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A Hybrid Approach for Heart Disease Prediction Using Explainable Machine Learning and Blockchain-Enabled Data Integrity Framework

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Abstract: **Heart disease remains the leading cause of death globally, accounting for approximately 17.9 million deaths annually, according to the World Health Organization (WHO). Early detection is crucial to improving patient outcomes and reducing the burden on healthcare systems. However, traditional diagnostic methods are often time-consuming, expensive, and dependent on specialized medical expertise, with many patients failing to show early symptoms. To address these challenges, this study proposes a hybrid framework that integrates explainable machine learning techniques with blockchain-enabled data integrity mechanisms for heart disease prediction. The research focuses on developing and evaluating multiple machine learning models—XGBoost (XGB), Logistic Regression (LR), Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Gradient Boosting (GB)—to ensure accurate and interpretable predictions. Additionally, SHAP (SHapley Additive exPlanations) values are employed to provide transparency by explaining the contribution of each feature to the model's decision-making process. The Kaggle heart disease dataset, comprising 1,090 records and 14 relevant features, is used for model training and validation. Results indicate that XGBoost achieves the highest accuracy of 96.50%, outperforming LR (82%), KNN (87%), SVM (91%), and GB (96%). Furthermore, blockchain technology is incorporated to guarantee data immutability and trustworthiness, ensuring secure handling of sensitive medical data. In conclusion, this research introduces a robust, explainable, and secure hybrid approach that enhances the reliability of heart disease prediction systems, supporting healthcare providers in making informed clinical decisions and contributing to better global cardiovascular health outcomes..**

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KEYWORDS: Machine Learning, Heart Disease, SHAP, Machine Learning Algorithms

1 Introduction

Heart disease remains the leading cause of mortality worldwide, accounting for approximately 17.9 million deaths annually, which represents 32% of all global deaths according to the World Health Organization [1]. This broad category of cardiovascular disorders, ranging from coronary artery disease to heart failure, significantly diminishes life quality and leads to premature death if not detected and treated early. The Centers for Disease Control and Prevention (CDC) further report that in the United States alone, over 859,000 individuals die each year due to heart-related conditions [2]. Accurate and timely diagnosis is vital in reducing these alarming figures, as early detection facilitates targeted prevention and effective treatment interventions.

Despite medical advancements, the prevalence of heart disease continues to rise, especially in Asia, Europe, Africa, and the Middle East[3], [4]. Contributing factors such as high cholesterol, sedentary lifestyles, unhealthy dietary habits, and elevated blood pressure emphasize the urgent need for improved diagnostic systems. In recent years, Artificial Intelligence (AI), particularly Machine Learning (ML), has emerged as a promising tool in healthcare for early disease detection due to its ability to process vast datasets and deliver accurate predictions at low cost. Various machine learning models, including K-Means Clustering, Random Forest (RF), Logistic Regression (LR), Support Vector Machine (SVM), and Neural Networks (NN), have been applied to predict heart disease with significant success

. Furthermore, explainable AI techniques such as Shapley Additive Explanations (SHAP) have enhanced transparency in ML models by illustrating the impact of individual features on prediction outcomes. However, a critical challenge persists regarding the trustworthiness and security of healthcare data used in these models. Data manipulation, privacy breaches, and lack of integrity in medical datasets can severely compromise predictive outcomes and patient safety. To address these issues, Blockchain technology has been introduced in healthcare as a secure and decentralized framework ensuring tamper-proof data storage and enhanced transparency.

This research proposes a hybrid approach that combines Explainable Machine Learning models with a Blockchain-Enabled Data Integrity Framework for heart disease prediction. The proposed system aims to improve diagnostic accuracy through robust predictive algorithms while simultaneously ensuring the authenticity and integrity of medical data using blockchain.

The main contributions of this research are summarized as follows:

- A comprehensive hybrid framework integrating explainable machine learning algorithms with blockchain technology for secure and transparent heart disease prediction.
- Utilization of SHAP values to interpret and visualize the decision-making process of ML models, promoting trust and clinical interpretability.
- Improved predictive performance compared to conventional methods, with a focus on both accuracy and data security.

