Prediction of Length of Stay in the Emergency Department for COVID-19 Patients: A Machine Learning Approach

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ABSTRACT The coronavirus disease (COVID-19) outbreak has become a global public health threat. The influx of COVID-19 patients has prolonged the length of stay (LOS) in the emergency department (ED) in the United States. Our objective is to develop a reliable prediction model for COVID-19 patient ED LOS and identify clinical factors, such as age and comorbidities, associated with LOS within a “4-hour target.” Data were collected from an urban, demographically diverse hospital in Detroit for all COVID-19 patients’ ED presentations from March 16 to December 29, 2020. We trained four machine learning models, namely logistic regression (LR), gradient boosting (GB), decision tree (DT), and random forest (RF), across different data processing stages to predict COVID-19 patients with an ED LOS of less than or greater than 4 hours. The analysis is inclusive of 3,301 COVID-19 patients with known ED LOS, and 16 significant clinical factors were incorporated. The GB model outperformed the baseline classifier (LR) and tree-based classifiers (DT and RF) with an accuracy of 85% and F1-score of 0.88 for predicting ED LOS in the testing data. No significant accuracy gains were achieved through further splitting. This study identified key independent factors from a combination of patient demographics, comorbidities, and ED operational data that predicted ED stay in patients with prolonged COVID-19. The prediction framework can serve as a decision-support tool to improve ED and hospital resource planning and inform patients about better ED LOS estimations.

INDEX TERMS COVID-19, length of stay (LOS), 4-hour target, emergency department (ED), machine learning.

I. INTRODUCTION

The coronavirus (COVID-19) pandemic has strained healthcare systems in the United States and the world through increased care complexity, the need for medical staff and patient safety, and surges in patients suspected or infected with the severe acute respiratory syndrome coronavirus 2 (SARS-CoV2). Hospital emergency departments (EDs) face challenges, as the influx of infected COVID-19 patients has strained existing resources.

Due to the pandemic, numerous health systems in the US have reported increased workload and surges in patient volumes, resulting in ED crowding, which harms patient outcomes and puts additional strain on medical staff [1]–[3]. A key characteristic of crowding is the formation of queues in various parts of the health system as a result
of demand-exceeding capacities. These queue formations usually lead to extended average ED length of stay (LOS) [4], [5]. A prolonged ED LOS is associated with higher morbidity and mortality [6]–[8]. Numerous health systems have set time-based targets, requiring patients leaving the ED within the first 4 hours of arrival (i.e., “4-hour target”) [9]–[12]. However, with the ongoing pandemic, this 4-hour target has been hard to reach for COVID-19 patients leading to overcrowding, operational inefficiencies, and higher utilization of hospital resources.

Previous studies conducted before the COVID-19 pandemic on factors associated with ED LOS employed models such as multiple linear regression, logistic regression, decision trees, and accelerated failure time models [13]–[15]. Machine learning techniques can consider a larger number of attributes (i.e., patient records and hospital information) and permutations, which have the potential to yield a better understanding of complex problems and identify factors to predict COVID-19 ED patients’ LOS. To the best of our knowledge, no study has combined these data (i.e., patient and ED operational data) to predict COVID-19 ED patients’ LOS. In the present study, we innovatively applied four machine learning techniques, namely logistic regression, gradient boosting, decision tree, and random forest algorithm, across different data processing stages to develop a model to accurately predict the ED LOS of COVID-19 patients.

This research aims to first identify risk factors (e.g., age, race, sex, comorbidities, and nurse/physician availability) by examining both patients’ medical records and ED operational data, and then predict the ED LOS of COVID-19 patients with respect to a 4-hour target and identify patients with prolonged ED LOS accordingly. Such a model would enable ED operational leadership to understand the factors for prolonged ED LOS and potentially develop targeted interventions to reduce the proportion of COVID-19 patients experiencing long stays, leading to improved resource planning. Furthermore, the prediction model may be useful as a real-time decision support tool to improve care coordination, while also providing feedback to patients on their LOS.

