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Heart Attack Prediction: A Comparative Analysis of Supervised Machine Learning Algorithms for Early Detection and Risk Stratification

Shamim Forhad
Electrical and Computer Engineering
Uttara University
Dhaka, Bangladesh
mrshamimforhad@gmail.com

Tanha Mim
Information Technology
International American University
California, United States
Tanhamim2022@gmail.com

Zarin Mosarat
Management Information System
Westcliff University
California, United States
zarinpromy1@gmail.com

Md. Siam Taluckder
Electrical and Computer Engineering
Lamar University
Texas, United States
mtaluckder@lamar.edu

Abdullah Al Masum
Information Technology
Westcliff University
California, United States
a.masum.642@westcliff.edu

Md Tawfiqul Islam
Electrical and Computer Engineering
Lamar University
Texas, United States
tawfiq.ctgbd@gmail.com

Md. Riazat Kabir Shuvo
Electrical and Computer Engineering
North South University
Dhaka, Bangladesh
rkshuvo@gmail.com

***Abstract*—Heart attacks are a prominent source of morbidity and mortality globally, demanding the development of precise and efficient predictive models for early identification and risk stratification. This paper gives a complete review of supervised machine learning algorithms to measure their efficacy in predicting MI risk, allowing for timely medical intervention. A wide range of clinical data were used to train and verify six classification models. Based on accuracy, precision, recall, and F1-score, LR had the best prediction performance with an accuracy of 85.71%, followed by KNN (84.62%), SVM (80.22%), RF (79.12%), XGBoost (79.12%), and DT (71.43%). The performance of LR demonstrates its practical applicability and interpretability for clinical use, making it a viable candidate for clinical deployment. These findings emphasize the potential of machine learning-driven technologies in improving MI prediction, therefore leading to increased early diagnosis and individualized patient treatment. The study further emphasizes the need for integrating transparent and interpretable ML models into healthcare systems to facilitate informed clinical decision-making and optimize patient outcomes.**

Keywords—Heart Attack Prediction, Machine Learning in Healthcare, Supervised Learning Algorithms, Logistic Regression, Early Disease Detection, Predictive Analytics.

I. INTRODUCTION

Myocardial infarctions, usually referred to as heart attacks, constitute one of the primary causes for mortality globally. In medium and low-income nations, cardiovascular disease (CVD)-related morbidity accounts for roughly 75% of all mortality. According to estimates from the World Health Organization (WHO), cardiovascular diseases (CVDs) killed 17.7 million people globally in 2015, making up 31% of all deaths. Later, 17.9 million deaths worldwide in 2019 were anticipated to have been caused by CVDs, with a significant percentage of those deaths being attributed to heart attacks, constituting 32% of all fatalities, with 85% attributable to heart attacks and strokes [1]. Cardiovascular illnesses (CVDs), particularly heart attacks and strokes, cause about 80% of the four out of five CVD-related deaths globally.

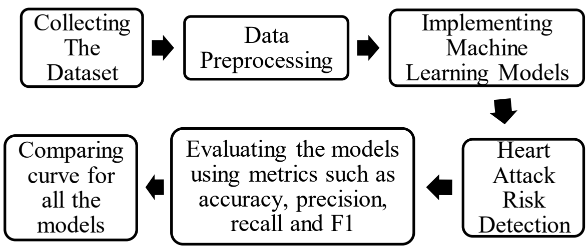

Fig. 1. Generalized Model Framework for Heart Attack Detection

About 70% of these deaths have place in countries with low and moderate incomes. Noncommunicable diseases in 2019, including CVDs, led to 38% of 17 million premature deaths. Cognitive risk mitigation and early detection are crucial for preventing CVDs, highlighting the need for intervention and lifestyle modifications.

