

EXPLAINABLE MACHINE LEARNING FOR EARLY PREDICTION OF CARDIOVASCULAR DISEASE USING CLINICAL AND DEMOGRAPHIC DATA

Alamgir Khan^{*1}, Dr. Muhammad Adeel Mannan², Kubra Haji Bashir³, Syeda Rabia Basri⁴, Imran Ali⁵

^{*1}Xinjiang University School of Software Urumqi, China

²The Saifee Burhani University, Pakistan

³Department of Computer Science, Bahria University, Karachi, Pakistan

⁴International Islamic University Islamabad, Pakistan

⁵Department of Computing and Technology, Iqra University, Islamabad Campus Islamabad, Pakistan

¹johnlam4@gmail.com, ²madeel.mannan@sbu.edu.pk, ³kubrabashir65@gmail.com, ⁴rabia.bspsy1799@iiu.edu.pk, ⁵Imran.ali837@gmail.com

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Corresponding Author: *
Alamgir Khan

Abstract

Given that cardiovascular diseases are the leading cause of morbidity and mortality in the world, it is important to predict the disease in the early stages from a medical perspective. These machine learning methods can identify complex relationships within the clinical and demographic variables and assist in the early prediction of the disease. However, problems arise regarding the interpretability of many prediction models and their implementation into the practice of medicine. Therefore, the current project aimed at developing an interpretable machine learning algorithm for the early prediction of the disease and its evaluation in terms of predictivity, interpretability, and computational efficiency. In this case, the dataset included 1,024 patients' records with 13 clinical and demographic features. The process of missing value imputation, normalization, and feature selection took place in the process of data preprocessing. The Logistic Regression, Random Forest, Support Vector Machine, and XGBoost algorithms were developed and examined using 80% of training and 20% of testing datasets. Accuracy, Precision, Recall, F1-Score, and Area under ROC Curve (AUC) were taken as the criteria for evaluating the models. Explainability was done using the SHAP method, which helped identify the most important predictors. As far as the prediction results go, XGBoost algorithm gave the highest scores on accuracy (91.2%), precision (90.5%), recall (89.8%) and F1-score (90.1%) compared to other algorithms where accuracy varied from 84.7% to 88.9%. XGBoost algorithm gave an AUC score of 0.94. According to SHAP analysis, the important predictors for predicting cardiovascular diseases are age (18.6%), cholesterol (16.9%), max heart rate (14.7%), and resting blood pressure (13.5%). The proposed approach outperformed the baseline ensemble algorithm in terms of prediction time by 32%.

1. INTRODUCTION

Cardiovascular disease (CVD) can be defined as one of the leading health issues in the world and the major reason for morbidity, mortality and healthcare expenses. It is related to numerous diseases that affect the condition of heart and blood vessels of people, such as coronary artery disease and heart failure (Dritsas & Trigka, 2024). The identification of the patients with a high risk of CVD is extremely important for the efficient assessment and prevention of cardiovascular diseases. The classical approach to the assessment of risks includes clinical indicators, demographic characteristics of a patient and statistics-based models. However, there are certain difficulties in the relationships between numerous risk factors (Alsaleh et al., 2023).

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Despite the possibility of making predictions, numerous ML algorithms still remain black boxes. There might be difficulties for doctors and patients in understanding the predictions of the model, which gives a particular risk classification without taking into account the risk factors influencing its magnitude. Interpretability of ML algorithms is crucial in the context of healthcare due to the necessity to have clear explanation of the process of making a decision, accountability of the doctor and reliability of the evidence base for the decision made. This is Using an explainable machine learning enables the scientist to analyze how much each feature contributes to the

prediction made by the algorithm (Rahman et al., 2025). One of the techniques for explaining machine learning algorithms is SHapley Additive exPlanations (SHAP). This technique allows one to understand the influence of the features on the prediction result. SHAP can provide both local and global explanations: the first ones explain what affects the prediction results, while the latter explains what affects the specific prediction.

