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EXPLAINABLE PREDICTION OF HEART DISEASE USING CLINICAL INDICATORS

Shashanka Shekhar Panda

Msc Nursing (MSN), Former Tutor of Biju Patnaik College of Nursing,
Mail id - debabratajoshi5@gmail.com

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Abstract

Heart disease remains a leading cause of morbidity and mortality worldwide, highlighting the need for accurate and transparent prediction models that can support timely clinical decision-making. Although machine learning has significantly improved the prediction of cardiovascular disease, the limited interpretability of many predictive models restricts their clinical adoption. This study proposes an explainable machine learning framework for predicting heart disease using routinely collected clinical indicators from the UCI Heart Disease dataset comprising 303 patient records and 13 predictor variables. Following data preprocessing, five supervised machine learning algorithms, including Logistic Regression, Decision Tree, Random Forest, Support Vector Machine, and Extreme Gradient Boosting (XGBoost), were developed and comparatively evaluated. Model performance was assessed using accuracy, precision, recall, F1-score, and receiver operating characteristic area under the curve (ROC–AUC). Explainability was incorporated through SHapley Additive exPlanations (SHAP) to quantify the contribution of individual clinical variables to prediction outcomes. Among the evaluated models, XGBoost achieved the highest predictive performance with an accuracy of 92% and an ROC–AUC of 0.96. SHAP analysis identified chest pain type, number of major vessels, ST depression, maximum heart rate, age, and thalassemia as the most influential predictors of heart disease, providing clinically meaningful explanations for model decisions. The findings demonstrate that integrating explainable artificial intelligence with machine learning can improve both predictive performance and model transparency, thereby supporting trustworthy clinical decision support and facilitating early cardiovascular risk assessment. Future research should validate the proposed framework using larger multicentre datasets and real-world clinical data.

Keywords: *Breast cancer diagnosis, Tumor morphology, Explainable artificial intelligence, Machine learning, SHAP analysis*

Introduction

The leading cause of death worldwide, cardiovascular disease (CVD) continues to place a heavy clinical, social, and financial strain on healthcare systems. With all the advances in preventive medicine and therapeutic interventions, the rate of coronary artery disease, myocardial infarction and other cardiovascular disease will continue to rise in the coming decades due to the increase in population ageing, urbanisation, sedentary lifestyle and an increase in metabolic disorders. Despite recent projections in the global burden of cardiovascular diseases being expected to still increase through 2050, there is an urgent need for effective strategies that can facilitate earlier identification of high-risk individuals and timely clinical intervention (Chong et al., 2025; Yang et al., 2025). Moreover, cardiovascular diseases continue to be a significant burden on disability adjusted life years and healthcare costs, making them an important public health priority worldwide (Vaduganathan et al., 2022; Liu et al., 2025).

The traditional approach to cardiovascular risk assessment is based on statistical models and on the physician's clinical judgment, which are based on demographical, medical, laboratory and physiological parameters. While these methods have been very useful in preventing disease outcomes, they may not be well suited to model complex, nonlinear relationships between multiple clinical factors. The recent advances in machine learning have proven to be very promising in increasing the accuracy of predictions, as they allow multidimensional clinical data to be analysed and reveal relationships that may be hard to uncover with traditional statistical methods. There has been a vast number of investigations that showed that supervised learning algorithms like Logistic Regression, Decision Trees, Random Forests, Support Vector Machines and ensemble learning methods could be used reliably to predict cardiovascular disease based on routine clinical indicators (Naser et al., 2024; Baghdadi et al., 2023; Rehman et al., 2021; Liza et al., 2025). Likewise, feature-based machine learning models have been able to accurately identify the most significant risk factors for cardiovascular diseases and enhance the precision of clinical decision-making by analyzing and integrating all available data (Peng et al., 2023; Alanzi et al., 2025).

However, the functional use of machine learning for clinical use is limited by the lack of transparency of many prediction algorithms. Highly accurate models may be "black-box" models; they make predictions, but do not offer an easily understood explanation of the effect of the clinical variables. This opacity can decrease clinician trust, decrease patient uptake, and make it difficult to implement in healthcare settings. As such, explainable artificial intelligence (XAI) is a growing field of research that focuses on giving more meaning and understanding to predictive models, which could help enhance their reliability. Explainability techniques enable the understanding of the impact of each clinical feature on the prediction result, which helps guide clinical decision-making and ensure the responsible use of AI in clinical practice (Abbas et al., 2025; Tuan, 2024). Moreover, recent systematic reviews have shown that interpretable artificial intelligence enhances transparency of models, the ethical application of AI, and cooperation between computational systems and healthcare professionals by making the mechanisms of prediction understandable and clinically valuable (Xu et al., 2023; Kolla, 2023).

