AI-Driven Decision Support in Emergency Medical Services for Real-Time Diagnosis and Hospital Coordination

Dr. C. Madan Kumar[1*], Sai Vaishnavi Ravula[2], Nunavath Jashwendar[2], Chiliveri Devaraj[2], Pitta Rohith[2]

[1]Assistant Professor, [2]UG Student, [1,2]Department of Computer Science and Engineering

[1,2]Vaagdevi College of Engineering (UGC – Autonomous), Bollikunta, Warangal, Telangana

*Corresponding author: Dr. C. Madan Kumar

ABSTRACT

Emergency Medical Services (EMS) traditionally rely on manual vital-sign recording and verbal reporting, leading to delays, transcription errors, and inconsistent triage decisions. This project presents an AI-driven decision-support system that automates pre-hospital diagnosis and hospital coordination through two Tkinter-based applications: an ambulance-side client and a hospital-side server. The client GUI enables batch upload of patient vital-sign CSV files, serializes each record, and transmits it over TCP to the server. The server GUI logs incoming data, applies a StandardScaler for feature normalization, and performs real-time inference using four machine-learning classifiers such as Decision Tree Classifier (DTC) model, Random Forest Classifier (RFC) model, K-Nearest Neighbors (KNN) classifier, and XGBoost model. On a held-out heart-disease dataset (80% train, 20% test), the DTC achieved 82.44% accuracy, 84.25% precision, 82.61% recall, and an F1-score of 82.25%. The KNN classifier reached 86.34% accuracy, 86.80% precision, 86.42% recall, and an F1-score of 86.32%. Both ensemble methods—RFC and XGBoost—attained perfect performance (100% across accuracy, precision, recall, and F1-score), demonstrating their superior ability to capture complex multivariate patterns in vital-sign data. The server's threaded socket design supports concurrent ambulance connections, ensuring scalability for mass-casualty scenarios. By automating data ingestion, normalization, and classification, the system reduces human error, accelerates triage, and provides objective, data-driven acuity assessments. This integrated solution lays the groundwork for enhanced EMS workflows, improved patient outcomes, and more efficient hospital resource allocation.

Keywords: Emergency medical services, Decision support systems, Predictive analytics, Artificial Intelligence, Standard scaling, Disease prediction.

1. INTRODUCTION

This research work deals with the need for a critical evaluation of the evidence supporting whether a clinical digital solution involving AI (Artificial Intelligence) in home, outpatient, and ambulance settings plays a key role in patient outcomes [1, 2]. Specifically, we propose the collection of data from different contexts starting from the home up to the ICU department, both of a clinical and socio-economic nature. This evaluation would concern the living context and social status, age, sex, clinical history, and current condition along with the measurement of various parameters and markers for validation and impact on patient outcomes. To date, few system providers have questioned their products and services in terms of healthcare parameters at home, in the community, and in the ambulance [3, 4].

In primary care patients, who often present with non-specific symptoms suggestive of an ongoing early disease process, diagnostic uncertainty is a pervasive issue. Often, the signs of the disease are not typical, either symptoms are too common or are not frequently associated with severe disease:

Dizziness, for instance, occurs in the majority of cases of stroke, but only very few cases of dizziness result in stroke. Major misdiagnosis-related mistakes are often related to the so-called "Big Three" (major vascular events, infections, and cancers), in which diagnostic uncertainty, resulting in diagnostic errors, is of particular concern [5, 6]. In addition, laboratory and diagnostic tests have significant limitations. For instance, laboratory biomarkers such as lactate, C-reactive protein (CRP), and procalcitonin (PCT), which can assist in diagnosis, are not definitive and can be influenced by other conditions, potentially leading to misdiagnosis [7].

Diagnostic errors in first care result from an inadequate amount of information among clinicians, patients, and families. Information certainty is crucial as it is involved in the diagnostic process and it is required for shared decision-making, thus impacting patients' disease evolving progress. Effectively managing diagnostic uncertainty can be challenging for doctors given unknown competing priorities and expectations and wide variability exist in the degree to which clinicians engage in first assessment and therapy [8]. Although there are protocols for how to proceed and perform in such critical circumstances, few are evidence-based. Recent AI models have elucidated the main traits and the management of the implications of diagnostic uncertainty in primary care.

