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Early Triage Prediction for Outpatient Care Based on Heterogeneous Medical Data Utilizing Machine Learning

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ABSTRACT

Traditional triage tools hospitals use face limitations in handling the increasing number of patients and analyzing complex data. These ongoing challenges in patient triage necessitate the development of more effective prediction methods. This study aims to use machine learning (ML) to create an automated triage model for remote patients in telemedicine systems, providing more accurate health services and health assessments of urgent cases in real time. A comparative study was conducted to ascertain how well different supervised machine learning models, like SVM, RF, DT, LR, NB, and KNN, evaluated patient triage outcomes for outpatient care. Hence, data from diverse, rapidly generated sources is crucial for informed patient triage decisions. Collected through IoMT-enabled sensors, it includes sensory data (ECG, blood pressure, SpO2, temperature) and non-sensory text frame measurements. The study examined six supervised machine learning algorithms. These models were trained using patient medical data and validated by assessing their performance. Supervised ML technology was implemented in Hadoop and Spark environments to identify individuals with chronic illnesses accurately. A dataset of 55,680 patient records was used to evaluate methods and determine the best match for disease prediction. The simulation results highlight the powerful integration of ML in telemedicine to analyze data from heterogeneous IoMT devices, indicating that the Decision Tree (DT) algorithm outperformed the other five machine learning algorithms by 93.50% in terms of performance and accuracy metrics. This result provides practical insights for developing automated triage models in telemedicine systems.

Keywords: Chronic disease, heterogeneous data, internet of medical things, machine learning, remote patient monitoring, triage

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INTRODUCTION

The number of deaths from Cardiovascular diseases (CVDs), mainly heart disease and stroke, is projected to rise to 23.6 million by 2030, according to the World Health Organization (WHO) (Şahin & İlgün, 2022). Cardiovascular disease (CVD) and hypertension, also referred to as high blood pressure (BP), are chronic medical conditions with detrimental effects on the cardiovascular system, including the heart and blood vessels. These conditions are associated with a range of consequences, including myocardial infarctions (heart attacks), cerebrovascular accidents (strokes), and congestive heart failure. Individuals afflicted with chronic illnesses frequently require continuous medical surveillance, a factor that significantly influences their health status and can precipitate a rapid deterioration if not effectively controlled (Hussein et al., 2020). In addition, patients with low and high BP, especially the elderly ones, should be monitored and measured, as these values are vital to the patient's life and needed level of care and can determine the triage of severity level (Salman et al., 2014).

The Internet of Medical Things (IoMT) is an emerging technology that supports the application of Machine Learning (ML) techniques in healthcare services (Manickam et al., 2022). Integrating IoMT with ML algorithms has the potential to transform the field of medical sciences by enhancing the quality of healthcare, providing improved treatment options, and creating more efficient and affordable systems (Khan et al., 2021). Moreover, integrated IoMT provides many solutions ranging from point-of-care health monitoring and diagnosis to chronic disease management (Mujawar et al., 2020). Note that quality and healthy lifestyles include adequate support for monitoring and assessing human health performance (WHO, 2022).

Telemedicine is a form of medical care that enables providers to diagnose and treat various diseases remotely (Sims, 2018). It aims to support healthcare providers in delivering medical assistance remotely through Information and Communications Technology (Alshammari & Hassan, 2019). Telemedicine consists of three essential layers: body sensors in Layer 1 that collect data; a gateway-based system in Layer 2 that sends data to the preceding layer (the institution's server); and the hospital server in Layer 3 that provides the services remotely to the patient (Hussein et al., 2020; Salman et al., 2022). Figure 1 shows this traditional telemedicine framework.

ML algorithms have shown considerable promise in accurately forecasting various critical cases by evaluating extensive patient data to detect patterns and risk factors, especially when dealing with the analysis of extensive data sets (referred to as "big data") that contain numerous data records and input variables, as well as unorganized data fields like those found in image and text recognition algorithms (Barjouei et al., 2021). Machine learning models can take into account several characteristics, including age, gender, blood pressure, cholesterol levels, oxygen saturation, and other medical

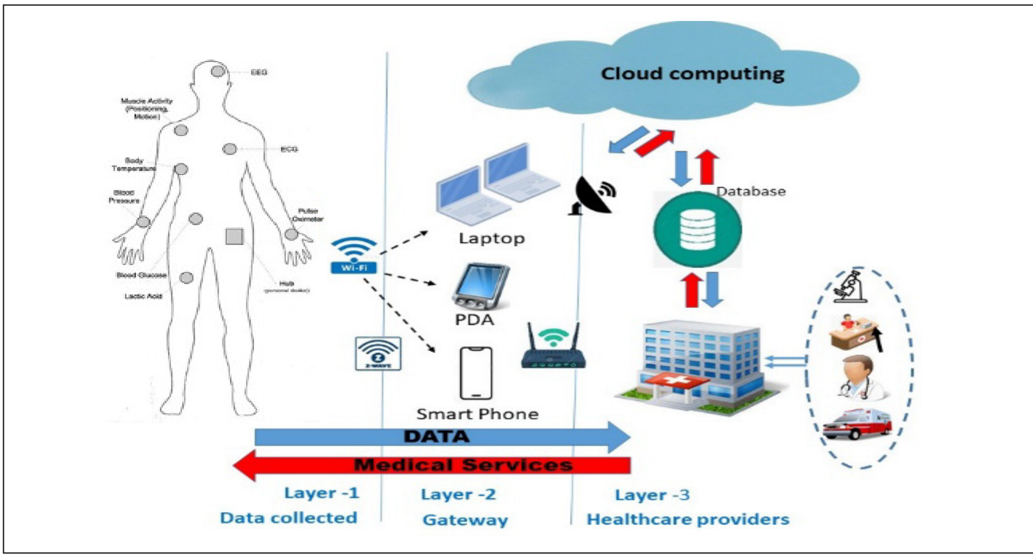

Figure 1. The telemedicine framework

issues, in order to predict the probability of developing CVD and BP diseases (Mohan et al., 2019). ML, a constituent of Artificial Intelligence (AI), has been embraced in healthcare domains due to its sophisticated capacity to analyze intricate and extensive data sets (Rashidi et al., 2021). The rapid growth of technologically driven systems, such as EHRs (electronic health records), yields substantial volumes of data that may be used to enhance decision-making processes. The utilization of AI facilitated a more comprehensive understanding of the data above, aiding in anticipating particular patient prognoses (Jampala et al., 2023). However, this requires substantial labeled data for effective learning and generalization (Onan, 2023).