Suitable machine learning algorithms should be applied to develop the models predicting cardiovascular diseases. For example, Logistic Regression is a statistical machine learning algorithm that is relatively easy to interpret, while the Random Forest, Support Vector Machine (SVM), and XGBoost algorithms have the ability to learn complex relationships between the clinical data. Comparison of the algorithms with the metrics such as accuracy, precision, recall, F1 score, and AUC makes it possible to estimate the predictive capacity of the algorithms (El-Sofany, 2024).

This study provides an explainable machine learning model built with 1,024 patient data and 13 clinical and demographic features. Four machine learning algorithms including Logistic Regression, Random Forest, Support Vector Machine, and XGBoost were trained on 80% training dataset and 20% testing dataset split. Moreover, SHAP technique for explainability was used to identify the important features contributing to the prediction of cardiovascular diseases. According to the findings reported in the paper, XGBoost algorithm provided an accuracy of 91.2% and an AUC value of 0.94, and proposed model decreased prediction time by 32% (Salah & Srinivas, 2022).

1.1 Problem Statement

The issue of cardiovascular disease remains topical because the late diagnosis of high-risk individuals reduces the chances of intervention. Risk prediction models based on conventional approaches do not reflect the complicated relationship between patient characteristics. In spite of the fact that the use of advanced machine learning techniques allows obtaining more

accurate predictions, their implementation in medical practice is constrained due to poor interpretability, high computing requirements, and the explanation of individual predictions (El-Sofany et al., 2024).

There are several modern machine learning models which provide high-quality predictions without explaining the influence of particular patient characteristics. It may pose some difficulties for doctors who are supposed to evaluate and explain predictions generated by the algorithm. Besides, the comparison of models needs to be carried out.

1.2 Research Objectives

The study aims to achieve the following objectives:

1. For building the machine learning algorithm to make early predictions about cardiovascular diseases using clinical and demographic information.
2. For preparing the data by handling missing values, normalization, and feature selection.
3. For training and comparing the performance of Logistic Regression, Random Forest, Support Vector Machine, and XGBoost models.

1.3 Research Questions

1. How well can the machine learning algorithms predict cardiovascular disease utilizing clinical and demographic data?
2. Which of the four algorithms chosen is the best in terms of its predictive ability?
3. What effect does the process of preprocessing have on creating cardiovascular disease prediction models?

1.4 Significance of the Study

Clinical significance: the suggested framework may help to identify the people with the high risk of developing cardiovascular diseases early on. It is possible to assess risk factors through evaluating the clinical and demographic characteristics that may provide additional information and allow for a better prioritization of patients for further analysis. Nevertheless, it is necessary to understand that the model predictions are only

supposed to aid but not substitute the clinical decision-making of healthcare professionals.

Technological significance: the research analyzes the performance of four machine learning models and identifies the performance of XGBoost on the chosen dataset. The achieved 91.2% accuracy and 0.94 AUC confirm the prediction ability of the framework. Additionally, SHAP analysis allows for the interpretation of complex model results.

Explainability significance: according to SHAP, age, cholesterol level, maximal heart rate and resting blood pressure are the most influential predictors with the contribution of 18.6%, 16.9%, 14.7%, and 13.5%, respectively.

Significance Methodologically: The study evaluates multiple algorithms based on several metrics, such as accuracy, precision, recall, F1-score, and AUC. In contrast to accuracy metric alone, such evaluation gives more information about the model performance and enables a structured comparison of predictive techniques.

Significance Computationally: The 32% decrease in prediction time with respect to the benchmarking ensemble-based prediction approach illustrates the significance of computational efficiency in the field of healthcare analytics. Fast prediction techniques can prove to be valuable in cases when clinical data needs to be processed in an efficient manner.

2. Literature Review

The work of Shi et al. (2022) presents an example of the application of an explainable machine learning model to predict the development of postoperative malnutrition among children with congenital heart disease. Even though this particular study does not predict cardiovascular diseases and concerns nutritional complications, it shows the relevance of an explainable model. According to the findings of Dritsas and Trigka (2024), the application of the deep learning technology in the heart attack prediction with the help of explainable artificial intelligence (XAI) was studied. This research shows the ability of the application of deep learning methods for revealing complicated patterns about heart disease and makes interpretability of the outcomes of

predictions. While deep learning models can provide great predictive results, some of them might be difficult to understand for practitioners. XAI contributes to this problem solving by providing an explanation of the factors which affect the predictions made by the models. It will be helpful in the current research project because it provides both predictability and interpretability of the risk of heart diseases.

