Journal of Healthcare Engineering

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Research Article

Text Messaging-Based Medical Diagnosis Using Natural Language Processing and Fuzzy Logic

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The use of natural language processing (NLP) methods and their application to developing conversational systems for health diagnosis increases patients' access to medical knowledge. In this study, a chatbot service was developed for the Covenant University Doctor (CUDoctor) telehealth system based on fuzzy logic rules and fuzzy inference. The service focuses on assessing the symptoms of tropical diseases in Nigeria. Telegram Bot Application Programming Interface (API) was used to create the interconnection between the chatbot and the system, while Twilio API was used for interconnectivity between the system and a short messaging service (SMS) subscriber. The service uses the knowledge base consisting of known facts on diseases and symptoms acquired from medical ontologies. A fuzzy support vector machine (SVM) is used to effectively predict the disease based on the symptoms inputted. The inputs of the users are recognized by NLP and are forwarded to the CUDoctor for decision support. Finally, a notification message displaying the end of the diagnosis process is sent to the user. The result is a medical diagnosis system which provides a personalized diagnosis utilizing self-input from users to effectively diagnose diseases. The usability of the developed system was evaluated using the system usability scale (SUS), yielding a mean SUS score of 80.4, which indicates the overall positive evaluation.

1. Introduction

Remote diagnosis systems are becoming increasingly popular and accurate, with enormous advantages such as cost-effectiveness, fast and reliable decision support for medical diagnostics, and treatment and prevention of disease, illness, injury, and other physical and mental damages in human beings. The rise in remote health services (or telehealth) offered by healthcare institutions coincided with the evolution of assisted living systems and environments, aiming to widen the possibility for older and disadvantaged people to access appropriate healthcare services and thus improve their health status and clinical outcome [1]. With the increase in the innovation of medical technologies, there is a need to adopt medical expert systems that will oversee and control diagnosis and treatment processes [2]. Medical diagnostic processes carried out with the aid of computer-related technology which is on the rise daily have improved the experience and capabilities of physicians to make an effective diagnosis of diseases while employing novel signal processing techniques for analysis of patients' physiological data [3, 4] and deep neural networks for decision support [5]. With the rise of the artificial intelligence (AI) techniques, the chatbots have appeared as a promising direction in streamlining the communication between doctors and patients [6]. Such chats are becoming increasingly popular as remote health interventions are implemented in the form of the synchronous text-based dialogue systems [7]. Patients with chronic diseases could make the most advantage from the use of chatbots which can continuously monitor their condition, provide reliable up-to-date information, and remind of taking medication [8]. For the effective use of chatbots in the healthcare domain, the chatbot technology need advanced reasoning capabilities based on the formalization of medical knowledge (semantics) and health state of patients coupled with language vocabularies and dialogue engines [9].

The natural language processing (NLP) technology can serve as an interaction between computers and humans using linguistic analysis and deep learning methods to obtain knowledge from an unstructured free text [10]. The NLP systems have shown their uniqueness and importance in the areas of information retrieval mostly in the retrieval and processing of large amount of unstructured clinical records and return structured information by user-defined queries. In general, the NLP system is aimed at representing explicitly the knowledge that is expressed by the text written in a natural language. There are few applications of the NLP techniques in diagnosing diseases despite the enormous amount of text-based information, which can be retrieved from patients' self-narrations [11]. The main challenges addressed by the application of NLP for medical records are flexible formatting, structure without sentences, missing expected words and punctuation, unusual parts of speech (POS), medical jargon, and misspellings [12]. Linguistic structures such as coreferences make medical texts difficult to be interpreted [13]. Moreover, unique linguistic entities such as medical abbreviations make the inference of knowledge from medical texts much harder [14].

This study introduces the use of the NLP model via an SMS and a chatbot platform to improve the health self-assessment and decision support in digital healthcare systems. The extraction of knowledge from the electronic health record (EHR) is a growing area of interest in medicine, and the use of electronic medical records (EMRs) at the healthcare center and on the cloud [15] has provided a vast amount of data to be analyzed. An EMR is a digital record of health-related information that is created, collected, and managed by medical experts [16]. Compilation of existing and available medical data complications includes integrating NLP into multiple EMRs, ensuring privacy and security of patients' data [17] and clinical validation of a tool. All these can be overwhelming to medical research for improving patient care. However, the application of NLP techniques to screen patients and assist medical experts in their diagnosis would serve as a boost in successfully improving healthcare services through effective analysis of narrative text of symptoms provided by a patient.

For example, Langer et al. [18] used several NLP tools along with classification methods to process the drug-related questions. They developed a natural language-based interface that enables the users to phrase their queries and get an accurate result up to 81% in classifying drug-related questions. Pendyala et al. [19] presented an application which allows machines to take on the function of life support. The focus of the study was based on medical diagnosis, and an experiment was conducted to show the relationship of information retrieval and text mining to the medical diagnosis problem. The study concludes that the proposed system would help in improving the goals of providing a ubiquitous medical diagnosis. Fernandez-Millan et al. [20] presented a rule-based expert system using the list of likely diseases regarding laboratory test results for diagnosis. The authors concluded that the proposed system clinically gave a better accuracy and speed, thereby improving the efficiency and quality of service. Atutxa et al. [21] used deep learning models to extract the International Classification of Diseases (ICD) codes from the death certificates written in a regular natural language, obtaining an F-score of 0.963, 0.838, and 0.952 for Hungarian, French, and Italian, respectively. Combi et al. [22] proposed an NLP method for the transcoding of natural text descriptions of adverse drug reactions into MedDRA standard terms, reaching an average precision and recall of 91.8% and 86.9%. Evans et al. [23] analyzed patient safety incident reports written in free text to categorize incident type and the severity of outcome, reaching an accuracy of 0.891 and 0.708, respectively. Kloehn et al. [24] generate explanations for complex medical terms in Spanish and English using WordNet synonyms and summaries, as well as the word embedding vector as a source of knowledge. Sarker et al. [25] used fuzzy logic and set theory-based methods for learning from a limited number of annotated examples of unstructured answers in health examinations for recognizing correct concepts with an average F1-measure of 0.89. Zhou et al. [26] used deep learning models pretrained on the general text sources to learn knowledge for information extraction from the medical texts. Lauraitis et al. [27] used text input acquired by a smartphone app for evaluation of cognitive and motor deficits for people showing symptoms of central nervous system (CNS) disorders as a part of self-administered cognitive testing (SAGE) tests.

The development of the medical domain-oriented conversational chatbots has been addressed by several researchers. Such conversational agents powered by AI techniques may serve patients with minor health concerns while allowing medical doctors to allocate more time to treat more serious patients [28] or find suitable donors [29]. A chatbot-powered healthcare service can promptly respond to the problems that arise in daily life and to the health state changes of people with chronic diseases such as obesity, diabetes, or hypertension [30]. For example, Ahmad et al. [31] developed a chatbot that is able to advice on the kind of drugs to be taken based on the data submitted by the user. Avila et al. [32] developed a chatbot to find the best prices for medicines and suggest their best possible substitutes. Bao et al. [33] suggested a hybrid model composed of a knowledge graph and a textual similarity model to construct a system for responding to medical questions using Hierarchical BiLSTM Attention Model (HBAM). Chaix et al. [34] developed a chatbot for patients with breast cancer to provide support and answers to their concerns on their disease as well as to remind taking the prescribed drugs. Denecke et al. [35] developed a mobile app with a chatbot that uses the elements of the cognitive behavior therapy to support mentally ill people in addressing their psychological problems. Harilal et al. [36] developed a chatbot app aimed at supporting empathetic conversations, sensing the associated emotions, and extending medical advice for people with depression. Huang et al. [37] developed an AI-powered chatbot for promoting healthy lifestyle and providing advices for weight management. Hussain and Athula [38] developed a chatbot that uses Media Wiki API to extract information from Wikipedia to supplement the chatbot's knowledge for advising diabetic patients on diabetes management. Kökciyan et al. [39] integrated the data from commercial health sensors, EHR, and clinical guidelines with a conversational chatbot that provides further explanations about their overall well-being based on the argumentation-based dialogue. Ni et al. [40] suggested a knowledge-driven primary care chatbot system that has an analytic NLP-based engine for understanding the descriptions of patients' symptom, a reasoner for mapping symptoms to possible causes, and a question generator for creating further dialogue questions. On the other hand, Zini et al. [41] developed a deep learning framework-based conversational agent to represent a virtual patient that can be used for teaching medical students on patient examination.

Machine learning algorithms, especially SVM, have shown promising results in classifying free text such as Georgian language in medical records [42]. SVM with a polykernel was used for classifying primary care patient safety incident report content and severity [23]. However, authors claimed that improving definitions and increased training samples of select categories will further improve performance of the system. Deep learning methods were proposed by Zhou et al. [26]. The authors presented transfer learning methods based on the traditional multilayer neural network (NN) model to develop a clinical information extraction system. Other methods in existing studies include an interactive NLP tool for identifying incidents in radiology reports presented by Trivedi et al. [43]. The authors implemented and assessed usability based on an open-ended questionnaire and the system usability scale (SUS). The summary of the selected literature is depicted in Table 1.

Medical chatbot has been designed and implemented in various clinical areas for developing conversational tools with wide access to medical knowledge and healthcare issues. Existing chatbots are designed for either generic or specific disease purposes. A novel approach based on the AI method was proposed by Madhu et al. [46] for designing a simple and interactive medical assistance chatbot for medicine dosage intake considering the age and weight of patients. Mandy chatbot system was designed to assist healthcare staff in automating patient intake process [40]. The proposed chatbot is based on three sections which are the mobile app front for patient interaction, the diagnosis section, and the doctor's interface for assessing patient's records. The chatbots combine NLP with knowledge-driven diagnosis abilities. Similarly, Siangchin and Samancheun [47] developed a chatbot application using the auxiliary NLP library. The system was further compared with traditional ICD-10 application based on analytic hierarchy process (AHP) for analyzing, selecting, and classifying diabetes mellitus, trauma, and external causes. The integration of NLP and machine learning algorithms has also played a key role in creating chatbot application for disease prediction and treatment recommendation [48]. Deep learning framework was proposed by Zini et al. [41] for enhancing virtual patients' conversational skills. The authors integrated long-short-term memory networks and CNN for sentence embeddings in a given QA script. Other methods include a study by Roca et al. [8] which introduced the chatbots-patient interaction system for specific chronic disease psoriasis. Further study from Rosruen and Samanchuen [49] also developed an intent-based approach chatbot known as MedBot using Dialogflow for medical consultant services. The authors claimed that the proposed system was able to maximize user's convenience, increase service capability, and reduce operational cost.

The successful adoption of chatbot technology from Table 2 has shown effective interaction between users and machines especially in various domains within the healthcare system. However, there are some limitations with some of the methods proposed in the literature such as challenges associated with the static local knowledge based in chatbots and time consumption during training especially for a specific domain [38]. Therefore, there is a need for a future study to develop chatbot software with more scalability, increased data sharing and reusability, and improved standard conversation model [8].

The continuous growth of mobile technology has affected every facet of human life around the globe as its support of healthcare objectives through telemedicine, telehealth, and m-health [52] has helped to diagnose and treat patients at low cost especially in the developing countries, where there are limited options of diagnosis and treatment. Out of various communication media available on mobile devices, short messaging service (SMS) has proven to be unique and reliable due to its low cost, reliable delivery, personal to users, and not Internet-oriented service [53, 54]. Considering the need to provide good medical care to everyone including rural dwellers with poor electricity and slow Internet connections, it is therefore important to integrate SMS with a medical diagnosis system, thus establishing an SMS-medical diagnosis system to best meet the needs of a common man [55]. Considering the overall progress and research efforts made by researchers in improving e-health systems and designing decision support systems (DSS) [56–58], there is still much work to be done for effective understanding and identifying key features based on NLP for enhancing diagnosis, thus improving good health and well-being of the global society at large.

Summarizing the existing medical diagnosis systems (MDS) often adopts poor decisions due to interpretation of the text-based input provided by the patient. Therefore, there is a need to automate MDS for efficient diagnosis of diseases and support their decisions based on the severity of symptoms. Moreover, the medical experts need a platform to keep track of large text-based chunk of knowledge narrated by patients in a natural language, hence improving healthcare delivery for remote patients.

The contribution of this paper is as follows: (1) we have developed a text-based medical diagnosis system which

Table 1: Summary of related work on the medical diagnosis system.

References	Methods	Contributions	Limitations
Ayush et al. [44]	Developed integral model including probability and fuzzy models for determination of human constitutional types	Proposed MDES system creates and supports decision system to users via providing reliable information about disease manifestation	It has not enough practical evidence for effectiveness and efficiency
Korenevskiy [45]	Synthesis of fuzzy decision rules	Simple to calculate with high possibility of diagnosis and predetermined level of reliability	It requires larger training samples
Atutxa et al. [21]	ICD-10 encoding based on neural networks	Multilingual ICD-10 coding. The method is interpretable and it outperforms alternative approaches.	Worse performance was detected on larger datasets
Combi et al. [22]	MagiCoder, an NLP algorithm	Simple, efficient in terms of computational complexity for Italian pharmacovigilance language	Inability to handle negations in textual medical records
Lu et al. [14]	Combined classic enhanced sequential inference model (ESIM) and BiLSTM network	Achieved higher accuracy compared to existing methods without knowledge enhanced	Challenges of concepts with multiple definition was not addressed
Kloehn et al. [24]	Proposed a novel algorithm SubSimplify	Improved quality in English and Spanish by providing multiword explanations for difficult terms	There is a possibility of the proposed model generating incomplete explanations
Sarker et al. [25]	Combination of fuzzy matching and intersection	Increased accuracy against human annotations	Inability to detect negations in expressions

Table 2: Summary of the literature based on medical chatbots.

References	Method	Contributions	Domain
Bao et al. [33]	Hybrid model chatbot that combines knowledge graph and a text similarity model	Proposed method was able to identify and reduce similarity in large QA dataset	Generic
Harilal et al. [36]	Developed CARO, a chatbot app, which is capable of performing empathetic conversations and providing medical advice	Proposed method has the ability to sense the conversational context, intent, and associated emotions	Depression
Bibault et al. [28]	Vik chatbot: blind, randomized controlled noninferiority trial	Proposed method was able to improve conversation between chatbot and physician	Breast cancer
Bali et al. [50]	Ensemble learning using advanced NLU techniques	Improved accuracy in diabetes prediction when compared to generic health prediction	Diabetes and generic
Cameron et al. [51]	Proposed iHelper using questionnaire developed by chatbottest	Recommendations to increase the usability of a chatbot for mental healthcare	Mental healthcare
Chaix et al. [34]	Vik chatbot	Evaluated a yearlong of conversations between patients with breast cancer and a chatbot	Breast cancer
Chung and Park [30]	Chatbot-based healthcare service framework in cloud	Provides a smooth human-machine interaction for the chatbot healthcare service	Accident response
Hussein and Athula [38]	Virtual Diabetes Management System (VDMS) using modified open source AIML web-based chatbot	Proposed method provides a more robust knowledge using Wikipedia knowledge	Generic and diabetes patients
Huang et al. [37]	AI-based health chatbot known as “Smart Wireless Interactive Healthcare System” (SWITCHes)	Proposed system can provide advice to user on food intake based on calorie order, advice on physical activities, etc.	Weight control and health promotion
Ahmad et al. [31]	NLP	Ability to give adequate advice on the right type of medication based on information provided	Pharmacy

provides a personalized diagnosis utilizing self-input from users to effectively diagnose diseases. (2) The proposed system combines the NLP and machine learning algorithms for SMS and Telegram bot. (3) The system is able to diagnose using a direct approach of the question and answering technique to suggest a medical diagnosis.

The structure of the remaining parts of the paper is as follows. We present and discuss our methodology and the algorithm used in Section 2. In Section 3, we evaluate and discuss the results. We present conclusions and outline future work in Section 4.

2. Design Methodology

2.1. Outline of the Architecture. The study assesses the clinical data needs and requirements in diagnosing the tropical diseases in Nigeria and assesses the patients’ clinical data found in EHRs or manual records. The architecture of the proposed text-based medical diagnosis system is depicted in Figure 1.

The steps involved in the proposed text-based medical diagnosis system are as follows: (1) description of the knowledge base; (2) preprocessing of text-based documents;

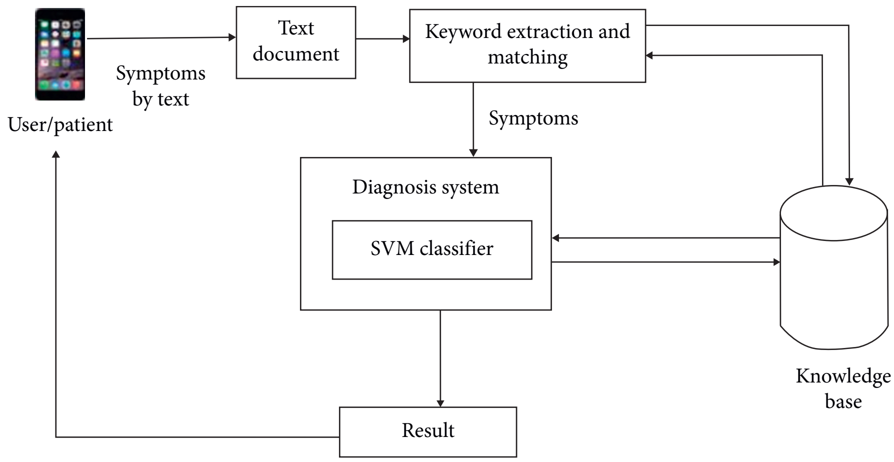

Figure 1: The architecture of the proposed system.

(3) tagging of document; (4) extraction of answer; and (5) ranking of candidate answers.

The implementation of the diagnosis system framework was done using the *Python* language due to the following functionalities: cross-platform and high availability of third-party libraries for tasks relating to machine learning and NLP. The system uses *Python* library packages to access the machine learning functions and NLP needed for categorization.

2.2. Knowledge Base. The knowledge base is the principal source of data in a question and answering system, and it could be in the structured or unstructured format. To develop the knowledge base, the information from a medical database system was collected and divided into categories which are referred to as context knowledge of the disease.

The main sources of information in the knowledge base are as follows: (1) WordNet [59], which provides a lexical database and defines the relationships of words and phrases; (2) YAGO (Yet Another Great Ontology) [60], an open source knowledge base which we use to construct a knowledge graph of common knowledge entities; (3) UMLS (Unified Medical Language System), which combines many medical vocabularies, including ICD-10-CM and SNOMED CT, and is used to link medical terms and extract medical concepts, relationships, or knowledge; UMLS is recognized as a comprehensive knowledge source in the healthcare domain [61]; and (4) Disease Ontology (DO) [62], which contains a knowledge base of over 10,000 human diseases.

We used WordNet as WordNet is used in most of the question-answering systems, and it has proved to be useful when dealing with words. An access to WordNet is implemented via WordNet HTTP API. An access to YAGO is implemented using a SPARQL [63] query engine, which sends queries to the SPAQL endpoint and returns the semantic fact triples (subject-predicate-object). An access to UMLs is implemented via UMLS REST API using the *Python* language. An access to DO metadata for a specific DO term is by using the REST metadata API by constructing a HTTP request. The knowledge base is specified using eXtensible Meta Language (XML), which ensures a common way to specify and share structurally organized data that are not dependent of an application.

For knowledge representation, we have adopted a three-layer model of disease-symptom-property (DSP) originally suggested in [64] as shown in Figure 2. The knowledge in the knowledge database is stored as resource description framework (RDF) triples (property, symptom, and disease), while the computational model is adopted from the disease compass [65], which allows us to query the causal chains of diseases.

Our knowledge base includes 71 instances of diseases (mainly tropical ones) and 542 pieces of information. The model (see Figure 3) uses the knowledge from the knowledge database and applies the fuzzy rules described in Section 2.6.