Furthermore, Machine Learning (ML) refers to a collection of computer methods that acquire patterns from data without explicit programming (Kotwal et al., 2022). Therefore, machine learning (ML) is extensively utilized as a valuable computational tool in numerous industries. An important characteristic of machine learning is its ability to facilitate learning without a previous understanding of the intricate correlations between the underlying variables. ML models possess the capability to efficiently manage and process extensive datasets containing numerous variables, even when the relationships between these variables are non-linear and distributed in complicated manners (Kamali et al., 2022). Moreover, they employed ML to analyze their prediction performance models (Onan et al., 2017). Predictive clinical apps possess advantageous attributes that may be meticulously crafted to provide consistent prognostications and discern patterns within a provided data set. Consequently, these applications possess the capacity to predict patient outcomes and offer essential aid in the areas of diagnosis and therapy in various clinical conditions (Vasina et al., 2022).

This study implemented supervised ML algorithms, which include Decision Tree (DT), Naive Bayes (NB), Random Forest (RF), Support Vector Machine (SVM), K-nearest neighbor (KNN), and Logistic Regression (LR), based on Hadoop and Spark environments to predict two chronic disease types—heart disease and hypertension. The data set was upgraded from Salman, Aal-nouman, et al. (2021) to get 55,680 patient records. While Salman, Aal-nouman, et al. (2021) comprises 11 features and 580 records, our study has utilized 13 features with 55,680 records, using Hadoop and Spark environments.

This study investigates the potential benefits of supervised machine learning (ML) techniques in automating the triage process by analyzing heterogeneous, massive medical data. Additionally, it seeks to determine if implementing ML may enhance the decision-making process for remote patients. This study will employ a comparative methodology to evaluate several supervised ML approaches in forecasting triage outcomes for outpatients. The objective is to determine the most effective machine-learning strategy for addressing this challenge.

RELATED WORKS

The assessment of triage in emergency care systems has presented a significant issue owing to the exponential rise in the number of patients exhibiting varying acuity levels (Riedel et al., 2023). Although traditional triage methods have demonstrated satisfactory effectiveness in addressing hospital overcrowding (Abdalkareem et al., 2022), they are found to be inadequate in efficiently categorizing and managing patients, including during peak situations such as disasters and flooding (Mahon & Rifino, 2024). As a result of the overcrowding problem, nursing staff has been compelled to use the classified decision method to manage all patients, potentially resulting in fatal decision errors that could jeopardize patient safety (Abdalkareem et al., 2021; Elhaj et al., 2023).

ML technologies have prompted several academics to capitalize on their potential. Recent technological advancements have emerged as promising contenders for automating the triage decision-making process. These advancements also facilitate the development of models to predict patients' medical treatment needs and then prioritize them based on their level of urgency (AlSereidi et al., 2022). Advanced ML models can potentially improve the patient triage process, leading to better distinction among patients (Jiang et al., 2021). Automated triaging procedures can be established by applying machine learning classification algorithms. Automated E-triage yields exceptionally dependable classification outcomes, diminishing the need for extensive medical expertise (Liu et al., 2018). Machine learning systems, characterized by adaptable and intelligent computer algorithms, leverage data-driven methods to augment the autonomous learning and predictive capacities of diverse systems. These algorithms achieve cognition and learning by analyzing relationships among recorded data variables and identifying patterns, ultimately enabling the creation of intelligent models for precise predictions and decision-making (Barjouei et al., 2021).

Several methods for using ML techniques to predict the severity of urgent cases have been implemented. Abe et al. (2022) proposed the adaptive model to develop a prehospital triage system for the identification of patients with head trauma according to trauma severity using XGBoost techniques, as well as to evaluate the predictive accuracy of these techniques. In addition, the work of Morrill et al. (2022) suggests developing a machine-learning strategy to offer immediate decision help to adults diagnosed with congestive heart failure. Compared to physician consensus opinion, the DT algorithm outperforms any physician in terms of exacerbation and triage classification.

The RF algorithm is an ensemble learning approach that uses trapping mechanisms. In RF, each model is trained separately and often simultaneously. Subsequently, the model utilizes the highest probability value to create a classification conclusion (Ghosh et al., 2021).

Moreover, it has been proposed in a previous study by Kadum et al. (2023) that the ML-Based Remote Triage (ML-ART) approach serves as a telemedicine framework. This framework involves collecting patient data, its transmission to telemedicine servers, and the subsequent classification of each patient into one of five distinct categories. The performance of the e-triage system was improved by utilizing the DT algorithm, which yielded the highest level of accuracy. Additionally, the study by Chatrati et al. (2022) proposed a smart home health monitoring system enabling patients to oversee their health, monitor the severity levels of their condition at home, and inform their healthcare practitioner of any problems using the SVM algorithm. In addition, the triage and priority model (TPM) presented by Salman et al. (2020) improves medical response time but requires an adaptive approach for heart monitoring. A study by Mohammed, Jaafar, et al. (2020) suggested that chronic diseases use vital signs and MCDM instruments. In addition, the work by Mohammed, Zaidan, et al. (2020) proposed the TROOIL method, which solves patient triage and ordering based on severity status but does not involve big data. A classification and prioritization framework for patients with chronic diseases in telemedicine was proposed by Hamid et al. (2022) based on a case study of 500 emergency patient records. The evaluation utilized the Dempster-Shafer theory and hybridized MLAHP and TOPSIS algorithms.