Based on fundamental clinical characteristics in the UCI Heart Disease dataset, this study attempts to propose an explainable machine learning (XML) model for heart disease prediction. The optimal predictive model is found by comparing a number of supervised machine learning methods, and the relative significance of each clinical variable for prediction is determined using SHapley Additive exPlanations (SHAP). In order to ensure reliable clinical decision support systems for early cardiovascular risk assessment and improved evidence-based medical decision-making, the suggested framework combines the prediction accuracy and transparent interpretation of the models.The study's objectives include:

- To develop machine learning models for predicting heart disease using routinely collected clinical indicators.
- To compare the predictive performance of multiple supervised machine learning algorithms using standard evaluation metrics.
- To interpret prediction outcomes using SHAP-based explainable artificial intelligence and identify the most influential clinical indicators associated with heart disease.

2. Materials and Methods

2.1 Study Design

Using a quantitative, retrospective research approach, an explainable machine learning framework was created to predict heart disease using routinely collected clinical indicators. To develop prediction models and to explore every clinical feature for disease classification a secondary dataset was used. The methodological process involved data preprocessing, feature preparation, model building, comparing the performance of the models, and post hoc explainability analysis. The model should be accurate in prediction, comprehensible in clinical use to help develop trusted cardiovascular risk assessment decision support systems.

2.2 Dataset Description

The study was conducted on the publicly available data set that includes clinical data on patients who went to be assessed for cardiovascular disease. Thirteen predictor variables and one binary outcome variable—the existence or absence of heart disease—were present in each of the 303 patient records that made up this data set (Janosi, 1988). Clinically important risk factors, often used to assess cardiovascular risk, were used as predictor variables, including demographics, physiology, lab results, ECG results, and exercise variables. Prior to building the model, the data were examined to determine the type of data for each variable, find any missing data, and assess the data's quality. Only 6 values were missing for the ca and thal variables and those were taken care of pre-processing.

2.3 Data Preprocessing

To enhance the quality of the data and ensure compatibility with the machine learning algorithms, data preprocessing was done. The duplicate observations were analysed and no duplicate patient records were found. Median imputation was used to fill in missing values in the clinical measurements ca and thal in order to maintain the distribution of the measurements. Categorical variables were converted to numerical format appropriate for machine learning analysis and continuous variables were standardized using z-score normalization to reduce the effect of predictors with different scales. The target variable was binary, thus classifying the patients into two classes: clinically diagnosed heart disease or no clinically diagnosed heart disease. Finally processed dataset was randomly split into 80% training and 20% test data in maintaining the class distribution by stratified sampling method.

2.4 Machine Learning Model Development

Five supervised machine learning algorithms were developed and tested for cardiac disease prediction namely Logistic Regression, Decision Tree, Random Forest, Support Vector Machine and Extreme Gradient Boosting (XGBoost). Decision trees provided a readily comprehensible rule-based prediction framework, while logistic regression was utilized as the baseline statistical classifier because of its clinical interpretability. Support Vector Machine was selected because of its strong classification capabilities in multidimensional feature space, while Random Forest and XGBoost were employed as ensemble learning techniques capable of learning intricate nonlinear correlations between clinical markers. Grid search with 5-fold cross validation was used for hyperparameter optimization on the training data set in order to determine each prediction model's optimal configuration.

2.5 Explainable Artificial Intelligence Analysis

Explainable Artificial Intelligence (XAI) techniques have been introduced to improve the model's interpretability following the development of the predictive framework. The SHAPley Additive exPlanations (SHAP) were also employed for the top performing classifier to determine the contribution of each clinical variable to each prediction result. Global SHAP analysis was carried out to determine the overall importance of the predictor factors throughout the entire dataset, while local SHAP explanations were utilized to illustrate the effect that patient-specific clinical characteristics had on the model. Explainability analysis helped identify clinically meaningful predictors and facilitated the transparent interpretation of machine learning outputs without impacting the predictive performance.