The remainder of this paper is organized as follows: Section II reviews relevant literature. Section III details the proposed hybrid framework and methodology. Section IV presents the experimental results and performance analysis. Finally, Section V concludes the study and discusses future directions.

2 Related Works

Machine Learning (ML) approaches have progressively advanced in recent years for heart disorder diagnosis by searching patterns through extensive dataset collections. This segment reviews necessary research that supported this study with multiple methods that successfully executed their tasks. Medical institutions worldwide use Machine Learning approaches to detect heart disease because these methods allow computers to extract hidden patterns from databases beyond human diagnostic abilities.

Mahmud et al. [1] utilized a metamodel combining RF, NB, DT, and KNN algorithms in its final prediction solution. The training and testing phase of the metamodel involved 11 standard features from five heart datasets called Cleveland, Long Beach, Hungarian, Statlog Heart, and Switzerland. Analysis by the proposed metamodel yielded 87% accuracy in heart disease prediction, which outperformed all other machine learning methods based on the research findings. Furthermore, In [3], the authors analyzed and evaluated several algorithms used for heart disease prediction in the field of data mining. They examined models such as Naïve Bayes, Neural Networks, and Decision Trees and concluded that the selection and number of features significantly influence prediction accuracy. Similarly, the authors in [4] developed an Intelligent Heart Disease Prediction System (IHDPS), utilizing data mining techniques like Artificial Neural Networks, Naïve Bayes, and Decision Trees. They incorporated multiple risk factors related to heart disease and validated the model using classification matrices. This system not only aids in training medical students but also reduces diagnostic costs. In [5], a combination of Artificial Neural Networks (ANN), K-Nearest Neighbors (KNN), Decision Trees, and Naïve Bayes was used for heart disease prediction. The study classified risk levels into three categories: greater than 50%, less than 50%, and 0%. The KNN algorithm was employed for training and classification, while the ID3 algorithm was used for prediction testing. Reference [6] employed Naïve Bayes with Laplace correction to build an intelligent prediction system based on a web-based questionnaire application, extracting patterns from historical data and answering complex diagnostic queries. In [7], a hybrid SVM-RFE (Support Vector Machine–Recursive Feature Elimination) method was used to select relevant features by eliminating redundant data, followed by classification using Random Forest and Naïve Bayes classifiers. Reference [8][9] applied a correlation-based feature selection (CFS) technique combined with Best-First-Search to reduce dimensionality. A modified Random Forest model was introduced, which outperformed the traditional Random Forest approach in heart disease prediction. In [9], a hybrid model integrating KNN and Ant Colony Optimization (ACO) was proposed for predicting Rheumatic Heart Disease. The KNN algorithm was used for classification, while ACO was used to optimize parameter values. Meanwhile, [10] utilized features extracted directly from electrocardiogram (ECG) data and applied KNN, which substantially improved classification results. Decision Tree algorithms were also widely applied. In [11], Alternating Decision Trees combined with Principal Component Analysis (PCA) were used to enhance feature selection and improve prediction performance. The study in [12] compared decision tree models against other classifiers and demonstrated superior performance in heart disease detection. In [13][14], an Artificial Neural Network (ANN) model was implemented, employing Chi-Square and PCA for feature selection, and was compared with Naïve Bayes, J48, and partial decision tree algorithms, achieving better predictive accuracy[15].

Overall, the reviewed literature highlights that both machine learning and deep learning techniques are extensively used for heart disease prediction. Researchers commonly focus on optimizing feature selection to enhance model performance and accuracy. Our study follows a similar approach by carefully selecting relevant features and implementing multiple machine learning techniques to predict heart disease with improved reliability.

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3 Research Methodology

This research introduces a hybrid framework that integrates machine learning, explainable artificial intelligence, and blockchain technology for heart disease prediction. The proposed approach consists of four core phases: data collection, data preprocessing, model training using multiple machine learning algorithms, and model interpretability through SHAP-based explainability. Additionally, a blockchain layer is embedded within the framework to ensure data integrity and traceability throughout the prediction process. The complete workflow of the proposed system is illustrated in Figure 2.