2.3. Communication System. The communication system was implemented based on the knowledge base for the efficient communication of users through Telegram or SMS with the medical doctor using question-answer rules. Each diagnosis question has certain features and attributes that give additional information about the request. The different attributes of a request/question can be as follows:

(1) Diagnosis question: the actual diagnosis question that will be sent across to the user
(2) Response: the list of responses that will be shown to the user that denote the answers that he/she can send to the system via the Telegram GUI or SMS
(3) Serial id: the order in which the question should be asked

The types of questions are as follows.

2.3.1. Basic Data Questions. These are the preliminary questions asked once a communication has been established by the user and the system. These questions are basic information about the users, some of which include information such as gender, age, height, and weight. The sample question sequence is demonstrated in Algorithm 1.

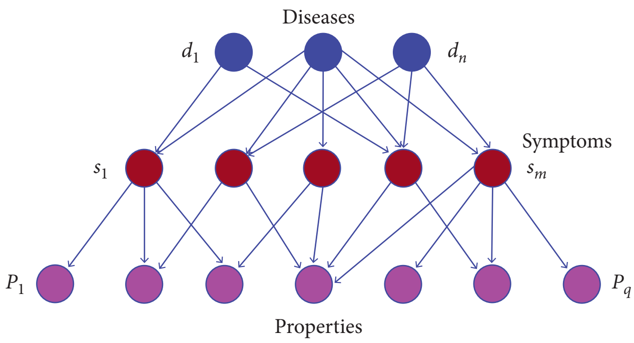

Figure 2: Three-layered "disease-symptom-property" model of knowledge representation.

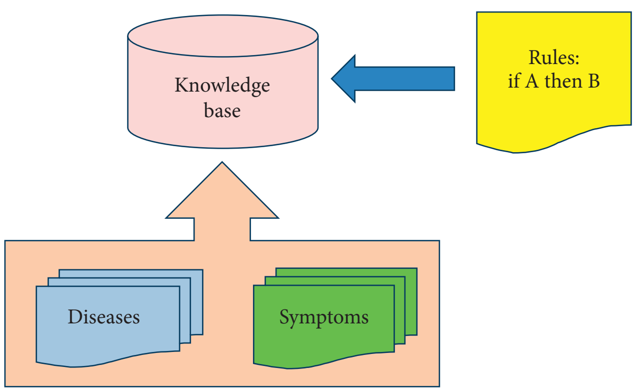

Figure 3: Integration of the knowledge representation model with fuzzy logic rules.

2.3.2. Symptom-Related Questions. These questions are the questions that will be asked from users to confirm whether they are showing signs of a symptom or not. They can gather specific responses based on predetermined constraints or either binary (yes/no) responses. These questions are subdivided into two types:

(i) Target diagnosis questions: these are questions that confirm if a symptom exists or not

(ii) Linked diagnosis questions: these are question used for asking more information about a symptom in case the user replies affirmatively to the target question of that symptom

Each of these questions is designed such that they give an affirmative response of the existing symptoms or non-existing symptoms. For instance, a top diagnosis question that will ask the users of the presence of certain symptoms is represented in Algorithm 2.

2.4. Content Extraction and Text Preprocessing. The content package is responsible for extracting the content knowledge from an SMS. For convenience, the package provides several different content extractors that specialize on extracting different sets of data from an SMS. The content extractors perform text processing using the NLP package. When a patient sends an SMS of his or her symptoms, the SMS receiver of the system receives it and passes the text (SMS body) to the NLP module, which looks at the text, makes necessary corrections if needed, and extracts important keywords.

The text processing operations include three major steps: noise removal, tokenization of document sentences, and splitting of sentences.

2.4.1. Noise Removal. Text contains a sequence of characters, both relevant and irrelevant characters. Therefore, noise is removed from the raw documents leaving only relevant content which is related to subjects for further processing.

2.4.2. Tokenization. This involves the fragmentation of strings of characters into its lexical elements. In this context, sentence splitting process was used for splitting of the text into a separate sentence. Here, we used the natural language toolkit (NLTK) tokenizer.

2.4.3. Tagging of Document. Useful information from the knowledge source is tagged for identifying quality information from the specific document. The names of diseases were used as labels for documents, and tools such as parser and WordNet were used for document tagging.

2.4.4. Parser. Stanford Parser was used as a tool for generating parts of speech (POS) of each word inputted by the user query, and, in addition, the candidate answers selected from the knowledge database. The WordNet was used to discover the relationship between the words of the user query and the data source. Words are grouped into nouns, verbs, adjectives, and adverbs.

2.4.5. Term Matching. Then, the system performs querying of the knowledge base to match the extracted words with information stored in the knowledge base.

2.5. Feature Selection and Extraction. The extracted collection of important words then was transformed into a feature vector suitable for use with the machine learning algorithm. For transformation into the feature vector, we used the word embedding [66] technique. Word embeddings are the representation of words in the semantic multidimensional space. For our system, we have adopted an available word embedding Glove [67], which is based on Twitter data, because it provides a good approximation to common English for an informal communication channel. For an effective training of data, the text messages were preprocessed and converted into feature vectors. This was achieved based on feature extraction using the word embeddings. The feature vector of the unlabeled document was then given to the classifier's decision function to return a category for the unlabeled document.

```
def question_data ():
    return {
        'user_age' : {
        'diagnosis_question': "What is your age?",
        'diagnosis _response': ['15-25', '25-40', '40-50', '>50'],
        'serial' : 1
        },
        'user_weight' : {
        'diagnosis_question': "What is your weight?",
        'diagnosis _response': ['40-50 kg', '50-70 kg', '70-90 kg', '>90 kg'],
        'serial' : 2
        },
        'user_height': {
'diagnosis_question': "What is your height?",
        'diagnosis _ response ' : ['4-5 ft', '5-6 ft', '6-7 ft'],
        'serial' : 1
        },
        'user_gender' : {
        'diagnosis_question'' : "What is your gender?",
        'diagnosis_ response' : ['Male', 'Female', 'Unspecified'],
        'serial' : 3
        }
    }
```

Algorithm 1: Algorithm showing the samples of basic data questions.

```
def diagnosis_top_data ():
    return {
        'fever' : {
        'diagnosis_question': "Do you have a fever?",
        'diagnosis_response': ['Yes, High (>103 F)','Yes, Mild (101-103 F)',
                'Yes, Very Mild (99 - 101 F)', no],
            },
        'head_ache' : {
        'diagnosis_question' : "Do you have a head ache?",
        'diagnosis_response' : [yes, no],
        },
        'body_chills' : {
        'diagnosis_question' : "Are you experiencing body chills?",
        'diagnosis_response' : [yes, no],
            },
        'diarrhea' : {
            'question' : "Are you having very frequent loose motions?",
            'response' : [yes, no],
            },
        'extreme_weakness': {
        'diagnosis_question': "Do you experience extreme weakness?",
        'diagnosis_response' : [yes, no],
        },
    }
```

Algorithm 2: Algorithm showing the samples of top diagnosis questions.

2.6. Fuzzy Reasoning Module. Its primary purpose is to use fuzzy logic-based algorithms [68] to read and interpret the responses from the user, track and monitor all the symptoms that the user has already responded to, and to administer questions to the user that are most relevant based on the dataset of diseases that is maintained. Each disease is modeled as a bucket, where each bucket is associated with a symptom. The appropriate fuzzy rules are formulated to deal with multiple symptomatic diseases. The algorithms employed by CUDoctor read the state of these buckets and send the most relevant question to the user. This helps us narrow down the number of questions that would be asked by the system to reach a diagnosis.

The weighted fuzzy logic rule system is used, where each fuzzy rule has a weight assigned based on the historic data. The Mamdani fuzzy logic model of fuzzy inference was used, in which the IF-THEN statement represents each rule. The fuzzy rules were specified as "If $x1$ is $A1$ and $y1$ is $B1$ then $z1$ is $C1$," where $A1$, $B1$, and $C1$ are fuzzy sets. The fuzzy rules are weighted by an assessment of the level of contribution of the properties and symptoms to diagnosing the disease. The crisp dataset D is described by n features and k samples [$F1$, $F1, \ldots, Fn$], and the n-dimensional tuple $Ti = [a1, a1, \ldots, an]$ is represented as a kn-dimensional feature vector:

$$\begin{aligned} Ti = [&\prec \mu FT1(a1), \mu FT2(a1), \ldots, \mu FTk(a1) \succ, \ldots, \\ &\prec \mu FT1(an), \mu FT2(an), \ldots, \mu FTk(an) \succ], \end{aligned} \tag{1}$$

where $\mu FTk(ai)$ is the membership degree of the fuzzy term FTk of feature Fi ($Fi = ai$). If the fuzzy variable Fn has k fuzzy terms, $FT1$, $FT2$, $\ldots$, FTk, then for each value v of Fn, the fuzzy value is computed as $\max\{\mu FT1(v), \mu FT2(v), \ldots, \mu FTk(v)\}$.

The max-min operators were used for implication. In order to obtain the crisp output, the center-of-gravity (centroid) defuzzification was employed, where the weights are expressed by the degree of membership of the value xi with the concept modeled by the fuzzy set A.

The process is implemented (Figure 4) as follows:

(1) Fuzzification: transforms the crisp inputs into fuzzy values. Expert judgement is used for defining the degree of membership function. During fuzzification, a fuzzy rule controller receives input data (fuzzy variable) and analyzes it according to membership functions.

(2) Knowledge base: it comprises a fuzzy definition database and a fuzzy IF-THEN rule base. The rule base describes the diseases for each combination of crisp input variables.

(3) Inference engine: applies the appropriate fuzzy rules on the input data.

(4) Defuzzification: produces the crisp output values from the fuzzy values as the results.

The final decision is made by selecting the fuzzy rule that achieved the highest score. The system architecture, which was adopted from [64], is presented in Figure 5.

2.7. Classification Module. In this study, the choice of our classifier was dependent on the practical requirements of the proposed application and the need for a classifier with better results based on the established literature for document classification. However, there were specific requirements in the proposed application which influence the selection of our classifier such as the computational complexity for the training and/or testing phase.

Machine learning was used to provide category prediction on the text messages using the fuzzy SVM classifier

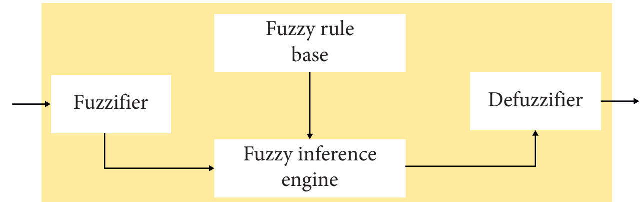

Figure 4: Structure of the fuzzy logic-based reasoning module.

[69]. It has only one hyperparameter C, which is a regularization parameter. The value of the hyperparameter was tuned by grid search. In a fuzzy SVM, a fuzzy membership values are used for each data point of SVM, and the SVM is reformulated such that different input points can make different contributions to the learning of the decision surface. Here, the fuzzy membership values are calculated using an algorithm suggested by Le et al. [70]. First, we use clustering techniques to find clusters of data. Fuzzy membership values of data points belonging to clusters are set to 1, and fuzzy memberships of other data points are determined by their distance to the closest cluster, respectively.

The classifier was trained using a set of training documents which have been processed by the NLP package and converted into word embedding used as feature vectors. The length of the feature vector is 300 as suggested by Mikolov et al. [66]. Finally, the feature vectors extracted from the user answers are passed to the fuzzy SVM model, which suggests the diagnosis by performing the classification on those important words contained in the SMS and then sends the result to the patient via an SMS.

2.8. Graphical User Interface (GUI). The system initiates a communication/conversation with the user/patient to obtain more insights about their basic personal data such as gender, age, height, and weight. Once the basic data are acquired, the CUDoctor moves to the second stage and proceeds to query the patient for symptoms based on the above algorithms. The Telegram API was used for the GUI design with an additional custom keyboard that is also provided by the Telegram API. The screenshot of a question-answer subsystem is shown in Figure 6.

The SMS text request and response were integrated for communication since the application does not require an Internet connection, and it is compatible with all mobile devices. The python-telegram-API library was used as the *Python* wrapper that executes communication with the Telegram API. It enables easy setting method hooks that are triggered whenever a function is executed on the part of the Telegram chatbot. In the same way, the application sends a request to the Twilio communication API for the SMS text formatting server for incoming requests and passes responses to the logical layer for actual processing and presentation of the result to the client users. The python-Twilio-communication-SMS-API library was used as the *Python* wrapper that executes communication with the Twilio communication SMS API. The SMS interface for diagnosis conversation is represented in Figure 7.

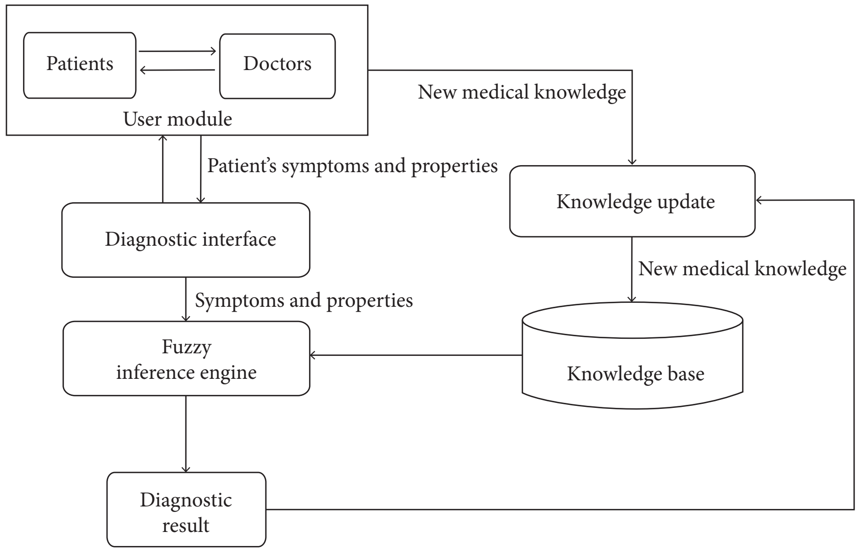

Figure 5: Architecture of the fuzzy logic inference system.

Figure 6: Telegram graphical user interface.

3. Evaluation and Results

3.1. Data Collection. The data used in this study were collected from a medical database, and an interview was conducted for extraction of text content from experts and individuals with knowledge about the various diseases. The extracted text content was then stored on the local file of the system.

3.1.1. Selection of Participants. Selection of respondents was based on snowball sampling. The inclusion criteria require participants who have recently been diagnosed of the disease we are working on, and/or specialist who is engaged in clinical research, or having an indebt experience with the diseases by coming in contact with or treating patients who in recent times have been diagnosed. To be included for the questionnaire, the participants must be actively working in the hospital, responsible for treating patients who have been to the hospital for treatment on the various selected diseases. Individuals who do not match any of these inclusion criteria were excluded. Information extracted for the implementation of the system was the selected result from some individuals' experience about the disease (individuals who can provide expert information about the selected diseases and their varying symptoms and individuals who have recently been diagnosed or hosted in the hospital for the selected diseases were recruited).

3.2. Evaluation of Results. To evaluate the performance of the developed service, we used the Bilingual Evaluation Understudy (BLEU) score [71], which has become a typical metric for evaluating chatbot services [72, 73]. BLEU scores an output response from the service as compared to the reference, where a BLEU score ranges from 0 to 1. Here, we used BLEU-2, which is based on unigram and bigram matches between the generated and the reference sentences. We also used the Recall-Oriented Understudy for Gisting Evaluation (ROUGE-L) metric [74], which is based on the longest common subsequence (LCS). The results are 25.29 for BLEU-2 and 31.56 for ROUGE-L.

3.3. Usability Testing. To perform the usability testing of the developed system, we followed the recommendations outlined by Cameron et al. [51]. We used the system usability scale (SUS), which is a questionnaire to evaluate the ease of use of a system using a Likert scale (five-point scale that varies from strongly disagree to strongly agree).

The SUS score is able to evaluate usability performance in terms of effectiveness, efficiency, and overall ease of use.

Figure 7: An example of SMS diagnosis conversation in natural language.

SUS is considered as a reliable tool for measuring the usability, and it allows to evaluate a wide variety of products and services. SUS has become an industry standard, with references in over 1300 articles and publications [75], which also includes medical chatbots and other NLP-based medical diagnostics systems such as presented by Tielman et al. [76] and Valtolina et al. [77]. SUS is designed to support assessment and comparison of the user experience when interacting with different tools and is recommended to be included in any evaluation of health chatbots [44].

SUS has only 10 questions. The results of an SUS fall between 0 and 100, while a score of 68 is considered average. SUS has already been applied before to assess the usability of chatbots [78, 79]. The SUS questions are easily adaptable for use with different types of systems; therefore, it was adapted to be used for our study. The SUS questions we asked are listed in Figure 8.

The participants of the usability test comprised 27 participants, including 11 females and 16 males, 13 were aged between 25 and 34, 9 aged between 35 and 44, and 6 aged between 45 and 53. The study participants have provided an informed consent to take part in this research. Usability study lasted less than 45 min per session. Information booklets informing about the study performed were distributed to the participants, and the participants were requested to communicate with the chatbot by using a mobile phone. All received answers were anonymized.

The SUS scores were computed using the procedure provided by Brooke [80]: subtracting 1 from the score for questions 1, 3, 5, 7, and 9, whereas subtracting the score from 5 for questions 2, 4, 6, 8, and 10 and multiplying the total of the scores by 2.5 to obtain the final evaluation score.

The SUS score is assessed as follows: >80.3 (excellent), 68–80.3 (good), 68 (okay), 51–68 (poor), and <51 (bad). As a result of evaluation, the mean SUS score obtained for CUDoctor was 80.4, which is above the threshold of 68, which means that the overall evaluation was excellent. The results for all SUS questions are presented in Figure 9. They show that the user provided the worst evaluation for Q2 ("I found CUDoctor unnecessarily complex") giving a score of 72.7, but still above the threshold of 68. The best evaluated feature was integration (Q5) with a score of 91.6.

3.4. Comparison with Other NLP-Based Services. Several chatbots with medical-related applications are provided on social networking platforms such as Facebook. For example, the FLORENCE bot that reminds the users when to take their medication and monitors their weight and moods. SMOKEY warns the users on bad air quality. HealthTap provides answers using a database of knowledge that contains similar questions. Google provides the Dialogflow Application Programming Interface (API) for the integration of NLP to the target applications. Woebot provides a cognitive behavior therapy service for patients with and has been tested with depression [81]. It allowed to reduce their symptoms of depression as evaluated by the depression questionnaire PHQ-9. XiaoIce is a social chatbot that

1. I think that I would like to use CUDoctor frequently.
2. I found CUDoctor unnecessarily complex.
3. I thought CUDoctor was easy to use.
4. I think that I would need the support of a technical person to be able to use CUDoctor.
5. I found the various functions in CUDoctor were well integrated.
6. I thought there was too much inconsistency in CUDoctor.
7. I imagine that most people would learn to use CUDoctor very quickly.
8. I found CUDoctor very cumbersome to use.
9. I felt very confident while using CUDoctor.
10. I needed to learn many things before I could use CUDoctor.

Figure 8: The questionnaire form for evaluation of CUDoctor.

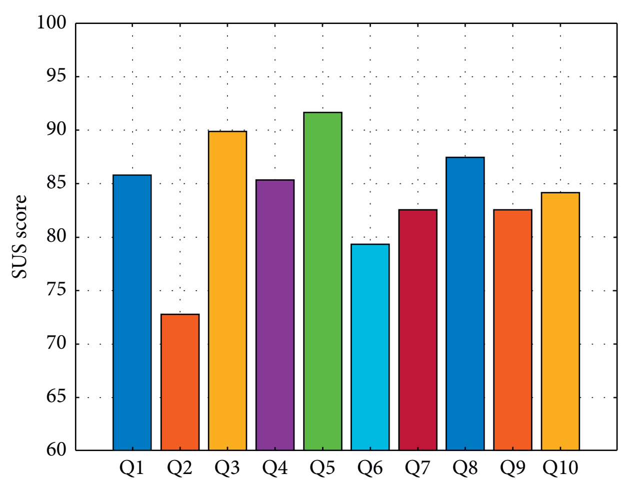

Figure 9: Results from usability evaluation of CUDoctor using SUS.

emphasizes emotional connection [82], while using deep learning for meaningful response dialogue tasks. Chatbots are also used in suicide prevention and cognitive behavioral therapy, aiming at risk groups such as HARR-E and Wysa [83]. The main difference of the system described in this paper is that the service is delivered over the SMS rather than social networks, which require very good Internet connectivity often unavailable in remote rural regions of developing countries. Moreover, the described solution focuses on the niche domain of tropical disease symptom assessment, and we are not aware of any other NLP-based systems focusing on this domain of application.

