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Research Article

Machine Learning Based A Comparative Analysis for Predicting Intensive Care Unit Admission of COVID-19 Cases

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ABSTRACT

COVID-19 is a disease caused by the SARS-CoV-2 virus that emerged in December 2019 in Wuhan, China. This virus, which can be transmitted quickly, spread worldwide quickly, causing many people to be infected and even killed. The rapid course of the epidemic made managing medical resources difficult. Intensive care units play an important role in saving the lives of severely ill COVID-19 patients. In this study, a machine learning-based detection system was developed to predict the hospitalization of COVID-19 patients in intensive care units. Using a dataset of demographic characteristics and clinical findings of COVID-19 patients, Decision Tree (DT), k-Nearest Neighbor (kNN), Linear Regression (LR), Multilayer Perceptron (MLP), Naive Bayes (NB), Random Forest (RF), and Support Vector Machine (SVM) were compared in practice using accuracy, recall, precision, and F-score. Experimental results showed that SVM has 0.964 accuracy, 0.957 precision, 0.971 recall, and 0.963 F-score.

Keywords: *COVID-19, Machine Learning, Intensive Care Unit, SVM.*

Introduction

COVID-19 is a disease caused by the SARS-CoV-2 virus that causes respiratory infections. The World Health Organization (WHO) first learned of COVID-19 in Wuhan, China, in December 2019 and designated it a pandemic in March 2020 [1]. COVID-19 can affect the upper respiratory tract, such as the sinuses, nose, and throat, or the lower respiratory tract, such as the trachea and lungs [2].

The COVID-19-causing SARS-CoV-2 virus can be spread directly by airborne droplets or touching the eyes, nose, or mouth after contacting a virus-containing object [3]. Once within the body, the virus settles in the nasal passage and the mucous membranes at the back of the throat. It sticks to cells, starts to grow, and invades lung tissue. When an infected individual coughs, sneeze, or talk, respiratory droplets are released into the air and spread the COVID-19 infection. It can be transmitted from person to person by inhaling these droplets or through close contacts, such as touching and shaking hands with an infected person [4].

Cough, fever, shortness of breath or difficulty breathing, sore throat, muscular or body aches, loss of taste or smell, and runny nose are some signs of COVID-19 [5]. Symptoms can appear 2 to 14 days after exposure to the virus. While some people infected with COVID-19 have mild illnesses, others have no symptoms. However, especially in people with chronic diseases and the elderly, COVID-19 can cause respiratory failure, permanent lung and heart muscle damage, nervous system problems, kidney failure, and death [6]. Therefore, to protect against COVID-19, it is necessary to wear a mask in public, wash frequently touched surfaces, maintain a social distance of 1.5 meters, wash hands with soap and water for at least 20 seconds, and be vaccinated [7].

The WHO warned that artificial intelligence might be a crucial tool in controlling the virus-caused issue soon after the COVID-19 pandemic was declared [8]. Artificial intelligence is vital in overcoming the current global health crisis, preparing for the next generation of pandemics, and optimizing healthcare [9]. Artificial intelligence was successfully used in application areas such as identifying disease clusters, case tracking, prediction of future outbreaks, mortality risk prediction, COVID-19 diagnosis from chest X-ray images, disease management with resource allocation, and pandemic trending [10].

Artificial intelligence technologies can be used to predict the spread of the virus and develop early warning systems for vulnerable areas by extracting information from social media platforms, emergency calls, and news sites [11]. Mobile health applications are being developed where watches, cell phones, cameras, and various wearable devices can be used for COVID-19 diagnosis, contact tracing, and case tracking [12]. Artificial intelligence methods can be applied in clinical settings to

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monitor patients and predict the course of treatment. The data obtained from people's clinical tests can provide vital information for resource allocation and decision-making by prioritizing the need for ventilator devices and respiratory support in the Intensive Care Unit (ICU) [13]. In addition, artificial intelligence technologies can help reduce the workload of healthcare personnel and healthcare workers by automating various processes, such as determining the type of treatment and care by analyzing the clinical data of patients and digitizing patient reports [14].

The remaining of this section review investigations on COVID-19 that were conducted using artificial intelligence techniques.

