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Explainable Artificial Intelligence Approach to Heart Attack Risk Prediction

Tülay TURAN[1*]

Abstract

This study examines the feasibility of explainable artificial intelligence (XAI) techniques for analyzing and accurately classifying heart attack risks. Given the complexity of heart attack risk factors, traditional machine learning models often do not provide the transparency needed for clinical decision-making. This research addresses this gap by incorporating XAI techniques, specifically SHAP (SHapley Additive exPlanations), to reveal model predictions. In this retrospective study, multiple databases were searched, and data on eight risk factors of 1319 patients were obtained. Prediction models have been developed using six different machine learning algorithms for heart attack classification. In heart attack risk classification, the XGBoost (eXtreme Gradient Boosting) model achieved the best predictive values with 91.28% Accuracy, 90% Precision, 92% Recall, and 91% F1-score. In addition, the model algorithms were evaluated according to AUC, and again, the XGBoost model achieved the best result 0.91. In the Random Forest Feature importance evaluation, troponin was the most critical variable affecting the diagnosis. SHAP graphs showed that troponin (+4.19) was the most critical risk factor. This research highlights the potential of XAI to bridge the gap between complex AI models and clinical applicability and suggests that future studies move in a promising direction to refine further and validate AI-powered healthcare solutions.

Keywords: Explainable Artificial Intelligence, Heart Attack Risk Prediction, Machine Learning, XGBoost, SHAP.

Kalp Krizi Riski Tahmininde Açıklanabilir Yapay Zeka Yaklaşımı

Öz

Bu çalışma, kalp krizi risklerinin analiz edilmesi ve doğru bir şekilde sınıflandırılması için açıklanabilir yapay zeka (XAI) tekniklerinin uygulanabilirliğini incelemeyi amaçlamaktadır. Kalp krizi risk faktörlerinin karmaşıklığı göz önünde bulundurulduğunda, geleneksel makine öğrenmesi modelleri genellikle klinik karar verme için gerekli olan şeffaflığı sağlamamaktadır. Bu araştırma, model tahminlerini açığa çıkarmak için özellikle SHAP (SHapley Additive exPlanations) gibi XAI tekniklerini dahil ederek bu boşluğu ele almaktadır. Çalışmada birden fazla veri tabanı taranarak 1319 hastanın 8 risk faktörüne ilişkin veriler elde edilmiştir. Kalp krizi sınıflandırması için altı farklı makine öğrenmesi algoritması kullanılarak tahmin modelleri geliştirilmiştir. Kalp krizi risk sınıflandırmasında XGBoost modeli %91,28 Accuracy, %90 Precision, %92 Recall ve %91 F1-Score ile en iyi tahmin değerlerini elde etmiştir. Ayrıca model algoritmaları AUC'a göre değerlendirildiğinde, XGBoost modelinin 0,91 doğruluk değeri ile en iyi sonucu elde edttiği görülmüştür. Random Forest özellik önem değerlendirmesinde değişkenler arasında tanıyı etkileyen en kritik değişkenin troponin olduğu görülmüştür. SHAP grafiklerinde de troponin (+4.19) en önemli risk faktörü olduğu görülmüştür. Bu araştırma, XAI'nın, karmaşık AI modelleri ile klinik uygulanabilirlik arasındaki boşluğu kapatma potansiyelini vurgulamakta ve gelecekteki çalışmaların AI destekli sağlık çözümlerini daha da rafine etmek ve doğrulamak için umut verici bir yönde ilerlemesini önermektedir.

Anahtar Kelimeler: Açıklanabilir Yapay Zeka, Kalp Krizi Risk Tahmini, Makine Öğrenmesi, XGBoost, SHAP.

