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Research Article

Towards Automated Multiclass Severity Prediction Approach for COVID-19 Infections Based on Combinations of Clinical Data

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The recent dramatic expansion of the COVID-19 outbreak is placing enormous strain on human society as a whole. Numerous biomarkers are being investigated in an effort to track the condition of the patient. This could interfere with signs of many other illnesses, making it more difficult for a specialist to diagnose or predict the severity level of the case. As a result, the focus of this research was on the development of a multiclass prediction system capable of dealing with three severity cases (severe, moderate, and mild). The lymphocyte to CRP ratio (C-reactive protein blood test) and SpO_2 (blood oxygen saturation level) indicators were ranked and used as prediction system attributes. A machine learning model based on SVMs is created. A total of 78 COVID-19 patients were recruited from the Azizia primary health care sector/Wasit Health Directorate/Ministry of Health to form different combinations of COVID-19 clinical dataset. The outcomes demonstrate that the proposed approach had an average accuracy of 82%. The established prediction system allows for the early identification of three severity cases, which reduces deaths.

1. Introduction

The ongoing COVID-19 pandemic, caused by the SARS-CoV-2 virus, poses an unprecedented public health crisis to the entire world. To date, of 105 million total cases, 2.28 million people were infected and died. Of currently infected patients, 98% are mild and moderate cases, while 2% are severe cases. Medical services suffer from overcrowding of severity cases, which leads to the inability of intensive care resources [1]. Several current studies focused on severity cases, which have a high mortality rate compared to other cases [2]; they also focused on the tasks of intensive care management [3], special groups [4], and comorbidities [5].

Medically, the biomarkers behavior same as C-reactive protein (CRP) levels can be used in the early diagnosis of pneumonia, and patients presenting with severe pneumonia had high CRP levels [6]. Besides, shortness of breath appears because of hypoxia, which means $SpO_2 < 90\%$, but with COVID-19, the normal level of SpO_2 is reduced and maybe even down to 70%, 60%, or 50%, although the patient had not have a feeling of breathlessness. SpO_2 is a major element in the understanding and management of patient's care. It measures how much hemoglobin currently bounds to oxygen as compared to how much hemoglobin stays unbound. To monitor blood oxygen saturation, a noninvasive medical device called a pulse oximeter is placed over a person's finger. It is routinely used in the intensive care unit (ICU), operation theatre, and postoperative ward in a hospital. Results of investigation other than RT-PCR tests such as normal or low total count of WBC, neutrophil, lymphopenia, high C-reactive protein (CRP), lymphocyte ratio, low procalcitonin, significant elevation of D-dimer, bilateral pneumonia in CXR, serum ferritin level, ground-glass opacity (GGO), and crazy paving appearance in CT scan of chest suggest the existence of COVID-19 during this pandemic situation [7]. All these biomarkers are important in monitoring the condition of a patient with COVID-19, but a large number of these biomarkers make it difficult for the doctors and emergency systems to decide or predict the severity of the patients.

At present, many hospitals and centers of medical research replaced the traditional methods of data analysis with a computer-aided system that relies entirely on artificial intelligence (AI). This came from the fact that artificial intelligence has the ability to produce quick solutions and diagnose COVID-19 accurately and reliably. Choosing an appropriate AI method that creates an efficient, fast, and error-free solution is a critical task despite the existence of a large number of automated AI methods [8].