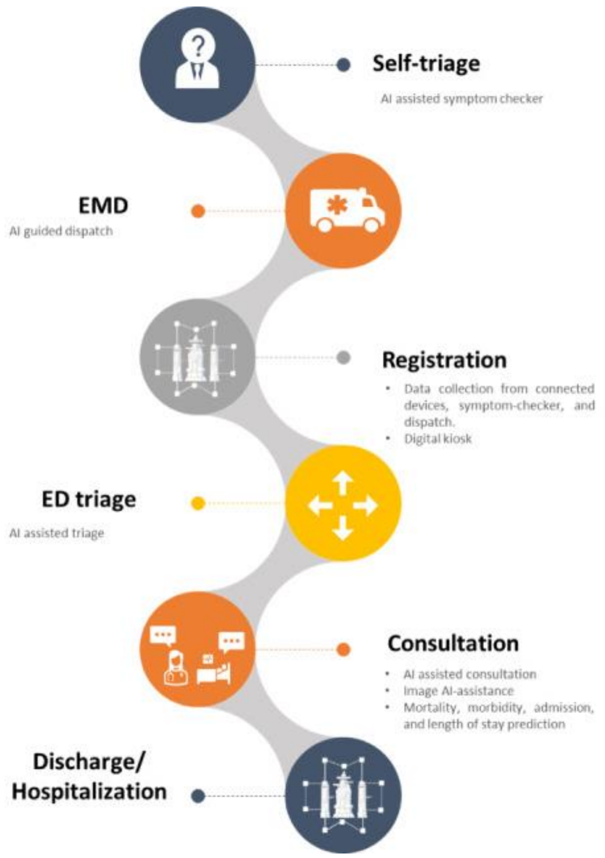


Fig. 1: The emergency patient journey and where artificial intelligence is making or can make an impact. AI: artificial intelligence; ED: emergency department; EMD: emergency medical dispatch.

Advances in machine learning and real-time networking present an opportunity to transform EMS triage from a subjective, manual workflow into a data-driven, automated process. By integrating AI models trained on large historical datasets directly into ambulance-hospital communication channels, clinicians can receive immediate, objective risk assessments, enabling faster decision making and better resource planning. The main contributions of this research are as follows:

1. Develop a preprocessing pipeline that reliably cleans, normalizes, and scales patient vital-sign data for model consumption.
2. Train and compare multiple classification algorithms (Decision Tree, Random Forest, KNN, and XGBoost) to identify the most accurate predictor of abnormal patient conditions.
3. Implement a threaded TCP server that performs real-time inference on incoming patient data and returns clear, actionable diagnoses.
4. Create a companion client application that batch-sends patient records and logs server responses in a user-friendly GUI.
5. Evaluate the end-to-end system's performance in terms of accuracy, latency, and usability compared to traditional EMS workflows.

2. LITERATURE SURVEY

According to the WHO estimate, the overall number of deaths from CVDs would rise to 23.6 million by 2030, with heart disease and stroke being the leading causes [9]. To save lives and decrease the cost burden on society, it is vital to apply data mining and machine learning methods to anticipate the chance of having heart disease. Heart disease, specifically cardiovascular disease (CVDs), is a leading cause of morbidity and mortality worldwide, accounting for over 70% of all global deaths. According to the Global Burden of Disease Study 2017, CVD accounts for more than 43% of all deaths. Common risk factors associated with heart disease include unhealthy food, tobacco, excessive sugar, and overweight or extra body fat, often found in high-income countries. However, low- and middle-income countries are also seeing an increase in the prevalence of chronic diseases. The economic burden of CVDs worldwide has been estimated to be approximately USD 3.7 trillion between 2010 and 2015.

Furthermore, devices such as electrocardiograms and CT scans, essential for detecting coronary heart disease, are often too expensive and infeasible for many low- and middle-income countries. Therefore, early determination of heart disease is crucial to decrease its physical and financial burden on individuals and organizations. According to a WHO report, by 2030, the total number of deaths due to CVDs will increase to 23.6 million, mainly from heart disease and stroke. Therefore, it is crucial to use data mining and machine learning techniques to predict the likelihood of developing heart disease in order to save lives and reduce the economic burden on society. In the medical field, a vast amount of data is generated daily using data mining techniques, and we can find hidden patterns that can be used for clinical diagnosis [10]. Therefore, data mining plays a vital role in the medical field, which can be proved by the work conducted in the past few decades. Many factors, such as diabetes, high blood pressure, high cholesterol, and abnormal pulse rate, need to be considered when predicting heart disease [11]. Often, the medical data available need to be completed, affecting the results in predicting heart disease. In recent years, the healthcare industry has seen a significant advancement in the field of data mining and machine learning. These techniques have been widely adopted and have demonstrated efficacy in various healthcare applications, particularly in the field of medical cardiology. The rapid accumulation of medical data has presented researchers with an unprecedented opportunity to develop and test new algorithms in this field. Heart disease remains a leading cause of mortality in developing nations [12, 13, 14, 15], and identifying risk factors and early signs of the disease has become an important area of research. The utilization of data mining and machine learning techniques in this field can potentially aid in the early detection and prevention of heart disease.