4. Conclusion and Future Work

The timely access to healthcare avoiding unnecessary time wastage of patients is a major issue in sub-Saharan Africa. However, considering the exponential growth of mobile users and the need for a real-time medical diagnosis assistance tool, it is therefore important to explore the need for a cost-effective telehealthcare platform, which allows the earlier detection of diseases and effective communication with patients (users) to a diagnosis system (remote doctor at proxy). Based on the highlighted needs, this study was able to successfully build a text-based medical diagnosis system, which provides a personalized diagnosis utilizing self-input response from users to effectively suggest a disease diagnosis. The proposed system was able to combine NLP and machine learning algorithm for SMS and Telegram bot. The system was able to suggest a diagnosis using a direct approach of the question and answering technique to offer a diagnosis. The limitation of the system is that it is not secure against the false-positive cases of falsely suggesting the disease; therefore, a final diagnosis still must be confirmed by the medical doctor.

The future recommendations include the automation of this medical diagnosis system to easily recognize diseases, recommend treatments, prescribe a medication, and perform medication adherence. Audio interaction will be incorporated to make the system more interactive. These improvements will serve towards reducing cost and mortality rate, thereby reducing the workload burden on medical doctors in underdeveloped regions.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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Review Article

Applications of Artificial Intelligence and Big Data Analytics in m-Health: A Healthcare System Perspective

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Mobile health (m-health) is the term of monitoring the health using mobile phones and patient monitoring devices etc. It has been often deemed as the substantial breakthrough in technology in this modern era. Recently, artificial intelligence (AI) and big data analytics have been applied within the m-health for providing an effective healthcare system. Various types of data such as electronic health records (EHRs), medical images, and complicated text which are diversified, poorly interpreted, and extensively unorganized have been used in the modern medical research. This is an important reason for the cause of various unorganized and unstructured datasets due to emergence of mobile applications along with the healthcare systems. In this paper, a systematic review is carried out on application of AI and the big data analytics to improve the m-health system. Various AI-based algorithms and frameworks of big data with respect to the source of data, techniques used, and the area of application are also discussed. This paper explores the applications of AI and big data analytics for providing insights to the users and enabling them to plan, using the resources especially for the specific challenges in m-health, and proposes a model based on the AI and big data analytics for m-health. Findings of this paper will guide the development of techniques using the combination of AI and the big data as source for handling m-health data more effectively.

1. Introduction

Mobile health is defined as the practice of applying mobile-based devices such as the mobile phones, patient monitoring devices, personal digital assistants (PDAs), and other wireless devices for the medical and public health. Therefore, this process requires the application of mobile phone's one of the most important benefits called the voice and short messaging service (SMS). At present, more than 500 projects are there for the m-health and nearly 40,000 medical-based mobile applications are also available worldwide [1]. There are mobile-based medical devices which are designed specifically for monitoring the heart rate [2], level of glucose [3], blood pressure [4], tracking the patterns of sleep [5], and also for monitoring the activity of brain [6]. It also uses more complicated operations and services such as the General Packet Radio Service (GPRS), 3rd and 4th generation mobile-based technologies, Global Positioning System (GPS), and Bluetooth-based technology. Big data [7–9] in the healthcare contains the medical images [10], clinical data of doctor, doctors' prescriptions and notes, computed tomography (CT) images, MRI scans, laboratory data, documents from the drugstore, files from the insurance EPR data, and other data related to the administrative operations. This is increasingly becoming favored within the worldwide communities of healthcare. However, there is a deficiency of understanding the most suitable framework based on the computational methodologies which are required for this approach. Big data analytics is the process of scrutinizing huge volume of data from various kinds of sources of data [11, 12]. These data are of different presentations and designs. Various analytical methods such as data mining and AI can be put in to examine the data. Approaches for big data analytics can be used to identify the abnormalities obtained as a result of combining large volume of data from different sources of data. Big data has become closely associative with the mobile health in recent years [13]. The main problems of big data analytics and the m-health are yet to be solved.

Various works have been done recently as proposals [14–28] or review [15, 27, 29–32] on m-health and applications of AI and big data analytics in healthcare sector. Applications of mobile phones have been successfully proven in medical-based applications for monitoring and have enhanced in the possibilities of assessing clinical data [27, 33]. Methods such as experience sampling methods (ESMs) and ecological momentary assessment (EMA) were applied in the process of assessing the patient's relationships between events and disease course [28]. These methods, which depend on providing contents which are informative in nature and questionnaires which were self-administered, reduce the recall since these applications will process in real time [34]. Recently, mobile devices can also able to perform passive gathering of data, i.e., to gather the information about the users without any effort on their part. Processes such as actigraphy, geolocation, and communication-based activities are usual features of current smartphones, and they can also be used in collecting the patient's behavior using the m-health-based systems. These m-health-based applications were also used to remotely monitor various physical and mental conditions [31]. Mobile-based health application can use various sensors for generating self-report of a patient. The authors in [26] proposed a mobile application for recognizing the human activity from inertial sensors to determine the user's activity level during the recording process. The signal from heart rate and galvanic skin response are also recorded in by their method to determine the emotional state of a user.

Following are the provocations that are still under consideration from the perspective of m-health:

(i) Better perception of the organized and unorganized sources of data produced from different sources of mobile and information.

(ii) Smart implementation and conversion of the big data of health data occurred from the users of 5G mobile health. This should be performed in order to compare the most awaited intelligent and predefined change of behavior or convincing tools for inspiring more users for comfort and improvement of their health.

(iii) Resilient, precise, and secure methods for data analytics for the explication of huge data of medical imaging and other relevant diagnostic data which are created and transferred from the future generation of mobile imaging devices should be developed.

The paper explores the applications of AI and big data analytics for providing insights to the users and enabling them to plan, uses resources especially for the specific challenges in m-health, and a proposes a model based on AI and big data analytics for m-health.

The remainder of the paper is organized as follows. Section 2 shows the motivation and scope of this work along with the systematic reviews and meta-analysis process. Section 3 depicts the definition of m-health and its schematic representation along with the mobile sensors and their applications in m-health. Section 4 explains a detailed review about the applications of AI in m-health along with the performance measurement indicators used to examine the quality of m-healthcare. Section 5 presents the applications of big data analytics in m-health followed by the additional summary of its applications in the healthcare sector. Section 6 presents the proposed model based on the AI and big data analytics for m-health. Section 7 depicts the limitations of the proposed review. Conclusion and the future enhancements are shown in Section 8.

2. Motivation and Scope

At present, there are many papers that have been published recently as proposals or review on m-health and applications of AI and big data analytics in healthcare sector. This paper outlines the characteristics and applications, scope/healthcare subarea, timeframe, and number of papers reviewed. This review is intended to answer the following research questions:

(1) What is m-health and what sensors have been developed along with their applications for m-health?

(2) What applications and benefits could AI technology bring to m-health?

(3) What applications and benefits could big data analytics bring to m-health?

(4) What are the challenges of adopting AI and big data analytics technology in m-health? anda proposed m-health model based on the combination of the AI and big data analytics.

The following sections describe how these questions were answered by this systematic review.

2.1. Methodology. The methodology of our review followed the checklist proposed by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [35]. This review also identified applications of AI and big data analytics in m-health system. The review is limited to English articles and reports from 2007 to present date.

2.1.1. Relevant Articles. Relevant articles and process of their selection for this systematic review are described in this section. In order to collect the relevant articles for this systematic review, we searched eight large scientific databases: the IEEE Xplore, ACM digital library, Taylor & Francis online, ScienceDirect, SAGE Journals, ProQuest, Springer, and Web of Science. This is done by an advance keyword searching process. The following terms were used in the search: "Artificial Intelligence AND m-Health," "Big data analytics AND m-Health," and "AI AND big data analytics in M-health." Various articles were also found from the Google Scholar search. The main aim of this search is to find other quality articles that might be missed during the initial search in scientific databases.

2.1.2. Inclusion and Exclusion of Articles. After completing the process of searching the article, the authors concealed the titles and abstracts of the retrieved articles using an inclusion and exclusion criteria. The articles that were not in English, the articles lacking full text, the articles that do not represent the applications of AI in m-health, the articles that do not represent the applications of big data analytics in m-health, and the articles with insufficient details were excluded. All the duplicate articles were removed. At last, 106 articles were obtained and kept for the review process. The above process is explained in the form of PRISMA flowchart in Figure 1.

2.2. Results. A total of 2543 articles were retrieved from the eight scientific databases. Then, another 130 additional articles were found through the search in Google Scholar. A total of 2437 articles have been excluded in the initial screening process. Among these, 1345 articles which do not represent the applications of AI in m-health, 902 articles which do not represent the applications of big data analytics in m-health, 78 articles which were from international journals, and 12 articles with insufficient details were excluded. Flowchart of the systematic reviews and meta-analyses (PRISMA) is shown in Figure 1.

3. Mobile Health

The application of mobile phones has inadequacies in infrastructure in developing countries which have led to huge changes in various healthcare sectors. Recently, mobile technology has played a significant role in various fields of technologies among various subscribers in almost all the countries. Mobile devices and communications assist the evolution of the proposed systems and their employment for the healthcare called m-health [36]. This comprises the combination of mobile devices, medical-based sensors [37], and portable devices [23, 38]. Health-based applications on smartphones are classified into the following: general health and fitness-based applications, information on medicine-based applications, and applications for managing the healthcare. m-Health is the innovative application of upcoming mobile-based technologies in concurrence with wearable devices especially in the application of healthcare informatics in order to enhance the practices of healthcare [39, 40]. m-Health has a scope of applying it to the mobile-based technologies. As a result, it produces various technologies such as the wearable devices, embedded systems, trackers for location, and legacy-based sensor devices. It also explores the facilitation in wireless-based communication [24, 41], ubiquitous computing, and other embedded technologies in healthcare to improve support of healthcare-based applications and also to reach into different pastoral areas [42, 43]. The schematic representation of m-health scenario is shown in Figure 2.

There are many advantages of using m-health. These devices can apprehend, save, recover, and transmit data to provide instantaneous, personalized informatics for individuals. m-Health could be a key element in healthcare systems [29] and can be useful in monitoring health status and improving patient safety and quality of care.

m-Health is becoming more popular in the smart device sector as it can provide remote assistance and data collection. Unlike an individual healthcare service, the collected data can be expanded and used across communities to understand common trends and thus improve the standards of healthcare. m-Health can provide support in vulnerable and remote communities via improvements to networks and the emergence of IoT [44].

The application of mobile technologies and their impact are likely to increase in the coming years. Surveys showed that mobile technologies and devices held about 80% of the overall global market in 2017, whereas in 2013, it was just 39%. The number of global users of smart mobile devices is anticipated to almost double in 2020 compared with 2014 and will reach 2.87 billion users [45]. This may increase the significance of m-health globally as shown in Figure 3. Low-cost smartphones have the required features and capabilities to cope with health-related applications and include the necessary connectivity [36].

As the popularity of m-health increases, countries are allotting more funding to this area helping society and communities to become more health literate. This promotes wellness rather than expensive medical intervention and hospitalization.

3.1. Mobile Sensors and Their Applications for m-Health. There are many mobile sensors which can be applied for a various applications of health [21, 47–52]. Various sensors such as camera sensor [53–55], microphone sensor [56–58], accelerometer sensor [59–61], and gyroscope sensor [59, 62] were used in the healthcare-based applications. Table 1 shows a detailed outline of how the mobile-based sensors can be applied for various healthcare-based applications.

4. Applications of Artificial Intelligence in m-Health

Artificial intelligence is the process of demonstration of intelligence by machines in disparity to the natural intelligence depicted by the humans [24, 75, 76]. Machine learning is one of the applications of AI that lay out the systems to create capability to learn automatically and to enhance it from its training without being programmed explicitly. It also puts emphasis on the evolution of algorithms, can obtain data, and can adopt it for the process of making it to train themselves. Due to the fast enhancement of the AI, it has been employed in various fields, such as the IoT [22, 41, 77], machine vision [78], driver assistance [79, 80], and natural language processing [81, 82]. AI has been put in application in various domains of healthcare [83–87] which includes cancer research [88], cardiology [89], diabetes [90], mental health [91], identification of prognosis [92], identification of Alzheimer's disease [93], identification of difference in

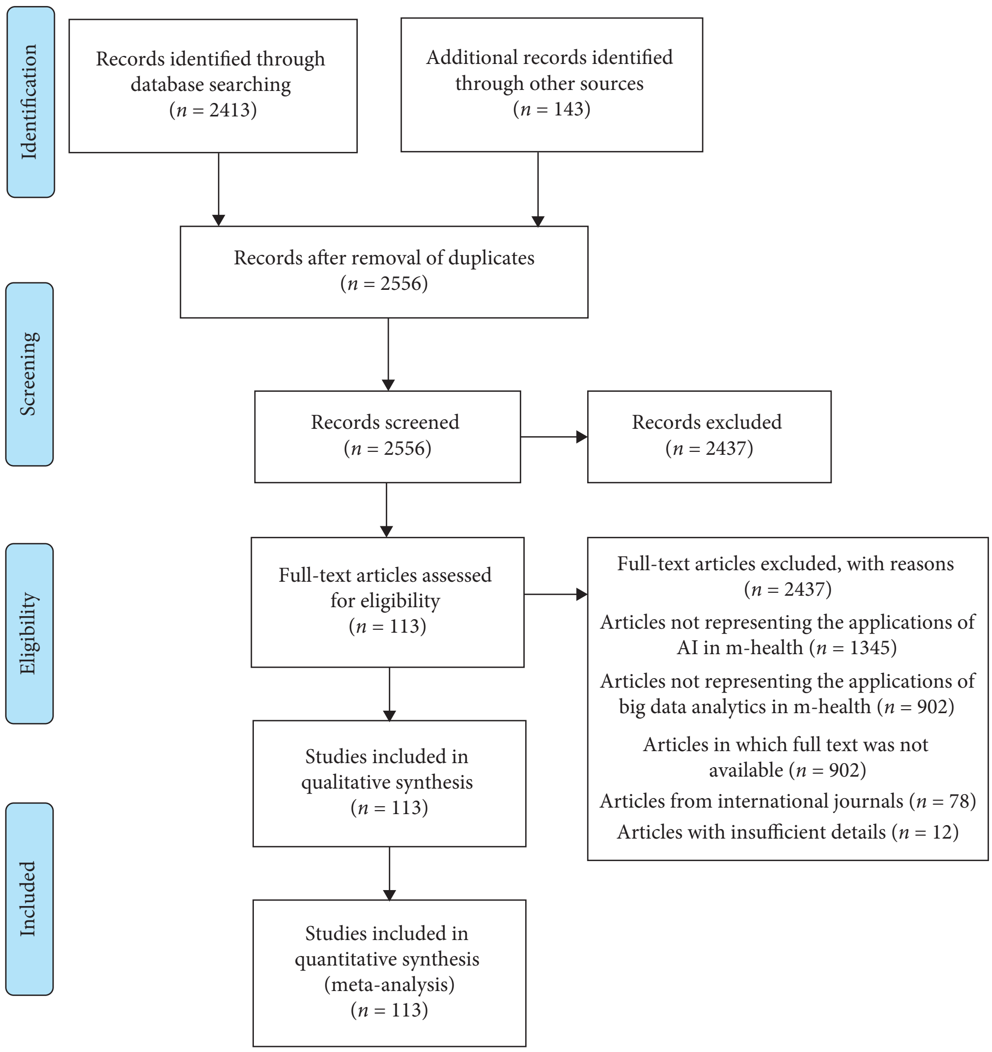

Figure 1: PRISMA flowchart for the entire review process.

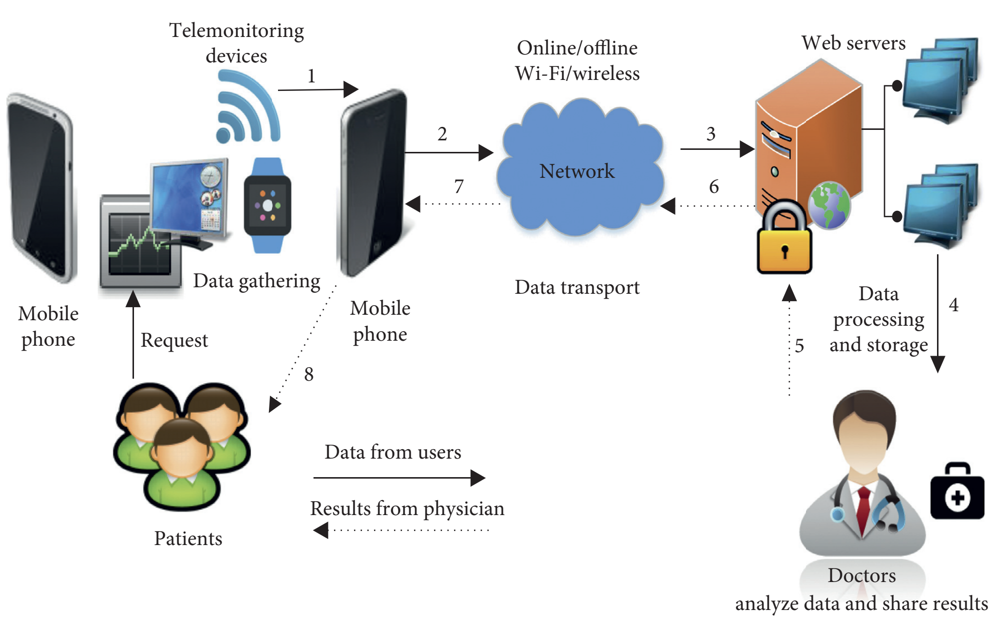

Figure 2: Schematic representation of the m-health scenario.

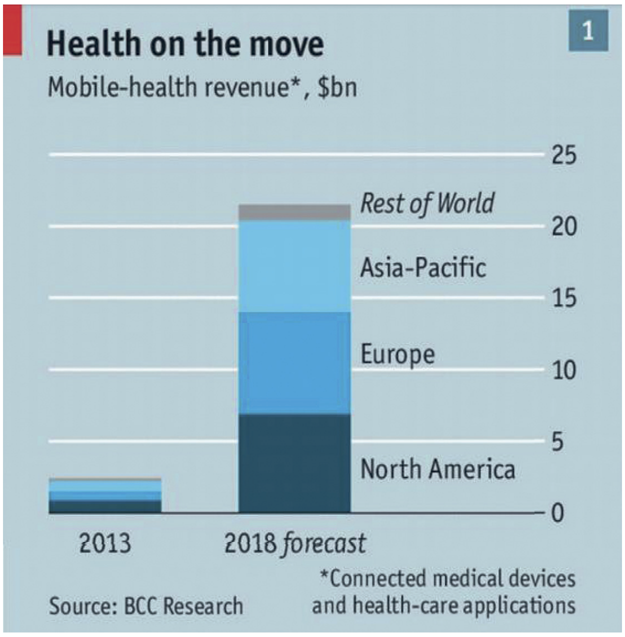

Figure 3: Global m-health markets [46].

the clinical groups [94], identification of cardiovascular disease [39], stroke-related studies [95], etc.

