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Development of Machine Learning Prediction Models to Predict ICU Admission and the Length of Stay in ICU for COVID-19 Patients Using a Clinical Dataset Including Chest Computed Tomography Severity Score Data

COVID-19 Hastalarının Yoğun Bakım Ünitesine Yatışlarını ve Hastanede Kalış Sürelerini Tahmin Etmek için Makine Öğrenimi Modellerinin Geliştirilmesi

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ABSTRACT

Objective: The chest computed tomography severity score (CT-SS) is significantly associated with the severity of the disease and subsequently intensive care unit (ICU) admission in coronavirus disease-19 (COVID-19) patients. However, there was a lack of information about the prognostic role of radiological manifestations in combination with demographics, clinical manifestations, and laboratory predictors to predict ICU admission and the length of stay (LOS) in the ICU (ICU LOS) of COVID-19 patients. The machine learning (ML) approach is a new and, non-invasive digital technology that can present an efficient risk prediction model for clinical problems. The purpose of the present study was to develop an effective ML model for predicting ICU admission and ICU LOS for COVID-19 patients using a more comprehensive dataset including imaging findings.

Methods: A COVID-19 hospital-based registry database that contained medical records of 6,854 patients was retrospectively reviewed. The incomplete records with missing values of more than 70% were excluded, and the remaining missing values were imputed using the mean and mode values for the continuous and discrete variables,

ÖZ

Amaç: Göğüs bilgisayarlı tomografi şiddet skoru (BT-SS), koronavirüs hastalığı-19 (COVID-19) hastalarında hastalığın şiddeti ve sonrasında yoğun bakım ünitesine (YBÜ) yatışla önemli ölçüde ilişkilidir. Ancak, COVID-19 hastalarının YBÜ yatışını ve YBÜ'de kalış süresini (LOS) (YBÜ LOS) tahmin etmek için demografik özellikler, klinik belirtiler ve laboratuvar öngörücüleriyle birlikte radyolojik bulguların prognostik rolü hakkında bilgi eksikliği vardı. Makine öğrenimi (ML) yaklaşımı, klinik sorunlar için etkili bir risk tahmin modeli sunabilen yeni ve invaziv olmayan bir dijital teknolojidir. Mevcut çalışmanın amacı, görüntüleme bulgularını içeren daha kapsamlı bir veri seti kullanarak COVID-19 hastaları için YBÜ yatışını ve YBÜ'de kalış süresini tahmin etmek için etkili bir ML modeli geliştirmekti.

Yöntemler: Altı bin sekiz yüz elli dört hastanın tıbbi kayıtlarını içeren bir COVID-19 hastane tabanlı kayıt veritabanı retrospektif olarak incelendi. %70'ten fazla eksik değere sahip eksik kayıtlar hariç tutuldu ve kalan eksik değerler, sürekli ve ayrık değişkenler için sırasıyla ortalama ve mod değerleri kullanılarak hesaplandı. Grupların veri sayılarındaki dengesizlik, sentetik azınlık örnekleme tekniği algoritması

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ABSTRACT

respectively. The imbalance in the data numbers of groups was resolved using the synthetic minority over-sampling technique algorithm. Two sets of prediction models were separately developed to predict ICU admission and ICU LOSs of COVID-19 patients. The most important and related predictors selected by the Boruta feature selection method were used to develop ML prediction models. The parameters obtained from the confusion matrix were used to evaluate the performance of the prediction models. The performance evaluation of the developed ML models for predicting ICU LOS of the patients utilized correlation coefficient, mean absolute error, and root mean squared error metrics.

Results: The records of 815 positive reverse transcription polymerase chain reaction (RT-PCR) patients were included in the study after applying the inclusion/exclusion criteria. Of the 815 positive RT-PCR patients, only 185 patients were admitted to the ICU to receive intensive care. The number of records in the ICU admission group was raised to 630 to deal with the data imbalance problem. For predicting the ICU admission of COVID-19 patients, k-nearest neighbors (k-NN) yielded better performance than J48, support vector machine, multi-layer perceptron, Naïve Bayes, logistic regression, random forest (RF), and XGBoostbased ML models. The sensitivity, specificity, accuracy, precision, F-measure, and area under the curve of the k-NN algorithm were 97.0%, 89.7%, 93.3%, 90.4%, 93.6%, and 99.1%, respectively. Results showed that with a correlation coefficient of 0.42, a mean absolute error of 2.01, and a root mean squared error of 4.11, the RF algorithm with a correlation coefficient of 0.42, mean absolute error of 2.01, and root mean squared error of 4.11demonstrated the best performance in predicting the ICU LOS of COVID-19 patients.