Several RF models may be utilized to assess the severity of emergencies in fail-safe and highly accurate operational scenarios (Etu et al., 2022). The work of Chen et al. (2023) utilizes multi-supervised ML, such as gradient boosting machines and RFs, to understand and aid in the progression of triage for CVD in young black women. Utilizing several ML algorithms accomplished the detection of Chronic Heart Disease (CHD). In studies conducted by Saranya and Pravin (2023) and Potdar et al. (2022), ML methods were employed to analyze historical medical data to predict the occurrence of CHD. The researchers employed three supervised learning methodologies, namely NB, SVM, and DT, to detect potential connections within the CHD data set that might enhance the accuracy of predictions. In the work of Onan et al. (2017), the experimental investigation demonstrated that the combination of NB, SVM, RF, and LR produces encouraging outcomes by evaluating the efficacy of various data representations, including diverse textual features and different categorization techniques achieved through the fusion of several features. As the other study, Onan (2022) illustrates, conventional supervised machine learning models introduced an ensemble classification model based on bootstrap aggregation for text prediction. In addition, it assessed the predictive performance of six different texts and five supervised learning models (NB, Maximum Entropy Classifier (MEC), KNN, DT, and SVM) in conjunction with three considered ensemble learning models (Bagging, AdaBoost, and Random Subspace).

The development rates of countries around the globe are currently increasing tremendously and continuously, and the global population growth rate is on the rise (Ahmad et al., 2014). It has led to a growing population of individuals with chronic illnesses residing in remote regions, presenting challenges for healthcare professionals in accurately interpreting their vital signs and determining the urgency of their medical condition. Hence, it is imperative to prioritize the real-time triage of patients afflicted with chronic illnesses by including urgent case prediction. Inaccurate assessments have the potential to impede timely treatment and, in severe cases, result in fatalities. Hence, accurate prediction of patient classification before hospital admission or outpatient visits holds significant importance for medical facilities and telemedicine patients. Accurate triage holds significant importance in managing all illnesses, particularly in the older population (Salman, Taha, et al., 2021). Furthermore, managing the rising data heterogeneity on hospital servers poses an unresolved research challenge, requiring further inquiry and analysis (Kadum et al., 2023). In addition, the data's quality has a substantial impact on the models' quality. Training machine learning models using faulty data carries the risk of generating predictions that deviate from reality due to biases or errors (Onan, 2023).

Therefore, research must include every remote patient as a multi-tiered severity case-cohort component while considering various manifestations of symptoms and diseases. This strategy is particularly significant for patients residing in remote areas who also require precise diagnosis of the severity of their diseases.

A literature review revealed that no particular study considered managing big medical data with increasing patient populations for any chronic condition, and it is available, as demonstrated in Table 1.

Hence, we propose a method for identifying and predicting the presence of five categories for triage levels to overcome these limitations. Relevant studies by Chatrati et al. (2022) and Kadum et al. (2023) have chosen these studies as benchmarks after thoroughly analyzing the existing literature. These studies align with our focus on triaging and determining urgent severity cases for patients through the utilization and evaluation of six models of supervised ML.

Table 1
Relevant state-of-the-art studies that addressed triaging patients in a scalable model of the healthcare monitoring system

References	**Salman et al., 2020)**	**Mohammed, Jaafar, et al., 2020)**	**Mohammed, Zaidan, et al., 2020**	**Hamid et al., 2022**	**Chatrati et al., 2022**	**Kadum et al., 2023**	**Proposed work**
Year	2020	2020	2020	2022	2022	2023	
MCDs	x	□	□	x	□	□	□
Remote monitoring out-patient	□	□	□	□	□	□	□
Remote monitoring in-patient	□	x	x	□	x	x	x
Scalability	□	□	□	x	x	□	□
The large scale of patients	□	□	□	□	□	□	□
Big Data Considered	x	□	x	x	x	x	□
Data pre-processing	x	x	x	x	x	x	□
Target Layer	Layer-2 and Layer-3	Layer-3 (server)	Layer-3 (server)	Layer-3 (server)	Layer-2	Layer-3 (server)	Layer-3 (server)
Time services Considered	□	x	x	x	x	x	x
Triage Considered	□	□	□	□	□	□	□
Priority Considered	□	□	□	□	□	□	x
IoMT	x	x	x	x	x	□	□
Temperature feature	x	x	x	x	x	□	□
Machine Learning	FCM	x	x	x	SVM KNN DT LR DA	NN SVM DT RF	SVM DT RF LR NB K-NN
Method	Evidence theory with FCM	Hybrid D.M. and voting method	TROOIL	Dumpster –Shafer and MLAHP and TROOIL	Support vector machine	Decision Tree	Decision Tree

METHODOLOGY

A comparative analysis was undertaken to assess the efficacy of several supervised machine learning models in assessing patients' real-time triage results. Using the dataset obtained from the data source (Salman, Aal-nouman, et al., 2021), the total data was upgraded to 55,680 patient records. While the original data set from Salman, Aal-nouman et al. (2021) comprises 11 features, our study utilized 14 features with 55,680 records using Hadoop and Spark environments. The Python 3.9 programming language and scientific libraries such as Pandas, NumPy, and Sklearn were utilized for data processing and analysis.

Data Preparation

Data preparation is a crucial stage in the machine learning pipeline and is among the most time-intensive activities in constructing machine learning models (Patel et al., 2022) (Rabash, Nazri, Shapii, & Hasan, 2023). Data pre-processing procedures were carried out after data collection, involving label encoding and imputation of missing data. The categorical feature labels were transformed into a numerical format to make them understandable by machines and to create easy-to-understand forms for ML algorithms. Missing values were computed by calculating the mean for each column that contains missing data in a provided data set and then filling in the missing value.

Data Set

The triage model incorporates a modified data set from a source, including sensors like BP, oxygen saturation, and ECG, and four non-sensory characteristics (Salman, Aal-nouman, et al., 2021). The model's performance is enhanced by adding temperature degree and non-sensory attributes like headache and left-hand discomfort, ensuring data organization by medical protocols. All the data has been formulated for patient triage information per medical guidelines, as shown in Table 2.