Larburu et al. in [96] proposed an m-health application based on artificial intelligence for avoiding heart failures in patients. At present, the doctors are applying simple methods for generating alerts in the identification of heart failure. More false alerts are generated in the present methodology. In this work, predictive models were proposed to avoid the impact of these false alarms. These predictive models are based on clinical data taken from 242 heart failure patients' mobile accumulated in 44 months. The finest predictive model is acquired by the merger of various alerts which are based on observing the data and a set of questions using the application of a Naive Bayes classifier. This proposed model lowered the false alerts for a patient for a year from 28.64 to 7.8 gradually. In this method, the proposed system forecasts the possible risk of heart failures among the patients with more possibility of a heart failure. Main drawback of their method is that the accuracy of detection is less when the patient had undergone any heart surgeries in his past.

Burns et al. in [97] depicted the importance of mobile-based multicomponent that can be applied in the models of AI in order to analyze the different types of emotions such as the mood, cognitive state, depression, motivation, various activities, environmental behavior of the patient, and social behavior of the patient. Their proposed methodology gives graphs for feedback for the process of behavioral self-reflection, and it also provides coaching using various special trainers. The proposed methodology is based on the combination of regression along with decision trees and the phone sensor-based devices. Overall accuracy of their proposed methodology was excellent for the prediction of location about 60%–91%. Main drawback of their method is that the accuracy of prediction was very less for emotions, for example, sadness. In their analysis, they have selected eight patients for identifying the depressive disorder, the depression symptoms, anxiety, etc. Even though the accuracy of their proposed methodology is promising, the authors suggested the proposed methodology has to be enhanced since the outcome of prediction in the case of mood and location has to be upgraded.

Hawley et al. [98] proposed an application of automated machine in the recognition of speech of persons who are affected with dysarthria. It also assists in the process of voice message generation. In their method, the authors employed the hidden Markov models to decide the overall proximity of a word which is spoken to a speech model and is personalized for a particular person. Yet, the accuracy of their methodology for the speech recognition is only 67% for real-life study which comprises nine persons. The persons who participated identified that the hurdles in the process of communication are decreased by their proposed device when compared with the already available method of communication while speaking. Main drawback of their methodology is that its support is done by a usual aid for the voice-output communication and the accuracy of speech recognition hardware is less.

Martin et al. in [99] proposed a predicting and an alert generating methodology about multiple modalities such as lung diseases or cardiovascular problems in patients. Alerts were generated and sent to professionals of healthcare who can monitor the alerts based on the predefined guidelines. Their proposed system was based on the information collected through the phone calls of patients. Features such as linguistic and metalinguistic were extracted along with the status of patient in order to instruct the models of prediction. A 70% positive predictive value was obtained for unplanned events by their proposed methodology. Their proposed methodology was tested in a controlled manner with a set of 214 patients in a time period of six months. This is the biggest testing of an algorithm in terms of patient's participation and also with respect to the time taken. This methodology depicted a reduction rate of 50% in the number of participants in unplanned events of hospitals in the group when compared with custom alert generating mechanism.

Morrison et al. in [100] used the push notifications to upgrade the application of smartphone users for the process of stress management. The authors have employed a classifier called Naive Bayes for predicting the response of a user. Their algorithm predicts if a user would respond for a personalized intelligent mechanism for notification delivery when a notification is received from it. It depends on the number of times a user views and reacts within a day for the messages he received. This methodology was carried out for 72 hours which includes 76 participants. The drawback in this method is that the response is less when there is a distraction in the mobile networks.

Ortiz-Catalan et al in [101] used the pattern recognition algorithms for controlling the virtual limb movement in patients suffering from phantom limb pain. They also used gaming-based methodology combined with augmented reality for the process of treatment. Their proposed methodology was trained with a group of 14 participants. The

Table 1: Mobile-based sensors applied for various healthcare-based applications.

Mobile sensors	Main area	Applications in healthcare
Camera	Capturing photo and video	Applied for identifying various categories of diseases, in the perspective of effects in surgery, diagnosis of diseases, observing the slash, analysis of skin disease [63], monitoring the health of child, etc. [18].
GPS	Location tracking	Provides an access to follow the patients who are vulnerable to some diseases such as the people with Alzheimer's disease [64] and Ebola [65] by the application of mobile-based applications [66].
Electrocardiograph	Cardiovascular disease monitoring	Mobile phones which are enabled with the electrocardiographs are being used in areas which are underdeveloped for the purpose of monitoring the patients with heart diseases [40, 67].
Bluetooth	Data sharing and communication	It allows a midrange data communication between mobile devises, various other healthcare monitoring devices, and wearable sensors.
Microphone	Voice recording	It allows the doctors to communicate with the patients regarding the support for identification and treatment of diseases. It also comes up with the way for analyzing the audio for assessing the feeling of a patient with various diseases such as muscular dystrophy [68].
Accelerometer	Acceleration measurement	It assists to compute the orientation of devices which are relative to Earth especially for calculating the motion. It can be executed in various activity monitoring techniques of patients such as counting the step of a person, gait analysis, and monitoring [19, 69].
Wi-Fi	Data sharing and communication	Wi-Fi-based mobile sensor enables the mobile device to communicate with the physician about the healthcare data to for the purpose of identification of a disease and its treatments.
Accelerometer, GPS, compass, gyroscope, and barometer	Physical activities	Combination of hardware and the sensors present in it is being utilized for computing the stationary vs nonstationary actions [20].
Microphone, accelerometer, and GPS	Social engagement	This combination makes the monitoring of psychological health by checking the social problems, talks from the conversationalists, consternation, strain, behaviors related to depression, etc. [70, 71].
Microphone, GPS, accelerometer, touch interface, and light sensor	Sleep pattern tracking	Combination of this hardware depicts the data of interrupted vs constant patterns of sleep in a patient [71–74].

results revealed that about 50% symptoms of phantom limb pain in patients were decreased significantly after 6 months of treatment. The authors also recommended that their novel method of treatment could be employed after clinical treatments. One of the disadvantages of their methodology is the time frame. Table 2 depicts the additional summary of various applications of machine learning in the healthcare sector.

4.1. Performance Measurement Indicators Used to Examine the m-Healthcare Quality. In order to assess the quality of m-healthcare-based apps, various performance measurement indicators were proposed earlier. These performance measure indicators were proposed by incorporating the challenges of mobile health apps and strategies to ensure appropriate design and development of the apps for healthcare providers, patients, and the general public. Following are the various performance measurement indicators used to examine the quality of m-healthcare:

(1) *Usefulness*. This metric enables the m-health user to achieve his or her specific goals and motivates the user to use the app repeatedly whenever necessary. This metric also analyzes how the mobile platform is effective in assessing how far the user is satisfied by the mobile healthcare system.

(2) *Effectiveness*. Effectiveness is defined as the extent to which the m-healthcare system app works in the way that users expect it to and the ease with which users can apply it to achieve their specific goals. This is an important metric used in the case of m-healthcare quality.

(3) *Veracity*. It is the measure of analyzing the accuracy and reliability of the information, data, or content present in the m-health application. Content in health apps is usually based on more than one source of information. The m-health application provides a method to enable the user to identify to the complete content more easily. Most of the m-health-based systems perform the functions of user or patient management, such as computation, tracking the data, and reminders, which should be more accurate.

(4) *Interactivity*. It is the process of providing a sense of engagement with the user, entertainment, satisfaction to the patient or user, and motivation for the users who are using the m-health systems. It also extends to interactivity between service providers and patients as facilitated by the m-health app.

Table 2: Additional summary of the AI methods suitable for the healthcare sector.

Name of the framework	System	Technique	Area of application
Apache Mahout [102]	Library for machine learning (open source)	A real-time computation system which is more flexible and scalable.	Provides mechanisms such as clustering, classification, and regression.
Skytree [103]	AI-based platform which is applied for general purpose algorithms	Applies artificial intelligence for producing complicated algorithms for more advanced analytics.	For processing very large organized and unorganized datasets more accurately without performing downsampling.
Karmasphere [104]	Platform of big data	Searches and scrutinizes the web-based, mobile-based, and sensor-based data in Hadoop for the social media.	Develops and issues a graphical-based environment which assists the way finding through any type of big data and identifies the recent trends and patterns present in it.
BigML [105]	Platform for AI-based programs	Gives various tools for performing tasks related to AI such as clustering, regression analysis, pattern classification, detection of anomaly, and discovery of association.	It combines the AI-based features along with the cloud-based infrastructure for developing applications which are cost-effective, highly accurate, reliable, and flexible.
Cognitive machine learning algorithm [106]	Cognitive computing tool	Associative memory classifier-based machine learning algorithm.	Echocardiography data are normalized using the machine learning algorithm in order to differentiate the constrictive pericarditis from restrictive cardiomyopathy.
Machine learning algorithms [107]	Support vector machine	Analyzes and classifies a multidimensional echocardiographic data based on gap in present in it.	To distinguish between athlete heart and hypertrophic cardiomyopathy.
Phenotypic clustering [108]	Hierarchical clustering	Classifies similar objects between the same clusters and calculates the hierarchy in the echocardiographic data.	To analyze the clustering of echocardiographic variables in order to compute the dysfunction in left ventricular and isolate high-risk phenotyping patterns.
Convolutional neural network [109]	Combination of AI and natural language processing	It reads the chest X-ray reports of patients and assists the antibiotic assistant system to alert physicians for anti-infective therapy.	It combines the AI-based features along with the natural language processing for effective diagnosis of diseases.

(5) *Customization*. The main purpose of designing the m-health-based system is to support the users in one or more healthcare domains. Examples include assessment of diseases, its diagnostics, prevention of further complications, expert's intervention, and recovery. Customization is crucial in aiding the m-health-based system to achieve what the users intend to do. For example, the systems may have to connect to one or more EHR systems to provide the medical data of a particular user/patient.

(6) *User Satisfaction*. User satisfaction can be defined as the proven willingness of a user for specified tasks in the overall m-health system or in using a specific system for repeated emergencies. This user acceptability has replaced most of the traditional metrics already available for assessing the usability in mobile health systems.

5. Applications of Big Data Analytics in m-Health

Recently, big data analytics has various options of providing advanced care for the patient and clinical decision support in the healthcare [14–17, 110, 111]. In general, application of big data in healthcare refers to the electronic datasets of health which are huge and complex and are difficult to manage with normal hardware, software, tools, and methods for managing the data [11]. Big data in the healthcare consists of clinical details of doctors, their notes and prescriptions, CT images, MRI images, laboratory data, documents from the drugstore, files from the insurance and other data related to the administrative operations, EPR data, etc. This comprises the big data. More methods have been proposed by various researchers to process these types of data. Still, there is a deficiency of understanding the most suitable framework based on the computational methodologies which are required for this approach. Hence, an enormous amount of data belonging to the healthcare is available for big data scientists. By understanding the advantages and disadvantages present in this, the big data analytics has to be enhanced in order to save the lives and to reduce the cost of processing data. Therefore, big data can be classified into two main categories [36] as follows:

(i) Organized data: in general, these data refer to the contents having defined format and length such as the numbers, generated date, and contents of strings. These data are formed by various sources such mobile phones, computers, various sensors, and logs of web. Examples of these types of data include EHR, home treatment and monitoring data, prescriptions from the doctors, etc.

(ii) Unorganized data: in general, these data refer to the contents which do not have a predefined format of big data. The majority of the data are generated from various sources, such as the data from social media, mobile data, and content from the video and web. Examples of unorganized health data include health data from the social platform such as from Twitter, Facebook, user blogs, notes of clinicians, and diaries of medication and its instructions.

The process of analyzing a huge amount of data from various sources of data and different formats in order to convey the perception of enabling a decision-making process in real time is called big data analytics. Various concepts of analytics such as data mining and AI can be used to analyze the obtained data. These analytical approaches in big data can be used to identify the anomalies by analyzing a huge amount of data from various datasets and their sources. Figure 4 shows an example of the smartphone-based m-health model with the combination of AI and big data analytics. Nowadays, the conversion of digital version of all exams done in clinical and medical fields yields huge data and records, which has formed a standard and has been widely accepted and implemented in practice.

EHRs are defined as the computerized form of medical records for all the patients. It has various information regarding the previous, current, and upcoming physical and the mental health situation of an individual. These electronic systems are used to apprehend, transfer, obtain, stock, connect, and change the data of multimedia. The primary purpose of this electronic system is to provide services related to the health [45]. Main advantages of these EHRs are that they enable faster retrieval of data and the professionals in healthcare have an enhanced access to the whole history of the patient about his medical details. Its benefits include providing better healthcare by making better classifications of the patient's health.

Similar to EHR, another record called electronic medical record (EMR) is used to store the medical and clinical data which are gathered from the patients. These are standard in nature. EHRs, EMRs, PHR, software for the medical practice management, and various other components of the healthcare data increase the quality and efficiency of service and reduce the overall cost of healthcare and medical errors. The healthcare big data consist of the data from healthcare provider and various experiments done in the laboratories and various other data obtained from the IoT-based devices.

Raghupathi and Raghupathi [112] proposed a novel architecture for the healthcare-based system applying the analytics of big data. Their methodology comprises various layers for data source, transformation, big data platform, and analytics. The layer for data source mainly focuses on the data sources of internal and external healthcare which can be found in different locations and in different formats. The layer for transformation is accountable for various tasks such as removal, conversion, and uploading of data in the platform of big data for the process of doing specific operations on the Distributed File System using a programming model called Map-Reduce. The main task of analytical layer is to do various operations such as inquiring, announcing, online analytical processing, and mining the data.

A patient-centric personalized framework for healthcare based on the collaborative filtering approach was proposed by Chawla and Davis in [113]. It apprehends the similarities in different patients and generates the personalized profiles for risky diseases for individuals. Collaborative filtering is one form of data analysis technique which is designed to guess the opinion of user regarding an entity item or its service; it is based on the preferences from a known group of a large number of users. In their framework, healthcare history of individual patients was collated with all the medical histories of other available patients. This is based on the following similarity constraints. Some of these are occupation, symptom, result from the laboratory, history of family, data of demography, etc. Based on the computation of similarity, a collection of patients who are similar is chosen and the prediction of diseases is done. Since the application of electronic healthcare records was increased, their framework depicts a proactive healthcare solution with respect to the context of big data. Even though their proposed methodology has various advantages, their proposed methodology handles only the identification of codes for various diseases.

An analytical framework of big data that employs ubiquitous healthcare system was proposed by Kim et al. in [114]. Their proposed framework analyzes the vital signs obtained from accelerometers in order to provide healthcare services. Vital signs are continuous time series data which are unstructured in nature having inadequacy to be stored in the traditional databases. Data obtained from ECG and from the respiratory system are considered as vital signs. Their proposed framework used a platform of open standard in order to support the inability of data exchange between various devices. This platform has been enlarged by including various algorithms for the process of extracting feature values from the fresh vital signs data and then storing them for the process of real-time analysis. Even though their proposed methodology has various advantages, their work has a major disadvantage in delivering considerable analytical models.

A detailed survey on the inference of computational methods in the big data-based health informatics has been done by Fang et al. in [30]. They focused on a novel framework called "Health informatics processing pipeline" which incorporates various steps to obtain significant patterns from healthcare-based big data. Their proposed framework consists of pipeline process such as capturing the data, storing the data, analysis, extraction, and decision support systems. Apart from the proposed framework, some directions for research in the heterogeneity of data such as organized and unorganized data of the healthcare, existing complexities which are available in the available data, issues of privacy, and analysis of the identified patterns are also traversed in their entire work. Their proposed healthcare-based framework offers a systematic pipeline of data processing for various stages of informatics of big data such as data acquisition, saving, finding, and analyzing data from diversified sources. Hence, the authors focused on enhancing the aspects of technological development by using the tools and techniques of big data. Due to the enhancement of mobile devices and wireless sensor networks, healthcare services

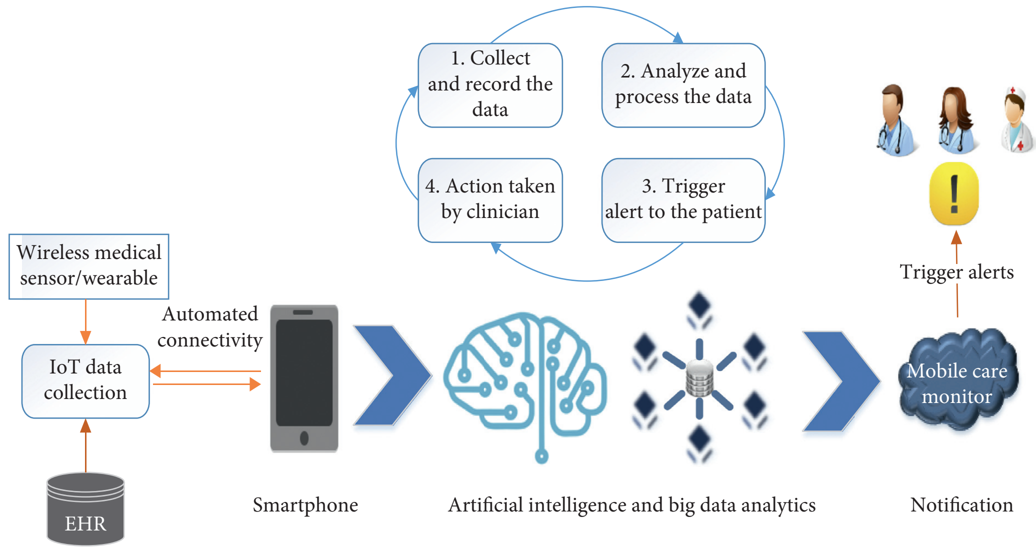

Figure 4: Smartphone-based m-health model with AI and big data analytics.

were improved. As a result, the services are offered at any time and at anywhere in the health informatics domain.

Pramanik et al. in [115] performed a detailed analysis on the latest improvements in healthcare-based systems. Their work mainly focuses on the applications of technologies based on smart system. They focused on a novel framework for the smart healthcare system enabled by big data for maintaining ubiquitous solutions for healthcare. It also offered a reduced cost with improved advancements. It consisted of the following layers:

(i) Data source layer: designed especially for maintaining the organized, unorganized, and semi-organized data sources.

(ii) Data analytics layer: designed mainly for processing calculations on big data, its visualization, and management.

(iii) Smart service layer: designed mainly for making ease of various favors such as the monitoring of data, agreement on privacy, and security between the providers, consumers, and their services. Also, this layer proposes various smart services and their infrastructure with the help of various devices and software.

(iv) Knowledge discovery layer: improved functionalities such as the guessing necessity of entities, proposal, and its cost evaluation of mechanism for providing the healthcare service were also included.

The authors proposed a framework for the organizations in healthcare in providing intelligence-based smart services. Their detailed research depicts a novel framework for the smart healthcare system based on big data and also makes the research directions interdisciplinary. In fact, the proposed framework is the combination of three technical streams such as the AI, agent-based systems, and data mining along with the smart health. Additional summary of the applications of big data in the healthcare sector is provided in Table 3.

6. Proposed Model Based on AI and Big Data Analytics for m-Health

The proposed framework comprises three essential parts such as the medical data obtained from the patients through the mobile phone and the telemonitoring devices, AI and big data analytics platform, and the output towards the mobile care monitor. The architecture of the proposed system is shown in Figure 5. The entire process of analyzing a huge amount of data obtained from various sources of data in different formats is processed by the combination of AI and big data platform. These are combined to convey the perception of enabling a decision-making process in real time. Various concepts of analytics such as data mining and AI are used to analyze the obtained data from a patient. These analytical approaches in big data can be used to identify the anomalies by analyzing a huge amount of data from various datasets and their sources such as biomedical signals, physiological sensing data, genomic data, and biomedical imaging. The AI-based engine comprises two modules such as the stream analysis module and the AI-based report management tool. These analyze the queries obtained from the big data analysis engine.

The main aim of the AI-based report management tool is to generate a better decision using the AI technology in order to report the status of the patient's health. It is also used as a platform for the disease control, treatment, and diagnosis tool. In this model, the AI-based report management tool collects, analyzes, performs, and triggers the action by classifying the code of a disease or condition using the free text approach. It also extracts the features from the EHR. It also detects the irregular records which are present in the EHR. All the processed streams are stored and updated in the big data engine.

Table 3: Additional summary of the applications of big data in the healthcare sector.