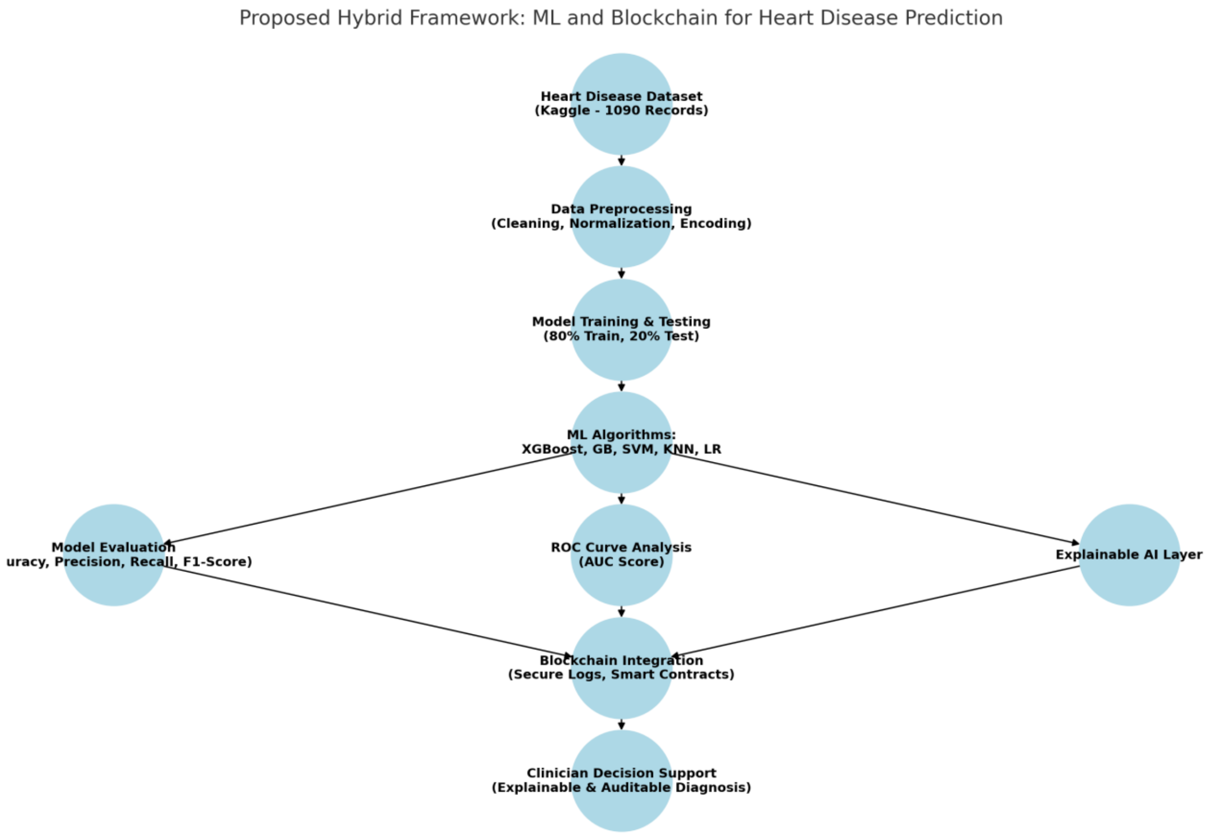

Figure 1: Proposed Model For Blockchain-Enabled Heart Disease Prediction

The proposed model is a comprehensive framework that integrates machine learning, explainable artificial intelligence (XAI), and blockchain technology to predict heart disease while maintaining transparency and data security. This model follows a structured pipeline that starts from data collection and proceeds through several analytical and security-enhancing stages to support clinical decision-making. The process begins with the collection of heart disease patient records from the Kaggle dataset, which contains 1090 instances with 14 medically relevant features. These features include patient age, cholesterol levels, resting blood pressure, chest pain type, and maximum heart rate achieved, among others. Once data is collected, it undergoes a data preprocessing stage. This step involves cleaning the data by removing missing or inconsistent entries, normalizing numerical features for model compatibility, and encoding categorical features into numerical format suitable for machine learning algorithms. Preprocessing ensures that the input data is clean, uniform, and ready for effective model training.The preprocessed data is then split into training and testing sets, with 80% used for training the models and 20% reserved for testing and evaluation. In the next stage, multiple machine learning models are applied, including XGBoost, Gradient Boosting, Support Vector Machine, Logistic Regression, and K-Nearest Neighbors. Each model is trained on the training data and evaluated on the testing set.