[1]Burdur Mehmet Akif Ersoy University, Department of Computer Engineering, Burdur, Turkey, tulayturan@mehmetakif.edu.tr

[*]Sorumlu Yazar/Corresponding Author

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1. Introduction

Heart diseases constitute a serious public health problem in global health and are among the leading causes of death and morbidity worldwide (URL-1). Early diagnosis and accurate identification of risk factors are vital in preventing and managing these diseases (Lee et al., 2006). Artificial intelligence (AI) and machine learning (ML) technologies in medical diagnosis and disease prediction have received increasing attention in recent years. These technologies enable more accurate prediction of disease risks thanks to their ability to extract and analyze complex patterns from large data sets (Johnson et al., 2018; Katarya and Meena, 2021). However, the decision-making processes of AI-based predictive models are often considered a "black box." This means the reasons and mechanisms underlying the models' predictions must be clarified and understandable (Mathews,2019; Hassija et al., 2024; Marcus and E, Teuwen, 2024). Explainable artificial intelligence aims to solve this problem by increasing the transparency and understandability of model predictions, thus increasing confidence in the models and making them easier to use in clinical applications (Arrieta et al., 2020; Kırboğa and Küçüksille, 2023; Hassija et al., 2024; Kumar et al., 2024). Heart attack risk prediction offers a critical area to demonstrate the potential of XAI. Studies in this area can help patients and healthcare providers better understand and implement treatment and prevention strategies (Chen and Guestrin, 2016; Hernandez et al., 2019; Vatansever et al., 2021).

The study aims to increase the understanding of heart attack risk prediction models and their effectiveness in clinical decision-making. Thus, maximizing the potential of AI-based healthcare applications and contributing to better patient health outcomes will be possible. In this context, the study first investigated the applicability of XAI techniques for predicting heart attack risk using a data set consisting of 1,319 records taken from the Kaggle data platform and containing variables critical for heart attack classification. In our research, models were developed using six different machine learning algorithms to predict heart attack risk. XAI techniques such as SHAP were used to explain and visualize the model's predictions, which make the dynamics underlying the model's prediction processes understandable (Mangalathu et al., 2020; Antwarg et al., 2021; Kim and Kim,2022; Movsessian et al., 2022). In the study, we compared the heart attack risk factors with the Random Forest importance feature and the SHAP method and evaluated all. We graphed and interpreted the comparisons in detail.

This article highlights;

- Troponin, kcm, and glucose are essential factors for heart attack.
- Combining ML and XAI techniques in heart attack risk prediction will significantly contribute to existing field methodologies. This integration increases the accuracy and reliability of risk prediction models.

• Extreme Gradient Boost model achieved a high prediction result of heart attack risk classification with 91.28% accuracy.

2. Materials and Methods

The study consists of 6 chapters. First, data set selection was made. With the second RF, the feature importance of the dataset variables was determined. In the third stage, the data content is divided into train/test data with the Holdout method. In the fourth stage, models were developed with Artifical Neural Network (ANN), K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Decision Tree (DT), Random Forest (RF), and XGBoost supervised learning model classification techniques. In the fifth stage, the classification performances of the models were compared with precision, recall, f1-score, and accuracy evaluation metrics. In the last section, model results are explained using SHAP plot techniques. The workflow diagram of the study is shown in Figure 1. Artificial intelligence and enabled technologies (Large Language Models [LLMs], chatbots, or image generators) were not used to produce our work.