Alakus and Türkoğlu [15] developed a deep learning-based clinical prediction model to predict patients likely to be infected with COVID-19. The model was tested with 18 laboratory findings of 600 patients. The model's performance was evaluated using accuracy, precision, recall, F-score, Receiver Operating Characteristic (ROC), and Area Under the ROC Curve (AUC). Experimental results showed that the prediction model classified patients with 86.66% accuracy, 91.89% F-score, 86.75% precision, 99.42% recall, and 62.50% AUC.

Arora et al. [16] aimed to predict the number of COVID-19 cases for 32 states and union territories in India. Daily and weekly forecasts were made using Long Short Term Memory (LSTM) variants such as Deep LSTM, Convolutional LSTM, and Bidirectional LSTM. The proposed method has a successful short-term forecasting performance with an error rate of about 3% for daily and 8% for weekly forecasts.

Alazab et al. [17] developed a CNN-based COVID-19 prediction model using 1000 chest X-ray images. Experimental studies showed that the proposed model successfully detects COVID-19 with an F-score of about 96%. Furthermore, 7-day short-term forecasts were made using Prophet Algorithm (PA), AutoRegressive Integrated Moving Average (ARIMA), and LSTM to predict the number of COVID-19 cases, deaths, and recoveries.

Cohen et al. [18] developed a DenseNet-based model for COVID-19 prediction from chest X-ray images. They used a dataset scored by experts in terms of the extent and severity of lung involvement. The developed prediction model aims to rate the severity of lung infections. Experimental results show that the developed model has 0.78 Mean Absolute Error (MAE).

Zhou et al. [19] proposed an ensemble learning-based deep learning model for COVID-19 detection from chest X-ray images. The proposed model is tested on 2500 images with AlexNet, GoogleNet, and ResNet models. The experimental results showed that the proposed approach has 99.05% classification accuracy.

Younis [20] presented a comparative analysis of VGG model variants, LeNet-5, AlexNet, and ResNet50 models for detecting COVID-19, SARS, and MERS viruses using chest X-ray images. Furthermore, LSTM was used to predict Italy's 10-day COVID-19 case count. The experimental results showed that LSTM and VGG have 99% and 91% classification accuracy, respectively.

Alassafi et al. [21] developed a deep learning-based prediction model to predict the spread of COVID-19 in Malaysia, Morocco, and Saudi Arabia. The proposed prediction model predicted 7-day COVID-19 cases and fatalities. Experimental results showed that LSTM and Recurrent Neural Network (RNN) had 98.58% and 93.45% accuracy, respectively.

Lorenzen et al. [22] used machine learning methods to estimate intensive care unit resources during the Covid-19 outbreak in Denmark. Various methods such as RF, LR, Logistic Regression (LogR) were designed to solve this problem and successful results were obtained.

Alabbad et al. [23], on the other hand, estimated the length of stay of patients hospitalized in the intensive care unit in a different study they conducted. During this study, RF, Extreme Gradient Boosting (XGBoost), Gradient Boosting (GB), and Ensemble models were used. Various parameters were taken into account while determining this during this study. Thus, a model that supports the health sector was put forward.

The contribution of this study to the literature can be summarized as follows:

- This dataset was used for the first time to predict intensive care unit admissions of COVID-19 patients.
- This study compared popular machine learning algorithms such as DT, LR, KNN MLP, MLP, NB, RF, and SVM.
- The experimental results showed that SVM detected the admission of COVID-19 patients to the ICU with 0.964 accuracy.

Materials and Methods

The operation of the health systems in most nations was adversely affected by the COVID-19 pandemic. Furthermore, intensive care wards, protective equipment, and medical personnel may need to be improved due to the increasing number of cases. This study presents a machine learning-based comparative analysis to determine whether treating COVID-19 patients in the ICU is necessary to maintain healthcare services' capacities. DT, LR, KNN, MLP, MLP, NB, RF, and SVM are compared practically using accuracy, recall, precision, and F-score metrics.

Dataset

This study used individual COVID-19 clinical data made publicly available through Kaggle as the dataset. The dataset contains clinical data for ICU admission of confirmed COVID-19 cases. The dataset used is publicly available on Kaggle [24].

