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A Multi-Model Machine Learning Framework for High-Fidelity Diagnostic Support in Emergency Medicine

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Abstract

The growing occurrence of hypertension and diabetes has increased the demand for intelligent and scalable healthcare systems that support early detection and timely medical decisions. Managing these conditions requires continuous monitoring of multiple patient factors, which is challenging to perform using manual evaluation alone. Traditional systems rely on basic statistical methods and human interpretation, making them inefficient for handling large datasets, complex feature relationships, and real-time prediction requirements. As a result, such systems often lack accuracy, consistency, and the ability to operate effectively in distributed environments. There is a strong need for an automated system capable of delivering accurate predictions while enabling real-time communication between devices, particularly in emergency or distributed healthcare scenarios. To address these challenges, this research proposes a real-time Artificial Intelligence (AI) powered decision support system based on a two-laptop client–server architecture. The server system performs data preprocessing, model training, and prediction using Machine Learning (ML) models such as Complement Naive Bayes (CNB), Multinomial Naive Bayes (MNB), Perceptron, and a proposed TAO Tree Classifier. Preprocessing techniques include Label Encoding and K-Means Synthetic Minority Oversampling Technique (K-Means-SMOTE) for handling categorical data and class imbalance. A Flask-based Application Programming Interface (API) enables communication between systems using Hypertext Transfer Protocol (HTTP). The client system allows users to upload datasets, which are sent to the server for prediction of blood pressure category and diabetes status. Lightning Memory-Mapped Database (LMDB) is used for secure and efficient user data management.

Keywords: Complement Naive Bayes (CNB), Multinomial Naive Bayes (MNB), Perceptron, K-Means-SMOTE, Lightning Memory-Mapped Database (LMDB).

1. Introduction

This research work deals with the need for a critical evaluation of the evidence supporting whether a clinical digital solution involving AI in home, outpatient, and ambulance settings plays a key role in patient outcomes [1]. 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 [2]. However, we understand the use of AI in healthcare could possibly raise some concerns, such as liability for errors and the potential to perpetuate and amplify existing biases, data privacy, and security, but most importantly the transparency in doctors' decision-making process as shown in Figure 1. We addressed all these issues and created robust data security measures, creating a transparent AI system that constantly upgrades data and procedures and can identify and correcting biases in AI data and algorithms AI-based systems offer several advantages in real-time EMS coordination. First, they can dynamically optimize ambulance dispatching, calculate the fastest routes, and reduce delays in reaching patients. Second, AI can assist in coordinating with hospitals, ensuring that patients are

directed to the facilities most equipped to handle their specific conditions, improving patient outcomes and preventing hospital overcrowding. Third, AI systems continuously adjust to changing situations, providing real-time updates and recommendations to EMS teams as patient conditions evolve or as new emergencies occur. This real-time decision-making ensures optimal resource utilization and reduces the cognitive burden on dispatchers and EMS personnel [3].