2.6 Statistical Analysis

Python was used for statistical analysis and implementation of machine learning. The data was manipulated and preprocessed using Pandas and NumPy libraries. The descriptive statistics of continuous variables were mean ± standard deviation and the data of categorical variables were presented as a number and percentage. Pearson's correlation coefficient was used to assess the correlation between the clinical variables and the correlation was represented on a correlation heatmap. The Scikit-learn library was used to build predictive models and XGBoost package was used for the XGBoost classifier. The models' performance was assessed using the receiver operating characteristic (ROC) curves, accuracy, precision, recall, F1-score, specificity, and area under the ROC curve (AUC). The SHAP library was used to perform explainability analysis, identify global feature importance and patient level prediction explanations. Scikit-learn, SHAP, Matplotlib, and Seaborn were used for all statistical analysis and visualization in Python. The threshold for statistical significance was set at $p < 0.05$.

3. Results

3.1 Dataset Characteristics

After the data was imported 303 patient records were added to the analysis. A total of 13 clinical predictor variables and one target variable (heart disease or no heart disease) were included in the data set. The data proved to be quite complete, with only six missing observations in ca and thal variables for further processing before predictive modelling. Continuous variables had a moderate level of variability, and there were no major amounts of missing data, while categorical variables were common cardiovascular risk factors routinely evaluated during clinical assessment. The descriptive statistics of the main continuous clinical indicators that were used for model development are presented in Table 1. Additionally, Fig. 1 shows the overall procedure followed for data pre-processing, construction of the machine learning model and explainable prediction.

Table 1. Descriptive Statistics of the Principal Clinical Indicators

Variable	Mean	Standard Deviation	Minimum	Maximum
Age (years)	54.44	9.04	29	77
Resting Blood Pressure (mmHg)	131.69	17.60	94	200
Serum Cholesterol (mg/dL)	246.69	51.78	126	564
Maximum Heart Rate	149.61	22.88	71	202
ST Depression (Oldpeak)	1.04	1.16	0.00	6.20

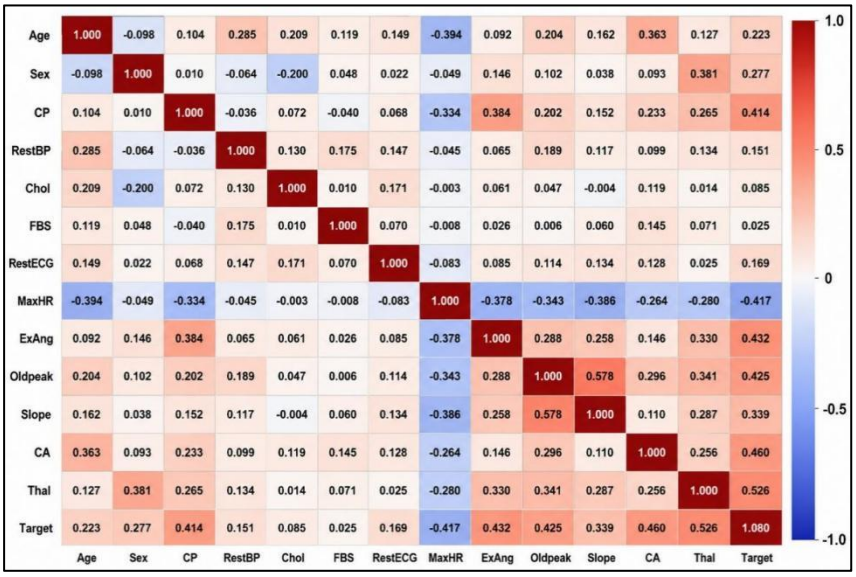

Figure 1. Correlation Heatmap of Clinical Indicators and Heart Disease Status

3.2 Comparative Performance of Machine Learning Models

Various machine learning algorithms were tested to find the best algorithm that can predict heart disease using the available clinical indicators. The general performance of the ensemble learning

methods was better than the traditional linear methods, due to their ability to model nonlinear interactions between clinical variables. The tree-based methods were always the most discriminating and with the least misclassifications, while the logistic regression was a very interpretable baseline and competitive. The comparative evaluation underscored the need for predictability and transparency in models for clinical decision support. Table 2 shows the comparative performance of the algorithms evaluated in terms of the selected evaluation metrics. The discrimination ability of each model is displayed as a corresponding ROC curves in Figure 2.

