. Wu, J. Li, R. Xu, and T. Yu, "A simulation study of appointment scheduling for multi-class MRI examination," in *Proceedings of the 2016 13th International Conference on Service Systems and Service Management (ICSSSM)*, pp. 1–6, IEEE, Kunming, China, 2016.

[36] K. E. Harding and J. Bottrell, "Specific timely appointments for triage reduced waiting lists in an outpatient physiotherapy service," *Physiotherapy*, vol. 102, no. 4, pp. 345–350, 2016.

[37] T. Rohleder and K. J. Klassen, "Using client-variance information to improve dynamic appointment scheduling performance," *Omega*, vol. 28, no. 3, pp. 293–302, 2000.

[38] Q. Kong, S. Li, N. Liu, C. P. Teo, and Z. Yan, "Appointment scheduling under time-dependent patient no-show behavior," *Management Science*, 2020 Mar 4.

[39] L. Liu, H. Xiang, and X. Li, "A novel perturbation method to reduce the dynamical degradation of digital chaotic maps," *Nonlinear Dynamics*, vol. 103, no. 1, pp. 1099–1115, 2021.

[40] Z. Wu, C. Li, J. Cao, and Y. Ge, "On scalability of association-rule-based recommendation: a unified distributed-computing framework," *ACM Transactions on the Web (TWEB)*, vol. 14, no. 3, pp. 1–21, 2020.

[41] Z. Wu, A. Song, J. Cao, J. Luo, and L. Zhang, "Efficiently translating complex SQL query to mapreduce jobflow on cloud," *IEEE transactions on cloud computing*, vol. 8, no. 2, pp. 508–517, 2020.

[42] A. Sharifi, M. Ahmadi, M. A. Mehni, S. Jafarzadeh Ghoushchi, and Y. Pourasad, "Experimental and numerical diagnosis of fatigue foot using convolutional neural network," *Computer Methods in Biomechanics and Biomedical Engineering*, vol. 24, no. 16, pp. 1828–1840, 2021.

[43] M. Q. H. Abadi, S. Rahmati, A. Sharifi, M. Ahmadi, and M. Ahmadi, "HSSAGA: designation and scheduling of nurses for taking care of COVID-19 patients using novel method of hybrid salp swarm algorithm and genetic algorithm," *Applied Soft Computing*, vol. 108, Article ID 107449, 2021.

[44] E. Eslami and H. B. Yun, "Attention-based multi-scale convolutional neural network (A+ MCNN) for multi-class classification in road images," *Sensors*, vol. 15, p. 5137, 2021.

[45] W. Zheng, Y. Xun, X. Wu, Z. Deng, X. Chen, and Y. Sui, "A comparative study of class rebalancing methods for security bug report classification," *IEEE Transactions on Reliability*, vol. 70, no. 4, pp. 1658–1670, 2021.

[46] A. Diamant, J. Milner, and F. Quereshy, "Dynamic patient scheduling for multi-appointment health care programs," *Production and Operations Management*, vol. 27, no. 1, pp. 58–79, 2018.

[47] F. A. Chervenak, L. B. McCullough, and L. B. McCullough, "How extreme religiosity and nationalism are predatory on the biopsychosocial health of patients and the professionalism of physicians," *Psychiatria Danubina*, vol. 32, no. 1, pp. 122-123, 2020.

[48] A. Davoudi, M. Ahmadi, A. Sharifi et al., "Studying the effect of taking statins before infection in the severity reduction of COVID-19 with machine learning," *BioMed Research International*, vol. 2021, Article ID 9995073, 12 pages, 2021.

[49] Q. Jia and C. Liu, "Intelligent scheduling method of port vehicles based on probability information," *Journal of Coastal Research*, vol. 103, no. 1, pp. 726–729, 2020.

[50] Y. Moshtaghi, M. Shariat Panahi, and E. Sadeghi Poor, "Intelligent detection of intrusion into databases using extended classifier system," *International Journal of Electrical & Computer Engineering*, vol. 3, p. 5, 2013.

[51] M. Rezaei, F. Farahanipad, A. Dillhoff, R. Elmasri, and V. Athitsos, "Weakly-supervised hand part segmentation from depth images," in *Proceedings of the 14th PErvasive Technologies Related to Assistive Environments Conference*, pp. 218–225, 2021.

[52] E. Sadeghipour and H. Ahmad, "Designing an intelligent system for diagnosing diabetes with the help of the XCSLA system," *Journal of Mathematics and Computer Science*, vol. 14, 2014.

[53] M. Ahmadi, F. Dashti Ahangar, N. Astaraki, M. Abbasi, and B. Babaei, "FWNNet: presentation of a new classifier of brain tumor diagnosis based on fuzzy logic and the wavelet-based neural network using machine-learning methods,"

*Computational Intelligence and Neuroscience*, vol. 2021, Article ID 8542637, 13 pages, 2021.
[54] R. F. Slocum, H. L. Jones, M. T. Fletcher et al., "Improving chemotherapy infusion operations through the simulation of scheduling heuristics: a case study," *Health Systems*, vol. 19, no. 1, pp. 65–98, 2022.
[55] Y. Deng and S. Sen, "Predictive stochastic programming," *Computational Management Science*, vol. 19, no. 1, pp. 65–98, 2021.
[56] P.-S. Chen, R. A. C. Robielos, P. K. V. C. Palaña, P. L. L. Valencia, and G. Y.-H. Chen, "Scheduling patients' appointments: allocation of healthcare service using simulation optimization," *Journal of healthcare engineering*, vol. 6, no. 2, pp. 259–280, 2015.
[57] F. Ben Abdelaziz and M. Masmoudi, "A multiobjective stochastic program for hospital bed planning," *Journal of the Operational Research Society*, vol. 63, no. 4, pp. 530–538, 2012.
[58] B. Akbarzadeh and B. Maenhout, "An exact branch-and-price approach for the medical student scheduling problem," *Computers & Operations Research*, vol. 129, p. 105209, 2021.
[59] M. D. Tobias Else, M. D. Robert Chang, and M. D. Nathan Houchens, "A branching algorithm," *Journal of Hospital Medicine*, vol. 14, no. 11, p. 707, 2019.
[60] L. En-nahli, S. Afifi, H. Allaoui, and I. Nouaouri, "Local search analysis for a vehicle routing problem with synchronization and time windows constraints in home health care services," *IFAC-PapersOnLine*, vol. 49, no. 12, pp. 1210–1215, 2016.
[61] J. Castaing, A. Cohn, B. T. Denton, and A. Weizer, "A stochastic programming approach to reduce patient wait times and overtime in an outpatient infusion center," *IIE Transactions on Healthcare Systems Engineering*, vol. 6, no. 3, pp. 111–125, 2016.
[62] G. Cavone, M. Dotoli, N. Epicoco, and C. Seatzu, "A decision making procedure for robust train rescheduling based on mixed integer linear programming and Data Envelopment Analysis," *Applied Mathematical Modelling*, vol. 52, pp. 255–273, 2017.
[63] S. R. Earnshaw and S. L. Dennett, "Integer/linear mathematical programming models," *PharmacoEconomics*, vol. 21, no. 12, pp. 839–851, 2003.
[64] M. Papi, L. Pontecorvi, R. Setola, and F. Clemente, "Stochastic dynamic programming in hospital resource optimization," in *Proceedings of the International Conference on Optimization and Decision Science*, pp. 139–147, Springer, Cham, 2017, September.
[65] A. Jafarbigloo, *Optimization and Simulation of the Medical Device Sterilization in Hospitals (Doctoral Dissertation)*, Université d'Ottawa/University of Ottawa, 2021.
[66] L. S. L. Bastos, J. F. Marchesi, S. Hamacher, and J. L. Fleck, "A mixed integer programming approach to the patient admission scheduling problem," *European Journal of Operational Research*, vol. 273, no. 3, pp. 831–840, 2019.
[67] S. H. Jacobson, S. N. Hall, and J. R. Swisher, "Discrete-event simulation of health care systems," in *Patient Flow: Reducing Delay in Healthcare Delivery*, pp. 211–252, Springer, Boston, MA, 2006.
[68] A. M. Yemane, H. A. Heniey, and K. G. Gebrehiwet, "Performance measurement and improvement of healthcare service using discrete event simulation in bahir dar clinic," *Journal of Optimization in Industrial Engineering*, vol. 14, no. 2, pp. 57–67, 2021.
[69] M. Murray, T. Bodenheimer, D. Rittenhouse, and K. Grumbach, "Improving timely access to primary care," *JAMA*, vol. 289, no. 8, pp. 1042–1046, 2003.
[70] D. Gupta, "Queueing models for healthcare operations," in *Handbook of Healthcare Operations Management*, pp. 19–44, Springer, New York, NY, 2013.
[71] K. Anderson, B. Zheng, S. W. Yoon, and M. T. Khasawneh, "An analysis of overlapping appointment scheduling model in an outpatient clinic," *Operations Research for Health Care*, vol. 4, pp. 5–14, 2015.
[72] S. Reddy, S. Allan, S. Coghlan, and P. Cooper, "A governance model for the application of AI in health care," *Journal of the American Medical Informatics Association*, vol. 27, no. 3, pp. 491–497, 2020.
[73] H. F. Dalky, N. Ghader, M. Al Kuwari et al., "Assessment of the awareness, perception, attitudes, and preparedness of health-care Professionals potentially exposed to COVID-19 in the United Arab Emirates," *Journal of Multidisciplinary Healthcare*, vol. 14, pp. 91–102, 2021.
[74] A. Ahmadi-Javid, P. Seyedi, and S. S. Syam, "A survey of healthcare facility location," *Computers & Operations Research*, vol. 79, pp. 223–263, 2017.
[75] E. Pérez and D. P. Dzubay, "A scheduling-based methodology for improving patient perceptions of quality of care in intensive care units," *Health Care Management Science*, vol. 24, no. 1, pp. 203–215, 2021.
[76] H. K. O. Eriksson, "Insights into physician scheduling: a case study of public hospital departments in Sweden," *International Journal of Health Care Quality Assurance*, vol. 27, no. 2, 2014.
[77] R. Jain, M. Gupta, A. Nayyar, and N. Sharma, "Adoption of fog computing in healthcare 4.0," in *Fog Computing for Healthcare 4.0 Environments*, pp. 3–36, Springer, Cham, 2021.

Hindawi
Journal of Healthcare Engineering
Volume 2022, Article ID 2170839, 11 pages
https://doi.org/10.1155/2022/2170839

*Research Article*

# LSGDM with Biogeography-Based Optimization (BBO) Model for Healthcare Applications

**A. Harshavardhan,[1] Prasanthi Boyapati,[2] S. Neelakandan,[3] Alhassan Alolo Abdul-Rasheed Akeji,[4] Aditya Kumar Singh Pundir,[5] and Ranjan Walia[6]**

[1]*Department of CSE, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India*
[2]*Department of CSE, R.V.R & J.C College of Engineering, Guntur, India*
[3]*Department of CSE, R.M.K Engineering College, Chennai, India*
[4]*Department of Marketing and Corporate Strategy, Tamale Technical University, Tamale, Ghana*
[5]*Department of ECE, Arya College of Engineering and Information Technology, Jaipur, India*
[6]*Department of Electrical Engineering, Model Institute of Engineering and Technology, Jammu, India*

Correspondence should be addressed to Alhassan Alolo Abdul-Rasheed Akeji; aaakeji@tatu.edu.gh

Received 19 February 2022; Revised 26 March 2022; Accepted 7 April 2022; Published 30 April 2022

Academic Editor: Mohsen Ahmadi



Several studies aimed at improving healthcare management have shown that the importance of healthcare has grown in recent years. In the healthcare industry, effective decision-making requires multicriteria group decision-making. Simultaneously, big data analytics could be used to help with disease detection and healthcare delivery. Only a few previous studies on large-scale group decision-making (LSDGM) in the big data-driven healthcare Industry 4.0 have focused on this topic. The goal of this work is to improve healthcare management decision-making by developing a new MapReduce-based LSDGM model (MR-LSDGM) for the healthcare Industry 4.0 context. Clustering decision-makers (DM), modelling DM preferences, and classification are the three stages of the MR-LSDGM technique. Furthermore, the DMs are subdivided using a novel biogeography-based optimization (BBO) technique combined with fuzzy C-means (FCM). The subgroup preferences are then modelled using the two-tuple fuzzy linguistic representation (2TFLR) technique. The final classification method also includes a feature extractor based on long short-term memory (LSTM) and a classifier based on an ideal extreme learning machine (ELM). MapReduce is a data management platform used to handle massive amounts of data. A thorough set of experimental analyses is carried out, and the results are analysed using a variety of metrics.

## 1. Introduction

Recent technologies, such as big data, the internet of things (IoT), wearables, and so on, have a significant impact on society, healthcare organisations, and our daily lives. Big data plays an important role in obtaining the necessary data during the decision-making process. Big data is defined as a complex and massive volume of data derived from various sources and clinical data sets that provide critical information for patient treatment [1]. Furthermore, big data has the potential to improve healthcare operations through data-driven decision-making in the ambiguous environment of Industry 4.0. Big data analytics provide significant benefits for evaluating and assimilation of massive amounts of complex healthcare data. The medical system keeps track of the world's most pressing social and economic issues in order to find innovative solutions through technology and science. The Industry 4.0 model was first proposed in 2011, and it was initially referred to as the production or manufacturing process. While incorporating, medical services and Industry 4.0 are complementary methodologies. Furthermore, with the rise of big data and the widespread use of electronic healthcare records of patients in healthcare organisations, chasing solutions to population medical problems is no longer viable. Using big data for better decision-making, on the other hand, poses some healthcare challenges.

In recent years, group decision-making has received a lot of attention in various areas of healthcare organisations [2]. The more severe the challenge, the more complex it can withstand the loss caused by a decision-making error. As a result, many civil organisations and government departments, as well as managers and experts in various fields, would be involved in decision-making. Based on the preferences of decision-makers, LSGDM selects sufficient alternates from a group of possible alternates [3]. When the number of decision-makers (DM) increases, the standard group decision-making problem transforms into the LSGDM problem. LSGDM problem-solving methods typically consist of four phases: (i) the cluster standardised individual decision matrices, (ii) standardising original individual decision metrics, (iii) selecting the best alternatives, and (iv) aggregating the cluster decision metrics.

Based on the conventional decision-making method, the current study significantly innovates by incorporating four factors: distinct decision-makers' preference data expression, attribute weight determination method, large-scale group clustering method, and large group preference data aggregation method [4]. One of the most common fields of study is large-scale group preference data aggregation. Despite the fact that the number of studies deliberating big data is steadily increasing, applications of large-scale group decision-making procedures in the context of big data studies and medical Industry 4.0 remain rare. This work creates a new MapReduce-based LSDGM model (MR-LSDGM) for the Industry 4.0 environment to improve decision-making in healthcare management. With the rapid advancement of information technology, as exemplified by the Internet, decision support systems will evolve toward socialisation in the era of big data. This is because DMs from various areas can be invited to collaborate on difficult issues on a single network platform. Simultaneously, we can conduct online voting on a particular item and perform automated statistical analysis. Additionally, it may analyse and research multitemporal and group events, such as those on e-commerce websites and search engines, to provide critical data support for qualitative decision-making. It appears to be worthwhile to develop large-scale group support tools to aid in decision-making, given that the big data era may contain a variety of data sources, including social media, mobile devices, and websites. Several researchers have developed software implementations of LSGDM, including the WTALGDM for LSGDM on energy network dispatch optimization, MENTOR for visualizing opinion evolution, and a multiagent system model for assisting with CRP. Other application fields, such as healthcare and engineering, require the use of these tools. A large number of simulations are run to demonstrate the improved results of the MR-LSDGM technique, and the experimental findings are examined using several metrics.

## 2. Related Works

Li and Wei [5] created an LSGDM model for making medical management decisions. For describing the decision data, the HFLTS is used. For clustering the DM into many subgroups, a clustering technique based on the ideal point is presented. The DM preference is then combined with the PDEHFLTS model to retain the decision data. A subgroup weight method is proposed for calculating the ranking weight based on the subgroup size and the presented hesitant entropy of PDEHFLTS. For large-scale GDM problems, Li et al. [6] used a fuzzy cluster analysis to integrate heterogeneous data. Fuzzy cluster analysis is used to divide large groups into smaller ones, and F-statistics are used to calculate the number of clusters required. The original data is kept depending on the degree of similarity. A consensus-building process is then used among these smaller groups to reach a common understanding. While other groups could not agree, a feedback system was devised to update the smaller GDM matrix, and the TOPSIS model was used to select the best option.

Song and Yuan [7] proposed a new GDM method based on arithmetic programming and employing IMGFLPR. As a result, a consensus procedure based on IMGFLPR is developed, while dynamic adaptation of expert weights is considered. Finally, problems with emergency plan election are solved using the presented method, which demonstrates the effective outcome of GDM. Wan et al. [8], inspired by multiplayer game concepts, proposed a two-step optimization algorithm that first maximises individual fulfilment while minimizing group conflict. The provided approach effectively saves decision-making time when it comes to ensuring the quality of LSGDM.

Hsu et al. [9] identified eight potential developments for providing a proper approach to the medical industry. The modified Z-DEMATEL method is used to build the mutually important relationship and prioritises this trend. By optimising the classic fuzzy number and representing the assessment environments' confidence under uncertainty, the Z-number technique improves the consistency of expert evaluation. Liu et al. [10] developed an LGDA approach for managing dependency in HRA based on the interval two-tuple linguistic variable and cluster analysis model. In addition, an expanded Muirhead mean operator was developed to determine the amounts of reliance between the activities of consecutive operators. Finally, empirical medical dependency analysis is used to demonstrate the applicability and effectiveness of the presented LGDA model [11].

Du and Shan [12] proposed a dynamic intelligent integration suggestion approach for product ideas. They began by creating one-of-a-kind product concept assessment condition systems that included both output and input criteria. The following section describes a step for static data combination and data extraction. Later, the fundamental likelihood assignments function is used as a data extraction approach to accurately reflect and effectively capture the validity of experts' evaluations. Dursun et al. [13] proposed a fuzzy multicriteria GDM architecture based on the fuzzy integral and measure principle to evaluate the HCW treatment alternatives for Istanbul. In the case of the GDM problem, an expert consensus is required for the calculation method to be carried out correctly. The OWA operators are used in this work to aggregate DM opinions.

Pan et al. [14] concentrated on using dynamic programming to solve the large-scale GDM problem, in which the data is in the form of linguistic variables. Because the linguistic variable cannot be directly computed, the interval type-2 fuzzy set is used for encoding. The distinct similarity and distance models are then constructed concurrently in order to determine the relationship between the interval type-2 fuzzy set. Later, a dynamic programming approach based on clustering models was presented for clustering the DM from an overall perspective. Gao et al. [15] created a novel paradigm for selecting an appropriate physician in the index system that balances the 2D calculation result. The researchers created questionaries and conducted field research to bring the given technique closer to the actual situation in China. They then calculated the best outcome for the best medical services provided by doctors [16].

## 3. The Proposed MR-LSDGM Technique

The MapReduce tool is used in this study to create a new MR-LSDGM approach for the healthcare industry. The MR-LSDGM approach includes BBO-FCM-based DM clustering, 2TFLR-based preference modelling, and LSTM-OELM-based classification procedures. The proposed MR-LSDGM model is depicted in its entirety in Figure 1. The MapReduce tool is used by the MR-LSDGM approach to managing massive amounts of data in the healthcare industry. The sections that follow provide a more detailed explanation of these processes [17].

*3.1. MapReduce.* The primary goal of the Map procedure is to compute the geometric distance between cluster centres and sampling point data. Read the data from Hadoop Distributed File Systems (HDFS) and use the stated (value, key) pair input formats as Map function input values, where "key" denotes the sampling point data ID numbers and "value" means the entire data sampling point and then read the maximal consumption. The minimal distance approach would evaluate the major cluster centre, compute Euclidean distances between other cluster centres using sample point data, and integrate the membership degree (MD) [18].

The primary goal of Reduce functions, on the other hand, is to obtain a large number of Map function outputs. To begin, obtain the key values pair from the Map functions, where "key" represents the cluster centres and "value" represents the sampling point data equivalent to the cluster centres. The data sample from a number of distinct cluster centres is then merged, and a new cluster centre is evaluated. Finally, it is determined whether the geometric distance between the novel and equivalent cluster centres exceeds a

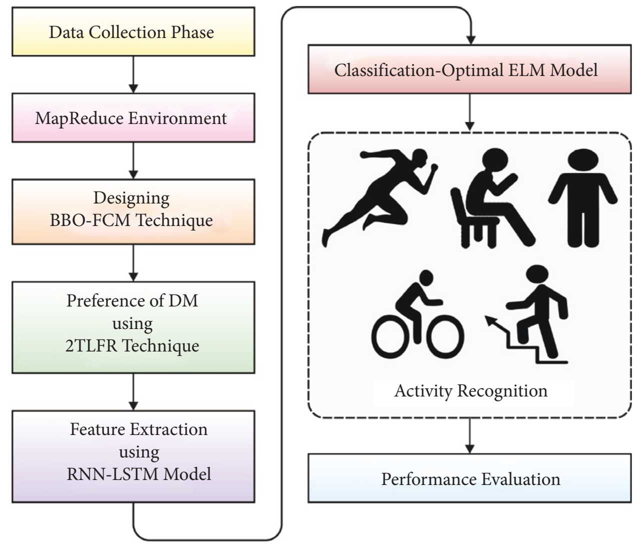



Figure 1: Overall process of MR-LSDGM model.

predetermined threshold or whether the number of iterations exceeds that threshold.

Despite outperforming traditional hard clustering algorithms in terms of clustering effects, fuzzy clustering algorithms have a few drawbacks. The current clustering algorithms are extremely sensitive to early clustering centres. Because the algorithms use the concept of gradual iteration, the objective functions are continuously reduced during the iteration. As a result, when the $c$ clustering centre is arbitrarily chosen in each sample data set at first, the geometric distance that would produce the last clustering results for falling to the current optimum solution is smaller. To avoid situations in which the geometric distance between the arbitrarily chosen cluster centre is smaller, the minimum and maximum distance methods were used to determine the early cluster centre in this study.

*3.2. Design of BBO-FCM Technique.* In the beginning, the BBO-FCM approach is used to divide the DMs into subgroups. Every feature vector with a coefficient between [0, 1] belongs to one of the FCM clusters. Finally, the algorithm labels all of the data points (feature vectors) based on the maximum coefficient of these data points across all clusters. By minimizing the following equation, the cluster centre and fuzzy membership matrix are calculated.

$$\sum_{g=1}^{c} u_{i,j} = 1, \tag{1}$$

where $u$ represents the sum of data; $c$ indicates the quantity of clusters; $u_{g,j}$ signifies the fuzzy association of $j$th point to $i$th clusters; $d_{g,j}$ means the cluster centres and data point $l \in (1, \infty)$, a fuzzy weight factor that determines the quantity of fuzziness produced as a result In most cases, and $l = 2$ is chosen (it can be stated that this value of $m$ does not generate optimum solutions for each problem).

Because of the constraints in (1), all points must completely allocate their memberships to each cluster [19]. The fuzzy weight centre of gravity of the data is used to define the cluster centre (centroid)X.

$$v_j = n\sum_{j=1}^{n} u_{i,j}, x^l x_j. \quad (2)$$

As $u_{g,j}$ influences the calculation of the cluster centres $v_i$, data with more memberships would have a greater influence on the prototype position than data with fewer memberships. Because $u(g, j)$ has an effect on the calculation of the cluster centres $v_i$, it is necessary to consider it. The distance $d\_$ is used in the fuzzy C-means technique $(g, j)$. Clustering using fuzzy logic (sometimes referred to as soft clustering or soft k-means) allows each individual data point to be assigned to more than one cluster. For fuzzy $C$-means approach, distance $d_{g,j}$ is determined by

$$d_{g,j}u^2 = \left\| x_j - v_i \right\|^2. \quad (3)$$

The cluster centre $v_i$ represents the common value of that cluster, where the $u_{g,j}$ components of the association matrix denote the range where the data point $x_j$ is related to its model. The minimalization of divide function (1) would derive the following equation:

$$\frac{d_{g,j}}{d_{g^j}}, x^{1/(l-1)} + u_{g,j} = \frac{1}{2}. \quad (4)$$

Equation (4) is defined in an iterative manner as the distance $d_{g,j}$ is based on membership $u_{i,k}$. The process to compute the FCM is given below:

(i) Opt for the number of cluster $c$, $2 \le c < n$; select $m$, $1 \le l < \infty$.Initialize$U^{(0)}$.
(ii) Compute the cluster centre $v_i$ by (2).
(iii) Compute the novel partition matrix $U^{(1)}$ by (4).
(iv) Relate $U^{(j)}$ & $U^{(j+1)}$. When the variations of the MD $u_{k,i}$ computed by proper standards are smaller when compared to the provided threshold, end the process and return to step (2).

The BBO algorithm is used to define the optimal initial cluster centre of the FCM technique. The BBO has a population-based optimised technique that simulates the development and the balance of predator and prey in different ecosystems. According to research, the BBO produces better results than the other population-based techniques [20]. This technique utilises the BBO algorithm to select the optimal initial cluster centre to use for its initial cluster centre determination process. For each setting, the BBO uses an optimal population-based technique to simulate development and the balance between predators and prey. It has been discovered through research that the BBO generates superior results when compared to other population-based approaches. From one iteration to the next, a collection of solutions is retained, and all habitats send and receive inhabitants. The various habitats are determined by their immigration and emigration rates, which are probabilistically modified. An arbitrary number of habitats are occasionally mutated during all iterations. All of the solution parameters are now referred to as suitability index variables (SIV). Simon was the first to propose the concept of a biogeography-based optimization method. Using the scientific understanding of migration and the dispersion of species from one habitat to another, this method has been devised and tested. Each location has a habitat suitability index (HSI), which is based on the concepts of this algorithm and acts in a similar way to the fitness function in other population-centred algorithms. In addition, the suitability index variables refer to the independent factors that are used to determine the suitability index of a settlement (SIV).

The mathematical method of immigration $(\lambda_k)$ and emigration $(\mu_k)$ is expressed as follows:

$$\begin{aligned} \lambda_k &= I\left(1 - \frac{S_k}{S_{\max}}\right), \\ \mu_k &= E\left(\frac{S_k}{S_{\max}}\right), \end{aligned} \quad (5)$$

where $I$ refers to the maximal rate of immigration, $E$ defines the maximal rate of emigration, $S_{\max}$ implies the maximal number of habitats, and $S_k$ represents the habitant count of $k$.

The following are the modifications to all habitats that improve the evaluation of BBO:

$$m(s) = m_{\max} \times \left(1 - \frac{P_n}{P_{\max}}\right), \quad (6)$$

where $m_{\max}$ represents the higher value of mutation determined as a user, $P_{\max}$ demonstrates the superior mutation probabilities of every habitat. and $P_n$ refers to the mutation probabilities of $n^{\text{th}}$ habitat that is given by

$$P'_n = \begin{cases} -(\lambda_n + \mu_n)P_n + \mu_{n+1}P_{n+1}, & n = 0; \\ -(\lambda_n + \mu_n)P_n + \mu_{n+1}P_{n+1} + \lambda_{n-1}P_{n-1}, & 1 \le n \le S_{\max} - 1 = 0; \\ -(\lambda_n + \mu_n)P_n + \lambda_{n-1}P_{n-1}, & n = S_{\max}. \end{cases} \quad (7)$$

At this point, $I: \overset{\varnothing \longrightarrow \{H^n, HSI^n\}}{}$ sets an ecosystem of habitat and calculates all equivalent HSIs, and $\Gamma = (n, m, \lambda, \tau, \Omega, M)$ describes the function that switches from one optimised cycle to the next. The six tuples of elements are described, where $n$ implies the number of habitats, $m$ refers to the number of SIVs, $\lambda$ represents the rate of immigration, $\tau$ demonstrates the rate of emigration, $\Omega$ refers to the migration function, and $M$ indicates the mutation operator.

*3.3. Modelling Preferences of DMs Using 2TLFR Technique.* Once the DMs have been clustered, their perspectives can be defined and fused using the 2TLFR technique to retain as much decision information as possible. Decision-making in healthcare is based on dynamic conditions and ambiguous information, and most decision-makers prefer linguistic variables or fuzzy values over hard numbers. In the two-tuple linguistic depiction method, the data measured in the linguistic hierarchy term set could be unified with no data loss.

*Definition 1.* $S = \{s_0, s_1, \ldots, s_g\}$ represents a linguistic term set; $\beta \epsilon [0, g]$ denotes the outcome of an aggregation index of a group of labels measured in $S. (s_\gamma, \alpha)$ indicates linguistic two tuples; $s_\gamma \epsilon S$ and $\alpha \epsilon [-0.5, 0.5]$; $s_\gamma$ characterises the linguistic label of the data; and $\alpha$ means the mathematical value that expresses the values of the translation from the original results $\beta$ to the nearest index label $\gamma$ in $S$, namely, the symbolic translation.

The following function converts mathematical numbers and linguistic two tuples. They can convert mathematical values to linguistic two tuples using (9) [8].

$$\Delta\colon\ [0, g] \longrightarrow s\times, \tag{8}$$

$$\Delta(\beta) = \begin{cases} s_\gamma, & \gamma = \mathrm{round}(\beta), \\ \alpha = \beta - r, & \alpha \in [-0.5, 0.5]. \end{cases} \tag{9}$$

Using the eq., they can convert a linguistic phrase to a real value (between 0 and $g$).

$$\begin{gathered} \Delta^{-1}\colon\ s \times [-0.5, 0.5] \longrightarrow [0, g] \\ \Delta^{-1}(s_\gamma, \alpha) = \gamma + \alpha = \beta \end{gathered}. \tag{10}$$

To further unify the dimension, they could use the eq. to map the linguistic term between zero and one.

$$\begin{gathered} \Delta^{-1}\colon\ s \times [-0.5, 0.5] \longrightarrow [0, 1], \\ \Delta^{-1}(s_\gamma, \alpha) = \frac{\gamma + \alpha}{g}. \end{gathered} \tag{11}$$

*3.4. Automated Disease Classification Model.* Finally, the disease classification process is divided into three stages: feature extraction using LSTM, classification using ELM, and parameter tuning using tree growth algorithm (TGA). As previously stated, convolution models can work on a single image and transform it from input pixel to matrix/vector representation. Current CNN pretrained models are used for feature extraction. The main goal is that CNN may not be trained, but training may be provided by the BP errors from the LSTM-DL classifiers via CNN multiple input images. Convolutional neural networks (CNNs) are used because of their improved transferability. Knowledge of this cutting-edge technology will benefit not just researchers who use CNN for radiology and medical imaging jobs but also clinical radiologists, since deep learning may influence their practise in the near future. Following CNN training, medical professionals or computer-aided detection (CADe) systems can specify the target lesions in medical pictures during the deployment phase. Figure 2 depicts a general LSTM cell. The LSTM cell contains various gates and parameters that control the behaviour of each memory cell. Every cell state is governed by the activation function of gates. For different types of gates, the input value is fed into the input gate (I), forget gate (f), activation vector (c), and output gate (o).

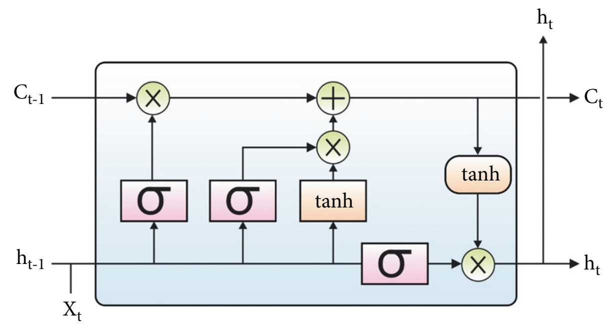



Figure 2: LSTM structure.

$$\begin{aligned} j_t &= \in j\left(w_{pj} p_t + w_{hj} h_{t-1} + w_{aj} a_{t-1} + bj\right), \\ f_t &= \in f\left(wPp_t + w_h h_{t-1} + w_{af} a_{-1} + bf\right), \\ a_t &= f_t a_{t-1} + j_t \epsilon_a\left(w_{pc} p_t + w_{ha} h_{t-1} + ba\right), \\ 0_t &= \epsilon_o\left(w_{po} p_t + w_{hot-1} h + w_{ao} a_{t-1} + bo\right), \\ h_t &= 0_t \in h(a_t), \end{aligned} \tag{12}$$

where $w_{pj}, w_{hj}, w_{aj}, w_{hf}, w_{af}, w_{pa}, w_{ha}, w_{po}$, and $w_{ao}$ denote weight (input weight, hidden weight, output weight, etc.) and $b_j$, $b_f$, $b_a$, and $b_0$ indicate the bias weight [21].

Each time step includes a single CNN series and an LSTM model. As a single step, CNN could be passed and used on every output to the LSTM input image for all input images. The result could be achieved by folding up a CNN input framework with multiple layers in a time distribution method. The same layer is used multiple times to achieve a similar result. To determine the presence of diseases, the extracted features are fed into the ELM classifier. Assume a training data $A\ \{(x_i, t_i)\}_{i=1}^{N}$, the output functions of SLFN using $L$ hidden neuron could be determined by

$$f(x_i) = \sum_{j=1}^{L} \beta_j h_j\left(a_j, b_j, x_i\right) = h(x_i)\beta, i = 1, \ldots, N, \tag{13}$$

where $\beta = \beta_1, \ldots, \beta_L^T$ denotes the output weight matrix and $h(x_i) = [h_1(a_1, b_1, x_i), \ldots, h_j(a_L, b_L, x_i)]$ represents the network output equivalent to the training samples $x_i$. $h_j(\cdot)$ indicates a nonlinear piecewise continuous function and $a_j \in R^d$, and $b_j \in R(j = 1, 2, \ldots, L)$ means a parameter of $j$th hidden node. The training network is to discover appropriate network parameters for minimizing the error functions $\|H\beta - T\|_2$, where

$$H = \begin{bmatrix} h(x_1) \\ \vdots \\ h(x_N) \end{bmatrix},$$
$$T = \begin{bmatrix} t_1^T \\ \vdots \\ t_N^T \end{bmatrix}. \tag{14}$$

It represents an SLFN using an $L$ hidden neuron and denotes the hidden, output matrix, and target output.

ELM uses arbitrary hidden node parameters and the tune-free trained approach to FFNN instead of iteratively upgrading network parameters as in traditional gradient descent algorithms. ELM is flexible because it employs a hidden activation function, as demonstrated by the universal approximate ability theorem. Almost any nonlinear piecewise continuous function and its linear combination perform well in the ELM algorithm [22]. The extreme learning machine (ELM) is a fast convergent training method for single hidden layer feedforward neural networks (SLFNs). This type of SLFN allows for faster convergence training and avoids the need for many iterations to update the hidden layer weights. Compared to other classical learning algorithms in applications with increasing noise, ELM appears to outperform ELM in regression and classification tests. With a single hidden layer of neurons and random feature mapping, an ELM model learns quicker than other models. High dimensions and large data sets have aroused substantial scholarly interest in the low computing complexity.

The TGA is used to optimise the ELM model's parameter computation, resulting in improved overall classification performance. The TGA approach is stimulated by the competition between trees in the forest. A tree's attention is divided between food and sunlight. Exploration and exploitation are the two major stages of the approach. During the exploration stage, the tree moves toward the sunlight, allowing it to investigate new locations. The tree is now fulfilled with light in the exploitation stage, and thus, it moves towards better nutrients in the root, as it moves towards the global/local optimal. The forest's tree population is classified into four types.

The first group of trees has found a light source, and they can now compete for food. To compete with light, the tree in the second group switches to the two optimal options that are closest to it. In the third group, a new tree is planted in place of the worst tree. Finally, an optimal tree is used to create a novel plant [23]. Initially, this approach arbitrarily creates the early population of the tree (solution) within the lower and upper bounds, where the fitness values for all solutions are calculated. The following is how the early population is produced.

$$x_{i,j} = \min_j + \text{rand} \cdot \left(\max_j - \min_j\right), \tag{15}$$

where $x_{i,j}$ is the $j$th variable of $i$th solution of the population, rand represents an arbitrary value derived by the uniform distribution, and $\min_j$ and $\max_j$ indicates lower bound and upper bound of $j$th variable, respectively.

Next, the population is arranged based on the fitness values, and the present optimal solution at the $j$th iterations is established. The global optimal solutions are represented as $T_{GB}^j$. The optimal solution is allocated to the initial group $(N_1)$, and the solution from this population carries out the local search as follows:

$$T_i^{j+1} = \frac{T_i^j}{\theta} + r \times T_i^j, \tag{16}$$

where $T_i^{j+1}$ represents the novel $i$th solution and $T_i^j$ is the $i$th solution in $j$th iteration. $\theta$ represents the rate of power decreases, and $r$ specifies an arbitrary number between [0,1].

When the novel solution has a higher fitness value than the current solution, greedy selections are used to find it. The novel solution either replaces the current one or keeps the current solutions for the next generation.

The second optimal solution is allocated to $N_2$ subpopulation. All solutions from the $N_2$ group must be shifted to the two nearest solutions (from the initial and second subpopulation) at distinct $\alpha$ angles. The Euclidean distance is used to measure the distance between two solutions.

$$d_i = \left( \sum_{i=1}^{N_1+N_2} \left(T_{N_2}^j - T_i^j\right)^2 \right)^{1/2},$$
$$d_i = \begin{cases} d_i \text{ if} T_{N_2}^j \neq T_i^j, \\ \infty \text{ if} T_{N_2}^j = T_i^j, \end{cases} \tag{17}$$

where $d_j$ denotes the distance of $i$th solution, The trees that exist now are depicted as $T_{N_2}^j$, and the $i$th solution in the population are signified as $T_i^j$.

The poorest solution from the population is found in the third subpopulation, $N_3$. This solution is calculated by replacing it with a recent arbitrary solution.

$$N_3 = N - N_1 - N_2, \tag{18}$$

where the population sizes are represented by $N.N_1$ and $N_2$ are the first and second subpopulation, respectively. Next, the novel population ($N$) is determined by adding the initial groups $N_1, N_2$, and $N_3$.

$$N = N_1 + N_2 + N_3. \tag{19}$$

The last group $N_4$ includes arbitrary novel results.$N_4$ is the final group of entire set outcomes which contains arbitrary novel findings.. Using mask operators, the population adapts an optimal solution from the initial group ($N$), and the adapted solution is fused. The fitness values are used to organise the novel population, and the best $N$ solution is chosen for the next iteration. The procedure is repeated until the desired result is obtained. Finally, the best solution is determined.