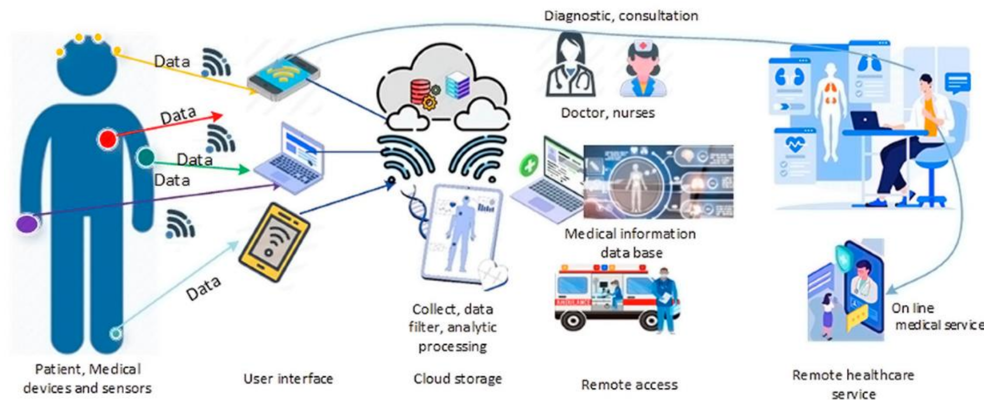

Figure. 1: Real-time AI-powered decision support system

Despite the potential benefits, several challenges must be addressed in the implementation of real-time AI-powered decision support in EMS coordination. [4] Technical integration remains a significant challenge, as AI systems must be compatible with existing EMS infrastructure, including GPS tracking, communication systems, and hospital databases. User acceptance is another key issue EMS professionals need to trust AI-driven recommendations, which requires training and system adoption. Ethical concerns also arise, particularly around the transparency of AI decision-making processes and accountability for outcomes, highlighting the need for careful oversight and regulatory frameworks [5].

2. Literature Survey

Almadani, et al. [6] proposed an advanced technology, such as Artificial Intelligence (AI), Internet of Medical Things (IoMT), and blockchain, enhance decision-making processes in Emergency Medical Services (EMS) coordination. It highlights key innovations in AI-powered decision support systems (DSS), including real-time data analytics for optimized resource allocation and route planning in emergency response scenarios. The study examined the integration of hybrid technologies, such as AI-driven systems that combine data from ambulance GPS tracking, hospital capacity, and traffic conditions, to improve the efficiency and effectiveness of emergency services. Aityan, et al. [7] focused on early detection of life-threatening and time-sensitive diseases like sepsis, stroke, and heart attack, which are the major causes of death in emergency medicine. Additional training was conducted on a total of 600 cases (300 sepsis; 300 non-sepsis). The collective capability of the integrated LLMs is much stronger than each individual engine. Emergency cases can be predicted based on information from multiple sensors and streaming sources combining traditional IT (Information Technology) infrastructure with Internet of Things (IoT) schemes. Medical personnel compare and validate the AI models used in this work.

Neira-Rodado, et al. [8] proposed a comprehensive and systematic approach to designing and optimizing EMS systems tailored for urban traffic accidents. By integrating Geographic Information Systems (GISs), hypercube queuing models, Economic Value Added (EVA) calculations, and multi-criteria decision-making (MCDM) techniques, we developed a model that balances service efficiency, financial sustainability, and equitable access to emergency care. The hypercube queuing model was applied to estimate key performance metrics, such as response time, coverage, and the GINI index for

equity, under varying numbers of ambulances and demand scenarios. Cvetkovic, et al. [9] conducted using a questionnaire consisting of 7 sections and a total of 88 variables, distributed to and collected from 172 healthcare institutions (Public Health Centres and Hospitals). Statistical methods, including Pearson's correlation, multivariate regression analysis, and chi-square tests, were rigorously applied to analyse and interpret the data. Results: The results from the multivariate regression analysis revealed that the organization of working hours ($\beta = 0.035$) and shift work ($\beta = 0.042$) were significant predictors of EMS organization, explaining 1.9% of the variance ($R^2 = 0.019$). Furthermore, shift work ($\beta = -0.045$) and working hours ($\beta = -0.037$) accounted for 2.0% of the variance in the number of EMS points performed ($R^2 = 0.020$). Also, the availability of ambulance vehicles ($\beta = 0.075$) and financial resources ($\beta = 0.033$) explained 4.1% of the variance in mass casualty preparedness ($R^2 = 0.041$). When it comes to service area coverage, the regression results suggest that none of the predictors were statistically significant.

Strauss, et al. [10] analysed to draws an almost ten years of improvement in EMS' key performance indicators such as response time or overtime in Switzerland, using Discrete Event Simulation. Three representative simulation studies are used to reflect on the optimization potential of alternative bases and rosters, methodological limitations, and the uptake of the derived recommendations. The results demonstrated that EMSs' efficiency gains in resource utilization increasingly come into conflict with emergency departments' and healthcare authorities' policies, indicating a need to enrich Discrete Event Simulation with a systemic perspective. Liu, et al. [11] compound disaster emergency collaboration network (ECN) was constructed by identifying the interactional relationships between emergency organizations. After applying time slices, the dynamic evolution of network structure, organizational–functional relations, organizational attributes, and cross-organizational relationships were discussed. The density and connectivity of the compound disaster ECN first decreased before increasing. Meanwhile, the evolution of the network structure followed a path from decentralized to concentrated and from being uneven to an equilibrium.