Conclusion: The ML approach, utilizing a more comprehensive dataset that includes CT-SS, could efficiently predict ICU admission and ICU LOS of COVID-19 patients. Timely prediction of ICU admission and ICU LOS of COVID-19 patients would improve patient outcomes and lead to the optimal use of limited hospital resources.

Keywords: Computed tomography, COVID-19, machine learning, intensive care unit, length of stay

ÖZ

kullanılarak çözüldü. COVID-19 hastalarının YBÜ yatışını ve YBÜ'de kalış sürelerini tahmin etmek için ayrı ayrı iki tahmin modeli seti geliştirildi. Boruta özellik seçimi yöntemi ile seçilen en önemli ve ilgili tahmin ediciler, ML tahmin modellerini geliştirmek için kullanıldı. Karışıklık matrisinden elde edilen parametreler, tahmin modellerinin performansını değerlendirmek için kullanıldı. Hastaların YBÜ kalış sürelerini tahmin etmek için geliştirilen ML modellerinin performans değerlendirmesinde korelasyon katsayısı, ortalama mutlak hata ve kök ortalama kare hata ölçümleri kullanıldı.

Bulgular: Dahil etme/dışlama kriterleri uygulandıktan sonra 815 pozitif ters transkripsiyon polimeraz zincir reaksiyonu (RT-PCR) hastasının kayıtları çalışmaya dahil edildi. Sekiz yüz on beş pozitif RT-PCR hastasından yalnızca 185 hasta yoğun bakıma alınmak üzere YBÜ'ye yatırıldı. YBÜ kabul grubundaki kayıt sayısı, veri dengesizliği sorunuyla başa çıkmak için 630'a çıkarıldı. COVID-19 hastalarının YBÜ kabulünü tahmin etmek için k-NN, J48, destek vektör makinesi, çok katmanlı algılayıcı, Naïve Bayes, lojistik regresyon, rastgele orman (RF) ve XGBoost tabanlı ML modellerinden daha iyi performans gösterdi. k-NN algoritmasının duyarlılığı, özgüllüğü, doğruluğu, kesinliği, F-ölçüsü ve eğri altında kalan alanı sırasıyla %97,0, %89,7, %93,3, %90,4, %93,6 ve %99,1 idi. Sonuçlar, 0,42 korelasyon katsayısı, 2,01 ortalama mutlak hata ve 4,11 kök ortalama kare hatası ile 0,42 korelasyon katsayısı, 2,01 ortalama mutlak hata ve 4,11 kök ortalama kare hatası olan RF algoritmasının COVID-19 hastalarının YBÜ kalış süresini tahmin etmede en iyi performansı gösterdiğini gösterdi.

Sonuç: BT-SS'yi içeren daha kapsamlı bir veri setini kullanan ML yaklaşımı, COVID-19 hastalarının YBÜ yatışını ve YBÜ kalış süresini etkili bir şekilde tahmin edebilir. COVID-19 hastalarının YBÜ yatışının ve YBÜ kalış süresinin zamanında tahmin edilmesi hasta sonuçlarını iyileştirecek ve sınırlı hastane kaynaklarının optimum şekilde kullanılmasını sağlayacaktır.

Anahtar Sözcükler: Bilgisayarlı tomografi, COVID-19, makine öğrenimi, yoğun bakım ünitesi, kalış süresi

INTRODUCTION

In December 2019, the novel coronavirus disease-19 (COVID-19), also known as severe acute respiratory syndrome coronavirus 2, was detected in Wuhan City, China. Since the first reports, over 690 million cases of infection with COVID-19 and 9.6 million deaths among these individuals have been reported (19 Jun 2023) (1). The COVID-19 virus has heterogeneous and mutable clinical manifestations which result in poor outcomes (2). Its clinical presentations range from asymptomatic to severe complications and death in some cases (2,3). For many patients with mild symptoms, clinical manifestations of the disease can rapidly change to severe complications including acute respiratory distress syndrome and multi-organ failure, which lead to intensive care unit (ICU) hospitalization (2,4).

Approximately 20% of COVID-19 patients over 80 years old needed hospital care, and ICU care requirements of COVID-19 in-hospital patients ranged from 5% to 32%, depending on the location of the study and characteristics of the studied community (5). The mortality rate of patients with severe disease manifestations is as high as 50% (6).

The complex clinical features and mutable clinical manifestation patterns of the disease have increased the demand for hospitalization and healthcare services. Under normal conditions, more than 50% of ICU resources are occupied (5,7), and during the outbreak of diseases such as COVID-19, there will be a significant limitation in medical resources and hospital beds. Therefore, early risk stratification has a critical role in patient management and medical resource allocation.