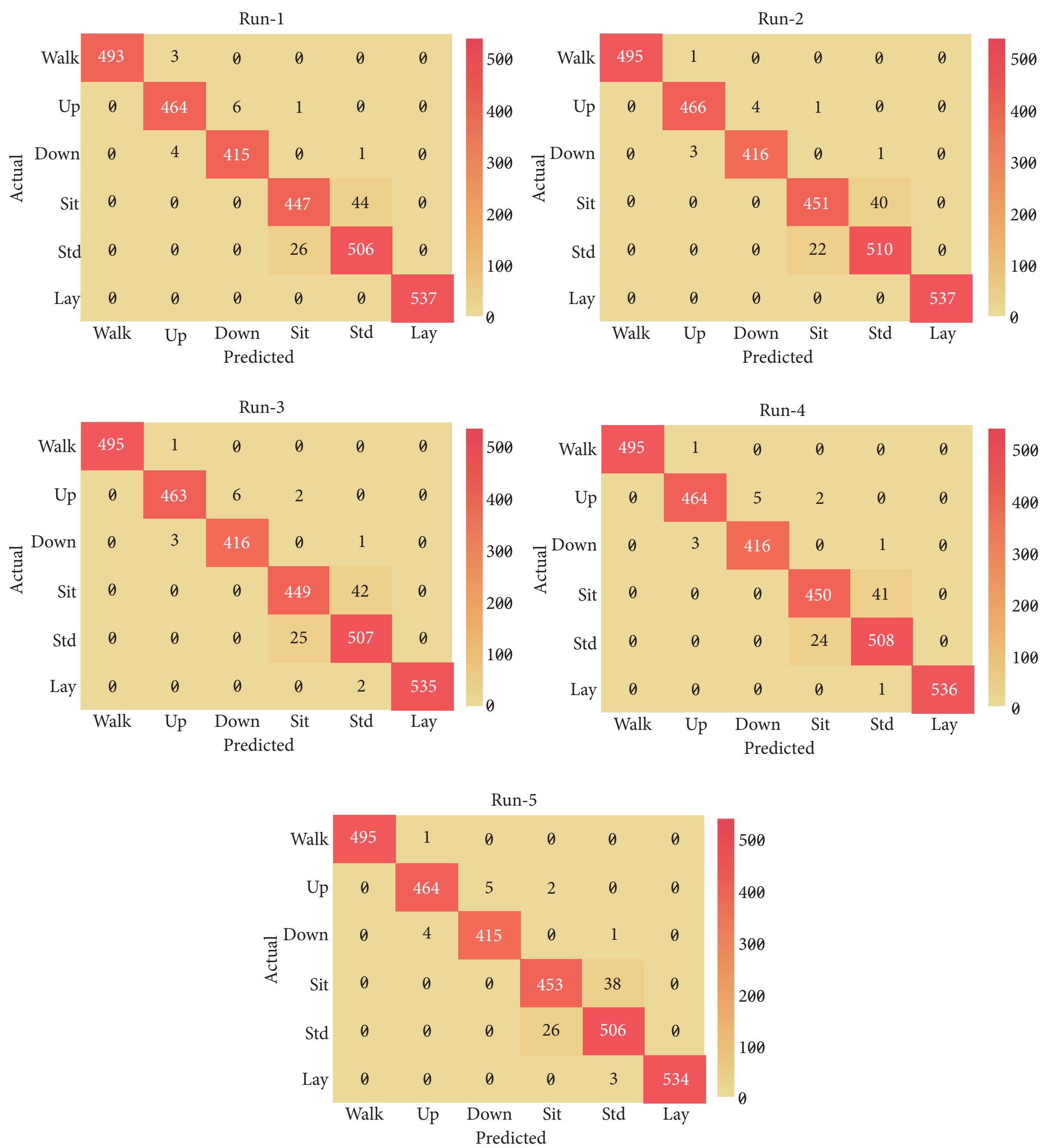



Figure 3: Confusion matrix analysis of MR-LSDGM model.

## 4. Performance Validation

The performance of the MR-LSDGM approach is investigated in this section using the benchmark activity recognition data set from the UCI repository [24]. The data set contains information on 30 people, each with 561 attributes. The data set contains 496 instances from the Walk class, 471 instances from the Up class, 420 instances from the Down class, 491 instances from the Sitting class, 532 instances from the Standing class, and 537 instances from the Lying class.

After five repetitions, the MR-LSDGM approach produced a collection of five confusion matrices, as shown in Figure 3. The graph shows that the MR-LSDGM method yielded the best possible result in each execution run [25]. For example, the MR-LSDGM technique classified 493 instances as Walk, 464 instances as Up, 415 instances as Down, 447 instances as Sit, 506 instances as Stand, and 537 instances as Lay under run-1. Similarly, the MR-LSDGM approach classified 495 instances as Walk, 466 instances as Up, 416 instances as Down, 451 instances as Sit, 510 instances as Stand, and 537 instances as Lay in run-2. Similarly, the MR-LSDGM method classified 495 instances as Walk, 464 instances as Up, 416 instances as Down, 450 instances as Sit, 508 instances as Stand, and 536 instances as Lay under run-4. Furthermore, under run-5, the MR-LSDGM algorithm classified 495 instances as Walk, 464 instances as Up,

Table 1: Result analysis of MR-LSDGM technique under different runs.

| No. of runs | Methods | Sensitivity | Specificity | Precision | Accuracy | *F*-score |
|---|---|---|---|---|---|---|
| Run-1 | Walk | 0.994 | 1.000 | 1.000 | 0.999 | 0.997 |
| | Up | 0.985 | 0.997 | 0.985 | 0.995 | 0.985 |
| | Down | 0.988 | 0.998 | 0.986 | 0.996 | 0.987 |
| | Sit | 0.910 | 0.989 | 0.943 | 0.976 | 0.926 |
| | Std | 0.951 | 0.981 | 0.918 | 0.976 | 0.934 |
| | Lay | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | **Average** | **0.971** | **0.994** | **0.972** | **0.990** | **0.972** |
| Run-2 | Walk | 0.998 | 1.000 | 1.000 | 1.000 | 0.999 |
| | Up | 0.989 | 0.998 | 0.992 | 0.997 | 0.990 |
| | Down | 0.991 | 0.998 | 0.991 | 0.997 | 0.991 |
| | Sit | 0.919 | 0.991 | 0.952 | 0.979 | 0.935 |
| | Std | 0.959 | 0.983 | 0.926 | 0.979 | 0.942 |
| | Lay | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | **Average** | **0.976** | **0.995** | **0.977** | **0.992** | **0.976** |
| Run-3 | Walk | 0.998 | 1.000 | 1.000 | 1.000 | 0.999 |
| | Up | 0.983 | 0.998 | 0.991 | 0.996 | 0.987 |
| | Down | 0.991 | 0.998 | 0.986 | 0.997 | 0.988 |
| | Sit | 0.915 | 0.989 | 0.943 | 0.977 | 0.929 |
| | Std | 0.953 | 0.981 | 0.919 | 0.976 | 0.935 |
| | Lay | 0.996 | 1.000 | 1.000 | 0.999 | 0.998 |
| | **Average** | **0.973** | **0.994** | **0.973** | **0.991** | **0.973** |
| Run-4 | Walk | 0.998 | 1.000 | 1.000 | 1.000 | 0.999 |
| | Up | 0.985 | 0.998 | 0.992 | 0.996 | 0.988 |
| | Down | 0.991 | 0.998 | 0.988 | 0.997 | 0.989 |
| | Sit | 0.917 | 0.989 | 0.945 | 0.977 | 0.931 |
| | Std | 0.955 | 0.982 | 0.922 | 0.977 | 0.938 |
| | Lay | 0.998 | 1.000 | 1.000 | 1.000 | 0.999 |
| | **Average** | **0.974** | **0.995** | **0.975** | **0.991** | **0.974** |
| Run-5 | Walk | 0.998 | 1.000 | 1.000 | 1.000 | 0.999 |
| | Up | 0.985 | 0.998 | 0.989 | 0.996 | 0.987 |
| | Down | 0.988 | 0.998 | 0.988 | 0.997 | 0.988 |
| | Sit | 0.923 | 0.989 | 0.942 | 0.978 | 0.932 |
| | Std | 0.951 | 0.983 | 0.923 | 0.977 | 0.937 |
| | Lay | 0.994 | 1.000 | 1.000 | 0.999 | 0.997 |
| | **Average** | **0.973** | **0.995** | **0.974** | **0.991** | **0.973** |

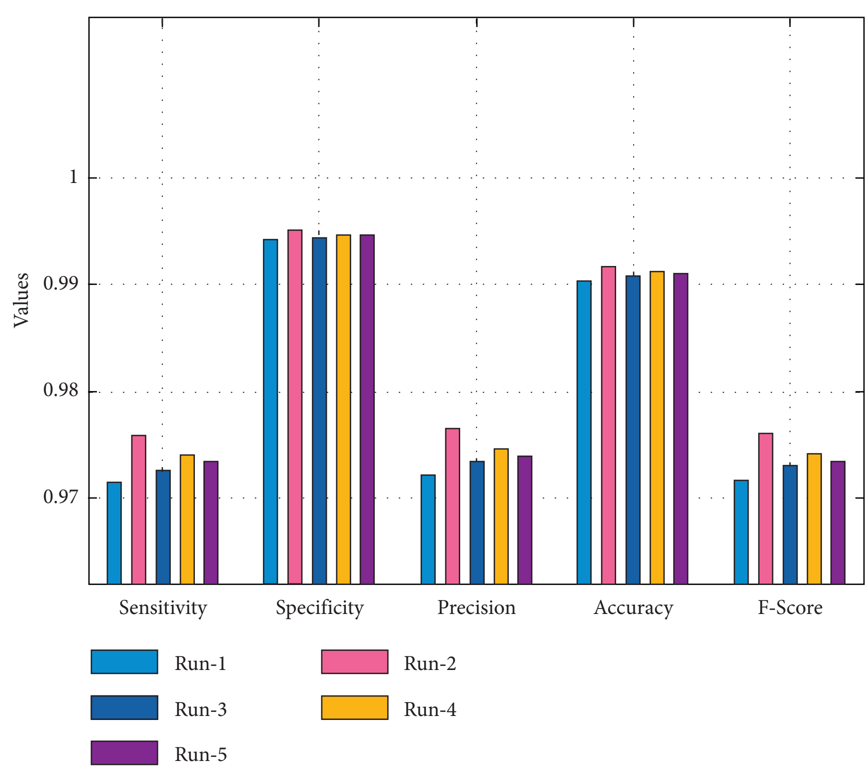



Figure 4: Result analysis of MR-LSDGM model with different measures.

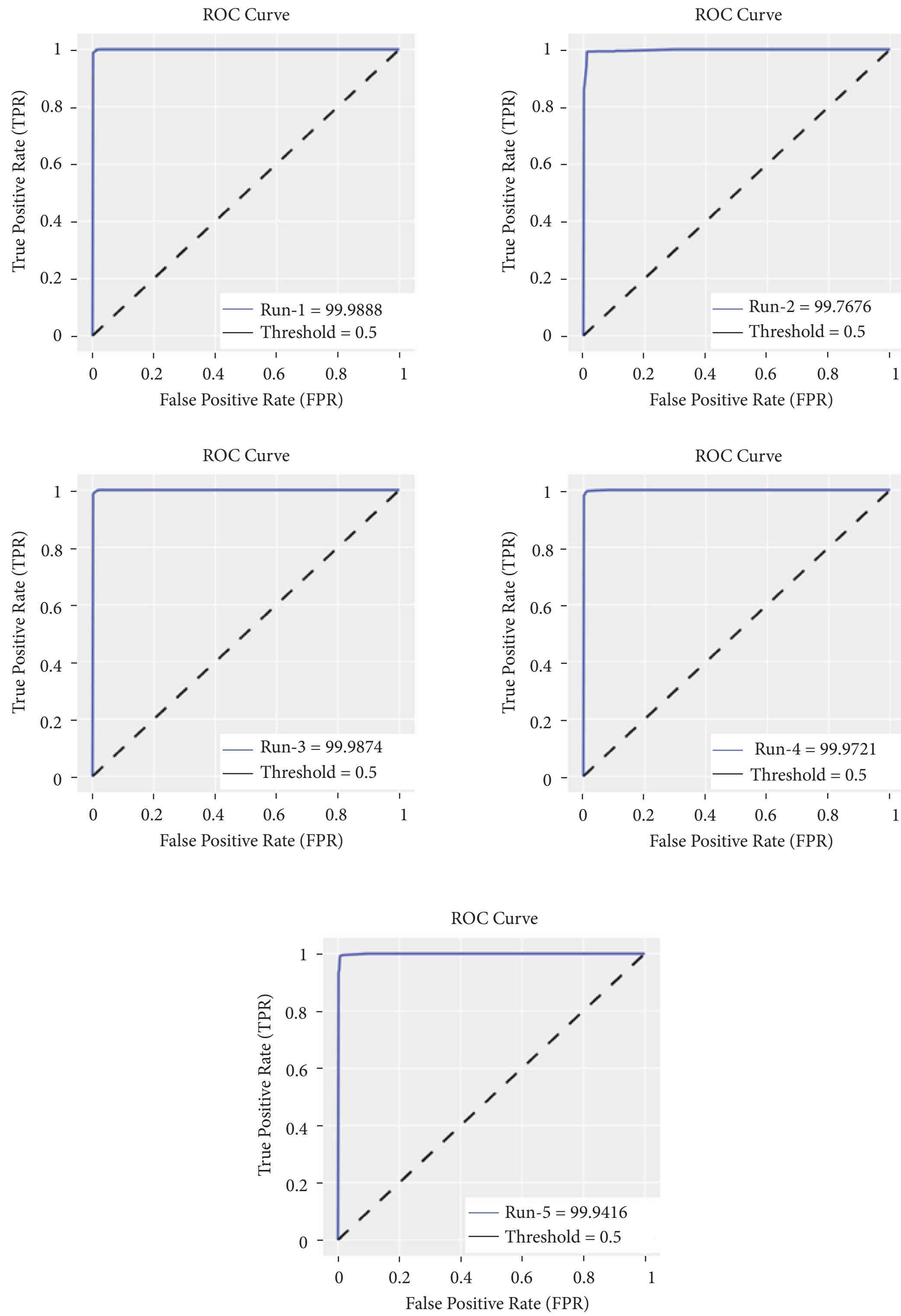



Figure 5: ROC analysis of MR-LSDGM model.

415 instances as Down, 453, Sit, 506, Stand, and 534 instances as Lay [26].

The classification result analysis of the MR-LSDGM technique under varying execution runs is reported in Table 1 and Figure 4. The MR-LSDGM technique has resulted in superior performance across all runs, as shown in Table 1. For example, the MR-LSDGM technique achieved maximum performance with run-1, with an average sensitivity of 0.971, specificity of 0.994, precision of 0.972, accuracy of 0.990, and *F*-score of 0.972. The MR-LSDGM method also performed optimally in run-2, with an average sensitivity of 0.976, specificity of 0.995, precision of 0.977, accuracy of

Table 2: Comparative accuracy analysis of MR-LSDGM with other techniques.

| Methods | Accuracy | Precision | ROC |
|---|---|---|---|
| CNN-2016 | 0.9375 | 0.9554 | 0.9454 |
| CNN-2018 | 0.9531 | 0.9638 | 0.9538 |
| CNN-SF | 0.9763 | 0.9655 | 0.9555 |
| CNN-LSTM | 0.9580 | 0.9755 | 0.9655 |
| Lightweight CNN | 0.9627 | 0.9822 | 0.9722 |
| CNN-BiLSTM | 0.9705 | 0.9852 | 0.9752 |
| MR-LSDGM | 0.9910 | 0.9925 | 0.9825 |

0.992, and *F*-score of 0.976. Furthermore, with run-3, the MR-LSDGM method achieved an average sensitivity of 0.973, specificity of 0.994, precision of 0.973, accuracy of 0.991, and *F*-score of 0.973. With run-5, the MR-LSDGM approach improved efficiency, achieving an average sensitivity of 0.973, specificity of 0.995, precision of 0.974, accuracy of 0.991, and *F*-score of 0.973.

Figure 5 depicts the ROC analysis of the MR-LSDGM method on the applied data set under various runs [27]. According to the results, the MR-LSDGM approach had the highest ROC value in every run. For example, in run-1, the MR-LSDGM technique achieved an increased ROC of 99.9888. In line with run-2, the MR-LSDGM method has a better ROC of 99.7676. The MR-LSDGM methodology then achieved a maximum ROC of 99.9874 in run-3. Concurrently, the MR-LSDGM technique achieved a superior ROC of 99.9721 in run-4. Finally, under run-5, the MR-LSDGM method achieved a maximum ROC of 99.9416 [28].

An extended comparison analysis is provided in Table 2 [25] to demonstrate the improved performance of the MR-LSDGM technique. With accuracy of 0.9375 and 0.9531, respectively, the CNN-2016 and CC-2018 approaches produced ineffective results [29]. At the same time, the CNN-LSTM and lightweight CNN approaches improved their accuracy to 0.9627 and 0.958, respectively. Furthermore, the CNN-BiLSTM and CNN-SF approaches have acceptable accuracy values of 0.9705 and 0.9763, respectively. In contrast, the proposed MR-LSDGM approach achieved an effective performance of 0.991 [30].

As evidenced by the tables and statistics above, the MR-LSDGM technique is clearly more effective than the other procedures.

*4.1. Discussion.* The healthcare IoT data sets and performance criteria for the proposed MR-LSGDM strategy are briefly outlined in this section [31]. The complete approach was developed using the MATLAB 2021a tool on a Core i3-3110M processor running Windows 8 with 2 GB RAM, and it was tested on 8 healthcare IoT data sets (Table 1) [32]. Over 30 separate runs, the new BBO-FCM approach was compared to existing algorithms such as CNN 2016, CNN 2018, CNN-SF, CNN-LSTM, lightweight CNN, and CNN-BiLSTM in terms of intracluster distance, purity index, standard deviation, root mean square error, accuracy, and *F*-measure [33].

## 5. Conclusion

The MapReduce tool is used in this study to create a new MR-LSDGM approach for the healthcare sector. The MR-LSDGM approach includes BBO-FCM-based DM clustering, 2TFLR-based preference modelling, and LSTM-OELM-based classification procedures. To manage big data in the healthcare sector, the MR-LSDGM technique employs the MapReduce tool. Furthermore, the design of the BBO algorithm for determining the primary cluster centres of the FCM technique, as well as parameter optimization of ELM using the TGA technique, contribute to improved overall classification results. A large number of simulations are run to demonstrate the improved outcomes of the MR-LSDGM technique, and the experimental results are examined using several metrics. According to the simulation results, the MR-LSDGM methodology outperformed the other methods. In the future, the model presented here could be used in telemedicine applications to help patients in remote areas.

## Data Availability

The manuscript contains all of the data.

## Conflicts of Interest

The authors declare that they do not have any conflicts of interest.

## References

[1] S. Neelakandan and D. Paulraj, “A gradient boosted decision tree-based sentiment classification of twitter data,” *International Journal of Wavelets, Multiresolution and Information Processing*, vol. 18, no. 4, Article ID 2050027, pp. 1-27, 2020.

[2] S. Neelakandan, S. Divyabharathi, S. Rahini, and G. Vijayalakshmi, “Large scale optimization to minimize network traffic using MapReduce in big data applications,” in *Proceedings of the International Conference on Computation of Power, Energy Information and Commuincation (ICCPEIC)*, pp. 193–199, Melmaruvathur, India, April 2016.

[3] A. Labella, Y. Liu, R. M. Rodríguez, and L. Martínez, “Analyzing the performance of classical consensus models in large scale group decision making: a comparative study,” *Applied Soft Computing*, vol. 67, pp. 677–690, 2018.

[4] T. Kavitha, P. P. Mathai, C. Karthikeyan et al., “Deep learning based capsule neural network model for breast cancer diagnosis using mammogram images,” *Interdisciplinary Sciences: Computational Life Sciences*, vol. 14, no. 1, pp. 113–129, 2021.

[5] S. Li and C. Wei, “A large scale group decision making approach in healthcare service based on sub-group weighting model and hesitant fuzzy linguistic information,” *Computers & Industrial Engineering*, vol. 144, Article ID 106444, 2020.

[6] G. Li, G. Kou, and Y. Peng, “Heterogeneous large-scale group decision making using fuzzy cluster analysis and its application to emergency response plan selection,” *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 324, pp. 1–13, 2021.

[7] Y. Song and F. Yuan, “An interactive consensus model for

group decision-making with incomplete multi-granular 2-tuple fuzzy linguistic preference relations," *Mathematical Problems in Engineering*, vol. 2018, Article ID 8197414, 11 pages, 2018.

[8] Q. Wan, X. Xu, X. Chen, and J. Zhuang, "A two-stage optimization model for large-scale group decision-making in disaster management: minimizing group conflict and maximizing individual satisfaction," *Group Decision and Negotiation*, vol. 29, no. 5, pp. 901–921, 2020.

[9] W. C. J. Hsu, J. J. Liou, and H. W. Lo, "A group decision-making approach for exploring trends in the development of the healthcare industry in Taiwan," *Decision Support Systems*, vol. 141, Article ID 113447, 2021.

[10] H. C. Liu, Z. Li, J. Q. Zhang, and X. Y. You, "A large group decision making approach for dependence assessment in human reliability analysis," *Reliability Engineering & System Safety*, vol. 176, pp. 135–144, 2018.

[11] H. Singh, D. Ramya, R. Saravanakumar et al., "Artificial intelligence based quality of transmission predictive model for cognitive optical networks," *Optik*, vol. 257, Article ID 168789, 2022.

[12] Y. W. Du and Y. K. Shan, "A Dynamic Intelligent Recommendation Method Based on the Analytical ER Rule for Evaluating Product Ideas in Large-Scale Group Decision-Making," *Group Decision and Negotiation*, vol. 30, pp. 1–21, 2020.

[13] M. Dursun, E. E. Karsak, and M. A. Karadayi, "A fuzzy multi-criteria group decision making framework for evaluating health-care waste disposal alternatives," *Expert Systems with Applications*, vol. 38, no. 9, Article ID 11453, 2011.

[14] X. Pan, Y. Wang, S. He, and K. S. Chin, "A dynamic programming algorithm-based clustering model and its application to interval type-2 fuzzy large-scale group decision making problem," *IEEE Transactions on Fuzzy Systems*, vol. 30, 2020.

[15] Y. Gao, Y. Du, H. Liang, and B. Sun, "Large Group Decision-Making Approach Based on Stochastic MULTIMOORA: An Application of Doctor Evaluation in Healthcare Service," *Complexity*, vol. 2018, Article ID 5409405, 13 pages, 2018.

[16] D. Anguita, A. Ghio, L. Oneto, X. Parra, and J. L. Reyes–Ortiz, "A public domain dataset for human activity recognition using smartphones," in Proceedings of the 21th European Symposium on Artificial Neural Networks, Computational Intelligence and Machine Learning, ESANN 2013. Bruges, Belgium, April 2013.

[17] O. Nafea, W. Abdul, G. Muhammad, and M. Alsulaiman, "Sensor-based human activity recognition with spatio-temporal deep learning," *Sensors*, vol. 21, no. 6, p. 2141, 2021.

[18] C. Zhen, "Using Big Data Fuzzy K-Means Clustering and Information Fusion Algorithm in English Teaching Ability Evaluation," *Complexity*, vol. 2021, Article ID 5554444, 9 pages, 2021.

[19] S. M. Zabihi and M. R. Akbarzadeh-T, "Generalized Fuzzy C-Means Clustering with Improved Fuzzy Partitions and Shadowed Sets," *International Scholarly Research Notices*, vol. 2012, Article ID 929085, 6 pages, 2012.

[20] X. Pu, S. Chen, X. Yu, and L. Zhang, "Developing a Novel Hybrid Biogeography-Based Optimization Algorithm for Multilayer Perceptron Training under Big Data challenge," *Scientific Programming*, vol. 2018, Article ID 2943290, 7 pages, 2018.

[21] S. Rani, H. Babbar, S. Coleman, A. Singh, and H. M. Aljahdali, "An efficient and Lightweight deep learning model for human activity recognition using smartphones," *Sensors*, vol. 21, no. 11, p. 3845, 2021.

[22] S. Neelakandan, S. Tripathi, V. B. Devi, I. Bhardwaj, and N. Arulkumar, "IoT-based traffic prediction and traffic signal control system for smart city," *Soft Computing*, vol. 25, no. 18, Article ID 12241, 2021.

[23] N. Bacanin, T. Bezdan, E. Tuba, I. Strumberger, and M. Tuba, "Optimizing convolutional neural network hyperparameters by enhanced swarm intelligence metaheuristics," *Algorithms*, vol. 13, no. 3, p. 67, 2020.

[24] R. Kamalraj, S. Neelakandan, M. Ranjith Kumar, V. Chandra Shekhar Rao, R. Anand, and H. Singh, "Interpretable filter based convolutional neural network (IF-CNN) for glucose prediction and classification using PD-SS algorithm," *Measurement*, vol. 183, Article ID 109804, 2021.

[25] G. Reshma, C. Al-Atroshi, V. Kumar Nassa et al., "Deep learning-based skin lesion diagnosis model using dermoscopic images," *Intelligent Automation & Soft Computing*, vol. 31, no. 1, pp. 621–634, 2022.

[26] S. Neelakandan, A. Arun, R. Ram Bhukya, B. Hardas, T. Ch Anil Kumar, and M. Ashok, "An automated word embedding with parameter tuned model for web crawling," *Intelligent Automation & Soft Computing*, vol. 32, no. 3, pp. 1617–1632, 2022.

[27] S. Satpathy, M. Prakash, S. C. Sengupta Aditya, and K. D. Bhattacaryya Bidyut, "Design a FPGA, fuzzy based, insolent method for prediction of multi-diseases in rural area," *Journal of Intelligent and Fuzzy Systems*, vol. 37, no. 5, pp. 7039–7046, 2019.

[28] S. Satpathy, P. Mohan, and S. Debbarma, "A new healthcare diagnosis system using an IoT-based fuzzy classifier with FPGA," *The Journal of Supercomputing*, vol. 76, no. 8, pp. 5849–5861, 2020.

[29] M. Sundaram, "An analysis of air compressor fault diagnosis using machine learning technique," *Journal of Mechanics of Continua and Mathematical Sciences*, November - December, vol. 14, no. No.-6, pp. 13–27, 2019.

[30] J. Rene Beulah, L. Prathiba, G. L. N. Murthy, E. Fantin Irudaya Raj, and N. Arulkumar, "Blockchain with deep learning-enabled secure healthcare data transmission and diagnostic model," *International Journal of Modeling, Simulation, and Scientific Computing*, 2022.

[31] C. P. D. Cyril, J. R. Beulah, N. Subramani, and D. Sivabalaselvamani, "An automated learning model for sentiment analysis and data classification of Twitter data using balanced CA-SVM," *Concurrent Engineering*, vol. 29, no. 4, pp. 386–395, 2021.

[32] D. Venu, A. V. R. Mayuri, S. Neelakandan, G. Murthy, N. Arulkumar, and N. Shelke, "An efficient low complexity compression based optimal homomorphic encryption for secure fiber optic communication," *Optik*, vol. 252, 2022.

[33] P. Asha, L. Natrayan, B. T. Geetha et al., "IoT enabled environmental toxicology for air pollution monitoring using AI techniques," *Environmental Research*, vol. 2022, Article ID 112574, 2022.

Hindawi
Journal of Healthcare Engineering
Volume 2022, Article ID 2117031, 8 pages
https://doi.org/10.1155/2022/2117031

*Research Article*

# Study of Complexity Systems in Public Health for Evaluating the Correlation between Mental Health and Age-Related Demographic Characteristics: A General Health Study

**Fereshte Haghi,[1] Shadi Goli,[2] Rana Rezaei,[3,4] Fatemeh Akhormi,[4] Fatemeh Eskandari,[4] and Zeinab Nasr Isfahani[1,4]**

[1]*Shahid Beheshti OB&GYN Hospital Isfahan University of Medical Sciences, Isfahan, Iran*
[2]*Nursing and Midwifery Sciences Development Research Center, Najafabad Branch, Islamic Azad University, Najafabad, Iran*
[3]*Department of Midwifery, Shoushtar Faculty of Medical Sciences, Shoushtar, Iran*
[4]*Department of Midwifery, Ahvaz Jundishapur University of Medical Sciences, Ahvaz, Iran*

Correspondence should be addressed to Zeinab Nasr Isfahani; nasrisfahani.z@ajums.ac.ir

Received 28 December 2021; Revised 8 February 2022; Accepted 3 March 2022; Published 6 April 2022

Academic Editor: Mohsen Ahmadi



The main objective of this study is to evaluate the quality of nurses' work lives and mental health during outbreaks. We also use the General Health Questionnaire–28 and Walton's QWL technique to assess the association between these two and their dimensions with demographic variables and each other. First, 165 nurses from COVID-19 medical centers in Iran filled surveys for this research. In an SPSS program, the data were examined. There was a strong link between mental health and age-related demographic factors. There was no evidence of a link between the quality of nurses' work life and their psychological health. However, there was a strong link between somatic symptoms and fair and appropriate compensation, as well as constitutionalism. The worst situations for work life quality were linked to the whole living area dimension. In contrast, the worst conditions for mental health were linked to the somatic symptoms dimension.

## 1. Introduction

In December 2019, an acute respiratory syndrome caused by SARS-CoV-2 caused a global pandemic in Wuhan, China, where almost the entire human community has been directly affected by the disease or associated safety social restrictions. Numerous studies have been published on the mechanism of action of this coronavirus and its individual and social effects and consequences, which indicate the occurrence of physical disease in the form of clinical complications and manifestations such as fever, chills, sore throat, contusion, cough, respiratory problems, vomiting, and diarrhea [1], as well as psychological complications such as fear and anxiety [2]. Of course, clinical complications have affected patients, and psychological complications have affected both patients and nonpatients. The pandemic has had a tremendous impact on various occupations. It has imposed different consequences on the working community, active in various business sectors [3]. COVID-19 has attracted special international attention as a serious threat to global public health. The increasing prevalence of this disease and the prolongation of the disease process have made the activities of the medical staff exhaustive [4]; Thus, with the over-admission of patients in medical centers, the availability and readiness of the medical staff is a determining factor in overcoming the crisis [5]. Considering that various studies and reports indicate the effect of health care providers' satisfaction on patient satisfaction [6–11] and on the other hand, job satisfaction has a two-way relationship with the mental and psychological condition of employees [12], it is essential to consider psychological conditions and their improvement methods in the medical center.

According to the World Health Organization definition, mental health is "a state of wellbeing in which the individual realizes his or her abilities, can cope with the normal stresses of life, can work productively and fruitfully, and can make a contribution to his or her community." Good mental health is one of the pillars of health and is necessary for a useful, effective, and satisfying life [13]. Quality of work life (QWL) is essential for attracting and retaining employees. When an organization provides a good QWL for employees, it intends to retain employees [14]. Quality of work life is one issue that affects almost all people regardless of the situation. In hospitals and medical centers, the quality of hospital services will not be guaranteed without the participation of nurses [15]. Various factors such as incompatibility and dissatisfaction with work, stress, fatigue, illness, and lack of leisure time of nurses affect their behavior [16]. Nurses who have dealt with patients for a more extended period are more likely to be vulnerable. Critical and painful patients, dying patients, complex equipment, inappropriate behaviors of patient companions, patients' reactions, and many other issues give different aspects to nurses' work, and such conditions affect burnout, job satisfaction, and the tendency of nurses to continue working [17]. These characteristics in the workplace increase stress and the risk of mental disorders [18]. Nursing is one of the 130 most stressful occupations and is ranked 27th among 130 occupations with a high prevalence of mental disorders [19]. Nurses face several stressful sources such as time, long-term work, change of work shift, insomnia, death observation, malignancy, high patient expectations of nurses, and a low tolerance for error [20]. Job stress can lead to disorders that put nurses at serious risk of mental disorders [21].

From December 2019 onward, medical staff, especially nurses, are under severe pressure. Various waves of COVID-19 have swept across many countries, including Iran. In this situation, not only do medical staff rescue infected patients but they also oversee the entire process of combating health events. In addition to the stress of the job itself, they are involved in a conflict between their safety needs and job requirements. They may be exposed to anxiety, depression, insomnia, and other psychological disorders [22]. High-sensitivity patient care imposes significant physical and emotional burdens, exacerbated by increased workload, staff shortages, and equipment shortages. Direct contact with the patient increases the risk of infection [23]. Meanwhile, the measures taken by the government, especially with an emphasis on social distance and restricting communication and travel outside the workplace, are also significant. Therefore, it is impossible to take many common strategies to reduce stress and anxiety, which increases the responsibility of medical centers to take the initiative and create the appropriate conditions to compensate for the shortcomings. Paying attention to the QWL and improving it is one of the approaches used by organizations. However, the QWL includes several aspects, and consequently, a variety of solutions in this area is considerable.

It is necessary to properly understand the psychological problems of nurses in the context of the COVID-19 pandemic, the relationship between various problems and mental disorders with different aspects of work life, and to create the right mentality to adopt an appropriate solution. These strategies may vary even concerning the nurses' workplace. From this point of view, it is necessary to conduct the necessary research. According to the explanations provided, it can be said that this study seeks to answer the following questions:

(i) What are the most important problems and inadequacies related to the quality of work life?
(ii) What are the most important problems and mental disorders?
(iii) What is the correlation between the aspects of quality of work life and mental disabilities?

## 2. Literature Review

Numerous studies have been conducted on mental health and QWL and their relationship. A significant part of these studies goes back to nurses working in medical centers. Javadi-Pashaki and Darvishpour [24] in their study on stress and coping strategies to predict the general health of nursing staff considered 318 nurses working in health centers of Guilan University of Medical Sciences [24]. The results showed that stress and coping strategies could explain about 2.5% of the variance in public health. However, the results showed that coping strategies are significantly more predictive of public health. Accordingly, attention to coping strategies to predict general health in nurses has been highlighted. Mahmoudi [3] studied the economic effect of COVID-19. This model is enhanced with additional characteristics to assess the economic impact of COVID-19 on the labor market. The findings indicate that the US government might employ a straightforward technique to mitigate the harmful effects of COVID-19.

Zhang et al. [22] in their study of the mental health status of Chinese healthcare-related infection control specialists during the coronavirus outbreak investigated data from 9,228 cases from 3,776 hospitals across China in the form of an online questionnaire. A 12-item Chinese version of the General Health Questionnaire and a Chinese version of the Psychological Capital Questionnaire suitable for medical personnel were used as tools in this study. By performing univariate and multivariate analysis, it was found that the risk of mental health problems is higher with more self-sufficiency and working in a public hospital. Working in a second-degree rather than a third-degree hospital poses a significantly lower risk. However, fewer psychological problems have been observed in single people than in married ones. In addition, fewer working hours per week, hope, and optimism played a role in reducing risk. Hardiyono [25] in their study on burnout of nurses working in the hospital for the treatment of patients with COVID-19 concluded that burnout is present in nurses who were exposed to a large number of patients with the virus [25]. The high workload, and at the same time, the worry of transmitting the virus to themselves and their family members is one of the most important factors that put them under psychological pressure and lead to burnout. Quchan et al., in their study, compared the mental health of nurses working in COVID-19 referral hospitals and regular hospitals [2]. 60

nurses related to the COVID-19 wards and 62 non-COVID-19 nurses participated in the study. A standard public health questionnaire was provided to them online. There was no statistically significant difference between the two groups. However, both groups had poor mental health, which the researchers said was probably due to the pandemic. Sadeghipoor and Moradisabzevar [26] developed a smart toy car to screen children for autism. The findings indicate that the system has an accuracy rate of 85 percent, a sensitivity of 93 percent, and a specificity of 76 percent. The findings are same for boys and girls, indicating that this approach may be widely used by all youngsters.

Dehkordi et al. [27] conducted a study on the effect of COVID-19 disease on anxiety, quality of work life, and fatigue of health care providers in health centers in southwestern Iran. The statistical population includes 181 people directly related to patients and 261 employees in other wards who had no direct contact with patients with COVID-19 [27]. They concluded that both groups' work life quality had decreased, and fatigue and anxiety caused by COVID-19 had increased. However, there is no statistically significant difference between the fatigue caused by the anxiety of the staff involved with COVID-19 and the personnel of other departments. In terms of QWL, no significant difference was observed in other components except for human resource development. The results also showed a statistically significant relationship between the level of component anxiety with QWL and fatigue. Kelbiso et al. [28] have identified and analyzed the determinants of QWL among nurses working in public health facilities in Hawassa, Ethiopia [28]. In this study, 253 nurses from two hospitals and nine health centers participated. Findings showed that at least 60% of nurses were dissatisfied with their quality of work life. This study showed that independent predictors of QWL among the study population were educational status, monthly income, position, and work environment. Abadi et al. [29] used a unique hybrid salp swarm technique and genetic algorithm to schedule nurses to care for COVID-19 patients. Zhang et al. [30] expected that perceived social distance would positively buffer the effect of anger on trust and that gender would moderate the effect of perceived social distance on trust. According to the findings, female participants, but not male participants, sent more money to their counterparts in the low social distance than in the control condition. Women's optimistic risk assessment and consequently greater trust in others may be triggered by the high certainty, higher individual control, and approach motivation associated with anger, according to the findings of both studies. This is due to women's perception of a smaller social distance. Public transportation networks, mobile operators, and mobile phone applications were taken as the three key sources of mobility data by Hu et al. [31]. Sadeghipour et al. (2016) concentrated on facial recognition with the use of an enhanced SIFT algorithm. The results demonstrate that the suggested method outperforms the SIFT. The suggested approach is evaluated by applying it to the ORL database and then comparing it to existing face identification techniques [32]. In order to assess human mobility, four following ways are typically used: public transit-based flow, societal activity patterns, index-based movement data, and social media-derived movement data. Sharifi et al. [33] studied the impact of artificial intelligence and digital style on the industry and energy following COVID-19. According to Chen et al. [34], a Markov chain position predictions model based on multilevel correction was presented. This approach is also helpful in determining the correlation between the variables in the COVID-19 dataset. Ala et al. [35] studied how the whale optimization algorithm and the NSGA-II can be used to optimize appointment scheduling for healthcare systems based on the quality of fairness service provided. According to Hankir et al. [36]; a study protocol is being developed to study an anti-stigma program and long-term reductions in mental health stigma among medical students. Abbas [37] drew on data on coronavirus infections obtained from the Ministry of Health and National Institute of Health Pakistan to conduct his research. This study evaluation includes data provided by the National Institutes of Health, and responses were from all areas of Pakistan, limiting the generalizability of the findings to empirical evidence.

## 3. Methodology

In the present study, data collection has been performed based on 250 General Health Questionnaire – 28 (GHQ-28) of Goldberg and Hillier [38] and Walton's QWL questionnaire [39] distributed among nurses of ten hospitals in Iran with surgical, orthopedic, COVID-19, intensive care units, emergency, cardiology, and neurology wards. The validity and reliability of both questionnaires have been repeatedly reviewed and found appropriate for screening the QWL and job-related factors [40, 41].

The GHQ-28 questionnaire is multiple choice and has four dimensions: somatic symptoms, anxiety and insomnia, social dysfunction, and severe depression. Its scoring method is in the form of Likert, which has a number between zero and 3 (never = zero, sometimes = 1, most of the time = 2, and always = 3). Each dimension consists of 7 questions. The maximum score in each dimension is 21, and the person's total score is from zero to 84. A higher score indicates lower health. On the other hand, the Walton's QWL questionnaire has eight dimensions in the following order: fair and adequate payment (questions 1, 2, 3), safe and healthy working environment (questions 4, 5, 6), opportunities for continuous growth, and security (questions 7, 8, 9), constitutionalism (questions 10, 11, 12, 13), social dependence of working life (questions 14, 15, 16), the total living space (questions 17, 18, 19), social integration and cohesion in the organization (questions 20, 21, 22, 23), and development of human capabilities (questions 24, 25, 26, 27). This questionnaire is also based on the Likert scale from very low to very high, 1 to 5. The questionnaire does not have a reverse question.