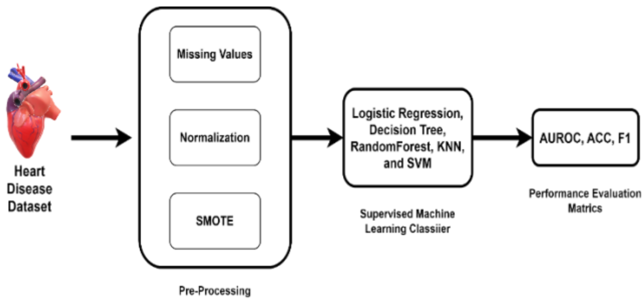

Fig. 2. Workflow of Implemented Supervised Machine Learning Model for Heart Attack Prediction

A major advancement is evident in the move from manual record-keeping to automated systems, a trend represented by the thorough digitalization of patient details [6]. Later on, the incorporation of machine learning (ML) techniques developed as a basic paradigm in the analysis of healthcare data. ML approaches have been adeptly leveraged to construct systems aimed to enhance complex decision-making within medical contexts [4]. Based on dynamic risk factors, a machine learning-based prediction model is put forth to forecast heart attack occurrences, based on empirical evidence confirming their significant impact on heart attack probability.

The major goal of this study is to construct an accurate prediction model for heart attack incidence, enabling early warnings for high-risk individuals. This involves identifying anomalies in heart function and their impact on physiological homeostasis. By addressing existing gaps in awareness, the study employs a data-driven approach to analyze cardiovascular risk factors. To ensure high predictive accuracy, multiple supervised ML algorithms are systematically evaluated and refined using AutoML techniques. This work contributes to the growing field of analytical prediction in cardiovascular healthcare, emphasizing the importance of early diagnosis and preventive interventions for individuals at elevated risk of myocardial infarction.

II. Literature Rivew

In [8], the author introduced a stroke risk estimation approach leveraging a recurrent neural network (RNN) with a unique loss function. The model incorporated substantial patient medical data arranged as a time series, stretching from early diagnosis to therapy and test findings. Fully linked layers produced from these layers were employed for class prediction, enhancing accuracy. The study explored interpretability by limiting attribute vectors and evaluated accuracy vector rate of change. The model with the highest performance obtained an AUC ROC score of 66.9%, suggesting its usefulness in stroke risk assessment.

In [9], the authors applied machine learning to assess stroke risk using regular medical records. Analyzing data from around 380,000 patients with 30 variables impacting stroke risk, they utilized known methods: gradient-boosting neural networks, random forest classifiers, and logistical regression. Their neural network outperformed, generating an AUC ROC of 76.4%. The analysis focuses on the trade-off that exists between the clarity of interpretation and the effectiveness of performance in machine learning, stressing the more accurate yet less interpretable forecasts of neural networks, contrasted with the comprehensible, albeit less exact outputs of Random Forest and logistic regression methods.

In this research [10], the researchers integrated machine learning methods and assessed the effectiveness of Cox models in forecasting the likelihood of stroke among Chinese adults. The study included data from 503,842 persons residing in various districts of China. It encompassed a wide range of information, including sociodemographic, nutritional, medical, and physical data. A comprehensive analysis was performed on multiple machines learning techniques, suggesting the utilization of a combined GBT or Cox model strategy using individual data. GBT showcased remarkable discriminatory capability, achieving AUROC values of 0.833 for males and 0.836 for females. Conversely, the combined approach improved accuracy, reaching 76% for men and 80% for women. Both the Cox model and GBT demonstrated enhanced precision in predicting stroke risk [10].

In [11], scientists explored stroke prediction utilizing distinct machine learning algorithms, employing closely comparable class identification attributes as feature features. Ten classifiers, including Stochastic Gradient Descent, AdaBoost, Decision Tree, Logistic Regression, and others, were trained, providing accuracies of 65%, 94%, 91%, 78%, 79%, 78%, 79%, 96%, 87%, and 95%, respectively. Notably, the recommended weighted voting model beat basic classifiers, demonstrating a remarkable 97% accuracy.

TABLE I. Comparative Overview of Prediction Models Across Related Literature and the Present Study

Study	Dataset Size	Accuracy	Model Type	Strength / Remarks
Teoh et al. [8]	Not specified	66.9%	RNN with custom loss	Time-series EHR data, interpretable attribute vectors.
Weng et al. [9]	~380,000 patients	76.4%	Neural Net / RF / Logistic Reg.	Large EHR dataset, trade-off between interpretability and performance.
Cox + GBT [10]	500,000 +	83.3–83.6%	Ensemble (Cox + Gradient Boost)	Demographically stratified predictions (men/women), large-scale national cohort.
Our Study (LR)	918	85.7%	Logistic Regression	Simple, interpretable model with high recall (91.5%) and best F1-score among peers.