Artificial intelligence (AI) is a new and non-invasive digital technology that can present an efficient risk prediction model for clinical problems. In pioneer studies, an AI approach had also been implemented to predict the ICU admission and lengths of stay of COVID-19 patients. The machine learning (ML) approach, as a subfield of AI, is used to generate risk prediction models in retrospective datasets (2,7,8). In several studies, ML prediction models have been developed to predict the ICU admission and ICU LOS of COVID-19 patients (2,7, 9-15). In these studies, prognostic factors related to the severity of the disease, the ICU admission, and ICU LOSs of the patients, including age, comorbidities, and laboratory results were reported. There was a lack of information about the prognostic role of radiological manifestations in predicting ICU admission and ICU LOSs of COVID-19 patients.

Chest imaging is an indispensable diagnostic method for the diagnosis, monitoring, and management of COVID-19 patients.

The severity of pulmonary involvement on computed tomography (CT) scans, or the chest CT severity score (CT-SS), is significantly associated with the severity of the disease, ICU admission, and mortality of patients (16-19).

Therefore, CT-SS could improve the prognostic performances of the ML algorithms to predict the ICU admission and ICU LOSs of COVID-19 patients. To the best of our knowledge, the prognostic role of imaging manifestations in combination with demographics, clinical manifestations, and laboratory predictors to predict ICU admission and ICU LOS of COVID-19 patients has not yet been evaluated.

The purpose of the present study is to develop an effective ML prediction model the ICU admission and ICU lengths of stay of COVID-19 patients using a more comprehensive dataset including demographics, clinical manifestations, laboratory results, and imaging findings. Therefore, the most relevant predictors related to ICU admission and ICU LOSs of the patients were first determined. In the next step, using these predictors, we developed and evaluated ML prediction models to predict ICU admission and ICU LOSs of the COVID-19 patients.

MATERIALS AND METHODS

Ethics Approval and Consent to Participate

This article is extracted from a research project supported by Abadan University of Medical Sciences and all experimental protocols were approved by the ethical committee of Abadan University of Medical Sciences (approval number: IR.ABADANUMS.REC.1402.108, date: 14.11.2023). All methods of the study were performed in accordance with the relevant guidelines and regulations of the Ethics Committee of Abadan University of Medical Sciences. Participation was voluntary and informed consent was obtained from all subjects and/or their legal guardians. Participants had the right to withdraw from the study at any time.

Dataset Description

In this study, a COVID-19 hospital-based registry database that contained 6,854 patients was retrospectively reviewed. Of the 6,854 patients, 1,853 cases were COVID-19-positive, 2,472 cases were COVID-19-negative, and 2,529 cases were unspecified. In this COVID-19 registry database, demographic information (eight features), clinical pictures (21 features), comorbidities (13 features), laboratory results (28 features), and radiological findings (CT-SS) were collected at the time of patient admission. The primary outcome was defined as admission to the ICU, and the output feature was registered as either ICU-admission or non-ICU-admission.

CT-SS quantifies the severity of pulmonary involvements in CT images. For radiological evaluation of the patients, each lung lobe was visually scored as 0 (no involvement), 1 (less than 5% involvement), 2 (5%-25% involvement), 3 (25%-50% involvement), 4 (50%-75% involvement), and 5 (more than 75% involvement). The sum of these lobar scores determines CT-SS, which ranges from 0 to 25. For each patient, chest CT images were separately evaluated by two radiologists in a double-blind fashion. Any disagreements between them were resolved through further discussions and consulting with a third attending radiologist with 23 years of experience.

Data Pre-processing

Data pre-processing is used to address irrelevant, redundant, and unreliable instances in ML studies. A substantial number of inconsistencies could be resolved using data pre-processing. Data pre-processing will be performed before the training of the ML models. First, the presence of missing values is one of the common issues for the independent features of a medical dataset (20). To deal with this issue, incomplete records with many missing values (more than 70%) were excluded. For the continuous and discrete variables, the remaining missing values were imputed using the mean and mode values, respectively. Noisy, abnormal, and meaningless data were checked, and if necessary, we contacted the corresponding physicians.

The patients with negative reverse transcription polymerase chain reaction (RT-PCR) COVID-19 test, unknown dispositions, discharge or death from the emergency department, missing data >70%, and ages younger than 18 years old were excluded from the study. Figure 1 illustrates the schematic representation of the study inclusion and exclusion criteria. The final sample size of the included cases was 815 patients who tested positive with RT-PCR.

This dataset contains 630 and 185 cases in the non-ICU-admitted and ICU-admitted groups, respectively. The imbalance in the sample sizes of these groups delivers biased results toward the dominant class. To deal with this issue, the synthetic minority over-sampling technique (SMOTE) was used (https://imbalanced-learn.org/stable/). SMOTE generates synthetic data until the minority cases are balanced with the majority.