## 4. Results

Ultimately, 165 nurses working in different wards provided their answers, which the summarized results and related parameters are shown in Table 1. Based on Table 1, The reliability of GHQ-28 based on Cronbach's alpha coefficient is 0.922. The QWL Questionnaire is 0.933, which is excellent. Table 2 shows the significance of the difference between mental health and QWL for respondents based on their demographic characteristics. As can be seen in this table,

Table 1: Summary of information about the respondents and their status in terms of mental health (MH) and QWL.

| | | | Number | Mean | Std. dev. | Max | Min | Median | Mode | % |
|---|---|---|---|---|---|---|---|---|---|---|
| Age | | | 165 | 33 | 7 | 54 | 24 | 32 | 25 | 100.0 |
| Work experience | | | 165 | 9 | 7 | 27 | 0 | 8 | 3 | 100.0 |
| Ward | Orthopedic | MH | 11 | 20.27 | 7.73 | 30.00 | 11.00 | 18.00 | 30.00 | 6.7 |
| | | QWL | 11 | 100.45 | 16.80 | 122.00 | 77.00 | 99.00 | 82.00 | 6.7 |
| | Emergency | MH | 14 | 18.71 | 8.16 | 38.00 | 8.00 | 18.50 | 19.00 | 8.5 |
| | | QWL | 14 | 103.43 | 8.99 | 119.00 | 92.00 | 102.00 | 93.00 | 8.5 |
| | Surgical | MH | 10 | 30.00 | 23.90 | 63.00 | 6.00 | 17.50 | 54.00 | 6.1 |
| | | QWL | 10 | 106.10 | 9.00 | 114.00 | 83.00 | 106.50 | 105.00 | 6.1 |
| | Cardiology | MH | 15 | 24.27 | 14.27 | 52.00 | 9.00 | 19.00 | 9.00 | 9.1 |
| | | QWL | 15 | 107.93 | 14.78 | 133.00 | 72.00 | 109.00 | 117.00 | 9.1 |
| | COVID-19 | MH | 89 | 27.44 | 9.25 | 71.00 | 9.00 | 27.00 | 31.00 | 53.9 |
| | | QWL | 89 | 91.67 | 11.13 | 124.00 | 68.00 | 93.00 | 91.00 | 53.9 |
| | Intensive care units | MH | 15 | 25.67 | 15.62 | 60.00 | 9.00 | 22.00 | 9.00 | 9.1 |
| | | QWL | 15 | 98.27 | 19.05 | 121.00 | 64.00 | 100.00 | 118.00 | 9.1 |
| | Neurology | MH | 11 | 25.36 | 14.08 | 57.00 | 9.00 | 21.00 | 9.00 | 6.7 |
| | | QWL | 11 | 104.45 | 17.60 | 135.00 | 78.00 | 105.00 | 78.00 | 6.7 |
| Education | Associate degree | MH | 18 | 31.50 | 9.37 | 54.00 | 18.00 | 30.00 | 27.00 | 10.9 |
| | | QWL | 18 | 97.61 | 10.34 | 121.00 | 81.00 | 97.00 | 97.00 | 10.9 |
| | Bachelor’s degree | MH | 128 | 25.03 | 11.67 | 63.00 | 6.00 | 23.50 | 31.00 | 77.6 |
| | | QWL | 128 | 96.20 | 14.91 | 135.00 | 64.00 | 96.00 | 94.00 | 77.6 |
| | Master’s degree | MH | 19 | 25.47 | 15.66 | 71.00 | 7.00 | 21.00 | 11.00 | 11.5 |
| | | QWL | 19 | 102.32 | 11.95 | 121.00 | 81.00 | 101.00 | 96.00 | 11.5 |
| Employment status | Conscription | MH | 39 | 21.28 | 11.65 | 54.00 | 6.00 | 18.00 | 9.00 | 23.6 |
| | | QWL | 39 | 100.10 | 13.83 | 121.00 | 71.00 | 101.00 | 118.00 | 23.6 |
| | Temp-to-perm | MH | 27 | 29.52 | 12.55 | 71.00 | 11.00 | 28.00 | 31.00 | 16.4 |
| | | QWL | 27 | 96.11 | 13.07 | 124.00 | 64.00 | 96.00 | 91.00 | 16.4 |
| | Contractual | MH | 34 | 25.09 | 8.66 | 40.00 | 10.00 | 25.50 | 32.00 | 20.6 |
| | | QWL | 34 | 92.65 | 15.44 | 121.00 | 66.00 | 92.50 | 92.00 | 20.6 |
| | Permanent | MH | 65 | 27.31 | 13.00 | 63.00 | 7.00 | 25.00 | 30.00 | 39.4 |
| | | QWL | 65 | 97.94 | 14.01 | 135.00 | 70.00 | 97.00 | 93.00 | 39.4 |
| Gender | Male | MH | 64 | 23.75 | 11.47 | 57.00 | 6.00 | 23.50 | 9.00 | 38.8 |
| | | QWL | 64 | 98.47 | 13.89 | 135.00 | 70.00 | 99.50 | 82.00 | 38.8 |
| | Female | MH | 101 | 27.08 | 12.31 | 71.00 | 9.00 | 26.00 | 16.00 | 61.2 |
| | | QWL | 101 | 96.17 | 14.45 | 133.00 | 64.00 | 96.00 | 93.00 | 61.2 |
| MARSTA | Single | MH | 42 | 24.95 | 13.24 | 71.00 | 9.00 | 21.50 | 17.00 | 25.5 |
| | | QWL | 42 | 95.17 | 13.54 | 124.00 | 69.00 | 96.00 | 92.00 | 25.5 |
| | Married | MH | 123 | 26.07 | 11.68 | 63.00 | 6.00 | 25.00 | 30.00 | 74.5 |
| | | QWL | 123 | 97.71 | 14.46 | 135.00 | 64.00 | 97.00 | 91.00 | 74.5 |

Table 2: Significance of mean difference for mental health and QWL based on demographic characteristics.

| Demographic classification | Significance of mean difference for mental health | Significance of mean difference for QWL |
|---|---|---|
| Ward | 0.112 | Less than 0.001 |
| Education | 0.102 | 0.215 |
| Employment status | 0.026 | 0.143 |
| Gender | 0.084 | 0.313 |
| MARSTA | 0.605 | 0.319 |

according to the medical department, the difference in the mean QWL at the error level of one percent is significant.

At the 5% error level, the difference in the mean for mental health based on employment status is significant. There is no significant mean difference at the 5% error level in other cases.

Additionally, to examine the relationship between age and work experience with mental health and QWL, the Pearson correlation coefficient was used, the result of which

Table 3: Significance of correlation between mental health and QWL with age and work experience.

| | | Mental health | QWL |
|---|---|---|---|
| Age | Pearson correlation | 0.276 | 0.050 |
| | Significance | 0.000 | 0.527 |
| Work experience | Pearson correlation | 0.242 | -0.026 |
| | Significance | 0.002 | 0.744 |

Table 4: Significance of mean rank difference for mental health disorders.

| Mental health disorder | Mean | Std. dev. | Mean rank | Significant |
|---|---|---|---|---|
| Somatic symptoms | 7.70 | 4.07 | 2.96 | 1 |
| Social dysfunction | 7.50 | 2.85 | 2.95 | 2 |
| Anxiety and insomnia | 6.99 | 4.42 | 2.65 | 3 |
| Severe depression | 3.59 | 3.95 | 1.44 | 4 |
| Chi-square statistics for the significance of the difference in mean rank | | 162.6 | | |
| Probability of error | | Less than 0.001 | | |

Table 5: Significance of mean rank difference for QWL disorders.

| Mental health disorder | Mean | Std. dev. | Mean rank | Significant |
|---|---|---|---|---|
| The total life space | 10.42 | 2.21 | 2.92 | 1 |
| Social dependence of working life | 10.53 | 2.17 | 3.02 | 2 |
| Opportunities for continuous growth and security | 10.61 | 2.18 | 3.04 | 3 |
| Safe and healthy working environment | 10.67 | 2.32 | 3.19 | 4 |
| Fair and adequate payment | 10.87 | 2.14 | 3.44 | 5 |
| Social integration and cohesion in the organization | 14.20 | 2.54 | 6.48 | 6 |
| Constitutionalism | 14.12 | 2.43 | 6.56 | 7 |
| Development of human capabilities | 15.65 | 2.34 | 7.36 | 8 |
| Chi-square statistics for the significance of the difference in mean rank | | 755.64 | | |
| Probability of error | | Less than 0.001 | | |

is shown in Table 3. As can be seen, the respondents' mental health has a significant positive correlation with their age and work experience.

The ranking of mental health disorders and disorders related to QWL using the Friedman test indicates that Chi-square statistics to evaluate the significance of the difference in the mean rank for mental health and QWL are 162.6 and 755.6, respectively, with an error probability of less than 0.001. The results of this analysis are presented in Tables 4 and 5.

Pearson correlation was also used to examine the relationship between the dimensions of mental health and the dimensions of QWL. The degree of correlation and their significance are shown in Table 6. Even at the 10% error level, there is no significant correlation between QWL and dimensions of mental health. Also, there is no significant correlation between mental health and dimensions of QWL at the same level of error. At the 1% error level, only the correlation between fair and adequate payment and somatic symptoms is significant. However, at the 10% error level, the correlations between somatic symptoms with constitutionalism, anxiety symptoms, and insomnia with the development of human capabilities and social dysfunction with opportunities for continuous growth and security are significant.

## 5. Discussion

The present study is descriptive correlational in terms of purpose and applied in terms of the type of use. It attempts to understand a specific situation in the real world to apply the findings to provide solutions for development and improvement. Therefore, in terms of purpose, it is considered practical. This research is conducted from a descriptive point of view conducted in the field using the data of distributed questionnaires. On the other hand, because it seeks to understand the correlation relationships based on the opinions and desires of individuals, it is considered correlational. The researcher has no role in the relationship between different factors and only uses questionnaires with validity and reliability. In terms of time, it is a cross-sectional study that refers to the experiences and perceptions of nurses up to a specific period. It is also qualitative in terms of data type.

Further investigation in this regard by focusing on nurses with associate degrees shows that at the level of five percent error, there is a significant correlation between fair and adequate payment with depressive symptoms, opportunities for continuous growth and security with social dysfunction, and the total living space with somatic symptoms. Another essential point in this study is the significant correlation between age and work experience with the mental health of nurses. Due to the negative mental health index, as the age of nurses increases, their mental health deteriorates. However, the correlation between age and work experience with QWL is not significant. Therefore, older nurses are more likely to be psychologically vulnerable and need more support. These results can be delegated by the type of activity or responsibility, which requires further consideration. Regarding the dimensions of mental health, the worst conditions are related to somatic symptoms, and the best conditions are related to depressive symptoms. Regarding the QWL, the worst conditions are related to the total living space, and the best conditions are related to the development of human capabilities. It has been investigated whether specific pandemic protocols have put more pressure on nurses and resulted in fatigue or boredom of the overall living space and confirmed by Sun et al. [42]. The correlation between fair and adequate payment and

Table 6: Degree of correlation and their significance.

| | | Somatic symptoms | Anxiety and insomnia | Social dysfunction | Severe depression | Total mental health |
|---|---|---|---|---|---|---|
| Total QWL | Pearson correlation | −0.097 | 0.015 | −0.051 | 0.017 | −0.034 |
| | Significant error | 0.217 | 0.844 | 0.514 | 0.833 | 0.669 |
| Fair and adequate payment | Pearson correlation | −0.207* | −0.089 | 0.034 | 0.113 | −0.057 |
| | Significant error | 0.008 | 0.258 | 0.668 | 0.147 | 0.467 |
| Safe and healthy working environment | Pearson correlation | −0.100 | 0.025 | −0.055 | −0.022 | −0.045 |
| | Significant error | 0.199 | 0.746 | 0.485 | 0.775 | 0.567 |
| Opportunities for continuous growth and security | Pearson correlation | −0.032 | 0.067 | −0.141 | −0.054 | −0.037 |
| | Significant error | 0.687 | 0.393 | 0.070 | 0.491 | 0.635 |
| Constitutionalism | Pearson correlation | −0.150 | −0.040 | −0.027 | −0.051 | −0.089 |
| | Significant error | 0.054 | 0.608 | 0.732 | 0.512 | 0.257 |
| Social dependence of working life | Pearson correlation | −0.077 | −0.049 | 0.042 | 0.043 | −0.020 |
| | Significant error | 0.326 | 0.529 | 0.595 | 0.587 | 0.797 |
| The total life space | Pearson correlation | −0.044 | 0.002 | −0.094 | −0.037 | −0.049 |
| | Significant error | 0.572 | 0.985 | 0.228 | 0.634 | 0.533 |
| Social integration and cohesion in the organization | Pearson correlation | −0.091 | 0.038 | −0.079 | 0.022 | −0.028 |
| | Significant error | 0.246 | 0.632 | 0.314 | 0.777 | 0.719 |
| Development of human capabilities | Pearson correlation | 0.099 | 0.133 | 0.008 | 0.095 | 0.115 |
| | Significant error | 0.208 | 0.089 | 0.915 | 0.224 | 0.141 |

constitutionalism in QWL with the dimension of somatic symptoms in mental health is significant, indicating that nurses' fatigue is more pronounced concerning the soft aspects of QWL. Consequently, establishing appropriate performance appraisal systems and performance-based pay and rewards can be considered a vital decision-making option. Other issues such as symptoms of anxiety and insomnia and their significant negative relationship with the development of human capabilities are also debatable. Perhaps, more awareness of the pandemic situation has somehow led to anxiety. In this case, reapplying appropriate safety systems by hospitals and medical centers to build trust and confidence in invulnerability can be a desirable option for decision making. Social dysfunction also significantly correlates with opportunities for continuous growth and security. Perhaps, individuals will show more social dysfunction if they have the opportunity to grow and develop in their jobs and professions.

## 6. Conclusion

In the present study, nurses' mental health status and QWL during the COVID-19 pandemic were evaluated to a limited extent. As expected, the reliability of both questionnaires was acceptable. The study found that if mental health was considered a criterion, the pandemic affected almost all nurses with different demographic conditions. This did not depend solely on the ostensibly involved departments, such as the emergency or COVID-19. However, the study shows that nurses with associate degrees have significantly less mental health.

This study did not identify a significant relationship between age and QWL, same as [43], which is not consistent with the study of [44], stating that there is a close correlation between age and QWL of nurses. The findings of this study are in good agreement with the findings of Bakhshi et al. [14] that there is no significant difference in the mean QWL in different wards of hospitals and medical centers. On the other hand, as mentioned above, the need to pay attention to constitutionalism in this study is evident. In short, it can be said that in the medical centers under study, mental health and QWL in general and within the relevant dimensions are not in good condition. The relationship between them with demographic characteristics and each other indicates the existence of several potential solutions. It is necessary to evaluate the solutions and select the best ones in an appropriate decision-making approach. Suppose the quality of working life improves according to the specific requirements and protocols of the COVID-19 pandemic, it may be hoped that nurses' mental health will improve.

## Data Availability

The data are available and can be provided over the email queries directly to the corresponding author (nasrisfahani.z@ajums.ac.ir).

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## References

[1] M. Sadeghi Yarandi, A. Gholami, M. Ghasemi, M. Sadeghi Yarandi, A. Ghasemi Koozekonan, and A. Soltanzadeh, "Investigating the psychological consequences of the COVID-19 outbreak in the occupational society," *Journal Mil Med*, vol. 22, no. 6, pp. 562–569, 2020.

[2] A. D. M. Quchan, A. Tajabadi, F. Borzoee, N. Heshmatifar, Z. M. Tabrizi, and S. Rastaghi, "Comparison of mental health of nurses working in COVID-19 reference hospitals with other hospitals," *Journal of Military Medicine*, vol. 22, no. 11, pp. 1145–1152, 2020.

[3] M. Mahmoudi, "COVID lessons: was there any way to reduce the negative effect of COVID-19 on the United States economy? 2016, https://arxiv.org/abs/2201.00274.

[4] L. Morawska and J. Cao, "Airborne transmission of SARS-CoV-2: The world should face the reality," *Environment International*, vol. 139, Article ID 105730, 2020.

[5] G. M. McAlonan, A. M. Lee, V. Cheung et al., "Immediate and sustained psychological impact of an emerging infectious disease outbreak on health care workers," *Canadian Journal of Psychiatry*, vol. 52, no. 4, pp. 241–247, 2007.

[6] F. F. Al-Mailam, "The effect of nursing care on overall patient satisfaction and its predictive value on return-to-provider behavior," *Quality Management in Health Care*, vol. 14, no. 2, pp. 116–120, 2005.

[7] A. Kutney-Lee, M. D. McHugh, D. M. Sloane et al., "Nursing: A Key to Patient Satisfaction: patients' reports of satisfaction are higher in hospitals where nurses practice in better work environments or with more favorable patient-to-nurse ratios," *Health Affairs*, vol. 28, no. 3, pp. w669–w677, 2009.

[8] R. McCay, A. A. Lyles, and L. Larkey, "Nurse leadership style, nurse satisfaction, and patient satisfaction," *Journal of Nursing Care Quality*, vol. 33, no. 4, pp. 361–367, 2018.

[9] A. Naidu, "Factors affecting patient satisfaction and healthcare quality," *International Journal of Health Care Quality Assurance*, vol. 22, 2009.

[10] C. Tang, B. Tian, X. Zhang et al., "The influence of cultural competence of nurses on patient satisfaction and the mediating effect of patient trust," *Journal of Advanced Nursing*, vol. 75, no. 4, pp. 749–759, 2019.

[11] M. A. West, J. P. Guthrie, J. F. Dawson, C. S. Borrill, and M. Carter, "Reducing patient mortality in hospitals: The role of human resource management," *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior*, vol. 27, no. 7, pp. 983–1002, 2006.

[12] S. Bello, R. F. Afolabi, and D. A. Adewole, "Job satisfaction and psychiatric morbidity among resident doctors in selected teaching hospitals in southern Nigeria: a web-based survey," *Journal of Occupational Health and Epidemiology*, vol. 8, no. 4, pp. 199–206, 2019.

[13] Who, "Mental health: Strengthening our response," *World Health, rgani aAonS*, vol. 2, no. 12, pp. 3–5, 2016.

[14] E. Bakhshi, R. Kalantari, N. Salimi, and F. Ezati, "Assessment of quality of work life and factors related to it based on the Walton's model: a cross-sectional study in employment of health and treatment sectors in islamabad city," *Journal of Health in the Field*, vol. 6, no. 4, pp. 12–19, 2019.

[15] S. B. Thakre, S. S. Thakre, and S. N. Thakre, "Quality of work life of nurses working at tertiary health care institution: A cross sectional study," *International Journal of Community Medicine and Public Health*, vol. 4, no. 5, pp. 1627–1636, 2017.

[16] L. Esmaeilpour and E. Jafarjalal, "The association of the quality of work life and general health of the nurses in psychiatric wards," *Iran Journal of Nursing*, vol. 32, no. 117, pp. 69–79, 2019.

[17] A. Zaybak and K. Cevik, "Stressors in the intensive care unit: perceptions of patients and nurses," *Turkish Journal of Medical and Surgical Intensive Care*, vol. 6, no. 1, pp. 4–9, 2015.

[18] Y. Kawano, "Association of job-related stress factors with psychological and somatic symptoms among Japanese hospital nurses: effect of departmental environment in acute care hospitals," *Journal of Occupational Health*, vol. 50, no. 1, pp. 79–85, 2008.

[19] A. Najimi, A. M. Goudarzi, and G. Sharifirad, "Causes of job stress in nurses: a cross-sectional study," *Iranian Journal of Nursing and Midwifery Research*, vol. 17, no. 4, pp. 301–5, 2012.

[20] T. Rutledge, E. Stucky, A. Dollarhide et al., "A real-time assessment of work stress in physicians and nurses," *Health Psychology*, vol. 28, no. 2, pp. 194–200, 2009.

[21] M. S. Kim, T. Kim, D. Lee et al., "Mental disorders among workers in the healthcare industry: 2014 national health insurance data," *Annals of occupational and environmental medicine*, vol. 30, no. 1, pp. 31–38, 2018.

[22] Y. Zhang, L. Tian, W. Li et al., "Mental health status among Chinese healthcare-associated infection control professionals during the outbreak of coronavirus disease 2019: A national cross-sectional survey," *Medicine*, vol. 100, no. 5, 2021.

[23] M. C. C. Lee, S. Thampi, H. P. Chan et al., "Psychological distress during the COVID-19 pandemic amongst anaesthesiologists and nurses," *British Journal Anaesthesia*, vol. 125, no. 4, pp. e384–e386, 2020.

[24] N. Javadi-Pashaki and A. Darvishpour, "Survey of stress and coping strategies to predict the general health of nursing staff," *Journal of Education and Health Promotion*, vol. 8, 2019.

[25] H. Hardiyono, I. Aiyul, F. Ifah, W. Wahdaniah, and F. Reni, "Effect covid-19: Burnout on nurse," *Revista Especial*, vol. 41, no. 42, pp. 11–18, 2020.

[26] E. Sadeghipoor and M. Moradisabzevar, "Screening children with Autism by developing smart toy cars," *International*

*Journal of Research in Engineering and Science*, vol. 2, no. 10, pp. 23–30, 2021.

[27] A. H. Dehkordi, S. Gholamzad, S. Myrfendereski, and A. H. Dehkordi, *The Effect of COVID-19 on Anxiety, Quality of Work Life and Fatigue of Health Care Providers in Health Care Centers*, 2020.

[28] L. Kelbiso, A. Belay, and M. Woldie, "Determinants of quality of work life among nurses working in Hawassa town public health facilities, South Ethiopia: a cross-sectional study," *Nursing Research and Practice*, vol. 2017, Article ID 5181676, 8 pages, 2017.

[29] M. Q. H. Abadi, S. Rahmati, A. Sharifi, and M. Ahmadi, "HSSAGA: Designation and scheduling of nurses for taking care of COVID-19 patients using novel method of hybrid salp swarm algorithm and genetic algorithm," *Applied Soft Computing*, vol. 108, Article ID 107449, 2021.

[30] K. Zhang, T. Goetz, F. Chen, and A. Sverdlik, "Angry women are more trusting: The differential effects of perceived social distance on trust behavior," *Frontiers in Psychology*, vol. 2857, 2021.

[31] T. Hu, S. Wang, B. She et al., "Human mobility data in the COVID-19 pandemic: Characteristics, applications, and challenges," *International Journal of Digital Earth*, vol. 14, no. 9, pp. 1126–1147, 2021.

[32] E. Sadeghipour and N. Sahragard, "Face recognition based on improved SIFT algorithm," *International Journal of Advanced Computer Science and Applications*, vol. 7, no. 1, pp. 547–551, 2016.

[33] A. Sharifi, M. Ahmadi, and A. Ala, "The impact of artificial intelligence and digital style on industry and energy post-COVID-19 pandemic," *Environmental Science and Pollution Research*, vol. 28, no. 34, pp. 46964–46984, 2021.

[34] S. Chen, J. Zhang, F. Meng, and D. Wang, "A Markov chain position prediction model based on multidimensional correction," *Complexity*, vol. 2021, Article ID 6677132, 8 pages, 2021.

[35] A. Ala, F. E. Alsaadi, M. Ahmadi, and S. Mirjalili, "Optimization of an appointment scheduling problem for healthcare systems based on the quality of fairness service using whale optimization algorithm and NSGA-II," *Scientific Reports*, vol. 11, no. 1, pp. 19816–19819, 2021.

[36] A. Hankir, J. Fletcher-Rogers, J. Ogunmuyiwa, F. R. Carrick, and R. Zaman, "Reducing mental health stigma in medical students and doctors towards their peers with mental health difficulties: a protocol," *Psychiatria Danubina*, vol. 32, no. 1, pp. 130–134, 2020.

[37] J. Abbas, "The impact of coronavirus (SARS-CoV2) epidemic on individuals mental health: the protective measures of Pakistan in managing and sustaining transmissible disease," *Psychiatria Danubina*, vol. 32, no. 3-4, pp. 472–477, 2020.

[38] D. P. Goldberg and V. F. Hillier, "A scaled version of the general health questionnaire," *Psychological Medicine*, vol. 9, no. 1, pp. 139–145, 1979.

[39] R. E. Walton, "Quality of working life: what is it," *Sloan Management Review*, vol. 15, no. 1, pp. 11–21, 1973.

[40] F. Kermansaravi, A. Navidian, S. N. Rigi, and F. Yaghoubinia, "The relationship between quality of work life and job satisfaction of faculty members in Zahedan University of Medical Sciences," *Global Journal of Health Science*, vol. 7, no. 2, p. 228, 2015.

[41] M. Khaghanizadeh, A. Ebadi, N. M. Sirati, and M. Rahmani, "The Study of Relationship between Job Stress and Quality of Work Life of Nurses in Military Hospitals," *Journal of Military Medicine*, vol. 10, 2008.

[42] N. Sun, L. Wei, S. Shi et al., "A qualitative study on the psychological experience of caregivers of COVID-19 patients," *American Journal of Infection Control*, vol. 48, no. 6, pp. 592–598, 2020.

[43] T. Moradi, F. Maghaminejad, and I. Azizi-Fini, "Quality of working life of nurses and its related factors," *Nursing and midwifery studies*, vol. 3, no. 2, Article ID e19450, 2014.

[44] N. Dehghan Nayeri, T. Salehi, and A. Ali Asadi Noghabi, "Quality of work life and productivity among Iranian nurses," *Contemporary Nurse*, vol. 39, no. 1, pp. 106–118, 2011.

Hindawi
Journal of Healthcare Engineering
Volume 2022, Article ID 1450723, 7 pages
https://doi.org/10.1155/2022/1450723

*Research Article*

# Premature Ventricular Contraction Recognition Based on a Deep Learning Approach

**Nazanin Tataei Sarshar [1] and Mohammad Mirzaei [2]**

[1] *Department of Engineering, Islamic Azad University Tehran North Branch, Tehran, Iran*
[2] *Department of Electrical and Computer Engineering, Islamic Azad University Tehran North Branch, Tehran, Iran*

Correspondence should be addressed to Mohammad Mirzaei; m.mirzaie@iau-tnb.ac.ir

Received 3 February 2022; Revised 25 February 2022; Accepted 28 February 2022; Published 26 March 2022

Academic Editor: Saeid Jafarzadeh Ghoushchi



Electrocardiogram signal (ECG) is considered a significant biological signal employed to diagnose heart diseases. An ECG signal allows the demonstration of the cyclical contraction and relaxation of human heart muscles. This signal is a primary and noninvasive tool employed to recognize the actual life threat related to the heart. Abnormal ECG heartbeat and arrhythmia are the possible symptoms of severe heart diseases that can lead to death. Premature ventricular contraction (PVC) is one of the most common arrhythmias which begins from the lower chamber of the heart and can cause cardiac arrest, palpitation, and other symptoms affecting all activities of a patient. Nowadays, computer-assisted techniques reduce doctors' burden to assess heart arrhythmia and heart disease automatically. In this study, we propose a PVC recognition based on a deep learning approach using the MIT-BIH arrhythmia database. Firstly, 10 heartbeat and statistical features including three morphological features (RS amplitude, QR amplitude, and QRS width) and seven statistical features are computed for each signal. The extraction process of these features is conducted for 20 s of ECG data that create a feature vector. Next, these features are fed into a convolutional neural network (CNN) to find unique patterns and classify them more effectively. The obtained results prove that our pipeline improves the diagnosis performance more effectively.

## 1. Introduction

According to the World Health Organization, the main cause of death worldwide is cardiovascular diseases (CVD). An evaluation proved that 17.9 million people died from CVD in 2019, indicating 32 of all global deaths [1]. According to the report of the sudden cardiac death in 2006 and latest standard in the American Heart Association (AHA) on ventricular arrhythmias, the epidemiology of ventricular arrhythmias entails a series of clinical applications and risk factors. These arrhythmias vary from sustained ventricular tachycardia, ventricular tachycardia, and premature complexes in people without cardiac problems background or ventricular tachyarrhythmia which leads to a sudden death [2]. Electrocardiogram (ECG) is a graph that records the fluctuations in electrical activity and is the main tool for predicting heart diseases. This ECG signal is generated by each heart cycle of the heart and can be recorded from the surface of each individual's body. Each ECG entails abundant pathological information and basic functions of the heart [3, 4]. Hence, it is a vital means for the diagnosis and examination of numerous arrhythmias. It is also of great importance to the assessment of cardiac safety and the assessment of numerous treatment techniques [4, 5].

A heart regular activity condition is reflected by a normal heartbeat (NB). Premature ventricular contraction (PVC) is a kind of ECG arrhythmias that is recognized to demonstrate an anomaly in the regular cardiac rhythm. PVC is the most common and widespread arrhythmia in the clinic, and it characterizes the abnormal behaviour of signals generated by ECG. PVC generates some variations in the heart rate leading to disruption in the electric and mechanic heart activity because of these delayed contractions (premature) [6, 7]. It means that PVC can be considered a kind of arrhythmia caused by an ectopic cardiac pacemaker represented in the ventricle. On the ECG, these PVCs are represented by bizarrely shaped and premature QRS complexes that have a $T$ wave larger than normal and are typically wider than 120 ms. At present, doctors and experts can only employ the existing medical technology for recognizing PVCs using their personal experience. So, these decisions may lead to the wrong diagnosis because of long hours of high-intensity work. The issue of PVC diagnosis due to its pattern is quite changeable and is a challenging task, even for the same patient. Recently, employing ECG-based computer-aided diagnosis (CAD) systems, assisting doctors in the interpretation of PVC can successfully progress the efficiency of diagnosis [8–10].

In the last few years, machine learning (ML) approaches have gained much interest for the analysis of medical signals and images [11–16]. Deep learning (DL) pipelines are kinds of ML and have reached better feature extraction and classification outcomes compared to the state-of-the-art performance in the different fields of computer vision tasks [17–19].

Casas et al. [7] tried to simplify the process of extracting key features and employed some simple Bayesian generative models for classifying the extracted features. They used three classifiers including quadratic discriminant analysis (QDA), Gaussian linear discriminant analysis (LDA), and Gaussian Naïve Bayes (GNB). Twenty seconds of succeeding ECG beats that were recognized by an expert were used in [20] to characterize a PVC episode. They explored 7 statistical features and 3 morphological features. Then, all extracted features were normalized and used as the input of a classifier. They used an artificial neural network (ANN) for classifying these features to classify them into PVC or non-PVC classes. Oliveira et al. [21] suggested some simplified features and explored from geometric figures constructed over QRS complexes. In the first step, they rescaled the input signal using a wavelet denoising approach. Next, the signal was divided into separate parts to extract a new set of geometrical features. Finally, these extracted features were classified using eight different classifiers. Zhao et al. [22] suggested an approach by combining the convolutional neural network (CNN) and modified frequency slice wavelet transform (MFSWT). Firstly, in each recording, the first 10s ECG waveforms were transformed into time-frequency images employing MFSWT (frequency range of 0–50 Hz). Next, using a CNN model with 25 layers, these images are classified. The proposed CNN model comprises five convolution layers (kernel size of 3×3), five maximum pooling layers, five ReLU layers, a flatten layer, five dropout layers, and two fully connected layers.

In this paper, to overcome the problem of the similarity between PVC and non-PVC heartbeats, a deep learning approach is suggested which is based on an attention mechanism. Our pipeline not only obtains a high rate of accuracy but also diminishes the computation time.

## 2. Material and Method

We divide this section into two subsections. Firstly, we describe the method of extracting features from an ECG signal. Then, the process of finding more informative features employing a CNN model is described.

*2.1. Feature Extraction.* Feature extraction is a core building block of every artificial intelligence system. The main goal of the extracting features can be considered as finding distinct patterns (the most informative and compacted set of features) to increase the performance of the whole system [18, 23]. Besides, feature extraction is utilized for extracting features from the original 1D or 2D signals to perform a reliable classification task. This exploring step is the most fundamental part of each biomedical signal processing system because the performance of a classifier might be degraded if the features are not chosen well [24–26]. So, in this study, we aim to extract some key features from a ECG signal.

An example of a normal ECG signal is demonstrated in Figure 1. A normal ECG signal entails of 6 waveform parts: $T$, U, $R$, S, P, and Q. The fragment from $Q$ to S is demonstrated as the QRS complex [9, 21, 22]. It represents ventricular depolarization and contraction and is a key clinical feature. Also, the distance among two maximum points indicates the length of a heartbeat and is demonstrated as the RR interval [6, 27, 28].

Group features play a significant role in the recognition of the PVR. The heartbeat and statistical features can be applied directly to the sequential RR cycle parts, so they are good features for applying to a real-time recognition system [28, 29].

Normally, the shape and size of the QRS complex are changed using the PVC, so it can be observed that the amplitude of the normal QRS complex is highly varied by the PVC [9]. In this study, for each ECG segment, we generate 10 distinct features that include 3 morphological features (RS amplitude, QR amplitude, and QRS width) and 7 statistical features implied in Table 1. The extracted statistical features comprise of the mean and standard deviation of the RR fragment. Also, it should be noticed that the percentage of differences among the neighboring RR intervals is greater than 10 ms or 50 ms (pRR10 and pRR50) [30–32]. An explanation of the time-domain features is demonstrated in Table 1.

By employing the MIT-BIH arrhythmia database, 10 heartbeats and statistical features are computed for each signal. The extraction process of these features is conducted for 20 s of ECG data that create a feature vector. Moreover, each group of features is labeled as non-PVC or PVC. For instance, a feature vector for a 20-second period is considered the PVC if it includes 95% PVC data; otherwise, it is labeled a non-PVC. Also, using the min-max normalization approach, we can normalize these features to values between zero and one by (1) before applying them into the CNN model for classification [6, 30].

$$\mathrm{NV} = \frac{FV - F\mathrm{min}}{F\mathrm{max} - F\mathrm{min}}, \quad (1)$$

where FV is the feature value, NV implies the normalized value of the feature, $F$max and $F$min are the maximum and minimum values of features, respectively.

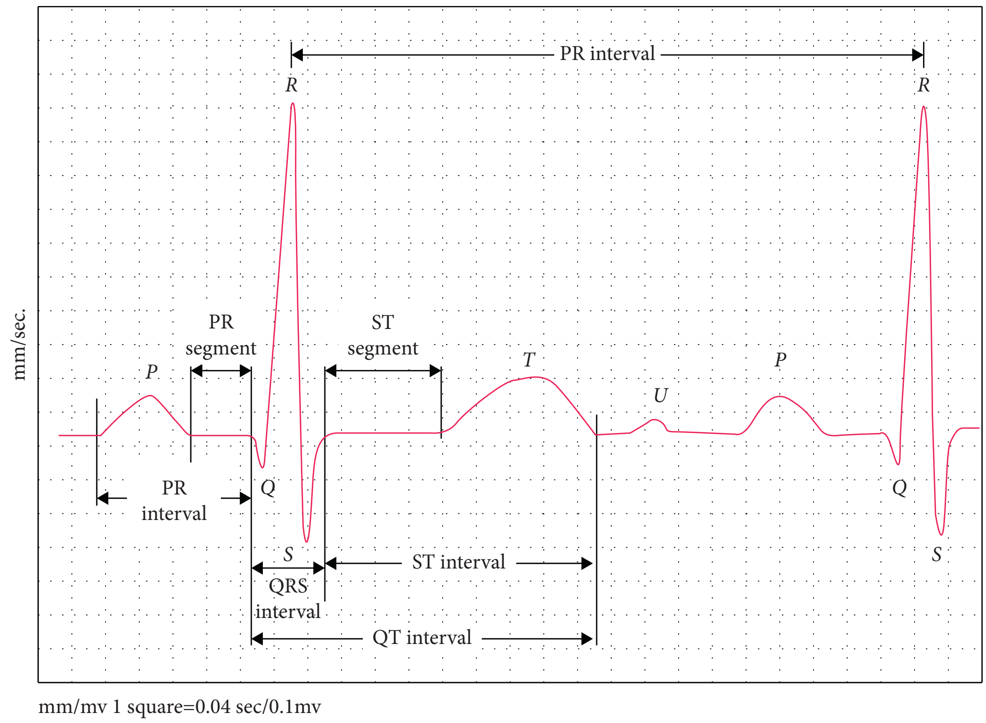



Figure 1: An example of a normal ECG signal [27].

Table 1: Explanation of statistical features.

| Features | Explanation |
|---|---|
| SDSD | Standard deviation of dissimilarities among sequential RR intervals. |
| Ratio | Ratio=(maxRR −minRR)/$\mu$rr |
| rMSSD | Square root of the mean of the squares of dissimilarities among neighboring RR intervals. |
| SDRR | Standard deviation of all RR intervals |
| pRR10 | Percentage of dissimilarities among neighboring RR intervals that are greater than 10 ms. |
| pRR50 | Percentage of dissimilarities among neighboring RR intervals that are greater than 50 ms. |
| MeanRR | Mean value of all RR intervals ($\mu$) |

*2.2. Our Deep Learning Model.* In this section, we clarify how the suggested convolutional neural network (CNN) is able to learn more informative and unique details from the extracted features. Convolutional neural networks (CNNs) are kinds of neural networks (NNs) in the machine learning (ML) fields that mimic the behaviour of a human brain. CNNs are implemented to learn the distinct pattern and relationship between the input and the output signals or images employing their biases and weights [28, 33]. The key parts of every CNN structure include (1) convolutional (Conv) layer, (2) pooling layer, and (3) fully connected (FC) layer [4, 34].

Each Conv layer is specified by its kernel biases and weights which are specified in the training procedure by an iterative update process. These Conv layers accept random values at the beginning of the process and then regulated by backpropagation strategy to minimize a cost function. All obtained biases and weights are fixed in the testing Step [35, 36].

CNNs work by passing data through some stack of neurons, which are created as a series of layers. Usually, a nonlinear activation function (or squashing function) is applied to the extracted feature maps produced by a convolution layer. This activation function is responsible for computing the weighted sum of inputs and biases and then activate a neuron. Some widely used activation functions are sigmoid, Tanh, and rectified linear activation function (ReLU) [37, 38]. In this study, the ReLU activation function is employed.

Pooling layers are employed for reducing the size of the extracted feature maps. Consequently, it diminishes the number of neurons that need to be learned and the amount of computation performed in the network. The pooling layer summarizes the features present in an area of the feature maps created by the former Conv layer. Some widely used pooling methods are max-pooling and mean-pooling. In this study, the max-pooling is employed. Fully connected layer (FC layer) is simply, a feed forward neural network. The FC layer forms one or more last few layers in the network. These layers accept the output of the final pooling or Conv layer, which is flattened before applying [13–39]. Our network is displayed in Figure 2.

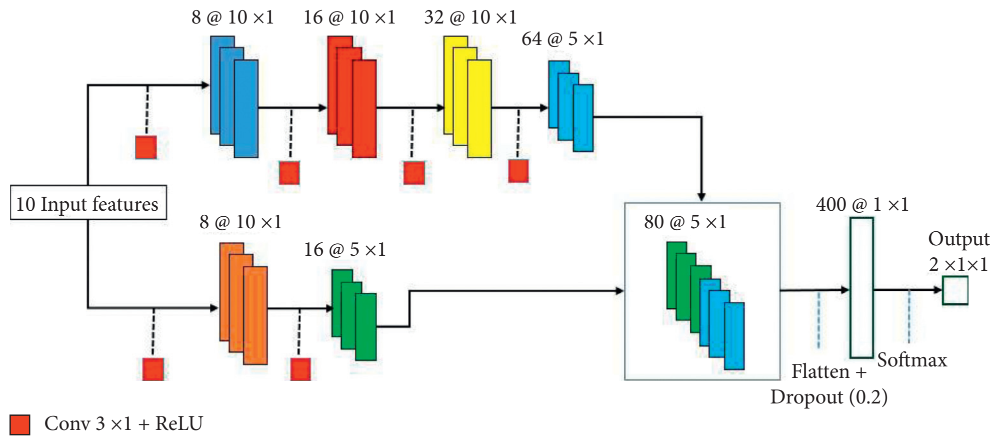



Figure 2: The proposed CNN structure with two separate feature extracting routes.

As clearly demonstrated in Figure 2, our CNN model accepts 10 features extracted from the last step and comprises of two feature extracting routes which are concatenated before applying to the FC layer. In the upper rout, there are four convolutional layers in which the first three of them do not use the pooling layer. In other words, the size of the input feature maps that are fed and are extracted from the first convolutional layers are the same. The first three Conv layers are responsible for extracting low-level features and the last Conv layer is used for extracting high-level features. The kernel size in all convolution layers is $3 \times 3$. We applied the pooling layer after the fourth convolution layer to decrease the dimension of the extracted feature maps. The next feature extracting route only has two convolution layers in which only the last one applies to the pooling layer. Also, the first and second Conv layers are responsible for extracting low-level and high-level features, respectively. These two separate routes permit the network to learn more informative details about the signal. The parameters utilized for training our network are described in Table 2.

Table 2: Parameters utilized to train our network.

| Parameters | Value |
|---|---|
| Input features | 10 × 1 |
| Output classes | 2 |
| Learning rate | 0.0001 |
| Max epochs | 40 |
| Activation function | Softmax |
| Batch size | 200 |
| Optimizer | Adam |
| Learning rate drop factor | 0.2 |

## 3. Experiments

*3.1. Dataset and Implementation Details.* In this study, the available public MIT-BIH arrhythmia database is employed for assessment of our strategy experimental data [41, 42]. This standard database is one of the popular and broadly utilized ECG databases in the world. The database includes an overall of 48 records, each covering two 360 Hz signals, each with a length of 650,000 samples and a duration of approximately 30 minutes. The 48 records enclosed 23 records which are randomly chosen from more than 4,000 Holter recordings and numbered from 100 to 124 (some numbers missing). The rest of 25 records which numbered from 200 to 234 (some missing numbers) are clinically noteworthy arrhythmias but are the records of uncommon. The MIT-BIH data entail of three sections: (1) the comment file [atr] that employs binary storage, (2) the data file [dat] that is stored in the 212 format, and (3) the header file [hea] that is stored in the ASCLL code.