Table 2
Patient triage information

Summary	Mean	(-/+) Std.	Range
Patients No.			55680
Patients Detail			
Age	67	14.063	40-89
Sex Female%	27870	50.05%	Male / Female
Vital Signs (Input)			
ECG Sensor			
Peaks	90.505	25.405	40 - 139
QRS	0.278	0.098	0.2 - 0.4

Table 2 *(continue)*

Summary	Mean	(-/+) Std.	Range
P_P	0.321	0.467	Regular / Irregular
ST.El.	0.535	0.499	Yes / No
Another sensor			
Spo2	92.993	6.165	80 - 100
Temp	37.741	1.228	36 - 40
Blood Pressures Measurements			
H-Blood	15.764	3.689	11-23
L-Blood	8.902	1.779	6 -12
Text Features			
ChP.	0.514	0.500	Yes / No
SH.B.	0.549	0.498	Yes / No
Palip.	0.473	0.499	Yes / No
Rest	0.627	0.484	Yes / No
L.H.P.	0.589	0.492	Yes / No
Hed.	0.593	0.491	Yes / No
Triage Outcome			
Normal			10360
Risk			14914
Sick			11216
Urgent			11484
Cold Case			7706

Considering the symptoms and diagnoses of the patients, the probability of a change in the values was evaluated based on the medical guidelines (Salman et al., 2020). It is important to acknowledge that 55,680 simulated sequences were utilized to illustrate the presence of CHD and hypertension, classified as chronic ailments, among 55,680 individuals. The number of patient requests hypothesis is derived from data from the medical institution's data center, which is responsible for the city. Every patient has been evaluated by physicians specializing in chronic diseases, and each set of medical symptoms has been categorized into five categories (risk, urgent, sick, cold case, and normal) based on the severity of the ailment, as per medical guidelines.

Pre-processing Data

The study encountered a significant challenge of a high-class imbalance in the collected data set for designing ML triage models. The Synthetic Minority Over-sampling Data Generation Technique (SMODGT) was applied to handle this imbalance (Ratih et al., 2022; Rabash, Nazri, Shapii, & Al-Jumaily, 2023). This technique oversamples the minority class by creating synthetic examples along the line segments joining the minority class's nearest neighbors. After applying SMODGT, the final training data set had a sample size of 55,680, with an equal distribution of samples across the target classes.

The start step was conducted to check and analyze the data to determine the correlation between attributes and comprehend the individual impact of each variable on the learning process. This technique facilitates the identification of the variable that keeps the most pertinent information, enabling prediction accuracy (Jebli et al., 2021). The next step is to check the missing values and fill out the missing data or modify it. Therefore, to improve the quality of the data set and reduce its size, the next step is to lower the dimensions between the features and the actual encoding. Additionally, since text features frequently appear in the data set, replacing them with values that the ML technique can understand and handle improves the quality of the results. All the values of the texts were replaced with integers. For instance, "male" or "female" were substituted with 1/0 in the gender feature and "yes" or "no" with 1/0 in the rest and short breath features, to name a few (Pan et al., 2018). Afterward, all integer values were converted to floats. Following this, it is necessary to normalize the ordinal variable and encode the category variable. In this study, the utilization of the Z score, also known as normalization Yang (2020), was implemented as a standardized approach for normalization. After subtracting the arithmetic mean from the variable, it is then normalized by dividing it by its standard deviation, as described in Equation 1:

$$X = (X - \mu)/\sigma \qquad [1]$$

where *"X"* is the input data, *"μ"* is the mean value of data *X*, and *"σ"* is the standard deviation of data *X*.

In addition, the data were divided into 80% training and 20% assessment or testing.

Machine Learning Models

The growth of automation and advanced machine monitoring technologies has facilitated the generation of extensive digital datasets for analyzing system behavior, empowering machine learning (ML) systems to improve automated learning and prediction capabilities (Barjouei et al., 2021). The present work employed a conventional (supervised) machine learning technique to train several models using a carefully constructed dataset for triage. Several algorithms were initially chosen for the study, namely Logistic Regression (LR), Decision Trees (DT), k-nearest Neighbors (KNN), Support Vector Machines (SVM), Naive Bayes (NB), and Random Forest (RF). These algorithms were initially selected as they exhibit higher predictive ability in triage classification problems (Chatrati et al., 2022; Kadum et al., 2023; Salman, Taha, et al., 2021). The description of each classification technique is provided as follows:

Support Vector Machine (SVM)

SVM is a supervised learning technique (Ahmad et al., 2014; Barjouei et al., 2021; Onan, 2021; Otoom et al., 2020). Given a set of labeled training examples (i.e., every single instance in the training set is related to either the positive or negative class), SVM discovers the area of the hyperplane that best separates cases from each class and achieves the maximum distance between instances of data and the hyperplane. The learned hyperplane is then used to assign (or predict) a class label for each new test instance.

Naive Bayes (NB)

NB is a technique for supervised learning that computes model parameters using the Bayes theory. Calculating the probabilities, it assigns a class designation to any test instance. It is associated with each possible class label. The probability with the highest value determines the designation (Berrar, 2019).

Random Forest (RF)

RF is an ensemble-supervised ML model that uses DTs as the base learner and frequently constructs regression trees based on training data. Node selection in RF differs, with a random subset selection from the present attribute set and a selection of one optimized attribute in the sub-feature set. It has been widely employed in classification and regression problems (Barjouei et al., 2021; Hadi et al., 2020).

Logistic Regression (LR)

In the LR technique, classification is based on probabilities. It can be considered a particular regression case where the outcome is categorical. It uses a sigmoid non-linear activation function to produce the output. However, this also indicates that it suffers high sensitivity to attribute vector values. This classifier method is a widespread tool in disease prediction (Hadi et al., 2020).

Decision Tree (DT)

The procedure for constructing involves dividing the dataset into child subsets. The process of partitioning continues with repetitive partitioning of child subsets. The underlying concept of the tree method is to employ a series of partitions to identify the optimal class. Furthermore, DTs are characterized by feature selection capability, straightforward comprehension, interpretability, visualization, and independence from non-linear relationships between parameters (Barjouei et al., 2021; Shiwangi et al., 2023).

K-Nearest Neighbor (KNN) Algorithm

The K-Nearest Neighbors (KNN) algorithm is a supervised machine learning algorithm for prediction and classification tasks. One of its notable features is its simplicity and effectiveness. The algorithm identifies the 'k' training instances in its vicinity closest to a new, unseen data point based on a specified distance metric, commonly the Euclidean distance. The algorithm then classifies the new data point by a majority vote of its k-nearest neighbors (Lestari & Sumarlinda, 2022).