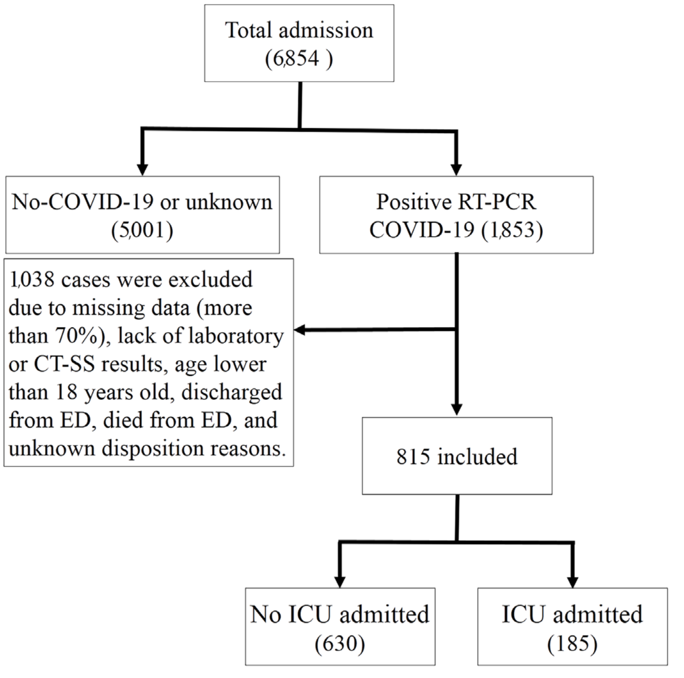

Figure 1. Flow chart describing patient selection.

COVID-19: Coronavirus disease-19, ICU: Intensive care unit, CT-SS: Computed tomography severity score, RT-PCR: Reverse transcription polymerase chain reaction, ED: Emergency department

Feature Selection

In data mining studies, the most important and related predictors are commonly determined using the feature selection process (21). Overfitting, as one of the critical problems in developing ML models, could be considerably avoided using the feature selection procedure (22).

In this study, the Boruta feature selection package implemented in the R programming environment (version 4.0.3; https://www.r-project.org/) was used. This method is a wrapper algorithm built upon the random forest algorithm. The Boruta algorithm determines the importance magnitudes of all relevant features in the prediction of the target output. The Boruta algorithm assesses the significance of each feature using the importance values derived from shadow attributes. These shadow attributes are generated by shuffling the values of the original attribute across the subjects. This approach involves extending the information system by adding copies of all variables, which are then shuffled to eliminate any correlations between the features and the output. The random permutation of features among the studied populations results in a decrease in classification accuracy. The importance of a given attribute is quantified using a Z score, which is calculated by dividing the average loss of classification accuracy by the attribute's standard deviation. The maximum Z score (MZSA) for the shadow attributes is identified, and any attribute with an importance value higher than this score is classified as a hit. Conversely, attributes with importance values lower than MZSA are considered unimportant and are subsequently removed from the information system. This process continues with the elimination of shadow attributes until the significance of each feature is established. For all feature selections, the maximal number of importance source runs and the verbosity level (doTrace) were set to 500 and 2, respectively.

Model Development

In this study, two sets of prediction models were separately developed to predict ICU admission and the ICU in COVID-19 patients. For ICU admission prediction, eight ML models including the J48 decision tree (J48), support vector machine (SVM), multi-layer perceptron (MLP), k-nearest neighbors (k-NN), Naïve Bayes (NB), logistic regression (LR), random forest (RF), and eXtreme gradient boosting (XGBoost) algorithms were developed. Gaussian processes (GP), linear regression (LinR), MLP, SVM, k-NN, locally weighted learning (LWL), M5-Prime (M5P), M5-based decision list for regression problems using separate-and-conquer (M5Rules), and RF algorithms were used to predict the ICU LOS in COVID-19 patients. All ML prediction models were implemented using Waikato Environment for Knowledge Analysis (Weka) software (version 3.9.2; University of Waikato, New Zealand). The 10-fold cross-validation method was used for evaluating the performance of the developed prediction models. In the ten-fold cross-validation method, the samples are randomly divided into ten subgroups. In this method, 10 training and validation iterations are performed with different data folds. For each iteration, nine subgroups of data are used to train the model, and the remaining subgroup is the validation dataset. The parameters obtained from the confusion matrix, including accuracy, precision, sensitivity, specificity, F-measure, and area under the curve (AUC) receiver operating characteristic (ROC) metrics, were used to evaluate the performance of prediction models for predicting ICU admission of the patients. The average magnitudes of the accuracy, sensitivity, specificity, among other indices, for these ten iterations are considered to evaluate the model performance.

For the performance evaluation of the developed ML models to predict ICU LOS of the patients, correlation coefficient, mean absolute error, and root mean squared error metrics were used.