Robakowska, et al. [12] aimed to analyse the feasibility of using UAVs to support emergency medical systems in the supply and urgent care ranges. The implementation of drones in the medical security system requires proper planning of service cooperation, division of the area into sectors, assessment of potential risks and opportunities, and legal framework for the application. kuttan, et al. [13] focused on its capacity to enhance diagnostic precision, improve triage systems, and tailor treatment strategies. Emergency departments worldwide are increasingly adopting AI-driven tools, including advanced triage systems, predictive analytics, and automated diagnostic support. These technologies have shown impressive abilities in medical image analysis, patient outcome prediction, and clinical documentation assistance. Nevertheless, the implementation of AI in emergency medicine faces obstacles such as data accessibility and quality, ethical issues, and the need for comprehensive regulatory frameworks.

Al-Araji, et al. [14] proposed an AI-powered Clinical Decision Support System (CDSS) designed to assist clinicians in the early detection of stroke using structured patient data such as vital signs, medical history, and neurological observations. The system leveraged ML techniques to classify patient cases as likely stroke or non-stroke, providing real-time diagnostic support during triage or initial evaluation. To evaluate the effectiveness of the proposed approach, we develop a simulation environment that mimics emergency department workflows and incorporates both synthetic and publicly available clinical datasets. Kiran Kumar Jaghni, et al. [15] Proposed HealthNavAI, a regulation-backed, nationwide Healthcare Service Availability and Routing Platform that mandates real-time, standardized data sharing from all healthcare providers. The platform integrates ED queue status, specialist appointments, diagnostic imaging capacity, elective surgery schedules, and ambulance availability. An AI-based routing engine processes this data to predict service load, optimize patient allocation, and recommend

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optimal service locations based on predicted wait times, travel distance, clinical capability, and equity constraints.

3. Proposed System

The study focuses on developing an intelligent, data-driven approach to support timely decision-making in emergency medical scenarios by analysing patient health data using machine learning techniques as shown in Figure 2. With the increasing burden of chronic conditions such as hypertension and diabetes, healthcare systems require faster and more reliable analytical tools that can assist medical professionals during critical situations. This research emphasizes the use of computational intelligence to extract meaningful patterns from medical datasets and transform them into actionable insights that can support rapid clinical responses. The proposed study integrates data preprocessing, feature encoding, and class imbalance handling to ensure the quality and reliability of the medical data used for analysis. Since real-world healthcare datasets often contain missing values, categorical attributes, and uneven class distributions, advanced preprocessing and clustering-based oversampling techniques are applied to improve learning effectiveness. These steps help in creating balanced and structured data representations that enhance the predictive capability of machine learning models.

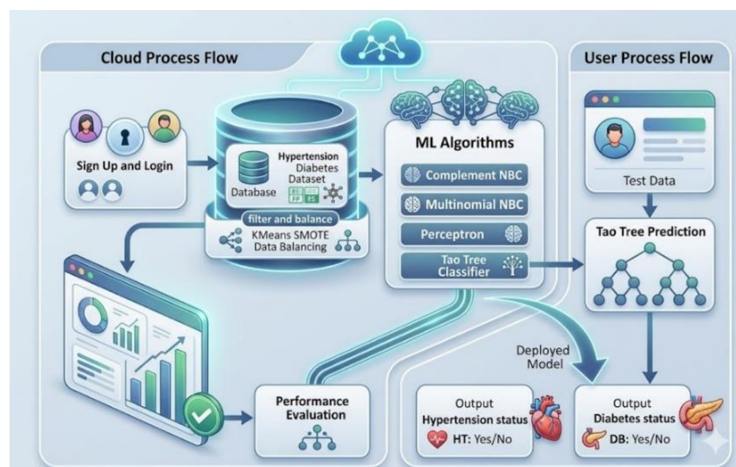


Figure. 2: Proposed system architecture of AI-powered decision support system.