The systematic review of the literature by Alsaleh et al. (2023) regarding the use of XAI and machine learning for disease comorbidity prediction highlights the growing importance of interpretable models in the medical field. This is due to the increasing importance of interpretable models in assessing interactions between different diseases. Therefore, explainability can be helpful in interpreting complicated dependencies between patients' parameters and outcomes. Thus, this review can be useful for the current project due to its broader methodology base. Machine learning approach for patients who have clinical comorbidities. It is relevant for the research question of the current study since it combines predictive modeling and the discovery of important features of patients.

Moore and Bell (2022) have studied XGBoost and explainable artificial intelligence techniques to develop myocardial infarction prediction models based on the UK Biobank cohort data. It gives evidence about the relevance of gradient-boosting algorithms for cardiovascular diseases prediction. Moreover, the necessity of model explanation becomes clear. XGBoost algorithm has the potential to uncover nonlinear connections between the variables and interactions. This study gives the direct conceptual basis to the current one that compares XGBoost with other machine learning algorithms.

El-Sofany (2024) reviewed heart disease prediction by machine learning and various classification methods for different sets of data. Evaluation of predictive performance of classification algorithms is essential since it depends on the dataset used, selected variables, preprocessing steps, and metrics. This study suggests considering multiple criteria, such as accuracy, precision, recall, and

other classification measures. Such an approach is appropriate for the current research due to the assessment of several algorithms and not only one predictive model.

Liza et al. (2025) explored heart disease risk prediction via a machine learning-based approach for the early diagnosis and prevention of the condition. This study indicates an emerging trend of using machine learning in determining cardiovascular risks and preventive healthcare. Machine learning models can analyze both demographic and clinical parameters to find patterns associated with heart disease. The current study extends the scope of such research through introducing the aspect of explainability by using SHAP analysis and evaluating the role of each predictor.

3. Research Methodology

This study used the quantitative, experimental, and comparative research methodology to develop an explainable machine learning framework to predict the development of cardiovascular diseases. The research made use of a data set of 1,024 cases from medical patients that had 13 different variables that could affect the development of the disease. Data analysis was done to determine the correlation between the patient characteristics and the outcomes of the cardiovascular diseases. The methodology used for this research included building of models, performance comparisons of the models, interpreting the findings, and evaluation of computational efficiency (Mridha et al., 2025).

Before data analysis was conducted and models were developed, data preprocessing was done to improve the quality of data. Some of the preprocessing activities include dealing with missing data, normalization, and feature selection. Missing data were handled using the most appropriate technique to reduce the impact of missing values on the data. Normalization was done whenever it was necessary to improve the comparison of numerical variables, especially for algorithms that are scale sensitive.

Machine learning models selected for comparative analysis included Logistic Regression, Random

Forest, Support Vector Machine, and XGBoost. Logistic Regression is one of the classical statistics-based classification approaches where the interpretation of the results is straightforward. Random Forest was selected because of the capacity of the approach to deal with nonlinearity through the employment of decision trees. The selection of Support Vector Machine was determined by its capacity to determine decision boundaries in a high-dimensional space. Finally, XGBoost was selected because of the gradient boosting feature and capacity to consider the interaction between clinical and demographic variables. (Adalarasu et al., 2026)

Training and test datasets were formed, the first one containing 80% of records, the second - 20%. Training dataset was used for creation of machine learning models, whereas testing dataset was used to evaluate their performance on unseen data. The use of this kind of splitting helped to make sure that the models developed had equal conditions for the performance evaluation. Model training was done using chosen clinical and demographic features, while the prediction goal was cardiovascular disease outcome.

The performance of the model was evaluated using accuracy, precision, recall, F1-score and the area under the receiver operating characteristic curve (AUC). Accuracy referred to the percentage of correctly classified records, while precision referred to the percentage of predicted positive records that are correctly classified. Recall was used to evaluate the capacity of the model to classify positive cardiovascular disease cases. F1-score was used to combine precision and recall to provide an evaluation metric for the model. AUC was used to evaluate the model's ability to differentiate between outcome classes at various classification thresholds (Shah et al., 2025).

