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Early prediction of myocardial infarction using proposed score tree algorithm

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ABSTRACT

Early detection and diagnosis of a diseases will have a big impact on the medical field and help to prevent loss of life. This study begins by gathering information on myocardial infraction patients from hospitals and focuses on earlier diagnostics. In fact, the pre-processed, confirmed data from a qualified doctor is used for this research. Early prediction of myocardial infarction (MI) is proposed by many researchers. They have used Kaggle datasets that is not recent, and they work on post MI. We have proposed early myocardial infraction detection works on unsupervised datasets. To identify myocardial infraction, numerous machines learning supervised algorithms, including decision tree (DT), random forest (RF), are employed in the literature. In this study, we use the score tree algorithm (STA), which operates on an unsupervised dataset, to present a unique early MI prediction method.

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1. INTRODUCTION

The body's most crucial organ is the heart. We cease to exist if our heart stops beating. From conception to death, it is the only organ that never shuts down, not even for a single second. Our body continues to function if the heart remains healthy. If the heart is beating, we still consider someone to be alive after our brains stop functioning. Any deviation from the heart's natural rhythm has grave repercussions and prevents the body from functioning normally. One of the most prevalent diseases we are aware of, myocardial infarction (MI), sometimes known as a heart attack, is caused by the death of heart muscles. It is closely related to cancer and has a very high death rate. The medical term for a heart attack caused by a clogged artery that results in the destruction of cardiac muscle is known as MI. Patients who have survived a MI incidence are more likely to have additional heart-related health issues in the future. The most common MI include coronary involvement. 17.9 million fatalities worldwide occur each year because of heart disease [1].

Since ancient times, medical professionals have used a variety of symptoms and warning signs to identify heart diseases. These include signs and symptoms like breathlessness and body swelling, clinical findings like heart rate and blood pressure readings, electrocardiograms (ECG), and cardiac enzymes like troponin, as well as personal and family histories of heart disease. To get an accurate diagnosis, researchers have worked to expand automated diagnosis systems. The most current strategy employed in automated prognosis Automated machine learning (ML) and AI-based approaches have been increasingly employed in data mining. Consequently, early and efficient diagnosis of affected individuals is critical for clinical support, as incorrect diagnoses made by doctors can have fatal consequences. Therefore, ensuring accurate and timely diagnosis of coronary heart disease remains a significant biomedical challenge [2].

Artificial intelligence (AI)-based techniques play a vital role in the early prediction and diagnosis of various diseases by analyzing complex medical data such as patient history, imaging, and lab results. These AI models, including ML and deep learning algorithms, identify hidden patterns and correlations that may not be apparent through traditional diagnostic methods. Comparative studies evaluate the effectiveness of these models using key performance metrics such as accuracy, sensitivity, specificity, prediction rate, area under the curve (AUC), precision, recall, and F1-score to determine their reliability and clinical utility [3].

Through a comprehensive review of research reports and in-depth discussions with MI specialists, several gaps were identified where contributions toward veracious and early diagnosis of MI remain limited. Prior studies have predominantly focused on traditional risk factors commonly associated with MI, such as high blood pressure, cholesterol levels, and electrocardiograms, as advised by cardiologists. The same conventional methods are used by doctors in clinical settings to diagnose MI.

However, a disconnect exists between the research conducted and the clinical diagnosis by doctors. This gap arises from insufficient attention to the evolving lifestyles, dietary habits, stress levels, and other factors that impact patients already diagnosed with MI. The increasing prevalence of MI suggests that new, unanticipated factors might be contributing to higher susceptibility, which have not been adequately explored. Additionally, researchers have not incorporated the wealth of experience from doctors into models aimed at improving diagnostic accuracy.

The literature on early MI diagnosis also reveals that contemporary Indian datasets have not been utilized, with researchers relying on older Kaggle datasets. Moreover, patients with angina-a condition often preceding MI-have not been addressed in prior studies. There is a pressing need to enhance the efficiency and inaccuracy of current models by integrating recent and relevant parameters for MI, instead than solely distrust on traditional factors.

2. BACKGROUND STUDY

This section reviews state-of-the-art approaches for early-stage MI prediction. AI has significantly transformed medical diagnosis, enabling early disease detection to reduce mortality. Early identification is crucial, as delayed treatment often leads to irreversible complications. Cardiovascular diseases, including MI, remain the leading cause of death worldwide, accounting for nearly 32 million deaths annually-approximately one death every 33 seconds, or one in four global deaths [4].

