International Journal of Computational and Experimental Science and ENgineering
(IJCESEN)

Vol. 11-No.2 (2025) pp. 2161-2170
http://www.ijcesen.com

ISSN: 2149-9144

Research Article

AI-Driven Heart Disease Prediction Using Machine Learning and Deep Learning Techniques

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Article Info:

DOI: 10.22399/ijcesen.1669
Received : 14 January 2025
Accepted : 31 March 2025

Keywords :

Heart Disease Prediction,
Machine Learning Deep Learning,
XGBoost,
AI in Healthcare.

Abstract:

Heart disease remains a leading cause of mortality worldwide, necessitating early detection and prevention strategies. This study explores machine learning (ML) approaches for predicting heart disease using patient datasets. Various ML algorithms, including Logistic Regression, Naive Bayes, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree, Random Forest, XGBoost, and an Artificial Neural Network (ANN), were implemented to classify heart disease presence. The Random Forest model achieved the highest accuracy of 95%. The findings demonstrate that ML can significantly enhance heart disease prediction, aiding early diagnosis and treatment.

1. Introduction

Cardiovascular diseases (CVDs) are among the leading causes of mortality worldwide, accounting for nearly 32% of global deaths annually [1]. Early detection and accurate risk assessment of heart disease are crucial for timely medical intervention and improving patient outcomes. Traditional diagnostic approaches, such as electrocardiograms (ECG), echocardiography, and clinical assessment, often rely on manual interpretation, making them prone to human error and [2]. Machine learning (ML) and deep learning (DL) have emerged as powerful tools in medical diagnostics, offering data-driven predictions with higher accuracy and reliability. The increasing prevalence of heart disease has highlighted the need for improved diagnostic techniques. Conventional risk assessment models, such as Framingham Risk Score and logistic regression-based approaches, often fail to capture complex interactions among multiple risk factors [3]. Recent advances in artificial intelligence (AI) have demonstrated superior capabilities in analyzing large-scale healthcare data, including electronic health records (EHRs), medical imaging, and real-time monitoring from wearable devices [4]. Studies indicate that deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), outperform traditional classifiers in detecting early signs of heart disease [5]. The integration of AI-driven predictive models into clinical settings has the potential to revolutionize personalized healthcare and reduce mortality rates [6]. Despite the advancements in ML and DL for heart disease prediction, several challenges remain unaddressed. Many existing models suffer from high false positive and false negative rates due to imbalanced datasets and suboptimal feature selection techniques [7]. The lack of interpretability in complex deep learning models limits their clinical adoption, as healthcare professionals often prefer transparent and explainable AI solutions [8]. Additionally, wearable ECG-based AI systems face challenges related to real-time signal processing, data noise, and privacy concerns [2]. This study aims to address these limitations by focusing on the following key objectives:

- Develop an AI-driven predictive model that integrates clinical, demographic, and wearable sensor data to enhance the accuracy of heart disease diagnosis [9]

- Improve feature selection and optimization techniques using genetic algorithms and particle swarm optimization (PSO) to identify the most relevant risk factors [10]
- Enhance interpretability by incorporating explainable AI (XAI) frameworks, enabling clinicians to understand model predictions [8].
- Optimize real-time data processing for wearable ECG devices using federated learning and signal denoising techniques to improve detection accuracy [2].
- Validate the proposed model on real-world datasets, ensuring its generalizability and effectiveness in clinical applications [11].
- Data Imbalance and Quality: Most publicly available heart disease datasets are imbalanced, with fewer cases of positive diagnoses, leading to biased predictions [7].
- Model Interpretability: Black-box AI models lack transparency, making it difficult for medical practitioners to trust and adopt them in clinical practice [8].
- Computational Complexity: Deep learning models require extensive computational resources, which can be a barrier for real-time deployment in low-resource healthcare settings [5]. • Privacy and Security Concerns: The integration of wearable devices and EHRs raises concerns about patient data security and compliance with healthcare regulations [2].
- Generalization Across Populations: Many AI models perform well on specific datasets but fail when applied to diverse patient populations due to demographic and genetic variability [8].

