Intelligent Heart Disease Prediction Using CatBoost Empowered with XAI

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Abstract: Heart disease refers to a class of diseases involving the heart and blood vessels, including coronary artery disease, heart failure, and arrhythmias. Concerns associated with heart disease include increased risk factors like hypertension, smoking, high cholesterol, and a sedentary lifestyle. Early prediction and effective management are crucial to mitigate these risks and prevent complications. In the context of heart disease prediction, the CatBoost machine learning (ML) classifier was applied to a dataset divided into training and testing, resulting in a notable testing accuracy of 84.4%. The SHAP (SHapley Additive exPlanations) explainability technique was employed to illuminate the decision-making process of CatBoost predictions. This approach enhances transparency, fairness, and interpretability through computation and visualization of SHAP values, revealing insights into the pivotal features influencing heart disease prediction. Integrating the XAI (Explainable Artificial Intelligence) technique in this research seeks to deepen the knowledge of the complex dynamics involved in heart disease prediction.

Keywords: Machine learning (ML); CatBoost; Explainable artificial intelligence (XAI); Heart disease; SHapley Additive exPlanations (SHAP)

1 Introduction

According to data delivered by the World Health Organization (WHO), heart disease is responsible for over 31% of all global deaths [1]. Heart disease is a general term that contains a spectrum of diseases involving the heart. It includes blood vessel diseases like irregular heartbeats (arrhythmias), heart defects present at birth, and coronary artery disease. Signs of heart disease can vary but may contain fatigue, shortness of breath, irregular heartbeat, chest pain, and fainting. Some of the most common risk aspects for heart disease include smoking, family history, high blood pressure, diabetes, and high cholesterol [2].

Treatment for heart disease often involves a mixture of medication, lifestyle changes, and, in some cases, surgery. Medications are utilized to manage symptoms and reduce the risk of complications, like high cholesterol and high blood pressure medications. Surgical procedures may be necessary to treat heart disease in some severe cases [3], [4].

Machine learning (ML) is preferred over traditional methods for predicting heart disease because it can detect complex patterns, provide real-time predictions, and offer personalized risk assessments based on diverse patient data. The adaptability and continuous learning capabilities of ML contribute to more accurate and efficient risk prediction in cardiovascular health.

However, ML has a limitation of the black-box nature, meaning it does not explain its decision-making on what grounds a specific model reached its conclusion. The ML technique CatBoost, empowered with the explainable artificial intelligence (XAI) technique SHapley Additive exPlanations (SHAP), is utilized in this article to address the issue of black-box [12-16].

Section 2 briefly reviews related work. Section 3 presents the proposed methodology. Section 4 presents the experiment and results, while section 5 offers a conclusion and future work.

2 Related Work

ML methodologies have been utilized to predict heart disease with high accuracy. The accuracy of Khemphila et al.'s [5] multi-layer perceptron (MLP) diagnosis of heart disease was 80.17%. In the study by Vikas Chaurasia et al. [6], the authors downloaded a dataset including 14 distinct qualities from the UCI laboratory. They only employed 11 attributes, utilizing Naïve Bayes (NB) and decision tree (DT) ML methods, to predict heart disease. Using the WEKA tool, they obtained 84% accuracy for DTs and 82% accuracy for NB in their work.

Princy et al. [7] utilized data mining techniques such as NB, ID3, and neural networks to classify the risk level of heart disease by selecting various parameters. The authors discovered that accuracy increased with the number of features, with more accuracy occurring with a higher feature count. This study's outcome yielded an accuracy of 80.6%.

J. Maiga et al. [8] created a model for predicting heart disease that uses a variety of feature combinations. Several classification techniques, including K-Nearest Neighbor (KNN), NB, logistic regression (LR), and random forest (RF), were employed. The authors used RFs to obtain the best accuracy possible, 73%.

2.1 Gap in Related word

Following are the gaps identified in previous methodologies:

1. Accuracy can be improved.
2. There needs to be an explanation of how these previous methodologies reached this decision-making, i.e., the need for more fairness and transparency.

3 Proposed Methodology

The architecture of the proposed model is shown in Figure 1. After the data acquisition of the heart disease dataset, it goes through data preprocessing. The dataset is checked for duplicate and missing values in data preprocessing. After successful data preprocessing, the dataset is split into training and testing. 70% of the dataset is used for training, while 30% is used for testing. ML classifier CatBoost is applied to the training dataset.