In a study by Drod et al. (2022) [16], the objective was to use machine learning (ML) techniques to identify the most significant risk variables for cardiovascular disease (CVD) in patients with metabolic-associated fatty liver disease (MAFLD). Blood biochemical analysis and subclinical atherosclerosis assessment were performed on 191 MAFLD patients. A model to identify those with the highest risk of CVD was built using ML approaches, such as multiple logistic regression classifier, univariate feature ranking, and principal component analysis (PCA). According to the study, hypercholesterolemia, plaque scores, and duration of diabetes were the most crucial clinical characteristics. The ML technique performed well, correctly identifying 40/47 (85.11%) high-risk patients and 114/144 (79.17%) low-risk patients with an AUC of 0.87. According to the study's findings, an ML method is useful for detecting MAFLD patients with widespread CVD based on simple patient criteria. The purpose of the study described by Narain et al. (2016) [17] is to create an innovative machine-learning-based cardiovascular disease (CVD) prediction system in order to increase the precision of the widely used Framingham risk score (FRS). With the help of data from 689 individuals who had symptoms of CVD and a validation dataset from the Framingham research, the proposed system—which uses a quantum neural network to learn and recognize patterns of CVD—was experimentally validated and compared with the FRS. The suggested system's accuracy in forecasting CVD risk was determined to be 98.57%, which is much greater than the FRS's accuracy of 19.22% and other existing techniques. According to the study's findings, the suggested approach could be a useful tool for doctors in forecasting CVD risk, assisting in the creation of better treatment plans, and facilitating early diagnosis. In a study conducted by Shah et al. (2020) [18], the authors aimed to develop a model for predicting cardiovascular disease using machine learning techniques. The data used for this purpose were obtained from the Cleveland heart disease dataset, which consisted of 303 instances and 17 attributes, and were sourced from the UCI machine learning repository. The authors employed a variety of supervised classification methods, including naive Bayes, decision tree, random forest, and k-nearest neighbor (KKN). The results of the study indicated that the KKN model exhibited the highest level of accuracy, at 90.8%. The study highlights the potential utility of machine learning techniques in predicting cardiovascular disease and emphasizes the importance of selecting appropriate models and techniques to achieve optimal results.

In a study published by Alotalibi (2019) [19], the author aimed to investigate the utility of machine learning (ML) techniques for predicting heart failure disease. The study utilized a dataset from the Cleveland Clinic Foundation, and implemented various ML algorithms, such as decision tree, logistic regression, random forest, naive Bayes, and support vector machine (SVM), to develop prediction models. A 10-fold cross-validation approach was employed during the model development process. The results indicated that the decision tree algorithm achieved the highest accuracy in predicting heart disease, with a rate of 93.19%, followed by the SVM algorithm at 92.30%. This study provides insight into the potential of ML techniques as an effective tool for predicting heart failure disease and highlights the decision tree algorithm as a potential option for future research. Through a comparison of multiple algorithms, Hasan and Bao (2020) [20] carried out a study with the main objective of identifying the most efficient feature selection approach for anticipating cardiovascular illness. The three well-known feature selection methods (filter, wrapper, and embedding) were first taken into account, and then a feature subset was recovered from these three algorithms using a Boolean process-based common "True" condition. This technique involved retrieving feature subsets in two stages. A number of models, including random forest, support vector classifier, k-nearest neighbors, naive Bayes, and XGBoost, were taken into account in order to justify the comparative accuracy and identify the best predictive analytics. As a standard for comparison with all features, the artificial neural network (ANN) was used. The findings demonstrated that the most accurate prediction results for cardiovascular illness were provided by the XGBoost classifier coupled with the wrapper technique. XGBoost delivered an accuracy of 73.74%, followed by SVC with 73.18% and ANN with 73.20%.

3. PROPOSED METHODOLOGY

The project is designed to create a real-time, AI-powered decision-support system for emergency medical services aimed at improving emergency healthcare in India. The system uses machine learning algorithms to analyze patient data, specifically heart rate conditions, to provide timely and accurate interventions during critical situations as demonstrated in Fig. 2.