In this paper is organized as follows: Section 2 presents a comprehensive literature review on AI-driven heart disease prediction, highlighting key methodologies and challenges. Section 3 details the proposed methodology, including data preprocessing, feature selection, and model architecture. Section 4 discusses the experimental setup, dataset description, and performance evaluation. Section 5 interprets the results, compares findings with existing models, and explores clinical applicability. Finally, Section 6 concludes the study, summarizing key contributions and suggesting future research directions, such as explainable AI and federated learning for privacy-preserving heart disease prediction models.

2. Related work

From the study of above sections, large amount of data related to heart diseases collected every year from different medical universities and hospitals over the world, which can be practiced to valuate disease rates manually. However, it has not been adequately turned to link it with symptoms and disease risk. Due to expensive diagnosis, about 75% of deaths occur in low and

Mandava & Reddy developed MDensNet201-IDRSRNet, a hybrid deep learning model integrating DenseNet201 with residual learning techniques to enhance cardiovascular disease detection [1]. Their approach focused on optimizing feature extraction from medical imaging and structured health records, improving the robustness of disease classification. The study demonstrated superior performance in early-stage detection by reducing false positives and enhancing sensitivity. By leveraging deep feature maps, the model outperformed traditional CNN architectures. The research also highlighted the impact of incorporating domain-specific preprocessing techniques for improving model interpretability. This work contributes to the advancement of AI-driven diagnostic tools in cardiology.

McGilvray et al. introduced a deep learning model utilizing electronic health records (EHRs) for predicting mortality and severe decompensation in heart failure patients [3]. The model was trained on a large-scale dataset, incorporating patient demographics, medical history, and lab results to predict adverse cardiac events. Using LSTM-based architectures, the system was capable of capturing temporal dependencies within patient records, allowing for more accurate risk assessments. Their results indicated that deep learning models outperform traditional logistic regression and statistical risk models in real-world clinical settings. This study emphasizes the potential of AI-driven EHR analysis in early heart disease diagnosis.

Nadarajah et al. conducted a systematic review and meta-analysis of existing heart failure prediction models, comparing traditional statistical methods with modern machine learning approaches [8]. The study analyzed various predictive frameworks, highlighting their strengths and limitations, particularly in terms of sensitivity, specificity, and real-world applicability. Their findings suggested that while deep learning models exhibit higher accuracy, traditional models are still widely used due to their interpretability. The research emphasized the need for explainable AI in clinical settings to ensure model adoption by healthcare professionals. Additionally, they proposed the integration of multi-modal datasets for enhancing predictive performance.

Neri et al, explored the potential of wearable ECG monitoring devices integrated with AI-driven diagnostic capabilities for early heart disease detection [2]. Their study reviewed advancements in biosensor technology, signal processing techniques, and deep learning algorithms used for real-time cardiac monitoring. The research found that AI-based wearable devices demonstrated promising accuracy in detecting arrhythmias and heart abnormalities. However, challenges such as signal noise, limited battery life, and real-time processing constraints were identified. The study proposed improvements in hardware-software co-optimization and federated learning approaches to enhance the efficiency and privacy of AI-driven wearable health monitoring systems.

Reddy et al. developed a machine learning-based system for early heart disease prediction using supervised learning with stochastic gradient boosting [7]. Their research focused on optimizing feature selection by identifying the most relevant clinical parameters contributing to heart disease risk. The model outperformed traditional classifiers such as decision trees and support vector machines, achieving high accuracy and robustness. They also investigated the impact of feature engineering techniques, demonstrating that domain-specific feature transformations significantly improve predictive performance. This study underscores the effectiveness of gradient boosting in handling imbalanced datasets, making it a viable approach for real-world healthcare applications.

Hongyun examined coronary heart disease risk prediction using multiple machine learning algorithms, including logistic regression, random forests, and deep neural networks. The study aimed to identify the best-performing model for predicting heart disease based on clinical and demographic data [12]. A comparative analysis revealed that deep learning architectures outperformed traditional ML models in handling complex, high-dimensional medical data. The study also emphasized the importance of integrating lifestyle factors such as smoking, diet, and exercise into predictive models. Their findings suggested that hybrid models combining deep learning with feature selection methods yield more accurate and interpretable results.