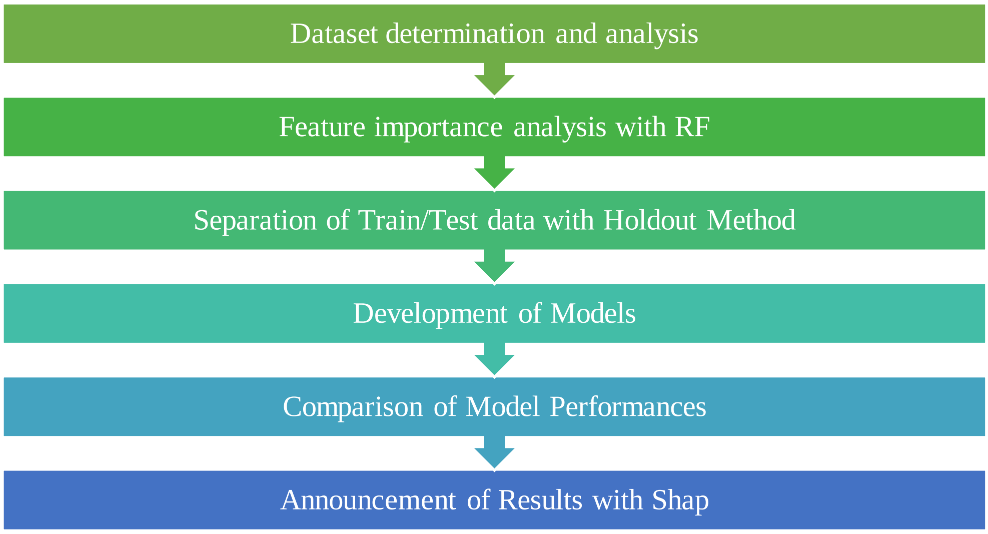

Figure 1. Flowchart illustrating the stages of this retrospective study.

2.1. Data Properties and Processing

A comprehensive data set was used in our study, aiming to facilitate the classification of the presence of heart disease in individuals. The dataset is retrieved from the widely recognized Kaggle platform (URL-2) The dataset can be accessed at https://www.kaggle.com/datasets/bharath011/heart-disease-classification-dataset/data?select=Heart+Attack.csv. The dataset consists of 1,319 records with eight different features that are critical for heart disease diagnosis and classification. The content of the data set is given in Table 1.

Table 1. Dataset properties overview.

Attribute	Description	Data Type
Age	Age of the patient	Integer
Gender	Gender of the patient (0, 1)	Categorical
Heart Rate (Impulse)	Patient's heart rate	Integer
Systolic BP (PressureHigh)	Systolic blood pressure	Integer
Diastolic BP (PressureLow)	Diastolic blood pressure	Integer
Blood Sugar (Glucose)	Blood sugar level	Integer
CK-MB (kcm)	Creatine Kinase MB level	Float
Test-Troponin (Troponin)	Troponin level	Float

In the data set, records with a positive heart attack risk are shown with "1", and records with a negative heart attack risk are shown with "0". Data set classification diagnostic information is given in Figure 2, and the 2D PCA graph in Figure 3.

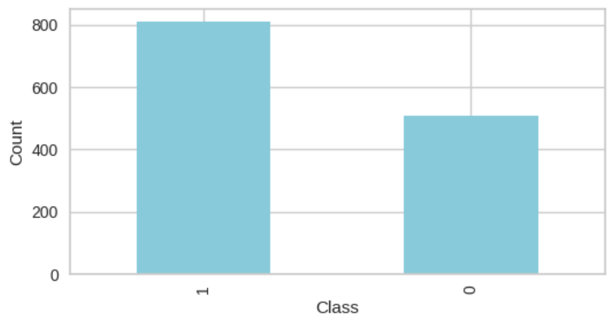

Figure 2. Number of diagnoses with positive and negative heart attack risk in the data set.