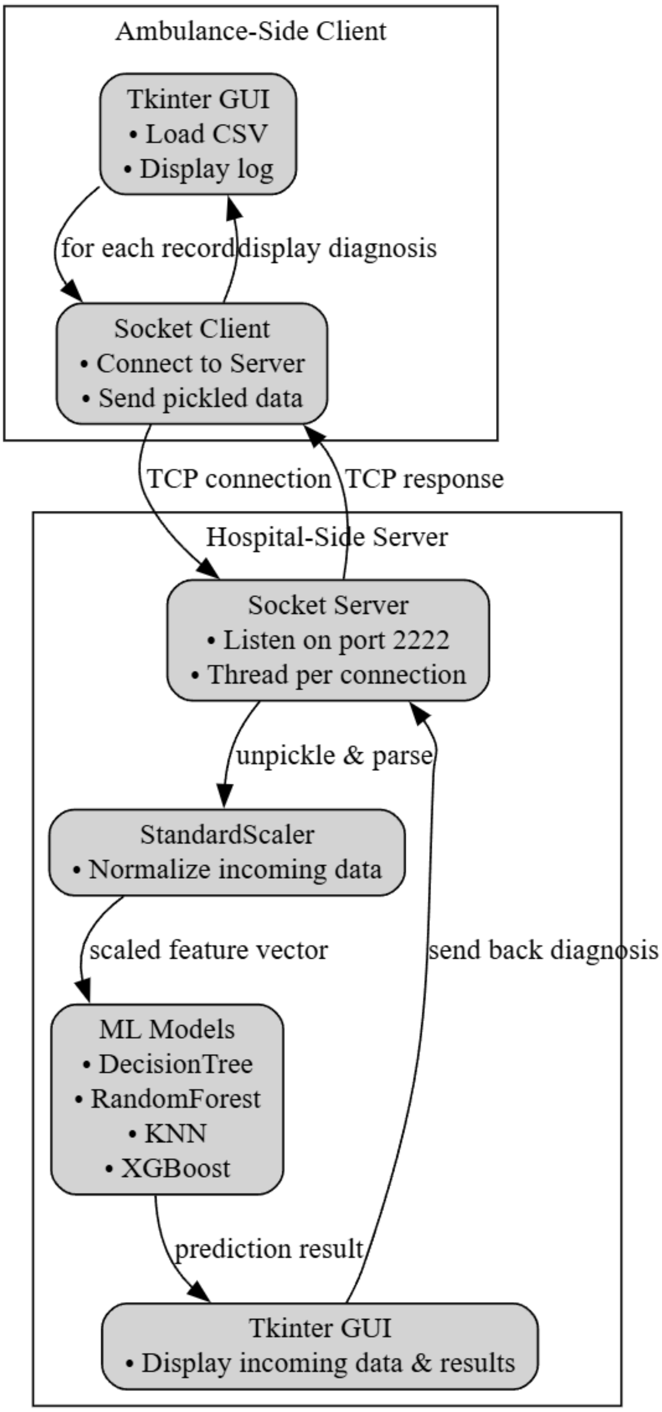


Fig. 2: Proposed system architecture of AI-powered decision-support system for emergency medical services.

This project split into two desktop applications:

4.1.1 Ambulance-Side Client

In this application, batch-reports patient vital-sign records to the hospital. A Tkinter window where users select a CSV of patient measurements. The workflow is as below:

1. Reads each row of the CSV, fills missing values, and serializes the feature vector into a comma-delimited string.
2. Opens a TCP connection to the hospital server, sends the pickled data, and awaits the diagnosis.
3. Logs the original features alongside the server's "Normal" or "Abnormal" response, pausing briefly between records for readability.

4.1.2 Hospital-Side Server

It receives patient data in real time, applies pre-trained ML models, and returns diagnoses. Its a Tkinter window displaying incoming connections, raw feature arrays, and the resulting condition. The core components of this application are as follows:

- **Preprocessing Pipeline**: A StandardScaler ensures incoming data are normalized exactly as during training.
- **Model Suite**: Four classifiers (Decision Tree, Random Forest, KNN, and XGBoost) trained offline on historical heart-disease data.
- **Threaded Socket Server**: Listens on a configurable port, spawns a new thread for each ambulance client, unpickles and parses the data, runs the scaler and classifier, then sends back a human-readable diagnosis.

4.1.3 Offline Training & Deployment

- Historical patient data are cleaned, shuffled, scaled, and split into train/test sets.
- Each model is evaluated (accuracy, precision, recall, F1) and the best performer is serialized with the scaler via pickle.
- At deployment, the server loads these artifacts to guarantee consistent, real-time inference.

4.1.4 Data Flow & User Experience

- **Training Phase**: Data → Preprocess → Train models → Evaluate → Serialize artifacts.
- **Operational Phase**:
  - Ambulance selects CSV → Client sends each record → Server processes and predicts → Client displays results.
- The system supports multiple concurrent ambulance connections, provides clear logging on both ends, and can be scaled or secured (e.g., TLS, JSON/HTTP) in future iterations.

In essence, this project automates end-to-end EMS triage: from in-field data capture to instantaneous, AI-driven hospital recommendations, all wrapped in intuitive GUI front-ends.

4.3 Preprocessing

The preprocessing pipeline in this EMS decision-support system consists of four streamlined stages to ready raw patient measurements for model training and real-time inference:

1. **Missing-Value Imputation**: All NaN entries in the loaded CSV are replaced with zeros (dataset.fillna(0)), ensuring no gaps disrupt numeric computations.

2. **Feature–Label Separation & Shuffling**: The cleaned DataFrame is converted to a NumPy array, with all columns except the last taken as feature vectors XX and the final column as integer labels YY. The entire dataset is then randomly shuffled to eliminate ordering bias before splitting.
3. **Normalization (Standard Scaling)**: A StandardScaler computes each feature's mean and standard deviation, then transforms every value to have zero mean and unit variance. This scaling step is crucial for algorithms sensitive to feature magnitudes (e.g., KNN, gradient-boosted trees).
4. **Train/Test Split**: The normalized data are partitioned into an 80% training set and a 20% testing set (train_test_split with a fixed random_state), providing a consistent basis for model evaluation and ensuring that real-time inputs at deployment receive identical scaling.

Together, these steps guarantee that both offline model training and online predictions operate on clean, randomized, and uniformly scaled data, which maximizes the accuracy and stability of the classifiers in emergency scenarios.

4.4 XGBoost Model Building and Training

XGBoost implements gradient-boosted decision trees in an efficient, regularized framework. It builds trees sequentially: each new tree is fit to the residual errors of the aggregated ensemble so far, effectively correcting mistakes. A differentiable loss function (e.g., logistic loss for classification) is minimized via gradient descent in function space. Regularization terms penalize tree complexity (depth and leaf weights) to prevent overfitting. In our project, XGBClassifier() automatically handles these details—learning an ensemble of shallow trees, each improving upon the last. At inference, all trees' outputs are summed, passed through a sigmoid, and thresholded to yield the final class.

