# Predictive Modeling for COVID-19 Emergency Department Stay using Machine Learning

[1] G.Anjali, [2]Dr.M.Dhanalakshmi

*[1]MCA Student, Department of Information Technology, Jawaharlal Nehru Technological University, India*

*[2]Professor of IT, Department of Information Technology, Jawaharlal Nehru Technological University, India*

**Abstract: The COVID-19 pandemic has significantly increased emergency department (ED) stays for patients in the United States. To address this issue, a study aimed to create a reliable model predicting the length of stay (LOS) for COVID-19 patients in the ED and identify factors influencing meeting the '4-hour target.' Data from diverse urban hospitals in Detroit, collected from March 16 to December 29, 2020, informed this research. Using data processing, four machine learning models (logistic regression, gradient boosting, decision tree, and random forest) were trained to forecast whether COVID-19 patients' ED stays would surpass 4 hours. The study involved 3,301 patients with 16 clinical factors. The gradient boosting (GB) model outperformed others, achieving 85% accuracy and an F1-score of 0.88 in predicting LOS within the test data, surpassing the logistic regression baseline, decision tree, and random forest models. Further data splitting did not notably improve accuracy. This investigation identified critical factors, including patient demographics, existing health conditions, and operational ED data, as predictors of extended stays for COVID-19 patients. The predictive model could serve as a decision-making tool, aiding in resource planning for EDs and hospitals. Moreover, it offers patients estimations of their ED LOS, enhancing their understanding and potentially improving their experience. In summary, this study's model effectively predicts ED LOS for COVID-19 patients, enabling better resource allocation and informed decision-making in managing ED stays during the pandemic, potentially improving patient care and hospital efficiency.**

***Keywords – COVID-19, length of stay (LOS), 4-hour target, emergency department (ED), machine learning.***

## 1.INTRODUCTION

The coronavirus (COVID-19) pandemic has put a burden on healthcare systems throughout the globe by increasing treatment complexity, the requirement for medical staff and patient safety, and an increase in patients suspected or infected with the severe acute respiratory syndrome coronavirus (SARS-CoV2). The inflow of infected COVID-19 patients at hospital emergency rooms (EDs) has put current services under pressure. As a consequence of the pandemic, multiple health-care institutions in the United States have reported increased workload and spikes in patient volumes, resulting in ED congestion, which worsens patient outcomes and places extra burden on medical personnel. The creation of lineups in different sectors of the health system as a consequence of demand surpassing capacity is a significant feature of crowding. These queue formations are often associated with increased average ED lengths of stay (LOS) . A longer ED stay is related with increased morbidity and death. Numerous health systems have established time-based standards, requiring patients to leave the ED within four hours of their admission (i.e., the "four-hour target"). However, because to the continuing epidemic, this 4-hour goal for COVID-19 patients has been difficult to meet, resulting in congestion, operational inefficiencies, and increased consumption of hospital resources.

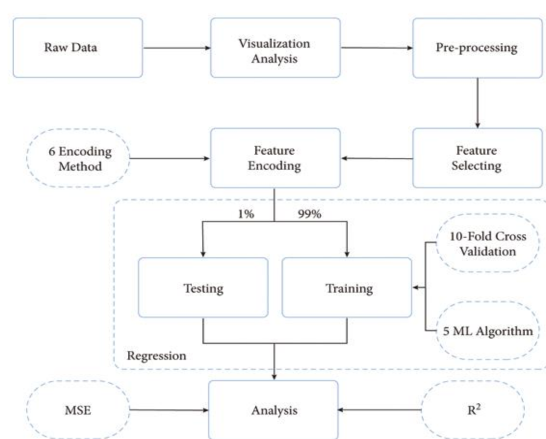


Fig.1: Example figure

## 2.LITERATURE REVIEW

Effect of emergency department crowding on outcomes of admitted patients:

Crowding in the emergency department (ED) is a common health-care delivery issue that may have a negative impact on the outcomes of patients who need hospitalisation. We investigate the relationship between ED congestion and subsequent outcomes in a wide group of hospitalised patients. Methods We conducted a retrospective cohort study of patients admitted via the emergency departments of nonfederal, acute care hospitals in California in 2007. Inpatient mortality was the main outcome. Hospital duration of stay and expenses were secondary outcomes. The proxy measure of ambulance diversion hours on the day of admission was used to determine ED congestion. To account for hospital-level confounders of ambulance diversion, we characterised high ED congestion as days that were within the top quartile of diversion hours for a single institution. Demographics, temporal factors, patient comorbidities, main diagnosis, and hospital fixed effects were all adjusted for in hierarchical regression models. We employed bootstrap sampling to quantify the extra outcomes caused by ED crowding. Results We looked at 995,379 ER visits that resulted in admission to 187 hospitals. Patients treated on days with high ED congestion had a 5% higher risk of inpatient mortality (95% CI 2% to 8%), a 0.8% longer hospital duration of stay (95% CI 0.5% to 1%), and a 1% increase in expenses per admission (95% CI 0.7% to 2%). Excess outcomes due to high ED congestion included 300 inpatient deaths (95% CI 200 to 500 inpatient deaths), 6,200 hospital days (95% CI 2,800 to 8,900 hospital days), and $17 million in expenses (95% CI $11 to $23 million). Conclusion High ED congestion was linked to higher inpatient mortality as well as minor increases in length of stay and expenses for admitted patients.

Association between waiting times and short term mortality and hospital admission after departure from emergency department: Population based cohort study from Ontario, Canada

To see whether patients who are not admitted to the hospital after visiting an emergency department during long-waiting shifts are at risk for adverse occurrences. Design Using health administrative records, a population-based retrospective cohort research was conducted. Setting Emergency rooms with a high number of patients in Ontario, Canada, fiscal years 2003-7. Participants All non-admitted emergency department patients (seen and discharged; left without being seen). Outcome metrics The risk of adverse events ( hospitalisation or death within seven days) was adjusted for relevant patient, shift, and hospital factors. Results 13 934 542 patients were seen and dismissed, while 617 011 were not seen. The risk of adverse outcomes rose with the average duration of stay of comparable patients in the emergency department on the same shift. The adjusted odds ratio (95% confidence interval) for death and admission in high acuity patients was 1.79 (1.24 to 2.59) for death and 1.95 (1.79 to 2.13) for admission in low acuity patients was 1.71 (1.25 to 2.35) for death and 1.66 (1.56 to 1.76) for admission in high acuity patients. Leaving without being seen was not connected with an increase in adverse events at the patient level or in hospital yearly rates. Conclusions Presenting to an emergency department during shifts with longer waiting times, as represented in a longer mean duration of stay, is related with a higher risk of mortality and hospitalisation among patients who are healthy enough to leave the department in the immediate term. Patients who depart without being seen are not more likely to have short-term harmful outcomes.

Measures of crowding in the emergency department: A systematic review

Despite agreement on the conceptual underpinning of crowding and rising research on crowding determinants and effects, there is no criteria or measure of crowding. The goal was to provide a thorough evaluation of crowding metrics and compare their conceptual base and validity. Methods: A systematic, thorough evaluation of four medical and health care citation databases was conducted to uncover research linked to emergency department congestion (ED). Publications that "explain the theory, development, implementation, assessment, or any other component of a 'crowding measurement/definition' instrument (qualitative or quantitative)" were eligible for inclusion. A "measurement/definition" tool is anything that lends a numerical value to the occurrence of congestion in the emergency department. The following information was gathered from studies that met the inclusion criteria: research design, objective, crowding measure, and evidence of validity. All measurements were classified into five kinds (clinician opinion, input factors, throughput factors, output factors, and multidimensional scales). All metrics were then indexed to six validation criteria (clinician opinion, ambulance diversion, time to care, forecasts or projections of future congestion, and other). The databases found 2,660 documents; 46 of these papers satisfied inclusion criteria, were original research investigations, and were abstracted by reviewers. A total of 71 distinct crowding measurements were discovered. Clinician opinion was the least generally utilised form of crowding metric, whereas numerical counts (number or percentage) of patients and process durations connected with patient care were the most regularly employed. Many of the metrics demonstrated a moderate to strong association with the validation criteria. Conclusions: Time intervals and patient counts seem to be the most promising instruments for monitoring flow and nonflow (i.e., crowding). Standardized definitions of time intervals (flow) and numerical counts (nonflow) will help with validation across many locations and explain which possibilities emerge as the metrics of choice in this "busy" area of measurements.