Name of the framework	Source of data	Technique	Area of application
Substructure for preserving privacy in healthcare systems based on RFID [116]	Data produced from the tags of RFID	Privacy preservation methods	Reliable healthcare-based services. Enhanced isolation in healthcare system based on RFID.
Novel framework for distributed and secured HIS [46]	Electronic-based health records	Providing security limitation and control mechanisms for accessing the data	Secure healthcare system. Distributed and secured multitier framework.
Smart framework for healthcare system enabled with big data [115]	EHR, report on diagnosis, data from the social media, biometric data, and monitoring data	Providing services of smart healthcare by infrastructure which is service oriented	Technologies based on smart system especially for the healthcare system. Combining the healthcare knowledge data mining strategies with the infrastructure of smart services.
Framework for policy enforcement towards IoT-based smart health [117]	Patients' various biological parameters, data related to environmental factors, and data generated from the instruments such as RFID	Providing access control based on policy mechanism for offering resources of healthcare	Smart health applications for avoiding threats in security for large scale and heterogeneous scenarios.
Framework for prediction of protein structure using big data and ensemble learning [118]	Protein structure dataset	Ensemble learning technique based on distributed tree	Design of drugs. Depicts a distributed framework with enhanced accuracy.
Framework for smart health [44]	Datasets of the patient from various sources such as the health information system and the radiology department	Pattern recognition and its matching techniques	Big data-based analytics for the applications of smart healthcare. Improving the services of healthcare by combining the sensor-based technologies along with the cloud computing and big data analytics.
A semantic web-based technology for maintaining and reusing the archetypes present in clinical data [119]	EHR	Building the ontology through ontology web language	Classification of patient based on various clinical criteria. Combining the semantic-based resources along with the EHR.

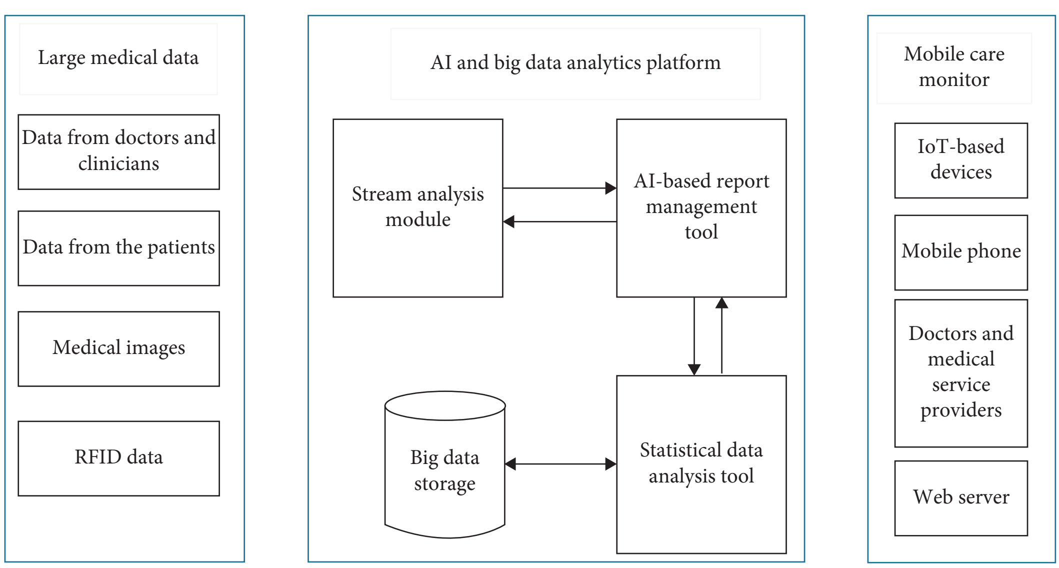

Figure 5: Architecture of the proposed AI and big data analytics-based m-health system.

The big data analysis engine consists of two modules such as storage for big data and a statistical data analysis tool. The statistical data analysis tool retrieves the input data, processes it into queries, and then sends it to the AI-based engine. All the processed queries and streams were given as output towards the mobile care monitor.

The proposed model enhances the overall performance of m-health since AI and big data analytics are combined. The proposed methodology improves the process of m-health by processing each and every query, and it also enables a decision-making process in real time.

7. Limitations

Despite the various advantages of the proposed m-health model based on AI and big data analytics, some limitations were also there that need to be considered: a large section of population, system can never be too accurate, have to depend completely on the technology, and several privacy and security issues.

With regard to a large section of population, the access to m-health-based system is denied because of their numbers, their incapacity to afford it, and the lack of knowledge and skill to use it. The system can never be too accurate to replace the humans and their predictions. These systems have been made to ease out the health structure but they cannot be a substitute to human. Even the most well designed and technologically best developed apps can also never be hundred percent accurate.

These m-health systems also make a user/patient to be dependent completely on them. If the user loses his or her mobile phone and user id/password, there is a possibility for all the information to be lost temporarily or even permanently. There might be a chance for various issues in the privacy and security of the health data present in it. In such cases, there is a chance for the personal information to be leaked and shared to unauthorized users.

8. Conclusion and Future Works

m-Health is a technique which uses mobile devices and technology for health interventions and is the biggest technological advancement of recent research. Similarly, the application of AI and the analytics of big data in healthcare are considered as one of the important achievements for the intelligent healthcare system. In this paper, a detailed review of the m-healthcare system is proposed based on the application of AI and big data analytics. Various advantages from this combination for the m-health perspective are presented. Particularly, all applications of relevant technological areas and the building blocks such as communications, sensors, and computing which are associated with mobile health are explained in detail. The role of various tools of machine learning within the current m-health model is also illustrated. Future works can be a comprehensive review on the retrospective validation of models of the AI and combining them with various digital health tools and evaluating their clinical validation and efficacy issues on these systems. Future works can be the proposal of application of intelligent agent-based systems for providing privacy and security in m-health big data.

Data Availability

The data that support the findings of this study are available from the corresponding author on request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Research Article

A Comparison of Three-Dimensional Speckle Tracking Echocardiography Parameters in Predicting Left Ventricular Remodeling

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Three-dimensional speckle tracking echocardiography (3D STE) is an emerging noninvasive method for predicting left ventricular remodeling (LVR) after acute myocardial infarction (AMI). Previous studies analyzed the predictive value of 3D STE with traditional models. However, no models that contain comprehensive risk factors were assessed, and there are limited data on the comparison of different 3D STE parameters. In this study, we sought to build a machine learning model for predicting LVR in AMI patients after effective percutaneous coronary intervention (PCI) that contains the majority of the clinical risk factors and compare 3D STE parameters values for LVR prediction. We enrolled 135 first-onset AMI patients (120 males, mean age 54 ± 9 years). All patients went through a 3D STE and a traditional transthoracic echocardiography 24 hours after reperfusion. A second echocardiography was repeated at the three-month follow-up to detect LVR (defined as a 20 percent increase in left ventricular end-diastolic volume). Six models were constructed using 15 risk factors. A receiver operator characteristic curve and four performance measurements were used as evaluation methods. Feature importance was used to compare 3D STE parameters. 26 patients (19.3%) had LVR. Our evaluation showed that RF can best predict LVR with the best AUC of 0.96. 3D GLS was the most valuable 3D STE parameters, followed by GCS, global area strain, and global radial strain (feature importance 0.146, 0.089, 0.087, and 0.069, respectively). To sum up, RF models can accurately predict the LVR after AMI, and 3D GLS was the best 3D STE parameters in predicting the LVR.

1. Introduction

Acute myocardial infarction (AMI) has been the leading cause of cardiac death among all the cardiovascular events. According to the China cardiovascular disease report 2018 [1], the prevalence of AMI in Chinese urban area is 0.999‰, which is still growing, with a total number of 753,142 percutaneous coronary interventions (PCIs) being carried out in 2017. Left ventricular remodeling (LVR), an structural adaptation of the myocardium to compensate for the contractile dysfunction of myocardial fibers [2], is an important reference in early cardiac rehabilitation treatment for it is the main cause of heart failure after AMI [3–6]. Therefore, a robust prediction on the occurrence of LVR is invaluable to the recovery of AMI patients.

Some studies have explored the values of serological indicators, echocardiographic parameters, cardiac magnetic resonance imaging (CMRI) [7–10], and coronary angiography (CAG) in LVR prediction. Among all the imaging examinations, echocardiography is most vastly applied because it is less costly, less time-consuming, and friendly to almost all types of patients, with a good balance of simplicity and predictive power. Three-dimensional speckle tracking echocardiography (3D STE) is a noninvasive method that outmatches traditional echocardiography in diagnostic power and other imaging methods both in an economical or a practical term [10–12]. 3D STE tracks the deformation of the myocardium through actual three-dimensional observations rather than geometrical assumptions. There have been some studies that used 3D STE to predict LVR [13–16], but few studies have compared the abilities of different 3D STE parameters in predicting LVR or built a comprehensive model to predict LVR using factors that include 3D STE.

With the growing attention on machine learning, the medical application of this technology has become a new focus [17]. Machine learning is an interdisciplinary subject, which involves probability theory, statistics, approximation theory, convex analysis, algorithm complexity theory, and other disciplines [18–22]. It is flexible, expandable, and automatic, which makes it adaptable for risk stratification, diagnosis, and predictions, but currently, we cannot find any machine learning algorithm being applied to predict the occurrence of LVR.

In this study, we attempted (1) to investigate the prediction power of machine learning methods in predicting LVR and (2) to investigate the difference of 3D STE parameters in predicting LVR.

2. Materials and Methods

2.1. Patient Population and Protocols. 172 consecutive patients with first-onset AMI were initially enrolled in this study. All the AMI patients were diagnosed according to the guideline recommendations. Exclusion criteria were as follows: age <18 years, a history of previous coronary heart disease requiring a PCI, severe valvulopathy, left bundle branch block, atrial fibrillation, malignant arrhythmia, and/or any condition compromising the patient's ability to comply. Patients received reperfusion within 12 hours. 24 h after effective PCI, patients went through a standard transthoracic echocardiography and a 3D STE examination. After three months, patients went through another standard transthoracic echocardiography. We defined LVR as an increase ≥20% in LVEDV at three-month follow-up [2, 23–28]. The study protocol was approved by the ethics committee of the General Hospital of the Southern Theatre Command, PLA, and oral informed consent was obtained from all the patients. Due to the sensitivity of patients' personal information in a military hospital, an application for waiver of written informed consent was applied and approved by the same ethics committee (No. 202041).

2.2. 3D STE Examinations. 3D STE was performed using a GE Vivid E9 ultrasound diagnostic system (Horten, Norway) with a 4D volume probe (4 V-D). First, left ventricular volume data from an apical four-chamber view of four to six consecutive ECG-gated cardiac cycles were obtained and stored during a single end-expiratory breath hold. Then, we outlined the LV endocardial and epicardial borders as a region of interest. Then, the 3D GLS, 3D GCS, 3D GRS, and 3D GAS values were displayed in a bulls-eyed plot (Figure 1).

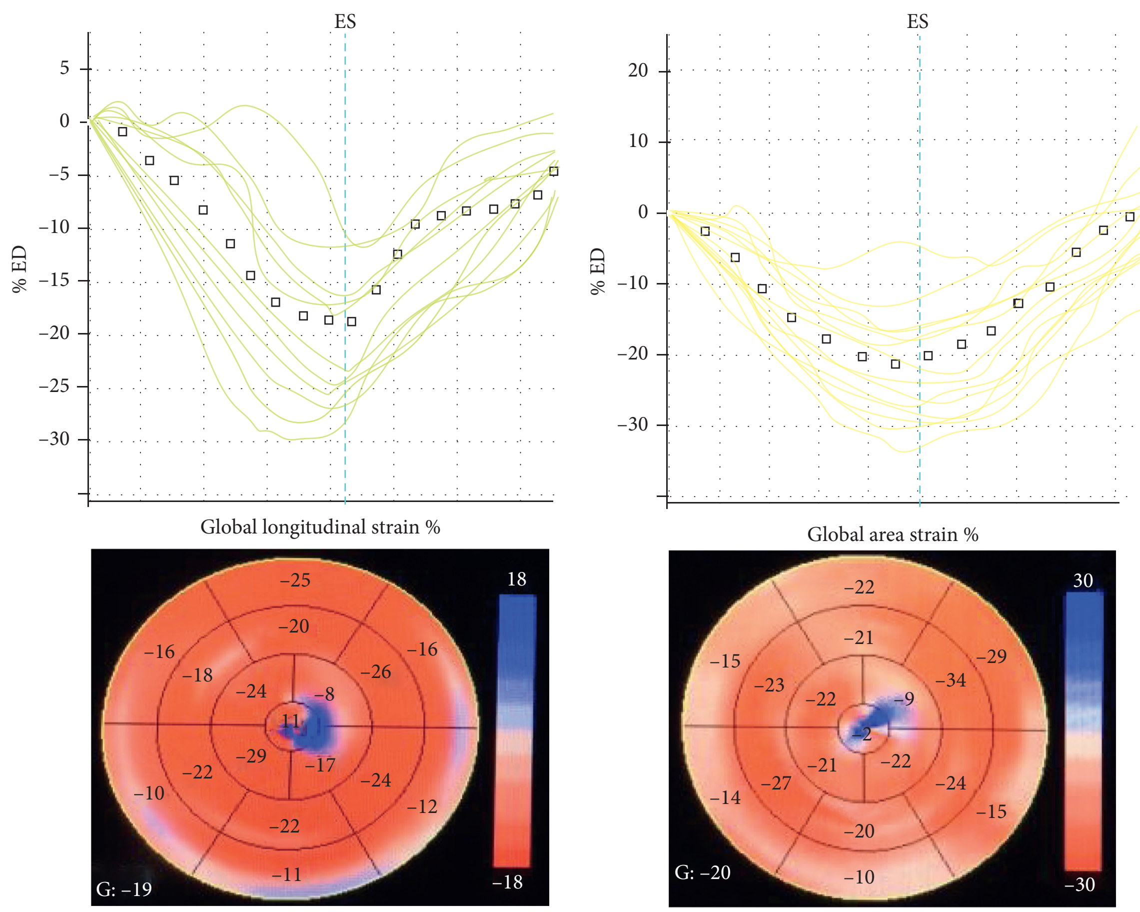
According to Korup et al., left ventricular dilatation began within three hours after acute myocardial infarction, and no further progress was made after that in the first six days [29]. Sakuma et al. reported that the optimal timing to detect myocardial changes for predicting LVR is 24 hours after reperfusion of the culprit artery [30]. Based on these studies, we assessed 3D myocardial contractions at 24 hours after PCI.

2.3. Coronary Angiography. All patients went through CAG to identify an infarct-related artery (IRA), measure the thrombolysis in myocardial infarction (TIMI) grade, and carry out revascularization through PCI. CAG was performed with a digital subtraction angiography machine. For coronary artery reperfusion therapy, subsequent PCI was performed to recover blood flow in the IRA. The blood flow level of the coronary artery was measured with the TIMI grade during CAG both at baseline and after coronary angioplasty. Patients with a TIMI grade ≥3 after coronary angioplasty were included in the statistical analysis.

2.4. Statistics. All statistical analyses were performed using IBM SPSS 21.0 (Chicago, IL, USA) software and Python with modules including Scikit-learn based on Abraham A's method [31], as well as Pandas, Numpy, Tensorflow, and Matplotlib. Data as continuous variables were expressed as means ± SD. Categorical variables were presented as absolute numbers and relative frequencies. Normal distribution of variables was checked with the Kolmogorov–Smirnov test. Continuous variables were compared using Student's *t*-test. Fisher's exact test or the chi-squared test was used to compare categorical variables.

In this study, before we compared 3D STE in a specific model, we used 15 risk factors to build six models including Decision Tree (DT), Random Forest (RF), eXtreme Gradient Boosting (eXGB), K-Nearest Neighbors (K-NN), Gaussian Naive Bayes (GNB), and Logistic Regression (LR) and compared the prediction power of all six models. The modules of the above machine learning methods were imported into Python so that no extra coding was needed. 5-fold cross-validation was performed to enhance the effect of testing and modeling capability. A receiver operator characteristic (ROC) curve was performed, and area under the curve (AUC), accuracy, sensitivity, specificity, and F1 score were calculated to evaluate classifiers.

In this study, data analysis proceeded according to the following steps. (1) Preliminary analysis: input patient data set and conduct one-way ANOVA, chi-square, and correlation analysis. (2) Model construction: input significant factors from step one, and import modules including DT, RF, eXGB, K-NN, GNB, and LR to Python. Each parameter was tested under 5-fold cross-validation that randomly selected 75% of the dataset as the training set and the rest 25% as the test set. (3) Tuning: conducted multiple program running and sorted out the best values of the model parameters such as n_estimators, max_depth, and



(a) (b)

Figure 1: Three-dimensional speckle tracking echocardiography (3D STE) analysis shows the result of global longitudinal strain (GLS) and global area strain (GAS) on a bull's eye depiction acquired by EchoPAC 112 (GE Medical System, Horten, Norway) from a patient. (a) Curves of instantaneous segmental 3D GLS in a patient (−18.9%). (b) Curves of instantaneous segmental 3D GAS in a patient (−21.8%).

random_state. (4) Model comparison: compared constructed models using AUC, accuracy, sensitivity, specificity, and F1 score. (5) 3D STE comparison: after the best classification method was confirmed, we compared 3D STE parameters through feature importance from the model. The data analysis work flow is displayed in Figure 2.

3. Results

3.1. Demographic and Clinical Characteristics. Initially, there were 172 patients enrolled in this study. 37 were further excluded due to the following reasons: (1) 13 patients with a TIMI grade < 3, (2) 12 patients due to poor myocardial tracking (>2 nonvisualized segments), (3) 10 patients for disagreement to participate, and (4) 2 patients died. Eventually, 135 patients (mean age, 54 ± 9, 88.9% males) were included in our study.

Patients were divided into two groups according to the occurrence of LVR. Table 1 displays baseline demographic and clinical characteristics. Age, sex, body mass index, body surface area, medical history, angiographic findings, blood tests findings as well as medication during follow-up were compared. Patients with LVR were older than patients without LVR (56.85 ± 11.80 yrs vs. 53.22 ± 7.92 yrs, $p = 0.044$, S). There is no significant difference among the other characteristics.

3.2. Echocardiographic Data. Baseline and three-month follow-up standard echocardiographic parameters as well as baseline 3D STE parameters are presented in Table 2. 26 patients (19.3%) were defined as LVR (>20% increase in LVEDV), and 109 patients (80.7%) did not have LVR. No significant differences were found in baseline standard echocardiographic characteristics between LVR and non-LVR patients. Follow-up LVEDV, LVESV, and LVEF were all significantly different between the two groups (respectively, 126.94 ± 19.77 vs. 105.32 ± 25.53, $p < 0.001$; 62.39 ± 14.12 vs. 47.86 ± 18.34, $p < 0.001$; 51.43 ± 7.00 vs. 55.42 ± 8.79, $p = 0.025$). Follow-up LVMI was not significant between the LVR and non-LVR patients.

A 3D STE assessment was carried out 24 hours after effective PCI (defined as a TIMI grade ≥ 3). The results are also presented in Table 2. 3D GLS and 3D GRS in patients with LVR were significantly reduced (respectively, $-9.90 \pm 2.60\%$ vs. $-12.99 \pm 3.10\%$, $p < 0.001$ and $28.13 \pm 7.13\%$ vs. $32.29 \pm 9.43\%$, $p = 0.037$).