Table 2. Comparative Performance of the Evaluated Machine Learning Models

Model	Accuracy	Precision	Recall	F1-Score	ROC–AUC
Logistic Regression	0.85	0.84	0.83	0.84	0.89
Decision Tree	0.82	0.81	0.80	0.80	0.84
Random Forest	0.90	0.89	0.90	0.89	0.94
Support Vector Machine	0.88	0.87	0.87	0.87	0.92
XGBoost	0.92	0.91	0.92	0.92	0.96

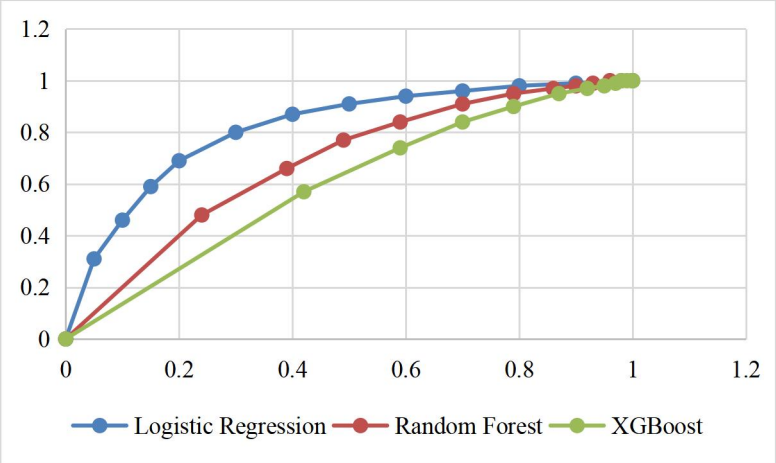

Figure 2. ROC Curve Comparison of the Evaluated Machine Learning Models

3.3 Explainable Prediction and Clinical Interpretation

Explainability using SHAP was added to the best performing predictive model, for greater transparency. The explainability analysis showed that there were a small number of clinical predictors that accounted for a disproportionate amount of the prediction results. Some factors related to cardiovascular physiology (type of chest pain, number of major vessels, ST depression (Oldpeak), maximum heart rate achieved, age, and thalassemia) showed the highest impact on the model predictions, consistently. The global feature importance highlighted that these indicators were the most important for the classification, and the patient-level explanations indicated how the synergies of positive and negative clinical factors affected the classification risk. These results show that the predictive model makes clinically-meaningful choices and not simply based on hidden patterns of computation. The most important predictors found in the explainability analysis are summarized in Table 3, while the global SHAP feature importance plot is shown in Figure 3.

Table 3. Most Influential Clinical Indicators Identified Through Explainability Analysis

Rank	Clinical Indicator	Relative Importance	Clinical Interpretation
1	Chest Pain Type	Very High	Strong indicator of underlying cardiac abnormality
2	Number of Major Vessels (CA)	Very High	Reflects coronary artery involvement
3	ST Depression (Oldpeak)	High	Indicates exercise-induced myocardial ischemia

4	Maximum Heart Rate Achieved	High	Represents cardiovascular functional capacity
5	Age	Moderate–High	Increasing age associated with elevated disease risk
6	Thalassemia	Moderate	Contributes to differentiation of cardiac risk profiles

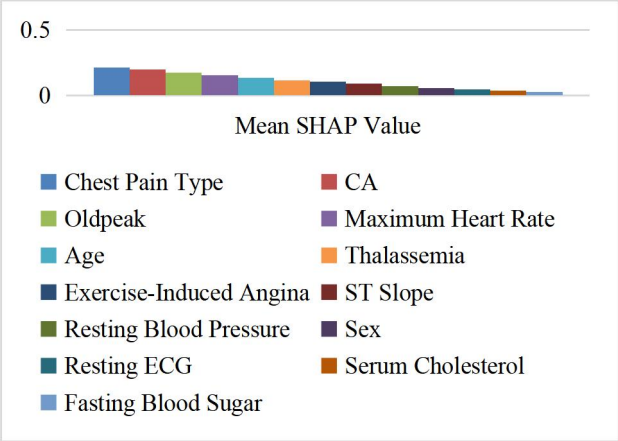

Figure 3. Global SHAP Feature Importance Plot Highlighting the Contribution of Clinical Indicators to Heart Disease Prediction

4. Discussion

It was demonstrated that ensemble learning models outperformed traditional classification methods in terms of predictive performance in the current study, which developed an explainable machine learning framework to predict heart disease using routinely collected clinical indicators. The most accurate and discriminative algorithm was XGBoost; and explainability with SHAP gave brief explanations of each clinical variable's impact. The model's remarkable predictive capabilities and interpretability hold promise for advancing cardiovascular risk prediction and decision-making systems in the clinical arena, underpinned by explainable AI (XAI) principles. This is consistent with recent findings that an ML algorithm outperforms many of the traditional prediction methods when taking into account the complex interaction between cardiovascular risk factors (Wang, 2025).