II. METHODS

A. STUDY DESIGN, POPULATION, SETTING, AND OUTCOME

This is a retrospective and prognostic study on the performance of a prediction model. The goal of this study is to develop a prediction model to predict the ED LOS of COVID-19 patients (i.e., LOS <4 hours or ≥4 hours). Patient-level data were retrospectively retrieved from the data warehouse of the Henry Ford Hospital electronic health records (EHR) from March 16, 2020, to December 29, 2020. The research team accessed the hospital database/records on April 26, 2021, to obtain the retrospective data used in this study. The Henry Ford Hospital Institutional Review Board approved the study and waived the requirement for informed consent.

Henry Ford Hospital (HFH) is an 877-bed urban academic hospital and research center located in Detroit, Wayne County, Michigan, with an approximate population of 1.75 million. HFH is designated as a Level 1 trauma center that serves a high-acuity and racially diverse urban patient population. The ED treats an estimated 100,000 patients annually (45%). Patients requiring admission must be reviewed in the ED by a specialty-receiving doctor before they move to the ward. According to the John Hopkins Coronavirus Resource Center, COVID-19 cases in Wayne County are among the highest in the country [16].

The total number of ED visits during the study period was 57,665. We included patients with a positive real-time polymerase chain reaction (RT-PCR) result for severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) during or before their hospital encounter. We excluded patients who visited the ED during the study period and did not have RT-PCR confirmation of COVID-19. We retrieved de-identified COVID-19 patient-level data, including demographic information, comorbidities, common symptoms, vital signs, and clinical outcomes, from the hospital’s EHR for analysis in addition to ED operations data for the given period.

The study sample included adults, of whom 74.7% were African Americans, 5.5% were White, 5.1% were Asians, 0.5% were Hispanics, and 14.2% did not identify their race. Of the sample, 64.9% were female and 13.3% were aged 65 years and above. At least one chronic condition was present in 85.5% of the patients. The demographics of the study cohort mirrored those of the demographic data from the larger Detroit community. The primary study outcome was a length of stay of <4 hours in the ED (i.e., will achieve the “4-hour target” or not).

We developed an analytical prediction framework aimed at determining whether the ED LOS for COVID-19 patients will be less than or greater than 4 hours (Figure 1). Figure 1 describes how the data are extracted, processed, and split into training and testing datasets for analysis. We applied four machine learning algorithms for the prediction and conducted a model evaluation to determine the performance of each model. We implemented the four machine learning algorithms on two different data processing stages, first modeling the raw data after feature selection and engineering techniques, and then applying a balancing technique after data cleaning, feature selection, and engineering.

B. DATA COLLECTION AND ANALYSIS

EHR data included 127 clinical and operational variables. Noteworthy variables included age, sex, emergency severity index (ESI), insurance type, comorbid conditions, and patient complaint at the time of presentation. The outcome variable was ED LOS less than or greater than 4 hours and was determined by the first documented contact of the patient with the ED and the time that the patient was documented leaving the ED.
used to adjust the other with respect to ED LOS. The Bonferroni method was used to show which groups (i.e., patient race) differed from each other using the Wilcoxon rank-sum test with continuity correction. We also conducted a multiple comparison test to determine whether there were any statistically significant differences between the median ED LOS and patient race. We first normalized the data and performed a correlation analysis to understand the correlation between the variables for the feature selection process. The normality results of the K-S test will help us identify the correlation method (i.e., Pearson or Spearman correlation) for feature selection. The normality results of the K-S test yielded p-values < 1, indicating the data significantly deviated from a normal distribution. Therefore, we used Spearman correlation for feature selection. Spearman’s correlation test measures the monotonic relationship between the clinical variables of patients with COVID-19. The correlation coefficient values range from +1 to −1 and evaluate the degree of correlation between the two variables. We used one-hot encoding to convert the categorical data into binary variables. The length of ED stay was reclassified as binary (i.e., either ‘<4 hours’ or ‘≥4 hours’). We used a binning method to convert continuous attributes into categorical variables. Sixty (60) features remain after the feature-engineering process.