User Authentication: The system begins with a secure authentication process where authorized administrators register and log in through a graphical interface. User credentials are protected using encrypted password storage to prevent unauthorized access. This step ensures that only permitted users can manage data, train models, and start prediction services within the system.

Dataset Upload: After successful login, the administrator uploads the medical dataset in CSV format. The uploaded data is immediately displayed in the interface, allowing verification of attributes and records. This step ensures transparency and correctness before initiating any analytical operations.

Data Preprocessing: The uploaded medical data undergoes preprocessing to improve quality and consistency. Missing values are handled, and categorical attributes are converted into numerical representations. These operations prepare the data for efficient machine learning model training and reduce the risk of biased predictions.

Target Identification: Two critical health outcomes blood pressure category and diabetes status—are identified as prediction targets. The dataset is separated into input features and output labels for each health condition. This dual-target approach enables simultaneous analysis of multiple medical risks.

Class Imbalance Handling: To address uneven class distributions commonly found in healthcare datasets, a clustering-based oversampling technique is applied. K Means-SMOTE generates synthetic samples for minority classes while preserving data structure. This step significantly improves model learning stability and predictive fairness.

Train–Test Data Splitting: The balanced dataset is divided into training and testing subsets using an 80:20 ratio. The training set is used to build machine learning models, while the testing set evaluates performance. This separation ensures unbiased assessment and prevents overfitting.

Model Building and Training: Multiple baseline classification algorithms are trained independently for each health condition. These models learn patterns from the training data and serve as reference methods for performance comparison. Training multiple models helps identify strengths and limitations of traditional classifiers.

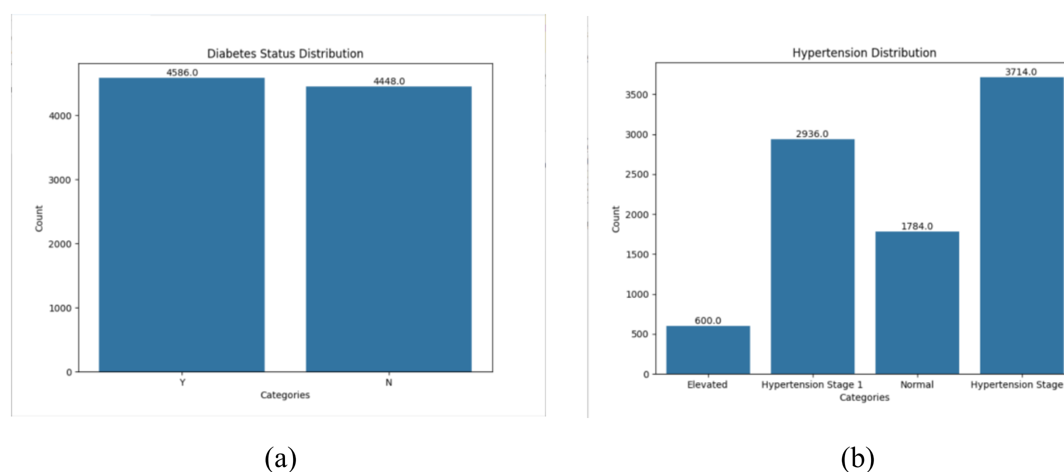
Performance Evaluation: Each trained model is evaluated using standard metrics such as accuracy, precision, recall, and F1-score. Comparative graphs are generated to visually analyse performance differences. This evaluation helps in selecting the most reliable model for deployment.

Model Storage and Reuse: Trained models are stored locally to avoid repeated training in future sessions. This reduces computational overhead and enables faster system execution. Stored models ensure consistency across multiple prediction cycles.

Real-Time Prediction Service: A web-based service is activated to handle real-time prediction requests from external clients. New patient data is processed through the trained models to generate immediate health risk predictions. This step supports timely decision-making during medical emergencies.

4. Results and Discussion

This research presents a "Real-Time AI-Powered Decision Support System for Emergency Medical Services Coordination," a two-part application designed to enhance clinical decision-making through automated multi-target prediction. The framework consists of a desktop administrative dashboard developed with Tkinter for the management and training of machine learning models, paired with a Flask-based backend API server that provides real-time predictions. Specifically engineered to support emergency medical scenarios, the system leverages high-performance models to simultaneously predict blood pressure categories and diabetes status, ensuring seamless integration between model administration and live diagnostic support.