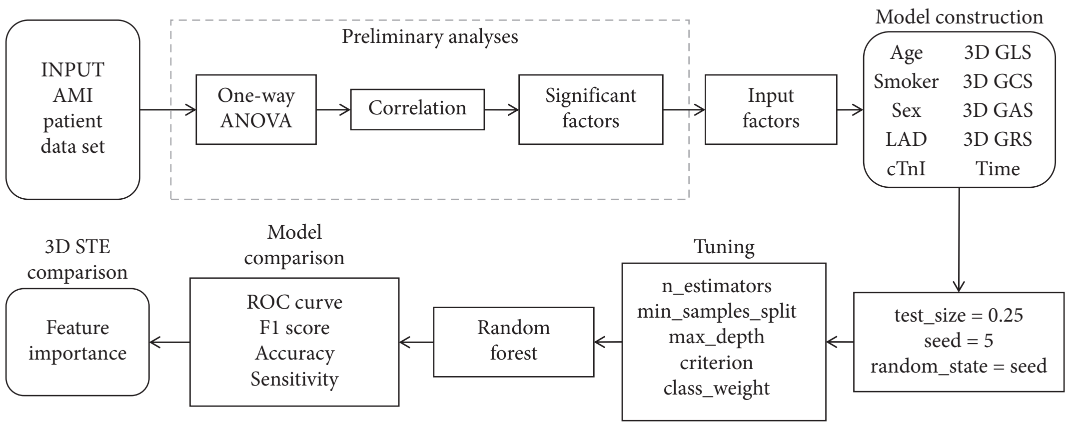


Figure 2: Data analysis work flow.

Table 1: Demographic and clinical characteristics.

	LVR ($n = 26$)	Non-LVR ($n = 109$)	p
Age, yrs	56.85 ± 11.80	53.22 ± 7.92	0.044
Male, %	88.5	89.0	NS
Body mass index, kg/ m^2	25.67 ± 2.65	24.57 ± 2.77	NS
Body surface area, m^2	1.75 ± 0.18	1.72 ± 0.14	NS
Medical history			
Hypertension (%)	46.2	42.2	NS
Diabetes (%)	42.3	26.6	NS
Smoking (%)	84.6	89.9	NS
Angiographic findings			
Time to reperfusion (h)	12.69 ± 5.33	10.81 ± 5.67	NS
Multivessel disease (%)	46.2	49.5	NS
LAD as the IRA (%)	65.4	57.4	NS
Blood tests findings			
cTnI	11.54 ± 6.77	9.84 ± 8.49	NS
SCr, μmol/l	85.92 ± 19.05	84.69 ± 21.75	NS
Medications during follow-up			
Antiplatelets (%)	100	100	—
ACEI/ARB (%)	100	95.4	NS
β-Blockers (%)	100	95.4	NS
Statins (%)	100	100	—

LAD: left anterior descending branch. IRA: infarct-related artery. ACEI: angiotensin-converting enzyme inhibitors. ARB: angiotensin receptor blockers. NS: $p > 0.05$, nonsignificant.

Table 2: Echocardiographic characteristics according to the occurrence of LVR.

	LVR ($n = 26$)	Non-LVR ($n = 109$)	p
LVEDV (baseline) (ml)	99.68 ± 16.56	105.431 ± 25.07	NS
LVEDV (follow-up) (ml)	126.94 ± 19.77	105.32 ± 25.53	<0.001
LVESV (baseline) (ml)	47.75 ± 9.96	48.98 ± 18.40	NS
LVESV (follow-up) (ml)	62.39 ± 14.12	47.86 ± 18.34	<0.001
LVEF (baseline) (%)	51.70 ± 6.23	54.40 ± 8.55	NS
LVEF (follow-up) (%)	51.43 ± 7.00	55.42 ± 8.79	0.025
LVMI (baseline) (g/ m^2)	79.79 ± 19.00	85.82 ± 9.33	NS
LVMI (follow-up) (g/m^2)	81.87 ± 19.34	85.54 ± 8.79	NS
3D GLS (%)	−9.90 ± 2.60	−12.99 ± 3.10	**<0.001**
3D GCS (%)	−14.10 ± 7.53	−18.07 ± 19.49	0.071
3D GAS (%)	−19.72 ± 3.84	−21.33 ± 6.28	NS
3D GRS (%)	28.13 ± 7.13	32.29 ± 9.43	**0.037**

LVEDV: left ventricular end-diastolic volume. LVESV: left ventricular end-systolic volume. LVEF: left ventricular ejection fraction. LVMI: left ventricular mass index. 3D GLS: three-dimensional global longitudinal strain. GCS: global circumferential strain. GAS: global area strain. GRS: global radial strain.

3.3. LVR Risk Factors. A correlation analysis was conducted to find out possible risk factors that have impact in predicting LVR. The results are presented in Table 3. Age, 3D GLS, 3D GCS, and 3D GRS were correlated with the occurrence of LVR. Among all of the 3D STE parameters, the r value of 3D GLS is the best, the second is 3D GRS, and the third is 3D GCS. In this correlation analysis, 3D GAS does not correlate with the occurrence of LVR.

Univariate analysis showed that 3D GLS, 3D GRS, and LVMI were associated with LVR occurrence. The odds ratio (OR) and 95% CI for each of 3D STE parameters along with other factors are displayed in Table 4. One of the important findings in the univariate analysis was that 3D GLS was the best predictor of LVR occurrence (OR, 1.374; 95% CI, 1.176–1.604; $p < 0.001$). And 3D GRS was also a good predictor (OR, 0.949; 95% CI, 0.903–0.998; $p = 0.040$). Further assessment of these factors was conducted by using machine learning methods to build models that contained most of the clinically important factors.

3.4. LVR Predictive Models. DT, RF, eXGB, K-NN, GNB, and LR were applied to construct models with 15 clinical risk factors including age, sex, smoking, BMI, body surface area, serum creatinine, cTnL, time to perfusion, left anterior descending branch occlusion as the infarct-related artery, multivessel occlusion, LVMI, and four 3D STE parameters.

Table 3: The correlation of factors with LVR occurrence.

Factors	r	p value
Age	0.174	**0.043**
cTnI	0.134	0.121
LAD	0.064	0.462
Sex	−0.007	0.939
TTP	0.129	0.137
Smoker	−0.066	0.444
Multivessel	−0.027	0.758
3D GLS	0.396	**<0.001**
3D GAS	0.139	0.107
3D GCS	0.179	**0.038**
3D GRS	−0.185	**0.031**
LVMI	−0.106	0.220
Scr	0.036	0.677

TTP: time to perfusion. BMI: body mass index.

Table 4: The univariate analysis of LVR predictive factors.

Factors	OR	95% CI	p value
3D GLS	1.374	1.176–1.604	**<0.001**
3D GAS	1.047	0.974–1.125	0.214
3D GCS	1.059	0.992–1.131	0.087
3D GRS	0.949	0.903–0.998	**0.040**
Age	1.049	0.998–1.104	0.061
LVMI	0.962	0.925–1.000	**0.047**
Scr	1.003	0.983–1.023	0.789

The constructed models were then compared to show which was the best in predicting LVR in this sample.

Merged ROC curves of all six classifiers are presented in Figure 3. Table 5 shows all the evaluation parameters of the constructed models. As a result, the RF model predicted LVR with the best AUC of 0.96, the best accuracy of 90.48%, and the second best specificity of 94.12%, surpassing the other models. eXGB ranked second to RF with an AUC of 0.90. DT and LR ranked third with equal AUCs of 0.83. The K-NN model had an AUC of 0.77, and GNB had the lowest AUC of 0.60. LR and K-NN had the best sensitivity (94.64% and 92.86%).

Since the RF model was the best in this work, we further ran a visualization of the model structure. The structure of one of the decision trees that formed the RF model is visualized and displayed in Figure 4. For each sample, a decision tree identifies it through multiple nodes and finally contributes a vote to decide if it is LVR or non-LVR. Each decision tree might have different features and different number of nodes. In the example given in Figure 4, the decision tree votes its decision through three processes: first, the value of a sample's age; second, the BSA or 3D GLS; and final, the BSA or age.

3.5. Comparison of Different 3D STE Parameters in Predicting LVR. As a result of the above section, we found that RF can construct the best model to predict LVR, and consequently, we used such model to display the comparison of different 3D STE parameters' ability in predicting LVR. The model was trained under 5-fold cross-validation that randomly selected 75% of the sample as the training set ($n = 101$) and 25% of the sample as the test set. A feature importance analysis of the RF model was conducted, and the resulted diagram is displayed in Figure 5. The five most important features of the RF model were 3D GLS, age, 3D GCS, time to perfusion (TTP), and 3D GAS (feature importance: 0.146, 0.140, 0.089, 0.087, 0.087, respectively).

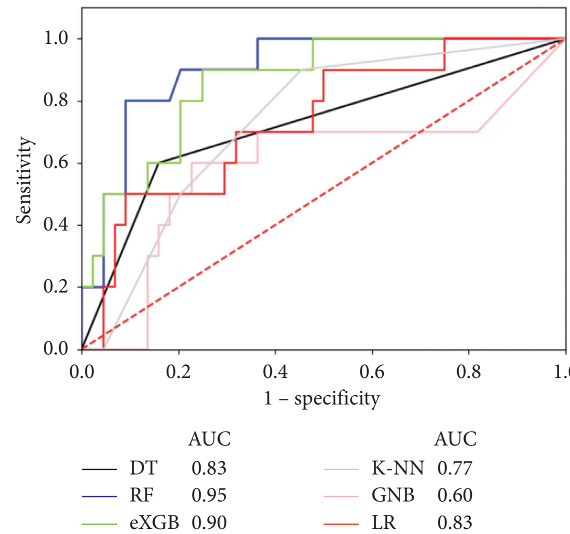


Figure 3: Comparison of the ROC curves of all models. The Random Forest model showed the best AUC of 0.96 (blue line), and eXGB showed the second best AUC of 0.90 (green line).

Table 5: Evaluation of constructed models.

Classifier	AUC	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1 score
DT	0.83	85.71	75.00	88.24	0.81
RF	**0.96**	**90.48**	50.00	**94.12**	**0.85**
eXGB	0.90	76.19	50.00	82.35	0.87
K-NN	0.72	83.82	94.64	**94.87**	0.83
GNB	0.60	70.73	44.44	79.49	0.79
LR	0.83	85.37	92.86	92.31	0.83

4. Discussion

It is difficult to predict which AMI patients will and which will not develop LVR after a successful PCI. We built several prediction models including the conventional model and machine learning models and discovered that RF achieved higher predictive power than other models in our work and used the Random Forest model to compare 3D STE parameters, finally discovering the overwhelming predictive value of 3D GLS, thus bringing more attention to possible future investigation into 3D GLS. Our study was the first to build a machine learning model for LVR prediction using factors that were mostly encountered in clinical practice plus four 3D STE parameters and compare 3D STE parameters values for predicting LVR in AMI patients after effective PCI by using the Random Forest method.

4.1. Predictive Models for LVR. In this study, we built a strong RF model for LVR prediction, using most of the

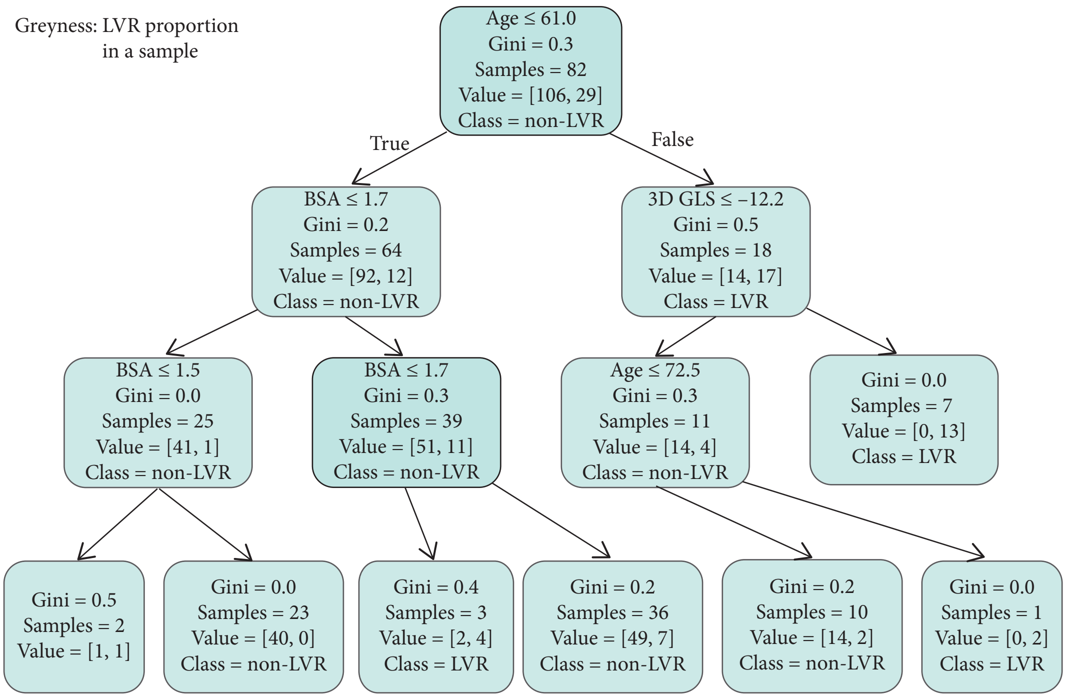


FIGURE 4: One of the decision trees in the resulted Random Forest model. A Random Forest model is a combination of multiple diverse decision trees. The decision tree displayed in this figure had age, 3D GLS, and BSA as classification features. The grayness in a box means the probability of a node being predicted as LVR. The parameter "sample" means the number of randomly chosen samples in this node. The parameter "Gini" measures the diversity of the samples, that is, the probability of inconsistent categories between two samples from a data set. The smaller the Gini index, the higher the purity of the sample. The parameter "class" means this node tendency of this vote.

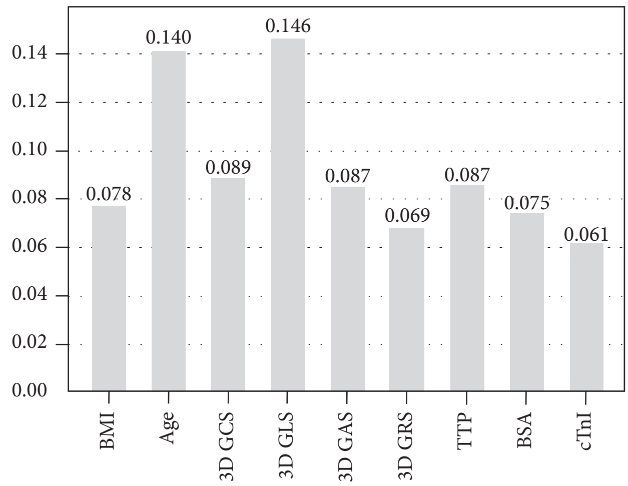


FIGURE 5: Feature importance in the Random Forest model. It showed that among all the 3D STE parameters, 3D GLS was the most important one, with an importance of 0.146, followed by 3D GCS with an importance of 0.089, 3D GAS with an importance of 0.087, and 3D GRS with an importance of 0.069.

important factors we encountered in the clinical practices. Some studies also built various predictive models for LVR in AMI patients. Bochenek et al. built a regression model using global longitudinal strain solely as a risk factor, with an AUC of 0.77 and accuracy of 80% [32]. Sugano et al. used 3D GCS to predict LVR, with an AUC of 0.73 and sensitivity of 84% [33]. Xu et al. built regression models that contained several clinical risk factors, but their work focused on evaluating these factors and did not assess these models' ability as a whole in predicting LVR [34]. Most of the studies build regression models to investigate the predictive value of a separate risk factor. We did not find studies that assessed models using various clinical risk factors, whether it included 3D STE parameters or not.

4.2. The Predictive Value of 3D STE for LVR. This study demonstrated that 3D GLS, among all the 3D STE parameters, is the strongest in predicting LVR in AMI patients undergoing effective PCI, the power of which exceeded other conventional markers such as cTnI, which is consistent with most similar studies [15, 32, 35–37]. We assumed that this phenomenon partly resulted from the intuitive feature of 3D STE in observing heart movement. The effect of cTnI on the occurrence of LVR is subtle, and the same goes for other serological biomarkers, while 3D STE detects detailed heart movement to predict probable myocardial changes in the future.

In our study, due to its original characteristics, the RF model constructed requires less calculation and fits better in real-world clinical cases, in which the samples are usually small and imbalanced.

4.3. Different 3D STE Parameters in Predicting LVR. In our model generated by RF, 3D GLS was the most important feature, as shown in Figure 5 (feature importance of 3D GLS: 0.146, age: 0.140, 3D GCS: 0.089, TTP: 0.087, and 3D GAS:

0.087). This result is in consistence with many other studies that used traditional biostatistical models. A reasonable explanation for the excellent performance of 3D GLS lies in the anatomic characteristic of the coronary artery and the capillary network inside the heart muscles. 3D GLS observes the most vulnerable myocardium layer, the sub-endocardium, which is anatomically far from the coronary artery and receives the least nutrition from its capillary network, rendering it the most vulnerable to coronary artery blockage. These myofibrils are the first to show abnormality in a heart attack and remain poorly cared for after the revascularization, in which the affected endocardial movement is uncoordinated, and the amplitude is reduced.

In one of our previous studies, we compared 3D STE parameters with 2D STE in predicting LVR in ST-elevated myocardial infarction patients, coming to the conclusion that 3D GRS was the second best 3D STE parameter, followed by 3D GAS, while 3D GCS showed no predictive effect [36]. However, in this study, we had a different result. 3D GCS was the second best 3D STE parameter, followed closely by 3D GAS (feature importance 0.089 and 0.087). As Random Forest commonly has a better result in small and imbalanced sample and we included more risk factors in this work, we believe this result is more accurate, but further investigation is needed to confirm this theory.

4.4. Random Forest Model. In this work, we decided to compare the 3D STE parameters with the RF model for it had the best performance, outmatching DT, eXGB, K-NN, GNB, and LR models. The DT is simple in calculation and vastly used, but overfitting remains as one of its main disadvantages, which might be the reason why it did not have a good performance in this work. The eXGB is a highly efficient and optimized distributed gradient boosting library [38]. It is highly flexible and portable, which excels in big data analysis. However, the imbalance of a dataset can affect the training of an eXGB model, which explains why it was not as good as RF in this work. The K-NN algorithm searches the most similar training samples to predict the observation value of a new sample. It usually performs well in numerical data and discrete data, but performs badly when the sample is imbalanced, which is quite opposite to the RF. The Gaussian NB usually has a good performance in small sample studies, but in this study, it still performed badly. We assumed the main reason was that many of the variables in this study were discontinuous, which may affect the power of Gaussian NB. The other reason is that the Gaussian NB presumed that none of the variables interact with each other, which is unlikely in this study, and this may heavily affect the predictive power of the Gaussian NB model, and the LR performed badly in this work for the same reason.

Random Forest is a highly flexible machine learning algorithm that performs well in small and imbalanced samples [19]. That explains why it excelled in this study. It is based on bagged decision trees that are trained on bootstrap samples. And these decision trees combined and formed a Random Forest. Its coding was uploaded in the supplement files.

In the our RF model, Gini impurity was used to measure the partitioning attribute. Assuming that the proportion of the k^{th} sample in the current sample set D is p_k ($k = 1, 2, \ldots, K$), the purity of the dataset D can be measured by the Gini value:

$$\mathrm{Gini}\,(D) = \sum_{k=1}^{K} \sum_{k' \neq k} p_k p_{k'} = 1 - \sum_{k=1}^{K} p_k^2. \quad (1)$$

When Gini (D) = 0, the sample was the purest, and then, the category extracted was of the same type, either LVR or non-LVR. When Gini (D) = 0.5, the probabilities of two categories were the same, meaning the tree cannot distinguish LVR or non-LVR. Therefore, the smaller the Gini (D), the higher the purity of the dataset D. For the tuning of parameters, see the supplementary materials (available here).

An RF can be described as a cluster of many decision trees in which each decision tree independently votes for the most possible classification at input x [39, 40]. It is a highly flexible and expandable machine learning algorithm based on the concept of integrated learning, which integrates many basic decision tree units into a "forest." Every decision tree can classify a result through its own features (as shown in Figure 4), and the RF assembles the decisions of all these trees and gives the final decision. It is capable of simultaneously handling thousands of input variables without deletion, and the speed of RF calculation is a lot faster than traditional models.

In this study, we showed that RF is a more powerful method of predicting LVR after AMI. Furthermore, due to its flexibility, scalability, and faster calculation speed, RF is promising in the clinical practice of predicting LVR after AMI.