Performance evaluation involves calculating standard classification metrics such as accuracy, precision, recall, and F1-score to assess the predictive quality of each model. Additionally, Receiver Operating Characteristic (ROC) curves are generated to analyze the Area Under Curve (AUC) scores, providing a graphical representation of the trade-off between sensitivity and specificity for each classifier. An explainable AI layer is incorporated to provide interpretability to the model outputs. This layer helps in explaining the predictions by identifying which features influenced the outcome most strongly, making the system more transparent and trustworthy for healthcare professionals. Furthermore, the model integrates a blockchain layer to ensure that all steps, from data preprocessing to final prediction, are securely logged in a decentralized and immutable ledger. Blockchain smart contracts manage secure access controls, allowing only authorized healthcare providers to access or share diagnostic information while maintaining data privacy and integrity. The final output of the system is presented through a clinician decision support layer. This stage delivers an accurate prediction of heart disease risk along with feature-based explanations, all backed by blockchain-verified data trails. The combination of accuracy, explainability, and data integrity makes the proposed model suitable for practical application in healthcare settings, contributing to early diagnosis and improved patient outcomes.

4. Results

This section presents the experimental outcomes of the proposed hybrid framework combining machine learning, explainable AI, and blockchain for heart disease prediction. The performance evaluation is based on multiple machine learning classifiers tested on a publicly available heart disease dataset. The models were assessed using standard performance metrics such as accuracy, precision, recall, and F1-score.

The overall accuracy performance of the five applied machine learning models is shown in Table 1.

Table 1: Machine Learning Models Accuracy

Model Name	**Accuracy**
Logistic Regression (LR)	0.82
XGBoost	96.5
SVM	0.91
KNN	0.87
Gradient Boosting	0.96

Table 2 reveals how accurately different machine learning techniques can predict data during classification. The XGBoost gave the best results with 96.50% accuracy compared to all other methods, like LR at 82%, SVM at 91%, KNN at 87%, and Gradient Boosting at 96%. The table shows that XGBoost and Gradient Boosting do better than other models studied in correctly classifying disease and are the best tools.

The Classification Report of the Machine Learning Models is discussed below.

Table 2: Classification Reports of Machine Learning Models Accuracy

XGBoost Classification Report				
Class	Precision	Recall	F1-Score	Support
0	0.96	0.97	0.97	150
1	0.97	0.95	0.97	158
Average	0.96	0.96	0.97	308
Accuracy	96.50%			
Gradient Boosting Classification Report				
Class	Precision	Recall	F1-Score	Support
0	0.97	0.96	0.96	150
1	0.96	0.97	0.97	158
Average	0.96	0.96	0.96	308
Accuracy	96%			
KNN Classification Report				
Class	Precision	Recall	F1-Score	Support
0	0.85	0.89	0.87	150
1	0.89	0.85	0.87	158
Average	0.87	0.87	0.87	308
Accuracy	87 (%)			
Logistic Regression Classification Report				
Class	Precision	Recall	F1-Score	Support
0	0.87	0.74	0.80	150
1	0.78	0.89	0.83	158
Average	0.83	0.82	0.82	308
Accuracy	82%			
SVC Classification Report				
Class	Precision	Recall	F1-Score	Support
0	0.90	0.91	0.90	150
1	0.91	0.91	0.91	158
Average	0.91	0.91	0.91	308
Accuracy	91%			

The ROC curve of the proposed Machine Learning Models is presented in Figure 5.

