Machine Learning Based Patient Classification In Emergency Department

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***Abstract*—This work contains the classification of patients in an Emergency Department in a hospital according to their critical conditions. Machine learning can be applied based on the patient's condition to quickly determine if the patient requires urgent medical intervention from the clinicians or not. Basic vital signs like Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Respiratory Rate (RR), Oxygen saturation (SPO2), Random Blood Sugar (RBS), Temperature, Pulse Rate (PR) are used as the input for the patients' risk level identification. High-risk or non-risk categories are considered as the output for patient classification. Basic machine learning techniques such as LR, Gaussian NB, SVM, KNN and DT are used for the classification. Precision, recall, and F1-score are considered for the evaluation. The decision tree gives best F1-score of 77.67 for the risk level classification of the imbalanced dataset.**

***Index Terms*—machine learning, classification, patients, risk level, healthcare, triage.**

I. Introduction

In the Emergency Departments of hospitals, patients are sorted based on their need for immediate medical treatment. This sorting is done according to the urgency or severity of the health conditions of patients. When a patient arrives, an ER (emergency room) nurse performs a brief, focused assessment and assigns the patient a triage acuity level, also known as a triage score. Triage [1] establishes priorities for care and determines the clinical area of treatment. The acuity level is a proxy measure of how long the patient can safely wait for medical evaluation and treatment. For this purpose, healthcare workers categorize them as per their risk level. Priority level 1 patients are critically ill or high-risk category patients and need immediate medical attention to save their life. This is done by nurses or the assigned staff at hospital triage considering their vital signs and clinical observations. Priority level 2 patients are those who need medical attention but can wait as long as 30 minutes for assessment and treatment. These patients are considered medium-risk level patients. Other cases are considered low-risk patients. They can wait for medical help. This type of patient classification is done by considering their basic vital signs and clinical conditions.

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Triage is the prioritization of injured or sick individuals based on their need for emergency treatment. Each organization will have its own triage system, which often includes color coded categories. Triage may be used to meet an organization's short or long-term needs to help determine who gets care first. Based on these results, Machine Learning can determine the patient's criticality. In this study, basic vital parameters are used for patient classification as input. Medium-risk patients and low-risk patients are considered non-critical patients while high-risk cases are considered critical patients. The vital parameters used are Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Respiratory Rate (RR), Oxygen saturation (SPO2), Random Blood Sugar (RBS), Temperature, and Pulse Rate (PR). The output is taken as the patient whose condition is critical falls under class 1 and non-critical patients are classified under class 0.

This work focuses on machine learning algorithms to automatically classify critical and non-critical patients based on measured signs. Machine Learning algorithms executed in this work are Gaussian Naïve Bayes Classifier (NBC), Logistic Regression (LR), Support Vector Machine (SVM), K Nearest Neighbours (KNN), and Decision Trees (DTs). All obtained results are compared to evaluate the effectiveness of each method.

The remaining part of the paper is organized as follows: Section II is Literature Survey describing already existing works. Section III is Methodology which highlights the dataset being worked on and the proposed algorithms. Section IV describes the Experimental results that are obtained after building classifiers and discusses the performance evaluation of all classifiers. Section V is the Conclusion that concludes the overall work.

II. LITERATURE SURVEY

Different research papers on disease prediction were reviewed. Various diseases were predicted that use supervised and ensemble methods. The authors gathered datasets from the UCI repository and Kaggle for the majority of their works.

D. Sharathchandra et al. [2] implemented both Support Vector Machine and Logistic Regression model for heart and diabetic disease prediction. These are developed with limited datasets and both Logistic Regression Model and Support Vector Model work with a better accuracy score. For cardiac and diabetic diseases, LR and SVM were predicted with 85 and 78% accuracy, respectively.

In the study, R. Krishnamoorthi et al. [3] developed and assessed decision tree (DT)-based random forest (RF) and support vector machine (SVM) learning models for diabetes prediction. The authors also developed and evaluated an intelligent diabetes mellitus prediction framework (IDMPF) using machine learning-based architecture for diabetes prediction. The proposed work gives 83% accuracy with a minimum error rate.