2.1. Survey on MI

Several studies have applied ML and data mining (DM) techniques for cardiac disease detection and prognosis. The hierarchical temporal memory (HTM) algorithm demonstrated high accuracy in detecting ECG abnormalities in real-time monitoring systems [5]. DM techniques revealed meaningful clinical patterns, with parameter normalization significantly improving classification accuracy [6]. Comparative studies among Bayesian Network, decision tree (DT), LAD Tree, and J48 showed that LAD Tree achieved the lowest error rates [7], while SVM was found most effective for heart disease prediction, with recommendations for ensemble methods to enhance performance [8].

Alternating Decision Trees with PCA improved MI prognosis [9]. Combining techniques such as KNN, DT, evolutionary algorithms, and Naïve Bayes increased prediction accuracy for tachycardia [10]. Several studies focused on ECG preprocessing, denoising (wavelet, FIR/IIR, adaptive filtering), and ST-segment analysis to improve signal clarity and diagnostic accuracy [11]. Sensor-based remote monitoring systems integrated with mobile applications enabled real-time tracking of vital signs for MI patients [12].

It concludes that integrating multiple data mining approaches and optimizing feature selection can significantly enhance early detection and prediction of heart disease, supporting better clinical decision-making [13]. The study by A. Anbarasi and R. Subban focuses on detecting abnormalities in the mitral valve using echocardiography images, emphasizing image processing techniques for accurate identification of structural defects [14]. It highlights the integration of sensor data with mobile (Android) applications, enabling continuous monitoring and early detection of critical health conditions for timely medical intervention [15].

Artificial neural networks (ANN) performed well on linear datasets, while Decision Trees showed limitations with complex datasets [16]. Selection of algorithms depends on dataset characteristics-classification for labeled data and clustering for unlabeled data [17]. Predictive models for MI achieved moderate accuracy (70%) but require refinement [18]. They conclude that integrating signal processing with machine learning enhances the accuracy and reliability of automated diagnosis systems [19]. Big data analytics remains underutilized in cardiac prediction models [20]. It highlights that effective noise reduction significantly enhances the accuracy of ECG analysis and supports better diagnosis of cardiovascular diseases [21]. Additional studies examined PAD-related acute limb ischemia risk [22], attribute-based KNN and ID3 models for coronary disease [23], advanced MI detection pipelines using kernel regression [24], cardiovascular risks associated with eczema [25], ANN-based ECG classification frameworks [26], and feature extraction approaches with potential future expansion into deep learning techniques [27].

2.2. Survey on early MI

Table 1 shows the literature review of early MI revealed that no one has utilized contemporary Indian datasets. The older Kaggle datasets has been used by all researchers. Also, it was observed that no one treated angina patients, which is a medical term for an early MI.

Table 1. Literature survey on early MI

Sr No.	Reference Id	Methods	Accuracy
1	Polat *et al.* [28]	K-NN based fuzzy – AIRS	87.00%
2	Detrano *et al.* [29]	Logistic Regression	77.00%
3	Shouman *et al.* [30]	Decision tree	81.41%
4	Tu *et al.* [31]	Bagging algorithm	81.41%
5	Muhammad *et al.* [32]	SVM, AB, ET, GB, LR, KNN, DT, RF, NB, and ANN	Extra-Tree Classifier (ET) - 94.41%
6	Shorewala *et al.* [33]	Decision Tree, Random Forest, Naive Bayes, K-Nearest Neighbours', SVC	75.1%
7	Methaila *et al.* [34]	NB, DT, NN	DT-89%
8	Zhao *et al.* [35]	receiver operating curve (AUC), identifying STEMI	0.9954
9	Wu *et al.* [36]	the receiver operating characteristic (AUROC) and ANN	98.4, and 92.86 respectively

The earlier research was predicated on the diagnosis of post-MI. Identifying the early possibility of MI is essential in the current context. To improve the effectiveness and accuracy of the models, research needs to be done on the ones that already exist. This research needs to collect new, responsible MI parameters rather than only using the ones that already exist. The proposed and effectively implemented score tree algorithms (STAs) for early prediction are presented in the next section.

3. PROPOSED METHODS

The proposed work as shown in Figure 1. focuses on Early prediction of MI instead of post MI which helps to save life of a mankind. The implemented work extracts information from various hospitals and expertise opinion is also considered at every steps. Datasets are prepared and authenticated from experts. Figure 1 shows the outline of the proposed work. This paper focuses on various ML algorithms as well as STA is proposed for early prediction of MI. STA is implemented and validated with various inputs.