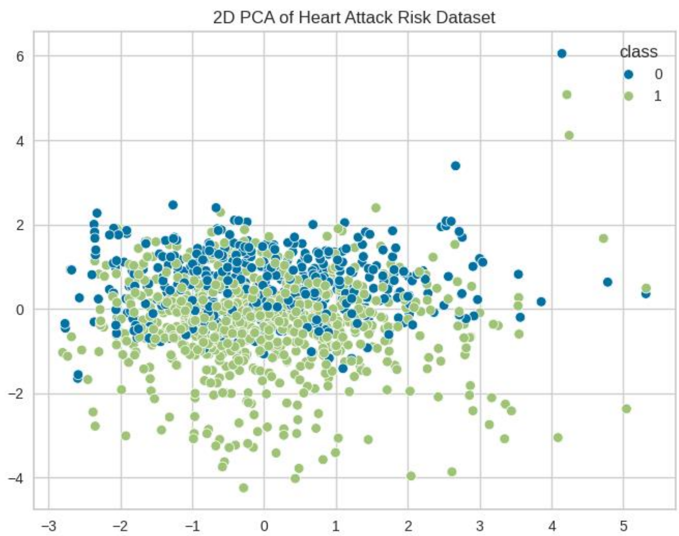

Figure 3. Data set classification diagnostic information 2D PCA plot.

The data set offers a unique opportunity to conduct a comprehensive study to develop heart attack prevention strategies. Using the data set with ML, DL, and AI techniques, a better understanding of heart attack risk factors, how these factors interact, and what measures can effectively reduce the risk of heart attack have been examined in detail.

2.2. Random Forest Feature Importance

Random Forest Feature Importance is a method used to evaluate the importance of each feature in the model's predictions. This technique allows us to determine which variables most influence the prediction outcome by measuring the contribution of each feature to the model's accuracy (Wang et al., 2016; Hasan et al., 2016; AlSagri and Ykhlef, 2020; Akhiat et al., 2021).

The study's Random Forest Feature Importance analysis revealed that Troponin and CK-MB (kcm) features are more important than all other variables in the heart attack risk prediction model. This finding suggests that Troponin and CK-MB levels are critical biomarkers when assessing heart attack risk. While troponin is considered an indicator of myocardial damage and acute coronary syndrome (Ebashi et al., 1968; Ebashi et al., 1971; Filatov et al., 1999), CK-MB is another critical marker used in determining heart muscle damage (Thiele et al., 2021; Doğan and Küçükakçalı,2023; Abubaker et al., 2024). Figure 4 shows the Random Forest Feature Importance analysis of heart attack risk factors.

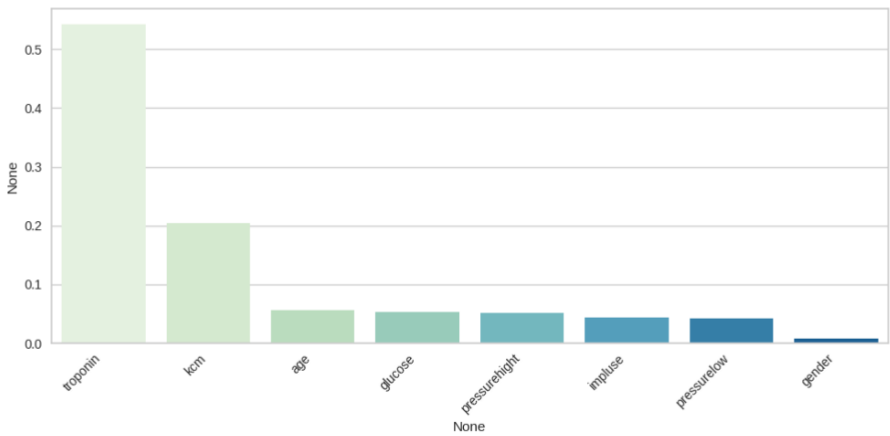

Figure 4. Random Forest Feature Importance analysis of heart attack risk factors.

2.3. Holdout Model Verification Method

Before developing the models, the data set was divided into an 80% training set and a 20% test set using the Holdout method. Accordingly, out of 1319 records in our data set, 264 test sets are divided into 1055 training sets. If we gave all the data to our models without dividing it, our models would start to memorize the entire content after a certain period, resulting in overfitting (Hawkins, 2004; Coolen et al., 2017; Pothuganti et al., 2018). As a result of dividing the data, our models were trained with training data, while the test data enabled them to perform on data they had never encountered.