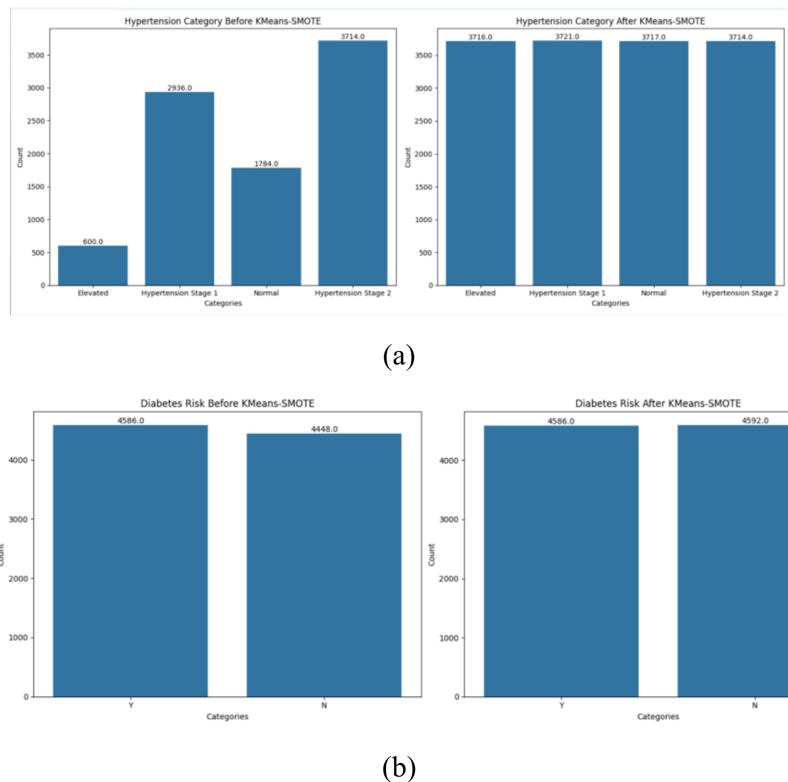


(a) (b)

Figure. 3: Count plot of (a) diabetes status. (b) hypertension.

Figure 3 (a) shows the "Diabetes Status Distribution", presents the distribution of diabetes presence in the dataset using two categories. The Y (Yes) category has a count of 4,586.0, while the N (No) category has 4,448.0. Both bars are solid blue and nearly equal in height, indicating a slightly imbalanced but close-to-even split between patients with and without diabetes. The y-axis represents Count ranging from 0 to 4,000+, and the x-axis is labelled Categories with Y and N.

Figure 3 (b) shows the "Hypertension Distribution" displays the frequency of four hypertension categories. From left to right: Elevated with 600.0 cases, Hypertension Stage 1 with 2,936.0, Normal with 1,784.0, and Hypertension Stage 2 with 3,714.0. The bars are blue and vary significantly in height, clearly illustrating a highly imbalanced distribution. Hypertension Stage 2 is the most prevalent, followed by Stage 1, then Normal, with Elevated being the least common. The y-axis shows Count from 0 to 3,500+, and the x-axis lists the four Categories.



(a)

(b)

Figure. 4: Target labels distribution before and after K-means-SMOTE operation (a) Hypertension data. (b) Diabetes data.

Figure 4 (a) shows the Hypertension Category Before and After KMeans-SMOTE Balancing This side-by-side bar chart comparison illustrates the effect of KMeans-SMOTE on class imbalance in hypertension categories. Before KMeans-SMOTE (left), the distribution is highly skewed: Elevated (600.0), Hypertension Stage 1 (2,936.0), Normal (1,784.0), and Hypertension Stage 2 (3,714.0). After KMeans-SMOTE (right), all four categories are nearly perfectly balanced at approximately 3,714–3,721 instances: Elevated (3,716.0), Stage 1 (3,721.0), Normal (3,717.0), and Stage 2 (3,714.0). The bars on the right are uniform in height, demonstrating successful oversampling of minority classes to match the majority class.