The dataset consists of demographic information, past illnesses, blood values, vital signs, and blood gas values of 385 patients. In the dataset, five entry values were defined to indicate the time from each patient's admission to the ICU. For example, 0-2 means 0-2 hours after admission, 2-4 means 2-4 hours after admission, 4-6 means 4-6 hours after admission, 6-12 means 6-12 hours after admission, and above 12 means 12 hours or more after admission. With these different input values defined, there are 1925 rows of data for 385 patients with five different periods for each patient. Of these patients, 195 were admitted to the ICU, and 190 were not admitted to the ICU. Patient demographics include age in percentages, gender, and whether the patient was 65 years or older. Strong values have diastolic and systolic blood pressure, oxygen saturation, pulse rate, respiratory rate, and temperature. Blood values consist of blood test values with 36 attributes.

Figure 1 shows the rate of admission to the ICU according to the time intervals after admission to the hospital.

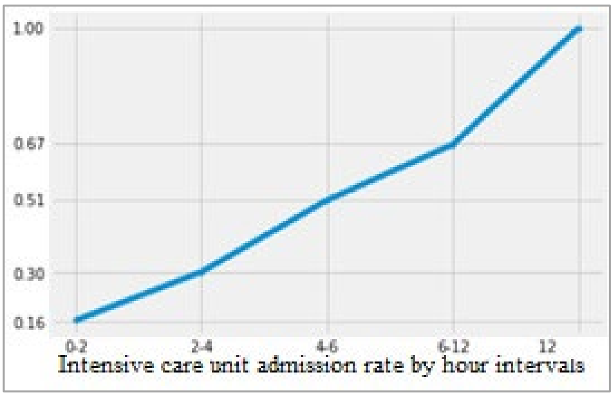

Figure 1. ICU admission rate by hour intervals

As shown in Figure 1, the number of admissions to the ICU increases by 12 hours or more after admission to the hospital. Figure 2 shows the number of patients admitted to the ICU according to time intervals.

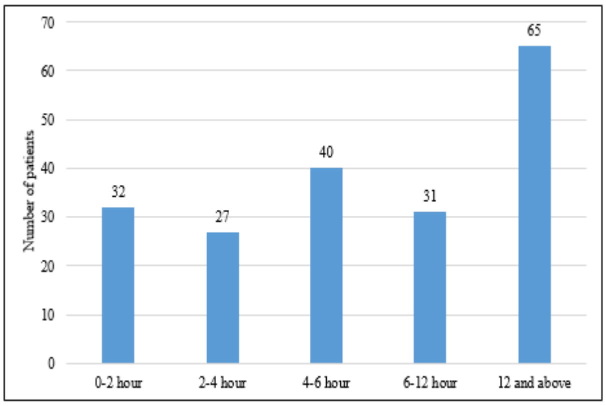

Figure 2. Number of patients admitted to ICU according to time intervals

Figure 2 shows the number of intensive care admissions of 195 patients admitted to intensive care according to the time intervals since their admission to the hospital. There is a significant increase in ICU admissions at time intervals of 12 hours and above. Another high time interval in intensive care admission is 4-6 hours. 8.31% of the patients were admitted to the ICU between 0-2 hours, 7.01% between 2-4 hours, 10.39% between 4-6 hours, 8.05% between 6-12 hours, and 16.88% between 12 and more hours. Figure 3 shows the age distribution of patients admitted to the ICU.

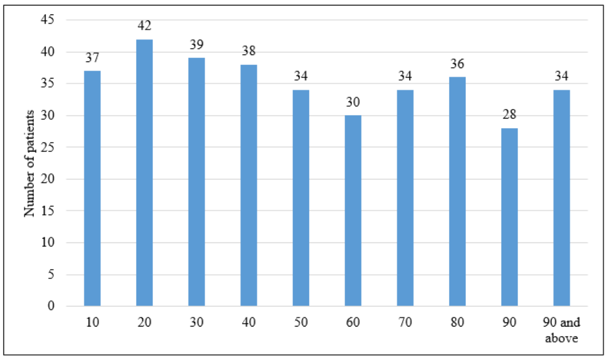

Figure 3. Age distribution of patients admitted to the ICU

As seen in Figure 3, it was observed that patients in their 20s were admitted to the ICU. This shows that patients in their 20s are likelier to be admitted to the hospital.

In the data pre-processing stage, duplicate data columns were removed, and all rows were replaced with patient IDs. Using Pearson's Correlation Coefficient, 87 attributes were obtained based on the relationships between the attributes. Figure 4 shows the ICU admission rates of patients according to the time intervals after their admission to the hospital.