Recent studies have shown that AI models such as machine learning and deep learning methods have a high ability to predict and diagnose COVID-19 accurately and reliably [9, 10]. Despite pure medical perspective research, in prediction research, ML and DL support COVID-19 diagnosis through medical image inspection. These studies utilized chest X-ray (CXR) images for early diagnosis of severe cases using ML AND DL tools where researchers focused have focused either on achieving high prediction and classification scores using any set of features and an appropriate algorithm to accomplish that, thus providing a technically robust system regardless of the real effectiveness of these features in COVID-19 diagnosis from a medical perspective [11–15]. In references [11, 12, 14], the authors proposed an automated deep learning model for the detection and classification of COVID-19 cases based on patients' X-ray images. Similarly, reference [15] proposed the patch-based DL model but the final classification result is obtained by majority voting from inference results at multiple patch locations. In the chest X-ray dataset side [13], the authors presented a deep transfer learning model based on generative adversarial networks (GANs) to overcome the overfitting problem and generated more images from the dataset. On the other hand, some researchers concentrated on testing blood samples of infected patients trying to figure out the best biomarkers available to provide noninvasive detection solutions that prevent medical personnel from contracting infections and provide severity score of the patient for further treatment [16–18]. In reference [16], the authors identified only three biomarkers (LDH, CRP, and lymphocytes) for COVID-19 prediction by developing an ML-based model, which can predict the patient's mortality rate. Similarly, in reference [17], a customized machine learning model for COVID-19 severity prediction has been built with eleven clinical biomarkers. In reference [18], the prediction of COVID-19 was carried out with deep learning models based on 18 laboratory findings, which were analyzed by 6 different deep learning models. However, most of these research have been discussed from the technical concept or medical separately. No previous work was attempted to build a robust system to combine both technical and medical visions in order to assist doctors to finally have a clear decision about how severe the patient's case is. Additionally, moderate and mild cases were considered the majority cases, yet they were mostly neglected in previous research attempts; therefore, the studies should also focus on the development of well-tolerated drugs that may affect symptoms and the disease course of mild and moderate patients to avoid long-term pulmonary damage [19]. Furthermore, the dataset used was taken from medical laboratories and the patient's vital functions in a manner that may give high technical accuracy, but it may interfere with the normal flu or flu caused by other viruses [20, 21].

The main contributions of this work can be summarized in the following points:

(i) Present a dataset termed as the IRAQ/WA_COVID_19. This dataset is built based on different clinical features such as patient's medical history, blood, urea tests, and patient's vital functions.

(ii) Features selection approach based on feature importance in detection of COVID-19 virus from medical and technical perceptive.

(iii) Propose a multiclass case severity prediction system for COVID-19 patients in the early stages of infection.

(iv) Finally, besides the severe cases, this work directs attention to mild and moderate cases since they considered the majority of mobile patients who have a high risk of transmission of the virus.

2. Data Collection and Resources

Samples collected between August 4, 2020, and December 3, 2020, were used for model development. The total number of people infected with the COVID-19 virus was 78, who were diagnosed under the supervision of specialized doctors and were distributed among governorates. For 78 patients, lost sense of taste and smell were the most common symptoms (92.3% and 91.02, respectively), followed by fever (67.95%), generalized weaknesses (66.67%), cough (58.97%), sore throat (57.69%), sneezing (56.41%), pleuritic chest pain (53.84%), diarrhoea (52.56%), and nasal congestion and rhinorrhea (42.30%), as listed in Table 1. The average ages of the patients were 52.83 ± 35.39 years, and 58.97% were male. The laboratory results listed in Table 1 were raised to the following data:- C-reactive protein (CRP) positive more than 12 mg/L, white blood cell (WBC) up to 44 $*$ 109/L(NV 4–8

Table 1: Clinical, laboratory, vital function, and medical history information collected from hospital records.