Early detection of chronic kidney disease is crucial for preventing and slowing its progression. In this study, D.A Debal et al. [4] used RFECV and UFS as feature selection methods and Random Forest, Support Vector Machine, and Decision Tree as machine-learning models. Tenfold cross-validation was used for the model evaluation.

To classify a Chronic Kidney Disease (CKD) dataset, K.M. Almustafa [5] implemented different classifiers. Random tree, decision table (DT), K-nearest neighbor (K-NN), J48, stochastic gradient descent (SGD), and Naïve Bayes classifiers are used for this. To accurately predict CKD cases, feature selection is done. With 99% of accuracy, J48 and decision table classifiers outperformed the other classifiers. 0.0807 and 0.2507 are root mean square errors (RMSE) respectively. Parameters are adjusted to attain better performance for these classifiers.

Classification based machine learning techniques were implemented by A. R. Rao et al. [6] to identify the early stage prediction of thyroid patients in this work. Initially, classification predictive modeling is used then followed by binary classification with Decision Tree ID3 and Naive Bayes algorithms for the prediction of thyroid disease. To reduce the unwanted redundant data from the patient's database with various levels of precision and accuracy, the above mentioned algorithms were used. To find the thyroid stage of a patient, Decision Tree and Naïve Bayes algorithms were applied after confirming the detection of the thyroid.

Using Naïve Bayesian, Linear Regression, and Decision Tree algorithms T. Nibareke et al. [7] predicted diabetes. Using the parameters such as accuracy, error, and f1-score for the performance analysis of these three models. The results showed that Decision tree is the best model for this data while Naïve Bayes model gave the worst values of f1-score, accuracy, and error (RMSE).

S. Uddin et al. [8] compared the relative performance of disease prediction using supervised machine learning algorithms and its variants. The authors find out that the most frequently used algorithm (in 29 studies) is Support Vector Machine (SVM) then followed by the Naïve Bayes algorithm (in 23 studies). Among different machine learning techniques, Random Forest (RF) algorithm showed better accuracy. Of the 17 studies, 53% of the results showed the highest accuracy obtained for RF and Support Vector Machine with 41% accuracy ranking second.

To screen the infected patients, T. T. Han et al. [9] developed prediction models with machine learning algorithm. F1 score is used as the evaluation metric. K-fold cross validation is used to evaluate accuracy. Results showed the Decision Tree algorithm obtained training accuracy, test prediction and recall as 88.07%, 85.29% and 85.15% respectively. F1 score for DT is 85.8% and is the highest while SVM got the lowest value as 80.4%. DT also achieved the best testing and training time.

M. Deepika et al. [10] conducted a study on several disease diagnoses such as Diabetes, Breast Cancer, Heart Disease, and Thyroid Prediction with different working tools and algorithms. Using SVM, Decision Trees, Naïve Bayes, Logistic Regression and Artificial Neural Networks they compared the prediction and accuracy rate.

Mir et. al [11] built a classifier model using WEKA tool to predict diabetes disease. For the classifier model, machine learning algorithms used are Naive Bayes, Support Vector Machine, Random Forest, and Simple CART. This work showed the best algorithm based on efficient performance results for predicting diabetes disease. Experimental results proved Support Vector Machine performed best with maximum accuracy for the prediction of the disease.

Using machine learning algorithms, E. A. Choi et al [12] implemented a prediction model for the severity of Chronic obstructive pulmonary disease (COPD) in patients. Random forest outperformed other models, with an AUC of 0.886 among 368 samples for classifying COPD patients into mild and severe groups.

The related studies demonstrated that machine learning can be successfully used to predict diseases in advance for a variety of medical datasets. The majority of the research demonstrated that Decision Tree outperformed all other algorithms. For most of the work, preprocessing steps include feature extraction. The classification of the patient's critical condition is done in this work using basic vital features.