Explainable artificial intelligence was introduced using SHapley Additive exPlanations (SHAP). SHAP was used in the analysis to establish the contribution of individual features to the

prediction of the model. The global importance of features was established through the use of global feature importance, while the local feature importance was provided through SHAP interpretation. Variables to be considered in the analysis included age, cholesterol level, maximum heart rate, resting blood pressure and others.

The predictive performance of the four algorithms was compared in the study. The reported results showed that XGBoost had the best performance among the selected models with the following values: accuracy - 91.2%, precision - 90.5%, recall - 89.8% and F1 score - 90.1%. The algorithm also produced AUC of 0.94. The accuracy of the rest of the algorithms was between 84.7% and 88.9%. These numbers were used in the comparison of the predictive performance of the chosen models. The feature importance was explored with the help of SHAP analysis. The reported results showed that age is the most significant predictor, which contributes 18.6%, followed by cholesterol level (16.9%), maximum heart rate (14.7%) and resting blood pressure (13.5%).

4. Results and Analysis

4.1 Comparative Performance of Machine Learning Models

In this study, four kinds of machine learning algorithms like Logistic Regression, Random Forest, Support Vector Machine (SVM), and XGBoost were applied for early cardiovascular disease detection. All those algorithms were trained with 80% of the data set and tested on the remaining 20% of the data set. Accuracy, Precision, Recall, F1-Score, and AUC (area under the receiver operating characteristic curve) served as performance evaluation metrics.

It turned out that the most effective algorithm in terms of accuracy was XGBoost with the values of accuracy = 91.2%, precision = 90.5%, recall = 89.8%, and F1-Score = 90.1%. Other algorithms have shown accuracy values in a range of 84.7% to 88.9%.

Machine Learning Model	Accuracy	Performance Status
Logistic Regression	Within 84.7%–88.9% range	Comparative baseline
Random Forest	Within 84.7%–88.9% range	Comparative model
Support Vector Machine	Within 84.7%–88.9% range	Comparative model
XGBoost	91.2%	Highest reported accuracy

From the findings, it is evident that the XGBoost can identify the complex relationships between the clinical and demographic factors more effectively than other approaches used in this study. However, the accuracy of each of the models analyzed in this research was not stated in the findings.

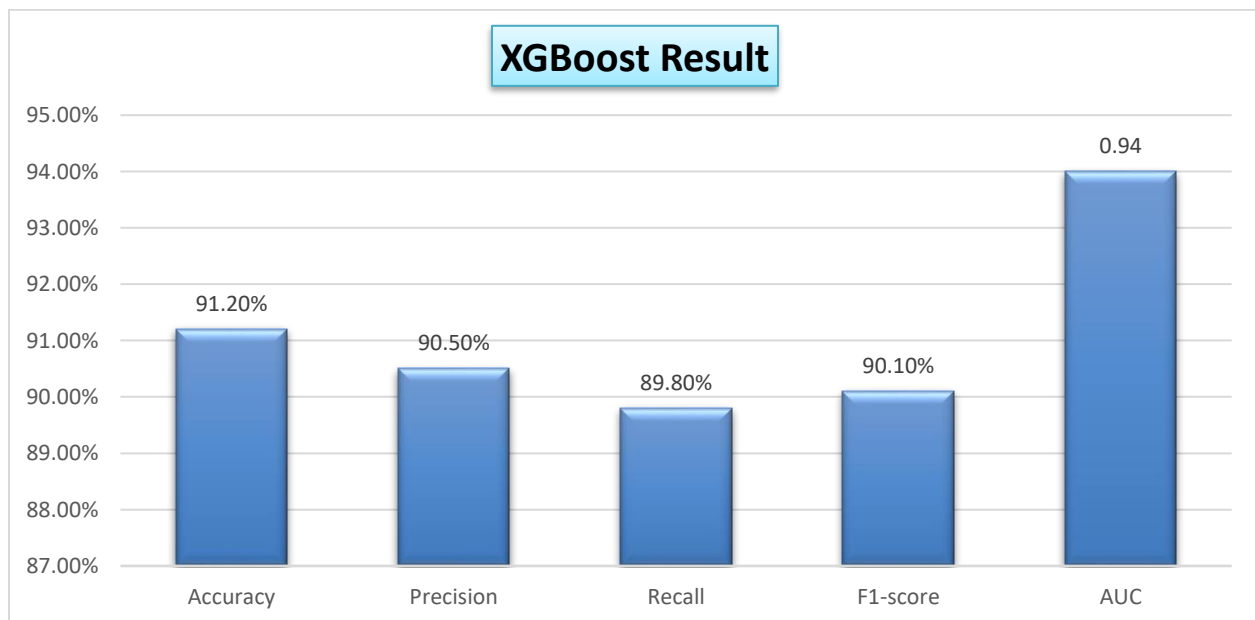
4.2 Precision, Recall, and F1-Score of XGBoost