III. Methodology

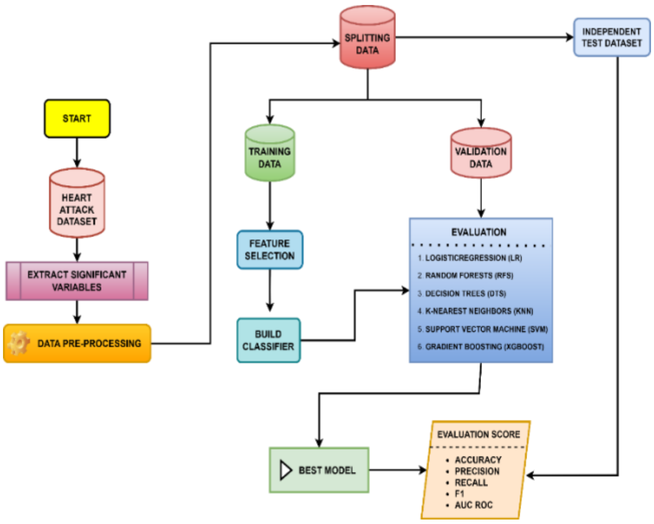

Fig. 3. Proposed Model Flowchart to determine finest supervised model

The design of the suggested ML-driven prediction framework is depicted in Fig. 3, highlighting essential phases such as data preprocessing, model selection, and performance evaluation.

A. Dataset

The algorithms are trained using data sourced from clinical records. This dataset comprises 12 pieces of information pertaining to 1190 patients [13].

TABLE II. NUMBER OF DIFFERENT TYPES OF INFORMATION IN DATASET

No.	Feature Name	Feature Description	Fixed PV Setup (V)
1	Age	Patient's age	years
2	Sex	Patient's gender	M: Male and F: Female
3	ChestPainType	Typical Angina	TA
		Atypical Angina	ATA
		Non-Anginal Pain	NAP
		Asymptomatic	ASY
4	RestingBP	Low blood pressure levels	mHg
		High blood pressure levels	mHg
5	Cholesterol	Cholesterol in the serum	mm/dl
6	FastingBS	Blood sugar after fasting	1: if FastingBS > 120 mg/dl, 0: otherwise
7	RestingECG	Results from resting electrocardiogram	Normal
			ST-T wave abnormality
			LVH
8	MaxHR	Maximum heart rate reached	Numeric value between 60 and 202
9	ExerciseAngina	Angina triggered by exercise	Y: Yes, N: No
10	Oldpeak	oldpeak = ST	Numeric value measured in depression
11	ST_Slope	Slope of the peak ST segment during exercise	Up: upsloping, Flat: flat, Down: downsloping
12	HeartDisease	Disease output class	1: heart disease, 0: Normal

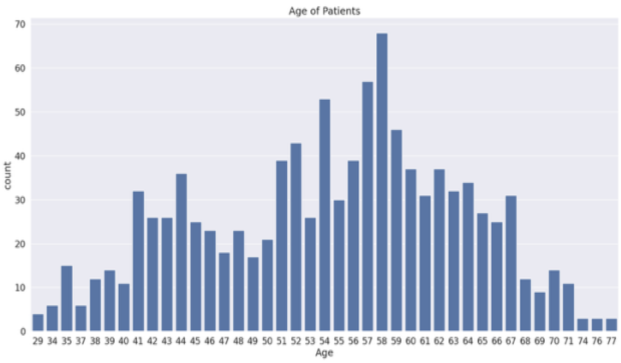

Fig. 4. Correlation Between Patient Age and Myocardial Infarction Incidence

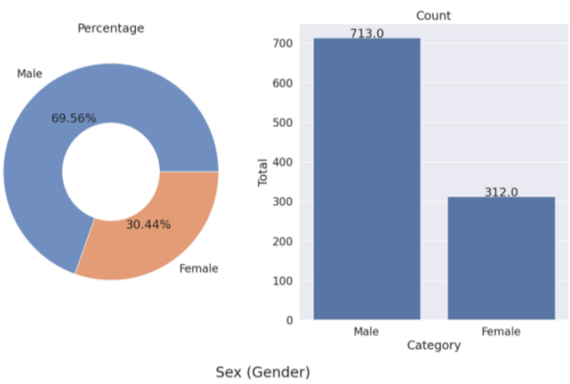

Fig. 5. Doughnut and Bar Chart Representing the Male and Female Percentage of Affected Individuals