Peculiarity of the Method

Machine learning (ML) algorithms have shown promise in predicting urgent cases by analyzing vast amounts of patient data, particularly when processing large data sets. ML models can consider multiple factors (heterogeneity medical data) such as age, gender, BP, oxygen rate, and other medical conditions to predict the possibility of developing CVD and BP chronic diseases. Machine learning is extensively utilized in the healthcare industry due to its advanced ability to analyze complex and vast data sets. This study investigates the potential benefits of ML techniques in automating the triage process. The study revealed a promising future vision in the healthcare field by analyzing heterogeneous, massive medical data and assessing whether ML can enhance the decision-making process for remote patients.

Performance Evaluation Metrics

Multi-class classification problems play a crucial role in assessing the efficacy of learning methodologies and facilitating comparisons between various models. The selection of appropriate assessment measures is of utmost importance for reporting the success of prediction models, specifically within the sector of healthcare assessment models (Alsinglawi et al., 2022). Given that triage is an issue characterized by a high-class imbalance, relying just on a single assessment parameter, such as accuracy or precision, would be insufficient for assessing the performance of a model. Nevertheless, there is currently a lack of a globally approved set of performance metrics that apply to all multi-class issues. Since the current investigation pertains to a multi-class classification issue, it is important to note that the range of accessible performance metrics is restricted. Typically, these metrics include accuracy, recall, precision, and F1-score (Ozsahin et al., 2022). Moreover, Hameed et al. (2022) also suggested that the assessment of multi-class issues may be conducted using Receiver Operating Characteristics (ROC) and Areas Under The ROC Curve (AUC). However, it should be noted that the analytical difficulty escalates as the number of classes grows.

Hence, this research will only focus on the established assessment measures for assessing the performance of the chosen models. The next step involved the enervation of the confusion matrix for each model. A confusion matrix is a fundamental concept in ML that offers insights into the expected and true categorization values produced by a prediction system (Huang & Wang, 2023). The data consists of two dimensions: the first dimension reflects the true class of the data, while the second dimension indicates the predicted class of the data set. The evaluation metrics designed for binary classification are not fully appropriate for multi-class classification problems, mainly because of the discrepancy in matrix dimensions between the two types of classification matrices (Hameed et al., 2022).

- True Positives (TP) refers to correctly identifying individuals who are correctly classified as patients with a certain chronic condition.
- True Negatives (TN) refer to instances where a forecast accurately identifies individuals who do not have a specific sickness or any other ailments.
- False positives (FP) refer to the erroneous identification of a healthy individual as being afflicted with a certain ailment.
- False negatives (FN) refer to the erroneous classification of the target as a non-healthy individual.

Performance metrics evaluate the performance of these ML algorithms. Various performance assessment metrics may be established using the confusion matrix, as presented in Table 3. The final review considered accuracy, precision, recall, and F1-score for each class, as represented in Performance Measure with formal in Table 4.

Table 3
Confusion matrix

	Predicted Negative	Predicted Positive
Actual Negative	TN	FP
Actual Positive	FN	TP

Table 4
Performance evaluation metrics

Performance Measure with formal	**Description**
$\mathbf{Accuracy} = \frac{(\mathbf{TP}+\mathbf{TN})}{(\mathbf{TP}+\mathbf{TN}+\mathbf{FP}+\mathbf{FN})}$	It assesses the accuracy of a classification model in making predictions.
$\mathbf{Precision} = \frac{\mathbf{TP}}{(\mathbf{TP}+\mathbf{FP})}$	The assessment assesses the accuracy ratio of correctly predicted instances belonging to a certain class and the total number of instances anticipated as belonging to the same class.
$\mathbf{Recall} = \frac{\mathbf{TP}}{(\mathbf{TP}+\mathbf{FN})}$	The accuracy rate is assessed by calculating the proportion of accurate predictions for a certain class and the overall count of instances belonging to an actual class.
$\mathbf{F1-score} = \frac{\mathbf{2*Precision*Recall}}{\mathbf{Precision+Recall}}$	This analysis aims to assess the harmonic mean of precision and recall.

RESULTS AND DISCUSSION

Several ML models were tested for the severity of urgent cases and for determining patient results on a dataset with a balanced number of classes (Table 2). In this study, the above-mentioned supervised ML classifiers made 11,088 predictions, and 11,088 patient records were used to test how to classify the triage levels for people with chronic heart and hypertension diseases. Of those 11,088 records, 2,083 are normal cases, 1,542 are cold cases, 2,936 are risk cases, 2,274 are urgent cases, and 2,253 are sick cases.

Table 5 summarizes the performance and accuracy results of the evaluated ML algorithms. The results indicate that three of the six models, namely DT, KNN, and RF, had higher accuracy than others. The DT and KNN models exhibited outstanding results compared to the other models, as evidenced by their better prediction metrics: accuracy (93.50%); precision (100.00%, 100.00%, 89.00%, 85.00%, 95.00%); recall (100.00%, 100.00%, 86.00%, 86.00%, 97.00%); and F1-score (100.00%, 100.00%, 88.00%, 86.00%, 96.00%) for triage levels (normal, cold state, risk, urgent, and sick, respectively). Meanwhile, the performance of the KNN algorithm regarding accuracy was (92.0%); precision (97.00%, 92.00%, 92.00%, 86.00%, 87.00%); recall (99.00%, 88.00%, 85.00%,

Table 5
Performance for all six algorithms (SVM, LR, DT, RF, KNN and NB) for triage categorization for normal, cold state, risk, urgent, and sick, respectively