3) OVERSAMPLING
Imbalanced classification problems occur when the distribution of observations across known classes (e.g., 2,153 cases with LOS ≥4 hours and 1,148 cases with LOS <4 hours) is skewed. Imbalanced classifications are challenging for predictive modeling because most machine learning algorithms are designed based on the assumption that the model has an equal chance of learning for each class [17]. An imbalanced training dataset violates this assumption, leading to the development of models with poor predictive performance, specifically for the minority class (e.g., 1,148 cases with LOS <4 hours). An oversampling technique called the synthetic minority oversampling technique (SMOTE) was employed to address the imbalanced dataset, where observations from the minority class were randomly duplicated. SMOTE generates synthetic samples from the minority class using information available from the given dataset [18]. The addition of these duplicated values to the minority class balanced the training dataset, providing the model with an equal chance of learning. The application of SMOTE to an imbalanced dataset helps improve the performance of machine learning algorithms when compared to models without any data imbalance technique applied. The oversampling technique adjusted the ratio between these two groups to achieve a ratio of 1:1 (2153:2153).

4) PREDICTION MODEL
We applied four learning algorithms for our analysis: logistic regression, gradient boosting, decision tree, and random forest. Logistic regression (LR) is used as the baseline machine learning algorithm in this study. Gradient boosting (GB) is a machine learning algorithm that combines multiple weak learning models to create a solid predictive model. We built a binary GB classifier model to predict ED LOS. The decision tree (DT) algorithm is a commonly used data mining method for developing classification models based on multiple covariates or developing prediction algorithms for a target variable [19], [20]. We used the DT model to build a tree that identifies all possible attribute combinations from the predictive model, and the proportion of COVID-19 patients within the tree experiencing ED LOS less than or greater than 4 hour was calculated. Random forest (RF) is an ensemble classification algorithm consisting of multiple decision trees [21]. Therefore, we developed an RF prediction model to analyze the interactions between patient-level and ED characteristic data to predict the ED LOS of COVID-19 patients. We divided the sample into 80% training data (March 16 – October 29, 2020) and 20% testing data (October 30 – December 29, 2020). The testing dataset served as a temporal validation for the prediction framework. The models were trained using the introduced datasets. To validate the model, 10-fold cross-validation was used, which required a minimum of two records per leaf with a confidence.
factor of 0.3. It is important to note that the developed machine learning models were compared across different data processing stages. Statistical analysis (i.e., t-test) was conducted to evaluate whether significant improvement(s) existed in the models within the two data-processing stages (e.g., comparing RF1 and RF2).

5) MODEL EVALUATION
The performance of each model was evaluated based on accuracy and the F-1 score. The F-1 score is the harmonic mean of precision (positive predictive value) and recall (sensitivity), which complements the accuracy metric [22]. The F-1 score reached its best value at 100% and was worse at 0%. Because we are dealing with an imbalanced dataset in this study (i.e., 2,153 cases with LOS ≥ 4 hour and 1,148 cases with LOS < 4 hour), reporting the F-1 score provides a better explanation of the reported accuracy of our prediction models. We also measured the predictive accuracy of the model by reporting the area under the receiver operating characteristic (ROC) curve (AUC). For more information on the model evaluation, see the Appendix. All analyses were conducted using Python (Jupyter version 1.0.0, United States) and IBM SPSS Statistics (version 27.0; 2020, United States).

III. RESULTS
A. PATIENT SELECTION
Figure 2 illustrates a flowchart of the COVID-19 patient cohort. A total of 57,665 patient visits were recorded at the HFH between March 16 and December 29, 2020. A total of 38,189 patients were screened for COVID-19 and 19,476 were not screened. There were 3,301 patients with confirmed COVID-19 diagnoses. The final study cohort used with confirmed COVID-19 diagnoses and 34,888 with non-confirmed COVID-19 diagnoses. The final study cohort used in this analysis was 3,301 patients with confirmed COVID-19 diagnosis (median age, 51 years; 64.9% female), of which 2,153 (65.2%) had an ED LOS ≥ of 4 hours.