Characteristics	Overall appearance
Age, mean (years)	52.83
Gender, *n* (%)	
Male	46 (58.97%)
Female	32 (41.03%)
Chronic diseases, *n* (%)	
Chronic medical illness (hypertension, diabetes, and tumor or any type of cancer)	41 (52.56%)
Outcomes, *n* (%)	
Mortality rate	11 (14.1%)
Survival rate	67 (85.9%)
Symptoms onset, *n* (%)	
Fever	53 (67.95%)
Cough	46 (58.97%)
Generalized weakness	52 (66.67%)
Nasal congestion	33 (42.30%)
Rhinorrhea	33 (42.30%)
Sneezing	44 (56.41%)
Sore throat	45 (57.69%)
Pleuritic chest pain	42 (53.84%)
Diarrhoea	41 (52.56%)
Lost sense of smell	71 (91.02%)
Lost sense of taste	72 (92.30%)
Laboratory test, *n*: abnormal cases based on WHO test range (%)	
Hemoglobin (g/dL)	M: 11 (23.91%), F: 15 (46.87%)
White blood cell count	31 (39.74%)
Lymphocyte count	13 (16.66%)
Platelet count	13 (16.66%)
C-reactive protein (mg/L)	48 (61.53%)
Urea (mmol/L)	22 (28.20%)
Creatinine (μmol/L)	56 (71.79%)
Vital signs, n: abnormal cases based on WHO test range (%)	
Saturation of oxygen in the blood (SpO_2), (>90, 90–94, and 95–100)	46 (58.97%), 21 (26.93%), and 11 (14.10%)

$*$ 109/L), lymphocyte 13.3 $*$ 109/l (NV = 0.2–4 $*$ 109/L), platelet count 1087 $*$ 109/L (NV100-300), serum creatinine 21.9 mg/dL (NV 0.6–1.2), and serum urea 299 mg/dL (NV 15–45). Most of the time, patients used a nonrebreather mask except during taking food and sleep time. Of the 78 COVID patients included in this investigation, 67 were recovered and discharged from hospitals, while the remaining 11 were died. A patient's severity was assessed and categorized as severe, moderate, and mild by doctors according to the Iraqi hospitals' criteria at admission.

3. Development of Automated Multiclass Severity Prediction System

The proposed model was implemented in the following phases:

3.1. Data Preprocessing. In typical detection systems, a preprocessing step is essential, and it is implemented to prepare the data for the next step properly. In this phase, we normalized each feature's data in both the training and testing sets using the min-max formula:

$$y = \frac{(x - \min)}{\max - \min}. \tag{1}$$

A total of 78 patients have been included in the final collected datasets from Al-Aziziyah Hospital in Wasit Governorate, where we used 51 samples for training and 27 samples for the testing set.

3.2. Features Importance: Medical and Technical Perspectives. Many models have been used to predict progression risks to severity or death in patients with COVID-19 patients. The prominent prognostic factors that are frequently considered include comorbidities, age, sex, lymphocyte counts, and C-reactive protein (CRP), among others [22]. On the other hand, new researches reveal increased CRP levels and decreased SpO_2. Lymphocyte counts could serve as potential indicators of severe COVID-19, independent of comorbidities, advanced age, and sex [23], that is what we want to prove in this work technically as well as being proven medically.

Technically, the importance of features used was assessed using the same classifier adapted for the classification system in both training and testing sets. The model performance showed no increment when more features were added. This was clarified in Figure 1, where the lymphocyte, CRP, and SpO_2 biomarkers were utilized and tested by the classification accuracy they revealed when used with each other. Considering the potential relationship between the predictors, which has been already medically proven, three biomarkers were tested to verify their discrimination accuracy. This would technically approve the strength of these biomarkers in prediction. Using the training set of data, lymphocyte was first tested with fine Gaussian SVM to give an accuracy of 68%. Then, CRP was added to the previous step to gain an accuracy of 72%. Lastly, SpO_2 was appended to result in the final training accuracy of 88% for the machine learning model.