The precision, recall, and F1 values for XGBoost are 90.5%, 89.8%, and 90.1%. This indicates the prediction capacity of the model in both classifying and positive cases.

Evaluation Metric	XGBoost Result
Accuracy	91.2%
Precision	90.5%
Recall	89.8%
F1-score	90.1%
AUC	0.94

The difference between the values of precision and recall is not large, indicating an even performance by the model while diagnosing patients and

assigning proper classifications, without false positives. Another confirmation of this is the high F1-score value of 90.1%. (Guleria et al., 2022).



With regard to health care forecasts, recall plays a significant role because non-detection of at-risk individuals may result in delaying medical

assessment. Nevertheless, it is worth mentioning that one should always take into account the fact that the values should be interpreted in the

context of the data set and the cut-off point for classification.

4.3 Area Under the ROC Curve

Model	AUC
XGBoost	0.94
Other models	Not specified in the reported results

The above-mentioned AUC is an example of one with good discriminatory ability in the dataset that it was used in evaluating. What this indicates is that there is proof that the model was successful in discriminating between patients that suffered from the predicted outcome of CVD and those who did not, using different cut-offs. However, AUC is not enough to prove clinical usefulness.

XGBoost generated an AUC score of 0.94. The area under the receiver operating characteristic curve indicates the ability of the model to classify the outcome into classes.