III. Methodology

This section presents the methodology used to classify results for the better classification of patients' risk conditions. In this work, primary data are collected from the Emergency Medicine Department of a leading multi speciality hospital, Kerala, India. Basic emergency vitals are collected with a criticality index, which is the target value. 2578 cases are noted from the hospital, leaving patients' personal information behind. 519 cases are in critical condition out of 2578 cases. Figure 1 indicates the feature distribution of Triage Vital Dataset.

The proposed system employs various machine learning algorithms to build a system that classifies patients into different

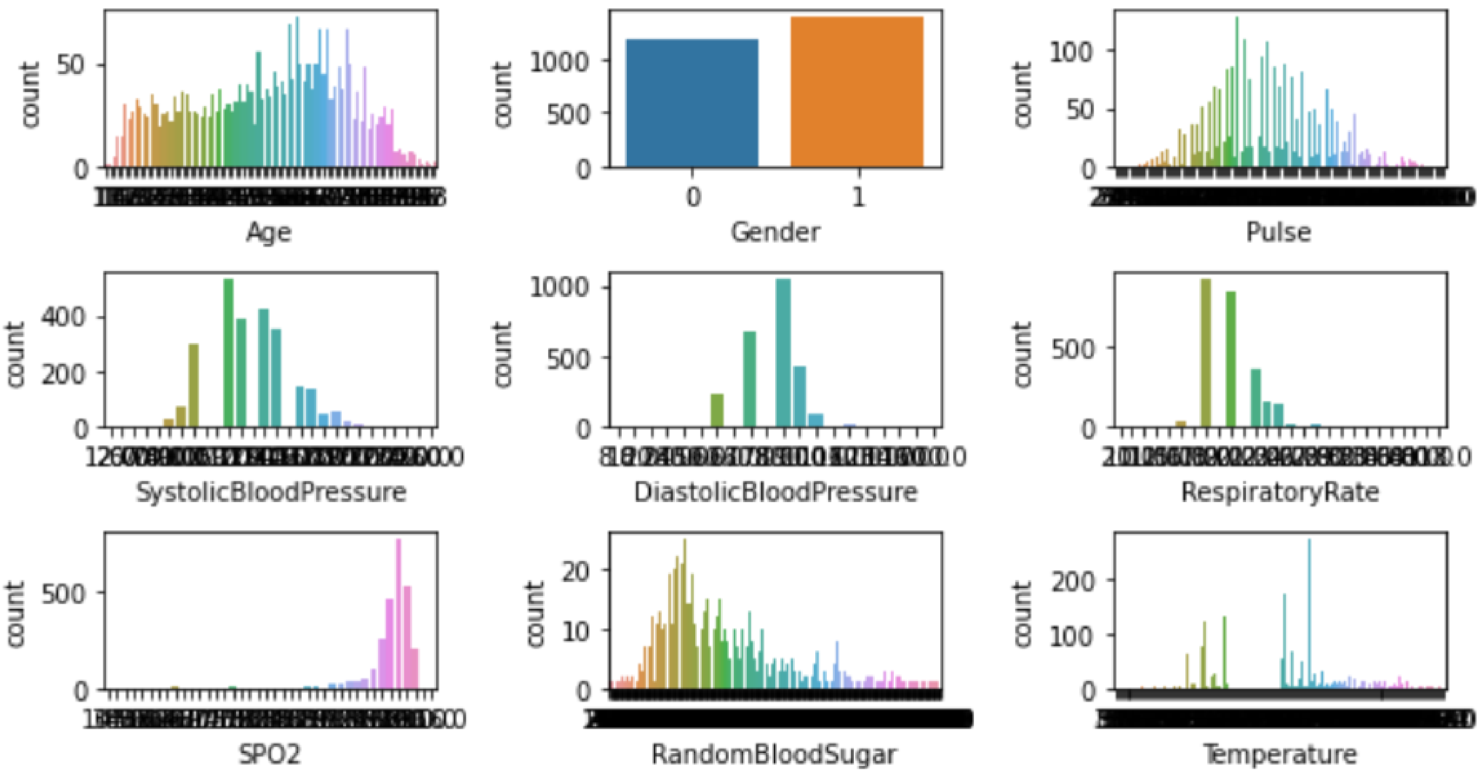

Fig. 1. Feature value distribution of Triage Vital Dataset

risk categories based on their basic vital statistics. We have considered 2 classes according to the patients risk level as Class 1: high risk level and class 0: low risk level. Out of 11 features in this Triage Vital Dataset, 7 features have missing values. Features with missing values and their corresponding numbers are shown in table I. For pre-processing, we used a statistical imputation method - mean value for filling missing values in Triage Vital Dataset.