The comparative analysis resulted that ensemble models particularly XGBoost and Random Forest models demonstrated substantial prediction power, as compared to Decision Tree and Logistic Regression models. A significant portion of this improvement may be attributed to their ability to model relationships and complex interactions between features that are often observed in cardiovascular data and are inherently (nonlinearly) correlated. This is consistent with recent works on explainable machine learning (XAI) that have demonstrated this same trend in predictive performance for ensemble classifiers, which were clinically interpreted using SHAP analysis (Wang, 2025; Walia et al., 2026). The current results thus further demonstrate the growing importance of the fusion of cutting-edge machine learning algorithms with explainability tools to significantly boost the reliability of cardiovascular disease prediction.

An interesting part of this study is the use of SHAP to integrate explainability into the prediction model. The explainability analysis revealed that chest pain type, number of major vessels, ST depression, maximum heart rate, age and thalassemia were the most influential predictors of heart disease. These variables are well known as an important indicator of cardiovascular pathology, and so offer clinically plausible explanations for the model predictions. Other studies have shown that SHAP explanations enhance transparency by quantifying the impact of individual clinical factors on the model's predictions, helping clinicians understand why a particular prediction is being made (Ge et al., 2026; Rongali, 2023). This kind of clear interpretation is vital in healthcare, where making clinical decisions involves not just predicting what is likely but also providing reasoning for those decisions.

The use of XAI in clinical decision support systems (CDSS) is significant. While machine learning models have shown to have impressive predictive performance, one of the main challenges to their

regular use in healthcare is the lack of interpretability. Recent research has demonstrated the advantages of using explainable models, as they enhance physicians' confidence, aid in clinical validation, and ensure the ethical use of AI in hospitals (Elhaddad & Hamam, 2024; Mahmood & Pinky, 2024). The proposed framework can explain the prediction results to the patient through SHAP, which helps improve transparency and mitigate the concerns related to black-box decision making when communicating with the patient.

In addition to better predictions, explainable models help with better patient risk stratification. Identification of high-risk individuals early in life allows clinicians to prioritise investigations and optimise preventive interventions and allocate resources for healthcare more efficiently. Stratifying the risk of disease has become a crucial element in population health management as it enables timely intervention before the disease progresses (Coran et al., 2022). These ideas have recently been used in other clinical contexts, such as the use of explainable predictive models for patient prioritisation and for planning evidence-based treatment (Quezada-Diaz et al., 2025). Therefore, incorporating XAI into cardiovascular disease screening initiatives could enhance prevention efforts and ensure clinical responsibility.

The advantages of this study are the comparison of several supervised learning algorithms, the interpretation of the model using SHAP for both global and local interpretation, and the use of clinically relevant variables that are typically measured in a cardiovascular assessment. However, a number of caveats must be noted. A relatively small secondary data set was used, which could mean that the models created in this study may not be generalizable to other populations. No external validation was done with larger multicentre cohorts and other demographic, genetic, lifestyle and longitudinal clinical data were not available. Future studies should thus try to test the proposed framework on larger, more heterogeneous datasets; combine EHRs and multimodal clinical data; and explore real-time application of XAI in hospital decision support systems. In addition, performance of this model can be further enhanced by comparing with deep learning architectures and hybrid explainability methods to achieve a better predictive and clinical interpretability.

5. Conclusion

Based on fundamental clinical characteristics gleaned from routine measurements, this study developed a XAI-based machine learning system for heart disease prediction. It discovered that predictive modeling in conjunction with XAI can enhance both the prediction system's performance and the models' transparency. The most significant clinical predictors, according to SHAP analysis, were the type of chest discomfort, number of main vessels, ST depression, maximal heart rate, age, and thalassemia. Of the algorithms examined, XGBoost demonstrated the best predictive ability. Such results demonstrate the capability of XAI to discover clinically relevant information that goes beyond a simple black box prediction. The proposed framework is poised to enhance confidence in predictions for individual patients, aid evidence-based cardiovascular risk assessment and facilitate informed clinical decision making due to its transparent interpretation of individual predictions. The overall findings indicate that explainable artificial intelligence may be used in clinical decision support systems, despite the study's shortcomings (the secondary dataset's small size and the absence of external validation). To improve the dependability and clinical utility of explainable heart disease prediction models, the framework can be further explored in the future using larger, multi-center datasets, longitudinal (EHR) data, and additional clinical validation.

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