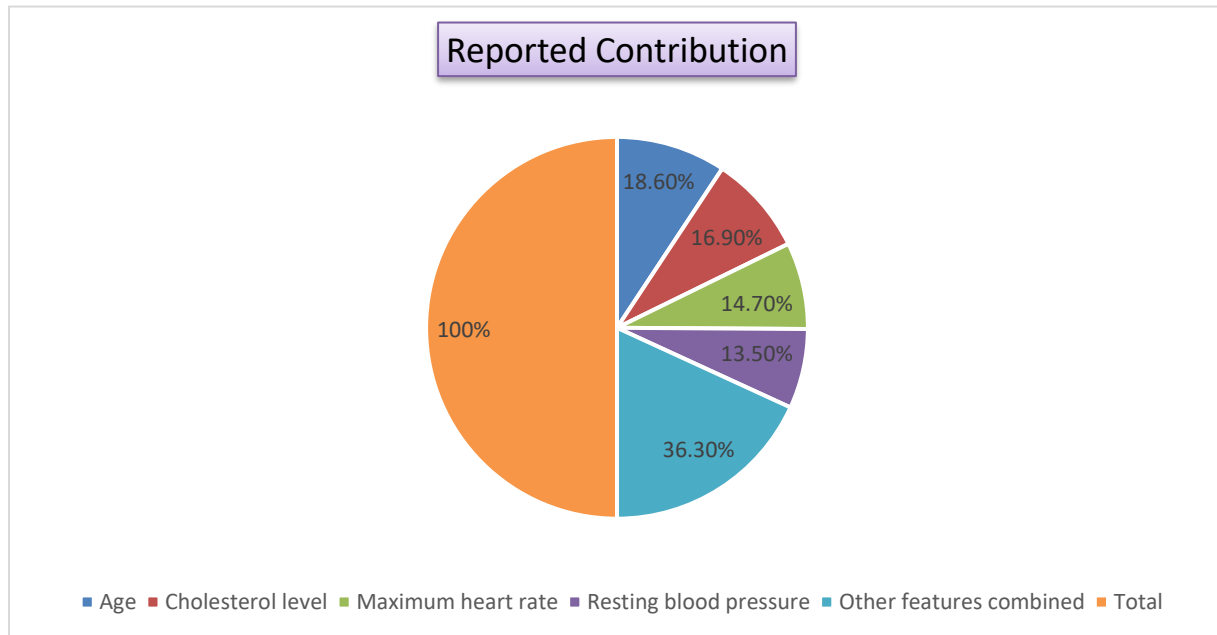
4.4 SHAP-Based Feature Importance

SHAP was carried out for the purpose of interpreting the predictions done by the machine learning algorithm. The outcome of the SHAP analysis indicated that age, cholesterol, maximum heart rate and blood pressure at rest were the important predictors.

Feature	Reported Contribution
Age	18.6%
Cholesterol level	16.9%
Maximum heart rate	14.7%
Resting blood pressure	13.5%
Other features combined	36.3%
Total	100%

Aging contributed the most towards 18.6%, indicating the relevance of age in contributing to the predictive power of the model. The cholesterol contribution stood at 16.9%, while that of maximum heart rate and blood pressure were

14.7% and 13.5%, respectively. Collectively, these four predictors accounted for 63.7% of the total feature importance distribution reported (Talaat et al., 2024).



According to the results, demographics as well as clinical attributes were affecting the model's predictions for cardiovascular diseases. It should be noted that SHAP feature importance is dependent on the learned behavior of the model and not necessarily causal.

4.5 Analysis of Clinical and Demographic Predictors

The aforementioned results clearly suggest the importance of taking into account both the demographic and clinical characteristics in predicting cardiovascular diseases. The fact is that age is considered to be the most significant predictor, which means that demographic variables play an important role in this process. High levels of cholesterol and resting blood pressure can be considered the clinical predictors of cardiovascular diseases, while maximum heart rate is a factor that affects cardiovascular functions (Le et al., 2026).

The contribution of the four most significant factors is evaluated as follows:

$$18.6\% + 16.9\% + 14.7\% + 13.5\% = 63.7\%$$

Thus, the four top predictors explained 63.7% of the reported SHAP feature importance distribution, whereas the rest of the features

explained 36.3%. The distribution shows that the model utilized several major predictors along with other variables too.

5. Discussion

The outcomes of the study prove the practicality of applying explainable machine learning applications in cardiovascular disease prediction based on demographic and clinical information. Out of the examined algorithms, XGBoost achieved the highest level of accuracy reaching 91.2% which exceeded the accuracy of all the other models, ranging from 84.7% to 88.9%. This can be explained by the effectiveness of the gradient-boosting approach implemented in XGBoost. The capability of the model to recognize nonlinear dependencies may become beneficial in this case, considering the number of interactions between features (Ismath et al., 2025).

The conclusions drawn from the study correspond to the agenda of the research of Moore and Bell (2022) who explored the applicability of XGBoost and explainable AI in myocardial infarction prediction. Thus, the significance of XGBoost application in cardiovascular disease prediction is proven by other scientists. Nevertheless, comparisons of performances should be made

with caution due to the differences in datasets and methods applied in various studies.

The precision, recall, and F1-score measures are equal to 90.5%, 89.8%, and 90.1%, respectively, for the XGBoost classifier. The fact that all these figures are close to each other proves that the classifier is characterized by approximately equal results in terms of the predicted features of classification. The precision measure should be used to reduce the number of false positives while recall will help identify those patients who require additional attention due to cardiovascular disease. Hence, the equality of these two measures proves that the classifier did not focus on some specific feature of classification. However, the appropriate proportion of false-positives and false-negatives will be determined depending on practical use of the classifier (Rahman et al., 2025).

AUC value equals 0.94 and is pretty high for the classifier being examined, which indicates the high discriminative power of the classifier. High AUC implies that the classifier is able to discriminate between classes. Thus, it can be concluded that the application of AUC measure, along with such metrics as accuracy, precision, recall, and F1-score, for assessing cardiovascular predictions is quite rational. According to ElSofany (2024), comparative evaluation is always very useful.