By exploring the MIT-BIH arrhythmia database, it is clear that the numbers of 102, 104, 107, and 217 cover paced beats. According to the Association for the Advancement of Medical Instrumentation (AAMI), we discard 4 records and use the rest of 44 records as investigational data. Moreover, to compare with some other structures, all remaining 44 records are divided into two datasets Data1 and Data2. Data1 is employed for training; Data2 is employed for testing. More details about them are shown in Table 3. Each dataset entails 22 records from the ECG database. Using the AAMI standard, there are five kinds of heartbeats: Q, V, S, F, and N. Before applying data into the classifier, we mark V type as PVC type and remaining as non-PVC so that the dataset entails only non-PVC and PVC groups.

*3.2. Assessment Metrics.* In this part, the assessment of the method is clarified. The performance of the model is evaluated by considering four basic criteria: true negative (TN), false positive (FP), false negative (FN), and true positive (TP). By using these four criteria, all the other statistical criteria can be computed. In this study, the true negative implies that the PVC was not identified, and the arrhythmia was not presented, while the true positive implies that a PVC was recognized and the arrhythmia actually happened. Moreover, the false negative demonstrates that a PVC was not recognized, whereas the arrhythmia was observed. Lastly, the false positive illustrates that a PVC was recognized, but it actually did not happen. Precision or positive predictive value (PPV) demonstrates the probability of being true positive when the test is positive. Sensitivity (true positive rate or recall) implies the ability of recognizing

Table 3: Description of the dataset and partitioning of all signals.

| Data | Signals | Used for train or test | PVC type (V) | Non-PVC type (non-$V$) | Total |
|---|---|---|---|---|---|
| Data2 | 100, 103, 105, 111, 113, 117, 121, 123, 200, 202, 210, 212, 213, 214, 219, 221, 222, 228, 231, 232, 233, 234 | Test | 3157 | 46539 | 49696 |
| Data1 | 101, 106, 108, 109, 112, 114, 115, 116, 118, 119, 122, 124, 201, 203, 205, 207, 208, 209, 215, 220, 223, 230 | Train | 3648 | 47573 | 51221 |
| DS1 + DS2 | 44 signals | - | 6805 | 94112 | 100917 |

Table 4: The performance of our strategy for some records.

| Record no. | PPV | Recall | F-score | Record no. | PPV | Recall | F-score |
|---|---|---|---|---|---|---|---|
| 100 | 99.5 | 100 | 99.7 | 201 | 97.5 | 94.1 | 95.8 |
| 105 | 95.4 | 94.3 | 94.8 | 210 | 98.7 | 96.3 | 97.5 |
| 113 | 98.2 | 93.1 | 95.3 | 217 | 95.2 | 91.9 | 93.1 |
| 119 | 97.3 | 100 | 98.3 | 231 | 97.8 | 93.7 | 95.7 |

positive cases; the result with higher sensitivity has fewer false negatives samples. The F-score (F-measure) is a measure of a model's accuracy on a dataset. These three criteria are computed as follows [16, 23, 26]:

$$\text{sensitivity or recall} = \frac{TP}{TP + FN} \times 100. \quad (2)$$

$$\text{PPV or precision} = \frac{TP}{TP + FP} \times 100\%. \quad (3)$$

$$F = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \times 100\%. \quad (4)$$

*3.3. Experimental Results and Discussion.* The suggested technique is implemented in MATLAB with the MatConvNet toolbox [43] on a PC with a GTX-1080 GPU, core i7 3.2 GHz CPU, and 8G memory. Table 4 exhibits the performance of our strategy for some records. In this study, we use QRS fragment analysis as an appropriate tool, contributing to the revealing of ventricular hypertrophy, heart arrhythmias, and other diseases [5]. We observed that PVC beats (abnormal beats) entail QRS patterns broader than normal beats. Also, their statistical features are meaningfully diverse that permits PVC beats to be recognized comparatively easily [3]. Many varieties of arrhythmia, chiefly tachycardia and bradycardia, lead to changing in statistical features [27]. Accordingly, heartbeat and statistical features can be extracted directly from the sequential QRS cycle items. So, we extracted 10 features for each ECG fragment that play a key role for a classification task. For instance, from record No. 119 that entails many PVC beats in Table 4, it is clear that no PVCs were missed, but two wrong (false) alarms are observed over the 30-minute classification.

The PPV, F-score, and sensitivity values employing all mentioned frameworks are described in Table 5. For each index in Table 5, the highest PPV, F-score, and sensitivity values are highlighted in bold. Notice that when using the Yu et al.'s approach [6], PPV was enhanced in comparison to other strategies, but the values of recall utilizing the approaches by Allami et al. [20] and Xie et al. [31] are still higher. Additionally, there is a minimum difference between the values of recall employing those by Yu et al. [6] and Xie et al. [31]. Pierleoni et al. [44] gained the worst outcomes for all three measures. There was a diminish chiefly in the positive class scores.

Table 5: Comparison between the suggested network and other baseline models on MIT-BIH arrhythmia database.

| Method | PPV (mean) | Recall (mean) | F-score (mean) |
|---|---|---|---|
| Allami et al. [20] | 97.8 | 98.7 | 98.2 |
| Pierleoni et al. [44] | 86 | 87 | 86.5 |
| Xie et al. [31] | 95.4 | 97.8 | 96.6 |
| Yu et al. [6] | 98.1 | 97.2 | 97.6 |
| Our approach | 98.6 | 99.2 | 98.9 |

Moreover, it is clear that our approach and Allami et al.'s approach [20] are more stable than the Grad-CAM by Pierleoni et al. [44] and Xie et al. [31]. Meanwhile, Xie et al. [31] showed the same performance, getting only one more false negative and two more false positives. For Pierleoni et al. [44], all measures are less than the other approaches and it suffers from overfitting. The gap between the values of PPV by employing Yu et al. [6] and Allami et al.'s approaches [20] is not significant which is relatively smaller than this gap when using Xie et al. [31] and Pierleoni et al.'s approaches [44]. In ML techniques, how to design a suitable feature exploring technique is a challenge task and the classification performances are lower than the suggested pipeline. Moreover, our technique not only enhances the accuracy of traditional ML strategies but also is capable of automatically exploring and biasing key features of raw ECG signals.

## 4. Discussion and Conclusions

In this study, a novel premature ventricular contraction recognition based on a deep learning approach has implemented benefits from the characterization of an ECG signal. It means that each ECG signal has many informative and unique characteristics to aid our method efficiently even if dissimilar shapes are presented. We employed 10 distinct features that include 3 morphological features (RS amplitude, QR amplitude, and QRS width) and 7 statistical features which are able to highlight distinction between different parts of ECG signals. Moreover, we have employed a CNN structure for identifying more unique features that allows our pipeline to reach a higher classification performance. This approach leads to diminishing the false positive rate and increasing the true positive rate. Moreover, our technique not only enhances the accuracy of traditional ML strategies but also is capable of automatically exploring and biasing key features of raw ECG signals. We conducted comprehensive investigations, which demonstrate the effectiveness of our technique by the comparison with the state-of-the-art strategies [40].

## Data Availability

In this study, the available public MIT-BIH arrhythmia database is employed for assessment of our strategy experimental data.

## Disclosure

The funding sources had no involvement in the study design, collection, analysis, or interpretation of data, writing of the manuscript, or decision to submit the manuscript for publication.

## Conflicts of Interest

The authors declare no conflicts of interest.

## References

[1] Cardiovascular diseases (CVDs), 2021, https://www who int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds).

[2] D. P. Zipes, "[Guidelines for management of patients with ventricular arrhythmias and the prevention of sudden cardiac death. Executive summary]," *Revista Espanola de Cardiologia*, vol. 59, no. 12, p. 1328, 2006.

[3] D. Nabil and F. Bereksi Reguig, "Ectopic beats detection and correction methods: a review," *Biomedical Signal Processing and Control*, vol. 18, pp. 228–244, 2015.

[4] R. S. Andersen, A. Peimankar, and S. Puthusserypady, "A deep learning approach for real-time detection of atrial fibrillation," *Expert Systems with Applications*, vol. 115, pp. 465–473, 2019, https://www.sciencedirect.com/science/article/abs/pii/S0957417418305190.

[5] K. Ranjeet, A. Kumar, and R. K. Pandey, "An efficient compression system for ECG signal using QRS periods and CAB technique based on 2D DWT and Huffman coding," in *Proceedings of the 2013 International Conference on Control, Automation, Robotics and Embedded Systems (CARE)*, Jabalpur, India, December 2013.

[6] J. Yu, X. Wang, X. Chen, and J. Guo, "Automatic premature ventricular contraction detection using deep metric learning and KNN," *Biosensors*, vol. 11, no. 3, p. 69, 2021.

[7] M. M. Casas, R. L. Avitia, F. F. Gonzalez-Navarro, J. A. Cardenas-Haro, and M. A. Reyna, "Bayesian classification models for premature ventricular contraction detection on ECG traces," *Journal of Healthcare Engineering*, vol. 2018, pp. 1–7, 2018.

[8] Z. Chen, H. Xu, J. Luo, T. Zhu, and J. Meng, "Low-power perceptron model based ECG processor for premature ventricular contraction detection," *Microprocessors and Microsystems*, vol. 59, pp. 29–36, Jun. 2018.

[9] F.-y. Zhou, L.-p. Jin, and J. Dong, "Premature ventricular contraction detection combining deep neural networks and rules inference," *Artificial Intelligence in Medicine*, vol. 79, pp. 42–51, 2017.

[10] J. Wang, "Automated detection of premature ventricular contraction based on the improved gated recurrent unit network," *Computer Methods and Programs in Biomedicine*, vol. 208, Article ID 106284, 2021.

[11] A. Baghban, M. Kahani, M. A. Nazari, M. H. Ahmadi, and W.-M. Yan, "Sensitivity analysis and application of machine learning methods to predict the heat transfer performance of CNT/water nanofluid flows through coils," *International Journal of Heat and Mass Transfer*, vol. 128, pp. 825–835, 2019.

[12] A. Hojatimalekshah, Z. Uhlmann, N. F. Glenn et al., "Tree canopy and snow depth relationships at fine scales with terrestrial laser scanning," *The Cryosphere*, vol. 15, no. 5, pp. 2187–2209, 2021.

[13] Z. Xu, F. R. Sheykhahmad, N. Ghadimi, and N. Razmjooy, "Computer-aided diagnosis of skin cancer based on soft computing techniques," *Open Medicine*, vol. 15, no. 1, pp. 860–871, 2020.

[14] R. Ranjbarzadeh, S. B. Saadi, and A. Amirabadi, "LNPSS: SAR image despeckling based on local and non-local features using patch shape selection and edges linking," *Measurement*, vol. 164, p. 107989, 2020.

[15] Y. Pourasad, R. Ranjbarzadeh, and A. Mardani, "A new algorithm for digital image encryption based on chaos theory," *Entropy*, vol. 23, no. 3, p. 341, 2021.

[16] N. Karimi, R. Ranjbarzadeh Kondrood, and T. Alizadeh, "An intelligent system for quality measurement of Golden Bleached raisins using two comparative machine learning algorithms," *Measurement*, vol. 107, pp. 68–76, 2017.

[17] Z. Liu, Y.-Q. Song, V. S. Sheng et al., "Liver CT sequence segmentation based with improved U-Net and graph cut," *Expert Systems with Applications*, vol. 126, pp. 54–63, 2019.

[18] A. Hu and N. Razmjooy, "Brain tumor diagnosis based on metaheuristics and deep learning," *International Journal of Imaging Systems and Technology*, vol. 31, no. 2, pp. 657–669, 2021.

[19] I. Matias, N. Garcia, S. Pirbhulal et al., "Prediction of Atrial Fibrillation using artificial intelligence on Electrocardiograms: a systematic review," *Computer Science Review*, Elsevier Ireland Ltd, vol. 39, Article ID 100334, 2021.

[20] R. Allami, "Premature ventricular contraction analysis for real-time patient monitoring," *Biomedical Signal Processing and Control*, vol. 47, pp. 358–365, 2019.

[21] B. R. d. Oliveira, C. C. E. d. Abreu, M. A. Q. Duarte, and J. Vieira Filho, "Geometrical features for premature ventricular contraction recognition with analytic hierarchy process based machine learning algorithms selection," *Computer Methods and Programs in Biomedicine*, vol. 169, pp. 59–69, 2019.

[22] Z. Zhao, X. Wang, Z. Cai, J. Li, and C. Liu, "PVC recognition for wearable ECGs using modified frequency slice wavelet transform and convolutional neural network," *Computers in Cardiology*, vol. 2019, 2019.

[23] S. M. Mousavi, A. Asgharzadeh-Bonab, and R. Ranjbarzadeh, "Time-frequency analysis of EEG signals and GLCM features for depth of anesthesia monitoring," *Computational Intelligence and Neuroscience*, vol. 2021, pp. 1–14, Article ID 8430565, 2021.
[24] L. Liu, S. lao, P. W. Fiegutin, Y. Guo, X. Wang, and M. Pietikäinen, "Median robust extended local binary pattern for texture classification," *IEEE Transactions on Image Processing*, vol. 25, no. 3, pp. 1368–1381, 2016.
[25] A. Aghamohammadi, R. Ranjbarzadeh, F. Naiemi, M. Mogharrebi, S. Dorosti, and M. Bendechache, "TPCNN: two-path convolutional neural network for tumor and liver segmentation in CT images using a novel encoding approach," *Expert Systems with Applications*, vol. 183, Article ID 115406, 2021.
[26] R. Ranjbarzadeh and S. B. Saadi, "Automated liver and tumor segmentation based on concave and convex points using fuzzy c-means and mean shift clustering," *Measurement*, vol. 150, Article ID 107086, 2020.
[27] T.-B. Nguyen, W. Lou, T. Caelli, S. Venkatesh, and D. Phung, "Individualized arrhythmia detection with ECG signals from wearable devices," *2014 International Conference on Data Science and Advanced Analytics (DSAA)*, in *Proceedings of the DSAA 2014 IEEE Int. Conf. Data Sci. Adv. Anal.*, pp. 570–576, Shanghai, China, October-November. 2014.
[28] L.-J. Ding, C.-X. Xie, S.–Y. Jiang et al., "Automated classification model with OTSU and CNN method for premature ventricular contraction detection," *IEEE Access*, vol. 9, pp. 156581–156591, 2021.
[29] Y. G. Kim, Y. Y. Choi, K. D. Han, K. J. Min, and H. Y. Choi, "Premature ventricular contraction increases the risk of heart failure and ventricular tachyarrhythmia," *Scientific Reports*, vol. 11, no. 1, pp. 1–8, 2021.
[30] Q. ul ain Mastoi, M. S. Memon, A. Lakhan, M. A. Mohammed, and M. Qabulio, "Machine learning-data mining integrated approach for premature ventricular contraction prediction," *Neural Computing & Applications*, vol. 33, no. 18, pp. 11703–11719, 2021.
[31] T. Xie, R. Li, S. Shen, X. Zhang, B. Zhou, and Z. Wang, "Intelligent analysis of premature ventricular contraction based on features and random forest," *J. Healthc. Eng.*vol. 2019, 2019.
[32] Y. Hori, T. Temma, C. Wooten et al., "Cardiac afferent signaling partially underlies premature ventricular contraction–induced cardiomyopathy," *Heart Rhythm*, vol. 18, no. 9, pp. 1586–1595, 2021.
[33] Y. He, I. Pan, J. Wu et al., "Deep learning-based classification of primary bone tumors on radiographs: a preliminary study," *EBioMedicine*, vol. 62, Article ID 103121, 2020.
[34] K. Munir, H. Elahi, A. Ayub, F. Frezza, and A. Rizzi, "Cancer diagnosis using deep learning: a bibliographic review," *Cancers*, vol. 11, no. 9, p. 1235, 2019.
[35] K. Wang and A. Kumar, "Cross-spectral iris recognition using CNN and supervised discrete hashing," *Pattern Recognition*, vol. 86, pp. 85–98, 2019.
[36] W. Liu, Y. Wen, Z. Yu, M. Li, B. Raj, and L. Song, "SphereFace: deep hypersphere embedding for face recognition," *CVPR*, pp. 212–220, 2017.
[37] G. Guo and N. Zhang, "A survey on deep learning based face recognition," *Computer Vision and Image Understanding*, vol. 189, Article ID 102805, 2019.
[38] M. Wilmanski, C. Kreucher, and J. Lauer, "Modern approaches in deep learning for SAR ATR," *Algorithms for Synthetic Aperture Radar Imagery XXIII*, vol. 9843, Article ID 98430N, 2016.
[39] M. Saha and C. Chakraborty, "Her2Net: a deep framework for semantic segmentation and classification of cell membranes and nuclei in breast cancer evaluation," *IEEE Transactions on Image Processing*, vol. 27, no. 5, pp. 2189–2200, 2018.
[40] E. Maiorana, "Deep learning for EEG-based biometric recognition," *Neurocomputing*, vol. 410, pp. 374–386, 2020.
[41] A. L. Goldberger, L. A. N. Amaral, L. Glass et al., "PhysioBank, PhysioToolkit, and PhysioNet," *Circulation*, vol. 101, no. 23, 2000.
[42] G. B. Moody and R. G. Mark, "The impact of the MIT-BIH arrhythmia database," *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 45–50, 2001.
[43] A. Vedaldi and K. Lenc, "MatConvNet: convolutional neural networks for MATLAB," in *Proceedings of the MM 2015 - Proc. 2015 ACM Multimed. Conf*, pp. 689–692, Brisbane Australia, October. 2015.
[44] P. Pierleoni, L. Pernini, A. Belli, and L. Palma, "An android-based heart monitoring system for the elderly and for patients with heart disease," *Int. J. Telemed. Appl.*vol. 2014, 2014.

Hindawi
Journal of Healthcare Engineering
Volume 2022, Article ID 4703682, 11 pages
https://doi.org/10.1155/2022/4703682

*Research Article*

# Investigation of Effectiveness of Shuffled Frog-Leaping Optimizer in Training a Convolution Neural Network

**Soroush Baseri Saadi**,[1] **Nazanin Tataei Sarshar**,[2] **Soroush Sadeghi**,[3] **Ramin Ranjbarzadeh**,[4] **Mersedeh Kooshki Forooshani**,[5] **and Malika Bendechache**[4]

[1]*Faculty of Medicine, Catholic University of Leuven (KU Leuven), Leuven, Belgium*
[2]*Department of Engineering, Islamic Azad University, Tehran North Branch, Tehran, Iran*
[3]*School of Electrical and Computer Engineering, University of Tehran, Tehran, Iran*
[4]*School of Computing, Faculty of Engineering and Computing, Dublin City University, Dublin, Ireland*
[5]*Department of Electronics and Telecommunications, Polytechnic University, Turin, Italy*

Correspondence should be addressed to Nazanin Tataei Sarshar; ab.tataee@gmail.com

Received 29 December 2021; Revised 4 February 2022; Accepted 7 March 2022; Published 23 March 2022

Academic Editor: Agostino Forestiero



One of the leading algorithms and architectures in deep learning is Convolution Neural Network (CNN). It represents a unique method for image processing, object detection, and classification. CNN has shown to be an efficient approach in the machine learning and computer vision fields. CNN is composed of several filters accompanied by nonlinear functions and pooling layers. It enforces limitations on the weights and interconnections of the neural network to create a good structure for processing spatial and temporal distributed data. A CNN can restrain the numbering of free parameters of the network through its weight-sharing property. However, the training of CNNs is a challenging approach. Some optimization techniques have been recently employed to optimize CNN's weight and biases such as Ant Colony Optimization, Genetic, Harmony Search, and Simulated Annealing. This paper employs the well-known nature-inspired algorithm called Shuffled Frog-Leaping Algorithm (SFLA) for training a classical CNN structure (LeNet-5), which has not been experienced before. The training method is investigated by employing four different datasets. To verify the study, the results are compared with some of the most famous evolutionary trainers: Whale Optimization Algorithm (WO), Bacteria Swarm Foraging Optimization (BFSO), and Ant Colony Optimization (ACO). The outcomes demonstrate that the SFL technique considerably improves the performance of the original LeNet-5 although using this algorithm slightly increases the training computation time. The results also demonstrate that the suggested algorithm presents high accuracy in classification and approximation in its mechanism.

## 1. Introduction

Currently, Deep Learning (DL) is the base for many cutting-edge artificial intelligence (AI) applications [1–3]. DL can learn features at a high-level state with more complexity and abstraction than shallower neural networks. It presents hierarchical features providing various methods, taking for instance, probabilistic models, and supervised and unsupervised methods [4, 5]. The most notorious feature of DL is its ability in reducing computer hardware and software manipulation, making advancements in computational capabilities, machine learning, and signal processing. Furthermore, it is proved to be a highly applicable solution in objects recognition [6–8], speech recognition [9–12], SAR image processing [13–16], and a highly viable method in medical image processing for the detection of potential drug molecules activities [17, 18], liver and lung tumor segmentation [19, 20].

DL principle can be employed for the design of a variety of neural networks, among which Deep Neural Network (DNN), Recurrent Neural Network (RNN), and Convolution Neural Network (CNN) are the most popular. There are also generative and hybrid models of DL. For the former, some examples are Deep Belief Network (DBN) and Boltzmann Machine (DBM), and for the latter referring to a combination of discriminative and generative models, a well-known example is pretrained deep CNN using DBN. Between the various models of DL, the focus of this study is on CNN [4, 21].

DL has a great ability for resolving learning problems. However, this method is challenging to be trained for producing the optimal results. A CNN model learns many patterns through many weights and biases inside the convolutional layers. These weights and biases obtain their best possible values through a learning process with a large number of data. Actually, in a CNN model, the number of the training samples plays a crucial role in the obtaining best possible solution [22–24]. To achieve this goal, many optimization methods have been proposed for manipulating the value of these weights and biases. The most well-known algorithms are Adaptive Gradient methods. Basically, these methods modify the learning rate by a backpropagation strategy. These approaches reduce the learning rate if the gradient of parameters is large or vice versa. Stochastic gradient descent (SGD) is the most preferred technique among adaptive gradient methods [25]. Nevertheless, they proved to have poor performance especially when the network is large like CNN since the learning rate needs to be manually tuned in SGD. This significantly increases the training time for large-scale datasets [26, 27]. To overcome this obstacle and improve the efficiency of adaptive, new variants of adaptive gradient methods are proposed such as Nostalgic Adam [28], which place bigger weights on the past gradient compared to the recent gradient, or YOGI [29], which increases in effective learning rate to achieve better convergence. However, they have not gained popularity for image processing applications with CNN, which gives rise to the use of Metaheuristic algorithms as alternatives.

Recently, metaheuristic methods have been employed to resolve complex problems such as scheduling [30] and detection problems [31]. The performance of metaheuristic algorithms in solving efficiently these problems makes them a good alternative to train neural networks with large parameters as they are simple to use, are independent form gradient, and avoid local optima [32, 33]. Metaheuristic algorithms could prove to be highly efficient in optimizing CNN parameters with large image datasets specifically in the field of image analysis. In a study carried out by Zhang et al. [34], a metaheuristic optimizer is employed to pretrain the CNN for the classification of skin cancer images. To achieve this goal, the Whale Optimization Algorithm (WOA), one of the subgroups of metaheuristic methods, was applied to reduce the error rate during the learning process. Their WOA method considers half value precision as the cost function during skin cancer validation steps that contains the simplified measured error between the output of the system and the reference. The results of this study demonstrated the accuracy prominence of this algorithm compared to the other popular classification methods used in this study. In another study performed by da Silva et al. [35], the hyperparameters of a convolutional neural network were trained with Particle Swarm Optimization (PSO), another subgroup of metaheuristic algorithm, for the classification of lung cancers (classify nodule candidates, benign or malignant tumors, into nonnodules and nodules). They used two preprocessing steps including (1) employing each CT slice as a separate sample and (2) resizing of all the samples into $28 \times 28$. The PSO method optimizes the size of trainable filters, number of batches in the training, type of pooling, number of neurons in the hidden layer, and number of kernels in the convolutional layers. Although, in this study, a large dataset of CT images was used, PSO demonstrated the accuracy of 97.62%, sensitivity of 92.20%, and specificity of 98.64%. Hoseini et al. [36] proposed an AdaptAhead optimization technique to learn a Deep CNN with robust architecture in relation to the high volume data. They utilized several MR images of BRATS 2015 and BRATS 2016 data sets to validate the proposed method. Their model fails to utilize the technique of Nesterov and the adaptive learning rate in computing the gradient leading to failure to reach the optimal convergence point.

Metaheuristic algorithms can be categorized into the following subgroups [37–39]:

(i) Swarm based methods act based on animal social behavior like PSO [40, 41], WOA [42]
(ii) Evolutionary methods act based on a natural evolutionary process like Genetic algorithm (GA) [43]
(iii) Biological based optimizers like Satin Bowerbird Optimizer (SBO) [44]
(iv) Human-based algorithms inspired from human behavior such as Life Choice Based Optimizer [45]
(v) System-based algorithms inspired by natural ecosystems such as Artificial Ecosystem-based Optimizer (AEO) [46]
(vi) Physics-based methods that mimic the physical phenomenon in nature like Equilibrium optimizer [47] and Simulated Annealing [48]

In this paper, to overcome the problem of overfitting and convergence, we optimize the values of weight and biases of a LeNet-5 by an optimization algorithm. From the various types of metaheuristic algorithms, we used the Shuffled frog-leaping algorithm (SFLA) to optimize the performance of the LeNet-5 CNN [49]. This is conducted by changing the values of weight and biases inside the model to reach a high accuracy of the model. This optimizer belongs to the Swarm-based algorithms of metaheuristic algorithms inspired by the natural behavior of frogs in searching for food. The reason for using this optimizer is that, at the time of working on this research work, based on our knowledge, there is no research to employ SFLA in training CNN and to make a good comparison with other optimizers to show the ability of this optimizer for image classification. Moreover, in order to verify our results, we applied the other well-known optimizers WOA, Ant Colony Optimizer (ACO), and Bacteria Swarm Foraging Optimization (BFSO) for comparison.

This paper is organized as follows: Section 1 is an introduction, Section 2 presents a literature review of convolution neural networks, Section 3 explains the SFL Algorithm mechanism, Section 4 describes the design of proposed methods, Section 5 presents the result and discussion of the experiment, and lastly, Section 6 is the conclusion.

## 2. Convolutional Neural Network

Neural networks or artificial neural networks are computing systems that have been inspired by the human brain. In other words, these networks mimic the biological functions that are transmitted the signal to other neurons such as synapses in a biological brain [11, 50–52]. A neural network contains mathematical functions, which compute the weighted sum of multiple inputs, output, and activation functions. Specifically, these functions are layers of interconnected nodes, which are known as artificial neurons. The convolutional neural network is one of the various classes of neural networks, which is often applied to analyze and process the vision dataset. Nowadays, a CNN model has a critical role since fast growth in deep learning and artificial intelligence. It is necessary to mention that deep learning is a neural network that is composed of more than three layers and, as well as CNN, is used multiple layers, such as convolution, pooling, and fully connected layers to learn features and detect patterns of image [4, 53–55].

The convolutional layer is a critical component of CNN that uses the information of adjacent pixels as a linear operation to extract features. Each location of the tensor is calculated through an element-wise product between input tensor, which is an array of numbers and kernel or filter, while its output is summed up in order to obtain a single value in the corresponding location of output tensor, which is known as a feature map. Several various kernels should be applied to represent a different characteristic of the input tensor in order to achieve variant feature extractors such as a horizontal edge detector or a vertical edge detector [4, 56]. The convolution operation reduces the size of the feature maps in comparison to the input tensor. Typically, the padding technique should be used to increase the dimension of the image and lose less information by adding zeros around the image. The stride is considered as a distance between two kernels in convolution operation, that is, commonly one, while sometimes usage of the values more than one is to obtain downsampling of feature map for a specified purpose [57, 58].

A pooling layer provides alternative and more robust downsampling, as well as avoiding overfitting and a lot of computation by representing abstracted feature maps. This layer is operated on each feature map independently to make a new set of the same number of pooled feature maps and reduce the number of subsequent learnable parameters. Specifically, filter size, stride, and padding are also applied as hyperparameters in pooling operations. There are two common functions in pooling operation, average pooling, which is computed average value for each patch of the feature map, and max pooling, which is calculated the maximum value. In all cases, polling supports that the value of pooled features is remained almost invariant by translating the small amount of input [4, 59, 60].

The linear output of convolution operation is passed through nonlinear activation function, which is considered as a fundamental component in order to learn the complex patterns and the ability to add nonlinearity into the network. There are various types of activation functions such as sigmoid or hyperbolic tangent function, which are taken into account as smooth nonlinear functions and rectified linear unit (ReLU) function, which is recently the most widely used activation function. This is due to the fact that sigmoid and tanh activation functions are commonly saturated and really sensitive to modify around their mid-point of their input [55, 61].

Typically, the output of the final convolution and pooling layer is transformed to a one-dimension array of numbers, which is known as flattening. The output of flattening is considered as the input of one or more fully connected layers, in which every neuron in one layer is connected to every neuron in the other layer. In other words, the nonlinear combination of high-level features, which is the output of the convolution layer, is learned by a fully connected layer in order to map the final output of the network such as the probability of each class in the classification task [4, 62]. It is important to mention that each fully connected layer is followed by an activation function such as ReLU except the last nonlinear function that is usually different from the others. The last activation function, which is applied in the classification task, is Softmax to obtain a probability of the input being in the specified class [58, 63, 64].

The cost function is another essential component in Neural Networks. Actually, cost and loss functions are synonymous; the only difference is that the single training batch uses the loss function, while the cost function is referred to apply the loss function over the entire training set. The loss function is evaluated by the compatibility between the predicted value and the ground truth label, in which the higher output of loss means the incapable performance of the model. Another hyperparameter that is required for assigning is selecting an appropriate loss function with respect to the performed task. Since the problem is an optimization problem, Gradient descent is usually applied as an optimization algorithm to minimize the loss function [4, 65, 66].

The type of CNN employed in this study is LeNet-5, which is one of the earliest CNN models [49] (Figure 1). It is a classical CNN developed originally for recognizing characters. The architecture of LeNet-5 is composed of seven layers, in which, except the input layer, the rest can be trained (weights). As shown in the Figure 1, the LeNet-5 network possesses three convolutional layers C1, C3, and C5 among its processing layers. These convolutional layers are composed of two pooling layers S2 and S4, and the output layer is F6. The arrangement of convolutional layers and subsampling layers is in the form of plans and form feature maps. Each neuron in convolutional layers is linked locally to the local receptive field in the previous layer. Neurons that have the same feature maps obtain data from different local receptive fields. This process continues until the entire input plane is skimmed, and similar weights are employed together. Feature maps are spatially downsampled in the subsampling layer, and their size is reduced by a factor of 2.

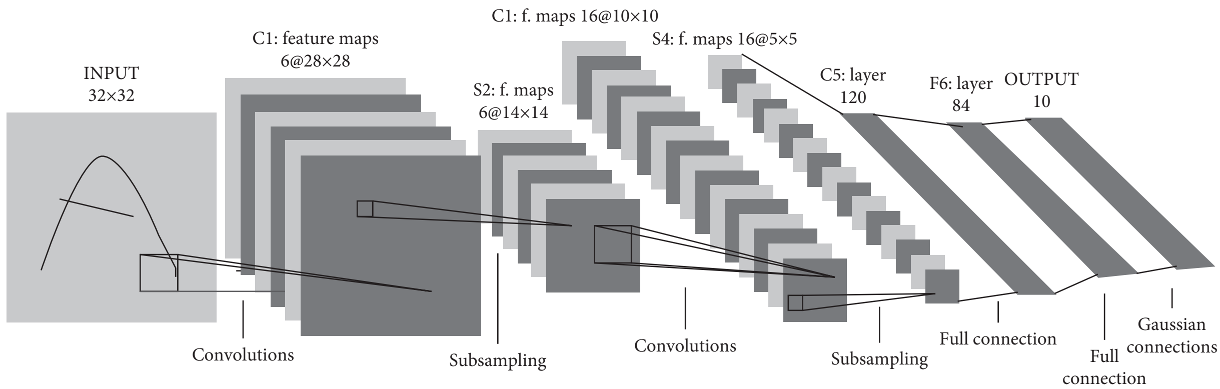



Figure 1: Illustration of LeNet-5 architecture, a convolution neural network. Each plan in the network indicates a feature map [48].

There is a similar kernel size of $5 \times 5$ for the three convolution layers C1, C3, and C5. However, the numbers of feature maps and parameters for each layer are different from each other (Table 1). The last convolution layer C5 is fully connected to the S4, and it has the feature maps size of $1 \times 1$. F6 is the last layer that performs the classification task. This layer is composed of 84 units and fully connected to the last convolutional layer C5.

Essentially, convolution layers are connected to several feature maps, kernels, and correlated to the prior layers. Each extracted feature matrix (feature map) is generated as a consequence of a sum of convolution from extracted feature matrices of the earlier layer, their corresponding mask (kernel), and a linear filter. Moreover, a bias value is summed to the extracted feature matrix and subsequently; it is applied to a nonlinear function. The tanh function is employed for this purpose. The $k$th feature map $M_{ij}^k$ with the weights $W^k$ and $b_k$ is achieved by applying the tanh function as follows:

$$M_{ij}^k = \tanh\left(\left(W^k \times x\right)_{ij} + b_k\right). \quad (1)$$

Through a subsampling layer, the size of each extracted feature matrix is reduced in relation to one of the extracted feature matrices of the former layer. This pooling strategy decreases the resolution of the extracted feature matrix. The pooling layers summarize the features present in an area of the feature map created by convolution layers. Also, a pooling layer diminishes the number of parameters for learning and the amount of computation performed in the network.

The classification task is carried out through the classification layer. This layer is placed after all the convolution and subsampling layers. In the classification layer, the output of each neuron is given to a single class label, and in the case of Oxford17, Oxford 102, Caltech/UCSD birds, and Caltech 101 airplanes dataset, this layer is composed often neurons corresponding to their labels.

## 3. Shuffled Frog-Leaping Optimizer

Shuffled Frog-Leaping Algorithm (SFLA) is a memetic metaheuristic approach that is employed to find a global solution through an informed heuristic search by employing a heuristic function [67]. This algorithm is a population-based technique that is occasioned by natural memetic. The term memetic is coming from "meme" considered as the unit of cultural evolution. Theoretically, the SFLA is similar to the particle swarm optimization (PSO). However, the values of weights and biases can be exchanged among local searches through a shuffling technique, thereby obtaining global optimum. The genuine aims of genes and memes are different from each other since they apply different mechanisms for data distribution from one population member to another [68, 69]. Gene's transmission is only possible from parents to offspring and only occurs between generations. However, memes can be transmitted between any two individuals, and instead of waiting for a full generation of genes to be replicated, it can cooperate with other memes immediately once an improved idea is found. Moreover, the replication of the genes is limited to the slight number of offspring that can belong to a single parent. On the other hand, a meme can be taken over by an unlimited number of individuals [70].

SFL algorithm is a population-based approach composed of frogs of the same attributes. Each frog can be considered as a solution. The total population of frogs is divided into numerous subgroups known as memeplexes. Diverse subgroups can be appreciated as dissimilar frog memes. Each memeplex is responsible for a limited exploration. At each memeplex, other frogs might affect the behavior of each frog, and the evolution will take place through the process of memetic evolution [70, 71]. After a number of memetic evolution periods, the memeplexes are forced to join together leading to the generation of novel memeplexes through a shuffling method. Shuffling will completely make unbiased the cultural evolution in the direction of any specific interest. The stopping criteria are satisfied once the local search and the shuffling procedure alternate [68]. The flowchart of SFLA is shown in Figure 2. The different steps are described as follows [67, 72, 73]:

(1) The algorithm contains a population "$p$" of the potential number of solutions, controlled by a set of virtual frogs ($n$).

(2) The population is split into subsets denoted as memeplexes ($m$). The memeplexes can be considered

Table 1: Properties of the layers of the LeNet-5 [48].

| Layer | Size | Num. of feature maps | Num. of parameters | Num. of connections |
|---|---|---|---|---|
| Input | $32 \times 32$ | ... | ... | ... |
| C1 | $28 \times 28$ | 6 | 156 | 122304 |
| S2 | $14 \times 14$ | 6 | 12 | 5880 |
| C3 | $10 \times 10$ | 16 | 1516 | 151600 |
| S4 | $5 \times 5$ | 16 | 32 | 2000 |
| C5 | $1 \times 1$ | 120 | ... | 48120 |
| F6 | $1 \times 1$ | 84 | 10164 | ... |

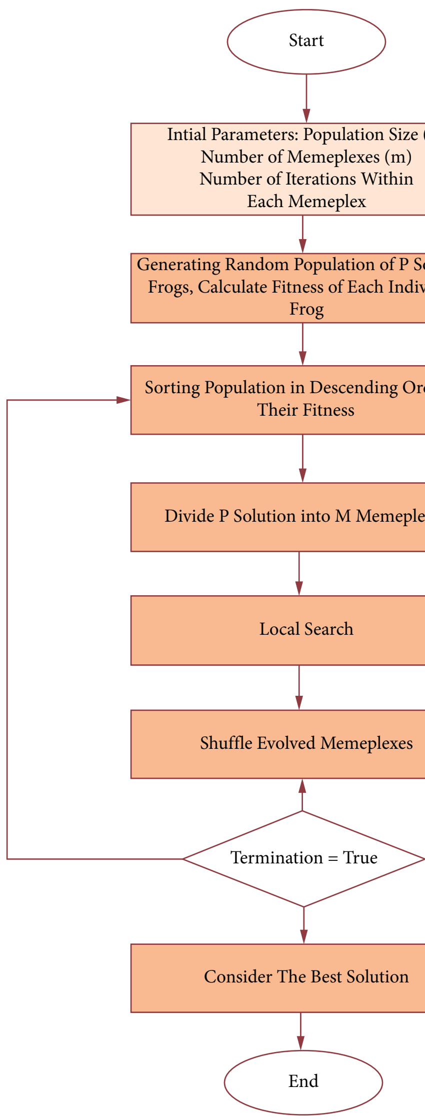



Figure 2: Flowchart of SFL algorithm.

as a set of parallel frog cultures trying to achieve some goals.

(3) Frog $i$ is shown by $X_i = (X_{i1}, X_{i2}, \ldots, X_{is})$ in which $S$ indicates the number of variables.

(4) Within each memeplex, each frog culture searches the space in different directions and exchanges ideas independently. The frogs with best and worst fitness are denoted as $X_b$ and $X_w$.

(5) Frog with global best fitness is identified as $X_g$.

(6) The frog with the worst fitness is modified based on the following equation:

$$D_i = \text{rand}\left(X_b - X_w\right),$$
$$X_{\text{neww}} = X_{\text{oldW}} + D_i \left(-D_{\max} \leq D_i \leq D_{\max}\right), \tag{2}$$

In which the rand function generates an arbitrary number between the range [0, 1], $D_i$ is the size of the leaping step of the frog$_i$ and $D_{\max}$ is the maximum value permitted to adjust frog position. If the value of fitness $X_w$ is better than the current value of $X_w$, it will be accepted. If the fitness value is not modified, then the calculation is repeated by replacing $X_b$ with $X_g$. If there is no potential for enhancement, a novel $X_w$ will be created arbitrarily. This shuffling process and the local search continue until defined convergence criteria provide satisfactory results [68, 70, 71].