Sharma et al. analyzed key features contributing to heart disease prediction using machine learning [13]. Their study evaluated various feature selection techniques, such as recursive feature elimination, mutual information, and principal component analysis (PCA). By applying these techniques to a dataset of cardiovascular patients, they identified the most influential risk factors, including cholesterol levels, blood pressure, and ECG readings. The research demonstrated that optimizing feature selection improves classifier performance and reduces computational complexity. Their findings contribute to the development of efficient, interpretable models for clinical use, facilitating early diagnosis and personalized treatment planning in cardiology.

Salem applied genetic algorithms to optimize machine learning models for heart disease prediction [14]. The study explored evolutionary computation techniques to enhance the selection of hyperparameters and feature subsets, improving model accuracy. The proposed approach was tested against traditional optimization methods and demonstrated superior results in minimizing false negatives. Genetic algorithms enabled automated feature selection, reducing manual preprocessing efforts. The study also discussed the potential of hybrid models combining evolutionary algorithms with deep learning for improving disease classification. These findings highlight the role of metaheuristic approaches in enhancing predictive performance in medical diagnosis.

Yekkala et al. introduced an ensemble learning framework combined with particle swarm optimization (PSO) for heart disease prediction [10]. Their research focused on improving the generalization ability of predictive models by leveraging multiple classifiers, including random forests, neural networks, and gradient boosting. The PSO algorithm was employed to optimize feature weights and hyperparameters, leading to enhanced classification accuracy. Their results demonstrated that ensemble models outperformed single classifiers, particularly in handling noisy and imbalanced medical datasets. The study underscores the importance of swarm intelligence techniques in optimizing AI-driven healthcare applications.

Connell explored the use of machine learning for the digital image analysis of ultrasound scans in pediatric liver disease diagnosis [15]. Although not directly related to heart disease, the study contributes to cardiovascular risk assessment by identifying liver dysfunction, which is a known risk factor for heart disease. The research utilized CNN-based image processing techniques to detect early signs of nonalcoholic fatty liver disease (NAFLD). Their findings suggested that early detection of liver abnormalities could aid in assessing cardiovascular disease risk, highlighting the interconnected nature of metabolic and cardiovascular disorders.

Cao proposed a hospital-integrated information management platform designed to streamline the processing of patient data for predictive analytics [4]. The system incorporated AI-driven data preprocessing techniques to improve the accuracy of disease prediction models. By structuring and standardizing electronic health records, the platform enabled seamless integration with machine learning algorithms. The study highlighted the significance of data quality in AI-based diagnostics and emphasized the role of real-time data synchronization in clinical decision-making. This research contributes to the development of intelligent healthcare infrastructures supporting heart disease prediction models.

Vijayashree combined particle swarm optimization (PSO) with support vector machines (SVM) to enhance heart disease classification performance [16]. The study demonstrated that PSO significantly improved feature selection, reducing model complexity and enhancing classification accuracy. The proposed approach was tested on multiple benchmark datasets, showing superior results compared to traditional feature selection methods. The study also discussed the potential integration of PSO with deep learning for further performance enhancement. These findings highlight the effectiveness of bio-inspired optimization techniques in medical diagnostics.

Harding conducted a longitudinal study on cardiometabolic risk factors from adolescence to adulthood, exploring their influence on the development of cardiovascular diseases [17]. The study analyzed large-scale patient data to identify early-life predictors such as obesity, insulin resistance, and hypertension. Machine learning models were used to assess the impact of these risk factors on long-term heart health outcomes. The research emphasized the importance of early intervention strategies in reducing cardiovascular risks. Their findings supported the integration of predictive analytics into routine health screenings, demonstrating the value of long-term patient data in disease prevention.