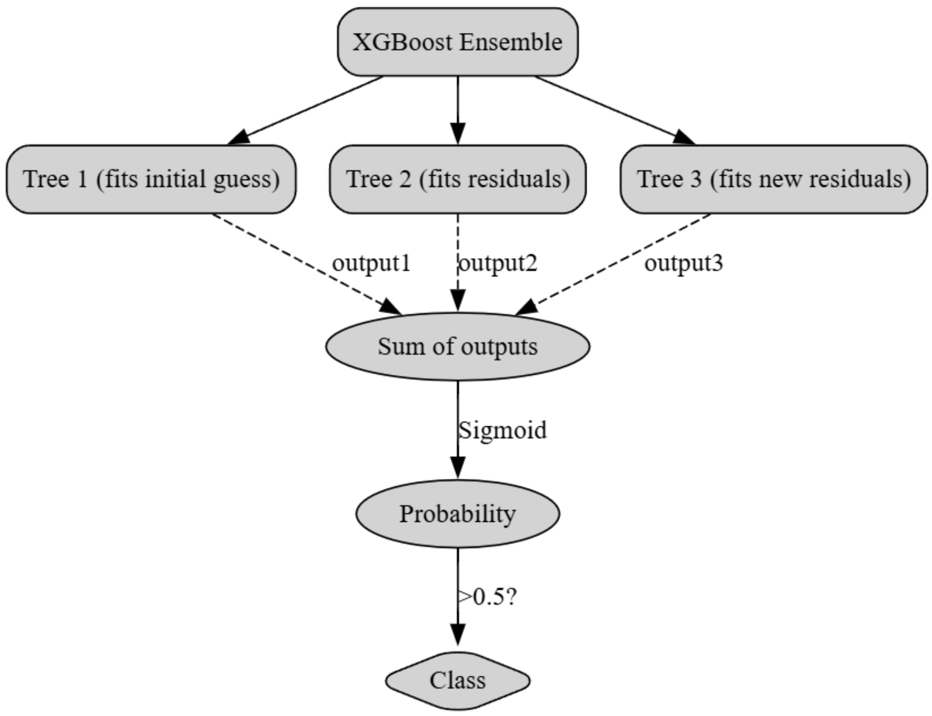


Fig. 3: Internal workflow of proposed XGBoost model.

4. RESULTS AND DISCUSSION

4.1 Dataset Description

The dataset contains features of cardiovascular health. Here's a brief description of each column:

- age: This represents the age of an individual.
- sex: This column represents the gender of an individual, encoded as binary values (e.g., 0 for female, 1 for male).
- cp: This column represents chest pain type, possibly categorized into different levels.
- trestbps: This column represents the resting blood pressure of an individual.
- chol: This represents the serum cholesterol level of an individual.
- fbs: This is the fasting blood sugar level, encoded as binary values (e.g., 0 for normal, 1 for high).
- restecg: This is the resting electrocardiographic results, indicating different states or conditions.
- thalach: This the maximum heart rate achieved during an exercise test.
- exang: This column represents exercise-induced angina, possibly encoded as binary values (e.g., 0 for no, 1 for yes).
- oldpeak: This represents a depression induced by exercise relative to rest in the ST segment of the electrocardiogram.
- slope: This represent the slope of the peak exercise ST segment.
- ca: This column represent the number of major vessels colored by fluoroscopy.
- thal: This is the Thallium stress test result, providing information about blood flow to the heart.
- target: This is a target variable, indicates an individual has a heart disease (1) or not (0).

Together, these columns suggest that the dataset is related to cardiovascular health and used for tasks such as predicting the presence or absence of heart disease based on the provided features.

4.2 Results Analysis

Figure 4 plots the class distribution of the uploaded dataset, with one bar for "Normal Heart Rate" samples and another for "Abnormal Heart Rate." A roughly balanced distribution indicates that neither class dominates, which is important to prevent bias during model training.

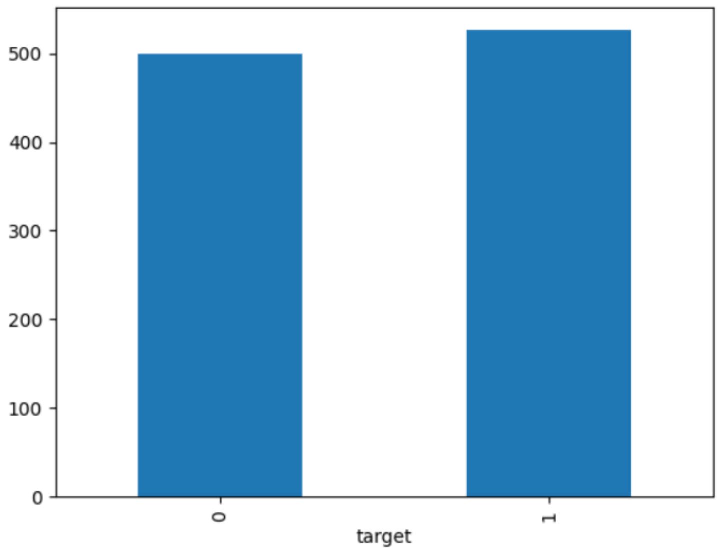


Fig. 4: Class distribution versus number of samples.