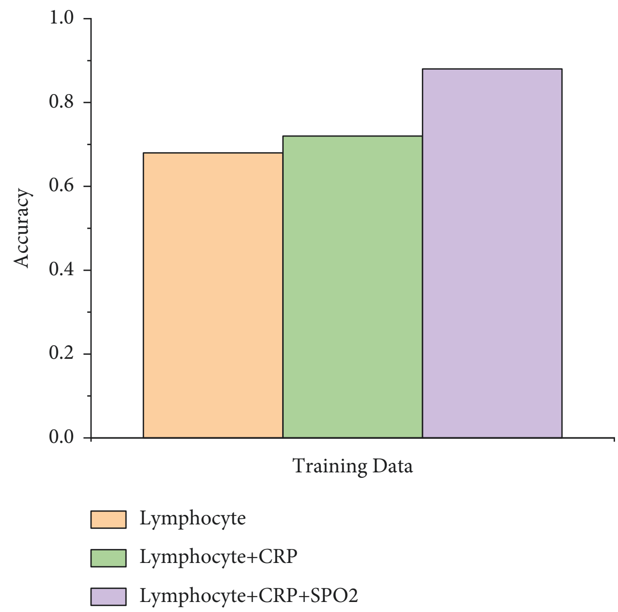

Figure 1: Feature importance in a technical point of view.

3.3. Trained Models Development. In this work, a case-severity detection system is proposed as a techno-medical aid system to help physicians make a decision regarding patients' case. An activity figure of the proposed work is illustrated in Figure 2. The proposed system implies that three basic important features such as lymphocyte, CRP, and SpO_2 are used to distinguish severe, moderate, and mild cases. The model output corresponds to the patient's case severity. By combining the data from three different tests (blood, urine, and vital functions) and testing their importance in the system which was already proven medically in literature. These features (i.e., biomarkers) were utilized to train the classifier to separate the classes.

Patients with the severe case were assigned to class 1, those with moderate to class 2, and the mild case with class label 3. The model performance was evaluated by calculating the accuracy, half total error rate (HTER), false-positive rate (FPR), and false-negative rate (FNR). Receiver operating characteristic (ROC) is also used to view the system's accuracy in terms of graphical representation:

$$\mathrm{HTRE} = \frac{(\mathrm{FPR} + \mathrm{FNR})}{2} \qquad (2)$$
$$\mathrm{Accuracy} = 100 - \mathrm{HTER}.$$

The cases are classified using both support vector machine (SVM) and decision tree (based on Gini's index). Generally, the extracted features from any sample are passed to the classifier to calculate a score for that sample. According to the decision threshold of the classifier, if the sample's score is higher than a threshold, then the sample is accepted; otherwise, the sample is discarded. The choice of a certain classifier can affect the overall system performance. Many kernel functions are available for SVM, such as Gaussian, radial basis function (RBF), and polynomials, which can be utilized to solve nonlinearity problems. In this work, the Gaussian SVM is applied for the case severity detection model. First, the classifier is trained using the training set of (Wasit) city database. The Gaussian kernel is used to obtain the matching scores. The SVM classifier with the Gaussian kernel formula is stated as follows:

$$f(x) = \sum_{i}^{N} \alpha_i y_i k(x_i, x) + b, \qquad (3)$$

where N represents the size of trained data, α represents the weight, X_i represents the support vector, and b represents the bias, and the Gaussian kernel formula is stated as follows:

$$k(x, x') = \exp\left(-x - \frac{x'^2}{2\sigma^2}\right). \qquad (4)$$

Here, σ is a free parameter that represents the kernels' width and is greater than 0. The Gaussian SVM provides fast prediction speed and high model flexibility in case of multiple classifications. It also proved its favorability upon other SVM kernels during experimental work by achieving the best accuracy as compared to others. The parameters of the training model are illustrated in Table 2.

On the other hand, the decision tree algorithm was employed for further validation of the proposed system, 80% of the overall data were used for the training of the prediction model using Gini's index as illustrated in the equation below [24], and Gini index specifies the data impurity. It is calculated for each feature of the dataset:

$$\text{Gini Index} = 1 - \sum_{i=1}^{k} Pi^2. \qquad (5)$$

In the above formula, k represents the number of classes of target feature, and Pi stands for the probability of ith classes.

4. Evaluation of Multiclass Prediction System

To evaluate the performance of proposed work collected database, the calculated accuracy, HTER, true positive rate (TPR), false-negative rate (FNR), and AUC are listed in Table 3. The performance of the tested system was also portrayed by the ROC graph in Figure 3, where the area under the curve (AUC) indicates good classification performance.