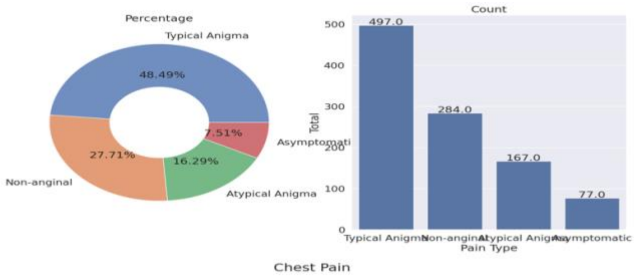

Fig. 6. Chest Pain Type and Percentage of Total Incident

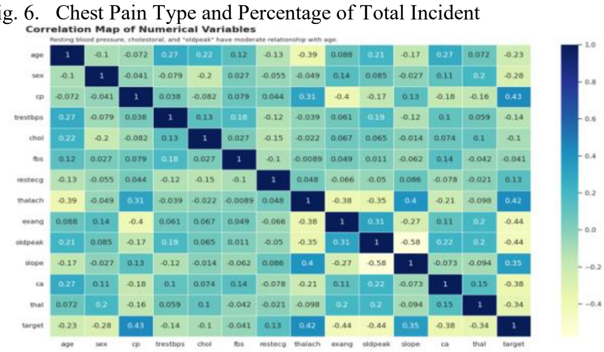

Fig. 7. Data Co-relation Graphical representation of heat map

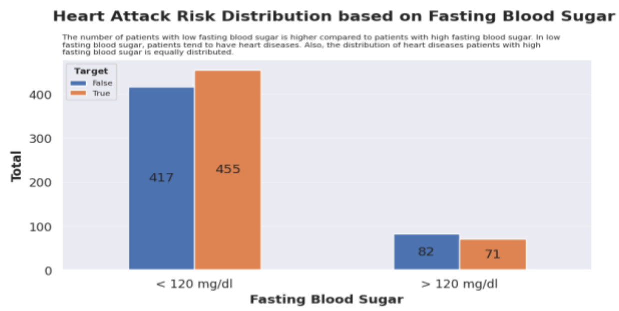

Fig. 8. Heart Attack Risk Distribution Based on Fasting Blood Sugar

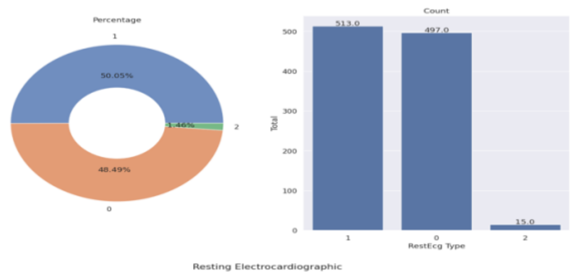

Fig. 9. Resting Electrocardiographic Value (RestECG)

This dataset combines five heart datasets across eleven shared features, making it the largest heart disease dataset currently available for research purposes. Data harmonization was conducted by aligning common features across all five datasets, followed by categorical encoding and normalization to ensure consistency. No missing values were detected, and 272 duplicates were removed. The five datasets used for its curation are:

1) Cleveland: 303 observations
2) Hungarian: 294 observations
3) Switzerland: 123 observations
4) Long Beach VA: 200 observations
5) Stalog (Heart) Data Set: 270 observations

The dataset includes a total of 1190 observations, with 272 of those being duplicates, which results in a final dataset of 918 observations. Out of the 12 pieces of information, 11 can be used as inputs, while the output for all algorithms is whether the patient experienced a death event (fatal heart attack). The 11 columns of the dataset indicate the patient's age, sex, exercise-induced angina, number of major vessels, type of chest pain, resting blood pressure, cholesterol level, fasting blood sugar, resting electrocardiographic readings, maximum heart rate achieved, and the target for the patients respectively [13].