TABLE I
MISSING VALES DESCRIPTION OF TRIAGE VITAL DATASET

Feature name	No.of missing values
Pulse	14
Systolic blood pressure	9
Diastolic blood pressure	11
Respiratory rate	22
SPO2	24
Random blood sugar	660
Temperature	40

Figure 2 shows the Pearson-ranking visualization of the Triage Vital Dataset after filling the missing values. A popular method Standard scalar is used to standardize the features, for data normalization in this work. Standard scalar removes means and scales the data into the unit variance.

Gini is used as a criterion for the decision tree, with a maximum depth of 5. The assumed random state is 33. In KNN, the number of neighbours is set to 5, each with uniform weight, and an auto algorithm is used. For the LR algorithm, the maximum iteration is taken as 1000 with C=1, and the l2 penalty is used along with the liblinear solver. Also in this case, the random state is taken as 33.

The machine learning approaches used in this work are Gaussian Naïve Bayes Classifier (NBC), Logistic Regression (LR), Support Vector Machine (SVM), K Nearest Neighbours (KNN) and Decision Tree (DT) for the classification of patients. For better performance of these algorithms with the triage vital dataset, the hyperparameter settings are utilized in each model are shown in table II.

TABLE II
HYPER PARAMETER SETTINGS FOR CLASSIFICATION MODELS

Model	Hyper parameter settings
LR	penalty ='l2', solver ='liblinear', C=1, max_iter=1000, random_state=33
Gaussian NB	BernoulliNB
KNN	n_neighbors=5, weights = 'uniform', algorithm='auto'
SVM	kernel= 'rbf', max_iter=4000, C=10, gamma=1
DT	criterion ='gini', max_depth=5, random_state=33