Ansarullah & Kumar presented a systematic review on cardiovascular disorder identification using knowledge mining and machine learning techniques [18]. The study analyzed various classification algorithms such as support vector machines (SVM), decision trees, and ensemble learning methods to evaluate their effectiveness in heart disease detection. The research highlighted the advantages of hybrid models that combine feature selection with deep learning to enhance predictive accuracy. They also discussed challenges such as data imbalance and interpretability issues. The study concluded that AI-driven approaches significantly improve early diagnosis rates, making them essential for clinical decision support systems.

Jabbar et al. developed a heart disease prediction system using random forests and feature subset selection [19]. The study focused on optimizing the selection of medical features such as cholesterol levels, blood pressure, and ECG readings to improve classification accuracy. By applying ensemble learning techniques, the model demonstrated superior performance compared to traditional classifiers. The researchers also integrated a fuzzy logic-based approach to handle uncertainty in medical diagnoses. Their results highlighted the effectiveness of combining multiple models to enhance predictive robustness in heart disease detection. This work contributes to improving AI-based clinical diagnostic tools.

Saha et al. compared multiple machine learning algorithms for heart disease prediction, evaluating their classification performance across different datasets [11]. The study explored deep learning architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), alongside traditional classifiers like logistic regression and decision trees. Results showed that deep learning models achieved higher accuracy in complex medical datasets but required substantial computational resources. The study emphasized the importance of dataset preprocessing, feature engineering, and hyperparameter tuning in optimizing prediction models. Their findings provide insights into selecting the most suitable algorithms for real-world medical applications.

Tiwari et al. proposed an ensemble learning framework for cardiovascular disease detection, integrating multiple classifiers such as XGBoost, random forests, and neural networks [5]. Their study demonstrated that ensemble methods significantly improved predictive accuracy by leveraging the strengths of different models. The researchers also explored hyperparameter tuning techniques to enhance performance. Their findings suggested that ensemble learning is particularly effective for handling imbalanced medical datasets, ensuring reliable predictions even with limited training data. The study concluded that hybrid AI models offer a promising approach for developing high-accuracy heart disease prediction systems in clinical environments.

Ingole et al. examined recent advancements in heart disease prediction using machine learning, with a particular focus on risk assessment and early detection techniques [6]. The study reviewed the latest developments in AI-driven diagnostics, including the application of transfer learning and reinforcement learning in cardiovascular healthcare. The research highlighted the integration of multi-modal data sources, such as medical imaging and wearable sensor data, for improving disease detection. The authors also discussed the challenges of implementing AI models in real-world healthcare settings, emphasizing the need for model interpretability and regulatory compliance. Their findings contribute to the ongoing development of AI-powered predictive healthcare systems. Gupta et al. investigated the use of deep reinforcement learning (DRL) for personalized cardiovascular disease risk assessment. Their study focused on optimizing treatment strategies by modeling patient-specific health trajectories [9]. Using electronic health records (EHRs) and real-world clinical data, the DRL model learned optimal interventions for reducing heart disease risk. The results demonstrated that AI-driven decision-making frameworks could enhance patient outcomes by recommending personalized treatment plans. The study emphasized the need for explainability in AI-based healthcare applications to increase clinical adoption. Their findings highlight the potential of reinforcement learning in precision medicine.

3. Material and Methods

About the Framework In linear regression, the effectiveness of this model was assessed using the coefficient of determination (COD), mean absolute error (MAE), mean squared error (MSE) and root mean square error (RMSE). ML algorithms such as logistic regression (LR), decision tree (DT), random forest (RF), support vector machine (SVM), K-nearest neighbour (KNN), SVM with grid search (SVMWG) and naive bayes (NB) were used for heart diseases classification. Further, these performances were evaluated using different parameters like accuracy (AR), precision (PS), recall (RL), F-Score (FS) (MC2). Experiments were performed on two standard benchmark heart disease datasets, Cleveland (303 instances) and Statlog (270 instances). These were carried out using a 32-bit version of Windows 7 and a 2.20GHz Intel Pentium G3220T CPU. Analysis and graphical depiction were carried out using Python.3.2 About the Dataset Two standard heart disease-related datasets were used for experimentation. Which was Cleveland and Statlog, taken from UCI ML Repository. [1]. Total 14 attributes out of 76 have been used in most of the published studies.