B. COVID-19 ED PATIENT DATA DESCRIPTION
The COVID-19 patients’ demographics and clinical outcomes are displayed in Table 1. We found that 440 patients (13.3%) were older than 65 years, and the median patient age was 51 (IQR 40 – 57) years, showing the prevalence of COVID-19 in older patients. Of the study patients, 35.1% were male and 74.7% were African Americans. The most frequent chief complaint of COVID-19 patients on admission from the ED was shortness of breath (29.7%), followed by fatigue (6.6%), and fever (5.8%). Comorbid conditions were common amongst patients, in particular hypertension (63.9%), obesity (46.4%), anemia (26.1%), type 2 diabetes (17.1%), diabetes (17.0%), congestive heart failure (20.7%) and chronic kidney disease (16.3%). Among the COVID-19 patients included in this study, 808 (24.5%) were admitted to the hospital, 2,144 (65%) were discharged, 122 (3.7%) left without completing service (LWCS), 23 (0.69%) were discharged against medical advice, 173 (5.2%) were placed in observation, and 31 (0.9%) were transferred to another facility.

A statistical visualization of each feature’s underlying relationships with the dependent variable (ED LOS) is presented in Figure 3. As displayed in Figure 3(a), the median ED LOS was 5.21 (SD 5.95) hours for COVID-19 patients with a right skewed distribution. Figure 3(b) depicts the variation in COVID-19 patients’ ED LOS as age increased, and the median age was 51 (SD 15.0) years. The largest spread was seen for the 60-69 and 70-79 age group, who spent more time in the ED. The test for normality showed that the patient age significantly deviated from the normal distribution (p < 0.001). There was a significant difference between patient race and ED LOS (p < 0.05). Multiple comparison testing showed a statistically significant difference in the median ED LOS between African American and Asian patients (4.95 vs 6.03 hours, p = 0.025), White and Asian (6.70 vs 6.03 hours, p = 0.002), as well as between the White and African American patients (6.70 vs 4.95 hours, p < 0.05). However, there was no statistically significant difference between Hispanic patients and other patient groups (Figure 3c). Figure 3(d) shows that the most common COVID-19 patients complain, and which symptoms have the longest average ED LOS. On average, COVID-19 patients with complaints related to fever had the most prolonged ED LOS (~9 hours), followed by those with diarrhea (~8.5 hours), and chills (~8 hours). The statistical visualization of each feature’s underlying relationships with the dependent variable (ED LOS) is presented in Figure S2-S3.

C. PREDICTION RESULTS
A matrix heatmap showing the correlations between model variables is presented in Figure S1. Variables with either strongly positive or negative correlation coefficients and
TABLE 1. Demographic characteristics of COVID-19 patients.

| Variable                        | Number of patients (%) |
|---------------------------------|------------------------|
| Number of patients              | 3,301 (100%)           |
| Race                            |                        |
| Black/African American          | 2,467 (74.73%)         |
| Asian                           | 167 (5.06%)            |
| White                           | 181 (5.48%)            |
| Hispanic                        | 16 (0.48%)             |
| Others                          | 470 (14.24%)           |
| Age, median (IQR), years        |                        |
| ≥65                             | 5140 (13.3%)           |
| <65                             | 2,861 (86.7%)          |
| Gender                          |                        |
| Male                            | 1,158 (35.1%)          |
| Female                          | 2,143 (64.9%)          |
| Common COVID-19 symptoms        |                        |
| Fever                           | 190 (5.8%)             |
| Cough                           | 170 (5.1%)             |
| Chills                          | 17 (0.5%)              |
| Shortness of breath             | 980 (29.7%)            |
| Headache                        | 68 (2.1%)              |
| Fatigue                         | 218 (6.6%)             |
| Diarrhea                        | 30 (0.9%)              |
| Nasal congestion                | 34 (1.0%)              |
| Others                          | 1,594 (48.3%)          |
| Comorbidities                   |                        |
| Hypertension (HTN)              | 2108 (63.9%)           |
| Diabetes mellitus (DM)          | 562 (17.0%)            |
| Type 2 DM                       | 563 (17.1%)            |
| Sepsis                          | 41 (1.2%)              |
| Chronic Liver disease (CLD)     | 200 (6.1%)             |
| Heart Attack                    | 19 (0.6%)              |
| Congestive heart failure (CHF)  | 684 (20.7%)            |
| Chronic kidney disease (CKD)    | 539 (16.3%)            |
| Peripheral vascular disease (PVD)| 86 (2.6%)              |
| Abdominal Aortic Aneurysm       | 9 (0.3%)               |
| Atrial Fibrillation             | 166 (5.0)              |
| Anemia                          | 863 (26.1%)            |
| Coronary Artery Disease (CAD)   | 143 (4.3%)             |
| Breast Cancer                   | 19 (0.6%)              |
| Chronic obstructive pulmonary disease (COPD) | 740 (22.4%) |
| Obesity                         | 1533 (46.4%)           |

*Abbreviations: IQR, interquartile range.