2.4. Classification Models

The dataset used in the study is suitable for the supervised binary classification task, where machine learning models can be trained to predict heart attack risk. The models aim to classify heart attack (1) or not heart attack (0). In our study, models were developed for heart attack risk classification with an Artificial Neural Network, K-Nearest Neighbor Algorithm, Support Vector Machines, Decision Trees, Random Forests, and XGBoost, supervised learning model classification techniques. The KNN algorithm is based on the logic of including data of unknown classes into the closest class by calculating their distances from other data (Zhang and Zhou, 2007). Support vector machines are algorithms that appropriately separate data from two or more classes (Huang et al., 2018). Separation of classes is called decision boundaries or hyperlinks. It is determined by planes (Jakkula, 2006). Random Forest is based on combining and evaluating the predictions produced by multiple decision trees. The combination of Bagging and Random Subspace methods forms it (Rigatti, 2017). The first cells of decision trees are called root nodes. Each observation is classified as “Yes” or “No” according to the root condition (De Ville,2013). XGBoost is an optimized high-performance version of the Gradient Boosting algorithm. It entered our lives with the article “XGBoost: A Scalable Tree Boosting System,” published by Tianqi Chen and Carlos Guestrin in 2016 (Osman et al., 2021). The most important features of the algorithm are that it can achieve high prediction power, prevent overlearning, manage empty data, and do it quickly (Qiu et al.,2022).

2.5. Model Evaluation Metrics

Confusion Matrix, Accuracy, Sensitivity, Precision, and Recall calculation methods are used to evaluate the performance success of classification models.

Accuracy was calculated as shown in Equation (1).

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \tag{1}$$

Sensitivity was calculated as shown in Equation (2).

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{2}$$

Precision was calculated as shown in Equation (3).

$$\text{Preccion} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{3}$$

Recall is calculated as shown in Equation (4).

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{4}$$

2.6. Explainable Artificial Intelligence and SHAP Method

Explainable artificial intelligence is the method used to understand the predictions of machine learning models and explain them in a way that humans can understand (Gunning et al., 2019). Machine learning is a field of research developed on interpretability techniques. The concept of explainable artificial intelligence dates back to the foundations of artificial intelligence research and the development of today's expert systems. The concept of explainable artificial intelligence, which helps us understand the model behavior of machine learning systems, is also critical for many tasks. Some of these;

- It describes predictions to inform and support human decision-making.
- It enables the improvement of modeling and data collection processes.
- Validating accepted model behavior.
- Presenting model predictions to stakeholders.

SHAP is a method introduced by Lundberg and Lee in 2017 to explain the outputs of machine learning models (Parsa et al., 2020). It is based on the Shapley game theory presented by Lloyd Stawell Shapley in 1952. The Shapley variable is a calculation of how much a member within a group contributes to the final value. This value can also be defined as the marginal contribution of the selected member to the group. To explain the marginal contribution of a feature, we only need to observe the model's outputs.

The Shapley value calculation for a selected feature is shown in Equation (5).

$$\emptyset_i = \frac{1}{|N|!} \sum_{S \subseteq N\{i\}} |S|!\,(|N| - |S| - 1)!\,[f(S \cup \{\dot{\mathrm{I}}\}) - f(S)] \quad (5)$$

In the equation, the Shapley value of feature *i* is calculated. First, the marginal contribution calculation is made on all subsets S with and without feature *i*. The Shapley value of feature *i* is found by summing the obtained values.

3. Findings and Discussion

Our study used a unique dataset of 1319 patient data containing clinical information on heart attack risk factors and outcomes. In the study, we built models with five different classification algorithms. The classification performances of the models were compared with precision, recall, f1-score, and accuracy evaluation criteria. The evaluation showed that the XGBoost model gave the best results with 91.28% accuracy, 90% precision, 992% recall, and 91% F1 score. Performance values of KNN, SVM, DT, RF, and XGBoost models are shown in Table 2.