TABLE III. NUMBER OF DIFFERENT TYPES OF PATIENT CASES

No.	Cases of Patient	Cases in (%)
0	Normal	9.5
1	Cold State	13.23
2	Risk	18.77
3	Urgent	22.05
4	Sick	36.45

B. Data Pre-processing

Initially, Initially, no null values were detected; however, 272 duplicate entries were removed based on patient ID and feature similarity. Class distribution was examined for imbalance; as a preventive step, stratified sampling was used during train-test splits to preserve label proportions.. There are four varieties in the type of chest discomfort and the consequence that increases one's chances of having a heart attack can be grouped under two types. In this instance, the categorization has been mapped corresponding to the needed class as 0,1,2 and so on. To facilitate the generation of features and the implementation of targeted machine learning algorithms, the parameters have been defined as follows: Chest Pain type:

1) Value 0: standard angina,
2) Value 1: unusual angina,
3) Value 2: pain not related to angina,
4) Value 3: without symptoms.

The findings from the resting electrocardiogram were categorized in this manner: Value 0 signifies normal conditions, Value 1 indicates an ST-T wave abnormality (which includes T wave inversions and/or ST elevation or depression exceeding 0.05 mV), Value 2 suggests probable or confirmed left ventricular hypertrophy based on Estes' criteria, and lastly, Value 3 denotes an increased risk of a heart attack. After this mapping process, machine learning algorithms were employed to train the modified data.

C. Implementation of ML Models

After thoroughly pre-processing the data, a range of Supervised machine learning algorithms was utilized on the polished dataset. Following this, a judicious test-train partitioning was executed, distributing the dataset in a ratio of 70:30. Specifically, 70% of the data underwent comprehensive training via diverse machine learning models, while the remaining 30% was allocated for rigorous testing to gauge predictive efficacy.

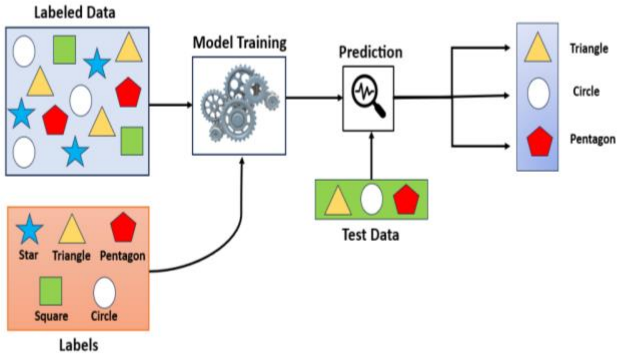

Fig. 10. Implemented Supervised Machine Learning Model.

The collection of machine learning models that were implemented included Logistic Regression, Decision Tree, Random Forest, K Nearest Neighbor, and Support Vector Machine (SVM). These chosen models cover various categories such as linear (Logistic Regression), non-linear (KNN, SVM), tree-based (DT, RF), and ensemble (XGBoost) to effectively represent a wide array of decision boundaries. Although XGBoost represents boosting methods, future work will include LightGBM and CatBoost for further comparison. Following the application of the model, the accuracy metrics were thoroughly examined to evaluate how well these models performed on the pre-processed dataset.

D. Heart Attack Risk Detection

The heart attack risk detection model assesses accuracy by strategies like train-test split or cross-validation. It measures parameters, including accuracy, precision, recall, and AUROC, measuring its efficacy in predicting heart attack risk. The model's effectiveness is evaluated using data it hasn't encountered before, ensuring its ability to generalize. Continuous monitoring permits refining, adjusting to shifting trends and enhancing predictive capacities. The iterative approach boosts the model's reliability over time. Clarity and openness are essential elements, allowing healthcare professionals to comprehend and have confidence in the model's forecasts. The validation procedure, significant to model creation, aims to generate a strong and dependable tool for recognizing potential heart attack risks, leading to preventative and successful healthcare interventions.

E. Comparison between models using Hyper-tuning and classifier AdaBoost and GridSearchCV

In the research, AdaBoost, a machine learning technique, was employed iteratively to enhance the performance of weak classifiers by learning from errors. Multiple models were incorporated as part of the boosting strategy to improve overall accuracy. GridSearchCV, a methodology within this context, systematically explored optimal parameter values in a predefined grid, using cross-validation techniques for robust evaluation. This involved specifying both the model and relevant parameters. Once optimal parameter values were identified, predictions were generated. Hyper-tuning improved LR accuracy from 84.2% to 85.7%, the top three algorithms underwent hyper-tuning, ensuring meticulous refinement of model parameters for enhanced predictive performance in our research paper.