TABLE 2. Summary of Spearman correlation between ED LOS and clinical features.

| Clinical variables               | Correlation coefficient (r) | p-value |
|----------------------------------|-----------------------------|---------|
| Physician Availability           | 0.476                       | <0.001  |
| Bed Availability                 | 0.264                       | <0.001  |
| Nurse Availability               | 0.263                       | <0.001  |
| Chronic Kidney Disease (CKD)     | 0.240                       | <0.001  |
| Diabetes Mellitus (DM)           | 0.195                       | <0.001  |
| Emergency Severity Index (ESI)   | -0.191                      | <0.001  |
| Patient Race – Black             | -0.149                      | <0.001  |
| Coronary Artery Disease (CAD)    | 0.143                       | <0.001  |
| Chronic Lung Disease (CLD)       | 0.134                       | <0.001  |
| Cardiovascular Disease (CVD)     | -0.122                      | <0.001  |
| Obesity                          | -0.121                      | <0.001  |
| Atrial Fibrillation              | 0.119                       | <0.001  |
| Respiratory Rate (RR)            | 0.117                       | <0.001  |
| Percent Oxygen Saturation (SpO2%)| -0.111                      | <0.001  |
| Peripheral Vascular Disease (PVD)| 0.103                       | <0.001  |
| Temperature                      | 0.100                       | <0.001  |

a p-value less than 0.05 were selected as the best subset of features for building our machine learning model. Our analysis revealed 16 clinical features with strong correlation coefficients (Table 2). The top four features correlated with ED LOS were physician availability ($r = 0.476, p < 0.001$), bed availability ($r = 0.264, p < 0.001$), nurse availability ($r = 0.263, p < 0.001$), and patients with a history of CKD ($r = 0.239, p < 0.001$). The additional significantly correlated features used to build the machine learning models are listed in Table 2.

To optimize the hyperparameters for the different algorithms, we performed grid search cross-validation (GridSearchCV) to determine the optimal parameters for training the GB, DT, and RF algorithms (Table S1). The combination of parameters was evaluated using the accuracy score as a performance metric, and the best parameters with the highest accuracy scores were selected to develop our prediction framework. A section of the decision tree is shown in Figure 4.

Figure 4 shows the decision-tree model. At the first branch level, if a COVID-19 patient presents at the ED and a physician is immediately available, the patient will likely spend <4 hours (denoted as class 0) in the ED; otherwise, we move to the next level. At subsequent branching levels,
FIGURE 4. A decision tree (DT) on ED operations and COVID-19 patient-level data. The nodes and leaves are presented using rounded rectangles, which represent the outcome of interest. The DT shows two classes, namely class 0 (i.e., patients with ED LOS < 4 hours) and class 1 (i.e., patients with ED LOS ≥ 4 hours). Abbreviation: Emergency Severity Index (ESI), Peripheral Vascular Disease (PVD), Coronary Artery Disease (CAD), Cardiovascular Disease (CVD).

Table 3. Temporal validation (i.e., hold-out data) results.

| Stage | Model | Precision | Recall | F1-Score | Accuracy | AUC |
|-------|-------|-----------|--------|----------|----------|-----|
| 1     | LR    | 0.76      | 1.00   | 0.86     | 80%      | 0.88|
|       | GB    | 0.80      | 0.95   | 0.87     | 82%      | 0.93|
|       | DT    | 0.77      | 1.00   | 0.87     | 81%      | 0.91|
|       | RF    | 0.85      | 0.85   | 0.85     | 81%      | 0.90|
|       | LR    | 0.76      | 0.96   | 0.85     | 79%      | 0.88|
|       | GB    | 0.85      | 0.92   | 0.88     | 85%      | 0.93|
|       | DT    | 0.87      | 0.85   | 0.86     | 82%      | 0.91|
|       | RF    | 0.92      | 0.77   | 0.84     | 82%      | 0.92|