RESULTS

The COVID-19 hospital-based registry database that contained 6,854 suspected cases was retrospectively reviewed. Records of 815 positive RT-PCR patients were included in the study after applying the inclusion/exclusion criteria. The mean age of COVID-19 patients was 57.22±16.76 years, and 54.85% of the study population was male.

Of the 815 positive RT-PCR patients, only 185 cases were admitted to ICU to receive intensive care. Therefore, there was a considerable data imbalance between the ICU-admission and non-ICU-admission groups (185 vs. 630 cases). To deal with this data imbalance, the SMOTE technique was used and the number of records in the ICU admission group was raised to 630.

Feature Selection

The magnitudes of importance of the features to predict ICU admission and ICU LOS of COVID-19 patients are shown in Figure 2. In this figure, the X and Y axes represent the features and their corresponding importance values. The irrelevant, tentative, and relevant features were represented by red, yellow, and green box plots, respectively. The blue box plots show the minimum, average, and maximum shadow variables.

Evaluation of The Developed Models

In this study, ML models for predicting the ICU admission of COVID-19 patients were developed using J48, SVM, MLP, k-NN, NB, LR, RF, and XGBoost algorithms. The ICU LOS of these patients was also predicted using nine ML models, including GP, LinR, MLP, SVM, k-NN, LWL, M5Rules, M5P, and RF algorithms. The ML prediction models were trained and tested using the selected features in the previous step. The sensitivity, specificity, accuracy, precision, F-measure, and AUC metrics were used to evaluate the prognostic performances of the ML models for predicting the ICU admission of COVID-19 patients. The performance metrics of the ML prediction models for the ICU admission of COVID-19 patients were listed in Table 1. Results of the performance evaluation for the developed ML models that are to predict the ICU LOS of COVID-19 patients are listed in Table 2.

For predicting the ICU admission of COVID-19 patients, k-NN yielded the best performance compared to other ML models. The sensitivity, specificity, accuracy, precision, F-measure, and AUC of the k-NN algorithm were 97.0%, 89.7%, 93.3%, 90.4%, 93.6%, and 99.1%, respectively. The comparison of the area under the ROC curves of the ML prediction algorithms for predicting the ICU admission of COVID-19 patients is presented in Figure 3.

For predicting the ICU length of stay of COVID-19 patients, results showed that the RF algorithm yielded better performance than other ML algorithms. The correlation coefficient, mean absolute error, and root mean squared error of the RF algorithm were 0.42, 2.01, and 4.11, respectively.