Methods	Performance Metrics	NORMAL	COLD STATE	RISK	URGENT	SICK	Accuracy
SVM	Precision	83.00%	80.00%	57.00%	69.00%	64.00%	43.00%
	Recall	100.00%	93.00%	74.00%	1.00%	83.00%	
	F1-score	91.00%	86.00%	65.00%	3.00%	72.00%	
LR	Precision	98.00%	92.00%	59.00%	55.00%	70.00%	45.00%
	Recall	100.00%	95.00%	69.00%	32.00%	80.00%	
	F1-score	99.00%	93.00%	64.00%	41.00%	75.00%	
RF.	Precision	100.00%	98.00%	85.00%	80.00%	94.00%	91.00%
	Recall	100.00%	99.00%	82.00%	80.00%	97.00%	
	F1-score	100.00%	99.00%	83.00%	80.00%	96.00%	
KNN	Precision	97.00%	92.00%	92.00%	86.00%	87.00%	92.00%
	Recall	99.00%	88.00%	85.00%	90.00%	92.00%	
	F1-score	98.00%	90.00%	88.00%	88.00%	90.00%	
DT	Precision	100.00%	100.00%	89.00%	85.00%	95.00%	93.50%
	Recall	100.00%	100.00%	86.00%	86.00%	97.00%	
	F1-score	100.00%	100.00%	88.00%	86.00%	96.00%	
NB	Precision	80.00%	73.00%	55.00%	56.00%	52.00%	41.00%
	Recall	100.00%	93.00%	53.00%	6.00%	79.00%	
	F1-score	89.00%	81.00%	54.00%	11.00%	63.00%	
	Support	2083	1542	2936	2274	2253	11800

90.00%, 92.00%); and F1-score (98.00%, 90.00%, 88.00%, 88.00%, 90.00%) for triage levels (normal, cold state, risk, urgent, and sick, respectively), as shown in Figure 2.

Figure 2(d) illustrates that the DT algorithm outperforms other algorithms, particularly in the normal and cold cases (100% and 100%, respectively). However, on the other three levels (sick, urgent, and risk), the values are roughly close between the DT, KNN, and RF algorithms. However, the decision tree consistently holds the highest accuracy.

Figure 3 shows the model performance in the form of a confusion matrix displayed standalone for each algorithm.

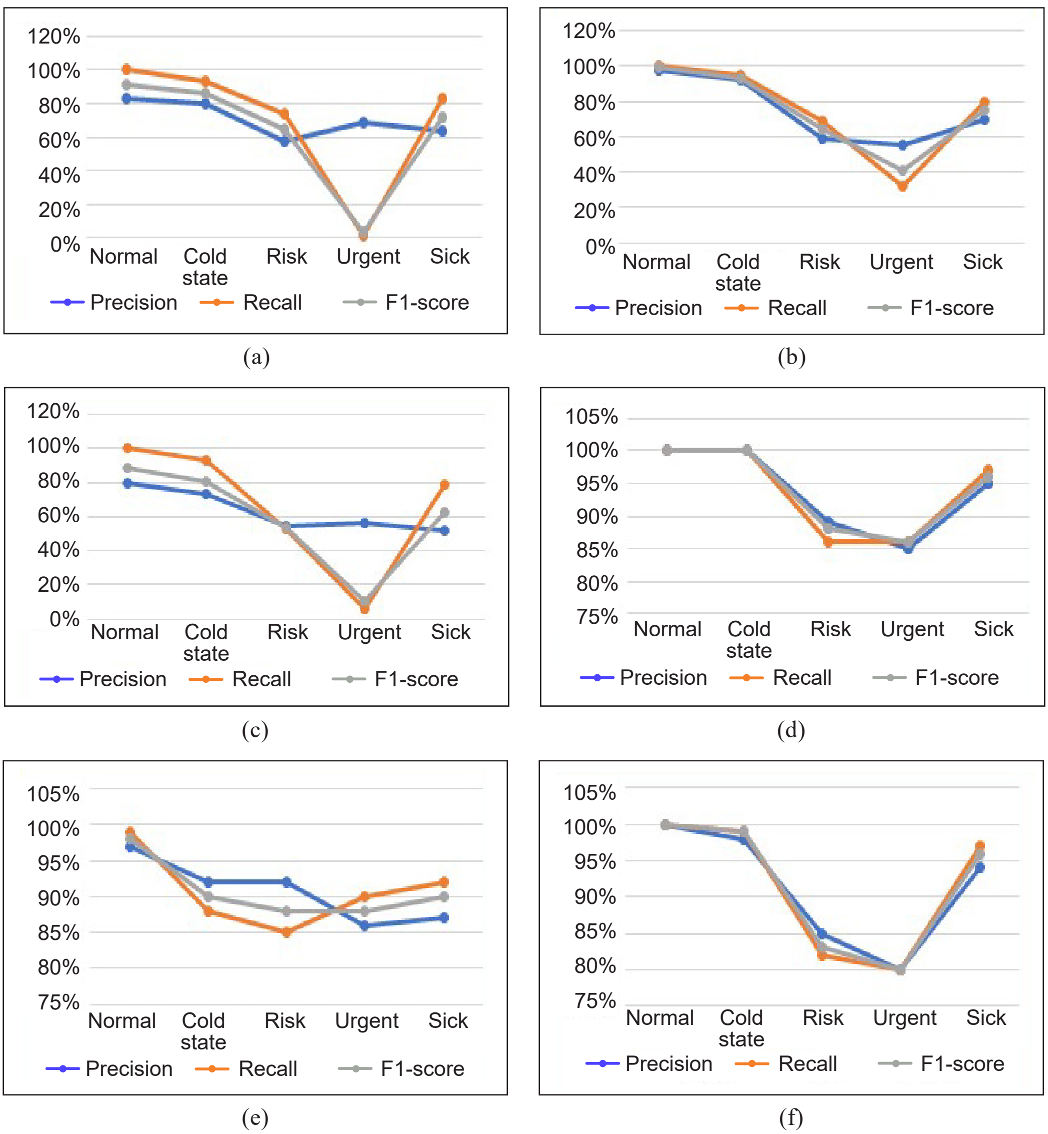

Figure 2. Performance metrics of six supervised machine learning methods: (a) SVM algorithm; (b) LR algorithm; (c) NB algorithm; (d) DT algorithm; (e) KNN algorithm; and (f) RF algorithm

Prediction Value

Actual Value	NORMAL	COLD STATE	RISK	URGENT	SICK
NORMAL	2067	159	25	52	147
COLD STATE	652	266	0	79	493
RISK	735	183	240	569	696
URGENT	537	194	254	706	655
SICK	411	129	64	275	1500

(a)