Systematic review of emergency department crowding: Causes, effects, and solutions

Crowding in emergency departments (EDs) is a global concern that may have an impact on health-care quality and access. We did a thorough PubMed search to find studies that (1) investigated the causes, impacts, or solutions of ED crowding; (2) provided data collection and analytic technique; (3) took place in a general ED context; and (4) focused on daily crowding. The relevant publications were determined by agreement by two independent reviewers. Each study's methodology was graded using a 5-level quality rating measure. The reviewers found 93 publications that met the inclusion criteria from 4,271 abstracts and 188 full-text articles. A total of 33 papers investigated the causes, 27 articles investigated the impacts, and 40 articles investigated the remedies to ED crowding. Nonurgent visits, "frequent-flyer" patients, influenza season, insufficient staffing, inpatient boarding, and hospital bed shortages were all often investigated causes of crowding. Patient death, transit delays, treatment delays, ambulance diversion, patient elopement, and financial impact were all often investigated impacts of crowding. Additional people, observation units, hospital bed access, nonurgent referrals, ambulance diversion, destination control, crowding measures, and queuing theory were all often investigated crowding solutions. The findings demonstrated the complicated, multidimensional nature of the ED crowding issue. Additional high-quality research may contribute significantly to a better understanding and alleviation of the everyday situation. This organised literature review may aid in identifying future paths for the crowding research agenda.

Emergency department length of stay: A major risk factor for pneumonia in intubated blunt trauma patients

Pneumonia is a major cause of morbidity and death in intubated patients. Pneumonia prevention measures have shown to be efficient in the critical care unit and are well-liked, cost-effective, and effective. In the prehospital or emergency department (ED), trauma victims are often intubated on the spot. Hospital overcrowding has resulted in increased ED length of stay throughout the country (LOS). We wanted to look at the link between lengthy ED wait times and pneumonia rates. Methods: This was a 2-year retrospective case-control study of pneumonia risk in blunt trauma patients admitted to an urban Level I trauma hospital and intubated immediately. Demographic and clinical data were obtained from the trauma registry. All patients who were intubated prehospital or in the emergency department and acquired pneumonia were considered cases. There was a set of matched controls who did not get pneumonia and had the same age, injury severity score, abbreviated injury score (AIS) chest, and AIS head. Conditional logistic regression was used to compare ED LOS between the two groups. We found 509 blunt trauma patients who needed to be intubated right away. Thirty-three of these patients developed pneumonia and could be compared with equivalent controls. The case patients had a mean age of 44.6 (24.3), an injury severity score of 32.7 (9.5), a chest

AIS of 1.5 (1.6), and a head AIS of 4.4 (1.2). The cases' ED LOS was substantially longer than the controls' (281.3 minutes vs. 214.0 minutes, p 0.05). Each hour raised the likelihood of acquiring pneumonia by almost 20%. Conclusions: Increased ED LOS is an independent risk factor for pneumonia in blunt trauma patients who are intubated urgently. Ventilator-associated pneumonia therapies, which have been shown to be effective in the intensive care unit, should be started early in the hospital course, and efforts should be made to reduce hospital congestion and ED LOS.

## 3. METHODOLOGY

Previous research on parameters linked with ED LOS done before to the COVID-19 pandemic included models such as multiple linear regression, logistic regression, decision trees, and accelerated failure time models. Machine learning algorithms may take into account a greater number of characteristics and permutations (e.g., patient records and hospital information), which has the ability to provide a better understanding of complicated issues and uncover factors that predict COVID-19 ED patients' LOS. To our knowledge, no research has integrated these data (patient and ED operational data) to predict the LOS of COVID-19 ED patients.

Disadvantages:
1. No research has integrated these data (patient and ED operational data) to predict the LOS of COVID-19 ED patients.