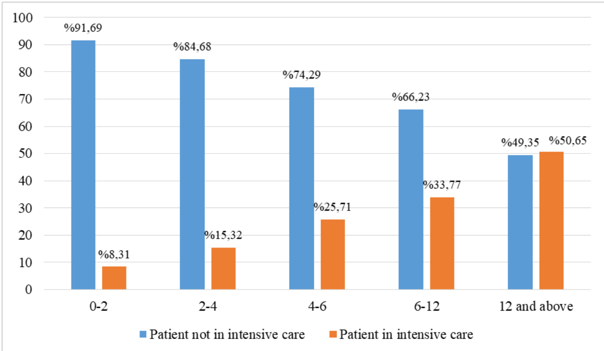

Figure 4. ICU admission rates of patients according to time intervals after admission to the hospital

As seen in Figure 4, there is a gradual increase in the rate of intensive care admission in the time intervals after the patient's admission to the hospital. Figure 5 shows the number of ICU admissions according to the age of the patients.

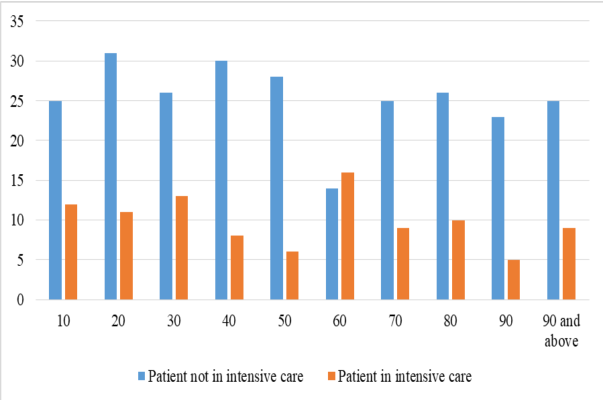

Figure 5. Number of ICUs according to patients' ages

As seen in Figure 5, the number of ICU admissions is higher, especially for patients in their 60s and 30s. Patients in their 20s and 40s have a lower number of ICU admissions.

Due to the large number of features in the dataset, it is impossible to show the relationships between them with a heatmap clearly. Therefore, only the relationships between the first thirteen features are shown in Figure 6 below.

Figure 7 shows the relationships between the ICU 's admission attribute and other attributes.

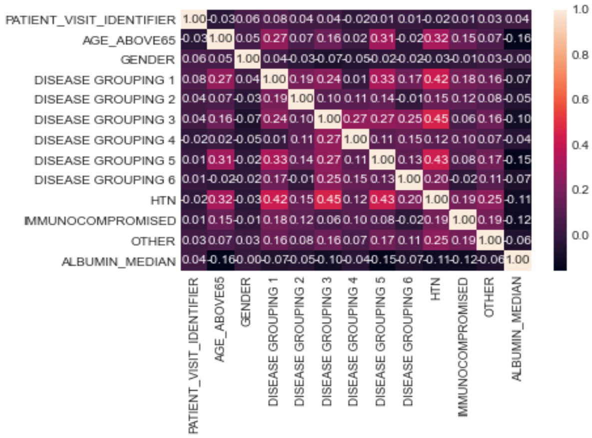

Figure 6. Relationship map of first thirteen features in the dataset

```
AGE_ABOVE65_1                      0.291010
RESPIRATORY_RATE_MAX_1             0.213938
RESPIRATORY_RATE_MEAN_1            0.207911
BLOODPRESSURE_DIASTOLIC_MEAN_1     0.201210
BLOODPRESSURE_DIASTOLIC_MIN_1      0.195703
HTN_1                              0.180555
RESPIRATORY_RATE_MIN_1             0.173043
BLOODPRESSURE_DIASTOLIC_MAX_1      0.166832
OXYGEN_SATURATION_MEAN_1           0.147612
OXYGEN_SATURATION_MIN_1            0.139034
OXYGEN_SATURATION_MAX_1            0.131615
DISEASE GROUPING 3_1               0.122514
DISEASE GROUPING 5_1               0.122200
GENDER_1                           0.117938
DISEASE GROUPING 4_1               0.112573
BLOODPRESSURE_SISTOLIC_MAX_1       0.109073
BLOODPRESSURE_SISTOLIC_DIFF_1      0.107106
RESPIRATORY_RATE_DIFF_1            0.093877
DISEASE GROUPING 2_1               0.087753
TEMPERATURE_MEAN_1                 0.086764
TEMPERATURE_MIN_1                  0.086575
BLOODPRESSURE_SISTOLIC_MEAN_1      0.084371
TEMPERATURE_MAX_1                  0.079548
DISEASE GROUPING 1_1               0.071825
IMMUNOCOMPROMISED_1                0.071221
BLOODPRESSURE_DIASTOLIC_DIFF_1     0.065228
BLOODPRESSURE_SISTOLIC_MIN_1       0.058086
OTHER_1                            0.050656
HEART_RATE_MEAN_1                  0.048263
HEART_RATE_MAX_1                   0.047453
HEART_RATE_MIN_1                   0.042645
PATIENT_VISIT_IDENTIFIER_1         0.041382
DISEASE GROUPING 6_1               0.026684
OXYGEN_SATURATION_DIFF_1           0.020897
HEART_RATE_DIFF_1                  0.013554
TEMPERATURE_DIFF_1                 0.006336
```