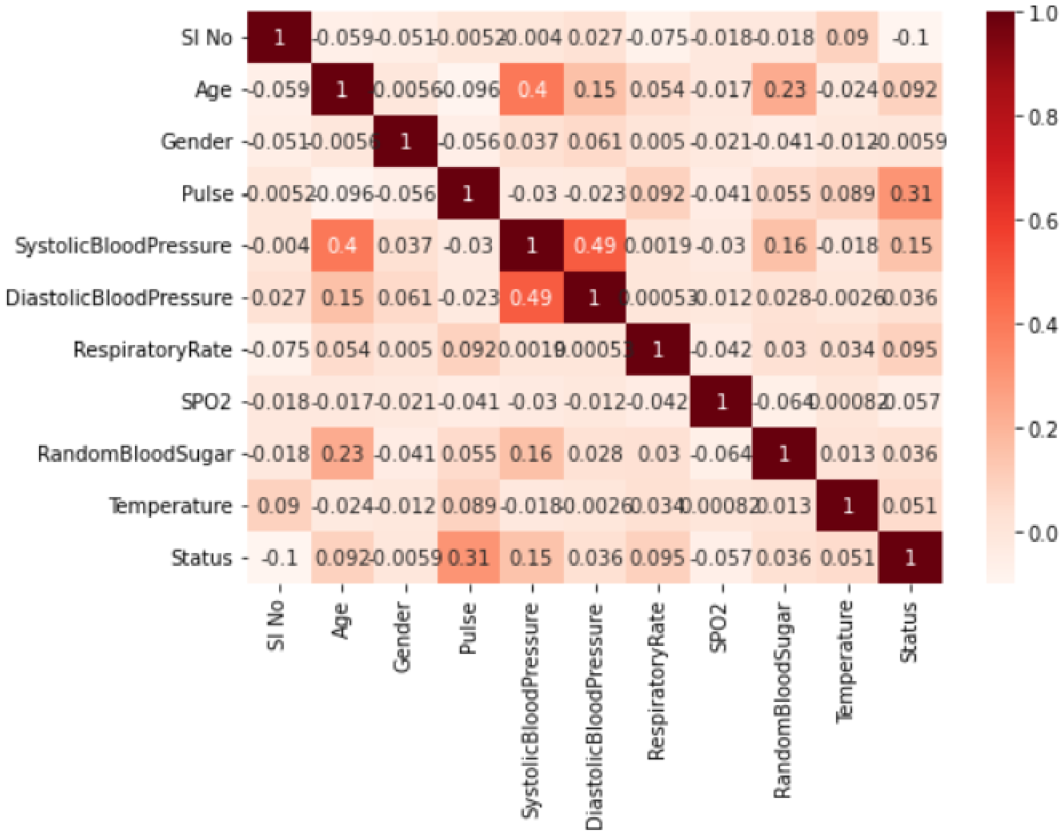

Fig. 2. Pearson-ranking visualization of the Triage Vital Dataset after filling missing values

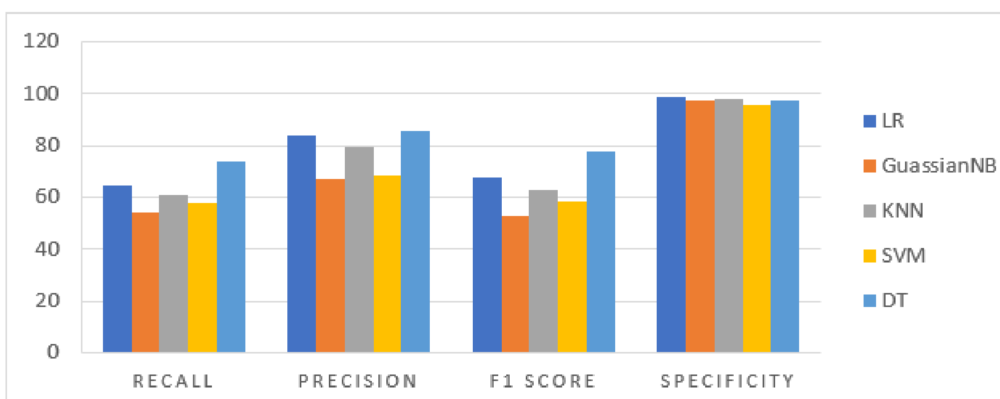

Fig. 3. Graphical representation of performance metric.

IV. RESULT AND DISCUSSIONS

This section outlines the experimental findings that were attained after the data set was trained and tested using classifiers such as the Support Vector Machine, Decision Tree, Logistic Regression, KNN and Gaussian Naive Bayes. These experimental findings used to evaluate the performance of all five classifiers and to suggest the algorithm that is most appropriate for classifying patients according to their risk level.

In this work, we divided the Triage Vital Dataset into training and testing purposes with a ratio of 70 and 30 respectively. Recall, precision, and F1-score with specificity

TABLE III
PERFORMANCE METRIC COMPARISON

	LR	**Gaussian NB**	**SVM**	**KNN**	**DT**
Recall	64.38	54.02	60.70	57.49	74.03
Precision	83.58	66.95	79.39	68.32	85.56
F1 score	67.41	52.57	62.54	58.13	77.67
Specificity	98.34	97.51	98.01	95.69	97.18

are the evaluation metrics for classification. Like any medical dataset, this Triage Vital Dataset is also an imbalanced dataset. Therefore, the F1-score is considered as the performance metric for the classification of patients' critical conditions. In this work, the classification is done with the above mentioned machine learning algorithms, and the hyperparameter settings are shown in Table II. The results are compared in table III and figure 3 shows graphical representation of performance metrics. The decision tree classifier gave a maximum F1-score of 77.67 for this data, along with a better specificity of 97.18. LR gives the maximum specificity of 98.34 for the Triage Vital Dataset.