In this work, we used four machine learning approaches, namely logistic regression, gradient boosting, decision trees, and the random forest algorithm, to construct a model that effectively predicted the ED LOS of COVID-19 patients across multiple data processing stages.

Advantages:
1. improving ED and hospital resource planning and informing patients about improved ED LOS projections.

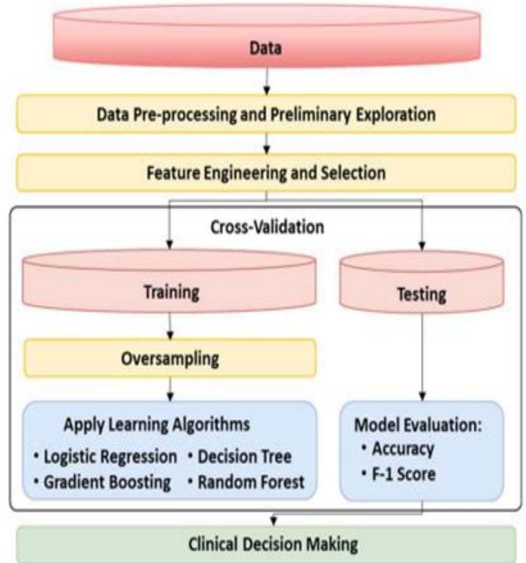


Fig.2: System architecture

MODULES:
To carry out the aforementioned project, we created the modules listed below.

- Data exploration: we will put data into the system using this module.
- Processing: we will read data for processing using this module.
- Using this module, data will be separated into train and test groups.
- Model generation: Building the model -Gradient Boosting, Random Forest, Decision Tree, Logistic Regression, XGBoost, and Voting Classifier. Calculated algorithm accuracy.
- User signup and login: Using this module will result in registration and login.
- User input: Using this module will result in predicted input.
- Prediction: final predicted shown

## 4. IMPLEMENTATION

ALGORITHMS:
Random Forest: A Supervised Machine Learning Algorithm that is commonly utilised in Classification and Regression applications. It constructs decision trees from several samples and uses their majority vote for classification and average for regression.
Decision Tree: Decision trees use numerous methods to determine whether or not to divide a node into two or more sub-nodes. The development of sub-nodes

promotes the homogeneity of the sub-nodes that arise. In other words, the purity of the node rises in relation to the target variable.

Logistic Regression: Logistic regression is a statistical analytic approach that uses past observations of a data set to predict a binary result, such as yes or no. A logistic regression model forecasts a dependent variable by examining the connection between one or more existing independent variables.

Voting classifier: A voting classifier is a machine learning estimator that trains numerous base models or estimators and predicts based on the results of each base estimator. Aggregating criteria may be coupled voting decisions for each estimator output.

XGBoost: Extreme Gradient Boosting (XGBoost) is a scalable, distributed gradient-boosted decision tree (GBDT) machine learning framework. It is the top machine learning package for regression, classification, and ranking tasks, and it supports parallel tree boosting.

Gradient boosting: Gradient boosting is a machine learning approach that is utilised in regression and classification applications, among other things. It returns a prediction model in the form of an ensemble of weak prediction models, usually decision trees.