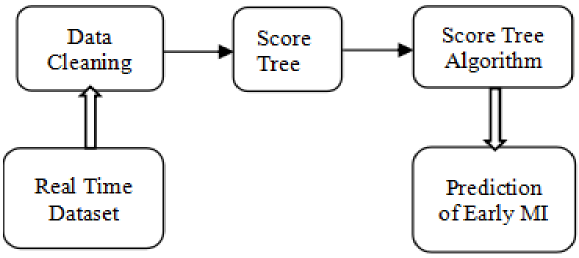

Figure 1. Outline of the proposed work

Implementing early MI diagnosis is essential, but it is more critical to forecast than to do so just after MI. In this study, we gathered real hospital information and identified new features to forecast early MI. In this study, extensive research was done to try to find a way to predict an early MI. SVM, DT, RF, KNN, NN, QDA, AdaBoost, and NB. are only a few examples of ML classification approaches that work with supervised data. But in this case, an unstructured dataset is used to make an early disease prediction. To forecast early MI in a patient while considering numerous special factors, we offer a novel technique called Score Tree. In the following part, ST algorithm information and its implementation are provided.

3.1. Score tree (ST)

The Score Tree employs a top-down methodology, often known as a waterfall model, in which, after a root node is chosen based on some criteria, the tree begins to extend downward until the leaf node is calculated. Each feature's weight is computed here. A score is determined by all feasible arrangements of each feature. The foundation for early MI prediction is the maximum score. The early MI score appears as a leaf node. The proposed score tree is shown in Figure 2.

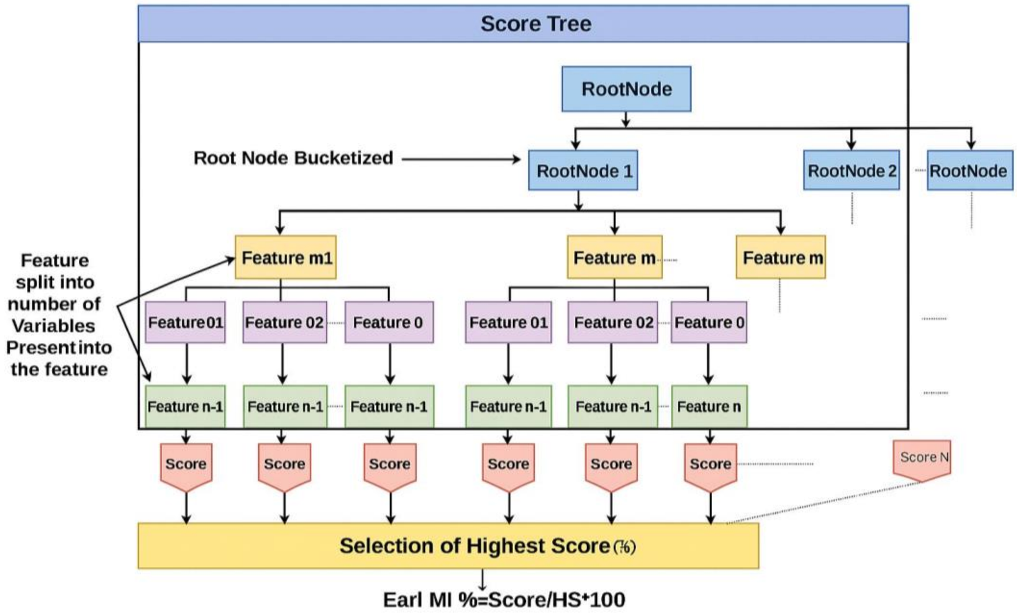

Figure 2. Score tree

The root node is initially selected based on the functionality offered. Age is the root node here. Then, using the given datasets, we bucketized the root node and determined each root node's weight. To the leaf node, the remaining features are divided. The overall variation present in each feature serves as the foundation for each split. There is a result from each leaf node. This score is further utilized in the STA as shown in Figure 2.