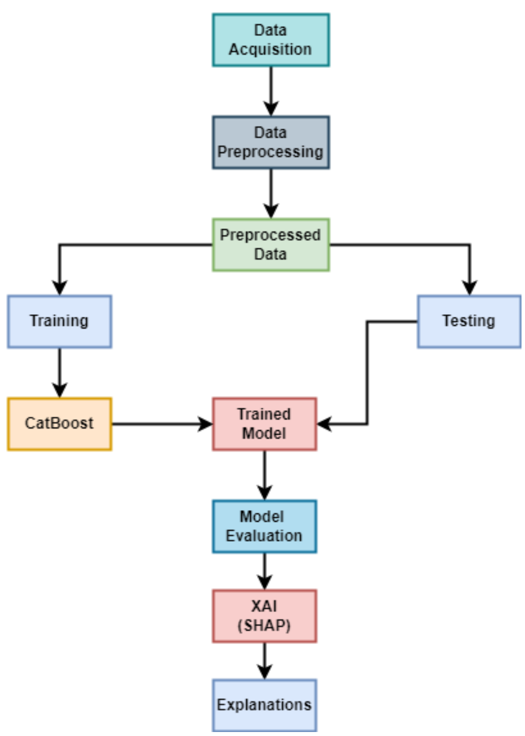

Figure 1: The architecture of the proposed model

After successful training, the testing dataset set is applied to the trained model to evaluate the model. The model evaluation exhibits that it has decent prediction accuracy but needs to explain what ground model reached its decision-making. The XAI technique SHAP is applied to bring transparency, fairness, and interpretability. SHAP will explain the decision-making behind the prediction made.

3.1 Dataset of the heart disease

The dataset of heart disease was acquired from Kaggle Respiratory [9]. Figure 2 displays the attributes of the dataset.

Sr. no.	Attributes	Information
1	Age	Age of the patient
2	Sex	Gender of the patient (1= male; 0= female)
3	Cp	Chest pain of the patient (0=typical angina; 1= atypical angina; 2= non-angina pain; 3= asymptomatic)
4	Trestbps	Blood pressure of resting patient (mm Hg)
5	Chol	Serum cholesterol of the patient (mg/dl)
6	Fbs	Fasting blood sugar of the patient >120 mg/dl (1= true; 0= false)
7	Restecg	Resting electrocardiographic of the patient (0= normal; 1= having ST-T wave abnormality; 2= left ventricular hypertrophy)
8	Thalach	Patient's maximum heart rate
9	Exang	Angina induced by exercise (1= yes; 0= no)
10	Oldpeak	ST depression induced by exercise relative to rest
11	Slope	The slope of the peak exercise ST segment (0= up sloping; 1= flat; 2= down sloping)
12	Ca	Number of major vessels (0-3) colored by fluoroscopy
13	Thal	Type of the defect (0= normal; 1= fixed defect; 2= reversible defect)
14	Condition	Checking for disease (0= no disease; 1= disease)

Figure 2: Attributes of the dataset

3.2 Catboost

CatBoost, developed by Yandex [10], is an ML gradient-boosting classifier designed to handle categorical features effectively. It reduces the need for extensive preprocessing by automatically converting categorical features into numerical features. It has an overfitting detector, and it stops training when it detects overfitting. It is an open-source library for C++, R, Python, and Java [11].

3.3 Shap

SHAP is an XAI technique that explains how an ML model makes individual predictions. It quantifies the contribution of each feature to a model's output. It is based on Shapley values from cooperative game theory. SHAP values deliver a fair method to distribute the impact of features among different predictions.

4 Experiment and results

The experiments and subsequent analysis of the study results are presented in this section. Different performance metrics like accuracy, misclassification rate, precision, sensitivity, and F1 score are utilized to evaluate the performance of the proposed model (equations 1-5).

$$\text{Accuracy}=\frac{TP+TN}{TP+FP+FN+TN}*100 \quad (1)$$

$$\text{Misclassification rate}=\frac{FP+FN}{TP+FP+FN+TN}*100 \quad (2)$$

$$\text{Precision}=\frac{TP}{TP+FP}*100 \quad (3)$$

$$\text{Sensitivity}=\frac{TP}{TP+FN}*100 \quad (4)$$

$$\text{F1 score}=2*\frac{Precision*Sensitivity}{Precision+Sensitivity} \quad (5)$$

TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative. Figure 3 displays the testing confusion matrix of the CatBoost classifier. In the case of no heart disease, 41 instances out of 48 were correctly classified, while 7 were misclassified as heart disease. In the case of heart disease, 35 instances out of 42 were correctly classified as heart disease, while 7 were misclassified.

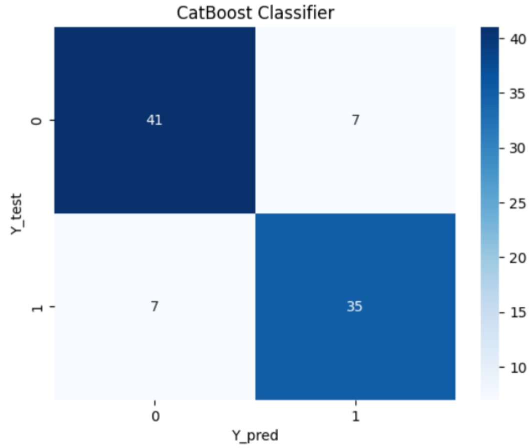

Figure 3: Testing confusion matrix of the CatBoost classifier

Table 1 shows the evaluation of different performance matrices.