Table2. Precision, recall, f1-score, model accuracy scores for developed algorithms

Model	Precision	Recall	F1-Score	Accuracy
ANN Model	0.85	0.87	0.86	0.8636
KNN Model	0.74	0.76	0.74	0.7462
SVM Model	0.75	0.77	0.73	0.7348
DT Model	0.89	0.90	0.89	0.9015
RF Model	0.89	0.91	0.90	0.9053
XGBoost Model	0.90	0.92	0.91	0.9128

Model algorithms were evaluated according to AUC, and the XGBoost model achieved the best result with AUC values of 0.91. XGBoost ROC performance value is given in Figure 5.

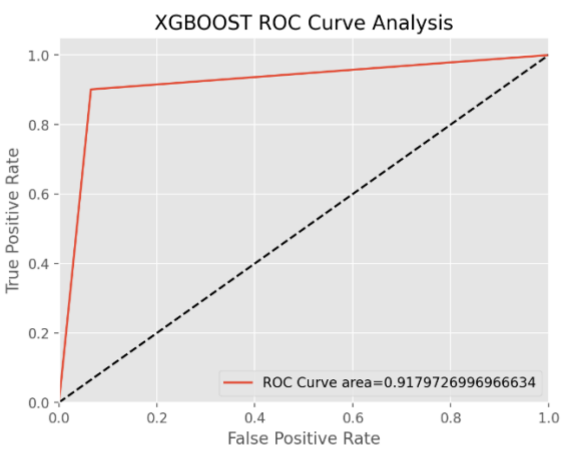

Figure 5. XGBoost ROC Curve Analysis

In the Random Forest feature importance evaluation, troponin was the most critical variable affecting the diagnosis. Variable importance rankings and importance weights are given in Table 3.

Table 3: Random Forest feature importance ranking and weights.

Ranking	Risk Factors	Importance
1	troponin	0.54
2	kcm	0.2
3	age	0.06
4	pressurehight	0.05
5	glucose	0.05
6	impluse	0.04
7	pressurelow	0.04
8	gender	0.01

The effects of heart attack risk factors on the outcome are explained in detail with SHAP, one of the XAI techniques. Beeswarm, summary, bar, heatmap, and SHAP plots were used in the study. According to the Beeswarm chart (Figure 6), troponin, kcm, and glucose are the most critical risk factors.

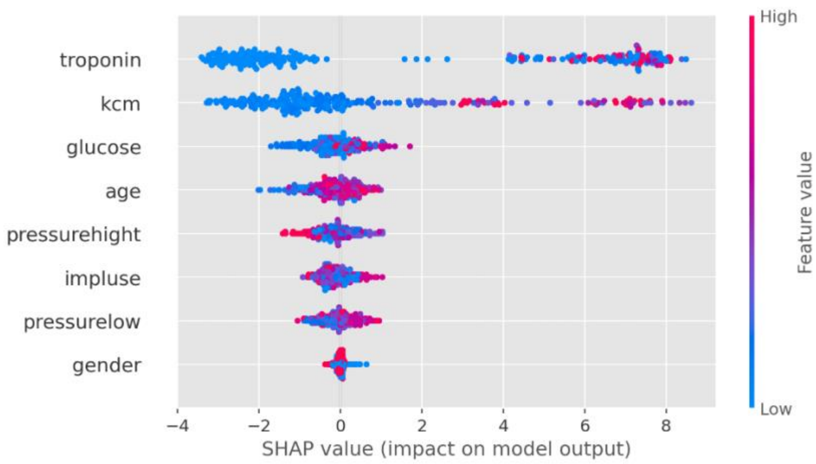

Figure 6. Beeswarm importance plot listing the most significant risk factors.