IV. RESULT ANALYSIS

A. Performance Evaluation Metrics

- Logistic Regression (LR)

- Random Forests (RFs)
- Decision Trees (DTs)
- K-Nearest Neighbors (KNN)
- Support Vector Machine (SVM)

Every algorithm was systematically performed to the specified dataset, and their performance was carefully assessed using a 10-fold cross-validation technique. This rigorous methodology enabled the evaluation of precision and other essential statistical parameters across various methods. The evaluation process thoroughly examined the performance metrics of each algorithm. To achieve this, we developed confusion matrices to assess the sensitivity, specificity, and accuracy of the results from each algorithm. The essential metrics were calculated using the appropriate equations outlined in earlier research [15, 16], with meticulous attention to detail.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} \quad \ldots\ldots\ldots\ldots\ldots \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

$$\text{F1} = 2 \,.\, \frac{precision{,}recall}{precision+recall} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (4)$$

$$\text{AUROC} = \frac{TP}{TP+FN} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (5)$$

The research examines how effective different algorithms are in classification tasks. Each algorithm is evaluated using a confusion matrix, which relies on four key parameters: True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN). To measure the effectiveness of the algorithms, three metrics are utilized: Sensitivity (recall rate), Specificity (accuracy), and Precision (precision). Sensitivity assesses the percentage of actual positive cases that are correctly identified, whereas specificity evaluates the algorithm's capability to accurately recognize negative cases. Accuracy reflects the overall rate of correctly classified instances, but it can be deceptive in cases of imbalanced datasets.

Furthermore, precision defines the ratio of predicted positives that are actually positive. A high precision score signifies that the algorithm reduces false positives, making its predictions trustworthy. Recall, which reflects sensitivity, emphasizes the ratio of true positives that are accurately identified. The F-Measure combines both elements into a single score, offering a more thorough assessment of the algorithm's performance. Lastly, the Area Under the Receiver Operating Characteristic Curve (AUROC) serves as a metric for discrimination. A high AUROC score shows that the model successfully distinguishes between cases and non-cases, indicating robust discriminatory ability. By examining these metrics, a detailed understanding of each algorithm's advantages and disadvantages is achieved, ultimately assisting in the selection of the most suitable model for the given task. Ensemble approaches enhance model performance by integrating multiple models, maximizing their diversity and predictive ability, rather than relying on a single champion. As indicated in Figure 11, an ensemble strategy provided a remarkable 85.7% accuracy, surpassing the individual performances of the constituent models. The Logistic Regression (LR) algorithm, part of the ensemble, proved to be the top performer, whereas K-Nearest Neighbors (KNN) and Support Vector Machine (SVM) achieved respectable accuracies of 84.6% and 80.2%, respectively.

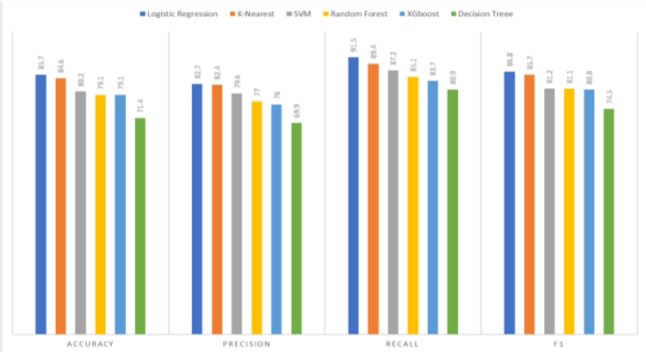

Fig. 11. Implemented Supervised Machine Learning Model.