V. CONCLUSION

The healthcare industry can be benefited from machine learning especially in classification of patients condition. The algorithms proved that it is more useful in classifying the risk level of patients' conditions in triage as critical or non-critical. This system would help in reducing time delay to classify patients at triage in the Emergency Department of a hospital. This work proved that for the unbalanced Triage Vital Dataset, Decision Tree experimentally verified F1-score of 77.67 with a high specificity of 97.18. Moreover, this system can be useful in a pandemic situation in which all the resources are exhausted that happened during the Covid 19. This will maximize the efficiency of the health infrastructure and if the health industry takes this approach, it will reduce the workload of doctors and allow them to provide proper treatment to patients as soon as possible. Finally, it can be stated that the proposed system will benefit both doctors and patients.

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REFERENCES

[1] Tintinalli, Judith E, "Disaster Preparedness", Tintinalli's Emergency Medicine: A Comprehensive Study Guide, 9th Edition, McGraw-Hill Education, 2019, ISBN: 1260019934.

[2] D. Sharathchandra and M. R. Ram, "ML Based Interactive Disease Prediction Model," 2022 IEEE Delhi Section Conference (DELCON), 2022, pp. 1-5, doi: 10.1109/DELCON54057.2022.9752947.

[3] R. Krishnamoorthi, S. Joshi, H.Z. Almarzouki, P.K. Shukla, A. Rizwan, C. Kalpana, B. Tiwari, "A Novel Diabetes Healthcare Disease Prediction Framework Using Machine Learning Techniques", Journal of healthcare engineering, 1684017, Jan 2022 https://doi.org/10.1155/2022/1684017

[4] D.A Debal, T.M. Sitote, "Chronic kidney disease prediction using machine learning techniques", Journal of Big Data 9, Nov 2022, 10.1186/s40537-022-00657-5.

[5] K.M. Almustafa, "Prediction of chronic kidney disease using different classification algorithms", Informatics in Medicine Unlocked, 2021, Volume 24, 100631, ISSN 2352-9148, https://doi.org/10.1016/j.imu.2021.100631.

[6] A. R. Rao and B. S. Renuka, "A Machine Learning Approach to Predict Thyroid Disease at Early Stages of Diagnosis," 2020 IEEE International Conference for Innovation in Technology (INOCON), 2020, pp. 1-4, doi: 10.1109/INOCON50539.2020.9298252.

[7] T. Nibareke, J. Laassiri, "Using Big Data-machine learning models for diabetes prediction and flight delays analytics Journal of Big Data, 2020, 7, pp1-18 10.1186/s40537-020-00355-0

[8] S. Uddin, A. Khan, M.E. Hossain, M.A. Moni, "Comparing different supervised machine learning algorithms for disease prediction" BMC medical informatics and decision making, Dec 2019, 19(1), 281, doi:10.1186/s12911-019-1004-8

[9] T. T. Han, H. Y. Pham, D. S. L. Nguyen, Y. Iwata, T. T. Do, K. Ishibashi, G. Sun, "Machine learning based classification model for screening of infected patients using vital signs", Informatics in Medicine Unlocked, Volume 24, 2021, 100592, ISSN 2352-9148, https://doi.org/10.1016/j.imu.2021.100592.

[10] M. Deepika and K. Kalaiselvi, "A Empirical study on Disease Diagnosis using Data Mining Techniques", 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT), 2018, pp. 615-620, doi: 10.1109/ICICCT.2018.8473185.

[11] A. Mir and S. N. Dhage, "Diabetes Disease Prediction Using Machine Learning on Big Data of Healthcare," 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), 2018, pp. 1-6, doi: 10.1109/ICCUBEA.2018.8697439.

[12] E. A. Choi et al., "Prediction of COPD severity based on clinical data using Machine Learning," 2021 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), 2021, pp. 1646-1648, doi: 10.1109/BIBM52615.2021.9669887, ET-SIP-2254415.2022.9791739.