4.5. Clinical Implications. Our study built LVR predictive models with machine learning techniques and discovered that the best 3D STE parameters in predicting LVR after AMI is 3D GLS, and the second is 3D GCS. This model is more accurate because (1) it included 15 risk factors that were encountered regularly in clinical practice and (2) in clinical practice, the sample is always a small and imbalanced one. And this model is more rapid for it needs less calculation steps. Though we have not verified the value of this model in clinical practice, because it is still in its early stage, we believe more and more research will transfer the value of this work into clinical application.

Rapid prediction of future LVR in patients with AMI after PCI is instructive for cardiologists to stratify patients, especially for the detection of patients with poor prognosis. These patients need careful treatment plans to avoid relapse, HF deaths, heart transplantation, and to prevent major ventricular arrhythmia. Further research is required to help supplement the clinical benefits of the model and 3D STE.

4.6. Limitations. One of the limitations of this study is that the positive and negative proportion was imbalanced (26 LVR patients vs. 109 non-LVR patients), thus affecting the robustness of the machine learning models. Though RF can reduce this effect, a more balanced data set is still required to give a more convincing result. The other limitation is this study only represents the results of an ultrasound machine from one kind of vendor, so it may be less comparable to results from different vendors. The rigor of this work should be demonstrated by using different ultrasound machines with the similar size of samples.

5. Conclusions

There are two main conclusions of this study: (1) the machine learning method Random Forest constructs the best model under the circumstances of predicting LVR with 3D STE; and (2) for AMI patients undergoing effective PCI, the 3D STE parameter 3D GLS acquired at 24 hours after the PCI is highly likely to best predict the occurrence of LVR.

Data Availability

The data used to support the findings of this study are included within the supplementary information files.

Conflicts of Interest

The authors declare that no conflicts of interest exist regarding the publication of this paper.

Authors' Contributions

Junda Zhong and Peng Liu contributed equally to this work.

Acknowledgments

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Supplementary Materials

1. Tuning: the tuning of parameters in the construction of a Random Forest model. 2. Random forest construction: the coding of the construction of Random Forest. 3. Raw data: raw data of the research, including all the data of all patients used in the statistical analysis. (*Supplementary Materials*)

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Research Article

An LSTM-Based Prediction Method for Lower Limb Intention Perception by Integrative Analysis of Kinect Visual Signal

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Recently, computer vision and deep learning technology has been applied in various gait rehabilitation researches. Considering the long short-term memory (LSTM) network has been proved an excellent performance in learn sequence feature representations, we proposed a lower limb joint trajectory prediction method based on LSTM for conducting active rehabilitation on a rehabilitation robotic system. Our approach based on synergy theory exploits that the follow-up lower limb joint trajectory, i.e. limb intention, could be generated by joint angles of the previous swing process of upper limb which were acquired from Kinect platform, an advanced computer vision platform for motion tracking. A customize Kinect-Treadmill data acquisition platform was built for this study. With this platform, data acquisition on ten healthy subjects is processed in four different walking speeds to acquire the joint angles calculated by Kinect visual signals of upper and lower limb swing. Then, the angles of hip and knee in one side which were presented as lower limb intentions are predicted by the fore angles of the elbow and shoulder on the opposite side via a trained LSTM model. The results indicate that the trained LSTM model has a better estimation of predicting the lower limb intentions, and the feasibility of Kinect visual signals has been validated as well.

1. Introduction

Stroke is a disease caused by acute rupture of blood vessels or vascular occlusion [1, 2]. About 15 million people suffer from it every year globally [3]. Hemiplegia is the major sequela of most stroke survivors which affects the quality of their daily life in the home, workplace, and community [4]. It presents with the weakness of one entire side of the body. Due to limb weaknesses leading to an inability to properly performing, hemiplegia patients could lose a number of motor functions especially the walking function [5, 6]. Walking abnormality makes performing everyday activities in the home, workplace, and community more difficult [7, 8].

Recovery of the walking ability for hemiplegia patients is crucial in order to perform daily activities [9, 10]. Key components of gait recovery are high-intensity, skill-oriented, and task-specific [11, 12]. Due to physically exhaustion of therapists to repeat hundreds of complex gait cycles in a training session [13], an amount of rehabilitation gait training robots have been developed to provide robotic assistance [14]. Robotic-assisted gait training refers to the rehabilitation therapists how to assist the patient in performing the gait cycle [15]. Considering the limb weaknesses leading to difficulty in supporting the body weight in training, current rehabilitation could support body weight to allow the lower limbs to maintain a pattern during gait training such as Lokomat [16]. These gait robot trainers passively move the patients on a treadmill. However, the control systems of most commercial robotic systems are passive in nature because the training subject is not considered in the system. By increasing active participation [17], the dependence of patients on robot assistance can be reduced by improving the effectiveness of rehabilitation training. Thus, we should make the robots include the ability that collects quantitative gait data to generate sensory stimulation synchronized to gait patterns.

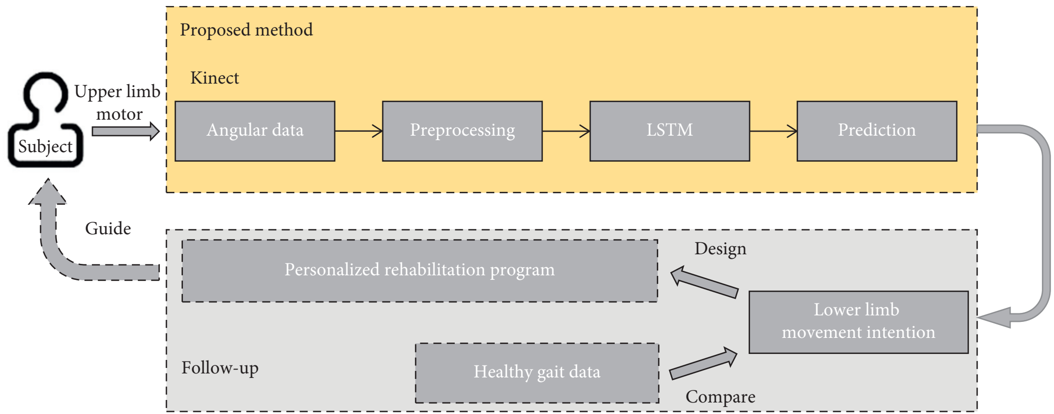

Figure 1: The framework of our method and follow-up studies.

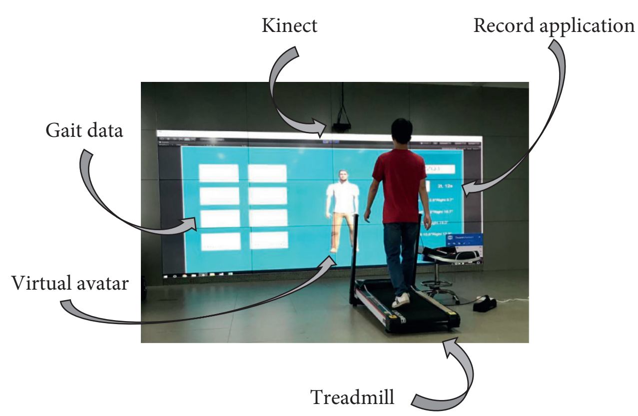

Figure 2: Treadmill and Kinect layout (the treadmill was angled at 45 with respect to the Kinect sensor, with the front of the treadmill positioned 140 cm to the right and at a distance of 150 cm in front of the sensor; the base of the Kinect sensor rested 100 cm above the floor).

To develop a noncontact signal prediction for an active rehabilitation robotic system, the synergy that is initiated by weight-bearing over the involved limb and supporting the human body was taken into consideration [18, 19]. Twitchell et al. proved that abnormal synergy is a motor impairment in patients with stroke [20]. The main factor that limited the motor rehabilitation of patients with stroke is abnormal synergy [21]. Studies have shown that interlimb and intralimb coordination of lower limbs in patients after stroke is diverse from that in normal subjects [22]. In 2018, Zebin et al. proposed a prediction method via inertial sensors and LSTM methods to predict the angle trajectory of the impaired lower limb [23]. Simultaneously, the security and privacy of medical data are also crucial. Sandeep et al. developed a biometric-based security framework for wearable health monitoring systems to extract ECG signal, and it proved that time-domain based biometric features plays an important role in security [24]. Wu et al. proposed an adaptive computing-based random binary sequences generation method to provide a balance between processing time and security in wireless body sensor networks [25]. Cai et al. quantified the concurrent accuracy and the test-retest reliability of a Kinect V2-based upper limb functional assessment system [26]. Liao et al. proposed a motion intention recognition system based on the Kinect V2 sensor. It can successfully provide an adequate assistance with a lesser time delay compared with the system without Kalman filter [27].

Recently, the time series prediction model has been effectively applied to several studies [28]. Long short-term memory (LSTM) networks widely used to have done a good job on this issue in fields including gait recognition owing to the ability of processing and predicting the time series with very long intervals [29, 30]. It works effectively to extract the gait feature [11].

As shown in Figure 1, in this paper, a lower limb joint trajectory generation framework was proposed to drive the lower limb robot using the trajectory of healthy upper limbs. This study aimed to utilize upper limb Kinect information during walking to estimate sagittal plane hip and knee kinematics trajectories. The trajectories will be used for driving a rehabilitation robotic system in follow-up studies.

2. Methods

2.1. Experimental Setup and Data Acquisition. To obtain human gait data, we have built and evaluate our model that used a "virtual skeleton" produced by the Kinect sensor and

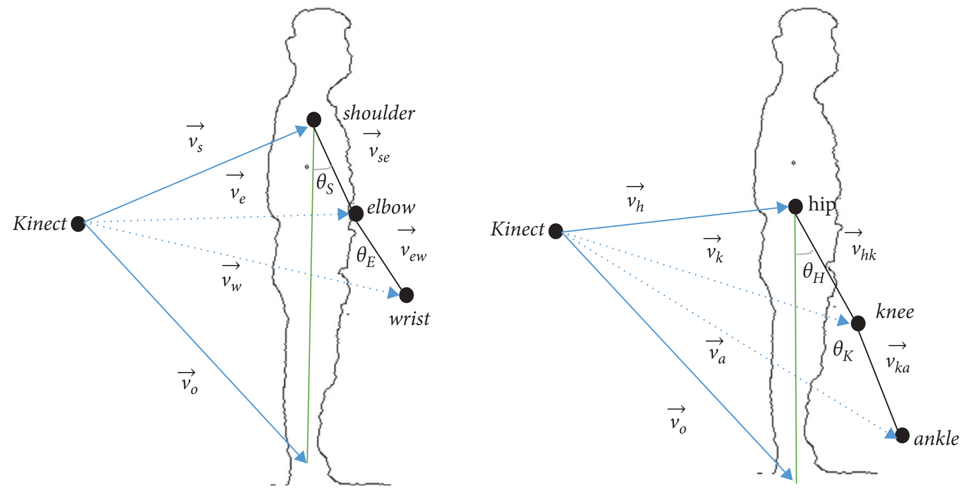

Figure 3: Determination of θ.

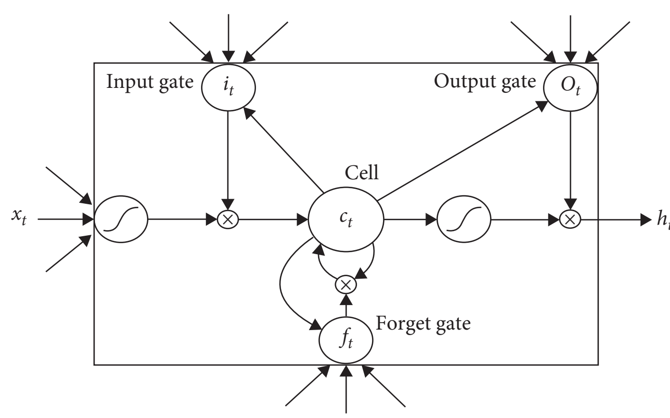

Figure 4: The structure of an LSTM neuron [36].

software. Kinect 2.0 provides a high-quality skeletal model to one user in front of the Kinect sensor, and Kinect SDK offers the tracking and detection of 25 different skeletal points, which could apply this skeletal data for feature extraction; the experimental setup is as shown in Figure 2.

Gait data were concurrently recorded by a Kinect sensor that provides approximately 30 skeleton frames per second [31]. Each participant wore a fitting and light color suit on the treadmill. In a 10 participants' database, they are generally divided into four walking velocities: 3.0, 3.5, 4.0, and 4.5 km/h.

The joint angle of the shoulder, ankle, hip, knee, arm of the right side, left knee, and hip in the sagittal plane were calculated based on the quaternion. For each joint of the Kinect virtual model, the x, y, and z coordinates are recorded. This study converts the joints into a vector for angle calculation. For each joint, the current position of the angle between a joint and a sagittal vector was recorded. Finally, we generate the following features: the angle in each of the frames, the difference in angle between consecutive frames, and these angular displacements providing basic gait characteristics.

2.2. Gait Joint Angle Design. The Kinect skeletal joints 3-D coordinated data reading is less susceptible to noise compared with their distance to the acquisition [32, 33]. Thus, for each limb, a shoulder joint angle was determined by considering the location of the shoulder and elbow in the Cartesian coordinate. The shoulder, elbow, hip, and knee position in Cartesian space are defined with four-vectors, the Kinect being at the origin of the 3-D space. The vector definition is formulated in equations (1)–(5). The angle of joints definition is formulated in equations (6)–(9):

$$\vec{v}_{se} = \vec{v}_s - \vec{v}_e, \quad (1)$$

$$\vec{v}_{ew} = \vec{v}_e - \vec{v}_w, \quad (2)$$

$$\vec{v}_{hk} = \vec{v}_h - \vec{v}_k, \quad (3)$$

$$\vec{v}_{ka} = \vec{v}_k - \vec{v}_a, \quad (4)$$

$$\vec{v}_{sag} = \vec{v}_s - \vec{v}_o. \quad (5)$$

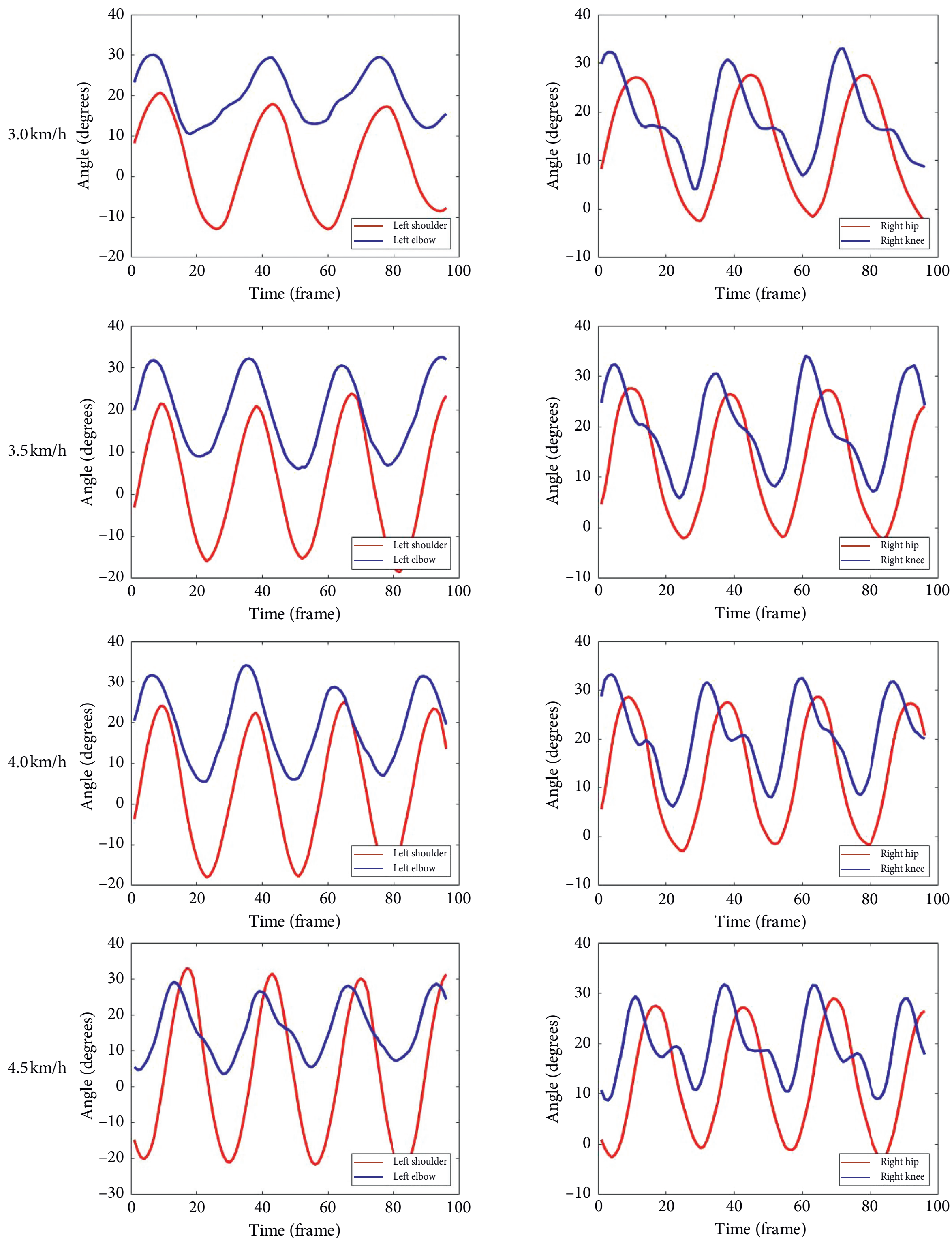

Figure 5: Left upper limb joint angle and right lower limb joint angle during walking at four velocities.

$$\theta_S = \cos^{-1}\left(\vec{v}_{se} \cdot \overrightarrow{v_{\mathrm{sag}}}\right), \tag{6}$$

$$\theta_E = \cos^{-1}\left(\vec{v}_{ew} \cdot \vec{v}_{\mathrm{sag}}\right), \tag{7}$$

$$\theta_H = \cos^{-1}\left(\vec{v}_{hk} \cdot \vec{v}_{\mathrm{sag}}\right), \tag{8}$$

$$\theta_K = \cos^{-1}\left(\vec{v}_{ka} \cdot \vec{v}_{\mathrm{sag}}\right), \tag{9}$$

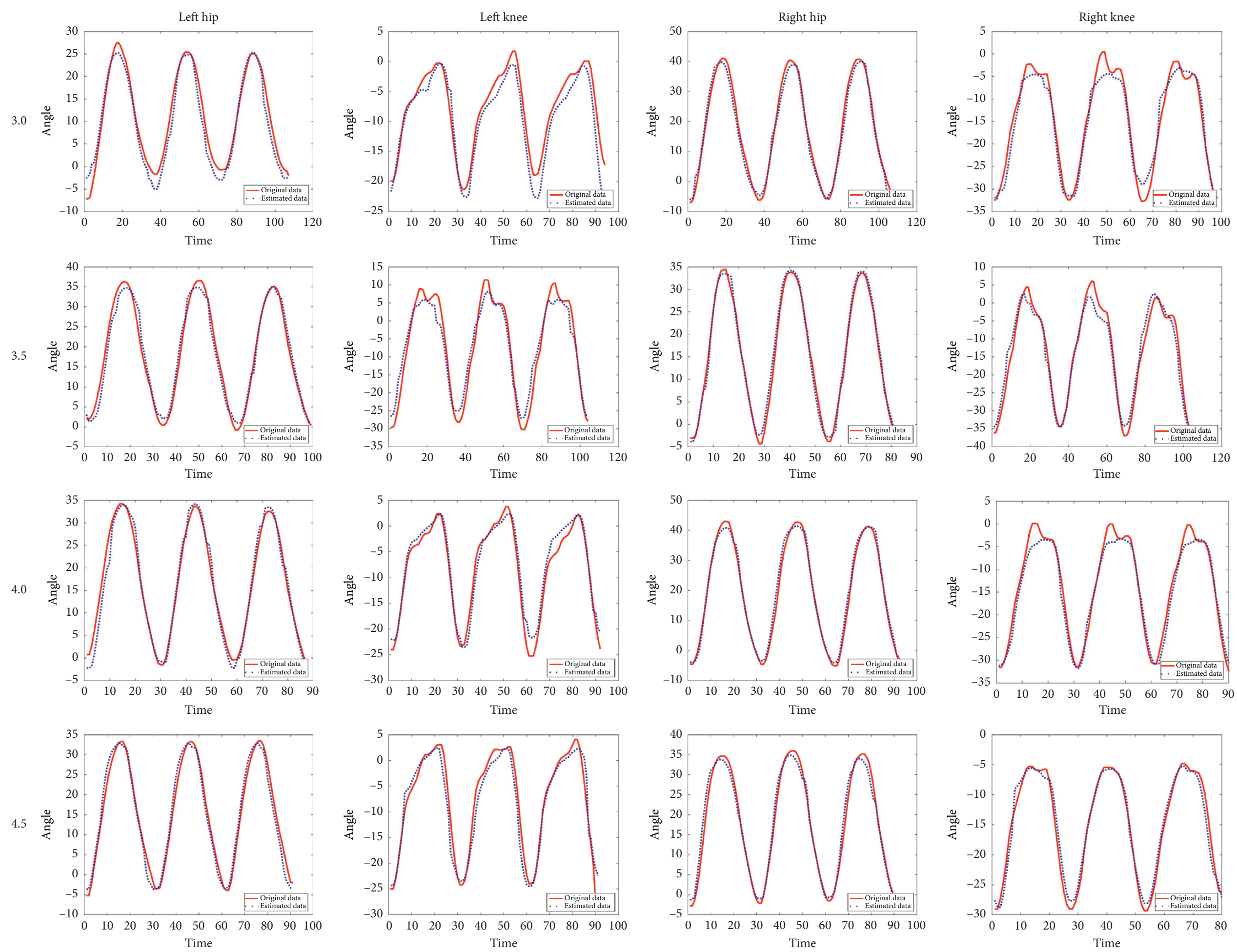

Figure 6: Estimated left hip and knee trajectories vs. original hip and knee trajectories through using the right shoulder and elbow in different velocities (3.0, 3.5, 4.0, and 4.5 km/h).

where $\vec{v}_{se}$, $\vec{v}_{ew}$, $\vec{v}_{hk}$, and $\vec{v}_{ka}$ are the 3-D vectors connecting the participants' shoulder to the elbow, elbow to the wrist, hip to the knee, and knee to the ankle, respectively, that is also depicted in Figure 3.