3.2. Score tree algorithm (STA)

The weights of each feature, including age, gender, angiography parameters, and others, are first determined. The scores are created from a score tree using a depth-first technique based on estimated weights. These results are considered as a dataset for MI early prediction. Based on the scores, linear regression is used to create equations. Following equation is derived from the scores generated from the score tree.

$$Score = RW + \beta_1 \times f_{w(n-1)} + \beta_2 \times f_{w(n-2)} + \beta_3 \times f_{w(n-3)} \ldots\ldots + \beta_n \times f_{w(1)} + C \quad (1)$$

Here,
RW = Weight of Bucketized Root Node
β = Coefficient
f_w = Weight of Features
C = Intercept

4. EXPERIMENTS AND VALUATION

The implementation of the STA is carried out as shown in Tables 2 and 3. Initially, the dataset is used to calculate the weight of all features. The Age feature is bucketized as per the availability in the dataset for male and female genders. First, a score tree is implemented, and afterwards all possible scores are generated.

4.1. Performance analysis of STA

Refer to "(1)" which is derived from linear regression method. Here, the CSV file of scores is provided to the linear regression method, and the algorithm calculates the various coefficients. Here various coefficients are discussed:

- β (Unstandardized Beta): Represents the slope of the regression line. It shows how much the dependent variable changes for a one-unit increase in the predictor (e.g., β = –1.65 means a decrease of 1.65 units).
- Unstandardized coefficients: Regression values calculated using the original measurement units of the variables.
- Standard error (SE): Measures the accuracy or variability of the coefficient estimate.
- Standardized Coefficients: Regression coefficients obtained after standardizing variables (variance = 1), used to compare the relative importance of predictors.

Table 2. Regression statistics

Regression statistics	
Multiple R	1
R Square	1
Adjusted R Square	0.99596123
Standard Error	6.173E-15
Observations	1248

Table 3. Coefficients and intercepts

	Coefficients	Standard error	t Stat	P-value	Lower 95%	Upper 95%	Lower 95.0%	Upper 95.0%
Intercept	1.384	5.00689E-16	2.76E+15	0	1.384	1.384	1.384	1.384
Agewt	1	6.14082E-15	1.63E+14	0	1	1	1	1
ECG-0	0	0	65535	#NUM!	0	0	0	0
ECG-1	0.89380531	3.86588E-16	2.31E+15	#NUM!	0.89380531	0.89380531	0.89380531	0.89380531
ANG-0	1	2.22835E-15	4.49E+14	0	1	1	1	1
ANG-1	1	2.09362E-15	4.78E+14	0	1	1	1	1
CP-0	0.3	1.07005E-14	2.8E+13	0	0.3	0.3	0.3	0.3
CP-1	0.96995708	4.59248E-16	2.11E+15	0	0.969957082	0.969957082	0.969957082	0.969957082
CP-2	0	0	65535	#NUM!	0	0	0	0
DB-0	0	0	65535	#NUM!	0	0	0	0
DB-1	0.31649832	5.88343E-16	5.38E+14	#NUM!	0.316498316	0.316498316	0.316498316	0.316498316
PFH-0	0.43014129	5.48628E-16	7.84E+14	0	0.430141287	0.430141287	0.430141287	0.430141287
PFH-1	0	0	65535	#NUM!	0	0	0	0
CHOL-0	0.03536346	6.86593E-16	5.15E+13	#NUM!	0.035363458	0.035363458	0.035363458	0.035363458
CHOL-1	0	0	65535	#NUM!	0	0	0	0

A standardized beta coefficient measures how strongly each independent variable has an impact on the dependent variable. The stronger the higher the beta coefficient's absolute value is. The formula for the standardized coefficient in linear regression is as follows.

$$Standerdized\ Coefficient(x1) = Unstanderdized\ Coefficient(x1) \times (standerd\ deviation\ of\ x1/standard\ deviation\ of\ y) \quad (2)$$

The coefficient is divided by its standard error to produce the t statistic. It can be viewed as an evaluation of the accuracy of the regression coefficient measurement. A coefficient is likely different from zero if it is significant in relation to its standard error. A substantial prediction in regression denotes that the predictor variable may explain a sizable amount of variability in the predicted variable [37].

4.2. Datasets

Real-time data that was extracted from patient records at different hospitals was used to generate the evaluation datasets. Age, ECG, Angiography (ANG), Chest Pain (CP), Diabetes (DB), Previous Family History (PFH), Cholesterol (CHOL), and other fields are included in this datasets. There are 800 records of patient information in this collection. The datasets were considered only for angina patients. Angina in medical terms is early MI. Therefore, a score tree (ST) is designed and implemented for angina patients record.