Figure 7. Relationships between the ICU admission attribute and other attributes

As seen in Figure 6, especially the attribute of being 65 years of age or older has a stronger relationship with the intensive care admission attribute than the others.

Data Pre-processing

First of all, incorrect and missing fields were checked in the dataset. The missing values found in the dataset are the values belonging to the time when the patients first entered the hospital. These values are since tests such as blood tests have yet to be performed on the patients. As the condition of the patients deteriorated in the following time intervals, various tests were performed. For this reason, the empty values were filled with the first non-empty value. After checking for missing and incorrect values and removing duplicate columns, a dataset of 352 patients and 44 attribute values were obtained.

The dataset was split into training-test sets with 60% training and 40% test. A training dataset comprising 211 items and a test dataset of 141 items were obtained after the training and test set were divided. Then, 10% of the training data was used to optimize the parameters of the applied models. The data was then normalized. Finally, 10-fold cross-validation was performed to avoid over-fitting the models. The validation data was used to optimize the parameters of the applied models. GridSearchCV library was used for the optimization of model parameters. By optimizing the parameters for each applied model, the models were ensured to have the most successful classification performance. This way, models were created using the obtained parameters, and confusion matrix, accuracy, recall, precision, and F-score values were obtained. The flow diagram of the developed model is shown in Figure 8.

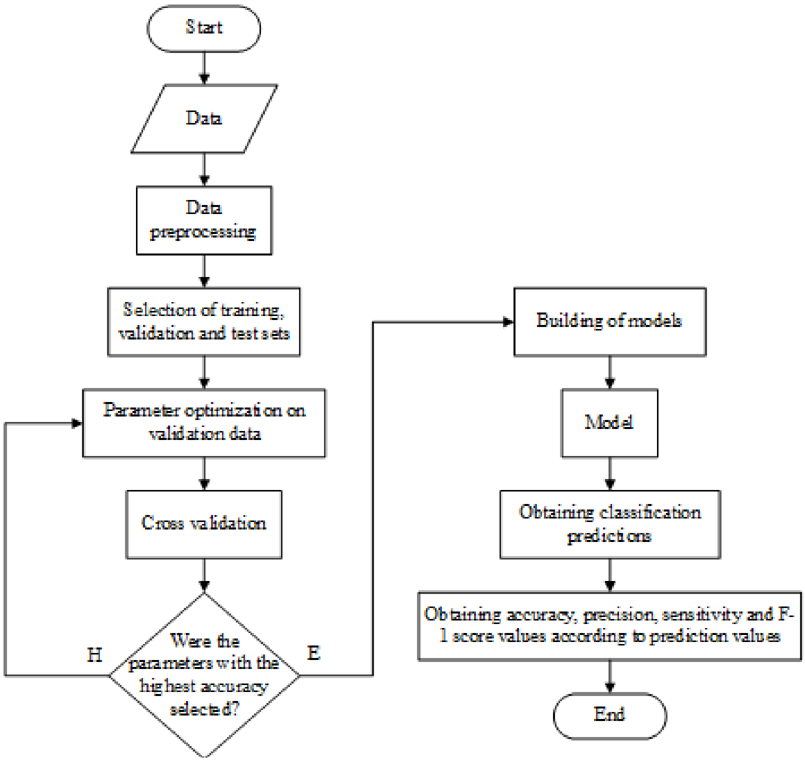

Figure 8. Flow diagram of the developed system

Evaluation Metrics

Accuracy, recall, precision, and F-score metrics are frequently used to assess how well classification methods work. Utilizing the confusion matrix, these metrics are computed. The links between the actual values of the classifiers and the predictions are assessed using the confusion matrix. In Table 1, the confusion matrix is presented.