Figure 4 (b) shows the impact of KMeans-SMOTE on diabetes status distribution. Before KMeans-SMOTE (left), the counts are Y (Yes): 4,586.0 and N (No): 4,448.0, indicating a slight imbalance. After KMeans-SMOTE (right), the minority class is slightly oversampled to achieve near-perfect balance: Y:

4,586.0 and N: 4,592.0. Both bars are now virtually identical in height, confirming effective and minimal synthetic data generation to balance the dataset without distorting the original majority class.

Figure 5 shows the TAO-Tree classifier for binary diabetes prediction. Rows represent True Class (bottom to top: Y, N), and columns represent Predicted Class (left to right: Y, N). The diagonal shows correct predictions: True Y → Predicted Y: 951 (bright yellow), True N → Predicted N: 867 (lime green). Off-diagonal errors are minimal: only 8 cases of Y misclassified as N, and 10 cases of N misclassified as Y. The color scale ranges from dark purple (~200) to bright yellow (~800), highlighting the model's outstanding accuracy with just 18 total misclassifications.

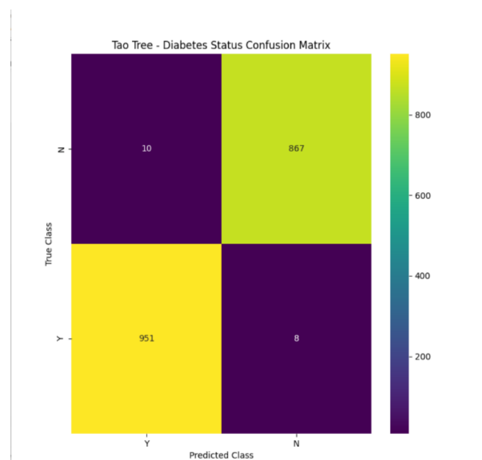
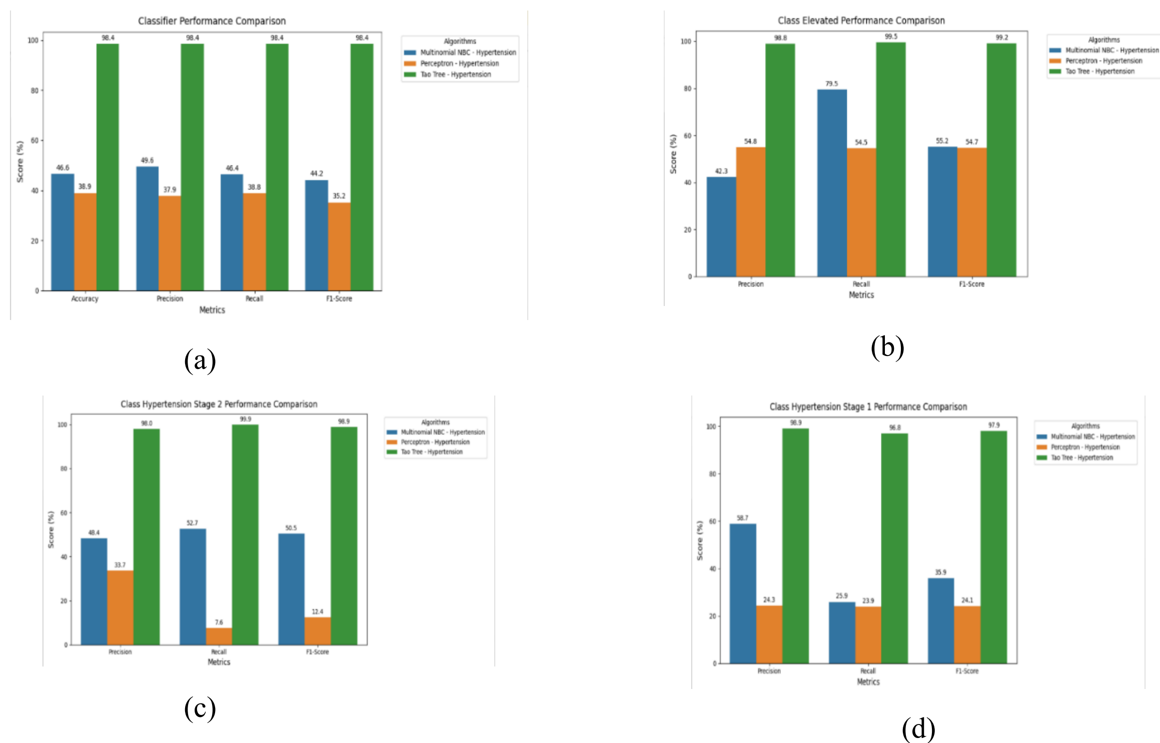