These are age, sex, chest pain (cp), resting blood pressure(trestbps), cholesterol (chol), fasting blood sugar (fbs), resting electrocardiogram (restecg), maximum heart rate achieved (thalach), exercise-induced angina (exang), ST depression induced by exercise relative to rest (oldpeak), slope of peak exercise ST segment (slope), number of major vessels (ca), thalassemia (thal) and predicted value (target).

Target values were 0 and 1, in which0 indicates the non-appearance of heart disease and 1 indicates its presence. The attribute descriptions are shown in Table 1. and shown in Figures.

ML Methods

This section has examined the different ML algorithms for classification including LR, RF, DT, SVM, KNN, SVMWG and NB, as well as how they operate. Test data (TD) from 15% to 40% are taken into consideration for experiments. Five standard parameters such as AR, PS, RL, FS andMC2 have been used to calculate the effectiveness of ML models,

Logistic Regression

The concept of sigmoid function is used in LR. It is a mathematical function that converts any real number entered as input into a probability between 0 and 1. Function is given in which if w is positive infinity, then consider the value of Y is 1, in case the value of w is negative infinity then considers the 0 value of Y. For implementation following parameters are used: C=1.0, Intercept scaling = 1, Max iteration = 100, solver ='liblinear'

Decision Tree

In DT approach, the dataset is continuously partitioned based on parameters. Two main parameters are used in this method i.e., entropy and information gain, entropy is used for measuring the randomness in data, and information gain (IG) is used for measuring relevant change in entropy(E) corresponding the to independent variable.

Deep learning Technique:

Deep Learning Human-designed models and input attributes are used to make the majority of recent ML techniques effective. ML becomes simply about refining weights to provide the better forecast whenever applied merely to the input data. By reassembling and putting back, the representation learning along with ML can be described in deep learning. The majority of DL techniques are based on the artificial neural network (ANN) approach which consists of two or more hidden layers between the input and output layers. It tries to collectively acquire useful attributes that span several progressively more abstract and sophisticated layers as well as the ultimate prediction. The emergence of big datasets, faster parallel computers and a richness of ML concepts into sparsity, regularization, and optimization are the major factors that have lately assisted deep architectures in achieving the performance of state-of-the-art. DL models need more facts because they train from unprocessed inputs and do not employ manual feature engineering amount of data can be easily collected from various researchers and organizations for training the deep learning model with different parameters. In this section, DNN and