Table 1. Confusion matrix

		Actual values	
		Positive (1)	Negative (0)
Prediction values	Positive (1)	TP	FP
	Negative (0)	FN	TN

The number of positive instances the classifier correctly predicts is known as TP. The number of negative instances the classifier predicts correctly is TN. The number of instances where the classifier predicted a positive value but the actual value was negative is known as FP. The number of instances where the classifier predicted negative but the actual value was positive is known as FN. Accuracy is calculated by the ratio of correctly classified samples to the total number of samples, as seen in Equation 1.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

As seen in Equation 2, precision expresses how many positively predicted values have positive true values.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Recall, as stated in Equation 3, is the percentage of predicted true positive values that are truly positive.

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

According to Equation 4, the harmonic average of the precision and recall values is used to generate the F-score.

$$F-1\ score = \frac{2*Precision*Recall}{Precision+Recall} \quad (4)$$

Experimental Results

This study presents a machine learning-based comparative analysis for predicting ICU admissions of COVID-19 patients. For this purpose, DT, LR, KNN, MLP, RF, NB, and SVM are comprehensively compared using accuracy, precision, recall, and F-score metrics. In order to determine the parameters of the machine learning algorithms, parameter analysis studies were conducted using GridSearchCV and the most appropriate parameters were selected. The confusion matrix for DT is shown in Table 2.

Table 2. Confusion matrix for DT

		Actual values	
		Patient in intensive care (1)	Patient not in intensive care (0)
Prediction values	Patient in intensive care (1)	67	6
	Patient not in intensive care (0)	2	66

According to Table 2, DT correctly classified 133 patients and misclassified 8 patients. The confusion matrix for KNN is shown in Table 3.

Table 3. Confusion matrix for KNN

		Actual values	
		Patient in intensive care (1)	Patient not in intensive care (0)
Prediction values	Patient in intensive care (1)	66	5
	Patient not in intensive care (0)	3	67

According to Table 3, KNN correctly classified 133 patients and misclassified 8 patients. The confusion matrix for LR is shown in Table 4.

Table 4. Confusion matrix for LR

		Actual values	
		Patient in intensive care (1)	Patient not in intensive care (0)
Prediction values	Patient in intensive care (1)	46	12
	Patient not in intensive care (0)	23	60

As shown in Table 4, LR correctly classified 106 patients and misclassified 35 patients. The confusion matrix for MLP is shown in Table 5.

Table 5. Confusion matrix for MLP

		Actual values	
		Patient in intensive care (1)	Patient not in intensive care (0)
Prediction values	Patient in intensive care (1)	55	8
	Patient not in intensive care (0)	14	64

As seen in Table 5, MLP correctly classified 119 patients and misclassified 22 patients. The confusion matrix for NB is shown in Table 6.

Table 6. Confusion matrix for NB

		Actual values	
		Patient in intensive care (1)	Patient not in intensive care (0)
Prediction values	Patient in intensive care (1)	39	16
	Patient not in intensive care (0)	30	56

As seen in Table 6, NB correctly classified 95 patients and misclassified 46 patients. The confusion matrix for RF is shown in Table 7.

Table 7. Confusion matrix for RF

		Actual values	
		Patient in intensive care (1)	Patient not in intensive care (0)
Prediction values	Patient in intensive care (1)	67	4
	Patient not in intensive care (0)	2	68

As seen in Table 7, RF correctly classified 135 patients and misclassified six patients. The confusion matrix for SVM is shown in Table 8.

Table 8. Confusion matrix for SVM

		Actual values	
		Patient in intensive care (1)	Patient not in intensive care (0)
Prediction values	Patient in intensive care (1)	67	3
	Patient not in intensive care (0)	2	69

As shown in Table 8, SVM correctly classified 136 patients and misclassified 5 patients.

Table 9. The comparative experimental results

Model	Accuracy	Recall	Precision	F-score
DT	0,943	0,971	0,917	0,940
KNN	0,943	0,956	0,929	0,942
LR	0,751	0,666	0,793	0,723
MLP	0,843	0,797	0,873	0,833
NB	0,673	0,565	0,709	0,628
RF	0,957	0,971	0,943	0,956
SVM	0,964	0,971	0,957	0,963

As shown in Table 9 and Figure 9, SVM has better classification performance than the other compared algorithms. SVM has 0.964 accuracy, 0.957 precision, 0.971 recall, and 0.963 F-score. Following SVM, RF, KNN, DT, MLP, LR, and NB are the other successful algorithms, respectively.