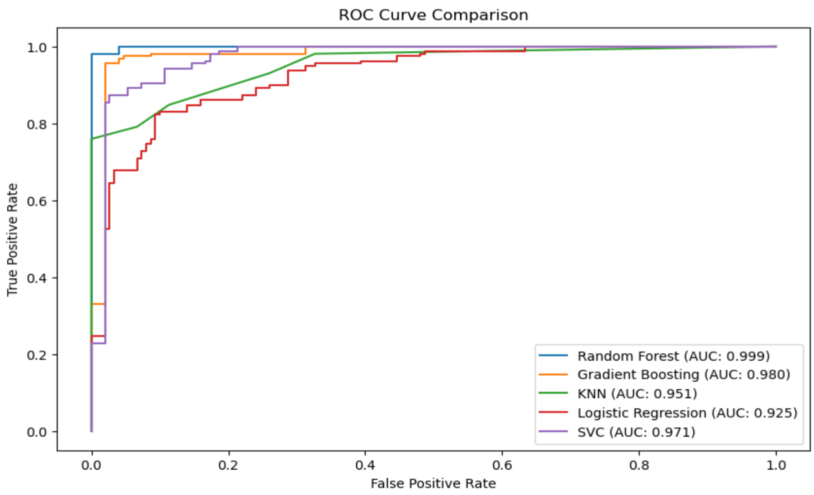

Figure 2: ROC Curve of the Machine Learning Models

Figure 2 represents the ROC (Receiver Operating Characteristic) curves of the various Machine Learning models that predict heart disease. The ROC curve evaluates classification model performance by representing the True Positive Rate (sensitivity) versus False Positive Rate (1 - specificity) at different threshold values. The curve evaluates how well the model detects heart disease in patients compared to those without heart disease. Predictive performance increases with higher area values under the curve (AUC). The research analysis presented in Figure 5 showcases the AUC scores of XGBoost, Logistic Regression, SVM, KNN, and Gradient Boosting. XGBoost's accuracy of 99% indicates it would generate the best AUC value, which signifies excellent class discrimination. A model with its ROC curve positioned near the top-left side of the graph demonstrates optimal performance. The curve proves essential for verifying the predictive algorithms' reliability when detecting heart diseases.

As the accuracy of the XGBoost's model is high, only the SHAP of the XGBoost's Model is selected.

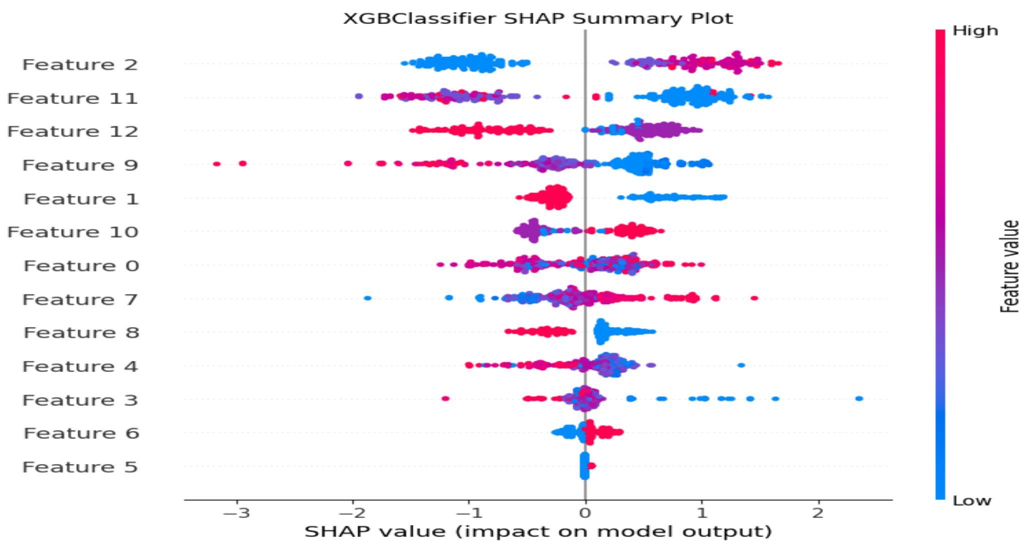

Figure 3: SHAP Value of Features

The XGBoost-based heart disease prediction model receives its SHAP (Shapley Additive Explanations) value analysis through Figure 3. SHAP values present a robust interpretability method to evaluate how each feature affects predictions generated by the model. Each dot in this summary plot represents a data point, and its color transition from red to blue shows the feature value scale, with high values appearing red and low values appearing blue. A particular feature's influence on model output appears as SHAP value measurements on the X-axis. The SHAP values measure the impact on heart disease probability where positive values shift the model toward heart disease class 1, but negative values move it toward class 0. Models make predictions primarily based on features identified at the top section of the plot because those features substantially affect prediction results. The model's heart disease prediction becomes higher when the maximum heart rate achieved reaches higher values because this feature shows mostly red points with positive SHAP values.