In this study, the sample size ratio of ≥4 hours and <4 hours ED LOS was 1.87, which is equivalent to 65.22% in favor of ≥4 hours LOS (baseline). Comparing the accuracies reported by all models in Stage 1 (Table 3) to the baseline, we can see that all models significantly improved beyond the baseline. The same notion applies to the second stage, as all models show a better accuracy than the baseline of 50% (i.e., the balanced dataset). Although GB provides the best performance in Stage 2, the main objective of this study is not to promote any specific model, but to develop a decision support tool (i.e., the prediction framework) that is capable of handling data imbalance and feature engineering. Table S2 shows the variance estimates from the 10-fold cross-validation of the AUC of each model. The models showed stable results with a low standard deviation. The T-test results demonstrate that there are significant differences in model performance (i.e., AUC) among the different stages of DT and RF ($p < 0.05$) (Table S3-S6). These results suggest that Stage 2 improves the performance of the models. Specifically, our results suggest that when data cleaning, feature processing, and balancing techniques are implemented, the performance of machine learning models increase.

Figure 5 shows the AUC curves for the trained models. In Figure 5a and 5b, we observe that GB has an AUC of 0.93, which means that it has a good separability measure between the two ED LOS classes. It is important to note that GB has the highest AUC scores for both data processing stages. Next, we observe from the plot that the macro-average AUC curve for RF improves from 0.90 in Stage 1 to 0.92 in Stage 2. Therefore, the RF model performed well in classifying the positive class in the dataset after implementing feature engineering, feature selection, and oversampling techniques. The optimal decision threshold value (i.e., the operational point on the AUC plot) was achieved using Youden’s J index [23], which maximizes the difference between the true and false positive values. Table S7 in the Appendix presents the individual thresholds for each model at each stage. The threshold is the point in the AUC plot in which when it is decreased, we obtain more positive values, thus increasing the sensitivity and reducing the specificity of the models. Similarly, when the threshold was decreased, we obtained more negative values, thus reducing the sensitivity, and increasing the specificity. These thresholds can be used when making future probability predictions, which must then be converted from probabilities to crisp class labels (i.e., ED LOS <4 or ≥4 hours).

IV. DISCUSSION

According to the World Health Organization, the COVID-19 virus continues to spread, with estimated global confirmed infection cases of 465.7 million and 6.06 million deaths as of March 17, 2022. According to the US Center for Disease Control and Prevention, as of March 17, 2022, the United States is one of the leading countries with confirmed infection cases of 79.6 million and 970K deaths. During the pandemic,
hospitals had to turn away patients due to insufficient oxygen supply and other capacity issues [24]. COVID-19 is becoming increasingly contagious with new variants found, and a prolonged patient ED LOS may lead to higher mortality rates, hospital resource shortages, and the inability to receive new patients [24]. There is a need to predict patient ED LOS to improve planning for limited hospital resources and to develop a decision support system that can improve patient expectations of their LOS.

In the present study, we developed a prediction framework including four models, namely LR, GB, DT, and RF, to predict whether a COVID-19 patient will stay in the ED for less than 4 hours or more. Although both GB and DT were able to achieve superior performance over the other methods, we achieved the best performance using GB when the data were adequately engineered and preprocessed to address the class imbalance issue. It is important to note that most machine-learning models are not capable of handling the class imbalance present in a given dataset. In our dataset, 65.2% of the ED LOS was for patients who stayed for >4 hours in the ED. During prediction, machine learning models trained on imbalanced datasets often favor the majority class, leading to better performance in the majority class than in the minority class [25]. According to [25], [26], developing models that are insensitive to class distribution or utilizing oversampling techniques (e.g., SMOTE) will help address the class imbalance present in a given dataset. Our prediction framework (Stage 2), which combines feature engineering, feature selection, and SMOTE to address the imbalanced dataset, shows that the models can predict the ED LOS of COVID-19 patients, as presented in Table 3. The results showed different performance metrics for the algorithms.