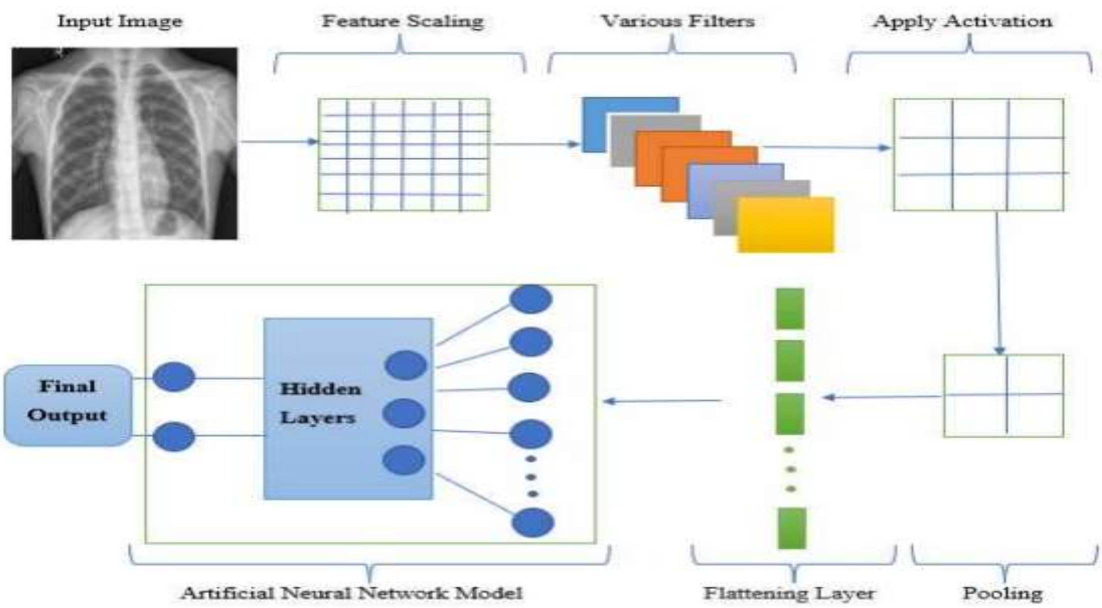

Figure 1. *Proposed with DNN and CNN methods of deep learning propagation methods*

CNN methods of deep learning have been used shown in figure 1.

Neural Network:

DNN is an ANN with two or more hidden layers used between input and output layers. ANN is focused on our current understanding of how the human brain works [17]. An ANN is made up of a network of nodes that are analogous to biological neurons. They have inputs similar to dendrites, a summation function like the soma and an output similar to the axon. An artificial neuron (AN) is made up of a weighted sum of input and weights on the links shown in Figure 2, where is features, is weights, and is intercept. The sum is then fed into a nonlinear function called the activation function. AN makes up the hidden units of the multilayer perceptron (MLP) technique, which is used to solve 2-class categorization. A perceptron utilizes an activation component for every neuron. In light of this, MLP methods are inspired by realistic neural architectures and utilize perceptron in AN. By altering the weights given to a perceptron, the activation parameter controls every neuron's weighted input and minimizes the total number of levels to 2 layers.