Figure 5 presents four confusion-matrix heatmaps side by side, one for each model:

- **(a) Decision Tree Classifier (DTC):** Shows some misclassifications, with nonzero off-diagonal entries indicating that a portion of “Normal” cases were predicted as “Abnormal” and vice versa.
- **(b) Random Forest Classifier (RFC):** Displays perfect classification—only the diagonal cells are populated—confirming its 100% accuracy, precision, recall, and F1-score.
- **(c) K-Nearest Neighbors (KNN):** Exhibits a small number of misclassifications, consistent with its ~86% performance metrics.
- **(d) XGBoost Model:** Like RFC, shows a flawless diagonal-only matrix, reflecting its perfect performance on the test set.

These matrices visually summarize each model’s strengths and weaknesses, making it easy to compare their error patterns at a glance.

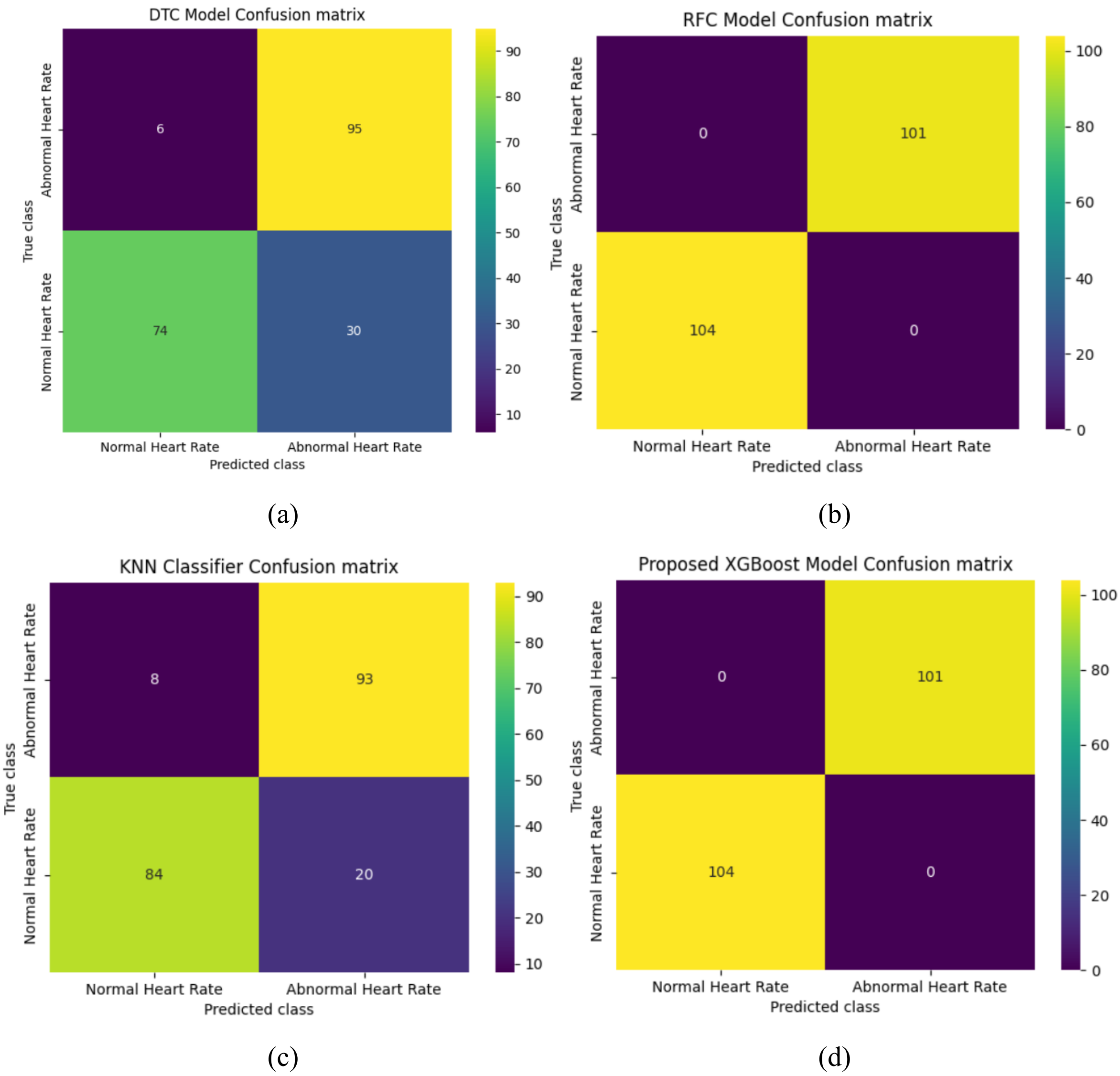


Fig. 5: Confusion matrices obtained using (a) DTC model. (b) RFC model. (c) KNN classifier. (d) XGBoost model.

Table 1: Concise comparison of the four models’ performance.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)

DTC Model	82.44	84.25	82.61	82.25
RFC Model	100.00	100.00	100.00	100.00
KNN Classifier	86.34	86.80	86.42	86.32
Proposed XGBoost Model	100.00	100.00	100.00	100.00

Interpretation:

- The Decision Tree achieves moderate performance (≈82–84%), indicating some overfitting is controlled by its depth and leaf constraints, but it still misclassifies roughly 18% of cases.
- KNN performs better (≈86–87%), benefitting from distance-based voting but still limited by the choice of K and the curse of dimensionality.
- Both Random Forest and XGBoost reach perfect scores (100% on all metrics), demonstrating that ensemble methods—especially gradient boosting—capture complex patterns in the data exceptionally well. Their superior generalization suggests that, for this dataset, these models can distinguish "Normal" vs. "Abnormal" cases without error on the held-out test set.