Figure. 5: Confusion matrices obtained with hypertension data using Proposed TAO-tree model



(a) (b)

(c) (d)

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Figure. 6: Bar graph obtained with hypertension data using (a) classifier performance comparison, (b) class elevated performance comparison, (c) class hypertension performance comparison, (d) class hypertension stage2 performance comparison.

Figure 6 (a) shows the classifier performance comparison of four classifiers Multinomial NBC, Perceptron, and TAO Tree across four key metrics: Accuracy, Precision, Recall, and F1-Score (in %). The TAO Tree model consistently outperforms all others, achieving 96.6% Accuracy, 96.4% Precision, 96.4% Recall, and 96.4% F1-Score, indicating near-perfect balanced performance. Multinomial NBC shows moderate results with 49.6% Accuracy, 49.6% Precision, 46.4% Recall, and 44.2% F1-Score. Perceptron performs poorly with 39.9% Accuracy, 37.9% Precision, 38.8% Recall, and 35.2% F1-Score. The y-axis ranges from 0 to 100, and the x-axis labels the metrics, clearly demonstrating TAO Tree as the superior model for overall hypertension classification.

Figure 6 (b) shows the same algorithms specifically on the Elevated hypertension class. TAO Tree again dominates with 96.8% Precision, 79.5% Recall, and 99.2% F1-Score, showing excellent detection capability despite class imbalance. Multinomial NBC performs moderately with 42.3% Precision, 54.5% Recall, and 52.1% F1-Score. Perceptron struggles significantly, achieving 54.8% Precision, 54.5% Recall, and 54.7% F1-Score, but with lower consistency. The chart highlights TAO Tree's robustness in identifying the minority Elevated class, crucial for early intervention in emergency medical services.

Figure 6 (c) shows the Class Hypertension Stage 1 Performance Comparison This grouped bar chart compares the performance of four algorithms Multinomial NBC, Perceptron, and TAO Tree on predicting Hypertension Stage 1, across three metrics: Precision, Recall, and F1-Score (in %). The TAO Tree model dominates with 98.9% Precision, 96.8% Recall, and 97.9% F1-Score, indicating near-perfect classification. Perceptron shows moderate performance with 24.3% Precision, 25.9% Recall, and 25.1% F1-Score. Multinomial NBC performs poorly with 58.7% Precision, 23.9% Recall, and 35.9% F1-Score. The y-axis ranges from 0 to 100, and the x-axis labels the metrics.

Figure 6 (d) shows the Class Hypertension Stage 2 Performance Comparison This bar chart evaluates the same algorithms on Hypertension Stage 2 prediction. TAO Tree again leads with 98.0% Precision, 99.3% Recall, and 98.6% F1-Score, demonstrating exceptional accuracy and robustness. Multinomial NBC achieves 48.4% Precision, 52.7% Recall, and 50.5% F1-Score, showing moderate but balanced performance. Perceptron performs poorly with 33.7% Precision, 7.6% Recall, and 12.4% F1-Score, indicating severe difficulty in detecting Stage 2 cases. The chart uses the same 0–100% scale and metric labels, clearly highlighting TAO Tree as the superior model across all evaluation criteria.