## 4. Design of Proposed Method

Problem representation is the foremost step in training a CNN employing metaheuristics algorithms. To train a CNN, the problem should be formulated in a suitable way for metaheuristics. The most important variables to training this type of network are weights and biases. In the trainer, the best biases and weights values are found to provide the highest classification, approximation, and prediction accuracy for the network. Thus, biases and weights are trainable variables. It means by changing the values of biases and weights of all neurons the output results of the network can be varied. So, controlling the process of applying new weights and biases by an optimizer approach leads to reaching higher accuracy. As the SFL procedure takes the variables in the format of a vector, the variables of a CNN denoted for this technique are as follows:

$$\vec{V} = \left\{\vec{W}, \vec{\theta}\right\} = \left\{W_{1,1}, W_{1,2}, \ldots, W_{n,n}, h, \theta_1, \theta_2, \ldots, \theta_h\right\}. \tag{3}$$

In which $n$ is the size of the input, $W_{ij}$ denotes the connection weight between layers $i$th and $j$th, and $\theta_j$ is the bias (threshold) of the $j$th hidden node.

Once the variables are defined, defining the objective function for the SFL technique is the next goal. Mean Square Error (MSE) is a common metric for the evaluation of networks. Once a set of training samples are given to the CNN, this equation measures the difference between the obtained output values and the desirable values through the following equation:

(a) (b) (c) (d)

Figure 3: Datasets sample pictures. (a) OxFord flowers 17. (b) OxFord flowers 102. (c) Caltech/UCSD birds. (d) Caltech 101 airplanes.

$$\mathrm{MSE} = \sum_{i=2}^{m} \left( o_i^k - d_i^k \right), \tag{4}$$

where $m$ indicates the output numbers, the preferred output of the $i$th input unit when the $k$th training data samples are utilized is denoted by $d_i^k$, and the actual output of the $i$th input unit when the k*th* training data appear in the input is $o_i^k$.

To design an effective CNN, the network should be adapted to the whole set of training samples. As a result, CNN performance is assessed according to the average of MSE with respect to the training samples as the following equation:

$$\overline{\mathrm{MSE}} = \sum_{k=1}^{s} \frac{\sum_{i=1}^{m} \left( o_i^k - d_i^k \right)^2}{s}, \tag{5}$$

$$\text{Minimize} : F(\overrightarrow{v}) = \overline{\mathrm{MSE}}.$$

As, at each iteration, the weights and biases move towards having the best CNN, the probability of an improved CNN increases gradually. However, due to stochastic nature of SFL algorithm, there is no guarantee that the optimal CNN is obtained. On the other hand, with sufficient number of iteration, the SFL algorithm finally reaches to a solution that works more efficient than random preliminary solutions. The following section assesses the advantages of the SFL algorithm in training a CNN practically.

## 5. Experimental Results and Discussion

In this part, the suggested SFL-based CNN is investigated by employing four standard classification datasets from [74–77], OxFord Flowers 17 (Figure 3(a)), OxFord Flowers 102 (Figure 3(b)), Caltech/UCSD Birds (Figure 3(c)), and Caltech 101 Airplanes (Figure 3(d)). The specifications of the datasets are presented in Table 2.

The classification datasets were intentionally selected with the diverse test/training data and difficulty levels to efficiently evaluate the performance of our SFL-based CNN. We employed a Hewlett-Packard (hp) computer with the processor of Intel (R) Core (TM) i7-6500U CPU @ 2.50 GHz 2.60 GHz, installed memory (RAM) of 8.00 GB, System type of 64-bit Operating System, and Windows 10 Home. For data processing, we used MATLAB and Statistics Toolbox Release 2019a. The SFL assumptions and other techniques are shown in Table 3. The accuracy of classification for each dataset using different optimization algorithms is demonstrated in Figure 4. It is considered that the optimization method begins by creating random biases and weights in the range of [−10, 10] for all four datasets.

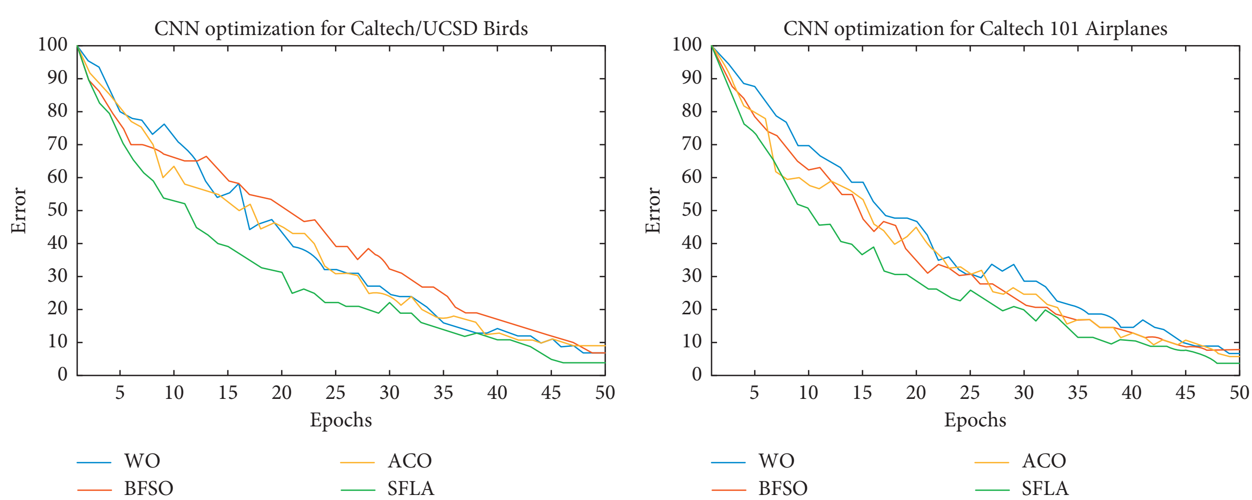
To generate the results, the datasets are solved 50 times by applying each technique. As illustrated in Figure 4, after the last iteration, the error of classification for all the datasets employing different optimizers decreases to approximately less than 10%, in which the SFL algorithm appears to be the most efficient optimizer. The average (AVE) and standard deviation (STD) shown in Tables 4–7 are actually the best MSEs obtained in the last iteration. Clearly, the lowest average and standard deviation of MSE in the final iteration illustrate the best result. The statistical outcomes are shown in the form of AVE ± STD. It should be noted that the best rates of classification attained by each method during 50 iterations are reported as another metric of comparison. Statically analysis of the results shows that training CNN with SFL algorithm provides the best accuracy of classification in all the mentioned datasets, as well as superior local optima avoidance, which is the reason for the improved MSE. Moreover, the results of this study demonstrate that, unlike other swarm-based algorithms, SFL algorithm has a better performance since it does not have a mechanism for substantial sudden movements to search the space. It is also demonstrated that ACO and WO optimizers reach a minimum time for training the model in comparison of BFSO and SFL methods. Also, the SFL method takes more time

Table 2: Dataset specifications.

| Dataset | Number of categories | Number of images per category | Training sample numbers | Test sample numbers |
|---|---|---|---|---|
| OxFord flowers 17 | 17 | 80 | 50 | 30 |
| OxFord flowers 102 | 102 | 40 to 258 | 20 to 200 | 20 to 58 |
| Caltech/UCSD birds | 200 | 6033 | 4000 | 2033 |
| Caltech 101 airplanes | 101 | 40 to 800 | 20 to 600 | 20 to 200 |

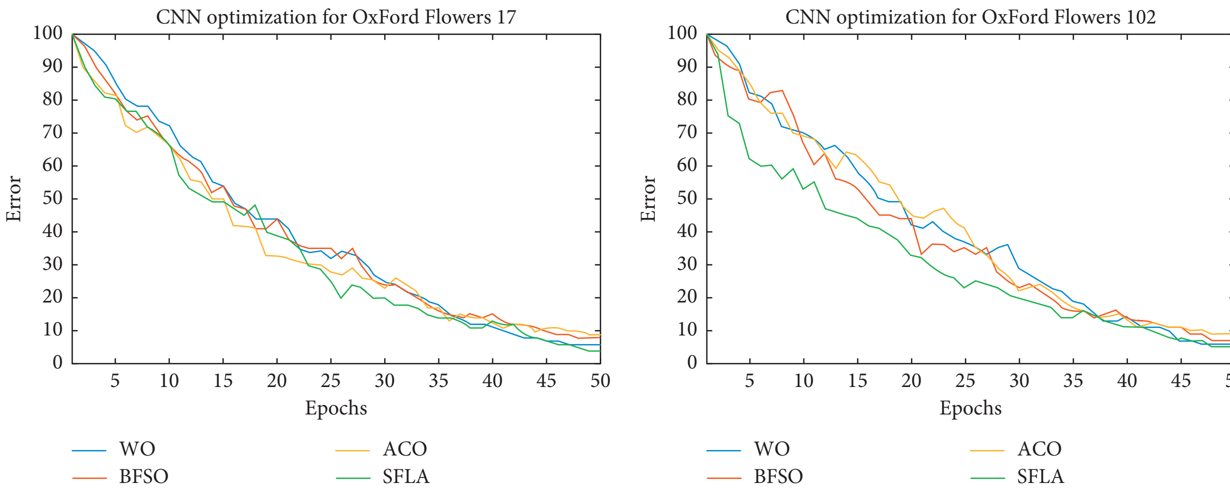
Table 3: The initial parameters of algorithms.

| Algorithm | Parameter | Value |
|---|---|---|
| SFL | Maximum permitted change in a frog's location | 10 |
| | Number of memeplex | 20 |
| | Number of frogs | 30 |
| ACO | Pheromone update constant ($Q$) | 15 |
| | Global pheromone decay rate ($pg$) | 0.7 |
| | Visibility sensitivity ($\beta$) | 7 |
| | Population size | 70 |
| | Number of ants | 15 |
| | Maximum number of iterations | 35 |
| | Local pheromone decay rate ($pt$) | 0.6 |
| | Initial pheromone ($\tau$) | 1e-06 |
| | Pheromone sensitivity ($\alpha$) | 1 |
| | Pheromone constant ($q$) | 1 |
| BFSO | Probability of elimination | 0.1 |
| | Spreading percentage $\%\sigma$ | 0.4 |
| | Population size | 60 |
| | Number of bacteria | 20 |
| | Maximum number of iterations | 35 |
| WHO | Strategies | Decreasing the value of $a$ |
| | Whales attacking | Encircling |
| | Max a | 5 |
| | Probability of choosing spiral model | $P \in [0, 1]$ |
| | Probability of choosing shrinking encircling | $p \in [0, 1]$ |
| | Population size | 70 |
| | Number of whales | 15 |
| | Maximum number of iterations | 35 |




(a) (b)

Figure 4: Continued.




(c) (d)

Figure 4: Error of classification using different datasets and optimization algorithms for LeNet-5. (a) OxFord flowers 17. (b) OxFord flowers 102. (c) Caltech/UCSD birds. (d) Caltech 101 airplanes.

Table 4: Experimental results for the oxford flowers 17 dataset.

| Technique | MSE (AVE ± STD) | Classification rate (%) | Training time |
|---|---|---|---|
| LeNet 5 | 0.190425 ± 0.031687 | 88 | 14 minutes |
| ACO-LeNet 5 | 0.121689 ± 0.011574 | 90 | 16 minutes |
| BFSO-LeNet 5 | 0.085050 ± 0.034945 | 91 | 25 minutes |
| WO-LeNet 5 | 0.032228 ± 0.039778 | 94 | 18 minutes |
| SFLA-LeNet 5 | 0.009210 ± .039100 | 97 | 23 minutes |

Table 5: Experimental results for the oxFord flowers 102 dataset.

| Technique | MSE (AVE ± STD) | Classification rate (%) | Training time |
|---|---|---|---|
| LeNet 5 | 0.040320 ± 0.002470 | 90 | 51 minutes |
| ACO-LeNet 5 | 0.024881 ± 0.002472 | 95 | 58 minutes |
| BFSO-LeNet 5 | 0.008026 ± 0.007900 | 93 | 67 minutes |
| WO-LeNet 5 | 0.0229 ± 0.0032 | 91 | 64 minutes |
| SFLA-LeNet 5 | 0.003026 ± 0.001500 | 97 | 65 minutes |

Table 6: Experimental results for the Caltech/UCSD birds dataset.

| Technique | MSE (AVE ± STD) | Classification rate (%) | Training time |
|---|---|---|---|
| LeNet 5 | 0.0321 ± 0.0045 | 92 | 97 minutes |
| ACO-LeNet 5 | 0.0019 ± 8.4257*e*−04 | 97 | 101 minutes |
| BFSO-LeNet 5 | 0.0078 ± 8.2189*e*−02 | 93 | 109 minutes |
| WO-LeNet 5 | 0.0045 ± 8.7654*e*−03 | 96 | 103 minutes |
| SFLA-LeNet 5 | 0.0021 ± 9.4298*e*−05 | 98 | 105 minutes |

Table 7: Experimental results for the Caltech 101 airplanes dataset.

| Technique | MSE (AVE ± STD) | Classification rate (%) | Training time |
|---|---|---|---|
| LeNet 5 | 0.050420 ± 0.003170 | 92 | 49 minutes |
| ACO-LeNet 5 | 0.031841 ± 0.004123 | 94 | 52 minutes |
| BFSO-LeNet 5 | 0.072218 ± 0.079235 | 93 | 57 minutes |
| WO-LeNet 5 | 0.00319 ± 0.0042 | 96 | 53 minutes |
| SFLA-LeNet 5 | 0.00286 ± 0.009700 | 97 | 55 minutes |

than ACO and WO approaches, but it obtains higher classification rates and minimum MSE scores.

## 6. Conclusion

This study presented Shuffled Frog-Leaping Algorithm (SFLA) as one model of metaheuristic algorithms to optimize one type of Convolutional Neural Network. At first, the training problem of a CNN was formulated for the SFL technique. This method was then applied to define the optimum values for biases and weights. Theoretically, the SFLA is similar to the particle swarm optimization (PSO). However, the values of weights and biases can be exchanged among local searches through a shuffling technique, thereby obtaining global optimum. The proposed SFLA was employed to train four standard classification datasets (OxFord Flowers 17, OxFord Flowers 102, Caltech/UCSD Birds, and Caltech 101 Airplanes). To verify the performance of SFLA, the results were compared to three other stochastic optimization trainers: WO, BFSO, and ACO. The resulting outcomes demonstrated that the suggested technique can effectively train the CNN. It improves the probability of finding optimal values for biases and weights for CNNs. Our optimization strategy can obtain noticeable accuracy for classifying objects in four standard classification datasets.

For future study, finding the proper parameters for SFL algorithm needs to be investigated. Moreover, by exploring the optimal values for number of batches in the training, type of pooling, number of neurons in the hidden layer, and number of kernels in the convolutional layers, we can obtain more noticeable results. Further optimal tuning of this method is worth further research using different datasets such as CKP and facial expression datasets, as well as ImageNet and ORI.

## Data Availability

These datasets are public datasets and are available at the following links: https://www.robots.ox.ac.uk/̃vgg/data/flowers/17/ http://www.vision.caltech.edu/Image_Datasets/Caltech101/ http://www.vision.caltech.edu/visipedia/CUB-200.html https://www.robots.ox.ac.uk/̃vgg/data/flowers/102/.

## Disclosure

The funding sources had no involvement in the study design, collection, analysis or interpretation of data, writing of the manuscript, or in the decision to submit the manuscript for publication.

## Conflicts of Interest

The authors declare that there are no conflicts of interest.

## References

[1] H. Cecotti, A. Rivera, M. Farhadloo, and M. A. Pedroza, “Grape detection with convolutional neural networks,” *Expert Systems with Applications*, vol. 159, Article ID 113588, 2020.

[2] N. Razmjooy and S. Razmjooy, “Skin melanoma segmentation using neural networks optimized by quantum invasive weed optimization algorithm,” *Lecture Notes in Electrical Engineering*, vol. 696, pp. 233–250, 2021.

[3] S. B. Saadi, R. Ranjbarzadeh, and K. Ozeir, “Osteolysis: a literature review of basic science and potential computer-based image processing detection methods,” *Computational Intelligence and Neuroscience*, vol. 2021, p. 21, 2021.

[4] R. Ranjbarzadeh, S. Jafarzadeh Ghoushchi, M. Bendechache et al., “Lung infection segmentation for COVID-19 pneumonia based on a cascade convolutional network from CT images,” *BioMed Research International*, vol. 2021, Article ID 5544742, 16 pages, 2021.

[5] W. A. Ali, M. Aljunid, M. Bendechache, and P. Sandhya, “Review of current machine learning approaches for anomaly detection in network traffic,” *Journal of Telecommunications and the Digital Economy*, vol. 8, no. 4, pp. 64–95, 2020.

[6] K. Nguyen, C. Fookes, A. Ross, and S. Sridharan, “Iris recognition with off-the-shelf CNN features: a deep learning perspective,” *IEEE Access*, vol. 6, pp. 18848–18855, 2018.

[7] Y. Cai, W. Wang, Y. Chen, and Q. Ye, “IOS-Net: an inside-to-outside supervision network for scale robust text detection in the wild,” *Pattern Recognition*, vol. 103, Article ID 107304, 2020.

[8] U. Albalawi, S. Manimurugan, and R. Varatharajan, “Classification of breast cancer mammogram images using convolution neural network,” *Concurrency and Computation: Practice and Experience*, Article ID e5803, 2020.

[9] T. Mikolov, M. Karafiat, L. Burget, J. Cernocky, and S. Khudanpur, “Recurrent neural network based language model,” *Process. INTERSPEECH*, vol. 2, pp. 1045–1048, 2010.

[10] A. Graves, N. Jaitly, and A.-R. Mohamed, “Hybrid speech recognition with deep bidirectional lstm,” in *Proceedings of the IEEE Work. Au- tomatic Speech Recognit Underst*, pp. 273–278, Olomouc, Czech Republic, 2013.

[11] T. Kooi, G. Litjens, B. van Ginneken et al., “Large scale deep learning for computer aided detection of mammographic lesions,” *Medical Image Analysis*, vol. 35, pp. 303–312, 2017.

[12] H. M. Fayek, M. Lech, and L. Cavedon, “Evaluating deep learning architectures for speech emotion recognition,” *Neural Networks*, vol. 92, pp. 60–68, 2017.

[13] F. Gao, T. Huang, J. Sun, J. Wang, A. Hussain, and E. Yang, “A new algorithm for SAR image target recognition based on an improved deep convolutional neural network,” *Cognitive Computation*, vol. 11, no. 6, pp. 809–824, 2019.

[14] F. Lattari, B. Gonzalez Leon, F. Asaro, A. Rucci, C. Prati, and M. Matteucci, “Deep learning for SAR image despeckling,” *Remote Sensing*, vol. 11, no. 13, p. 1532, 2019.

[15] R. Ranjbarzadeh, S. B. Saadi, and A. Amirabadi, “LNPSS: SAR image despeckling based on local and non-local features using patch shape selection and edges linking,” *Measurement*, vol. 164, Article ID 107989, 2020.

[16] A. Hojatimalekshah, Z. Uhlmann, N. F. Glenn et al., “Tree canopy and snow depth relationships at fine scales with terrestrial laser scanning,” *The Cryosphere*, vol. 15, no. 5, pp. 2187–2209, 2021.

[17] J. Y. Ryu, H. U. Kim, and S. Y. Lee, “Deep learning improves prediction of drug-drug and drug-food interactions,” *Proceedings of the National Academy of Sciences*, vol. 115, no. 18, pp. E4304–E4311, 2018.

[18] L. Zhang, J. Tan, D. Han, and H. Zhu, “From machine learning to deep learning: progress in machine intelligence for rational drug discovery,” *Drug Discovery Today*, vol. 22, no. 11, pp. 1680–1685, 2017.

[19] T. Zhou, H. Lu, Z. Yang, S. Qiu, B. Huo, and Y. Dong, "The ensemble deep learning model for novel COVID-19 on CT images," *Applied Soft Computing*, vol. 98, Article ID 106885, 2021.

[20] N. Coudray, P. S. Ocampo, T. Sakellaropoulos et al., "Classification and mutation prediction from non-small cell lung cancer histopathology images using deep learning," *Nature Medicine*, vol. 24, no. 10, pp. 1559–1567, 2018.

[21] A. Valizadeh, S. Jafarzadeh Ghoushchi, R. Ranjbarzadeh, and Y. Pourasad, "Presentation of a segmentation method for a diabetic retinopathy patient's fundus region detection using a convolutional neural network," *Computational Intelligence and Neuroscience*, vol. 2021, pp. 1–14, 2021.

[22] S. Aleem, T. Kumar, S. Little, M. Bendechache, R. Brennan, and K. McGuinness, "Random Data Augmentation based Enhancement: AGeneralized Enhancement Approach for Medical Datasets," 2022.

[23] N. Razmjooy, S. Razmjooy, Z. Vahedi, V. V. Estrela, and G. G. de Oliveira, "Skin color segmentation based on artificial neural network improved by a modified grasshopper optimization algorithm," *Lecture Notes in Electrical Engineering*, vol. 696, pp. 169–185, 2021.

[24] S. Jafarzadeh Ghoushchi, R. Ranjbarzadeh, S. A. Najafabadi, E. Osgooei, and E. B. Tirkolaee, "An extended approach to the diagnosis of tumour location in breast cancer using deep learning," *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–11, 2021.

[25] D. Soydaner, "A comparison of optimization algorithms for deep learning," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 34, no. 13, Article ID 2052013, 2020.

[26] A. Chandio, Y. Shen, M. Bendechache, I. Inayat, and T. Kumar, "AUDD: audio Urdu digits dataset for automatic audio Urdu digit recognition," *Applied Sciences*, vol. 11, no. 19, p. 8842, 2021.

[27] F. Zhan, H. Zhu, and S. Lu, "Scene text synthesis for efficient and effective deep network training," 2020, https://arxiv.org/abs/1901.09193v1.

[28] H. Huang, C. Wang, and B. Dong, "Nostalgic Adam: weighting more of the past gradients when designing the adaptive learning rate," *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence*, vol. 2019, pp. 2556–2562, 2019.

[29] M. Zaheer, S. J. Reddi, D. Sachan, S. Kale, G. Research, and S. Kumar, "Adaptive methods for nonconvex optimization," in *Proceedings of the 32nd International Conference on Neural Information Processing Systems*, Montreal Canada, December 2018.

[30] K. N. Reid, J. Li, A. Brownlee et al., "A hybrid metaheuristic approach to a real world employee scheduling problem," in *Proceedings of the 2019 Genetic and Evolutionary Computation Conference*, pp. 1311–1318, July 2019.

[31] F. Altunbey Ozbay and B. Alatas, "A novel approach for detection of fake news on social media using metaheuristic optimization algorithms," *Elektronika ir Elektrotechnika*, vol. 25, no. 4, pp. 62–67, 2019.

[32] K. Hussain, M. N. Mohd Salleh, S. Cheng, and Y. Shi, "Metaheuristic research: a comprehensive survey," *Artificial Intelligence Review*, vol. 52, no. 4, pp. 2191–2233, 2019.

[33] S. M. Mousavi, A. Asgharzadeh-Bonab, and R. Ranjbarzadeh, "Time-frequency analysis of EEG signals and GLCM features for depth of anesthesia monitoring," *Computational Intelligence and Neuroscience*, vol. 2021, pp. 1–14, Article ID 8430565, 2021.

[34] L. Zhang, H. J. Gao, J. Zhang, and B. Badami, "Optimization of the convolutional neural networks for automatic detection of skin cancer," *Open Medicine*, vol. 15, no. 1, pp. 27–37, 2020.

[35] G. L. F. da Silva, T. L. A. Valente, A. C. Silva, A. C. de Paiva, and M. Gattass, "Convolutional neural network-based PSO for lung nodule false positive reduction on CT images," *Computer Methods and Programs in Biomedicine*, vol. 162, pp. 109–118, 2018.

[36] F. Hoseini, A. Shahbahrami, and P. Bayat, "AdaptAhead optimization algorithm for learning deep CNN applied to MRI segmentation," *Journal of Digital Imaging*, vol. 32, no. 1, pp. 105–115, 2018.

[37] R. P. França, A. C. B. Monteiro, V. V. Estrela, and N. Razmjooy, "Using metaheuristics in discrete-event simulation," *Lecture Notes in Electrical Engineering*, vol. 696, pp. 275–292, 2021.

[38] A. C. B. Monteiro, R. P. França, V. V. Estrela, N. Razmjooy, Y. Iano, and P. D. M. Negrete, "Metaheuristics applied to blood image analysis," *Lecture Notes in Electrical Engineering*, vol. 696, pp. 117–135, 2021.

[39] S. Mahdinia, M. Rezaie, M. Elveny, N. Ghadimi, and N. Razmjooy, "Optimization of PEMFC model parameters using meta-heuristics," *Sustainability*, vol. 13, no. 22, p. 12771, 2021.

[40] S. Sengupta, S. Basak, and R. Peters, "Particle Swarm Optimization: a survey of historical and recent developments with hybridization perspectives," *Machine Learning and Knowledge Extraction*, vol. 1, no. 1, pp. 157–191, 2018.

[41] F. Cicirelli, A. Forestiero, A. Giordano, and C. Mastroianni, "Transparent and efficient parallelization of swarm algorithms," *ACM Transactions on Autonomous and Adaptive Systems*, vol. 11, no. 2, p. 26, 2016.

[42] S. Mirjalili and A. Lewis, "The Whale optimization algorithm," *Advances in Engineering Software*, vol. 95, pp. 51–67, 2016.

[43] B. Doerr, H. P. Le, R. Makhmara, and T. D. Nguyen, "Fast genetic algorithms," in *Proceedings of the 2017 Genetic and Evolutionary Computation Conference*, pp. 777–784, Berlin, Germany, July 2017.

[44] B. Duan, Q. Cao, and N. Afshar, "Optimal parameter identification for the proton exchange membrane fuel cell using Satin Bowerbird optimizer," *International Journal of Energy Research*, vol. 43, no. 14, pp. 8623–8632, 2019.

[45] A. Khatri, A. Gaba, K. P. S. Rana, and V. Kumar, "A novel life choice-based optimizer," *Soft Computing*, vol. 24, no. 12, pp. 9121–9141, 2020.

[46] W. Zhao, L. Wang, and Z. Zhang, "Artificial ecosystem-based optimization: a novel nature-inspired meta-heuristic algorithm," *Neural Computing & Applications*, vol. 32, no. 13, pp. 9383–9425, 2020.

[47] A. Faramarzi, M. Heidarinejad, B. Stephens, and S. Mirjalili, "Equilibrium optimizer: a novel optimization algorithm," *Knowledge-Based Systems*, vol. 191, Article ID 105190, 2020.

[48] A. Franzin and T. Stützle, "Revisiting simulated annealing: a component-based analysis," *Computers & Operations Research*, vol. 104, pp. 191–206, 2019.

[49] "MNIST Demos on Yann LeCun's Website," 2021, http://yann.lecun.com/exdb/lenet/.

[50] J. Zhong, Z. Liu, Z. Han, Y. Han, and W. Zhang, "A CNN-based defect inspection method for catenary split pins in high-speed railway," *IEEE Transactions on Instrumentation and Measurement*, vol. 68, no. 8, pp. 2849–2860, 2019.

[51] S. R. de Assis Neto, G. L. Santos, E. da Silva Rocha et al., "Detecting human activities based on a multimodal sensor data set using a bidirectional long short-term memory model:

a case study," *Challenges and Trends in Multimodal Fall Detection for Healthcare*, vol. 273, pp. 31–51, 2020.

[52] Y. Pourasad, R. Ranjbarzadeh, and A. Mardani, "A new algorithm for digital image encryption based on chaos theory," *Entropy*, vol. 23, no. 3, p. 341, 2021.

[53] A. Waleed Salehi, P. Baglat, and G. Gupta, "Review on machine and deep learning models for the detection and prediction of coronavirus," *Materials Today Proceedings*, vol. 33, pp. 3896–3901, 2020.

[54] M. Gour, S. Jain, and T. Sunil Kumar, "Residual learning based CNN for breast cancer histopathological image classification," *International Journal of Imaging Systems and Technology*, vol. 30, no. 3, pp. 621–635, 2020.

[55] R. Ranjbarzadeh, S. Dorosti, S. Jafarzadeh Ghoushchi et al., "Nerve optic segmentation in CT images using a deep learning model and a texture descriptor," *Complex & Intelligent Systems*, pp. 1–15, 2022.

[56] S. Iqbal, M. U. Ghani Khan, T. Saba et al., "Deep learning model integrating features and novel classifiers fusion for brain tumor segmentation," *Microscopy Research and Technique*, vol. 82, no. 8, pp. 1302–1315, 2019.

[57] G. Murtaza, L. Shuib, A. W. Abdul Wahab et al., "Deep learning-based breast cancer classification through medical imaging modalities: state of the art and research challenges," *Artificial Intelligence Review*, vol. 53, no. 3, pp. 1655–1720, 2020.

[58] A. Khatami, M. Babaie, H. R. Tizhoosh, A. Khosravi, T. Nguyen, and S. Nahavandi, "A sequential search-space shrinking using CNN transfer learning and a Radon projection pool for medical image retrieval," *Expert Systems with Applications*, vol. 100, pp. 224–233, 2018.

[59] A. Doğantekin, F. Özyurt, E. Avcı, and M. Koç, "A novel approach for liver image classification: PH-C-elm," *Measurement*, vol. 137, pp. 332–338, 2019.

[60] X. Yu, N. Zeng, S. Liu, and Y.-D. Zhang, "Utilization of DenseNet201 for diagnosis of breast abnormality," *Machine Vision and Applications*, vol. 30, no. 7-8, pp. 1135–1144, 2019.

[61] R. Ranjbarzadeh, A. Bagherian Kasgari, S. Jafarzadeh Ghoushchi, S. Anari, M. Naseri, and M. Bendechache, "Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images," *Scientific Reports*, vol. 11, no. 1, p. 10930, 2021.

[62] A. Rasmus, A. Peimankar, and S. Puthusserypady, "A deep learning approach for real-time detection of atrial fibrillation," *Expert Systems with Applications*, vol. 115, pp. 465–473, 2019.

[63] S. J. Ghoushchi and M. N. A. Rahman, "Performance study of artificial neural network modelling to predict carried weight in the transportation system," *International Journal of Logistics Systems and Management*, vol. 24, no. 2, pp. 200–212, 2016.

[64] A. Aghamohammadi, R. Ranjbarzadeh, F. Naiemi, M. Mogharrebi, S. Dorosti, and M. Bendechache, "TPCNN: two-path convolutional neural network for tumor and liver segmentation in CT images using a novel encoding approach," *Expert Systems with Applications*, vol. 183, Article ID 115406, 2021.

[65] M. Frid-Adar, I. Diamant, E. Klang, M. Amitai, J. Goldberger, and H. Greenspan, "GAN-based synthetic medical image augmentation for increased CNN performance in liver lesion classification," *Neurocomputing*, vol. 321, pp. 321–331, 2018.

[66] Q. T. Ain, M. Ali, A. Riaz et al., "Sentiment analysis using deep learning techniques: a review," *IJACSA Int. J. Adv. Comput. Sci. Appl*, vol. 8, no. 6, 2017.

[67] K. Lu, L. Ting, W. Keming, Z. Hanbing, T. Makoto, and Y. Bin, "An improved shuffled frog-leaping algorithm for flexible job shop scheduling problem," *Algorithms*, vol. 8, no. 1, pp. 19–31, 2015.

[68] M.-L. Pérez-Delgado, "Color image quantization using the shuffled-frog leaping algorithm," *Engineering Applications of Artificial Intelligence*, vol. 79, pp. 142–158, 2019.

[69] J. Cai, R. Zhou, and D. Lei, "Dynamic shuffled frog-leaping algorithm for distributed hybrid flow shop scheduling with multiprocessor tasks," *Engineering Applications of Artificial Intelligence*, vol. 90, Article ID 103540, 2020.

[70] M. Eusuff, K. Lansey, and F. Pasha, "Shuffled frog-leaping algorithm: a memetic meta-heuristic for discrete optimization," *Engineering Optimization*, vol. 38, no. 2, pp. 129–154, 2006.

[71] J. Tang, R. Zhang, P. Wang, Z. Zhao, L. Fan, and X. Liu, "A discrete shuffled frog-leaping algorithm to identify influential nodes for influence maximization in social networks," *Knowledge-Based Systems*, vol. 187, Article ID 104833, 2020.

[72] J. Siahbalaee, N. Rezanejad, and G. B. Gharehpetian, "Reconfiguration and DG sizing and placement using improved shuffled frog leaping algorithm," *Electric Power Components and Systems*, vol. 47, no. 16-17, pp. 1475–1488, 2019.

[73] R. Dash, "Performance analysis of a higher order neural network with an improved shuffled frog leaping algorithm for currency exchange rate prediction," *Applied Soft Computing*, vol. 67, pp. 215–231, 2018.

[74] "Visual Geometry Group, University of Oxford," 2022, https://www.robots.ox.ac.uk/~vgg/data/flowers/17/.

[75] "Caltech101," 2022, http://www.vision.caltech.edu/Image_Datasets/Caltech101/.

[76] "Caltech-UCSD Birds 200," 2022, http://www.vision.caltech.edu/visipedia/CUB-200.html.

[77] "Visual Geometry Group, University of Oxford," 2022, https://www.robots.ox.ac.uk/~vgg/data/flowers/102/.

Hindawi
Journal of Healthcare Engineering
Volume 2022, Article ID 2196096, 10 pages
https://doi.org/10.1155/2022/2196096

*Research Article*

# Deep Learning-Based Classification for Melanoma Detection Using XceptionNet

**Xinrong Lu[1] and Y. A. Firoozeh Abolhasani Zadeh[2]**

[1]*Gannan University of Science & Technology, Ganzhou 341000, Jiangxi, China*
[2]*Department of Surgery, Faculty of Medicine, Kerman University of Medical Sciences, Kerman, Iran*

Correspondence should be addressed to Y. A. Firoozeh Abolhasani Zadeh; f.abolhasani@kmu.ac.ir

Received 16 December 2021; Revised 4 January 2022; Accepted 19 February 2022; Published 22 March 2022

Academic Editor: Saeid Jafarzadeh Ghoushchi



Skin cancer is one of the most common types of cancer in the world, accounting for at least 40% of all cancers. Melanoma is considered as the 19th most commonly occurring cancer among the other cancers in the human society, such that about 300,000 new cases were found in 2018. While cancer diagnosis is based on interventional methods such as surgery, radiotherapy, and chemotherapy, studies show that the use of new computer technologies such as image processing mechanisms in processes related to early diagnosis of this cancer can help the physicians heal this cancer. This paper proposes an automatic method for diagnosis of skin cancer from dermoscopy images. The proposed model is based on an improved XceptionNet, which utilized swish activation function and depthwise separable convolutions. This system shows an improvement in the classification accuracy of the network compared to the original Xception and other dome architectures. Simulations of the proposed method are compared with some other related skin cancer diagnosis state-of-the-art solutions, and the results show that the suggested method achieves higher accuracy compared to the other comparative methods.

## 1. Introduction

The most common cancer in the United States is skin cancer, which occurs in the tissues of the largest part of the body, i.e., the skin [1]. The skin blocks heat, sunlight, wounds, and infections [2]. The skin has three layers: *epidermis*, dermis, and hypodermis [3]. The *epidermis* is the outmost layer of skin, which creates the skin tone and makes a waterproof barrier for the skin. The dermis is the second layer that comprises rough connective tissue, sweat glands, and hair follicles. And finally, the hypodermis, as the lowest layer, has been made by connective tissue and fat [4]. The main threat to skin is skin cancer. Skin cancer (like melanoma) is one of the most common types of cancer in the world, accounting for at least 40% of all cancers. It has been predicted that about 9,500 people in the US are diagnosed with skin cancer every day [5].

While cancer diagnosis is based on interventional methods such as surgery, radiotherapy, and chemotherapy, studies show that the use of new computer technologies such as image processing mechanisms in processes related to the diagnosis and classification of cancers has been acted successfully [6]. Among different kinds of skin cancers, melanoma is known as the 19th most commonly occurring cancer in men and women [7]. In 2018, about 300,000 new cases were recognized [8]. Based on the Cancer Cell Organization, melanoma cancer with 15000 cases is the fourth most common cancer in the world [9]. Also, based on this organization, melanoma is the 9$^{th}$ most common reason for cancer death in 2019 [10]. Skin cancer diagnosis is known as a tough task because of the advent of diverse kinds of skin lesions, especially melanoma and carcinoma [11]. Several noninvasive methods have been proposed to avoid unnecessary biopsy for diagnosing melanoma [12]. Most of the methods usually contain three main parts: segmentation, features extraction, and classification [13]. Several works were done in this case [1, 14–16]. Bansal et al. [17] proposed a technique for melanoma diagnosis based on deep learning-based image feature extraction. The authors used convolutional neural networks (CNN) for the extraction of the features based on the transfer learning and some different classifiers including k-nearest neighbor (KNN), AdaBoost, and random forest (RF) to the final classification. The method was performed to the ISIC dataset, and the results showed the accuracy of each classifier. The method was a good technique, but due to the complex configuration, it needs more time for doing the process.

Xu et al. [6] presented a method for early detection of melanoma. They used a sequential methodology including image noise reduction, image segmentation, feature extraction, and classification. The method of segmentation in the study was based on an optimized convolutional neural network (CNN) using the satin bowerbird optimization (SBO). To extract just important features from the segmented images, SBO was utilized. At last, Support Vector Machine (SVM) was used to classify the images based on the achieved features. The method was performed to American Cancer Society database, and the results showed efficient results for the proposed method. However, the method provided good results, using the proposed method, and due to the combination of deep learning and the SBO algorithm, it provided complex system.

Razmjooy et al. [18] proposed a diagnosis technique for determining the skin malignant cancer. They first eliminated extra scales by the smoothing and edge detection. Then, the method segmented the region of interest. The additional information was removed by mathematical morphology. The model used an optimized MLP neural Networks (ANN) based on World Cup Optimization algorithm to get more efficient results. In that study, the authors used the optimized ANN to diagnosis of the skin cancer. Simulations were performed to the Australian Cancer Database (ACD), and results indicated that the suggested technique modified the performance of the method. The method used ANN method that can be considered as an old and less accuracy in these years.

Vocaturo and Zumpano [19] used a method called multi-instance learning (MIL) algorithm to the diagnosis of the melanoma from dysplastic nevi. Simulation results showed that using the MIL technique can be considered as one of the suitable tools for using in skin cancer diagnosis. However, MIL was a simple form of weakly supervised classification technique with sets that can provide weaker results in some cases.

Dey et al. [20] proposed an optimal machine vision technique for the diagnosis of the melanoma. The Bat algorithm was used to improve the accuracy of the diagnosis system. Distance-regularized level-set (DRLS) segmentation method was used for efficient segmentation of the melanoma. The results were then verified by evaluating the important image performance metrics (IPM) on the PH2 database to show the method accuracy.

Literature review showed that although there are different types of diagnosis system for the melanoma detection, numerous research gaps are still to be addressed, for example, higher complexity of some works, complex configuration, and less accuracy. The shortcoming of all research works is given previously after each work. Therefore, this subject is still open and can be developed. However, the main configuration of the Xception network is based on the Inception module [21], blending of the inception modules, convolutional layers, residual connections, and depthwise separable convolutions to improve its efficiency.

The main target of the present research is to deliver a new improved version of Xception based on performing the Swish activation function to diagnose the skin cancer and verify the method by Skin Cancer MNIST: HAM10000 dataset. The presented system classifies the input images into three classes: normal, carcinoma, and melanoma. Furthermore, the results of the proposed Xception architecture are compared with some renowned methods, including VGG16 [22], InceptionV3 [23], AlexNet [24], and the original Xception [25] to show the superiority of the proposed methodology. The configuration of all methods can be achieved by their papers for reproduction. Therefore, the novelty of the presented study is based on proposing an automatic diagnosis method for the skin cancer dermoscopy images based on a new configuration of the XceptionNet. In this study, an improved version of the XceptionNet based on swish activation function has been presented, and the results show a higher accuracy toward the original XceptionNet, and some other related CNN-based methods for skin cancer diagnosis.

## 2. The Modified Xception Network Architecture

The Xception architecture is one of the popular and strong convolutional neural networks that is advanced under different important concepts, like convolutional layer, depthwise separable convolution layer, residual connections, and inception module [21]. Furthermore, the architecture of CNN for the activation function is essential, wherein *Swish* as a new activation function has been used for developing the traditional activation function [26]. In this study, a Swish activation function has been proposed for improving the Xception based on Swish image classification model for initial melanoma diagnosis [25].