In Figure 11, this research showcases the AUROC evaluation of six supervised machine learning models—Logistic Regression (LR), K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest (RF), Gradient Boosting (GB), and Decision Tree (DT)—to evaluate their ability to discriminate in predicting the risk of myocardial infarction. AUROC is an essential metric that reflects each model's effectiveness in distinguishing between patients with heart disease and those without across different thresholds. Among the evaluated models, Logistic Regression attained the highest AUROC score of 0.855, highlighting its strength and clinical dependability. This result is consistent with its top performance across accuracy (85.7%), precision (82.7%), recall (91.5%), and F1-score (86.8%)—metrics previously discussed in Figure 8. The strong AUROC performance of LR underlines its effectiveness not only in classification accuracy but also in maintaining a low false positive rate while ensuring high true positive rates, an essential requirement in critical applications like myocardial infarction detection. K-Nearest Neighbors followed closely with an AUROC of 0.845, reflecting its competitive generalization ability, particularly when high recall is prioritized. SVM (0.801), Random Forest (0.788), and Gradient Boosting (0.789) exhibited moderate performance levels, confirming their adequacy yet relative limitations when compared to LR and KNN in this clinical context.

Conversely, the Decision Tree model demonstrated the lowest AUROC at 0.711, aligning with its comparatively poor scores in precision and recall. This suggests a higher rate of misclassifications and limited model generalizability, rendering it less appropriate for deployment in risk-sensitive diagnostic tasks. These findings reinforce the central thesis of the study: interpretable, statistically grounded models like Logistic Regression can outperform more complex or ensemble-based approaches when applied to well-structured clinical datasets. This has important implications for real-world healthcare systems where transparency, computational efficiency, and ease of integration are equally vital as raw predictive accuracy. The analysis shows that the simple logistic regression model is the most suitable option for predicting the risk of heart attacks. Across all configurations, from baseline to meticulously tweaked parameters, and even against the formidable AutoML approach, logistic regression consistently provided the most accurate results. This exceptional constancy speaks to its inherent fit for this specific role, guiding precise forecasts. While future studies may reveal more advanced techniques, Logistic Regression proved most effective, indicating that simpler models can often yield superior results in clinical contexts.

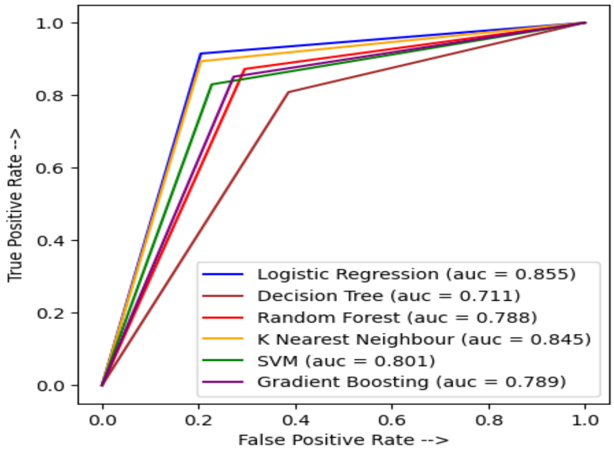

Fig. 12. Implemented Supervised Machine Learning Model.

V. Conclusion

This research tackled the issue of predicting the risk of myocardial infarction by systematically applying supervised machine learning algorithms to a detailed clinical dataset. Our methodology included thorough data preprocessing, feature engineering, and the assessment of six models—Logistic Regression, K-Nearest Neighbors, Support Vector Machines, Random Forest, XGBoost, and Decision Tree—each evaluated using standard performance metrics such as accuracy, precision, recall, F1-score, and AUROC. Among these models, Logistic Regression showed the best performance, achieving the highest accuracy (85.7%), precision (82.7%), recall (91.5%), F1-score (86.8%), and an AUROC of 0.855, indicating strong discriminatory ability. K-Nearest Neighbors followed closely with an AUROC of 0.845, while SVM, Random Forest, and XGBoost produced moderate AUROC values of 0.801, 0.788, and 0.789, respectively. The Decision Tree model exhibited the lowest performance across all metrics, with an AUROC of 0.711, underscoring its limited effectiveness for critical clinical predictions. Based on these results, Logistic Regression is suggested as the best model for early detection and risk assessment of myocardial infarction. However, the study does have some limitations. Although the dataset is diverse, it is relatively small and does not include real-time streaming input. Furthermore, challenges related to integration, such as explainability for clinicians, class imbalance, and constraints for real-world deployment, were not addressed in this research. Future studies may investigate secure and privacy-preserving ways to integrate machine learning models into clinical decision support systems, ensuring adherence to data protection regulations.

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