Summary Plot (Figure 7) was used on the entire data set to explain the importance of the variables and their contribution to the model. While each point in the graphs represents a person, the X-axis shows SHAP values. When we examine the results obtained in the graph, it is seen that the troponin feature makes the most marginal contribution to the predictions. Additionally, it is seen in the graph that as the value of this variable increases, the SHAP value also increases. As a result, the probability of the diagnosis resulting in a "heart attack risk positive" increases.

Figure 7. Summary importance plot listing the most significant risk factors.

Bar plot, its simple appearance, the bar chart clearly shows the effects of variables on the model output. Figure 8 shows troponin, kcm, and glucose are the most important risk factors.

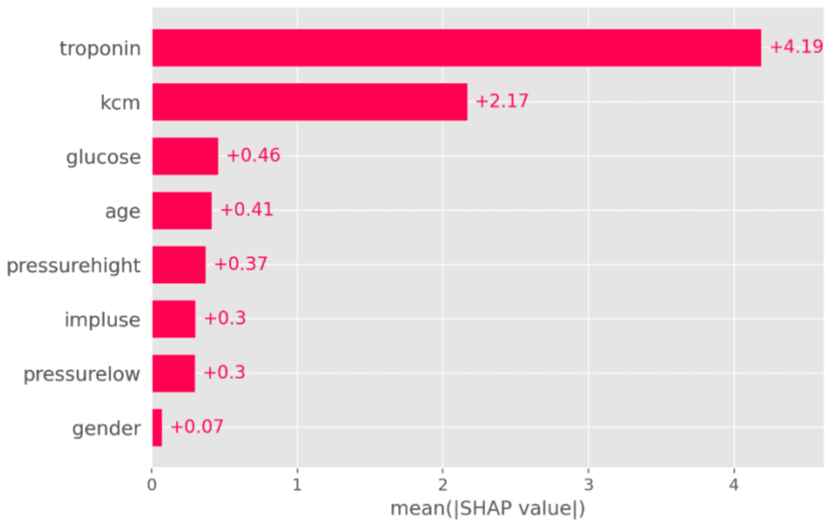

Figure 8. Bar importance plot listing the most significant risk factors.

The last SHAP plot used in the study is the Heatmap plot shown in Figure 9. This graph shows the global interpretability of the trained model. The figure, the x-axis represents the samples, and the y-axis represents the risk factors. The f(x) curve at the top of the graph is the model predictions of the samples. To the right of the graph are the SHAP values coded in the color scale. According to the graph, "troponin" is the most important variable and the impact value is shown for each diagnosis.

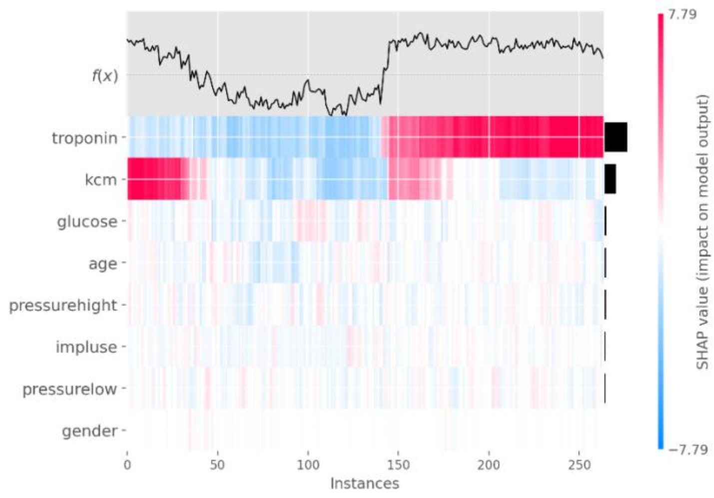

Figure 9. Hetmap importance plot listing the most significant risk factors.

4. Conclusions and Recommendations

This study demonstrates the usability and effectiveness of XAI techniques, especially the SHAP method, in predicting and analyzing heart attack risk. The research was conducted on extensive datasets obtained from the Kaggle database to predict heart disease using ML models, determining the importance of risk factors and providing clinicians with new treatment perspectives for these risk factors.