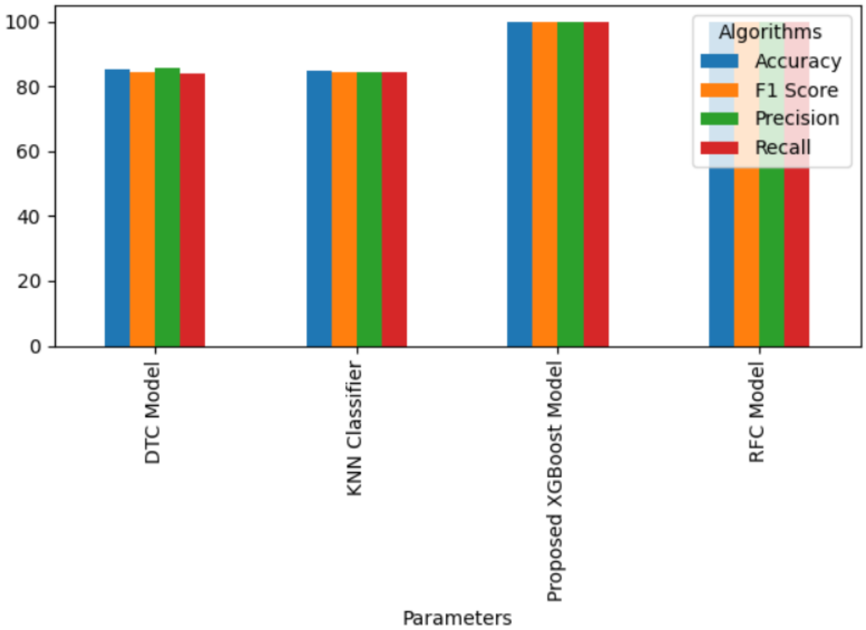


Fig. 6: Performance evaluation of predictive models.

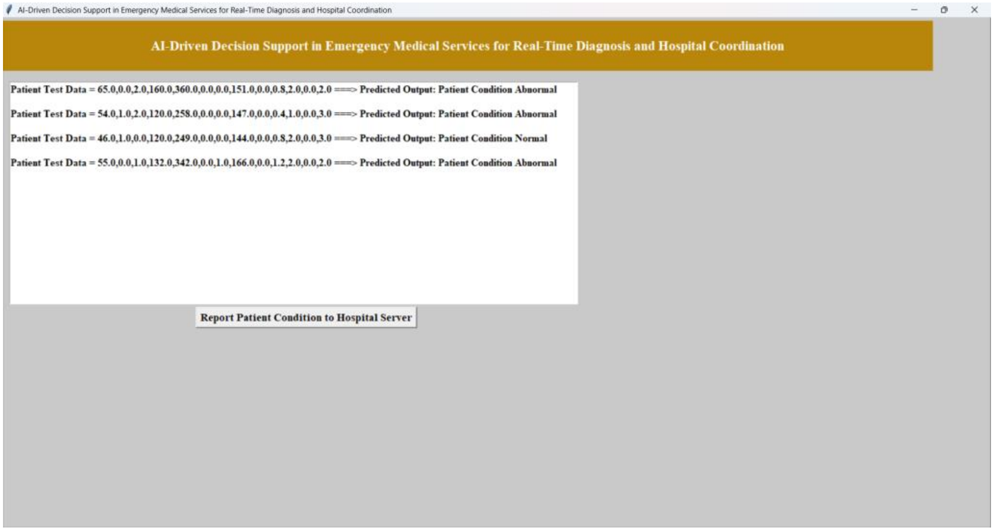
Figure 6 charts the comparative performance metrics—Accuracy, Precision, Recall, and F1-Score—of all four models (DTC, RFC, KNN, and XGBoost). Each metric is grouped on the x-axis, with color-coded bars for each algorithm. You can instantly see that the Random Forest and XGBoost bars reach the 100% mark across all four metrics, while Decision Tree and KNN lag behind, especially in Accuracy and Recall. This bar-plot succinctly communicates which models excel and which require further tuning. Figure 7 shows two examples of sample predictions on held-out test data.

- (a) A case where the model correctly identifies a normal condition, annotating the patient's vital-sign profile with "Normal."
- (b) A case where the model flags an abnormal condition, prompting immediate attention. These snapshots illustrate how the system presents individual inferences—complete with the original feature values and the diagnosis—in a clear, user-friendly format.