## 5. EXPERIMENTAL RESULTS

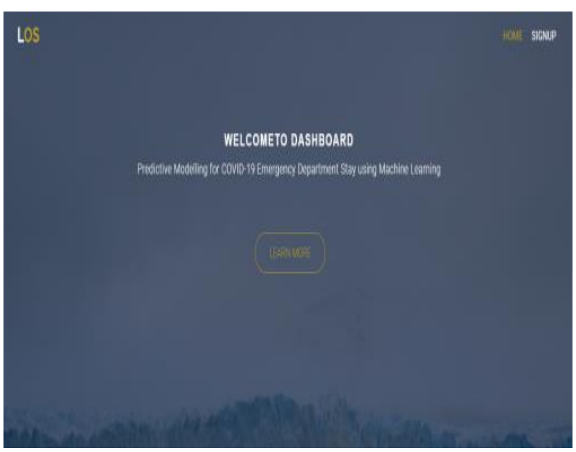


Fig.3: Home screen

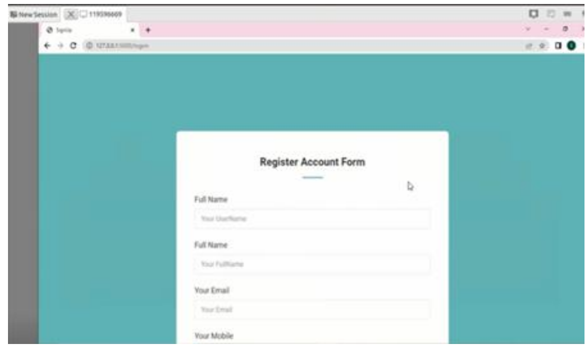


Fig.4: User registration

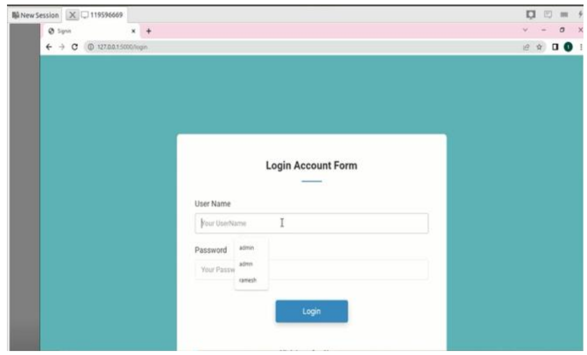


Fig.5: user login

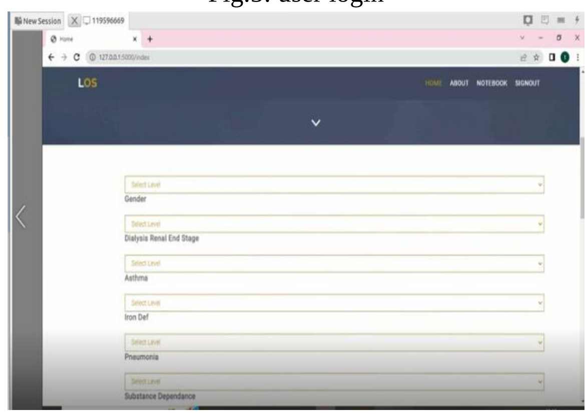


Fig.6: Main screen

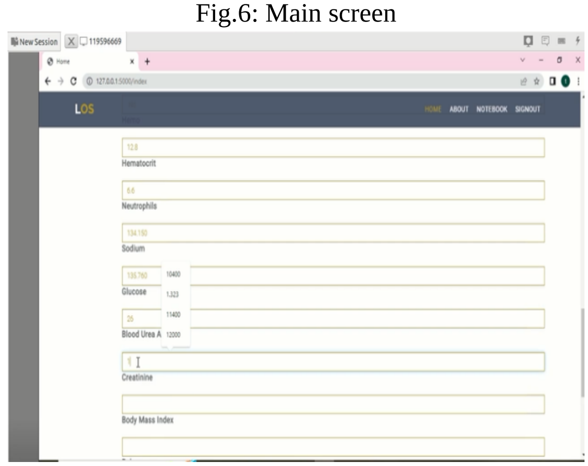


Fig.7: User input

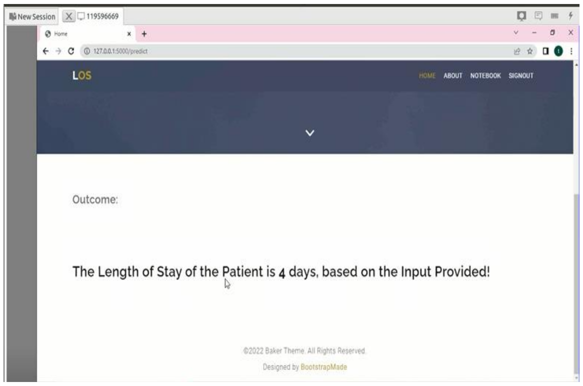


Fig.8: Prediction result

## 6.CONCLUSION

Finally, we present some of the medical and emergency department features of COVID-19 patients throughout ospitalization. The research revealed significant characteristics linked with extended stays in COVID-19 patients based on a mix of patient demographics, comorbidities, and ED operational data. We used these characteristics to train four prediction models to predict COVID-19 patients' ED LOS. The model and findings of this research, with additional validation, might serve as an effective decision-support tool to enhance healthcare delivery/resource planning and assist clinicians in developing appropriate treatments to address patient outcomes (e.g., reducing prolonged LOS). Although the models were built using locally obtained data and clinical information from Henry Ford Hospital, they may be retrained and updated to predict COVID-19 patient LOS in other Eds.