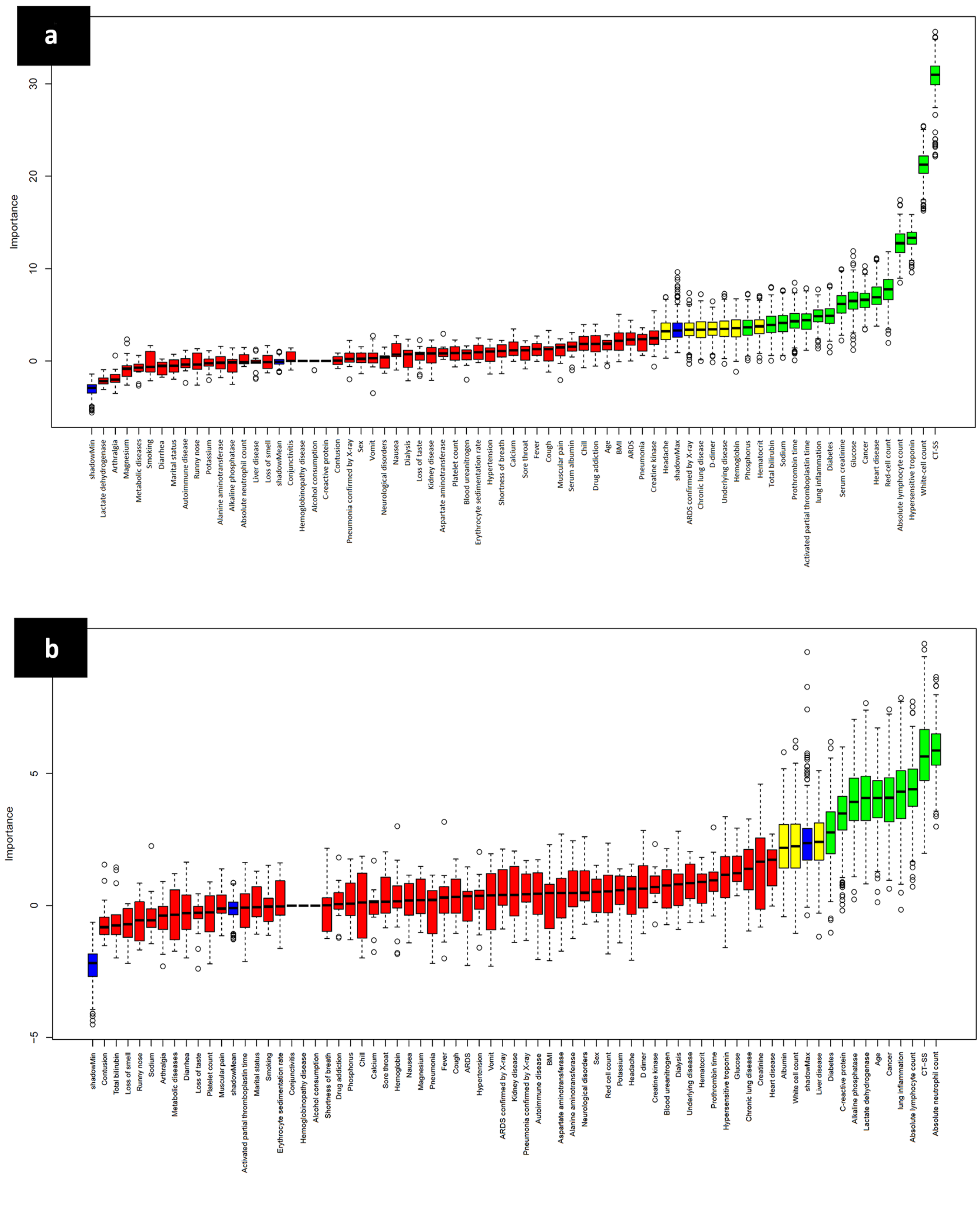

Figure 2. The plots show feature selections used to predict a) ICU admission and b) ICU LOS of COVID-19 patients using the Boruta algorithm. Green, yellow, and red boxes represent the relevant, tentative, and irrelevant features. Blue boxes denote the minimum, mean, and maximum of shadow variables.

COVID-19: Coronavirus disease-19, ICU: Intensive care unit, LOS: Length of stay

Table 1. Performances of ML algorithms for predicting ICU admission in COVID-19 patients

ML algorithm	Sensitivity	Specificity	Accuracy	Precision	F-measure	AUC
Decision tree	86.3	81.7	84.0	82.5	84.4	88.1
SVM	76.2	80.5	78.3	79.6	77.9	78.3
MLP	96.7	87.0	91.8	88.1	92.2	95.0
k-NN	97.0	89.7	93.3	90.4	93.6	99.1
Naïve Bayes	73.7	77.8	75.7	76.8	75.2	84.1
Logistic regression	76.2	81.3	78.7	80.3	78.2	85.4
Random forest	97.6	87.9	92.8	89.0	93.1	98.6
XGBoost	97.0	85.1	91.0	86.8	91.6	91.1

ML: Machine learning, AUC: Area under the curve, SVM: Support vector machine, MLP: Multi-layer perceptron, k-NN: k-nearest neighbors, XGBoost: eXtreme gradient boosting, COVID-19: Coronavirus disease-19

Table 2. Performances of ML algorithms to predict the ICU LOS of COVID-19 patients

	Gaussian processes	Linear regression	MLP	SVM	kNN	LWL	M5 rules	M5P	RF
Correlation coefficient	0.3541	0.3475	0.1821	0.1318	0.3696	0.2122	0.38	0.3714	0.4225
Mean absolute error	2.3453	2.3504	3.5832	1.632	1.9131	2.2123	2.1704	2.1937	2.0106
Root mean squared error	4.2317	4.2516	6.9122	4.7523	4.2789	4.4817	4.2022	4.2279	4.1096

LWL: Locally weighted learning, SVM: Support vector machine, RF: Random Forest, MLP: Multi-layer perceptron, ICU: Intensive care unit, SVM: support vector machine, k-NN: k-nearest neighbors, COVID-19: Coronavirus disease-2019