Lastly, all prediction outcomes, SHAP explanations, and inference logs were securely recorded on the blockchain infrastructure integrated within the proposed system. This blockchain-enabled architecture guarantees:

- Secure and immutable storage of patient data and prediction records,
- Transparent and auditable decision-making processes,
- Controlled access through smart contracts for medical staff.

In conclusion, this hybrid approach not only delivers highly accurate predictions but also empowers healthcare professionals with transparent AI outputs while ensuring complete security and integrity of patient data

5. Discussion

A comparison of binary classification models occurs against benchmark studies originating from [21] [20] [12]. **Table 3** compares the present work and benchmark cases through the accuracy scores obtained from each model generation.

Table 3: Compared Proposed Model with Existing Studies

Model Name & Reference Paper	Accuracy (%)
(Logistic Regression Naïve Bayes SVM KNN Decision Tree Random Forest ANN DNN MLP) [15]	Logistic Regression= 93.40 Naïve Bayes = 90.10 SVM =92.30 KNN= 71.42 Decision Tree =81.31 Random Forest =95.60 ANN =92.30 DNN =76.92 MLP= 75
(Proposed Model)XGBoost with Explainable AI	96.50

The table presents a comparison of various machine learning models applied for heart disease prediction, emphasizing the accuracy reported in previous studies alongside the performance of the model proposed in this research. The proposed XGBoost model achieved an outstanding accuracy of 99%, demonstrating its superiority among the evaluated models. As a powerful ensemble learning technique, XGBoost effectively captures complex data patterns, enhances computational efficiency, and reduces the risk of overfitting, all contributing to its superior predictive performance. The application of advanced preprocessing techniques, including data standardization and fine-tuned hyperparameters, has likely contributed to the improved performance of our model compared to earlier studies, such as Reference [15].

6. Conclusion

This research introduces a hybrid framework that integrates machine learning algorithms, explainable artificial intelligence, and blockchain technology for heart disease prediction. The experimental results clearly demonstrate the superiority of the XGBoost model, which achieved the highest accuracy of 99%, outperforming Gradient Boosting (96%), SVM (91%), KNN (87%), and Logistic Regression (82%). The findings confirm the significant potential of machine learning models in delivering highly accurate, rapid, and cost-effective alternatives to traditional manual diagnosis systems. Furthermore, the inclusion of explainable AI techniques, particularly through the use of SHAP values, enhances the interpretability of predictions by identifying critical factors influencing model decisions. This transparency empowers healthcare professionals with greater confidence in AI-generated diagnostic results. The integration of blockchain technology adds an essential layer of security and trust by ensuring immutable, tamper-proof storage of patient data and prediction outcomes. Overall, this hybrid approach offers a secure, explainable, and efficient decision support system for early detection of heart disease, addressing key clinical challenges in diagnostic accuracy, transparency, and data security.

7. Future Direction

Building on the promising results of this study, future research should focus on further enhancing the predictive capabilities, clinical applicability, and scalability of the proposed hybrid system. One direction is to expand the model beyond traditional machine learning algorithms by incorporating advanced deep learning architectures such as Convolutional Neural Networks (CNNs) for medical imaging analysis and Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, for processing time-series data like electrocardiograms (ECG) and continuous heart rate monitoring. Moreover, enriching the dataset with multi-modal data sources, including electronic health records, wearable device data, and echocardiographic images, could significantly improve prediction robustness and adaptability to real-world clinical environments. Transitioning from binary classification to multi-class classification will allow for more nuanced diagnostic capabilities, differentiating between various types of heart conditions for more personalized and targeted treatment recommendations. Finally, the blockchain component can be expanded towards real-time decentralized healthcare systems, enabling secure sharing of diagnostic insights across multiple medical institutions while preserving patient confidentiality and promoting interoperability. Such improvements would establish the proposed hybrid framework as a comprehensive, intelligent healthcare solution ready for large-scale deployment.

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