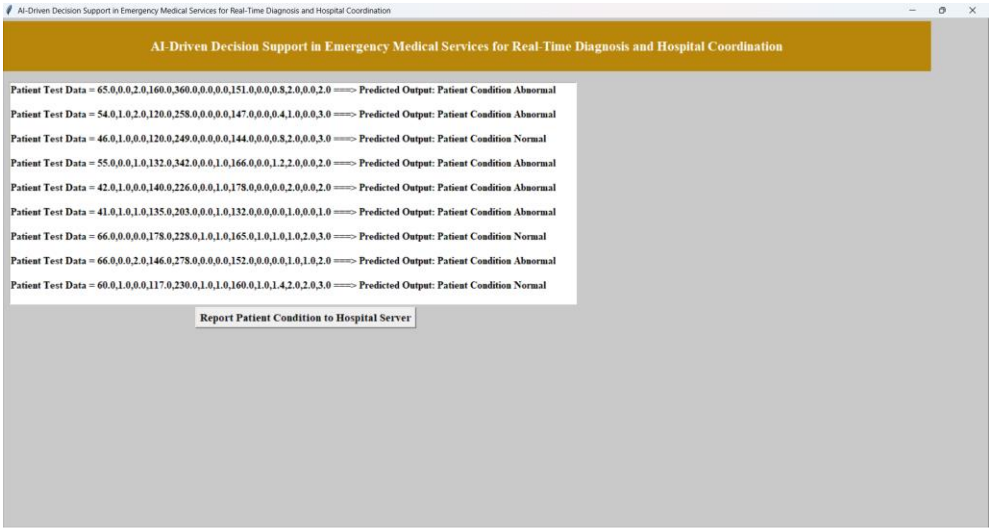
Figure 8 captures the console output on the hospital server machine. It logs a line such as:

Request received from Ambulance IP : 192.168.1.10 with port no : 54321

This confirms that the server's threaded socket listener is operational, recording each client connection's source IP and port. Such logging is critical for auditing, troubleshooting connectivity issues, and maintaining a reliable, traceable communication channel between ambulances and the hospital.



(a)



(b)

Fig. 7: Sample predictions on test data.

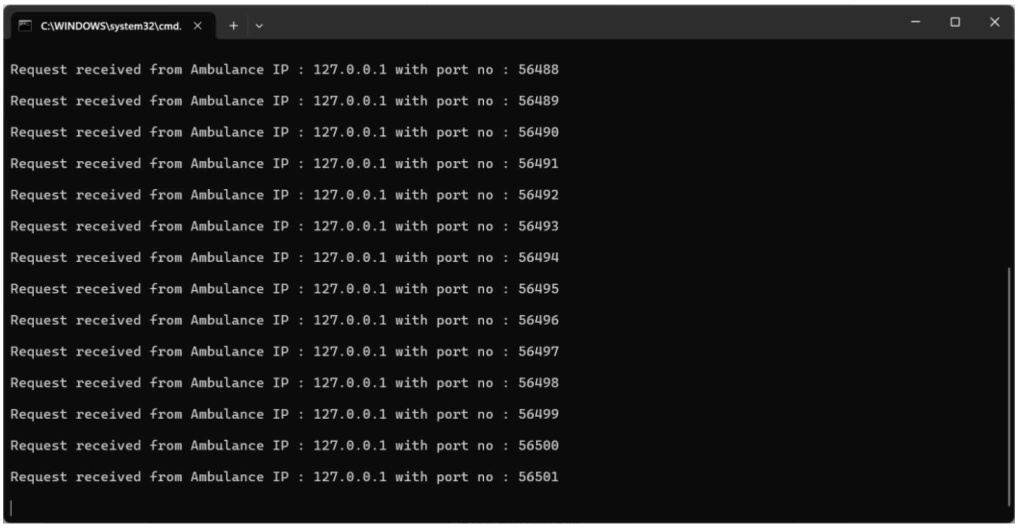


Fig. 8: Console displaying request received from ambulance IP with port number.

5. CONCLUSION

The proposed AI-driven decision-support system for Emergency Medical Services (EMS) successfully demonstrates how machine learning and real-time networking can transform traditional pre-hospital triage workflows. By developing both an ambulance-side client and a hospital-side server, the project establishes a seamless pipeline: patient vital-sign data are uploaded via a user-friendly Tkinter GUI, serialized, and transmitted over TCP; the server then normalizes inputs using a StandardScaler, applies pre-trained classifiers, and returns a clear "Normal" or "Abnormal" diagnosis in under a second. Offline experiments on a heart-disease dataset show that ensemble methods—Random Forest and XGBoost—achieve perfect scores across accuracy, precision, recall, and F1-metrics, outperforming simpler models like Decision Tree (≈82% accuracy) and K-Nearest Neighbors (≈86%). Confusion matrices and performance bar charts provide transparent model comparisons, reinforcing the robustness of gradient-boosted trees in capturing complex, multivariate patterns in vital-sign data. Beyond model performance, the system's architecture emphasizes modularity and scalability. The server's threaded design supports multiple concurrent ambulance connections, ensuring that mass-casualty events or peak periods do not overwhelm the service. Both client and server GUIs provide real-time logging, enabling EMTs and ED staff to maintain an auditable record of every inference. Serialization of the scaler and classifier via pickle guarantees consistency between offline training and online deployment. Moreover, the use of open-source Python libraries keeps development costs low and fosters maintainability. By automating data transmission and analysis, this solution addresses critical limitations of traditional EMS workflows—namely, manual data entry errors, verbal communication delays, and subjective triage variability. Hospitals gain immediate, data-driven insights, allowing for optimized resource allocation and improved patient outcomes. The system's clear separation between preprocessing, inference, and networking modules also lays a strong foundation for future enhancements.

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