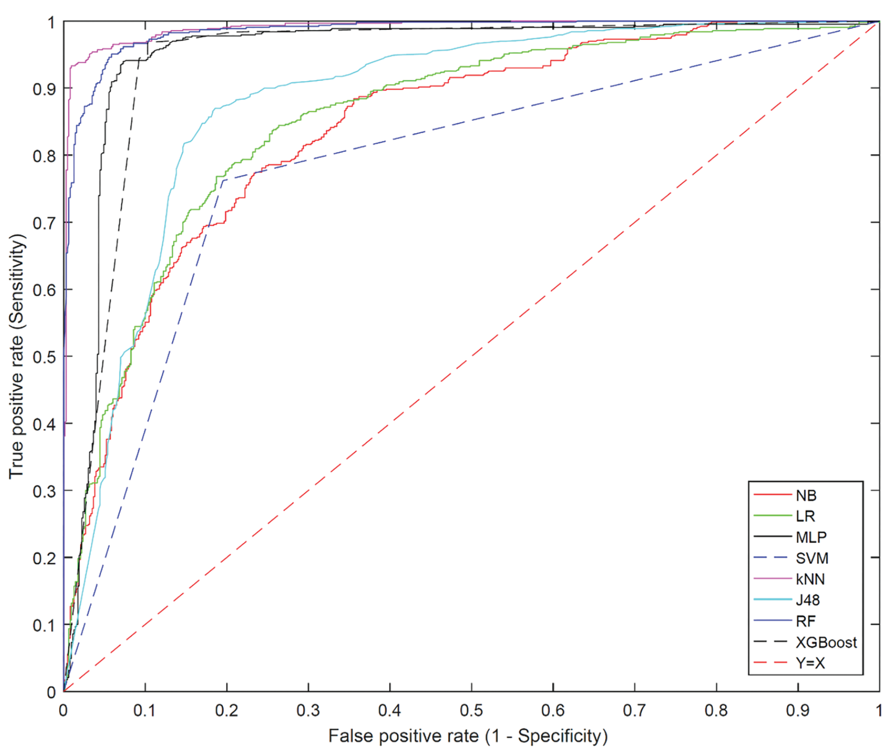

Figure 3. ROC curves for ML algorithms in the prediction of ICU admission in COVID-19 patients.

COVID-19: Coronavirus disease-19, ROC: Receiver operating characteristic, ICU: Intensive care unit, ML: Machine learning, NB: Naive Bayes, LR: Logistic regression, MLP: Multi-layer perceptron, SVM: Support vector machine, kNN: k-nearest neighbors, RF: Random forest

DISCUSSION

During the outbreak of a disease such as the COVID-19 pandemic, predicting a patient's disease course is essential for accurate triage and efficiently allocating resources (11,23). A high rate of mortality was reported for ICU-admitted COVID-19 patients, which varies between countries from 16% to 67% (5,24). Thus, early risk stratification could significantly improve patient outcomes and limit morbidity and mortality as much as possible.

The prediction models as a clinical decision-support tool would enable healthcare providers to identify the patients at significant risks associated with COVID-19 disease before the deterioration of their health condition (23). Determining the predictors related to patient ICU admission and identifying early the patients who will most likely benefit from increased care can assist in the effective allocation of limited hospital resources and optimization of patient management (4,5,7).

Chest CT is a common imaging method for diagnosing and screening patients with COVID-19, due to its high sensitivity to depict interstitial pneumonia (17,18). The severity of pulmonary involvements is significantly correlated with the severity of COVID-19, ICU admission, and patient mortality (16-19).

In the pioneering studies, ML-based prediction models were developed using demographics, clinical manifestations, and laboratory predictors (2,7,9-15).

There was a lack of imaging manifestations in ML prediction models to predict the ICU admission, and ICU LOS of COVID-19 patients. In our study, CT-SS was the most important predictor for the prediction of the likelihood of transferring COVID-19 patients to the ICU. ICU-admitted patients have higher CT-SSs; in other words, patients with higher CT-SS need more intensive care. There was a significant difference in the CT-SS index between the ICU-admitted and non-ICU-admitted patients ($p<0.001$). CT-SS was also the second most important feature to predict ICU LOS in COVID-19 patients. There is a statistically significant linear relationship between the CT-SS and ICU LOS of the patients ($r=0.257$, $p<0.001$).

These results showed that CT-SS is a strong predictor of ICU admission and ICU LOS of COVID-19 patients. Therefore, we evaluated the prognostic role of CT-SS in combination with demographics, clinical manifestations, and laboratory predictors to predict ICU admission and LOS of COVID-19 patients. In this study, we determined the most important features related to ICU admission and ICU LOS of COVID-19 patients. ML models for predicting ICU admission and ICU LOS of the patients were developed using these predictors. The results showed that k-NN yielded the best performance for predicting the ICU admission of COVID-19 patients. The sensitivity, specificity, accuracy, precision, F-measure, and AUC of the k-NN algorithm for predicting the ICU admission of COVID-19 patients were 98.1%, 83.5%, 90.8%, 85.6%, 91.4%, and 98.8%, respectively. For predicting the ICU LOS of COVID-19 patients, the RF algorithm, with a correlation coefficient of 0.42, mean absolute error of 2.01, and root mean squared error of 4.11, yielded better performance than other ML algorithms.