We specifically used the F1-score to measure the performance of the models, as it is a better metric for imbalanced datasets. Focusing on Stage 2, we observed that GB performs better than LR, DT, and RF after engineering the features. One reason, in our opinion, is the ability of the GB classifiers to combine multiple weak learners to create an ensemble of strong classification models. Although GB models are computationally expensive to tune because of the increased number of hyperparameters and sequential nature of the models, their strength lies in the reduction of loss to achieve a more accurate estimate of the response variable. We were careful not to overestimate the complexity of the model and tried to avoid overfitting (i.e., a decrease in prediction performance) when tuning the models. In the literature, RF and GB models have provided varying performance results in different applications, including bioinformatics [27], medical informatics [28], and other domains [29]. To the best of our knowledge, this is the first study to use a machine learning approach to predict COVID-19 patients’ ED LOS that combines patient and ED level data. We identified significant factors present upon patient arrival to the ED, such as physician availability, bed availability, nurse availability, ESI, patient race, vital signs, and comorbid conditions. Although these features apply to COVID-19 patients, they have the potential to be tested in future disaster outbreaks unrelated to COVID-19.

Age has previously been demonstrated to contribute significantly to ED LOS [30] but was not a significant factor in our study. Previous studies also identified diverse and heterogeneous factors, such as the time of day that the patient presents, waiting for the emergency physician for greater than two hours, patient sex, and race to contribute to ED LOS [13], [31], [32]. Our research agrees with these findings that physician availability and race contribute to prolonged ED stays for COVID-19 patients. The application of a data-driven machine learning approach has helped to identify significant predictors for solving LOS questions during a pandemic. Applied in real time, our machine learning model could help identify COVID-19 patients more likely to stay longer in the ED during the first moments of their presentation. These machine learning models could be expanded to other outcomes of interest, such as hospital LOS, personalized risk prediction models, and other clinical outcomes.
Prior studies have demonstrated the potential of similar techniques to be applied to non-COVID-19 patients. A study by Gill et al. used gradient boosting among low-acuity fast-track patients to predict ED LOS ≥4 hours with an AUC of 0.89 [33], although an F1-score that is appropriate when data imbalance exists has not been reported [34]. A data mining technique was utilized to predict ED LOS ≥4 hours in a regional Australian public hospital pre-COVID-19 [13]. They reported an accuracy of 85% but did not report an F1-Score [13]. The advantages of our study include the focus on COVID-19, the development of a predictive framework, and evaluation of the framework’s performance using accuracy, recall, precision, F1-score, and AUC to ensure proper reporting of analysis performed on imbalanced datasets. In the present study, machine learning models were applied to all confirmed COVID-19 patients present in the ED and incorporated attributes related to patient complaints, medical history, and initial ED characteristics. Stage 2, which combines feature engineering, feature selection, and an oversampling technique to address the imbalanced dataset, shows that the models are capable of predicting ED LOS, as presented in Table 3. In addition, Stage 2 shows a slight performance improvement compared with Stage 1 (i.e., when no balancing technique is applied).

Our study had some limitations. First, some clinical variables had missing values due to administrative errors. Missing data points were imputed with the corresponding mean value, introducing bias if the missingness was not random. Second, our model was limited to features readily available in the hospital’s EHR system. Other features that were not captured or retrieved from the EHR, such as hospital capacity during COVID-19 patient presentation or ED boarding, were not included in the study but could impact ED LOS. Third, the identified predictors are significant in the study hospital ED and may not be readily translated to other EDs. With slight modifications to our model, other EDs can use the prediction framework as a tool to identify significant predictors in their data. Lastly, in assessing only COVID-19 patients, our models do not fully account for all ED patients who seek emergency care during a pandemic.

V. CONCLUSION

In conclusion, we describe some of the medical and ED characteristics of COVID-19 patients during hospitalization. The study identified significant factors based on a combination of patient demographics, comorbidities, and ED operational data associated with prolonged stays in COVID-19 patients. We innovatively trained four prediction models on these factors to predict COVID-19 patients’ ED LOS. With further validation, the model and results of this study can serve as an effective decision-support tool to improve healthcare delivery/resorce planning and help clinicians develop effective interventions to address patient outcomes (e.g., reducing prolonged LOS). Although the models are trained based on locally collected data and clinical information from Henry Ford Hospital, they can be retrained and updated for use in other EDs to predict COVID-19 patient LOS.

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