## REFERENCE

[1] E. Walters, S. Najmabadi, and E. Platoff, ''Texas hospitals are running out of drugs, beds, ventilators and even staff,'' Texas Tribune, Austin, TX, USA, Tech. Rep., 2020.

[2] B. C. Sun, R. Y. Hsia, R. E. Weiss, D. Zingmond, L.-J. Liang, W. Han, H. McCreath, and S. M. Asch, ''Effect of emergency department crowding on outcomes of admitted patients,'' Ann. Emergency Med., vol. 61, no. 6, pp. 605–611, 2013. [Online]. Available:https://www.sciencedirect.com/science/article/pii/S019606441201699X

[3] A. Guttmann, M. J. Schull, M. J. Vermeulen, and T. A. Stukel, ''Association between waiting times and short term mortality and hospital admission after departure from emergency department: Population based cohort study from Ontario, Canada,'' Brit. Med. J., vol. 342, p. d2983, Jun. 2011.

[4] U. Hwang, M. L. McCarthy, D. Aronsky, B. Asplin, P. W. Crane, C. K. Craven, S. K. Epstein, C. Fee, D. A. Handel, J. M. Pines, N. K. Rathlev, R. W. Schafermeyer, F. L. Zwemer, Jr., and S. L. Bernstein, ''Measures of crowding in the emergency department: A systematic review,'' Academic Emergency Med., vol. 18, no. 5, pp. 527–538, May 2011.

[5] N. R. Hoot and D. Aronsky, ''Systematic review of emergency department crowding: Causes, effects, and solutions,'' Ann. Emerg. Med., vol. 52, no. 2, pp. 126–136, 2008, doi: 10.1016/j.annemergmed. 2008.03.014.

[6] S. Clair, A. Staib, S. Khanna, N. M. Good, J. Boyle, R. Cattell, L. Heiniger, B. R. Griffin, A. J. Bell, J. Lind, and I. A. Scott, ''The national emergency access target (NEAT) and the 4-hour rule: Time to review the target,'' Med. J. Aust., vol. 204, no. 9, p. 354, 2016. [Online]. Available: https:// onlinelibrary.wiley.com/doi/pdf/10.5694/mja15.0117 7?casa_token=ijKnv DmdfIIAAAAA: 8dfpe4v4 DN0Yo6d6yB–7f5CIdrUiFV5BZ6yq61odPXx cJRyns33RP1E4G5NmD73cFgjAlDaBsN4NHeq

[7] B. G. Carr, A. J. Kaye, D. J. Wiebe, V. H. Gracias, C. W. Schwab, and P. M. Reilly, ''Emergency department length of stay: A major risk factor for pneumonia in intubated blunt trauma patients,'' J. Trauma: Injury, Infection Crit. Care, vol. 63, no. 1, pp. 9–12, 2007.

[8] D. Liew, D. Liew, and M. P. Kennedy, ''Emergency department length of stay independently predicts excess inpatient length of stay,'' Med. J. Aust., vol. 179, no. 10, pp. 524–526, Nov. 2003.

[9] C. Morley, M. Unwin, G. M. Peterson, J. Stankovich, and L. Kinsman, ''Emergency department crowding: A systematic review of causes, consequences and solutions,'' PLoS ONE, vol. 13, no. 8, Aug. 2018, Art. no. e0203316.

[10] N. Bobrovitz, D. S. Lasserson, and A. D. M. Briggs, ''Who breaches the four-hour emergency department wait time target? A retrospective analysis of 374,000 emergency department attendances between 2008 and 2013 at a type 1 emergency department in England,'' BMC Emergency Med., vol. 17, no. 1, p. 32, Dec. 2017.