Prediction Value

Actual Value	NORMAL	COLD STATE	RISK	URGENT	SICK
NORMAL	2272	6	72	39	61
COLD STATE	7	1472	0	1	10
RISK	64	0	2186	35	138
URGENT	35	1	39	2189	82
SICK	68	13	122	58	2118

(b)

Prediction Value

Actual Value	NORMAL	COLD STATE	RISK	URGENT	SICK
NORMAL	1738	52	165	301	194
COLD STATE	478	1	57	444	510
RISK	351	48	688	843	493
URGENT	263	53	433	1092	505
SICK	160	59	428	302	1430

(c)

Prediction Value

Actual Value	NORMAL	COLD STATE	RISK	URGENT	SICK
NORMAL	1678	0	212	173	387
COLD STATE	477	0	173	303	537
RISK	549	0	562	60	704
URGENT	507	0	392	733	714
SICK	315	0	274	221	1569

(d)

Prediction Value

Actual Value	NORMAL	COLD STATE	RISK	URGENT	SICK
NORMAL	2111	4	150	75	110
COLD STATE	30	1420	0	4	36
RISK	50	48	2162	142	21
URGENT	26	4	157	2087	72
SICK	65	77	31	110	2096

(e)

Prediction Value

Actual Value	NORMAL	COLD STATE	RISK	URGENT	SICK
NORMAL	2323	10	49	20	48
COLD STATE	21	1460	4	1	4
RISK	108	17	2114	79	105
URGENT	37	5	65	2161	78
SICK	78	27	154	53	2067

(f)

Figure 3. Confusion matrix of six supervised machine learning methods: (a) SVM; (b) LR; (c) NB; (d) DT; (e) KNN; and (f) RF

A confusion matrix is a matrix used to evaluate the performance of a classifier on test data, where the actual values are believed to be known data values. In this work, the confusion matrix of each algorithm is r. The model performance in a confusion matrix is displayed as a standalone value for each algorithm, as shown in Figure 3. A confusion matrix is a matrix used to evaluate the performance of a classifier on test data, where the actual values are believed to be known data values. In this work, the confusion matrix of each algorithm is represented as a 5x5 matrix for the triage levels due to the result consisting of five category outputs: normal, cold case, risk, urgent, and sick. Each row in the matrix includes the number of actual classes, and each column includes the number of predicted classes. From the result of this matrix, we can determine the values for true positive (TP), false positive (FP), true negative (TN), and false negative (FN), as illustrated in Table 4. Moreover, the row values illustrate the prediction computed for each level within each triage class.

Consequently, using the actual and predicted values, the class precision and recall values are calculated (Figure 3). The class recall and class precision scores are useful for assessing the overall accuracy of the classifier. According to the values shown in the table, the decision tree classifier has the highest precision and recall values, whereas Naïve Bayes has the lowest values. The confusion matrix was applied to analyze model predictions in each class during testing.

In the DT algorithm, all the patients were accurately triaged, with false positives (FP) and false negatives (FN) being minimal, generally <100 or close to that, as explained in Figure 3(d).

A total of six models were trained and subsequently evaluated on the produced dataset, yielding a prediction accuracy range spanning 41.0% to 93.50%, as displayed in Figure 4, representing the correlation between algorithm accuracy and processing time.

On the other hand, the SVM, LR, and NB approaches seem to be the least effective models compared to the others, as they have the lowest prediction accuracy of 43.00%, 45.00%, and 41.00%, respectively.

However, the system has been verified and validated using another measure, the ROC-AUC score, which compares the relationship between TP and FP rates. In addition, it is ensured that the multi-class classification models perform well and make better decisions based on their predictions.

Figure 5 presents the ROC-AUC scores for various machine learning classification algorithms, facilitating a comparative assessment of their performance.

The ROC-AUC curve, a crucial metric for binary classification, visualizes the trade-off between recall and precision. The AUC, or area under the curve, quantifies a classifier's ability to differentiate between the two classes, with a desirable model exhibiting an AUC close to 1. The closer the ROC is to the top left of the graph, the better the model is. It