5. RESULTS AND DISCUSSION

The results shown in Figure 3 of early MI for males aged 26 to 30 are shown in the above graph. The datasets compiled from several hospitals is used to determine the highest score, which comes out to 4.77. Age, ECG, ANG, CP, DB, PFH, CHOL, and other input features are considered. Aged between 26-30 males' data is considered and the result is 54% of chances of MI if the person is having ECG changes, presence of blockage, family history present and cholesterol. Result shown in Figure 4 compared with the same age 26-30 with differents input values shows the early MI chances are 96% with score 4.558.

The results illustrated in Figure 5 present early MI risk for females aged 31 to 35, based on data compiled from multiple hospitals. The analysis considers various input features such as Age, ECG changes, ANG, CP, DB, PFH, CHOL, among others. The highest risk score observed is 2.856. For individuals in this age group exhibiting ECG abnormalities, arterial blockages, a positive family history, and elevated cholesterol, the likelihood of early MI is estimated at 61%. In comparison, Figure 6 displays results for the same age group with different input parameters, revealing a significantly higher early MI probability of 75% with a risk score of 4.695. The most vulnerable characteristics are others, such as smoking, food habit, and stress, but these characteristics are not recorded in the patient's records. These characteristics can help predict early MI more accurately.

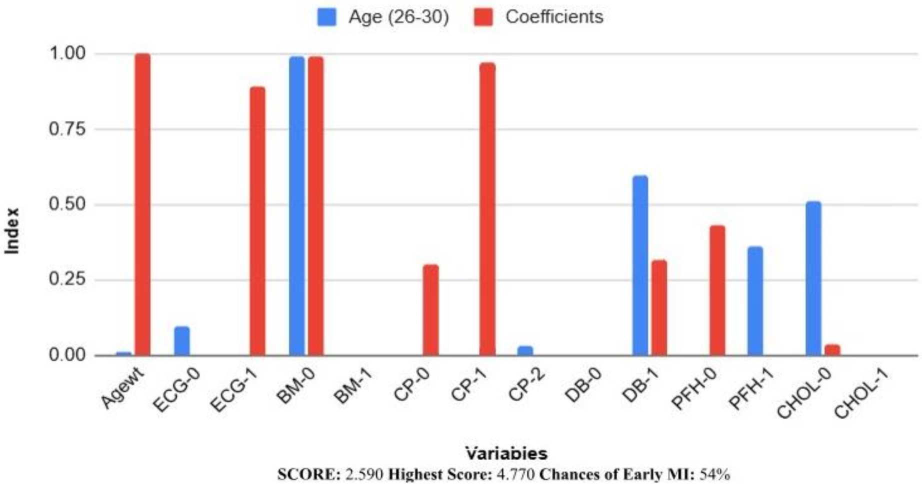

Figure 3. Prediction of early MI for male age (26-30)

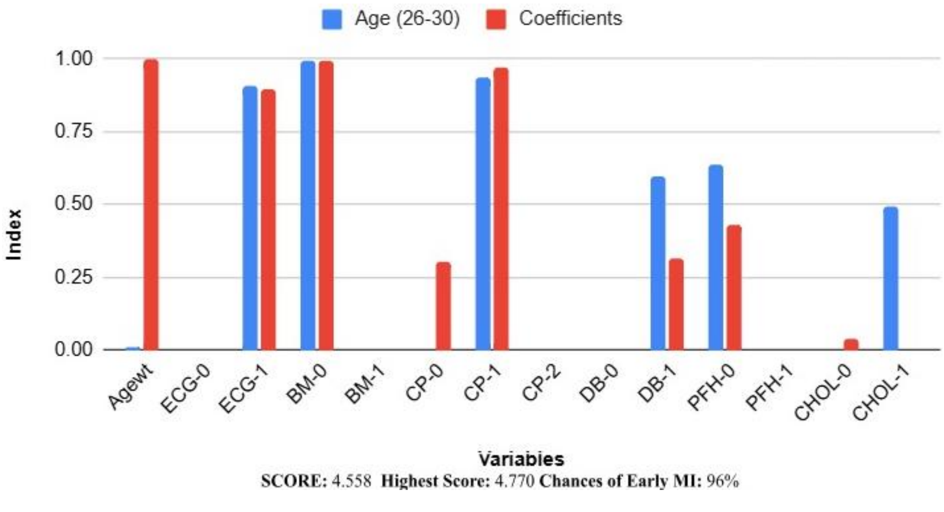

Figure 4. Prediction of early MI for male age (26-30)