The Xception is described as a theory based on the Inception module that generates cross-channels correlations and spatial relations within CNN feature maps to be entirely decoupled [27]. Figure 1 shows the overall module of an Inception v3.

As can be observed from Figure 1, the model is based on cross-channel correlations by input data separation into four ways to convolution size of $1 \times 1$ and average pooling and mapping correlations by the convolution of size $3 \times 3$ and finally forwarding to the concatenation layer. The overall module of the studied Xception module has been shown in Figure 2.

As can be seen from Figure 2, in this network, the data from the input uses just one size of $1 \times 1$ convolution to generate convolution sizes of $3 \times 3$ with no average pooling, which ensue avoiding overlapping of the output channels to inject to the concatenation. This module is more consistent, stronger, and reliable than the Inception module, which operates correlations of cross-channels and spatial relations

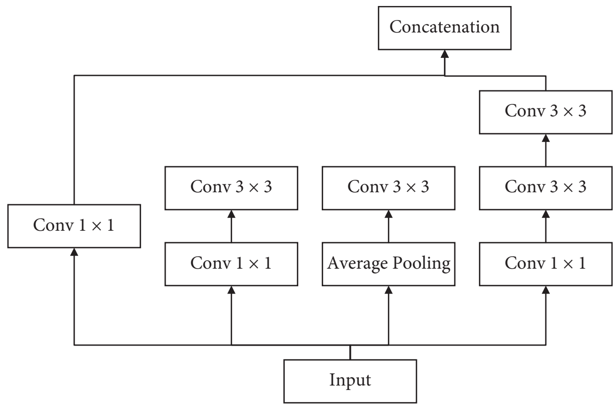



Figure 1: The overall module of an Inception v3.

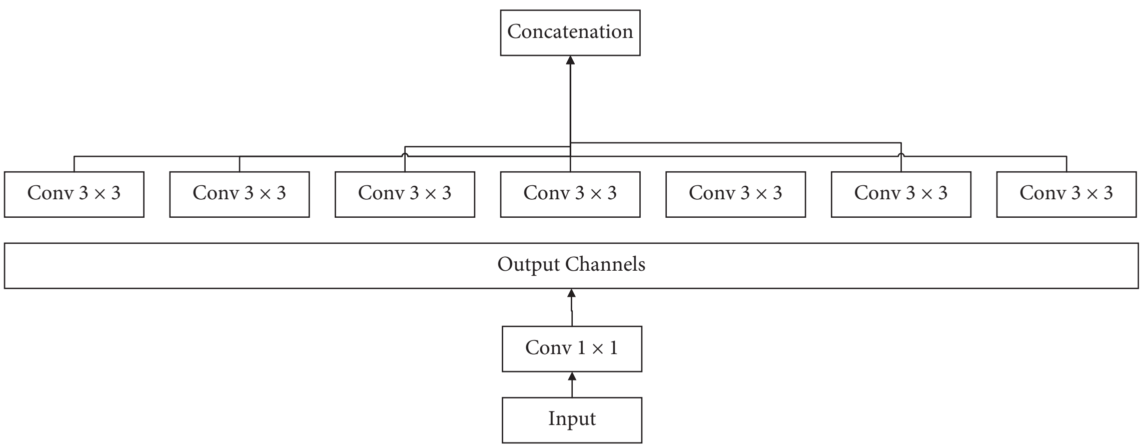



Figure 2: The overall module of an Xception module.

with maps fully decoupled. In the following, the stages for the Xception module are explained in detail:

*2.1. Convolutional Layer.* For generating feature maps, the convolution kernels have been separated into input data areas [25]. The different convolution kernels generate the absolute results of the feature maps, such that the position $(i,\ j)$ upon feature value in the feature map as the $k^{\text{th}}$ layer indicates the $l^{\text{th}}$, i.e.,

$$S^{l}_{i,j,k} = Bv^{l}_{k} + Wv^{l}_{k}C^{l}_{i,j}, \tag{1}$$

where $Wv^{l}_{k}$ describes the weight vector, $Bv^{l}_{k}$ describes for the bias value of the $k^{\text{th}}$ filter of the $l^{\text{th}}$ layer, and $C^{l}_{i,j}$ describes the input patch center on position $(i,\ j)$ of the $l^{\text{th}}$ layer.

The $Wv^{l}_{k}$ kernel has been generated in sharing the feature map of $S^{l}_{i,j,k}$. This process decreases difficulties and develops the network for graceful model training. Batch normalization is used to insert the convolutional layers of the Xception module, and the activation function is as ReLU, i.e.,

$$\text{RELU} = \begin{cases} x, & x \geq 0, \\ 0, & x < 0, \end{cases} \tag{2}$$

where $d$ describes the input data.

The ReLU activation function is not complicated mathematically with nonlinearity of the network that is vital in convolutional neural network for identifying the nonlinear features, which produce faster convergences and better predictions with less overfitting.

*2.2. Depthwise Separable Convolution Layer.* The depthwise convolutions contain the main part of the Xception modules. These can decrease the computation and the model parameters, which are prepared in depth dimensions and spatial dimensions of color channels. The depthwise convolution makes a filter to the input data set channels of $M$ and generates the feature map to define $\text{DF} \times \text{DF} \times M$. The depthwise convolution based on the input channel filter is obtained as follows:

$$\widehat{G}_{k,p,m} = \sum_{i,j,m} \widehat{K}_{i,j,m} \times F_{k+i-1,p+j-1,m}, \tag{3}$$

where $\widehat{G}$ describes the alternatives of the feature maps output produced by $F$ as the input feature map, and $\widehat{K}$ defines the depthwise convolution kernel.

The filter number $m$ in $\widehat{K}$ is employed to channel the $m^{\text{th}}$ in $F$ for estimation of the output of the feature map. Afterward, the image is presented in multiple channels that can be taken in each color channel. $1 \times 1$ convolution filters are then used to provide the output to be injected into the next layer. After the depthwise separable convolution layer, batch normalization is utilized, and then using the max-pooling layer, the computational complexity has been decreased.

*2.3. Residual Connection.* For accomplishing the residual connection, the ResNet architecture has been employed, where the internal network performs identity shortcut connections directly into the final layers. By considering the parameters as $p_i$, the residual block is explained as follows:

$$v_o = v_i + f(v_i, [p_i]), \tag{4}$$

where $v_i$ and $v_o$ describe the input and the output vectors of the layers, respectively.

The benefit of the residual connection is that it avoids signal mitigation by transforming of multiple stacked nonlinearities. It has also quicker training process. Figure 3 shows the residual shortcut connection of ResNet.

Also, the method of using the residual shortcut connection in Xception is shown in Figure 4.

As can be observed from Figure 4, the input of $X$ can direct a late layer by a shortcut of identity blocks. By considering Figure 4, $1 \times 1$ convolution operation directed data to a late layer via with a step of $2 \times 2$. Xception includes a network with 36 convolutional layers that is used for producing the feature extraction. It generates 14 modules that intersperse with residual connections excepting the first and the last modules. In Xception pretrained network, the input image should be of size $299 \times 299 \times 3$.

*2.4. Swish Activation Function.* Based on a new work from [28], the Swish activation function provides an efficient results for the classification results. In other words, Swish activation function develops the CNN performance rather than the traditional ReLU activation function [25]. The mathematical formulation of the Swish activation function is given as follows:

$$S = m \times \text{sigmoid}(\alpha \times m), \tag{5}$$

where $\alpha$ describes an adjustable per-channel parameter, $m$ defines the input data, and $\text{sigmoid}(\alpha \times m)$ signifies the evaluation of the sigmoid function. The architecture of the modified Xception network is shown in Figure 5.

As can be observed from Figure 5, the modules are similar to the original Xception, and just ReLU function has been replaced with Swish activation function position, which is located before logistic regression and after the global average-pooling.

## 3. Results and Discussion

*3.1. Dataset.* The skin cancer benchmark datasets in this study were collected from Skin Cancer MNIST: HAM10000 [29]. This dataset by license number CC BY-NC-SA 4.0 is considered as a guaranteed dataset for the skin cancer diagnosis techniques. The dataset was collected from the Kaggle public Imaging Archive. The dataset includes 10015 JPEG (8-bit color depth) training dermatoscopic images that are collected from different populations collected during a period of 20 years from two different sites, the Department of Dermatology at the Medical University of Vienna, Austria, and the skin cancer practice of Cliff Rosendahl in Queensland, Australia. The Australian site stored images and metadata in PowerPoint files and Excel databases. The Austrian site started to collect images before the era of digital cameras and stored images and metadata in different formats during different time periods. From the literature,

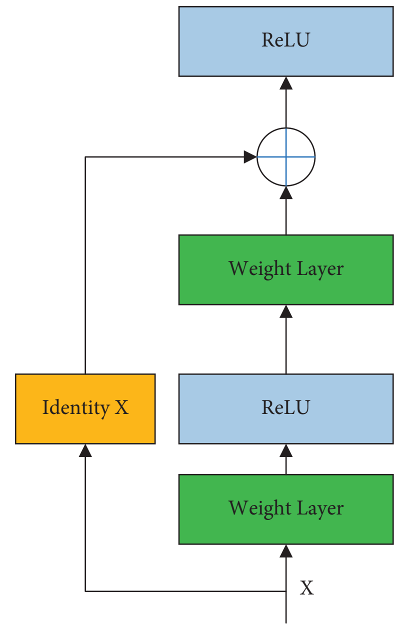



Figure 3: The residual shortcut connection of ResNet.

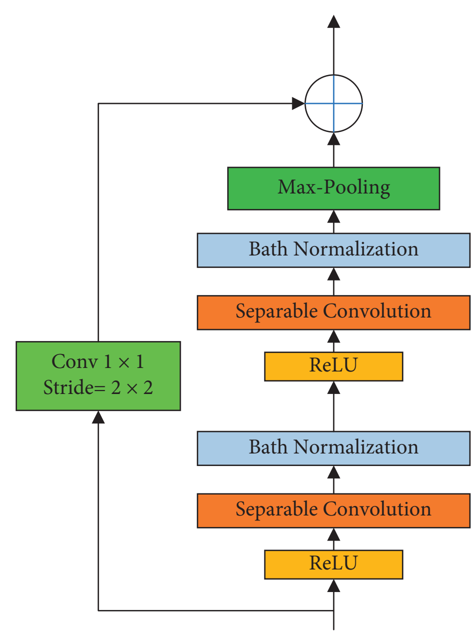



Figure 4: The method of using the residual shortcut connection in Xception.

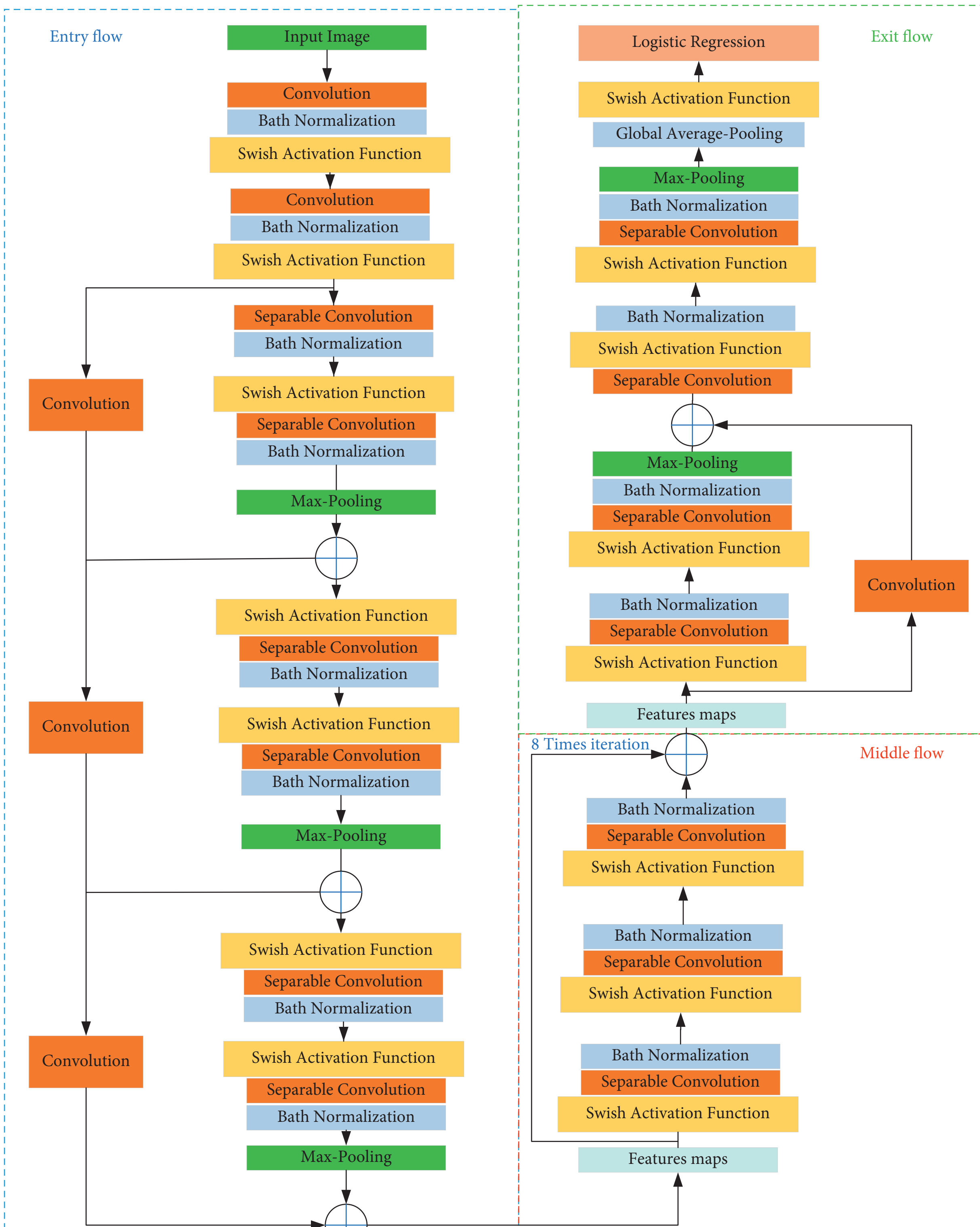



Figure 5: The architecture of the modified Xception network.

different techniques are confirmed based on this dataset [30–33]. In this paper, the data from this benchmark are used to train the proposed Xception network. The data was collected as dermatoscopic images from different populations, acquired and stored by different modalities [34]. 53.3% of lesions were confirmed by histopathology. Figure 6 shows some examples of the HAM10000 dataset.

We applied the proposed Xception network as a complete diagnosis system for the detection of the skin cancer. Here, we also employed data augmentation. Data

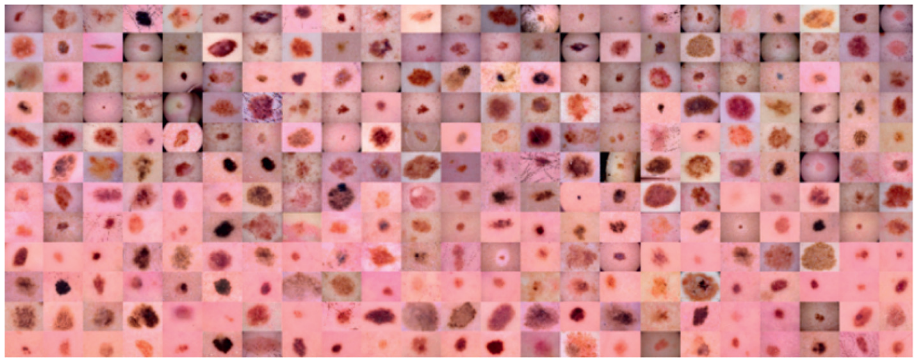


Figure 6: Some examples of the HAM10000 dataset.

augmentation is performed for increasing the number of images for training the CNNs. This is done to compensate the smaller number of training datasets. In other words, Augmentation is utilized to expand the small size datasets by adding supplementary images that are variations of available images in the dataset. This will help improve the ability and performance of the system. There are lots of variations that are introduced for augmentation. In this study, rotation, horizontal shifting, and cropping are used.

One of the transformations in this study is horizontal shift augmentation. A horizontal shift augmentation shifts image pixels horizontally with keeping the image dimension unchanged. This process has floating-point value between 0 and 1 that shows the step size of moving the process. Here, we used 0.3 step size. Another transformation is rotation. During rotation, a rotation angle is specified of specific angle that we want the image to be rotated. This study uses [15, 30, 45, 60] rather than letting it randomly pick it from −90 to 90. Another method for augmentation in this study is based on cropping. Based on cropping in this study, a section (here, center of image) is sampled from the original image and then, it resized to the original image size.

Indeed, the reason of data augmentation here is to increase the quantity of data by adding somewhat altered copies of already existing data or newly created synthetic data from the present data. In other words, we used data augmentation (i.e., shifting, rotation, and cropping) to regularize and help decrease overfitting of data when training the proposed Xception model.

*3.2. Training and Configuration of the Proposed Xception Network.* The dataset has been divided into two groups: 80% for training (8012 images) and 20% (2003 images) for test. In the training procedure, all of the images have been resized to $227 \times 227$. The CNN model runs 15 times independently to perform the training the dataset; in other words, the proposed network has been performed 15 times in MATLAB environment, and the average results of the model are considered as the measurement values of the model. The simulations were performed on a Core i7 CPU 2.00 GHz laptop, with 2.5 GHz, 16 GB RAM, and 64-bit operating system. The implementation was programmed on MATLAB 2019b as the main programming language on a Windows operating system. Table 1 indicates the specifications of the hardware and the software.

Also, the model configuration for the prosed CNN contains 12 batch sizes with $2e-2$ initial learning rate based on stochastic gradient descent with momentum (SGDM) optimizer. The data configuration is achieved based on trials and errors and close to the [35].

*3.3. Evaluation Criteria.* In this study, four evaluation criteria are utilized to indicate the capability of the proposed system. The mathematical formulation of the utilized measures is briefly given as follows:

$$\begin{aligned} \text{accuracy} &= \frac{TP + TN}{TP + TN + FP + FN}, \\ \text{precision} &= \frac{TP}{TP + FP}, \end{aligned} \tag{6}$$

where the accuracy describes the measurements closeness to a specific value, while precision is the measurements closeness to each other and

$$\begin{aligned} \text{sensitivity} &= \frac{TP}{TP + FN}, \\ F1\text{-score} &= \frac{2 \times \text{precision} \times \text{sensitivity}}{\text{precision} + \text{sensitivity}}, \end{aligned} \tag{7}$$

where sensitivity (True Positive rate) defines the positives proportion that is correctly recognized. Also, $F1$-score has been achieved by using the precision and sensitivity of the test; i.e., the $F1$-score determines the harmonic mean of the precision and the sensitivity.

In the above equations,

$$\begin{aligned} &\text{TP: True Positive,} \\ &\text{TN: True Negative,} \\ &\text{FP: False Positive,} \\ &\text{FN: False Negative.} \end{aligned} \tag{8}$$

*3.4. Results.* In this section, we investigate the method based on some different measurement indicators. Table 2 reports the performance analysis of the proposed Xception method compared with other studied algorithms.

Table 1: The specifications of the hardware and the software.

| Name | Setting |
|---|---|
| Hardware | Intel® Core™ i7-4720HQ |
| CPU | 1.60 GHz |
| RAM | 16 GB |
| Frequency | 1.99 GHz |
| Operating system | Windows 10 |
| Programming software | MATLAB R2019b |

Table 2: The performance analysis of the proposed Xception method compared with other studied algorithms.

| Method | Accuracy (%) | Sensitivity (%) | Precision (%) | *F*1-score |
|---|---|---|---|---|
| VGG16 [22] | 48.99 | 53.7 | 46.97 | 50.11 |
| InceptionV3 [23] | 52.99 | 53.99 | 52.99 | 53.48 |
| AlexNet [24] | 75.99 | 76.99 | 75.99 | 76.48 |
| Xception [25] | 92.90 | 91.99 | 91.99 | 91.99 |
| Proposed Xception | 100 | 94.05 | 97.07 | 95.53 |

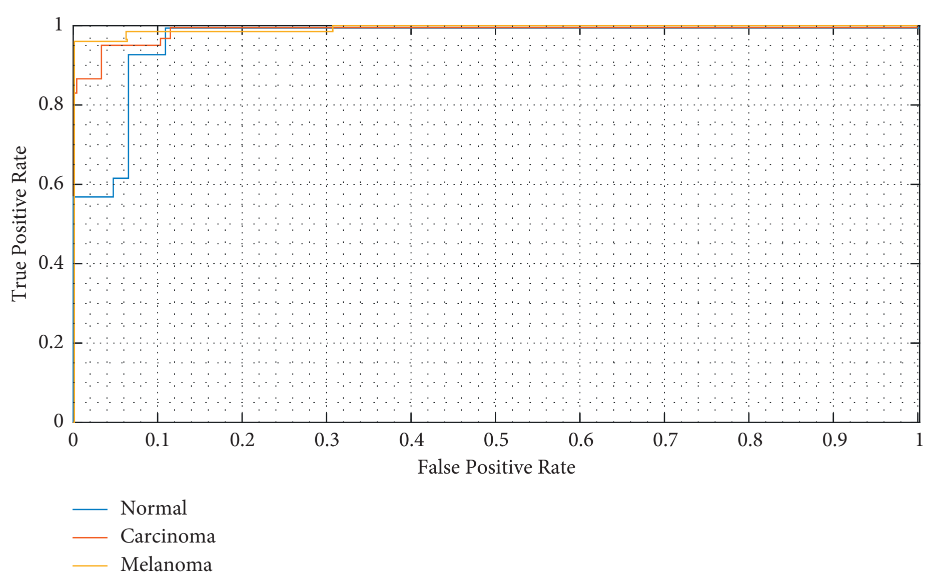



Figure 7: The Receiver Operating Characteristics curve for three classes including melanoma, carcinoma, and normal.

As can be observed from the results reported in Table 2, the proposed Xception method for the studied dataset offers the highest accuracy rate, which is 100%, and the original Xception, AlexNet, InceptionV3, and VGG16 have been ranked in the next places. The results also show that the sensitivity of the proposed Xception method with 94.05% provides the uppermost toward the others. This shows that how the proposed Xception is good in the test at detecting a positive Melanoma. The results also indicate that the proposed Xception method with 97.07% precision has the highest value, which shows its higher reliability toward the other studied methods. Finally, the *F*1-score of the suggested technique is 0.9553, which is the highest value among the others. In *F*1-score indicator, if the value gets closer to 1, it has the maximum precision and sensitivity.

For more declaration, the Receiver Operating Characteristics (ROC) curve for three classes, i.e., melanoma, carcinoma (BCC), and Normal, is shown in Figure 7. The ROC curve is a graphical profile that indicates the diagnostic ability of a binary classifier system as its discrimination threshold is varied. The method signifies the diagnosis ability for the model with measuring the separability degree among different classes. More area under ROC shows better results for the model; i.e., the ROC area will be ideal if the area under the diagram is 1, and it will be poor if the area is 0.

As can be observed from Figure 7, the average area under this curve for melanoma class is 1.0, normal class is 0.98, and pneumonia class is 0.98. The main cause of that the area of classes normal and pneumonia is 0.98, as our

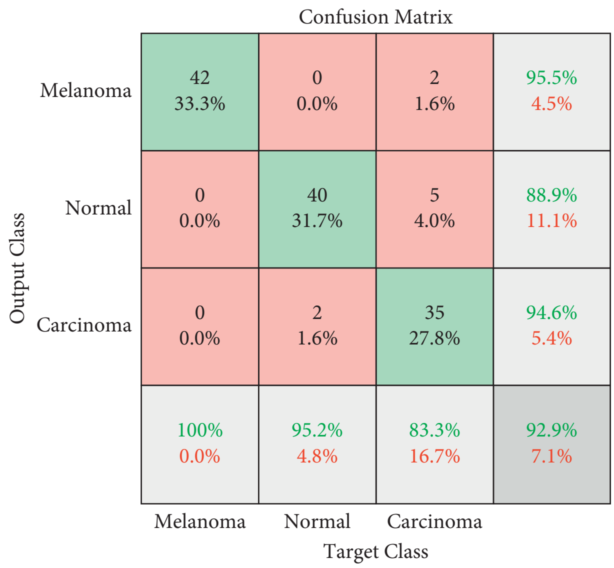



Figure 8: The confusion matrix of true class and predicted class for the traditional Xception [25].

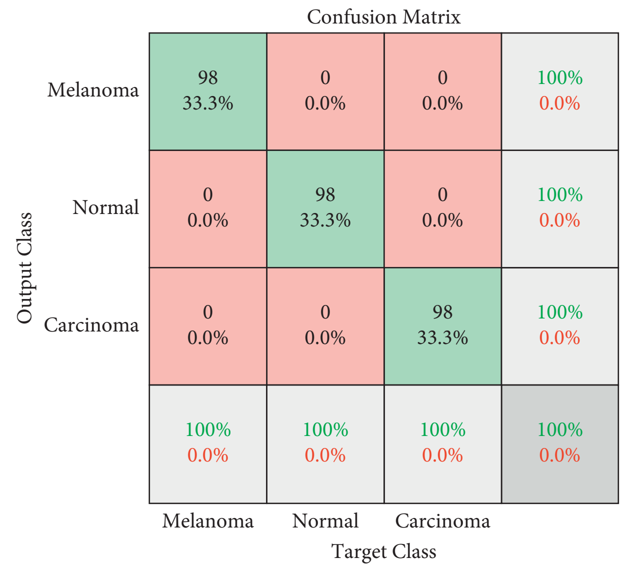



Figure 9: The confusion matrix of true class and predicted class for the proposed Xception.

model has forecasted 3 false positives in case of pneumonia and 1 false negative for normal patients, while melanoma is 1 due to the absence of no false negatives and false positives.

Based on the results, it is clear that both the proposed and the original Xception models provide the classification performance probability for three classes to progress an image diagnosis for the melanoma screening. The classification accuracy of the suggested Xception is better than the original Xception model as determined in the results. In defining the performance of the model classification, a confusion matrix of true class and predicted class for Xception has been shown in Figure 8 [25] and the confusion matrix of the proposed Xception method is shown in Figure 9.

As can be observed from the confusion matrix results for the diagnosis of the melanoma based on the original and the proposed Xception models for the diagnosis of the three-class dataset, the proposed method provides a high accuracy. Indeed, the original Xception achieved true prediction of melanoma in 42 images, accounting for 33.30%, true prediction of normal cases in 40 images, or 31.7%, with false prediction of 68.3%; and true prediction of the pneumonia is 27.8% of the accuracy.

Also, the proposed Xception model achieved true prediction of melanoma in 98 images, accounting for 33.33%, true prediction of normal cases in 40 images, or 33.33%, and true prediction of the pneumonia is 33.33% of the accuracy. Thus, the proposed Xception model based on Swish activation function provides higher accuracy compared with original Xception model.

As can be observed from the results, the proposed method has better effectiveness for the skin cancer diagnosis. However, there are some cases that ca be more improved for resolving its limitations: the method needs a large amount of data to deliver better results. Due to the need for the complex data, its training is expensive; i.e., it needs expensive GPU for better performance. Selecting a good topology and its other parameters is hard, which can be even harder for the less skilled people.

## 4. Conclusions

Among different types of cancer, skin cancer is considered as one of the most widely distributed ones. Melanoma is one of the most dangerous forms of skin cancer. If this type of cancer is diagnosed early, it can be treated 100%. But if it becomes aggressive and spreads to other tissues in the body, it will not be possible to treat it. Therefore, early detection of melanoma can increase a person's chances of recovery and prevention of transmission to others. This study proposed a new architecture of Xception deep network as a convolutional neural network to provide an efficient diagnosis system for melanoma detection. Two main improvements of this model are to use Swish activation function and depthwise separable convolutions to improve the accuracy of the classification stage of the CNN. The proposed Xception method was then implemented to MNIST skin cancer dataset, and the results were compared with some state-of-the-art methods. Results showed that the proposed method, with 100% accuracy, 94.05% sensitivity, 97.07% precision, and 95.53% $F1$-score, provided the highest performance among the others.

## Data Availability

The database utilized in this paper can be downloaded from https://www.kaggle.com/kmader/skin-cancer-mnist-ham10000.

## Conflicts of Interest

The authors declare no conflicts of interest.

## References


[1] A. Adegun and S. Viriri, "Deep learning techniques for skin lesion analysis and melanoma cancer detection: a survey of state-of-the-art," *Artificial Intelligence Review*, vol. 54, no. 2, pp. 811–841, 2021.

[2] A. Javaid, M. Sadiq, and F. Akram, "Skin cancer classification using image processing and machine learning," in *Proceedings of the 2021 International Bhurban Conference on Applied Sciences and Technologies (IBCAST)*, pp. 439–444, IEEE, Islamabad, Pakistan, 12-16 Jan 2021.

[3] S. Jiang, H. Li, and Z. Jin, "A visually interpretable deep learning framework for histopathological Image-based skin cancer diagnosis," *IEEE Journal of Biomedical and Health Informatics*, vol. 25, no. 5, pp. 1483–1494, 2021.

[4] F. P. Reinaldo and M. Vishnevski, "Computer-Aided Diagnosis of Skin Cancer: A Review," *Current Medical Imaging*, vol. 16, pp. 781–793, 2020.

[5] S. K. Clinton, E. L. Giovannucci, and S. D. Hursting, "The World Cancer Research Fund/American Institute for Cancer Research third expert report on diet, nutrition, physical activity, and cancer: impact and future directions," *Journal of Nutrition*, vol. 150, no. 4, pp. 663–671, 2020.

[6] Z. Xu, F. R. Sheykhahmad, N. Ghadimi, and N. Razmjooy, "Computer-aided diagnosis of skin cancer based on soft computing techniques," *Open Medicine*, vol. 15, no. 1, pp. 860–871, 2020.

[7] M. Q. Khan, A. Hussain, S. U. Rehman et al., "Classification of melanoma and nevus in digital images for diagnosis of skin cancer," *IEEE Access*, vol. 7, pp. 90132–90144, 2019.

[8] S. Bharathi, J. Premchand, A. Nivedeethaa, M. Kousiya, and V. Ajay Kumar, "Identification of melanoma from nevus images," in *Journal of Physics: Conference Series*vol. 1917, no. 1, IOP Publishing, Article ID 012027, 2021.

[9] R. Rokhana, W. Herulambang, and R. Indraswari, "Deep convolutional neural network for melanoma image classification," in *Proceedings of the 2020 International Electronics Symposium (IES)*, pp. 481–486, IEEE, Surabaya, Indonesia, 29-30 Sept 2020.

[10] A. Costa, Y. Kieffer, A. Scholer-Dahirel et al., "Fibroblast heterogeneity and immunosuppressive environment in human breast cancer," *Cancer Cell*, vol. 33, no. 3, pp. 463–479, e10, 2018.

[11] M. Babar, R. T. Butt, H. Batool, M. A. Asghar, A. R. Majeed, and M. J. Khan, "A refined approach for classification and detection of melanoma skin cancer using deep neural network," in *Proceedings of the 2021 International Conference on Digital Futures and Transformative Technologies (ICoDT2)*, pp. 1–6, IEEE, Islamabad, Pakistan, 20-21 May 2021.

[12] T. J. Brinker, M. Schmitt, E. I. Krieghoff-Henning et al., "Diagnostic performance of artificial intelligence for histologic melanoma recognition compared to 18 international expert pathologists," *Journal of the American Academy of Dermatology*, vol. 86, pp. 640–642, 2021.

[13] Q. Wang, L. Sun, Y. Wang et al., "Identification of melanoma from hyperspectral pathology image using 3D convolutional networks," *IEEE Transactions on Medical Imaging*, vol. 40, no. 1, pp. 218–227, 2020.

[14] H. Modi, B. Chhabra, and P. Mahalakshmi, "Melanoma Classification: A Survey," *Annals of the Romanian Society for Cell Biology*, vol. 25, pp. 801–805, 2021.

[15] M. M. Azad, A. Ganapathy, S. Vadlamudi, and H. Paruchuri, "Medical diagnosis using deep learning techniques: a research survey," *Annals of the Romanian Society for Cell Biology*, vol. 25, no. 6, pp. 5591–5600, 2021.

[16] E. Pérez, O. Reyes, and S. Ventura, "Convolutional neural networks for the automatic diagnosis of melanoma: an extensive experimental study," *Medical Image Analysis*, vol. 67, Article ID 101858, 2021.

[17] P. Bansal, S. Kumar, R. Srivastava, and S. Agarwal, "Using transfer learning and hierarchical classifier to diagnose melanoma from dermoscopic images," *International Journal of Healthcare Information Systems and Informatics*, vol. 16, no. 2, pp. 73–86, 2021.

[18] N. Razmjooy, F. R. Sheykhahmad, and N. Ghadimi, "A hybrid neural network – world Cup optimization algorithm for melanoma detection," *Open Medicine*, vol. 13, pp. 9–16, 2018.

[19] E. Vocaturo and E. Zumpano, "Dangerousness of dysplastic nevi: a multiple instance learning solution for early diagnosis," in *Proceedings of the 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, pp. 2318–2323, IEEE, San Diego, CA, USA, 18-21 Nov 2019.

[20] N. Dey, V. Rajinikanth, H. Lin, and F. Shi, "A study on the bat algorithm technique to evaluate the skin melanoma images," in *Applications of Bat Algorithm and its Variants*, pp. 45–60, Springer, Singapore, 2021.

[21] F. Chollet, "Xception: deep learning with depthwise separable convolutions," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 1251–1258, Honolulu, HI, USA, 21-26 July 2017.

[22] K. Manasa and D. G. V. Murthy, "Skin cancer detection using VGG-16," *European Journal of Molecular & Clinical Medicine*, vol. 8, no. 1, pp. 1419–1426, 2021.

[23] P. Ridell and H. Spett, *Training Set Size for Skin Cancer Classification Using Google's Inception V3*, Kth Royal Institute of Technology, Stockholm, Sweden, 2017.

[24] K. M. Hosny, M. A. Kassem, and M. M. Foaud, "Classification of skin lesions using transfer learning and augmentation with Alex-net," *PloS one*, vol. 14, no. 5, Article ID e0217293, 2019.

[25] D. Gavrilov, L. Lazarenko, and E. Zakirov, "AI recognition in skin pathologies detection," in *Proceedings of the 2019 International Conference on Artificial Intelligence: Applications and Innovations (IC-AIAI)*, pp. 54–542, IEEE, Belgrade, Serbia, Sept-Oct 2019.

[26] S. H. Kassani, P. H. Kassani, M. J. Wesolowski, K. A. Schneider, and R. Deters, "Breast cancer diagnosis with transfer learning and global pooling," in *Proceedings of the 2019 International Conference on Information and Communication Technology Convergence (ICTC)*, pp. 519–524, IEEE, Jeju, Korea (South), 16-18 Oct 2019.

[27] P. Kuritcyn, M. Benz, J. Dexl, V. Bruns, A. Hartmann, and C. Geppert, "Comparison of CNN models on a multi-scanner database in colon cancer histology," in *Proceedings of the Medical Imaging with Deep Learning*, Lübeck, Germany, 7-July 2021.

[28] E. Hussain, M. Hasan, M. A. Rahman, I. Lee, T. Tamanna, and M. Z. Parvez, "CoroDet: a deep learning based classification for COVID-19 detection using chest X-ray images," *Chaos, Solitons & Fractals*, vol. 142, Article ID 110495, 2021.

[29] N. Codella, V. Rotemberg, P. Tschandl et al., "Skin lesion analysis toward melanoma detection 2018: a challenge hosted by the international skin imaging collaboration (isic)," 2019, https://arxiv.org/abs/1902.03368.

[30] A. A. Nugroho, I. Slamet, and Sugiyanto, "Skins cancer identification system of HAMl0000 skin cancer dataset using convolutional neural network," *AIP Conference Proceedings*, vol. 2202, no. 1, Article ID 020039, 2019.

[31] S. S. Chaturvedi, K. Gupta, and P. S. Prasad, "Skin lesion analyser: an efficient seven-way multi-class skin cancer classification using mobilenet," in *Proceedings of the International Conference on Advanced Machine Learning Technologies and Applications*, pp. 165–176, Springer, Singapore, 2020.

[32] R. Garg, S. Maheshwari, and A. Shukla, "Decision support system for detection and classification of skin cancer using CNN," in *Innovations in Computational Intelligence and Computer Vision*, pp. 578–586, Springer, Singapore, 2021.

[33] D. N. Le, H. X. Le, L. T. Ngo, and H. T. Ngo, "Transfer learning with class-weighted and focal loss function for automatic skin cancer classification," 2020, https://arxiv.org/abs/2009.05977.

[34] P. Tschandl, C. Rosendahl, and H. Kittler, "The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions," *Scientific Data*, vol. 5, no. 1, pp. 180161–180169, 2018.

[35] K. K. Singh, M. Siddhartha, and A. Singh, "Diagnosis of coronavirus disease (covid-19) from chest x-ray images using modified xceptionnet," *Romanian Journal of Information Science and Technology*, vol. 23, no. 657, pp. 91–115, 2020.

Hindawi
Journal of Healthcare Engineering
Volume 2022, Article ID 5819813, 16 pages
https://doi.org/10.1155/2022/5819813

*Review Article*

# Appointment Scheduling Problem in Complexity Systems of the Healthcare Services: A Comprehensive Review

**Ali Ala [1] and Feng Chen [2]**

[1] *Department of Industrial Engineering & Management, Shanghai Jiao Tong University, Shanghai, China*
[2] *Sino-US Global Logistics Institute, Shanghai Jiao Tong University, Shanghai 200240, China*

Correspondence should be addressed to Feng Chen; fchen@sjtu.edu.cn

Received 26 November 2021; Revised 14 January 2022; Accepted 25 January 2022; Published 3 March 2022

Academic Editor: Saeid Jafarzadeh Ghoushchi



This paper provides a comprehensive review of Appointment Scheduling (AS) in healthcare service while we propose appointment scheduling problems and various applications and solution approaches in healthcare systems. For this purpose, more than 150 scientific papers are critically reviewed. The literature and the articles are categorized based on several problem specifications, i.e., the flow of patients, patient preferences, and random arrival time and service. Several methods have been proposed to shorten the patient waiting time resulting in the shortest idle times in healthcare centers. Among existing modeling such as simulation models, mathematical optimization techniques, Markov chain, and artificial intelligence are the most practical approaches to optimizing or improving patient satisfaction in healthcare centers. In this study, various criteria are selected for structuring the recent literature dealing with outpatient scheduling problems at the strategic, tactical, or operational levels. Based on the review papers, some new overviews, problem settings, and hybrid modeling approaches are highlighted.

## 1. Introduction

Today, it is widely recognized that a well-designed healthcare process must provide timely and easy access to healthcare facilities for all patients [1]. Appointment Scheduling (AS) can enhance the utilization of expensive staff and facilities' medical resources while reducing patient wait times. Appointment scheduling aims to build an appointment system that optimizes a specific quality standard in a healthcare application of scheduling tasks under uncertainty. The primary function of healthcare management programs is to minimize patient waiting times in public hospitals and increase patient satisfaction [2]. Healthcare services coping with a large number of outpatients may have several obstacles to address. For instance, a long waiting period for a treatment negatively impacts the patient's experience and may diminish the quality of care [3]. In general, healthcare centers such as hospitals and clinics accumulate an increasing number of patients needing their services. Hospitals have to implement quick and effective healthcare facilities to accommodate new patients and keep people patronizing them [4]. They must successfully identify the bottlenecks, anticipate the effect of diversity on-demand, and compute the optimal capacity distribution [5]. Healthcare centers are evaluated by recognizing the best methods, applying measurable techniques, and having an obligation to improve. Healthcare clinics use decision support systems to provide low-cost and assessable services to individuals to preserve the care quality of services [6]. The solutions presented in the literature aim to reduce waiting times by developing decision support systems to manage outpatient clinic services [7]. Over recent years, healthcare systems have been strained to provide patients with high-quality services despite insufficient funding. One of healthcare's most important issues, ASP, has improved quality and prompt access to health facilities. Time is an essential element in ensuring patient safety and performance, and time is a crucial determinant of patients' satisfaction [8].