2.3. Long-Short Term Memory Network for Angle Prediction. In our proposed approach, trajectory generation is to apply the interlimb synergy extracted from healthy participants by LSTM to generate a trajectory-based on gait data [34, 35].

To solve the difficulties in training the RNN model caused by the "vanishing gradient" effect, the long-short term memory (LSTM) architecture has been proposed. Figure 4 illustrates a typical LSTM neuron. It contains one self-connected memory cell c_t and three multiplicative units, i.e., the input gate i_t, the forget gate f_t, and the output gate o_t.

The memory cell has a self-connected recurrent edge of weight 1, ensuring that the gradient can pass across many time steps without vanishing or exploding [29]. The input gate and forget gate govern the information flow into and out of the cell [37]. The output gate controls how much information from the cell is passed to the output h_t. The activations of the memory cell and three gates are given as follows:

$$\begin{aligned}
i_t &= \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i\right),\\
f_t &= \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f\right),\\
c_t &= f_t c_{t-1} + i_t \tanh\left(W_{xc}x_t + W_{hc}h_{t-1} + b_c\right),\\
o_t &= \sigma\left(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_{t-1} + b_o\right),\\
h_t &= o_t \tanh\left(c_t\right).
\end{aligned} \tag{10}$$

where $\sigma(x)$ is the logistic sigmoid function and defined as $\sigma(x) = 1/(1 + e^{-x})$, $w_{\alpha\beta}$ are the weight matrices connecting α and β, and b_β denotes the corresponding bias vectors.

3. Experiment

3.1. Experiment Implementation. Since stroke patients show a lower extremity weakness of walking [38, 39], we target in studying the spatial correlations of gait features by using neural networks. To get enough training gait data, 10 healthy participants (aged 23.3 ± 1.4years, height 169.1 ± 6.9cm, and weight 55.5 ± 6.5kg) were recruited from our laboratory. They were free of any physical condition or limitation which prevented them from walking on the treadmill. They were required to walk for 150s per velocity.

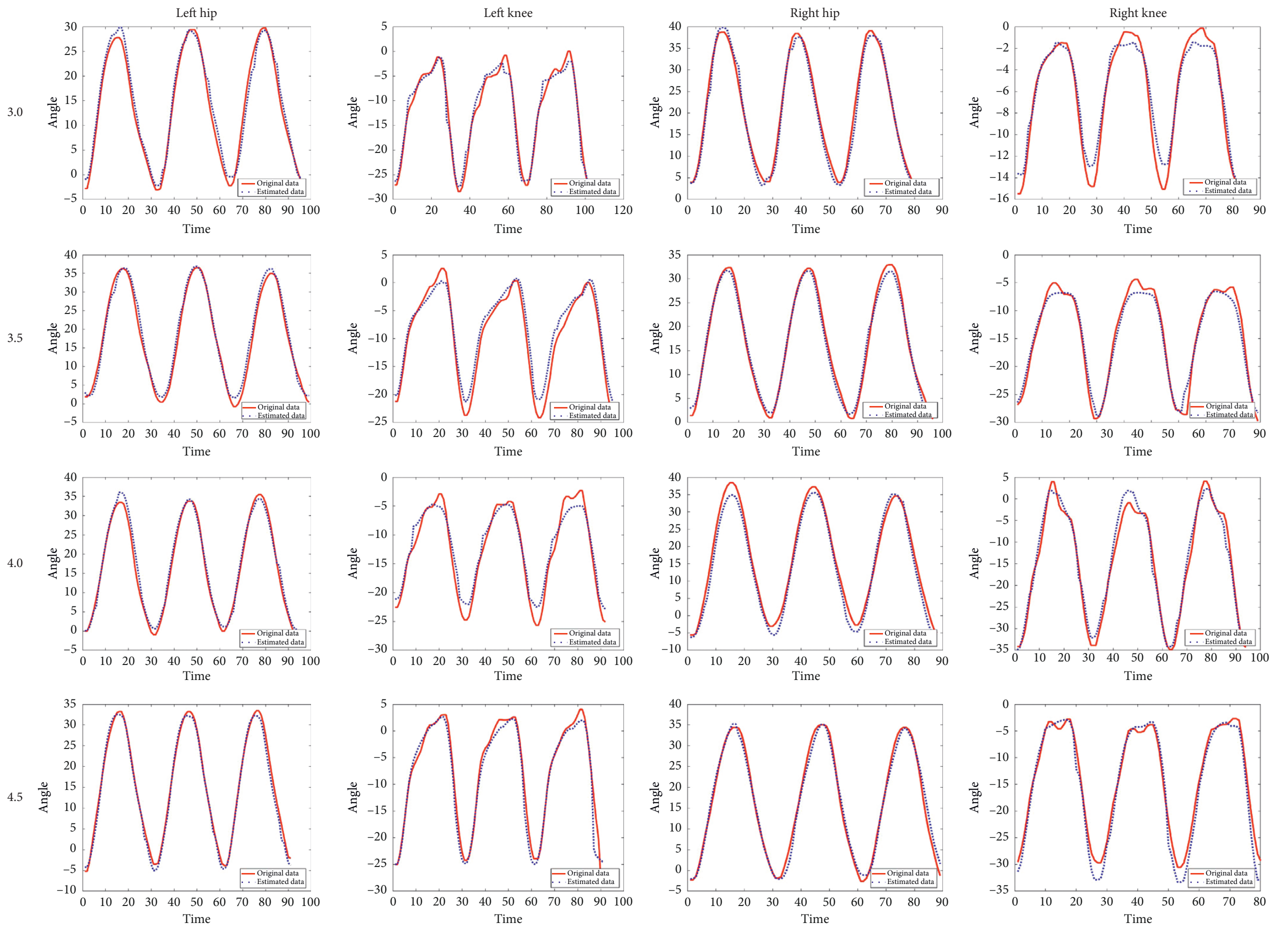

Figure 7: Estimated one side's hip and knee trajectories vs. original hip and knee trajectories through using the other side's shoulder, elbow, hip, and knee in different velocities (3.0, 3.5, 4.0, and 4.5 km/h).

For maintaining a stable recognition of the human body [40], the Kinect was placed at a height of 1 meter above the ground and the treadmill was set within 2.6 to 4 meters from the Kinect sensor.

During the experiment, there was a total of 10 (male/female:6/4) healthy participants enrolled. We prepared 40 gait feature data of upper and lower limbs from 10 subjects, while their skeletal data were captured by Kinect 2.0. Figure 5 illustrates a participant walking session and joints behavior during a gait cycle in different velocities.

Our experiments were implemented on the Tensorflow framework [36], a popular deep learning framework. The base learning rate was set to 0.0005, and the LSTM step size was set to 10 frames. The maximum number of iterations was set to 1000.

3.2. Results. This study estimated one side's gait data by using the other side's data based on the synergy. Figure 6 shows the estimated result of left hip joint and knee joint trajectories through using the right shoulder and elbow by LSTM. To validate the feasibility of LSTM synergy, we used right side upper limb joints and lower limb joints to predict left side lower limb and are shown in Figure 7; it shows the estimated result of one side's hip and knee trajectories through using the other side's shoulder, elbow, hip, and knee by LSTM. As can be seen from the figure, the error between the estimated trajectory and the original trajectory of the left hip and knee is low.

Results show that LSTM is a good approach for person identification based on gait recognition with Kinect. We also tested the quality of the prediction of the angular velocity, and we applied the root-mean-squared error (RMSE) to evaluate the model after each run. Here, we compared RMSE between the estimated angle and original angle in four different velocities on prediction based on LSTM. The result is shown in Figures 8 and 9. Especially, RMSE was poor for hip and knee joint angles at 3.0 km/h than the other three velocities by using the joints of the upper limb (Table 1); however, it was relatively good by using the joints of the upper limb and lower limb (Table 2).

4. Discussion

To estimate the hip and knee trajectory by using the upper limb joints trajectories, we applied the Kinect 2.0 to track the upper limb and lower limb sagittal plane movement in the walking period. The human body is in a continuous dynamic

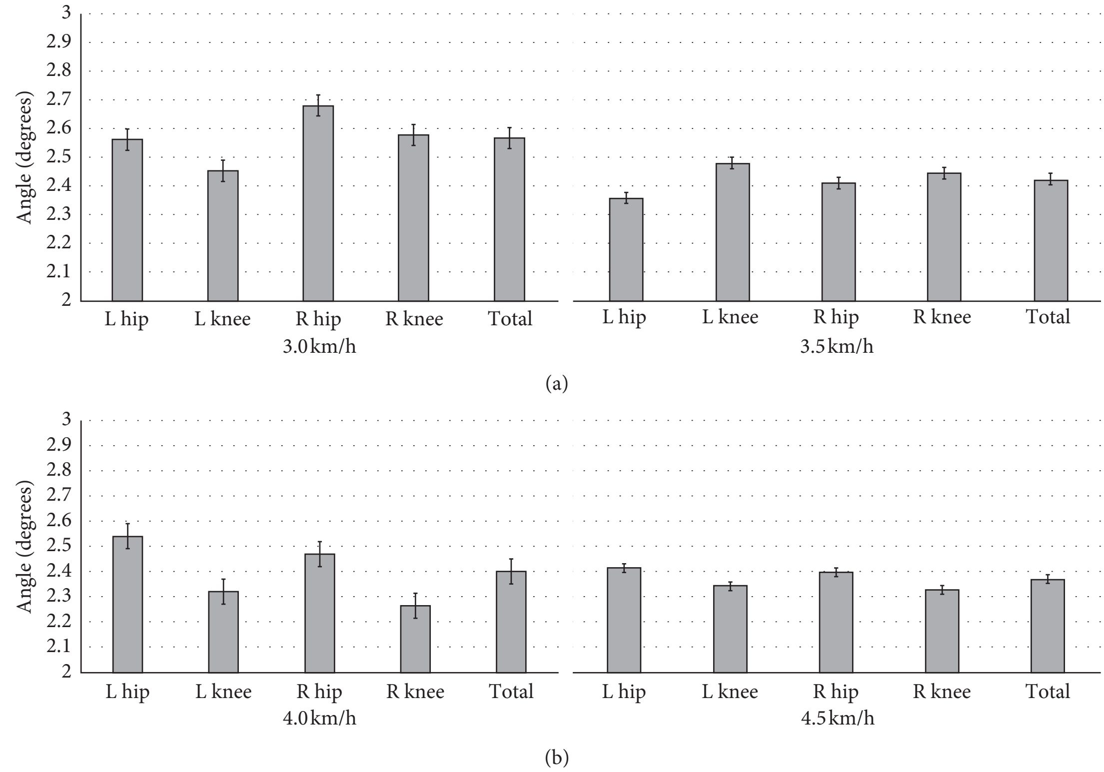

Figure 8: RMSE of LSTM estimation on hip and knee extension and flexion using the right shoulder and elbow in different velocities for Kinect.

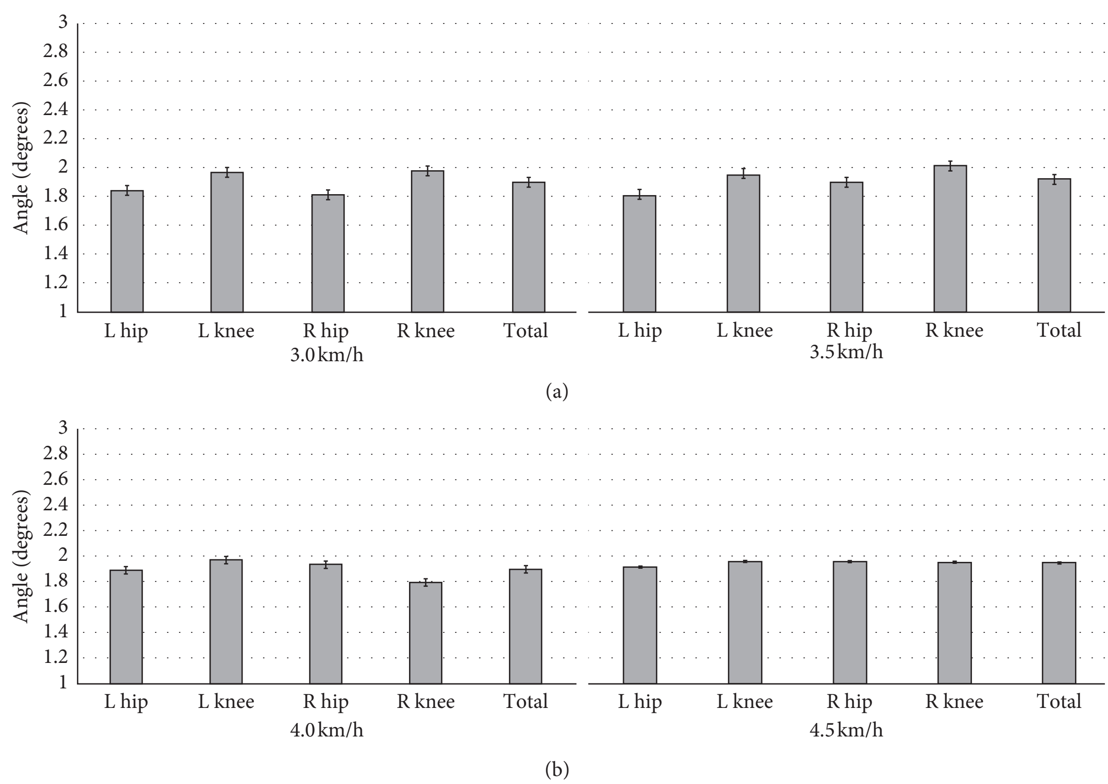

Figure 9: RMSE of LSTM estimation on hip and knee extension and flexion using the shoulder, elbow, hip, and knee in different velocities for Kinect.

Table 1: Mean and standard deviation at four velocities for Kinect by using the joints of the upper limb.

	3.0 km/h	3.5 km/h	4.0 km/h	4.5 km/h
L hip	2.56 ± 0.89	2.36 ± 0.69	2.54 ± 0.91	2.41 ± 0.58
L knee	2.45 ± 0.78	2.48 ± 0.70	2.32 ± 0.51	2.34 ± 0.64
R hip	2.68 ± 0.76	2.41 ± 0.65	2.47 ± 0.33	2.39 ± 0.57
R knee	2.58 ± 0.81	2.45 ± 0.54	2.26 ± 0.57	2.33 ± 0.69
Total	2.57 ± 0.81	2.43 ± 0.65	2.39 ± 0.58	2.37 ± 0.62

Table 2: Mean and standard deviation at four velocities for Kinect by using the joints of the upper limb and lower limb.

	3.0 km/h	3.5 km/h	4.0 km/h	4.5 km/h
L hip	1.84 ± 0.37	1.82 ± 0.39	1.89 ± 0.59	1.92 ± 0.36
L knee	1.97 ± 0.35	1.96 ± 0.44	1.97 ± 0.38	1.96 ± 0.43
R hip	1.81 ± 0.26	1.90 ± 0.43	1.94 ± 0.41	1.96 ± 0.29
R knee	1.98 ± 0.55	2.02 ± 0.33	1.79 ± 0.25	1.95 ± 0.47
Total	1.90 ± 0.38	1.93 ± 0.39	1.89 ± 0.41	1.95 ± 0.38

state during walking. In this study, the LSTM model was developed, and its performances were compared using RMSE. Because there is no need to go through a process of selecting features and having better stability, we chose it to estimate our trajectory. The LSTM model in this study showed improved results, and RMSE has been introduced above. It can see that LSTM has a better estimation on predicting the gait trajectory, which included human interlimb synergy. This model showed excellency in modeling that with the change over time such as walking to predict the data of current time from information in the previous step.

As the pace velocity increases, we can see that the accuracy of the prediction is getting higher. In the case of 3.0 km/h velocity, the gait prediction trajectory is relatively poor; however, in the case of 4.5 km/h velocity, LSTM presents the effect of prediction is quite amazing. This result indicates that when humans walk at 4.5 km/h velocity, the upper and lower limbs on the two sides are highly correlated.

In various velocities, the trajectory prediction effect of the knee joint is generally higher than that of the hip joint, except for the velocity in 3.5 km/h.

When using the joints of the upper limb and lower limb to estimate the hip and knee trajectory, we can get an obvious better estimation accuracy. From Table 2, we can see that the RMSE is basically maintained within 2, which is better than merely used the upper limb to predict hip and knee trajectory. Otherwise, in this case, the accuracy of the estimated hip trajectory is better than estimated knee trajectory, respectively; compared with the right hip, the left hip trajectory is great. In Figure 8, the trajectory only based on the upper limb trajectory still has a good estimation performance. It was concluded that LSTM has good exploitation in gait features.

This study has a limitation of not applying data of patients with stroke to the learning model for lower limb trajectory prediction. However, the study is to suggest the possibility of estimating the lower limb trajectory by using the upper limb trajectory and an artificial neural network model. In the next research, we can apply various data for the training model.

5. Conclusion

In this paper, an artificial neural network model was developed to estimate the lower limb joints trajectory of a complete gait cycle by using the joints of the opposite side. Accuracies of using the upper limb joints and the upper and lower limb joints to estimate another side lower limb joints were compared. As a result, the model showed RMSE values within 3.0. These trials demonstrate that this model can be used safely as a gait training intervention for those stroke patients. It suggests that the exoskeletal gait rehabilitation robot can apply this model to help patients try to walk like normal people.

Data Availability

The raw data required to reproduce these findings cannot be shared at this time as the data also forms part of an ongoing study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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