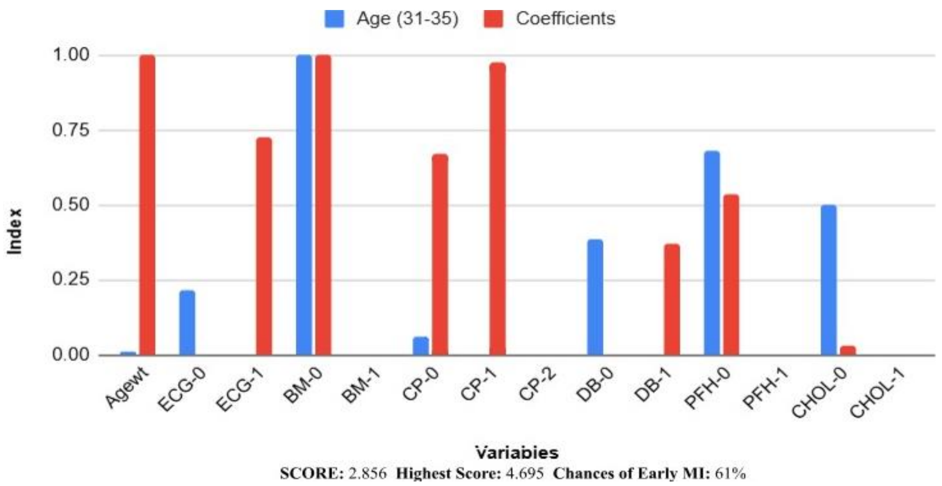

Figure 5. Prediction of early MI for female age (31-35)

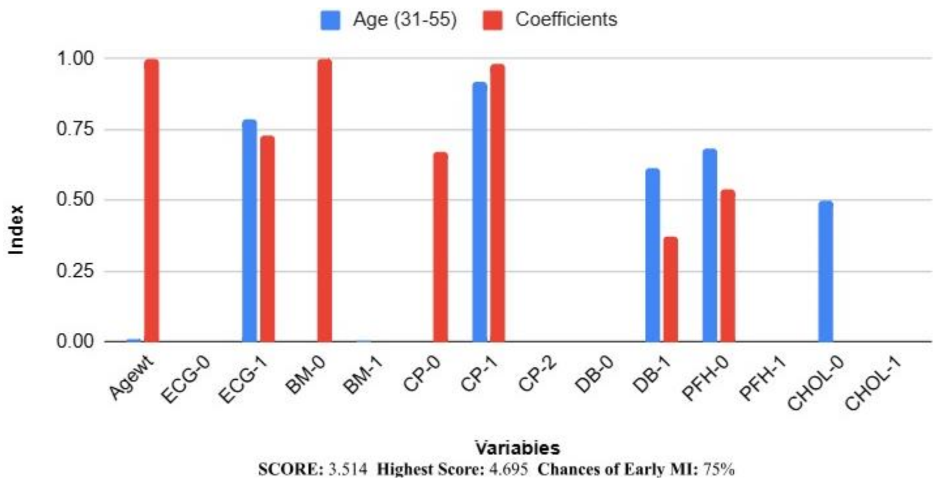

Figure 6. Prediction of early MI for female age (31-35)

6. CONCLUSION AND FUTURE WORK

Existing research on MI primarily relies on datasets from Western countries, making it less applicable to Asian populations due to differences in lifestyle and environment. To address this, the researcher collaborated with expert doctors and analyzed new reports to improve early MI detection. Additional parameters were incorporated into datasets specifically compiled for Indians, including age, gender, ECG changes, CK-MB, Trop-I, angiographic markers (LAD, LCA, RCA), blood pressure (systolic, diastolic), chest pain type, and total cholesterol, among other risk factors. Data collected from hospitals was cleaned and processed before being applied to the model. The model's accuracy, particularly using KNN, DT, and NN algorithms, has shown significant improvement. To forecast early MI, a STA is created and put into practice. ML algorithms like decision trees and random forest algorithms are used as examples of supervised algorithms. An unsupervised dataset is used in the Score Tree technique, and its leaf node is used to determine a score. Each node's weight is determined using data from actual patients. Based on the data, a forecast is made, and the hypothesis is successfully tested after being discussed with a cardiologist.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT
Authors state no conflict of interest.

DATA AVAILABILITY
Data from this study are available from the corresponding author upon reasonable request. Access to certain datasets may require ethical or legal review due to privacy or proprietary concerns.

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