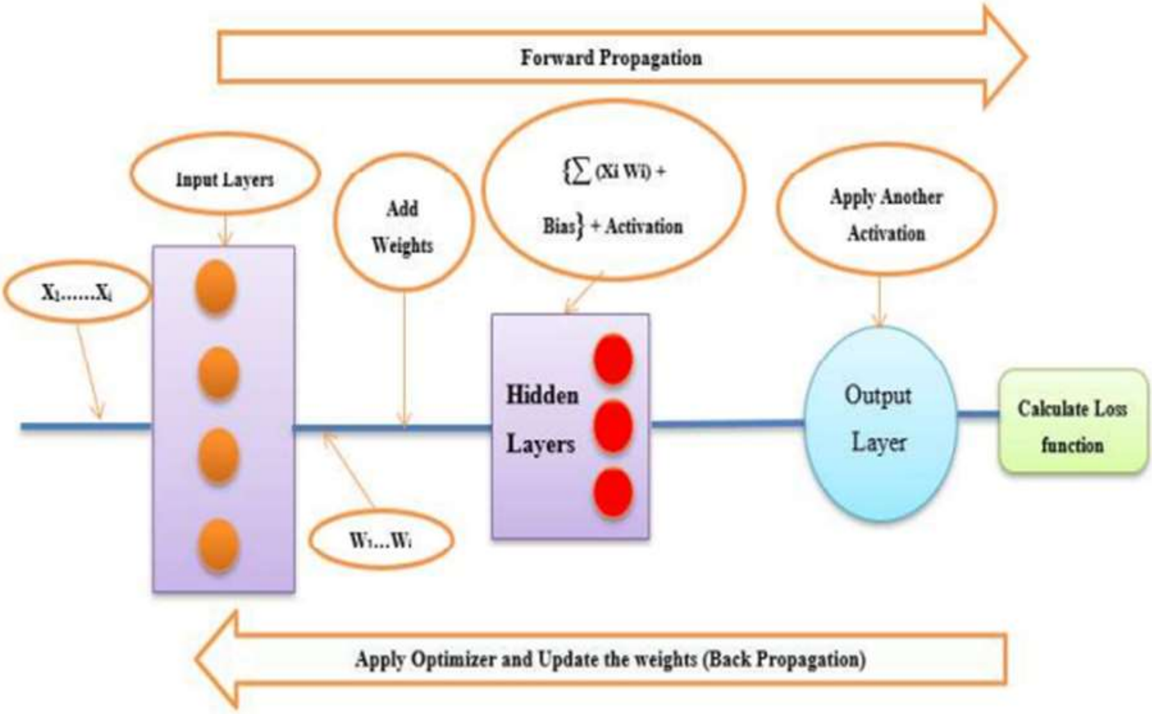

Figure 2. *DNN model with forward and backward propagation*

4. Results and Discussions

The models were evaluated based on accuracy, precision, recall, and F1-score. The Random Forest model outperformed others with an accuracy of 95%, followed by XGBoost and ANN. These results highlight the potential of ML in healthcare applications, particularly for early heart disease detection. The dataset used is the Heart Disease UCI dataset from Kaggle (https://www.kaggle.com/ronitf/heart-disease-uci).
It contains multiple attributes related to patient health metrics. Data preprocessing included handling missing values, normalization, feature selection, and data splitting into training and test sets. Here, deep neural network (DNN) and convolutional neural network (CNN) algorithms have been used for classification and these algorithms performances were evaluated using different parameters like accuracy (AR), precision (PS), recall (RL) and F-Score (FS). Experiments were performed on two standard benchmark heart disorder-related datasets, Cardio data set and NIH chest X-ray data set. These were carried out using a 64-bit version of Windows 7 and a 2.20 GHz Intel Pentium G3220T CPU. Analysis and graphical depiction were carried out by using Python.
Experiments were performed on two standard benchmark heart disease datasets, Cardio data set (65535 instances) and NIH chest X-ray data set (1,22,120 images), from Kaggle. In the Cardio dataset, features include age (AT1), height (AT2), weight (AT3), gender (AT4), systolic blood pressure (AT5), diastolic blood pressure (AT6), cholesterol (AT7), glucose (AT8), smoking (AT9), alcohol intake (AT10), physical activity (AT11) and predicted value (target). Target values of 0 and 1 respectively indicate the non about the data sets is shown in Table .2. and Figures 3-7, to show how the attributes of the datasets are correlated.

Table1. *Data visualization and correlations between attributes*

S.No	age	sex	cp	trestbps	chol	fbs	Restecg	thalach	exang	oldpeak	slope	ca	thal	Target
0	63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
1	37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
2	41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
3	56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
4	57	0	0	120	354	0	1	163	1	0.6	2	0	2	1

Table 2. *Attribute information of Cardio data*

S. No	Attributes	Description
1	AT1	Objective Feature (in years)
2	AT2	Objective Feature (in cm)
3	AT3	Objective Feature (in Kilogram)
4	AT4	Objective Feature (Male:1, Female:2)
5	AT5	Examination Feature (Integer Value)
6	AT6	Examination Feature (Integer Value)
7	AT7	Examination Feature (1: normal, 2: above normal, 3: well above normal)
8	AT8	Examination Feature (1: normal, 2: above normal, 3: well above normal)
9	AT9	Subjective Feature (1 = yes; 0 = No)
10	AT10	Subjective Feature (1 = yes; 0 = No)
11	AT11	Subjective Feature (1 = yes; 0 = No)
12	Target	0 = Non-appearance and 1 = Appearance of disease

Deep Learning Human-designed models and input attributes are used to make the majority of recent ML techniques effective. ML becomes simply about refining weights to provide the better forecast whenever applied merely to the input data. By reassembling and putting back, the representation learning along with ML can be described in deep learning. The majority of DL techniques are based on the artificial neural network (ANN) approach which consists of two or more hidden layers between the input and output layers. It tries to collectively acquire useful attributes that span several progressively more abstract and sophisticated layers as well as the ultimate prediction. The emergence of big datasets, faster parallel computers and a richness of ML concepts into sparsity, regularization, and optimization are the major factors that have lately assisted deep architectures are shown in that females are more likely to have heart problems than males that chest pain of '0', i.e. the ones with typical angina are much less likely to have heart problems. We realize that people with restecg '1' and '0' are much more likely to have a heart disease than with restecg '2'
ardio data