In principle, the purposes of ASPs can be divided into four categories: decreasing service costs, increasing patient satisfaction, reducing waiting time, improving fairness, and reducing costs in healthcare [9]. One of the central issues in healthcare is fairness, which is a primary concern when scheduling patients and doctors [10]. Aside from fairness in scheduling, further encouragement is attained through a novel gain framework unique to the division and was not reported previously. Another critical issue on fairness is mending personal scheduling preferences [11]. The appointment scheduling's main problem is optimizing healthcare resources by improving human resources and medical equipment utilization, leading to the depreciation of the patient waiting times. Several studies have shown that the primary explanation for patient dissatisfaction in outpatient scheduling is often extended waiting time, and fair waiting times are required based on clinical competence [12]. Simulation models are among the most well-known approaches to investigating random factors' influence on patients' waiting time and doctors' idle time in appointment scheduling [13]. The optimization model uses a Simulated Annealing method to optimize the patient appointment scheduling mitigating the average service period and whole patient waiting times. According to the obtained result, the entire service time and the patient waiting time have been reduced by about 5% and 38% compared with the current situation, respectively [14, 15]. They examined the quality of their solutions via structural results and compared them with heuristic scheduling practices using a discrete event simulation. Some scholars [16, 17] applied for advanced work inside the literature to layout models to maximize the variety of patient appointments, minimize affected patient waiting time, and increase patient satisfaction. They also defined the answer set programming to solve the proposed combinatorial optimization problem that exhibited a suitable assessment used in artificial intelligence [18–20]. This paper provides an overview of the no-show problem from the following perspectives: Our contribution in this review study is to assess and examine all scientific work in appointment scheduling from 2000 to 2021, emphasizing complexity techniques. In investigating patient admission scheduling with varied applications, we examine several types of problem descriptions.

Furthermore, we also review the works available in solving other healthcare scheduling, including waiting time, using artificial intelligence, and queuing theory in appointment scheduling. Our review work centered around appointment scheduling in the complexity of healthcare research considering this problem is the most studied healthcare scheduling problem as described, concentrating on various methods used in ASP to decrease waiting time and improve patient satisfaction in healthcare. The remainder of this paper is organized as follows.

Section 2 reviews the existing articles on outpatient scheduling problems and related works. Section 3 presents the broad performance criteria of the present methodologies in appointment scheduling problems. Section 4 discusses various application domains and healthcare application methods, while the patients' choice function has more areas. An affected person chooses a selected provider (which determines carrier fine and health facility revenue), a specific day of the week (carrier delay), and a particular time of appointment (convenience). Finally, the findings and conclusions for future guidance are discussed in Section 5.

## 2. Research Methodology

This search aims to uncover papers that seek to determine patients who will turn up for their appointments. As a result, the search is initially limited to articles focusing on the keyword emergency or its synonyms. The comprehensive review is based on the publications related to the issue of appointment scheduling published from 2000 to 2021 in the Web of Science (*WoS*) Core Collection database. As can be seen, the number of recent articles has overgrown. Figure 1 shows the percentage of application domains to the patient and outpatient scheduling problems. As can be seen, most of the existing outpatient appointment scheduling applications are in the field of chemotherapy and radiotherapy. Hence, we recommend a pie chart about different healthcare branches handling the green outpatient scheduling inside a radiotherapy department defined in such a manner to represent different actual-existence situations. The effectiveness of discussed studies is evaluated on randomly generated issues and a real case situation. The outcomes are very encouraging since the developed optimization models can overcome human experts' performance.

As seen in Figure 1, appointment scheduling has been discussed in many literature review topics. Generally, the problems are based on highly aggregated information at various times of the year. Nearly half of the contributions are seen in or after 2013, illustrating the increasing topics for researchers in the appointment scheduling program. Since the total number of manuscripts is massive, we restrict manuscripts to those posted in or after 2014 and 2015. The number of papers published in English regarding this issue between 2014 and 2015 is limited. However, the number of articles published after 2015 has risen due to the contribution achieved between researchers and the healthcare sector. They realized that they could benefit from this system's advantages, including better working time for staff and suitable follow-up for ordinary patients with chronic illnesses.

In Figure 2, we have also considered different publication indexes in appointment scheduling, such as SCI (blue), SJR (orange), IOS (grey), and JCR (yellow). As we can see, the number of papers from 2000–2021 on the SCI and JCR has increased slightly, and it has shown that many authors are believed to publish the article in some well-reputed journals. However, the Appointment scheduling topic is also going viral for many scholars these years as it is essential for healthcare services and management.

Also, in Figure 3, author keywords were more likely to define the difficulties and methods. In contrast, keywords plus included general terms like "appointment Systems," "health care," "arrival time," "WTS," and pleased. *VOSviewer* is used to display the cooccurrence connection of the network of the 200 keywords. The node's scale indicates the frequency of the keywords, and the thickness of the line indicates the vicinity of the relationship between the three

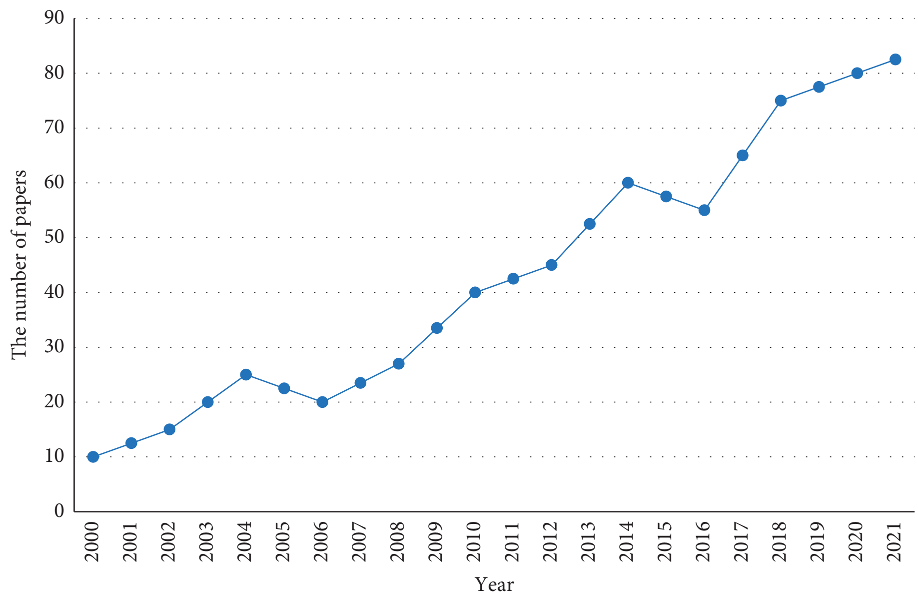



Figure 1: The trend of the published articles in the area of appointment scheduling 2000–2021.

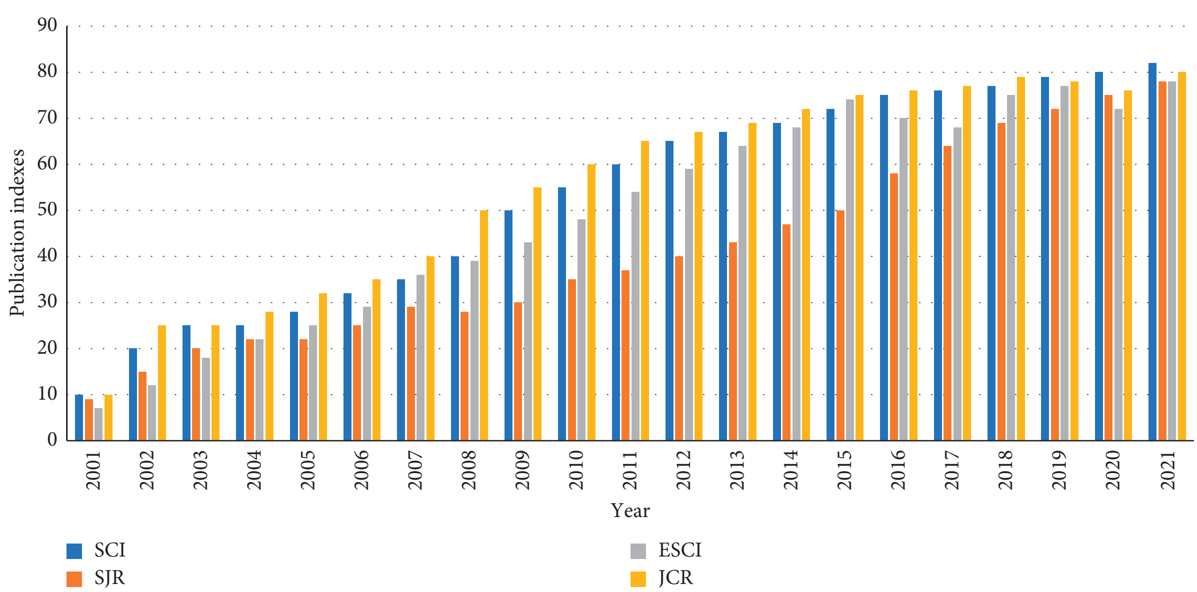



Figure 2: The trend of the publication based on various indexes SCI, JCR, SJR, and IOS in appointment scheduling.

main keywords. Three frequently used terms, "Appointment scheduling," "optimization," and "Healthcare," are highlighted in the center with a more prominent label and a circle. In the graphic, the difference between the two keywords reflects the similarity of the words in terms of the connections. For instance, the keyword "Healthcare" appeared with numerous other terms such as "Systems," "Optimization," "admission," and "arrival time." As a result, the keyword placement is determined by the number of other keywords that share positive similarities. The cooccurrence map reveals that simulation in appointment scheduling comprises a broad spectrum of issues, including the emergency department, hospital planning network, operation, outpatient capacity planning, appointment scheduling, and resource allocation. The smaller nodes, which are associated with keywords such as "time delivery," "algorithm," "fairness," "discharge," "delays," and "performance," represent the lower cofrequency of these words across the examined papers, despite their tight connection with the Appointment scheduling.

It also depicts the current patients' scheduling core elements in operation research (OR). The number of articles in which the keywords appear to be together, recreating the connection of their different research areas, is used to calculate the strength of the link between two keywords. This contribution has made it possible for researchers in this area to pick up more novel and appealing topics. Table 1 presents a list of outpatient scheduling models and methods' taxonomy. Most of the literature addresses modeling approaches presented earlier in this review paper that

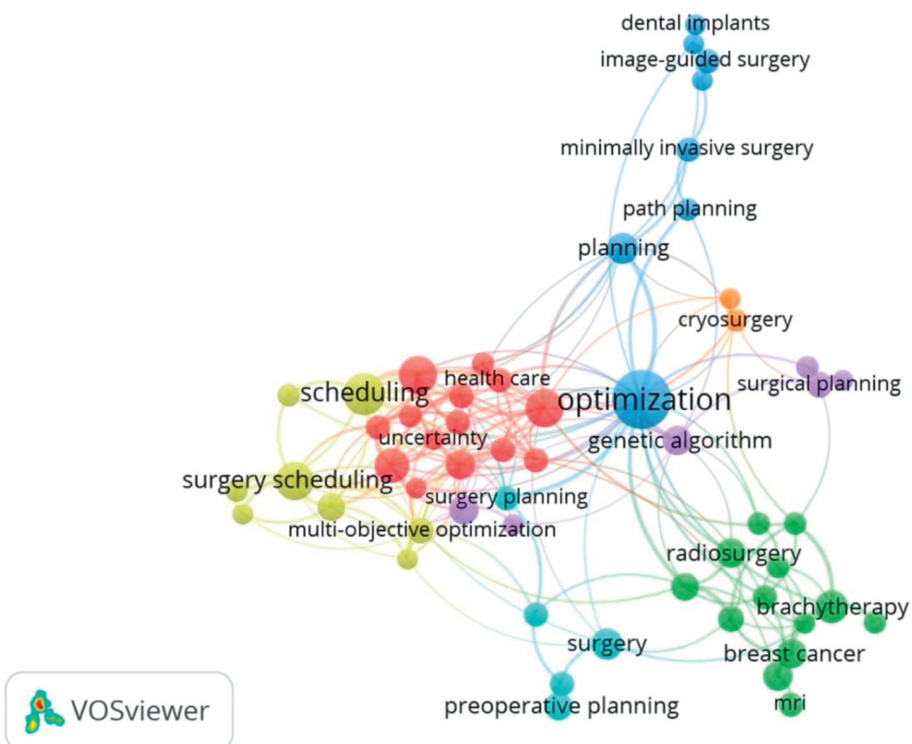



Figure 3: The keywords for the outpatient scheduling problems.

Table 1: Categorizing the various artificial intelligence methods in appointment scheduling 2021–2022.

| Publications | CNN | DNN | ANN | ACO | PSO | GA | WOA |
|---|---|---|---|---|---|---|---|
| Muhammad et al. [21] | * | | | | | | |
| Kumari et al. [22] | | | | | | * | * |
| Shilong et al. [23] | | | | * | | | * |
| Bisoy et al. [24] | | | | | * | | |
| Sarkar et al. [25] | | | | | * | | |
| Jiang et al. [26] | | | | * | | | |
| Gao et al. [27] | | | | | * | | |
| Vukobrat et al. [28] | | | * | | | | |
| Kirchohf et al. [29] | * | | | | | | |
| Nair et al. [30] | | * | | | | | |

considered obtaining stability between patients' wait time and doctors' utilization through a hospital consultation and resources. In reality, direct and indirect waiting time is one of the initial practical factors in appointment scheduling. However, this modeling is difficult for the whole process for many reasons. First, unlike the direct waiting period during which the appointment is stopped is a typical ending; waiting time issues are more realistically modeled as unlimited problems. Second, outpatients are assigned an appropriate appointment time to select several preferred providers in a scheduling problem. Also, ASPs made for a specific doctor are coupled with different days and doctors on an actual day.

## 3. Results and Analysis

There are many techniques in the healthcare research areas. One of the crucial areas is utilizing appointment scheduling. In this section, some methods are analyzed to determine which method is more efficient than the others with their advantages as bases. The admission process is introduced with or without appointment only by the online or call services. The fundamental goal is to minimize access time by assigning part of the resources to patients who call for scheduling on the same day or within a few days [31, 32].

*3.1. Overlapping Scheduling (OLAS).* The overlapping appointment scheduling (OLAS) model shortens the patient waiting time and the doctor's idle time in an outpatient healthcare hospital with a stochastic service time while maximizing the doctor's utilization and patient satisfaction [33–35]. OLAS model refers to deciding the optimal overlapping periods between the patient appointment and allocated service times. OLAS is usually formulated as an optimization problem to minimize the total cost of patients waiting and doctors' idle time, given the probabilistic distributions for patient flow and the service time [36, 37]. This discovery should help improve clinic services and ensure service quality [38]. Another study at the University Hospital of Egypt [39] analyzed patients' satisfaction with the quality of services in outpatient clinics, concluding that there is a need for continuous quality improvement and care in the healthcare environment, mainly to satisfy patients. The process of developing an overlap period in clinics with different assumptions is related to the service time distribution, over time, and no-shows [40, 41]. OLAS's primary advantages for appointment scheduling are its lack of specific scheduling services, such as alarm and warning of overlapping times. In general, OLAS increases productivity and profit despite the expense of additional staff. Also, some appointment analyses emphasize the importance of the number of operation researches. The OLAS model's objective is to determine the effect of overlapping appointments in a healthcare sector (clinic) setting. Different units are involved in this process [42, 43].

*3.2. Markovian Scheduling Method (MSM).* The queueing theory has numerous applications in the field of healthcare management. Because they play such a significant role in hospitals, the research of queuing systems has often focused on the busy period and waiting time. A queuing system is typically defined as a patient entering a queue, being served at a service point by a server (doctor), and then exiting the row [44]. A stochastic process, a type of embedded Markov chain, governs the state-to-state transitions. At the same time, a different probabilistic mechanism determines the time spent in each stage. The transition probabilities are assumed to depend on the current state, and the time spent in each step is considered to depend on the present and following conditions [45, 46]. Many researchers use Markovian methods to investigate service scheduling research, such as for ambulance unloading delays, a Markovian queueing model was used [47, 48]. Another analysis that used the Markovian model to estimate patient services was the basic Markovian model's waiting time in a hospital using order statistics [49, 50]. The Markovian models show that a healthcare condition often depends on the standard sequence of carefully followed steps. These actions can formulate the difficulty, purpose of study, data gathering, concept and validation, and the network model's systems. Markovian chain method for appointment scheduling has conceived a new idea wherein knowledge about that approach depends on one or two booking agents' expertise [12]. The Markov decision model's different number of sessions and duration determines an optimal policy for a given problem. For instance, the number of semiurgent patients scheduled in a particular week, given the expected demand or the number of appointment scheduling patients, considers walk-in patients' anticipated direction [51, 52]. In both cases, it is assumed that the number of this week's patient arrivals is not influenced by the number of patients who arrived last week. We also investigated these two healthcare methods (OLAS) and (MSM) based on how some others considered these in their work.

Based on the investigation in Table 2, we have shown that most of the papers on appointment scheduling between 2021 and 2022 are applied. Markovian systems other than OLAS as that model have many subsections to use various optimizations methods such as Mixed Linear Integer Programming (MILP), stochastic technique, and queuing theories.

The most significant difference between the Markov chain models and other approaches is patients' status during a specific period of time [60, 61], called different wait time penalties. A key factor is the order of patient treatment, i.e., first-come-first-serve (FCFS). In the case of a high number of patients requesting the care services, the ordered patients arriving later might be scheduled before those visiting earlier, thus causing the system to increase its "rate of service." However, enforcing fairness reduces flexibility, which is called different wait time targets. The fairness policy is motivated by expediting early arrivals rather than scheduling late arrivals ahead of them [62, 63]. Furthermore, it observed that an individual's waiting times are more variable for the contemporary approach than for the sequential one; this notable feature illustrates the difference in fairness [64] (Table 3).

*3.3. Simulation-Based Complexity of Healthcare.* Simulation models are rapidly becoming a well-known approach for dealing with healthcare appointment scheduling concerns and issues. Different simulation methods were investigated in most instances. The complexity of healthcare systems arises from their complex structure, which includes the concepts of queues and flows and social systems and decision making. Modeling complex systems at the personal level rather than the population level may be more beneficial with DES as an operational research technique. Individual entities travel through a succession of discrete events one by one at discrete intervals, among which they must wait in queues because of the limited availability of resources. The simulation approaches for outpatient scheduling problems are categorized mainly in Discrete events, Agent base simulation in healthcare problems, and those are recently widely used on this topic. As reported in the pie chart in Figure 3, most articles use discrete-event simulation (DES) techniques to improve patients' services to reduce the wait time in healthcare centers. As these two methods are mainly considered in most papers, we evaluated their differences in healthcare systems. Discrete event simulation and Agent-based simulation (ABS) have capabilities and limitations. DES and ABS methods are argued to be complementary to each other. Most healthcare systems are based on two major elements; the concept of queues and flows and decision making. DES models can consider the idea of queues and flows, while ABS models can capture human behaviors and decision-making in healthcare systems. A framework for a hybrid model of DES and ABS was proposed to capture both significant elements of healthcare systems.

Also, having those simulation approaches categories for appointment scheduling, discrete-event simulation is a

Table 2: Different methods and objectives in appointment scheduling publications between 2021 and 2022.

| Publications | Markovian | Overlapping | Objectives |
|---|---|---|---|
| Ntaimo et al. [53] | | * | Consider stochastic programming to improve computational speed time |
| Mueen [54] | * | | Consider a fuzzy set programming and MILP to measure healthcare scheduling |
| Lee et al. [55] | | * | Practical optimization considered to solve makespan scheduling in healthcare |
| Zhao and Wen [56] | * | | Design an algorithm with a lower-bounded competitive ratio to improve patient arrival time |
| Xie and Liu [57] | * | | Continuous-time Markov chain and uniformization method to solve waiting time |
| Bayram and Yu [58] | * | | Applied Markov and newsvendor model to maximize long-run average earnings |
| Soodan et al. [59] | * | | Applied a stochastic queuing model to optimize patient arrival time |

flexible strategy tailored to shape the methods required to notify healthcare scheduling. It allows a broad set of tools than the Markov standard method and enables the development of techniques at a depth suitable to the problem. Its dangers are few and without problems mitigated, bringing our field towards necessities for powerful modes that decision-makers can trust. Most discrete-event simulation has programmed Any Logic or Simulation Arena software to control the clock [112]. Also, adequately scheduled activities and recognizing the subsequent ones appear to allow for dynamic entities, assigning input variables, and acting technique activities appropriately.

Agent Base Simulation can also model complicated, stochastic, and nonlinear conditions and focus on specific patients. So based on the pie chart in Figure 3, we will determine these prior years; most of the simulation approaches on ASP have various percentages of each approach. On the other hand, DES varies from ABS in three different ways [113–116]: first, in the method, decision-making actions engage in ABS; second, in its depiction of queuing; and third, in the increased number of tools available to it. Patients that arrive early, late, or on time for their scheduled appointment may be addressed by the hybrid simulation model (HSM) and SO [117–120]. The most notable distinction between the HSM and SO approaches is patients' status at a certain point, referred to as differing wait time penalties. The order of patient care, i.e., FCFS, is important. [121–123]. If many patients need care services, the ordered patients who arrive later may be scheduled ahead of those who come earlier, causing the system to enhance its "rate of service." This study proposes a combination of ABS [124–126] and nonlinear mixed-integer programming (MIP) to reduce WTS in Ass [127–129]. ABS [130] updated their concept for broad adoption, and it has been effectively implemented at ten ASs and several hospital units. The machine-learning framework integrates patient information and matching therapies, which detects trends in the simulation platform. As a result, agents offer problematic symptoms to care providers in the form of recurrent patients whose complaints were possibly mistreated in previous visits to appointment scheduling. This ASP study highlights the type of uncertainties: one about the issues involved in the activities, one about the frequency of the tasks, and one about the available resources and employs fuzzy logic to deal with these uncertainties [131, 132]. The study divides agents into two types: software and physical. The latter refers to those who can act on their initiative, including everyone from doctors and patients to healthcare workers, nurses, and other hospital personnel.

### 3.4. Queuing Theory.

In theory, the typical queuing problem in appointment scheduling has long been a source of consternation for domestic and international specialists and scholars. Queue theory and accompanying better models have been frequently operated to overcome this challenge. This section adds to the theoretical optimization of queuing problems in hospital management and gives an analysis and decision-making mechanism for enhancing hospital queuing theory and medical service efficiency. The following four essential characteristics are usually used to describe the queuing system.

#### 3.4.1. Patient Arrival Mode.

The time it takes for patients to show up at the queuing system is either predictable or unpredictable. The majority of patients in the hospital's queue system arrive randomly. At this moment, the arrival rule of patients entering the procedure is called admission arrival. The focus of queue theory is also on this circumstance.

#### 3.4.2. Service Model.

Patient service hours are deterministic or random, and most service hours are random. The probability distribution often describes the time rule of patients receiving services.

#### 3.4.3. Queuing Rules.

Healthcare for emergency patients is among the first-come, first-served services. Whenever a patient with a higher priority appears to the system, the patient getting the service must stop and be changed to treat such patients, such as the hospital emergency department for severely ill patients.

#### 3.4.4. Number of Bed Resources.

A service system is typically comprised of one or more service stages. Patients' hospital diagnosis frequently necessitates many service phases, such as outpatient visits. After making an appointment, outpatients come to the queue (i.e., the waiting list, arrival time, and idle time) in a first queueing system. When the patient's appointment time arrives, they are withdrawn from the waiting list and placed into a second queueing system. The patient enters the queue at the service facility, receives the

Table 3: The taxonomy of outpatient scheduling models and methods.

| References | Mathematical optimization | Markov model | Dynamic approach | Artificial intelligence | Simulation approach | Robust approach |
|---|---|---|---|---|---|---|
| [65] | * | | * | | | |
| [66] | * | | | | | |
| [67] | | | | | | * |
| [68] | * | | | | | |
| [69] | * | | * | | | * |
| [70] | | | * | | * | |
| [71] | | | | | * | |
| [72] | * | | | * | | |
| [73] | * | | | | | |
| [74] | | | * | | | * |
| [75] | * | | | * | * | |
| [76] | | | | | | |
| [77] | * | | | | | |
| [78] | * | | * | | * | |
| [79] | | | | | * | |
| [80] | * | | * | | | |
| [81] | | * | | | | |
| [82] | | | | | | |
| [83] | * | | | * | | |
| [84] | * | | | | | |
| [85] | | | | | | |
| [86] | * | | * | | | * |
| [87] | | | | | * | |
| [88] | | | | * | | |
| [76] | | | * | | | |
| [78] | * | | | | | |
| [89] | | | * | | | |
| [90] | | | * | | | |
| [91] | | | | | | |
| [92] | * | | | | | |
| [83] | | | | | | |
| [93] | | | | * | | |
| [94] | * | | | | | |
| [95] | | | | | | * |
| [96] | * | | | | | |
| [97] | | | | | * | |
| [98] | | | | | | |
| [99] | | | * | | | |
| [100] | | | | * | | |
| [101] | | | | | | |
| [102] | * | | * | | | |
| [103] | | | | * | | |
| [104] | * | | | | | |
| [44] | * | | | | | |
| [105] | | | * | | * | |
| [106] | | | * | | | |
| [107] | * | * | | | | * |
| [108] | | | | | | |
| [109] | | | | * | | |
| [110] | * | | * | | | |
| [111] | | * | | | | |

accurate service, and then departs the appointment scheduling slot in this separate queueing system. Throughout the present paper, both queueing systems will be referred to as the appointment generating queueing system and the service facility queueing system (see Figure 4).

The most widely used queuing system is the *M/M/s* or Erlang delay model for outpatient scheduling waiting time study. This model assumes a single queue with an unlimited waiting room that feeds into *s* identical servers. It is usually assumed that the patients arrive according to a Poisson process with a constant arrival rate, and the service duration follows an exponential probability distribution. The primary use of the M/M/s method includes only three variables and could be used with little internal data to produce output

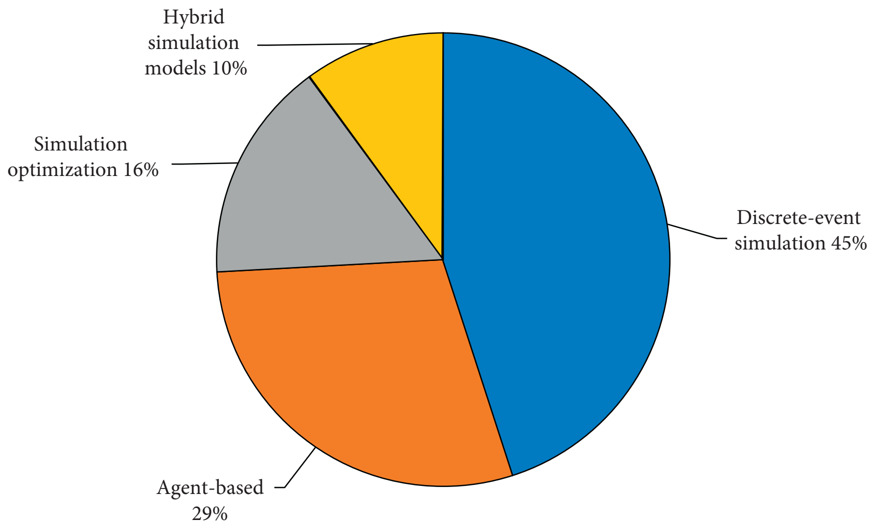



Figure 4: The percentage of different simulation approaches to an outpatient scheduling problem.

estimates [73, 133]. At the same time, it provided the average arrival rate, the average length of support, and several services. Also, to achieve performance measures such as the probability that arrivals will encounter a significant or average delay, a priority queueing model could be suitable if a facility intends to identify the ability required to assure a centered service level for the best precedence customers [134]. For example, Queuing analysis is also an essential method in predicting ability needs for potential future situations, including demand rises due to emerging or urgent new illnesses, wanting a physician's care more quickly to prevent extreme scientific consequences [135, 136].

*3.5. Artificial Intelligence (AI).* Healthcare is one of the research sectors in which Artificial Intelligence (AI) has high potential advantages. Recently, more state-of-the-art AI methods has been addressed through appointment scheduling. In order to improve the efficacy of scientific operations, numerous solutions have been introduced for online systems, appointment/surgical procedure scheduling, medical image analysis, and treatment plan and forecasting of uncommon diseases, and AI is easily carried out in appointment scheduling. The software can significantly affect the ultimate use of resources by considering these various demanding situations in a hospital's everyday working surroundings. AI-based scheduling Machine Learning (ML) models have a significant possible role in improving hospital healthcare services [78]. ML can maintain even more complicated models that can change several areas simultaneously, as in the postanesthesia treatment unit and surgical centers. Models of AI, which have significant economic consequences, may also restrict another organizational problem [137, 138].

Also, any bias against an underrepresented institution in an information set will result in a biased computerized decision. For example, an appointment scheduling software program can make racially discriminatory scheduling decisions. AI programs in healthcare need to avoid such inequalities. AI provides a lead to assuming the fundamentals of AI technologies (machine learning, healthcare) and their proper use in healthcare. It also offers practical support to help decision-makers promote an AI approach that can support its digital healthcare transformation. All investigation outcomes are tracked by AI, which then analyzes patterns to optimize future interactions [139, 140]. The AS system optimizes and duplicates the factors that lead to positive results. Each patient engagement is triggered by AI depending on the patient's specific needs. Using AI in the appointment scheduling system can then send out evaluations to patients via e-mail or text message, collecting feedback on the services. The system can then examine this data to identify areas where there is room for development and pass them on to the appropriate doctors. Several hospitals use AI to predict the number of patients to the emergency department two or three days in advance, allowing them to take proactive action in staffing and resource allocation [141–143]. Also, [144] examined the difficulties and prospects for hospitals to integrate AI into strategic planning and become intelligent systems with feedback-controlled operations and procedures (closed-loop systems). They [145] presented a model in healthcare scheduling during the COVID-19 outbreak healthcare service. They built on a considerable amount of theory and research on behavioral Internet of Medical Things, big healthcare data analytics, and artificial intelligence-based diagnostic algorithms, Creating a framework for categorizing artificial intelligence. For the sake of the analysis, we separate between care levels (primary, secondary, and tertiary care), planning levels (strategy, operational, and functional), and user groups (doctors, nurses, technicians, patients)

*3.5.1. Optimization Methods with AI.* This review gives a broad overview of artificial intelligence's role in healthcare. This review does not touch on all healthcare areas that benefit from optimization modeling. However, we have suggested a range of optimization and neural networking applications to healthcare research. These optimization methods have been recently utilized in many optimization methods. However, in healthcare, scheduling is considered more such as convolutional neural networks (CNN), recurrent neural networks (RNN), artificial neural networks (ANN), Ant Colony Optimization (ACO), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Whale Optimization Algorithm (WOA).

Based on what we have investigated in Table 1, we have different methods of artificial intelligence, and as we can see recently, many papers have considered appointment scheduling that utilized PSO and WOA. At the same time, the rest of the areas of the neural network are primarily used in different healthcare areas.

Many scholars have investigated Particle Swarm Optimization (PSO) in their research because this method is a swarm-based intelligent stochastic search technique encouraged in different ways in healthcare scheduling. Consequently, for the versatility of numerical experimentation, PSO has been chiefly applied to address the diverse kinds of optimization problems. The PSO algorithm could be utilized to solve various healthcare scheduling issues. The first entails optimizing the problem's objective function, while the second entails optimizing the cost function of a healthcare system. In different problems, good results are achieved, confirming the PSO method's efficiency over other AI methods. As we can see in Figure 5, during 2021–2022, many papers, especially in AI and healthcare, have been collected based on PSO with a greater number of publications than other methods in such a healthcare scheduling. Also, we still have some papers from WOA and ACO that form optimization methods that stand behind the PSO methods.

Moreover, the application sets for the outpatient scheduling problem are categorized in Table 1. The implementations' scope is pervasive, varying from patient scheduling, clinical applications, and medication schedules. In the case of a clinical emergency, it is so significant, for example, for an ambulance to reach the base as fast as possible. The patient waiting time in this situation is an essential indicator of healthcare performance [144, 145]. In the case of a scientific emergency, the number of distances is critical for ambulance offerings to reach the site as quickly as possible. In this example, the patient waiting time is a crucial indicator of ambulance system performance. With the upward thrust within the cost of providing first-rate fitness care, hospital and health facility administrators practice price containment by minimizing assets for health care provisions while still striving to provide the best health care for patients. This dilemma is becoming quite prevalent within the health care network, as indicated via the massive frame of literature that analyzes the allocation of scarce health care resources. The fundamental aim is to decrease the operational cost subject to constraints, i.e., maximum vehicle size and maximum waiting time for a patient. It pointed out that the customer waiting time can be reduced by sharing the link between a set of vehicles [146].

As shown in Table 4, various review articles have collected essential appointment scheduling applications using simulation, optimization, queuing theory, and artificial intelligence methods. The desired number of keywords in each application is indicated.

## 4. Discussion

The scheduling of appointments is a complex combinatorial subject. Since the problem was initially described in its solution, it has allowed patients to be assigned to particular slots or beds in specific relevant departments. At the same time, they allow patients' demands to be addressed to the highest standards possible to ensure that all healthcare limitations are fulfilled. Patients are usually assigned to beds by a centralized admission office, which contacts departments several days ahead of time to ensure effective appointment scheduling. As mentioned in Section 3.1 to 3.5, we have focused on addressing the practices and methods to decrease or resolve appointment scheduling problems. Scholars aspire to continue further investigating the research directions in this field. Appointment scheduling can be accomplished by developing a numerical or simulation model of the booking process, optimizing service resource setup. Many academics have explored the modeling of appointment systems and scheduling algorithms with excellent results. They thoroughly examined the current state of research on associated optimization problems, optimization methods, and models in the healthcare outpatient appointment system [148, 150]. If service time follows an exponential distribution, they considered that each patient had a predetermined probability of ASP [151]. A sequential appointment plan was used to estimate the number of bookings and the scheduled service time to maximize overall service revenue. Customers' priorities are continuously variable in the service system. The literature review discussed above significantly improves the quality of outpatient facilities of the various departments studied in the healthcare clinic. The main contribution is developing a patient-oriented appointment cycle focused on multiple approaches such as scheduling, modeling, and artificial intelligence and fit to improve the efficiency of the outpatient care system. The length of care depends on the patient's characteristics and varies greatly [145]. Still, we have reviewed numerous papers and several of those models and presented the benefits; nevertheless, determining which one is more efficient is difficult. Many researchers in this field have done simulation work, and we may infer that discrete event simulation has the most benefits and a better concept of solving the constraints. In general, discrete event simulation is a very flexible approach tailored to coordinate the procedures required to implement healthcare scheduling. It also delivers a larger scale than traditional Markov chain optimization, making the model ideal for the problem. Due to different service demands and various priority levels, patient scheduling is complicated. They created [152] a paradigm that combines stochastic service times into the scheduling problem as a first step in integrating appointment scheduling and advance scheduling. Then, they added to the existing literature by presenting analytical and experimental results for the case of multiclass, multipriority patients with predictable service times.

To settle for the additional waiting time created by appointment scheduling, the provider will approve the

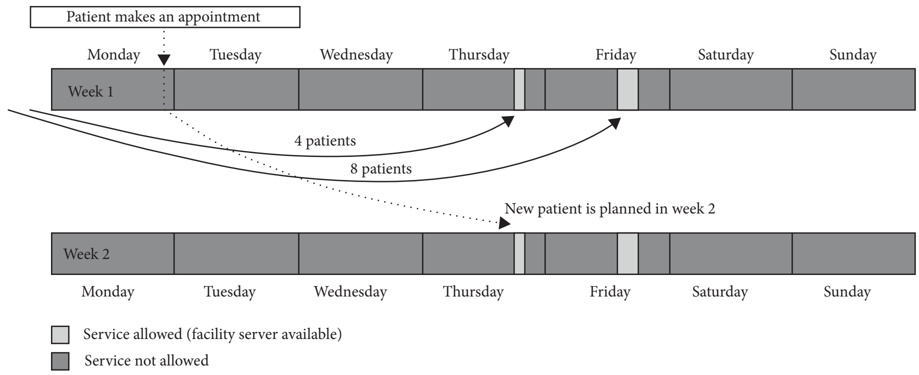



FIGURE 5: Traditional queueing scheduling of appointments during the week for the patient.

TABLE 4: Categorizing the application domains for the outpatient scheduling models.

| Application domain | Articles |
|---|---|
| Chemotherapy | [68, 73, 75, 78, 86, 87, 92, 95–99, 102, 103, 106–109, 118] |
| Oncology | [67, 69–71] |
| Radiotherapy | [66, 67, 72, 74, 76, 78, 83, 87–91, 93, 94, 101, 147] |
| Physiotherapy | [83–85] |
| Rehabilitation therapy | [77, 86, 104, 105, 111] |
| Hemodialysis | [79, 82, 148, 149] |
| Pathology | [80, 102, 110] |

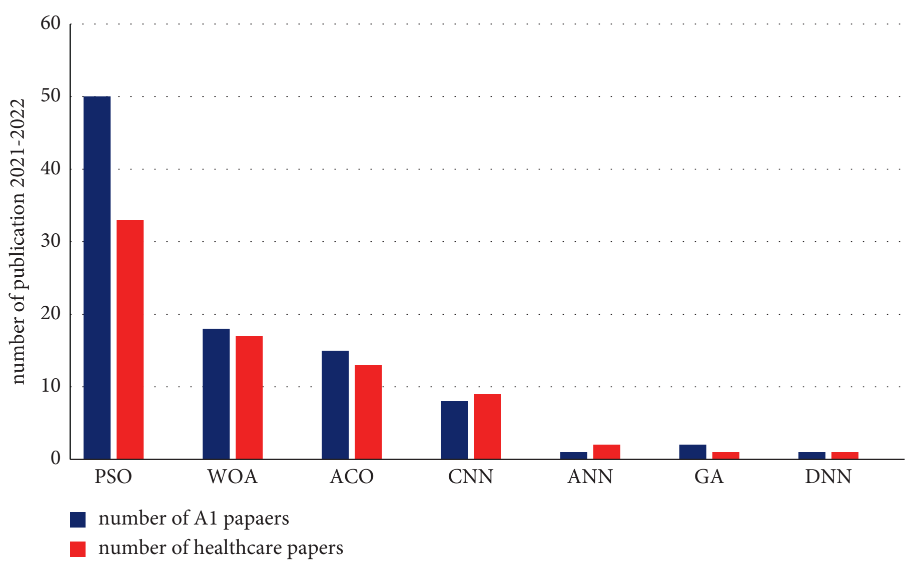



FIGURE 6: Number of papers in various AI methods in appointment scheduling between 2021 and 2022.

service requirement of arrival time. They analyzed [153–155] capacity allocation and appointment scheduling in the presence of arrival time and developed a connect rule dealing with helping to address decisions. Regarding how many slots to reserve for arriving and scheduled patients, the clinic session was given a fixed daily capacity to reduce missed appointments. They developed a finite-state Markov decision model and provided the best acceptable guidelines for determining which types of arriving patients are sufficient [149, 156, 157]. The experimental results show that when the arrival intensity of outpatients does not exceed 20% of the service intensity, accepting all is the best choice. This could be an essential route for future research.

Furthermore, another important research trend is developing a forecasting model to provide new information on the interrelationships of predictors and the conditional probability of forecasting appointment scheduling using machine learning. To examine the probabilistic links between prediction factors in appointment scheduling research, Topuz [147] built the Bayesian belief network. The predictive models may be linked to the scheduling workflow, and risk assessments can be produced based on various parameters.

*4.1. Limitations and Objectives.* The study demonstrates that appointment scheduling has shifted significantly from the setting indicated by the operations-research literature. Methods based on system flexibility and variability decrease appear more feasible than quantitative optimization, particularly in high complexity and uncertainty conditions. Also, the complexities of healthcare can describe a dynamic set of operations that interact with each other. Many appointment types, times, and constraints, on the other hand, might increase total system delay because each appointment type and time generates its differential delay and queue. Eventually, minimizing complexity reduces system delays. As a result, appointment scheduling is not without constraints: Our research has certain limitations. First, a healthcare facility with a high patient waiting time enhances the fundamental scheduled gap between patients or decreases the overloading percentage. Second, in our research, the unit cost of patient waiting time, patient dissatisfaction, and physician idle time was set at values based on our consultation with the administration. On the other hand, the goal of an outpatient appointment system is to optimize existing resources, include more doctors in those departments, and reduce the length of stay time waste.