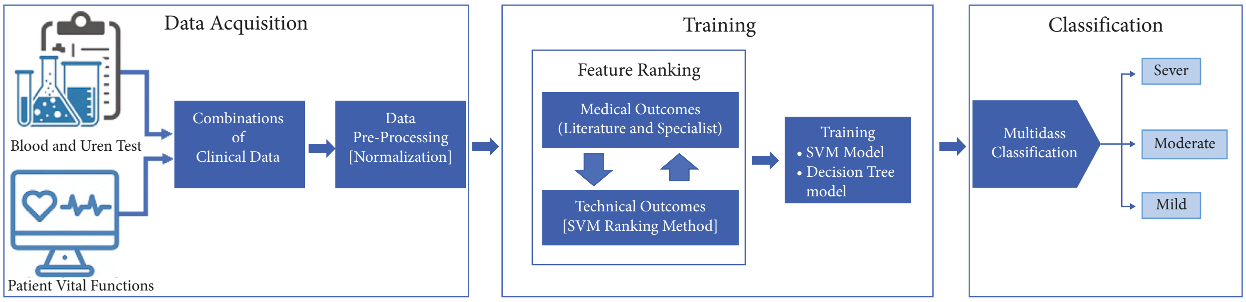

Figure 2: Automated multiclass severity prediction system.

Table 2: Experimental setup for training models.

Database parameters	SVM	Decision tree
Training samples	51 samples	80% of overall data
No. of features	3	3
Kernel function	Gaussian	Gini's index
Training accuracy	88.0%	80.6

Table 3: Performance evaluation of COVID-19 case severity prediction system.

Parameter	Value (SVM)	Value (decision tree)
HTER	18.518	25
Accuracy	81.481%	75%
TPR	9	4
FNR	0	0
AUC	0.98	0.84