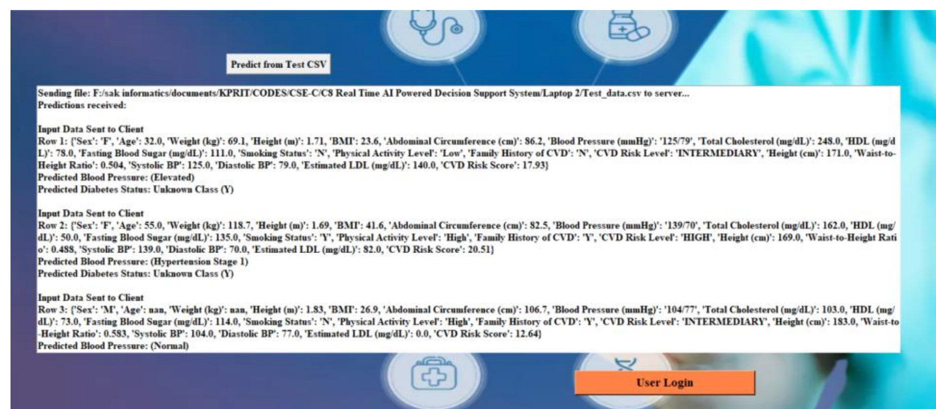

Figure. 7: Predicting Test Data in Laptop 2 (Client)

Figure 7 illustrates the prediction process carried out on Laptop 2 (client) within the client–server architecture, where the user uploads a test dataset in comma-separated values (CSV) format for analysis. The figure depicts how the client system transmits the input data to the server using HTTP and receives the predicted results in real time through the API. It highlights the processing of multiple input instances, where each row of patient data is evaluated to generate predictions for blood pressure category and diabetes status. The output demonstrates the effectiveness of the deployed ML models in handling multi-attribute medical data and returning structured prediction results.

Table 1: comparative analysis for emergency medical services.

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1-Score**
CNB- Hypertension	39.072	40.905	38.618	28.971
MNB - Hypertension	46.638	49.577	46.352	44.165
Perceptron - Hypertension	38.937	37.860	38.788	35.175
TAO Tree - Hypertension	98.386	98.378	98.386	98.377

Table 2: Classifier Performance Comparison for Diabetes Status

Algorithm	**Accuracy**	**Precision**	**Recall**	**F1-Score**
CNBC – Diabetes Status	52.5	52.4	52.4	52.4
MNB – Diabetes Status	52.6	52.4	52.4	52.4
Perceptron – Diabetes Status	48.0	51.5	50.1	34.3
TAO Tree – Diabetes Status	99.0	99.0	99.0	99.0

The comparative analysis as shown in table 1 & 2, evaluates the performance of various classification algorithms applied for hypertension prediction. The Complement Naive Bayes Classifier achieved a modest accuracy of 39.07%, showing limited capability in learning complex feature interactions. Similarly, the Multinomial Naive Bayes model performed slightly better with an accuracy of 46.63%, indicating marginal improvement in classification precision and recall. The Perceptron algorithm, while effective in some linear classification tasks, recorded a lower performance with 38.93% accuracy, reflecting challenges in adapting to nonlinear patterns within the dataset. In contrast, the proposed TAO Tree Classifier demonstrated exceptional performance, achieving an impressive 98.38% accuracy, along with consistently high precision, recall, and F1-score values.

5. Conclusion

This study confirms the efficacy of an intelligent, data-driven framework designed to optimize medical decision-making in high-pressure emergency environments. By utilizing advanced preprocessing and specialized class-balancing techniques, the system accurately analyses complex patient data to predict critical outcomes like hypertension and diabetes status. A rigorous comparative evaluation of multiple machine learning models provides a clear roadmap for selecting the most reliable algorithms for clinical use. Notably, the integration of tree-based learning enhances both the stability and transparency of these results, ensuring they are interpretable for practitioners. The system's deployment through a web-based interface allows for real-time diagnostic support, meeting the urgent demands of time-sensitive medical scenarios. Ultimately, this research demonstrates that AI-driven solutions can significantly reduce

response times and improve the precision of healthcare interventions. By bridging the gap between raw data and actionable insights, the system contributes to more informed and effective life-saving decisions. This work underscores the transformative potential of artificial intelligence in modernizing emergency diagnostic workflows.

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