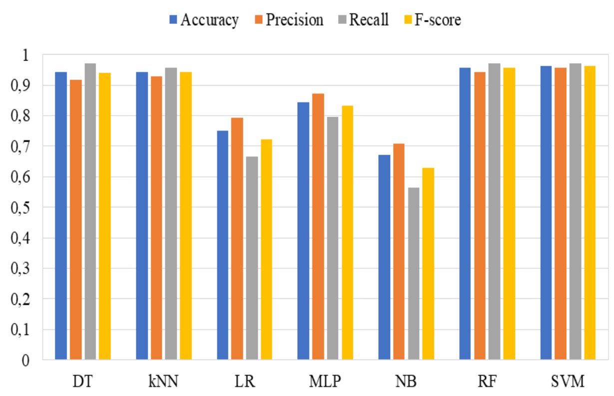

Figure 9. The comparative experimental results

Conclusions

Numerous cases and fatalities were reported due to the COVID-19 pandemic worldwide. The rapid spread of COVID-19 has meant that there has been limited time to identify the virus's infectiousness and effective treatments. During the pandemic, limited ventilators and medical equipment supplies have made providing life-saving treatment to patients challenging. Therefore, identifying patients who require intensive care or are at high risk of death on hospital admission can help healthcare professionals to direct patients to the most appropriate care setting. Predicting which patients are at high risk can guide healthcare professionals' treatment choices during critical periods of the disease course.

In this study, a machine learning-based detection system was developed to identify patients who need to be admitted to the ICU using demographic characteristics and clinical findings of patients infected with COVID-19. For this purpose, DT, LR, KNN, MLP, NB, RF, and SVM are comprehensively compared using accuracy, recall, precision, and F-score metrics. The experimental results show that SVM has 0.964 accuracy, 0.957 precision, 0.971 recall, and 0.963 F-score. Following SVM, RF, KNN, DT, MLP, LR, and NB are the other successful algorithms, respectively.

The reason that SVM performs better than RF can be explained by the dataset's use of both numerical and categorical features. Combining numerical and category characteristics is how RF operates. When features are present at several scales, RF is practical. For example, SVM determines the separation between points and maximizes the margin between them. Therefore, the dataset's combination of categorical and numerical variables makes SVM more effective than RF.

KNN and SVM are distance-based classification algorithms. KNN identifies the k training samples that are closest to the target sample. A distance function such as Euclidean finds which k is nearest. These neighborhoods are then used to classify the target. Thus, classification is based only on the samples close to the mark, and more distant instances are ignored. SVM tries to find a hyperplane that separates the different classes of training samples with a maximum margin of error. Therefore, SVM performs a broad margin classification, creating a large margin between the data points and the hyperplane. The most crucial training examples form the boundary—striking a balance between how many instances to allow on the wrong side and how complex the border controls the model's complexity. The models are usually much more complicated than distance-based classifiers such as KNN but take more information into account when classifying the target sample and are usually much more successful.

Integrating the results from many decision trees in RF can explain why RF is more successful than DT. Furthermore, RF generates and classifies various models on multiple decision trees with the bagging method by training each decision tree on a different observation sample. Therefore, RF is generally more successful than DT.

The fact that KNN is more successful than LR can be interpreted as the parametric structure of the models. KNN supports non-linear solutions, whereas LR only supports linear solutions.

The fact that RF and SVM are more successful than MLP can be interpreted as RF and SVM work better on tabular data. Neural network models such as MLP require scaling of attributes. This way, more important features will be treated as more important in training. This will prevent the neurons from working successfully in the training phase. The fact that NB has a poorer classification performance than the other models can be interpreted as the inability of NB to represent the complex patterns in the dataset due to the small model size.

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Declaration of Competing Interest

There is no conflict of interest.

Author Contributions

All the authors contributed to the study's conception, design, data analysis, and writing of the original manuscript. AU carried out data curation, methodology, and software development. UC contributed to the original draft's conceptualization, validation, supervision, rewriting, and editing. All authors read and approved the final manuscript draft.

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