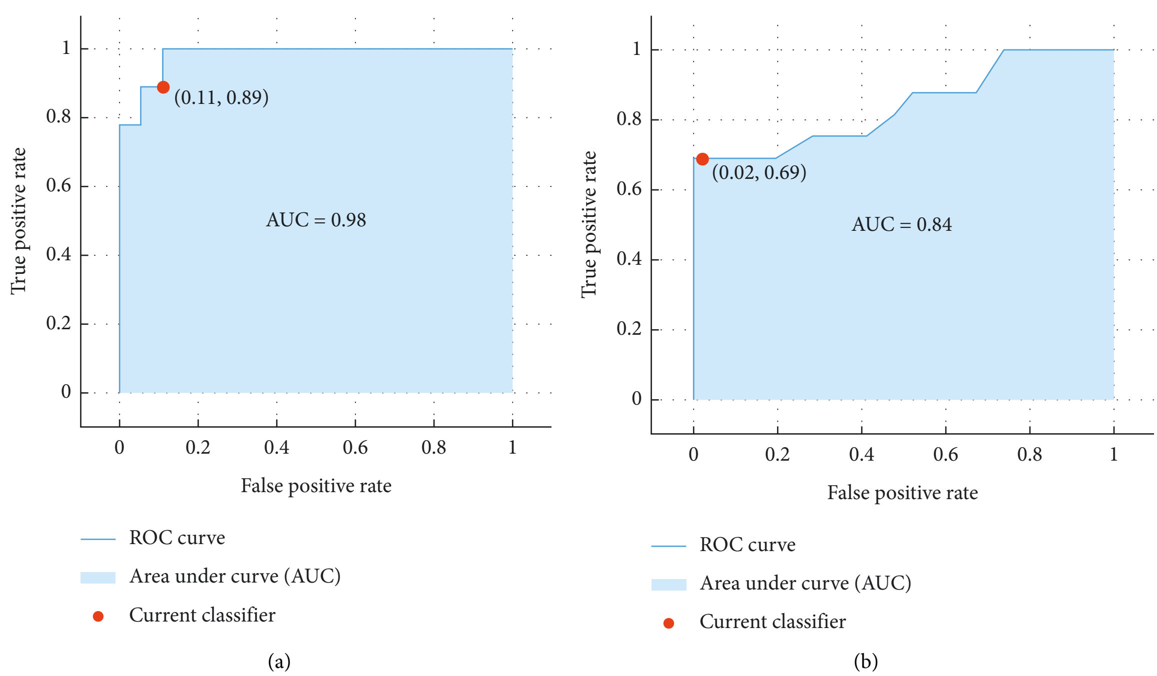

Figure 3: ROC curve graph for testing data. (a) SVM; (b) decision tree.

The proposed work showed a low error rate of approximately (18%), knowing that the testing data set consisted of 27 patients' samples, 9 samples for each class, severe, moderate, and mild classes, respectively. The outputs revealed fully successful predictions in cases of severe and moderate classes, while only 4 out of 9 were successfully predicted of moderate class samples. This indicates a quite high accuracy of almost 82%, where 22 out of 27 samples were accurately detected, as shown in Figure 4. This approves our basic postulate that the moderate cases were not being paid attention in previous literature despite their importance and the fact that they would develop a severe case if they were not treated properly. Most researchers focused on detecting severe and nonsevere cases only. The decision tree also showed a quite good accuracy using 20% of the dataset for the testing purpose. An accuracy of 75% was gained. This helps a further validation of both the proposed method and collected data to extend to different types of classifiers. Comparing our results with the state of art, a significant outcome was revealed, as listed in Table 4. The table illustrates better predictive accuracies as compared to the previous work using the same classification algorithms on different data and different types and numbers of features.

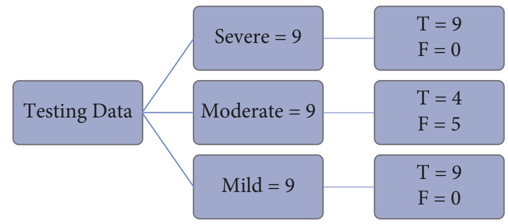

Figure 4: Multiclass predictions for testing data, T is the number of accurate classifications and F is the number of misclassifications.

Table 4: Comparison with state of art

Reference	No. of features	Algorithm	Accuracy (%)
Jiang et al. [25]	10	SVM	80
		Decision tree	70
Proposed work	3	SVM	81.5
		Decision tree	75

5. Discussion

The significance of our work lies in two paths; one is related to the fact that the resulted system combined, unlike previous work, both medical and technical perspectives to deal with the COVID-19 pandemic. The related work focused on either medical point of view to treat the virus, which may lead to a lack of statistical information or poor diagnostic procedure to be followed. On the other hand, some researchers focused on utilizing patient's data to build robust machine learning or deep learning systems and provide as high accuracy as possible neglecting the fact that the features used may not have a real effect on the virus from a medical perspective. As listed in Table 4, previous work utilized 10 features, while our proposed only 3 specific features that succeeded to provide higher accuracies.

To tackle this problem, the effectiveness of certain patients' tests on COVID-19 and the relationship between them were determined pathologically in this work. This was transformed to be technically proved using a machine learning model. The second considerable influence lies in the idea of classifying the virus into three major classes, such as severe, moderate, and mild, where the second two classes were ignored by most researchers. Previous work focused on severity only to detect death cases, while moderate cases for example need to be considered for the fact that they may worsen to be a severe case if not treated properly. In addition, this classification would help reduce the human efforts and medical resources required to deal with this pandemic. The mild cases can be given a medical procedure, sent home, and remotely monitored without the need to stay at the hospitals. This would allow patients with more serious conditions to have further medical care.

Several medical research attempts have proven the lymphocyte-CRP (LCR) relationship. It was observed that high CRP levels and low lymphocyte levels along with a SpO_2 decrease might be related to COVID-19 severity [23, 26]. This was technically proven using the machine learning model by testing the prediction accuracy when using these biomarkers as model features. A considerable accuracy increment was noticed when using these three indicators together rather than using only one or two of them. This was earlier explained in the section of feature importance.