## 5. Conclusions

This study addressed existing modeling approaches for outpatient appointment scheduling in the healthcare sector. In this regard, about 150 papers are investigated better to understand outpatient appointment scheduling problems in the literature. We considered research literature from 1990 to 2020 according to the WoS database. Then the research status and development trends are summarized by bibliometrics. Based on the statistical reports generated in this study, the reader can observe the growing trend of research interest in recent years (shown in Figure 6) due to the increased hospital resources. Despite the abundant literature for outpatient appointment scheduling, there are some opportunities to improve the existing research, including developing the planning models, performance measures, and forecasting skills under different generalized conditions. For instance, more experiments can be structured to improve schedules that are carried out well on this topic. Weak schedule performance (limited performance) is because of high overbooking levels. Understanding the performance dynamics of scheduling systems could lead to developing alternative healthcare access systems. An alternative area of examination is necessary to change the status of overbooking. General public interest in improving healthcare access and service delivery will likely lead to more analysis of the existing approaches. Moreover, mathematics modeling approaches can be further used for multiple providers such as double booking, overtime costs, and to increase efficiency time among visiting doctors.

Regarding the effect of uncertain factors on outpatient waiting times, we have mentioned several practical approaches that are well-known methods in this research. Specifically, the Markovian model has difficulty in fairness policy due to the complexity of observing an individual's waiting times and a difference in various fairness factors in healthcare appointment scheduling. However, the OLAS approach is beneficial for this field because of increasing productivity obtained by overlapping time to minimize the total cost of patient waiting time and doctor idle time. It is worth mentioning that discrete-event simulation and other optimization approaches are new trends for future research. Future studies must investigate the scheduled outpatient and walk-in patient with unexpected arrival to disturb the clinic operations.

A further issue that is not often discussed openly is the discrete-event simulation approach used for accurate decision-making in healthcare. Discrete-event simulation may be mainly accurate in healthcare delivery models in place of sickness and screening applications. If a version of healthcare optimization is used, various patients need to be convinced of their benefits and limitations in the healthcare sector. Moreover, other researchers should conduct a more in-depth analysis of walk-in outpatients' effect on the punctuality of the planned arrivals. The method needs more investigation due to the complexity of this problem and could also be expanded further in terms of emergency admissions and intensive care departments. Another field of future research is to formulate the sequencing problems based on individual unpunctuality behaviors. Using a game theory approach, the extension of current models would help account for the unpunctuality between doctors, nurses, and patients. As a research gap, outpatient appointment scheduling problems could be extended to model the multistage health process, i.e., preliminary examination, drug test, and patient preparation or optimizing multi-appointment schedules in clinics.

## Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

## Conflicts of Interest

The authors declare no conflicts of interest.

## Acknowledgments

The authors gratefully acknowledge the funding supported by the Natural Science Foundation of China (Grant no. 71931008) and Medicine and Engineering Interdisciplinary Research Fund of Shanghai Jiao Tong University (YG2013ZD05).

## References

[1] I. Almomani and A. Alsarheed, "Enhancing outpatient clinics management software by reducing patients' waiting time," *Journal of infection and public health*, vol. 9, no. 6, pp. 734–743, 2016.

[2] K. S. Shehadeh, A. E. M. Cohn, and R. Jiang, "Using stochastic programming to solve an outpatient appointment

scheduling problem with random service and arrival times," *Naval Research Logistics*, vol. 68, no. 1, pp. 89–111, 2021.

[3] A. Kuiper, J. de Mast, and M. Mandjes, "The problem of appointment scheduling in outpatient clinics: a multiple case study of clinical practice," *Omega*, vol. 98, Article ID 102122, 2021.

[4] M. Deceuninck, D. Fiems, and S. De Vuyst, "Outpatient scheduling with unpunctual patients and no-shows," *European Journal of Operational Research*, vol. 265, no. 1, pp. 195–207, 2018.

[5] J. Zhang, M. Dridi, and A. El Moudni, "A two-level optimization model for elective surgery scheduling with downstream capacity constraints," *European Journal of Operational Research*, vol. 276, no. 2, pp. 602–613, 2019.

[6] R. Konrad, S. Ficarra, C. Danko, R. Wallace, and C. Archambeault, "A decision-support approach for provider scheduling in a patient-centered medical home," *Journal of Healthcare Management*, vol. 62, no. 1, pp. 46–59, 2017.

[7] M. Radman and K. Eshghi, "Designing a multi-service healthcare network based on the impact of patients' flow among medical services," *Spectrum*, vol. 40, no. 3, pp. 637–678, 2018.

[8] M. Rezaeiahari and M. T. Khasawneh, "An optimization model for scheduling patients in destination medical centers," *Operations Research for Health Care*, vol. 15, pp. 68–81, 2017.

[9] J. Zhang, L. Wang, and L. Xing, "Large-scale medical examination scheduling technology based on intelligent optimization," *Journal of Combinatorial Optimization*, vol. 37, no. 1, pp. 385–404, 2019.

[10] C. Granja, B. Almada-Lobo, F. Janela, J. Seabra, and A. Mendes, "An optimization based on simulation approach to the patient admission scheduling problem using a linear programing algorithm," *Journal of Biomedical Informatics*, vol. 52, pp. 427–437, 2014.

[11] A. Diamant, J. Milner, and F. Quereshy, "Dynamic patient scheduling for multi-appointment health care programs," *Production and Operations Management*, vol. 27, no. 1, pp. 58–79, 2018.

[12] T. Garaix, S. Rostami, and X. Xie, "Daily outpatient chemotherapy appointment scheduling with random deferrals," *Flexible Services and Manufacturing Journal*, vol. 32, no. 1, pp. 129–153, 2020.

[13] R. Guido, G. Ielpa, and D. Conforti, "Scheduling outpatient day service operations for rheumatology diseases," *Flexible Services and Manufacturing Journal*, vol. 32, no. 1, pp. 102–128, 2020.

[14] L. Luo, Y. Zhou, B. T. Han, and J. Li, "An optimization model to determine appointment scheduling window for an outpatient clinic with patient no-shows," *Health Care Management Science*, vol. 22, no. 1, pp. 68–84, 2019.

[15] H. Su, G. Wan, and S. Wang, "Online scheduling for outpatient services with heterogeneous patients and physicians," *Journal of Combinatorial Optimization*, vol. 37, no. 1, pp. 123–149, 2019.

[16] Y. Sun, U. N. Raghavan, V. Vaze et al., "Stochastic programming for outpatient scheduling with flexible inpatient exam accommodation," *Health Care Management Science*, pp. 1–22, 2021.

[17] Z.-Y. Zhuang and V. F. Yu, "Analyzing the effects of the new labor law on outpatient nurse scheduling with law-fitting modeling and case studies," *Expert Systems with Applications*, vol. 180, p. 115103, 2021.

[18] K. S. Shehadeh, A. E. M. Cohn, and R. Jiang, "A distributionally robust optimization approach for outpatient colonoscopy scheduling," *European Journal of Operational Research*, vol. 283, no. 2, pp. 549–561, 2020.

[19] N. Li, X. Li, and P. Forero, "Physician scheduling for outpatient department with nonhomogeneous patient arrival and priority queue," *Flexible Services and Manufacturing Journal*, pp. 1–37, 2021.

[20] M. Benzaid, N. Lahrichi, and L. M. Rousseau, "Chemotherapy appointment scheduling and daily outpatient-nurse assignment," *Health Care Management Science*, vol. 23, no. 1, pp. 34–50, 2020.

[21] M. A. Khan, K. Muhammad, M. Sharif, T. Akram, and S. Kadry, "Intelligent fusion-assisted skin lesion localization and classification for smart healthcare," *Neural Computing and Applications*, vol. 8, no. 15, pp. 1–16, 2021.

[22] K. K. Kumari and R. S. R. Babu, "An efficient modified dragonfly algorithm and whale optimization approach for optimal scheduling of microgrid with islanding constraints," *Transactions of the Institute of Measurement and Control*, vol. 43, no. 2, pp. 421–433, 2021.

[23] W. Yankai, W. Shilong, L. Dong, S. Chunfeng, and Y. Bo, "An improved multi-objective whale optimization algorithm for the hybrid flow shop scheduling problem considering device dynamic reconfiguration processes," *Expert Systems with Applications*, vol. 5, no. 174, pp. 114–793, 2021.

[24] A. Pradhan, S. K. Bisoy, and A. Das, "A survey on PSO based meta-heuristic scheduling mechanism in cloud computing environment," *Journal of King Saud University-Computer and Information Sciences 10*, vol. 33, pp. 1275–1544, 2021.

[25] E. H. Houssein, M. A. Mahdy, D. Shebl, A. Manzoor, R. Sarkar, and W. M. Mohamed, "An efficient slime mould algorithm for solving multi-objective optimization problems," *Expert Systems with Applications*, vol. 5, no. 187, pp. 115–870, 2022.

[26] L. Jiang, X. Zang, J. Dong, and C. Liang, "A covering traveling salesman problem with profit in the last mile delivery," *Optimization Letters*, vol. 16, no. 1, pp. 375–393, 2022.

[27] X. Wang, M. Zhang, Y. Chen et al., "Risk for Hepatitis B virus reactivation in patients with psoriasis treated with biological agents: a systematic review and meta-analysis," *Dermatology and Therapy*, vol. 12, no. 8, pp. 1–16, 2022.

[28] N. Bacanin, N. Vukobrat, M. Zivkovic, T. Bezdan, and I. Strumberger, "Improved Harris Hawks Optimization Adapted for Artificial Neural Network Training," *Intelligent and Fuzzy Techniques for Emerging Conditions and Digital Transformation*, vol. 18, no. 4, pp. 281–289, 2022.

[29] A. Jiménez-Sánchez, D. Mateus, S. Kirchhoff et al., "Curriculum learning for improved femur fracture classification: Scheduling data with prior knowledge and uncertainty," *Medical Image Analysis*, vol. 7, no. 75, pp. 102–273, 2022.

[30] B. R. Brady, P. A. O'Connor, M. P. Martz, T. Grogg, and U. S. Nair, "Medicaid-Insured Client Characteristics and Quit Outcomes at the Arizona Smokers' Helpline," *The Journal of Behavioral Health Services & Research*, vol. 49, no. 1, pp. 61–75, 2022.

[31] S. Zhou and Q. Yue, "Sequencing and scheduling appointments for multistage service systems with stochastic service durations and no-shows," *International Journal of Production Research*, pp. 1–20, 2021.

[32] P.-S. Chen, H. W. Chen, R. A. C. Robielos, W. Y. Chen, J. H. B. De Pedro, and A. D. Archita, "Developing a hybrid data-fitting procedure and a case study for patient service time," *Journal of the Chinese Institute of Engineers*, vol. 44, no. 8, pp. 751–761, 2021.

[33] M. Hu, X. Xu, X. Li, and T. Che, "Managing patients' no-show behaviour to improve the sustainability of hospital appointment systems: Exploring the conscious and unconscious determinants of no-show behaviour," *Journal of Cleaner Production*, vol. 269, Article ID 122318, 2020.

[34] D. Golmohammadi, "A Decision-Making tool based on historical data for service time prediction in outpatient scheduling," *International Journal of Medical Informatics*, vol. 156, Article ID 104591, 2021.

[35] E. Torabi, T. Cayirli, C. M. Froehle et al., "FASStR: a framework for ensuring high-quality operational metrics in health care," *American Journal of Managed Care*, vol. 26, no. 6, p. e172, 2020.

[36] H.-J. Alvarez-Oh, H. Balasubramanian, E. Koker, and A. Muriel, "Stochastic appointment scheduling in a team primary care practice with two flexible nurses and two dedicated providers," *Service Science*, vol. 10, no. 3, pp. 241–260, 2018.

[37] S. J. Lee, G. R. Heim, C. Sriskandarajah, and Y. Zhu, "Outpatient Appointment block scheduling under patient heterogeneity and patient No-shows," *Production and Operations Management*, vol. 27, no. 1, pp. 28–48, 2018.

[38] M. R. M. Habibi, F. M. Abadi, H. Tabesh, H. Vakili-Arki, A. Abu-Hanna, and S. Eslami, "Evaluation of patient satisfaction of the status of appointment scheduling systems in outpatient clinics: identifying patients' needs," *Journal of Advanced Pharmaceutical Technology & Research*, vol. 9, no. 2, p. 51, 2018.

[39] J. Song, Y. Bai, and J. Wen, "Optimal appointment rule design in an outpatient department," *IEEE Transactions on Automation Science and Engineering*, vol. 16, no. 1, pp. 100–114, 2018.

[40] A. Ala, F. E. Alsaadi, M. Ahmadi, and S. Mirjalili, "Optimization of an appointment scheduling problem for healthcare systems based on the quality of fairness service using whale optimization algorithm and NSGA-II," *Scientific Reports*, vol. 11, no. 1, pp. 19816–19819, 2021.

[41] S. R. Finkelstein, N. Liu, D. Rosenthal, and L. Poghosyan, "When open access might not work: understanding patient attitudes in appointment scheduling," *Health Care Management Review*, vol. 43, no. 4, pp. 348–358, 2018.

[42] N. M. Van de Vrugt, S. T. Luen-English, W. A. P. Bastiaansen et al., "Integrated scheduling of tasks and gynecologists to improve patient appointment scheduling; a case study," *Operations Research for Health Care*, vol. 16, pp. 10–19, 2018.

[43] I. Bendavid, Y. N. Marmor, and B. Shnits, "Developing an optimal appointment scheduling for systems with rigid standby time under predetermined quality of service," *Flexible Services and Manufacturing Journal*, vol. 30, no. 1, pp. 54–77, 2018.

[44] C. Ramos, A. Cataldo, and J. C. Ferrer, "Appointment and patient scheduling in chemotherapy: a case study in Chilean hospitals," *Annals of Operations Research*, vol. 286, no. 1, pp. 411–439, 2020.

[45] A. L. A. Bolaji, A. F. Bamigbola, and P. B. Shola, "Late acceptance hill climbing algorithm for solving patient admission scheduling problem," *Knowledge-Based Systems*, vol. 145, pp. 197–206, 2018.

[46] Y. Lu, X. Xie, and Z. Jiang, "Dynamic appointment scheduling with wait-dependent abandonment," *European Journal of Operational Research*, vol. 265, no. 3, pp. 975–984, 2018.

[47] V. L. Dayarathna, H. Mismesh, M. Nagahisarchoghaei, and A. Alhumoud, "A discrete event simulation (des) based approach to maximize the patient throughput in outpatient clinic," *Engineering Science & Technology Journal*, vol. 1, no. 1, pp. 1–11, 2019.

[48] M. Afshar-Bakeshloo, F. Jolai, M. Mazinani, and F. Salehian, "One-for-one period policy and its optimal solution over a finite horizon," *International Journal of Operational Research*, vol. 35, no. 3, pp. 378–396, 2019.

[49] C. K. Y. Lin, "Dynamic appointment scheduling with forecasting and priority-specific access time service level standards," *Computers & Industrial Engineering*, vol. 135, pp. 970–986, 2019.

[50] C. Zacharias and M. Armony, "Joint panel sizing and appointment scheduling in outpatient care," *Management Science*, vol. 63, no. 11, pp. 3978–3997, 2017.

[51] C. Wang, R. Wu, L. Deng, Y. Chen, Y. Li, and Y. Wan, "A bibliometric analysis on No-show research: status, hotspots, trends and outlook," *Sustainability*, vol. 12, no. 10, p. 3997, 2020.

[52] H. K. Lee, X. Zhong, J. Li, A. J. Musa, and P. A. Bain, "Joint visit in primary care clinics: modeling, analysis, and an application study," *IISE Transactions on Healthcare Systems Engineering*, vol. 8, no. 2, pp. 93–109, 2018.

[53] M. Alvarado and L. Ntaimo, "Chemotherapy appointment scheduling under uncertainty using mean-risk stochastic integer programming," *Health Care Management Science*, vol. 21, no. 1, pp. 87–104, 2018.

[54] Z. Mueen, "Developing bulk arrival queuing models with the constant batch policy under uncertainty data using (0-1) variables," *International Journal of Nonlinear Analysis and Applications*, vol. 13, no. 1, pp. 1113–1121, 2022.

[55] M. Issabakhsh, S. Lee, and H. Kang, "Scheduling patient appointment in an infusion center: a mixed integer robust optimization approach," *Health care management science*, vol. 24, no. 1, pp. 117–139, 2021.

[56] J. Zhao and H. Wen, "Dynamic planning with reusable healthcare resources: application to appointment scheduling," *Flexible Services and Manufacturing Journal*, vol. 1, no. 20, pp. 156–178, 2021.

[57] X. Pan, N. Geng, and X. Xie, "Appointment scheduling and real-time sequencing strategies for patient unpunctuality," *European Journal of Operational Research*, vol. 295, no. 1, pp. 246–260, 2021.

[58] X. Yu and A. Bayram, "Managing capacity for virtual and office appointments in chronic care," *Health Care Management Science*, vol. 24, no. 4, pp. 742–767, 2021.

[59] R. Kumar, B. S. Soodan, and S. Sharma, "Modelling health care queue management system facing patients' impatience using queuing theory," *Reliability: Theory & Applications*, vol. 16, no. 1, pp. 61–82, 2021.

[60] D. Wang, K. Muthuraman, and D. Morrice, "Coordinated patient appointment scheduling for a multistation healthcare network," *Operations Research*, vol. 67, no. 3, pp. 599–618, 2019.

[61] A. F. Hesaraki, N. P. Dellaert, and T. de Kok, "Generating outpatient chemotherapy appointment templates with balanced flowtime and makespan," *European Journal of Operational Research*, vol. 275, no. 1, pp. 304–318, 2019.

[62] Y. L. Huang, I. Sikder, and G. Xu, "Optimal override policy for chemotherapy scheduling template via mixed-integer linear programming," *Optimization Letters*, pp. 1–14, 2021.

[63] C. Laan, M. van de Vrugt, J. Olsman, and R. J. Boucherie, "Static and dynamic appointment scheduling to improve patient access time," *Health systems*, vol. 7, no. 2, pp. 148–159, 2018.

[64] K. J. Klassen and R. Yoogalingam, "Appointment scheduling in multistage outpatient clinics," *Health Care Management Science*, vol. 22, no. 2, pp. 229–244, 2019.

[65] Y. L. Loo, A. Y. Tang, A. Ahmad, and A. Mustapha, "A generic agent-based dynamic process simulation framework: a self-adaptive modelling approach," *Journal of Theoretical and Applied Information Technology*, vol. 95, no. 2, pp. 340–351, 2017.

[66] S. Gill and R. Paranjape, "A review of recent contribution in agent-based health care modeling," *Health Information Systems: Concepts, Methodologies, Tools, and Applications*, IGI Global, Hershey, PA, USA, 2010.

[67] K. J. Klassen and R. Yoogalingam, "Improving performance in outpatient appointment services with a simulation optimization approach," *Production and Operations Management*, vol. 18, no. 4, pp. 447–458, 2009.

[68] Z. Zhang and X. Xie, "Simulation-based optimization for surgery appointment scheduling of multiple operating rooms," *IIE Transactions*, vol. 47, no. 9, pp. 998–1012, 2015.

[69] P. E. Joustra, J. De Wit, V. M. D. Struben, B. J. H. Overbeek, P. Fockens, and S. G. Elkhuizen, "Reducing access times for an endoscopy department by an iterative combination of computer simulation and linear programming," *Health Care Management Science*, vol. 13, no. 1, pp. 17–26, 2010.

[70] C. Kittipittayakorn and K. C. Ying, "Using the integration of discrete event and agent-based simulation to enhance outpatient service quality in an orthopedic department," *Journal of Healthcare Engineering*, vol. 2016, 2016.

[71] S. Ahmed, A. Shapiro, and E. Shapiro, *The Sample Average Approximation Method for Stochastic Programs with Integer Recourse*, , pp. 1–24, Submitted for publication, 2002.

[72] M. E. Zonderland, R. J. Boucherie, N. Litvak, and C. L. Vleggeert-Lankamp, "Planning and scheduling of semi-urgent surgeries," *Health Care Management Science*, vol. 13, no. 3, pp. 256–267, 2010.

[73] J. Patrick, M. L. Puterman, and M. Queyranne, "Dynamic multi-priority patient scheduling for a diagnostic resource," *Operations Research*, vol. 56, no. 6, pp. 1507–1525, 2008.

[74] S. Lee and Y. Yih, "Analysis of an open access scheduling system in outpatient clinics: a simulation study," *Simulation Series*, vol. 86, no. 8-9, pp. 503–518, 2010.

[75] S. Sevinc, U. A. Sanli, and E. Goker, "Algorithms for scheduling of chemotherapy plans," *Computers in Biology and Medicine*, vol. 43, no. 12, pp. 2103–2109, 2013.

[76] G. Lamé, O. Jouini, and J. Stal-Le Cardinal, "Outpatient chemotherapy planning: a literature review with insights from a case study," *IIE Transactions on Healthcare Systems Engineering*, vol. 6, no. 3, pp. 127–139, 2016.

[77] H. L. Romero, N. P. Dellaert, S. Van Der Geer, M. Frunt, M. H. Jansen-Vullers, and G. A. M. Krekels, "Admission and capacity planning for the implementation of one-stop-shop in skin cancer treatment using simulation-based optimization," *Health Care Management Science*, vol. 16, no. 1, pp. 75–86, 2013.

[78] A. Condotta and N. V. Shakhlevich, "Scheduling patient appointments via multilevel template: a case study in chemotherapy," *Operations Research for Health Care*, vol. 3, no. 3, pp. 129–144, 2014.

[79] G. Du, X. Liang, and C. Sun, "Scheduling optimization of home health care service considering patients' priorities and time windows," *Sustainability*, vol. 9, no. 2, p. 253, 2017.

[80] M. R. Hussain and M. E. Hussain, "A new neuroinformatics approach to optimize diagnosis cost in neurology: an operational research tool," *International Journal of Online & Biomedical Engineering*, vol. 15, no. 6, 2019.

[81] D. Petrovic, M. Morshed, and S. Petrovic, "Multi-objective genetic algorithms for scheduling of radiotherapy treatments for categorised cancer patients," *Expert Systems with Applications*, vol. 38, no. 6, pp. 6994–7002, 2011.

[82] I. A. Bikker, N. Kortbeek, R. M. van Os, and R. J. Boucherie, "Reducing access times for radiation treatment by aligning the doctor's schemes," *Operations research for health care*, vol. 7, pp. 111–121, 2015.

[83] J. D. Griffiths, J. E. Williams, and R. M. Wood, "Scheduling physiotherapy treatment in an inpatient setting," *Operations Research for Health Care*, vol. 1, no. 4, pp. 65–72, 2012.

[84] M. Alvarado and L. Ntaimo, "Chemotherapy appointment scheduling under uncertainty using mean-risk stochastic integer programming," *Health Care Management Science*, vol. 21, no. 1, pp. 87–104, 2018.

[85] S. Zhu, W. Fan, T. Liu, S. Yang, and P. M. Pardalos, "Dynamic three-stage operating room scheduling considering patient waiting time and surgical overtime costs," *Journal of Combinatorial Optimization*, vol. 39, no. 1, pp. 185–215, 2020.

[86] S. Hahn-Goldberg, M. W. Carter, J. C. Beck, M. Trudeau, P. Sousa, and K. Beattie, "Dynamic optimization of chemotherapy outpatient scheduling with uncertainty," *Health Care Management Science*, vol. 17, no. 4, pp. 379–392, 2014.

[87] Y. Gocgun and M. L. Puterman, "Dynamic scheduling with due dates and time windows: an application to chemotherapy patient appointment booking," *Health Care Management Science*, vol. 17, no. 1, pp. 60–76, 2014.

[88] L. W. Robinson and R. R. Chen, "A comparison of traditional and open-access policies for appointment scheduling," *Manufacturing & Service Operations Management*, vol. 12, no. 2, pp. 330–346, 2010.

[89] M. C. Riff, J. P. Cares, and B. Neveu, "RASON: a new approach to the scheduling radiotherapy problem that considers the current waiting times," *Expert Systems with Applications*, vol. 64, pp. 287–295, 2016.

[90] E. Castro and S. Petrovic, "Combined mathematical programming and heuristics for a radiotherapy pre-treatment scheduling problem," *Journal of Scheduling*, vol. 15, no. 3, pp. 333–346, 2012.

[91] A. Turkcan, B. Zeng, and M. Lawley, "Chemotherapy operations planning and scheduling," *IIE Transactions on Healthcare Systems Engineering*, vol. 2, no. 1, pp. 31–49, 2012.

[92] M. Heshmat and A. Eltawil, "Comparison between outpatient appointment scheduling and chemotherapy outpatient appointment scheduling," *Egyptian Journal for Engineering Sciences and Technology*, vol. 19, pp. 326–332, 2016.

[93] S. N. Ogulata, M. Koyuncu, and E. Karakas, "Personnel and patient scheduling in the high demanded hospital services: a case study in the physiotherapy service," *Journal of Medical Systems*, vol. 32, no. 3, pp. 221–228, 2008.

[94] J. R. Villamizar, F. C. Coelli, W. C. A. Pereira, and R. M. V. R. Almeida, "Discrete-event computer simulation methods in the optimisation of a physiotherapy clinic," *Physiotherapy*, vol. 97, no. 1, pp. 71–77, 2011.

[95] K. Schimmelpfeng, S. Helber, and S. Kasper, "Decision support for rehabilitation hospital scheduling," *Spectrum*, vol. 34, no. 2, pp. 461–489, 2012.

[96] C. F. Chien, Y. C. Huang, and C. H. Hu, "A hybrid approach of data mining and genetic algorithms for rehabilitation scheduling," *International Journal of Manufacturing Technology and Management*, vol. 16, no. 1-2, pp. 76–100, 2009.

[97] J. D. Griffiths, J. E. Williams, and R. M. Wood, "Modelling activities at a neurological rehabilitation unit," *European Journal of Operational Research*, vol. 226, no. 2, pp. 301–312, 2013.

[98] N. T. Huynh, Y. C. Huang, and C. F. Chien, "A hybrid genetic algorithm with 2d encoding for the scheduling of rehabilitation patients," *Computers & Industrial Engineering*, vol. 125, pp. 221–231, 2018.

[99] L. Ros-McDonnell, N. Szander, M. V. de-la-Fuente-Aragón, and R. Vodopivec, "Scheduling sustainable homecare with urban transport and different skilled nurses using an approximate algorithm," *Sustainability*, vol. 11, no. 22, p. 6210, 2019.

[100] A. Ahmadi-Javid, Z. Jalali, and K. J. Klassen, "Outpatient appointment systems in healthcare: a review of optimization studies," *European Journal of Operational Research*, vol. 258, no. 1, pp. 3–34, 2017.

[101] D. Conforti, F. Guerriero, and R. Guido, "Non-block scheduling with priority for radiotherapy treatments," *European Journal of Operational Research*, vol. 201, no. 1, pp. 289–296, 2010.

[102] S. Proctor, B. Lehaney, C. Reeves, and Z. Khan, "Modelling patient flow in a radiotherapy department," *Insight*, vol. 20, no. 3, pp. 6–14, 2007.

[103] M. S. Thomsen and O. Nørrevang, "A model for managing patient booking in a radiotherapy department with differentiated waiting times," *Acta Oncologica*, vol. 48, no. 2, pp. 251–258, 2009.

[104] A. Bouras, M. Masmoudi, N. E. H. Saadani, Z. Bahroun, and M. A. Abdeljaouad, "Multistage appointment scheduling for outpatient chemotherapy unit: a case study," *RAIRO - operations Research*, vol. 55, no. 2, pp. 589–610, 2021.

[105] Y. L. Huang, S. M. Bach, and S. A. Looker, "Chemotherapy scheduling template development using an optimization approach," *International Journal of Health Care Quality Assurance*, 2019.

[106] C. Dodaro, G. Galatà, A. Grioni, M. Maratea, M. Mochi, and I. Porro, "An ASP-based solution to the chemotherapy treatment scheduling problem," *Theory and Practice of Logic Programming*, vol. 21, no. 6, pp. 835–851, 2021.

[107] A. Agnetis, C. Bianciardi, and N. Iasparra, "Integrating lean thinking and mathematical optimization: a case study in appointment scheduling of hematological treatments," *Operations Research Perspectives*, vol. 6, Article ID 100110, 2019.

[108] M. Issabakhsh, S. Lee, and H. Kang, "Scheduling patient appointment in an infusion center: a mixed integer robust optimization approach," *Health Care Management Science*, vol. 24, no. 1, pp. 117–139, 2021.

[109] N. Dhieb, I. Abdulrashid, H. Ghazzai, and Y. Massoud, "Optimized drug regimen and chemotherapy scheduling for cancer treatment using swarm intelligence," *Annals of Operations Research*, pp. 1–14, 2021.

[110] I. Ferreira and A. Vasconcelos, "A supervised learning model for medical appointments no-show management," *International Journal of Medical Engineering and Informatics*, vol. 14, no. 1, pp. 90–104, 2022.

[111] X. D. Wu, M. T. Khasawneh, D. M. Yue, Y. N. Chu, and Z. T. Gao, "A simulation study of outpatient scheduling with multiple providers and a single device," *International Journal of Computational Intelligence Systems*, vol. 7, no. 2, pp. 15–25, 2014.

[112] H. Zhu, Y. Chen, E. Leung, and X. Liu, "Outpatient appointment scheduling with unpunctual patients," *International Journal of Production Research*, vol. 56, no. 5, pp. 1982–2002, 2018.

[113] X. Fan, J. Tang, C. Yan, H. Guo, and Z. Cao, "Outpatient appointment scheduling problem considering patient selection behavior: data modeling and simulation optimization," *Journal of Combinatorial Optimization*, pp. 1–23, 2019.

[114] M. Bakker and K. L. Tsui, "Dynamic resource allocation for efficient patient scheduling: a data-driven approach," *Journal of Systems Science and Systems Engineering*, vol. 26, no. 4, pp. 448–462, 2017.

[115] D. Kritchanchai and S. Hoeur, "Simulation modeling for facility allocation of outpatient department," *International Journal of Healthcare Management*, vol. 11, no. 3, pp. 193–201, 2018.

[116] N. Li, X. Li, C. Zhang, and N. Kong, "Integrated optimization of appointment allocation and access prioritization in patient-centred outpatient scheduling," *Computers & Industrial Engineering*, vol. 154, Article ID 107125, 2021.

[117] A. Aeenparast, S. J. Tabibi, K. Shahanaghi, and M. B. Aryanejhad, "Reducing outpatient waiting time: a simulation modeling approach," *Iranian Red Crescent Medical Journal*, vol. 15, no. 9, p. 865, 2013.

[118] S. Creemers and M. Lambrecht, "Queueing models for appointment-driven systems," *Annals of Operations Research*, vol. 178, no. 1, pp. 155–172, 2010.

[119] L. V. Green and S. Savin, "Reducing delays for medical appointments: a queueing approach," *Operations Research*, vol. 56, no. 6, pp. 1526–1538, 2008.

[120] J. W. Ko, G. G. Kim, and B. K. Yun, "A study on the optimal appointment scheduling for the ship maintenance with queueing system with scheduled arrivals," *Journal of the Korean Operations Research and Management Science Society*, vol. 38, no. 3, pp. 13–22, 2013.

[121] M. M. Alvarado, T. G. Cotton, L. Ntaimo, E. Pérez, and W. R. Carpentier, "Modeling and simulation of oncology clinic operations in discrete event system specification," *Simulation Series*, vol. 94, no. 2, pp. 105–121, 2018.

[122] M. R. Hribar, A. E. Huang, I. H. Goldstein et al., "Data-driven scheduling for improving patient efficiency in ophthalmology clinics," *Ophthalmology*, vol. 126, no. 3, pp. 347–354, 2019.

[123] J. R. Munavalli, S. V. Rao, A. Srinivasan, and G. G. van Merode, "An intelligent real-time scheduler for outpatient clinics: a multi-agent system model," *Health Informatics Journal*, vol. 26, no. 4, pp. 2383–2406, 2020.

[124] A. Apornak, S. Raissi, A. Keramati, and K. Khalili-Damghani, "A simulation modelling approach to improve waiting time for outpatients of hospital emergency department," *International Journal of Knowledge Management in Tourism and Hospitality*, vol. 2, no. 2, pp. 160–171, 2019.

[125] Z. Rahimi Rise and M. M. Ershadi, "An integrated HFMEA simulation-based multi-objective optimization model to improve the performances of hospitals: a case study," *Journal of Simulation*, pp. 1–22, 2021.

[126] D. J. Morrice, J. F. Bard, and K. M. Koenig, "Designing and scheduling a multi-disciplinary integrated practice unit for patient-centered care," *Health Systems*, vol. 9, no. 4, pp. 293–316, 2020.

[127] W. J. Chang and Y. H. Chang, "Design of a patient-centered appointment scheduling with artificial neural network and discrete event simulation," *Journal of Service Science and Management*, vol. 11, no. 01, p. 71, 2018.

[128] K. J. Glowacka, R. M. Henry, and J. H. May, "A hybrid data mining/simulation approach for modelling outpatient no-

shows in clinic scheduling," *Journal of the Operational Research Society*, vol. 60, no. 8, pp. 1056–1068, 2009.

[129] S. H. Jacobson, S. N. Hall, and J. R. Swisher, "Discrete-event simulation of health care systems," in *Patient Flow*, pp. 273–309, Springer, Boston, MA, USA, 2013.

[130] M. M. Günal and M. Pidd, "Discrete event simulation for performance modelling in health care: a review of the literature," *Journal of Simulation*, vol. 4, no. 1, pp. 42–51, 2010.

[131] N. Izady, "Appointment capacity planning in specialty clinics: a queueing approach," *Operations Research*, vol. 63, no. 4, pp. 916–930, 2015.

[132] A. Kuiper, B. Kemper, and M. Mandjes, "A computational approach to optimized appointment scheduling," *Queueing Systems*, vol. 79, no. 1, pp. 5–36, 2015.

[133] W. Xiang, J. Yin, and G. Lim, "A short-term operating room surgery scheduling problem integrating multiple nurses roster constraints," *Artificial Intelligence in Medicine*, vol. 63, no. 2, pp. 91–106, 2015.

[134] M. Chen and M. Decary, "Artificial intelligence in healthcare: an essential guide for health leaders," in *Healthcare Management Forum*, vol. 33, pp. 10–18, , no. No. 1, SAGE Publications, Los Angeles, CA, USA, 2020.

[135] D. Petrovic, M. Morshed, and S. Petrovic, *Genetic algorithm-based scheduling of radiotherapy treatments for cancer patients*, pp. 101–105, Springer, Berlin, Heidelberg, 2009.

[136] A. Azadeh, M. Baghersad, M. H. Farahani, and M. Zarrin, "Semi-online patient scheduling in pathology laboratories," *Artificial Intelligence in Medicine*, vol. 64, no. 3, pp. 217–226, 2015.

[137] C. Krittanawong, "The rise of artificial intelligence and the uncertain future for physicians," *European Journal of Internal Medicine*, vol. 48, pp. e13–e14, 2018.

[138] A. Nelson, D. Herron, G. Rees, and P. Nachev, "Predicting scheduled hospital attendance with artificial intelligence," *NPJ digital medicine*, vol. 2, no. 1, pp. 1–7, 2019.

[139] S. AlMuhaideb, O. Alswailem, N. Alsubaie, I. Ferwana, and A. Alnajem, "Prediction of hospital no-show appointments through artificial intelligence algorithms," *Annals of Saudi Medicine*, vol. 39, no. 6, pp. 373–381, 2019.

[140] J. Wang and R. Y. Fung, "Adaptive dynamic programming algorithms for sequential appointment scheduling with patient preferences," *Artificial Intelligence in Medicine*, vol. 63, no. 1, pp. 33–40, 2015.

[141] M. Reuter-Oppermann and N. Kühl, "Artificial intelligence for healthcare logistics: an overview and research agenda," *Artificial Intelligence and Data Mining in Healthcare*, Springer, Berlin, Germany, pp. 1–22, 2021.

[142] H. Zhang, T. J. Best, A. Chivu, and D. O. Meltzer, "Simulation-based optimization to improve hospital patient assignment to physicians and clinical units," *Health Care Management Science*, vol. 23, no. 1, pp. 117–141, 2020.

[143] S. Singla, "Demand and capacity modelling in healthcare using discrete event simulation," *Open Journal of Modelling and Simulation*, vol. 8, no. 04, p. 88, 2020.

[144] D. Gupta and B. Denton, "Appointment scheduling in health care: Challenges and opportunities," *IIE Transactions*, vol. 40, no. 9, pp. 800–819, 2008.

[145] P. M. Koeleman and G. M. Koole, "Optimal outpatient appointment scheduling with emergency arrivals and general service times," *IIE Transactions on Healthcare Systems Engineering*, vol. 2, no. 1, pp. 14–30, 2012.

[146] A. Mandelbaum, P. Momčilović, N. Trichakis, S. Kadish, R. Leib, and C. A. Bunnell, "Data-driven appointment-scheduling under uncertainty: the case of an infusion unit in a cancer center," *Management Science*, vol. 66, no. 1, pp. 243–270, 2020.

[147] S. N. Ogulata, M. O. Cetik, E. Koyuncu, and M. Koyuncu, "A simulation approach for scheduling patients in the department of radiation oncology," *Journal of Medical Systems*, vol. 33, no. 3, pp. 233–239, 2009.

[148] B. P. Berg, B. T. Denton, S. A. Erdogan, T. Rohleder, and T. Huschka, "Optimal booking and scheduling in outpatient procedure centers," *Computers & Operations Research*, vol. 50, pp. 24–37, 2014.

[149] B. L. Chen, E. D. Li, Y. Kazunobu, K. Ken, N. Shinji, and W. J. Miao, "Impact of adjustment measures on reducing outpatient waiting time in a community hospital: application of a computer simulation," *Chinese Medical Journal*, vol. 123, no. 5, pp. 574–580, 2010.

[150] F. S. Hsieh, "A hybrid and scalable multi-agent approach for patient scheduling based on Petri net models," *Applied Intelligence*, vol. 47, no. 4, pp. 1068–1086, 2017.

[151] B. Liang, A. Turkcan, M. E. Ceyhan, and K. Stuart, "Improvement of chemotherapy patient flow and scheduling in an outpatient oncology clinic," *International Journal of Production Research*, vol. 53, no. 24, pp. 7177–7190, 2015.

[152] S. H. Jacobson, S. N. Hall, and J. R. Swisher, "Discrete-event simulation of health care systems," in *Patient Flow: Reducing Delay in Healthcare Delivery*, pp. 211–252, Springer, Boston, MA, USA, 2006.

[153] C. L. Rau, P. F. J. Tsai, S. F. M. Liang et al., "Using discrete-event simulation in strategic capacity planning for an outpatient physical therapy service," *Health Care Management Science*, vol. 16, no. 4, pp. 352–365, 2013.

[154] M. Otten, S. Dijkstra, G. Leeftink et al., "Outpatient clinic scheduling with limited waiting area capacity," *Journal of the Operational Research Society*, pp. 1–22, 2021.

[155] S. Lee, D. Min, J. H. Ryu, and Y. Yih, "A simulation study of appointment scheduling in outpatient clinics: open access and overbooking," *Simulation Series*, vol. 89, no. 12, pp. 1459–1473, 2013.

[156] S. Chabouh, S. Hammami, E. Marcon, and H. Bouchriha, "Appointment scheduling of inpatients and outpatients in a multistage integrated surgical suite: application to a Tunisian ophthalmology surgery department," *Journal of Simulation*, vol. 12, no. 1, pp. 67–75, 2018.

[157] Y. Gocgun, "Simulation-based approximate policy iteration for dynamic patient scheduling for radiation therapy," *Health Care Management Science*, vol. 21, no. 3, pp. 317–325, 2018.