Among the artificial intelligence models developed in the study, the XGBoost model is the most effective model in heart attack risk prediction with an accuracy rate of 91.28%. Pre-processing the data before training the model and separating the data into training and testing is important for performance. In the study, the model was carried out separately for training and testing, which ensured that the model's training process achieved good results without being affected by extreme values. The XGBoost algorithm is described using the Tree SHAP method. Tree SHAP is an XAI technology designed to annotate tree-based models and was used in this study as an effective tool to annotate the predictions of the XGBoost model.

The Random Forest method determined the feature importance of heart attack risk factors. According to the RF results, the critical factors that most direct the model performance were determined to be troponin and kcm. The RF method explains how risk factors affect model performance. It charts the factors affecting SHAP model predictions, one of the XAI techniques. SHAP graphs also showed that the most important factors affecting the risk of heart attack are troponin and kcm.

Table 4 compares the AI models, prediction success rates, and methodologies utilized in the current study with those reported in the existing literature. The analysis highlights that the proposed research not only achieves a higher prediction success rate but also incorporates advanced Explainable Artificial Intelligence techniques, enhancing the model's transparency and interpretability. These findings demonstrate the distinct contributions of this study, positioning it as a noteworthy advancement in the field by addressing both predictive performance and the explainability of AI-driven outcomes.

Table 4: Comparison of algorithm, prediction success rates, and methods between the present study and existing literature.

Year	Article	Algorithm	Acc	XAI Methods
2019	Predicting Heart Attack Through Explainable Artificial Intelligence (Aghamohammadi et al., 2019)	ANFIS-GA	%84,43	-
2019	Improved Heart Disease Prediction Using Deep Neural Network (Ashraf et al., 2019)	DNN	%87,64	-
2020	Heart Disease Prediction using CNN Deep Learning Model (Harkulkar et al., 2020)	CNN	%75,2	-
2020	Heart diseases prediction using deep learning neural network model (Sharma et al., 2020)	DNN	%90,78	-
2022	Heart Attack Prediction using Machine Learning and XAI (Ahsan, 2022)	XGBoost	%86,88	SHAP ve LIME
2022	XGBoost, A Novel Explainable AI Technique, in the Prediction of Myocardial Infarction: A UK Biobank Cohort Study (Moore and Bell, 2022)	XGBoost	0.86	SHAP
2023	Performance-enhanced KNN algorithm-based heart disease prediction with the help of optimum parameters (Takci, 2023)	KNN	%90,11	-
2024	Application of Deep Learning for Heart Attack Prediction with Explainable Artificial Intelligence (Dritsas and Trigka, 2024)	Hybrid Model	%91	SHAP
2024	Heart disease prediction: Improved quantum convolutional neural network and enhanced features (Pitchal et al., 2024)	IQCNN	%91	-
2024	Comparison of Machine Learning Algorithms for Heart Disease Prediction (Abdulhussein and Bilgin, 2024)	LR	%91,60	-

This study elucidates the role of biomarkers such as Troponin and CK-MB in heart attack risk prediction, providing important insights that may help develop new strategies for the early diagnosis and management of cardiovascular diseases. Limitations of the study include the need for more data used for training and validation. This may enable the differences between groups to be revealed more clearly and the accuracy of the results to be increased by using more data.

This study demonstrates the potential of XAI techniques in the development of heart attack risk prediction models. The findings of the research aim to provide significant progress in the early diagnosis and treatment of cardiovascular diseases by contributing to the development of new strategies that can be used in the prevention and management of heart diseases.

Authors' Contributions

The author has completed the article alone.

Statement of Conflicts of Interest

There is no conflict of interest.

Statement of Research and Publication Ethics

This study complies with research and publication ethics.

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