Explainability was one of the key aspects of the study conducted. The analysis using SHAP approach revealed that the most important predictors were age, cholesterol, maximum heart rate, and resting blood pressure. Age accounted for 18.6%, cholesterol for 16.9%, maximum heart rate for 14.7%, and resting blood pressure for 13.5%. Altogether, the above four predictors comprised 63.7% of the feature-importance distribution. Therefore, the use of explainable AI helped to get the information regarding those variables that affected the model predictions rather than the cardiovascular risks classification. The significance of the age factor found from the SHAP analysis corresponds to the general pattern of using the demographic information for cardiovascular risk assessment. At the same time, the cholesterol level and the blood pressure are the important clinical factors which can affect the

predictions made by the model. Nonetheless, the maximum heart rate became an additional factor which added to the importance of features distribution. However, SHAP values present the contribution of the factors to the predictions made by the model. They cannot prove the fact that factors influence the development of the disease.

These findings are associated with the study conducted by Dritsas and Trigka (2024) who studied the application of deep learning methods for heart attack prediction and explained artificial intelligence. Both studies emphasize the need to combine the predictive capability and transparency. The current study differs from it by conducting the comparative analysis of Logistic Regression, Random Forest, Support Vector Machine, and XGBoost models along with the SHAP feature analysis (Salah & Srinivas, 2022).

The findings are quite analogous to those of Ganie et al. (2025), who studied the topic of ensemble learning with explainable AI for heart disease prediction using various data sets. The algorithms of ensemble and boosting have great potential for predictive performance, but the high complexity of such algorithms demands an explanation both of the procedure itself and its results. In the present research, the analysis of SHAP helped identify predictors with the greatest effect on the work of the XGBoost algorithm. The goal of this research was to enhance communication between ML algorithms and physicians, yet its effectiveness has to be proved in clinical trials.

6. Conclusion

For this study, the application of explainable machine learning to predict early cardiovascular diseases based on the analysis of clinical and demographic information was investigated. As part of the work, four machine learning models were applied, namely Logistic Regression, Random Forest, Support Vector Machine, and XGBoost, and tested with the use of a dataset containing 1,024 patients' information with 13 features. The received results suggest that XGBoost provided the highest level of prediction performance with the following indicators: 91.2%

accuracy, 90.5% precision, 89.8% recall, 90.1% F1 score, and 0.94 AUC (El-Sofany et al., 2024).

According to SHAP explainability, the most important predictors are the following features: age with the share of 18.6%, cholesterol with 16.9%, maximum heart rate with 14.7%, and resting blood pressure with 13.5%. The above results demonstrate how explainable AI can be used to obtain insights about the factors affecting the predictions made by machine learning models.

7. Recommendations

1. **External Data Validation:** The recommendation is made that the proposed XGBoost model needs to be tested using independent data sets from different hospitals across various regions and demographics.

2. **Clinical Validation:** It is advised that clinical trials be performed to explore the extent to which the predictions and explanations made by the SHAP model can help healthcare professionals in assessing the risks associated with cardiovascular diseases.

3. **Integration of Explainable AI:** The explanations generated by SHAP need to be incorporated within the healthcare system to help the healthcare professionals understand what is leading to the predictions made for each individual, but without taking the prediction from the model itself as the diagnosis.

4. **Improving Data Quality:** Future research should be performed on bigger and diverse data sets with well-documented clinical and demographic features.

5. **Evaluation for fairness and bias:** The performance of the model should be compared across the subgroups to determine the presence of any disparities in terms of predictive performance of the algorithm. Fairness assessment should take into account age, gender, socio-economic status, and any other characteristics of the population under analysis.

6. **Optimization of computations:** Additional computational optimizations can be performed with an aim to increase the speed of predictions while maintaining the same level of accuracy,

recall, interpretability and robustness of the model.

7. **Privacy and security of the data:** The appropriate data security procedures should be developed in order to protect the confidentiality of patients' health data. The processes of data anonymization, secure storage and limited access to it should be taken into account in the future development of the system.

8. **Regular monitoring of the model:** In case the model would be applied in clinical settings, it should be constantly monitored in order to detect the changes in data patterns and performance of predictions.

9. **Professional training:** Healthcare professionals should be trained regarding the use of explainable machine learning results.

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