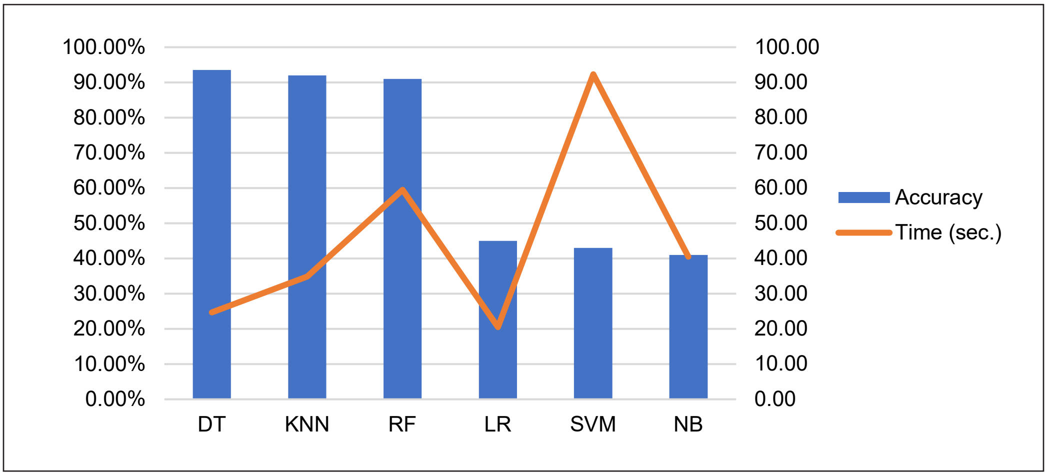

Figure 4. The Accuracy with the time process for six ML

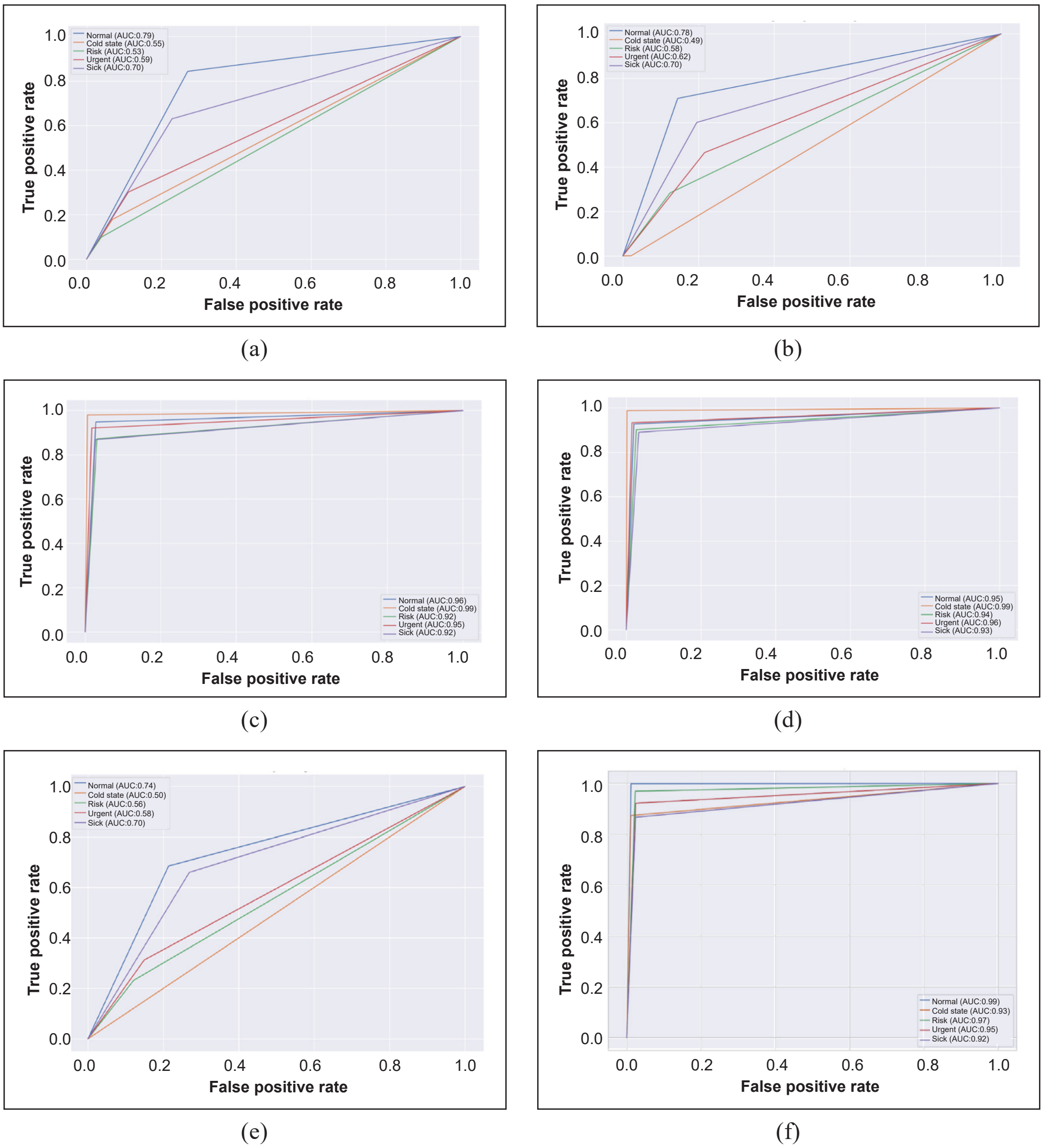

Figure 5. ROC Curves for six supervised machine learning methods: (a) SVM-AUC; (b) LR-AUC; (c) RF-AUC; (d) DT-AUC; (e) KNN-AUC; and (f) KNN-AUC

is an indication that the model has a good measure of separability. Therefore, the DT algorithm achieved the largest area under the ROC curve score of 0.9543, outperforming other algorithms, KNN, RF, LR, SVM, and NB, which had 0.9443, 0.9480, 0.6357, 0.6333, and 0.6135, respectively (Figure 5).

The DT algorithm outperforms other algorithms because it effectively combines decisions. In contrast, RF combines decisions from multiple trees, which may not always yield optimal results.

Additionally, KNN's reliance on proximity for decision-making can lead to inaccuracies in certain cases. Furthermore, the DT algorithm exhibits superior computational efficiency and reduced computational burden, making it particularly advantageous for handling categorical data. Also, the DT algorithm demonstrates enhanced capability in managing collinearity compared to SVMs. What is more, the DT algorithm demonstrates greater efficiency in managing outliers and missing values compared to the LR algorithm. Outliers do not influence DTs due to their ability to divide the data according to feature values. On the other hand, NB is not well-suited for intricate problems. In conclusion, the DT bears certain resemblances to the procedural steps followed by nursing staff in categorizing patients.

CONCLUSION

This paper suggests a way to find and predict the presence of five patient triage levels: normal, cold state, risk, urgent, and sick. These levels are for two chronic diseases: CVD and hypertension. The paper uses and evaluates six supervised machine learning models: SVM, NB, RF, DT, KNN, and LR. The goal is to make an automated triage model for remote patients in telemedicine systems and to provide more accurate health services. The DT algorithm obtained the highest accuracy and performance compared to the other five algorithms. This result was achieved by evaluating each algorithm as a standalone element and using three performance measurements: performance metrics (accuracy, precision, recall, and F1-score), confusion matrix, and ROC-AUC. All these measurements prove that the decision tree algorithm outperformed the other algorithms. Due to this, the results illustrate that the proposed system, with the DT algorithm, provides an accuracy of 93.50%, higher than that of the other algorithms. The suggested method supports the powerful combination of using machine learning in telemedicine and analyzing the huge amounts of medical data from different IoMT devices to make accurate decisions by predicting the triage levels of patients in real-time, particularly high-severity cases. Furthermore, it is advantageous to use structured and unstructured data from the data set with the proposed system Salman, Aal-nouman, et al. (2021), using 55,680 patient records. As a result of the proposed system, patients can be categorized based on the urgency and severity of the cases of patients suffering from CVD and hypertension. In future work, we need to consider adding new symptoms to help patients predict more chronic diseases, such as diabetes, through case studies.

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