In previous studies, ML prediction models were also evaluated to predict ICU admission and ICU LOS of COVID-19 patients. Islam et al. (25) evaluated eight ML classifiers, including RF, SVM, k-NN, XGBoost, MLP, LR, extra trees, and gradient boosting models, for predicting ICU admission in patients with COVID-19 infection eight ML classifiers including RF, SVM, k-NN, XGBoost, MLP, LR, extra trees, and gradient boosting models were evaluated. In this study, a clinical dataset containing 156 positive COVID-19 patients was retrospectively reviewed. Results showed that RF, ET, k-NN, and LR were the four top ML models for predicting ICU admission for patients. The stacking model developed by integrating RF, ET, and k-NN algorithms with a sensitivity of 84.48%, specificity of 84.47%, overall accuracy of 84.48%, weighted precision of 84.45%, and F1-score of 83.64% yielded the best performance. The main limitation of this study was the number of parameters studied. In this study, only 9 parameters from clinical, radiological, and laboratory indices were examined, of which 5 were selected as the most important parameters in the feature selection step. These prediction models were developed using 5 features, including C-reactive protein, chest CT lung tissue affected (%), age, time between disease onset and hospital admission (days), and fibrinogen indices. In our study, 73 clinical features were examined, and the most relevant features from this dataset were used to develop predictive models. Utilizing this comprehensive dataset, we developed predictive models with improved performance.

In Shanbehzadeh et al. (7) study, ICU admission of COVID-19 patients was predicted using decision tree models including decision stump, Hoeffding tree, LMT, J48, RF, random tree, and REP-Tree algorithms. Twelve features, which included demographics, clinical manifestations, and laboratory predictors from the records of 512 COVID-19 patients, were used to develop ML models. The J48 algorithm, with a sensitivity of 92.4%, specificity of 65.9%, accuracy of 81.9%, F-score of 81.4%, and AUC of 84.5, had the best performance for estimating ICU admission of COVID-19 patients. Our results showed that the severity of pulmonary involvement in radiological images is one of the most relevant features for predicting the ICU admission and ICU LOS of COVID-19 patients. In our study, in addition to a more comprehensive dataset from demographics, comorbidities, clinical manifestations, and laboratory predictors, to develop ML models. Although the results of the Shanbehzadeh et al. (10) study were in close agreement with our findings, ML models with better classification performance were obtained in our study.

Saadatmand et al. (10) also evaluated ML approaches for predicting ICU admission, ICU LOS, and mortality at the ICU in COVID-19 patients (12). Demographic data, comorbidities, clinical features, and laboratory results from 956 patients admitted to the ICU was a registered dataset. RF with a sensitivity of 91%, specificity of 96%, accuracy of 93%, and AUC of 97.6% achieved the best result for predicting patient admission to the ICU. For predicting ICU LOS, the XGB model with a sensitivity of 88%, specificity of 40%, accuracy of 78%, and AUC score of 79.5% had the best performance. In this study, the mean ICU LOS was considered 7 days, and the performances of the developed models were checked to determine how effectively they could predict whether the patient will be hospitalized for more than 7 days or not. In our study, the prognostic performances of the ML models in predicting ICU LOS of the patients were evaluated.

These observations showed that ML prediction models can help in the early and accurate identification of critical patients who need intensive care. Timely prediction of ICU admission in COVID-19 patients would improve patient outcomes and lead to the optimal use of limited hospital resources. Our results showed that the ML approach utilizing a more comprehensive dataset including CT-SS could efficiently predict ICU admission and ICU LOS of COVID-19 patients.

Study Limitations

This study had some limitations that must be acknowledged. First, this study was performed in a retrospective manner, and consequently, ML prediction models for ICU admission and ICU LOS of COVID-19 patients were not evaluated prospectively. Second, this is a single-center study, and external validation of the ML prediction models requires future multi-center studies with a larger sample size.

CONCLUSION

In this study, the predictive performance of ML models for ICU admission and ICU LOS of COVID-19 patients were evaluated using a dataset including CTSS data. Our results showed that the ML approach fed by a more comprehensive dataset including CT-SS could efficiently predict ICU admission and ICU LOS of COVID-19 patients. Timely and accurate prediction of ICU admission and ICU LOS of COVID-19 patients at the time of admission improves patient outcomes and leads to the optimal use of limited hospital resources.

Ethics

Ethics Committee Approval: This article is extracted from a research project supported by Abadan University of Medical Sciences and all experimental protocols were approved by the Ethical Committee of Abadan University of Medical Sciences (approval number: IR.ABADANUMS.REC.1402.108, date:14.11.2023).

Informed Consent: Participation was voluntary and informed consent was obtained from all subjects and/or their legal guardians. Participants had the right to withdraw from the study at any time.

Footnotes

Authorship Contributions

Surgical and Medical Practices: S.S.Z., N.N., H.K., Concept: S.S.Z., H.K., Design: S.S.Z., H.K., Supervision: S.S.Z., H.K., Resources: H.K., Material: S.S.Z., H.K., Data Collection or Processing: S.S.Z., N.N., H.K., Analysis or Interpretation: S.S.Z., H.K., Literature Search: S.S.Z., N.N., H.K., Writing: S.S.Z., N.N., H.K., Critical Review: S.S.Z., N.N., H.K.

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