The developed machine learning predictive system achieved a quite high accuracy rate for both single and overall system predictions. It also shows good flexibility to test additional data or to be trained with more data in the future. This would have the potential to serve direct patient's flowing and appropriate resources for COVID-19 patient care.

6. Study Limitations

The limitation of this work is basically related to the lack of data being used. However, the training and testing sets of data were collected from two different hospitals in two different cities, which provides sufficient indication of systems' expandability to deal with various data. Moreover, the moderate cases showed less prediction accuracy as compared to the other two case classes, but they were also finally highlighted to be considered in further research attempts.

7. Benefits of Using the Proposed Dataset

Testing COVID-19 is normally done using the RT-PCR technique, which is not always very accurate. As we mentioned previously, different types of data like blood and urine tests, symptoms like fever, cough, and body weakness, and vital signs like the saturation of oxygen in the blood can be indicative of the disease. Therefore, here, we want to propose possible scenarios that can be implemented by other researchers using the same data used in this study. We anticipate the benefits of the collected dataset; two main and useful scenarios can be applied to this data: prediction and diagnosis scenarios. Within each scenario, there are several subscenarios. Here, we will mention some of them.

7.1. Prediction Scenarios. The primary function of prediction is predicting mortality, severity, or recovery. Therefore, the suggestions might be as follows:

(i) Determine the health risk and predict the mortality of sufferers of COVID-19. This can assist hospitals, clinical facilities, and caregivers in determining who needs to get interested first earlier than other patients, triage patients. At the same time, the system is crushed through overcrowding and additionally put off delays in offering the important care.

(ii) Compare different machine learning algorithms (e.g., ensemble methods) to predict the patient's recovery. This provides the advantages of predicting the discharge time chance supported the clinical information based on many computational intelligence approaches that can be implemented.

(iii) From our observations on the data, the COVID-19 patients can also additionally display severe signs and symptoms, and a few patients with severe situations might die or suffer from the most important organ failure. Therefore, it is very important to predict the severity of symptoms.

(iv) Some mild and moderate conditions may develop into severe conditions; therefore, prediction of this infection probability should be considered.

7.2. Diagnosis Scenario. Efficiently diagnosing the medical type of COVID-19 patients is important to gain the most effective outcomes. Currently, severe and nonsevere patients are differentiated through some medical features, which do now no longer comprehensively characterize the complicated physiological and immunological reactions to the disease. Therefore, AI methods could be used in patient diagnosing using the collected dataset. We suggest here, utilizing the relation between the symptoms or the patient's medical history (e.g., chronic disease) and his/her gender. Furthermore, the relation between blood or urine tests and the effect of all those on the diagnosis of the patient's condition can be investigated.

8. Conclusion

COVID-19 prediction systems are currently one of the trendiest systems utilized in the ongoing pandemic. In this work, we identified three important indicators (lymphocyte, CRP, and SpO_2) that have been proven pathologically and technically. Previous medical findings by health care sector researchers were utilized to build an assistive technical system for severity prediction purposes. A self-collected dataset of 78 infected people was used. A patient's severity was assessed and categorized as severe, moderate, and mild by specialized doctors according to the Iraqi hospitals criteria at admission. By the combination of these medical and technical efforts and resources, health risks and losses of life are reduced. For COVID-19 prediction, we have developed two machine learning-based models that are able to predict multiclass of case severity (severe, moderate, and mild) with more than 81% accuracy (using SVM), enabling early intervention, detection, and a possible mortality reduction for COVID-19-affected patients. This study opens the door for new research directions that may use different machine learning models and utilize the database to explore other indicators' impact on COVID-19.

Data Availability

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

Ethical Approval

All data used in this research are authorized by Azizia primary health care sector/Wasit Health Directorate/Ministry of health, and there is a letter in this regard.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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