Table 1: Evaluation of different performance matrices

Performance matrices	**Evaluation**
Accuracy	84.44 %
Misclassification rate	15.56 %
Precision	85.42%
Sensitivity	85.42%
F1 score	0.85

Table 1 shows that CatBoost has decent prediction accuracy, but it needs to explain how the model reached this decision-making. To address this limitation, the XAI technique SHAP is employed. Figure 4 shows the mean absolute SHAP value bar plot for heart disease prediction. It shows the impact of each variable on the model's prediction. Thal has the highest impact, while fbs has the lowest impact.

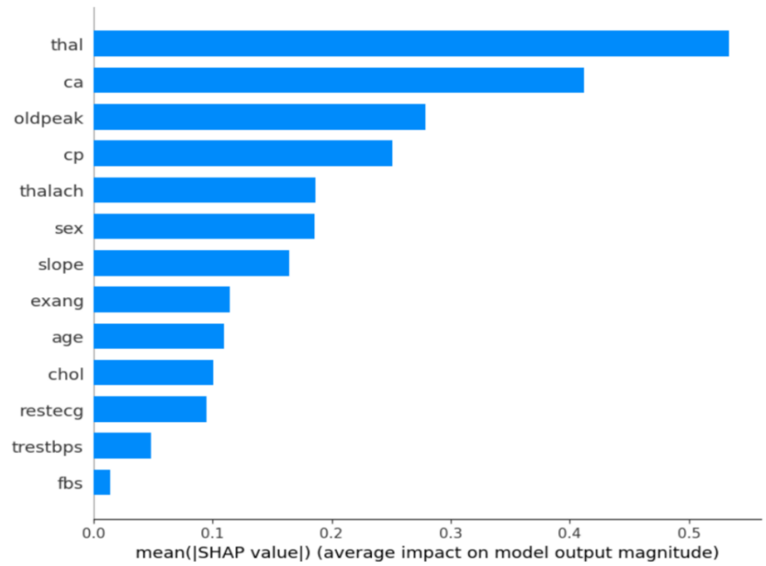

Figure 4: The Mean Absolute SHAP value bar plot for heart disease prediction

Figure 5 shows a beeswarm plot for heart disease prediction. This provides an overview of how each variable impacts the model's predictions across all of the data. Red dots show high impact, while blue dots show low impact.

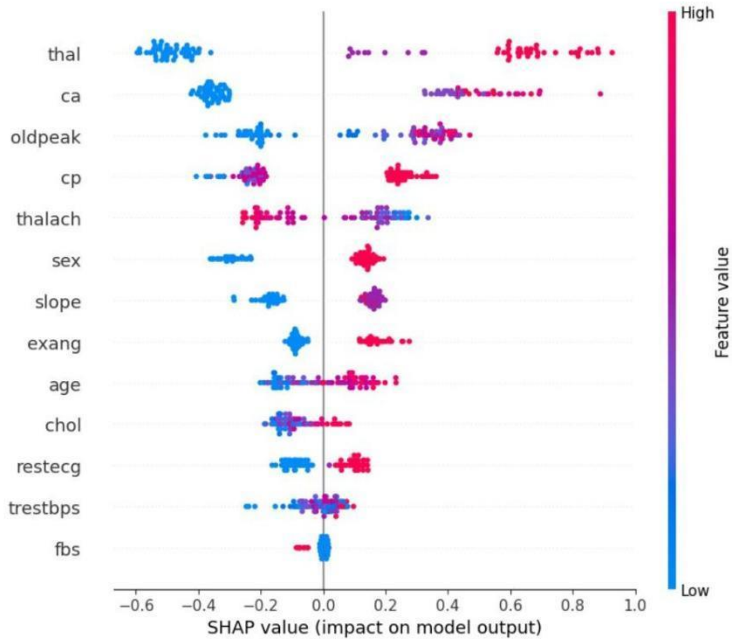

Figure 5: Beeswarm plot for heart disease prediction

Table 2 depicts a comparison of the proposed model with previous methodologies. The proposed model has better accuracy and uses XAI as compared to the previous methodologies.

Table 2: Comparison with previous methodologies

Author	Year	Methodologies	Accuracy (%)	Misclassification rate (%)	Use of XAI
Khemphila et al.'s [5]	2011	MLP	80.17	19.83	No
Chaurasia et al. [6]	2013	DT NB	84 82	16 18	No
Princy et al. [7]	2016	Data mining	80.6	19.4	No
J. Maiga et al. [8]	2019	RF	73	27	No
Proposed model	2023	CatBoost	84.44	15.56	Yes

5 Conclusion and Future Work

In conclusion, leveraging CatBoost as an ML classifier for heart disease prediction yielded promising results with a notable testing accuracy of 84.4%. Incorporating SHAP explainability techniques enhanced transparency and interpretability, shedding light on crucial features influencing predictions.

For future work, techniques like deep learning (DL) and federated learning can be utilized and empowered with XAI. For patient protection, Blockchain can also be utilized.

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