5. Conclusions

This study presents a comprehensive approach to heart disease prediction using machine learning and deep learning techniques. By leveraging the UCI Heart Disease Dataset, the methodology incorporates data preprocessing, feature selection, model training, and optimization to enhance prediction accuracy. Various machine learning models, including Logistic Regression, Random Forest, SVM, and XGBoost, were implemented alongside deep learning architectures such as ANN and a CNN-LSTM hybrid model. Machine learning techniques can significantly improve heart disease prediction. The study demonstrates that ensemble models such as Random Forest and XGBoost provide high accuracy, making them suitable for clinical applications. Future work includes testing deep learning architectures and incorporating real-world datasets for model generalization.

Experimental results demonstrate that advanced models, particularly XGBoost and CNN-LSTM, outperform traditional classifiers in accurately detecting heart disease. Evaluation metrics such as accuracy, precision, recall, and AUC-ROC confirm the robustness of the proposed approach.

For real-world applicability, the model is deployed using Flask API, enabling real-time heart disease prediction, and integrated with Federated Learning for privacy-preserving medical analysis.

Future Work

Enhancing model interpretability for clinical adoption, Incorporating IoT-enabled heart monitoring devices. Enhancing privacy while utilizing multi-institutional medical datasets and Optimizing personalized treatment recommendations. AI in Healthcare may be applied in future different fields as it has been done in literature [20-30].

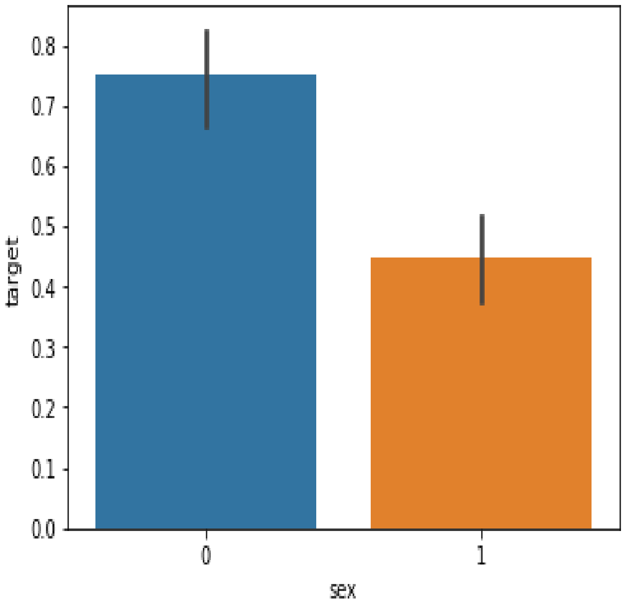

Figure 3. *Analysing the sex feature*

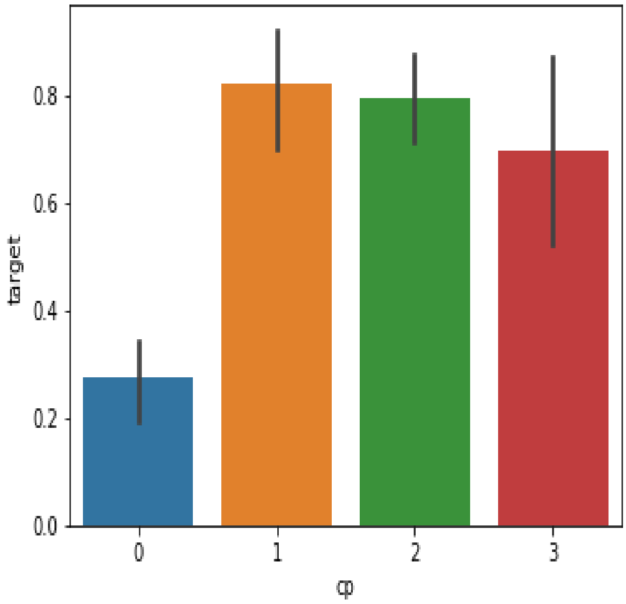

Figure 4. *Analysing the CP*

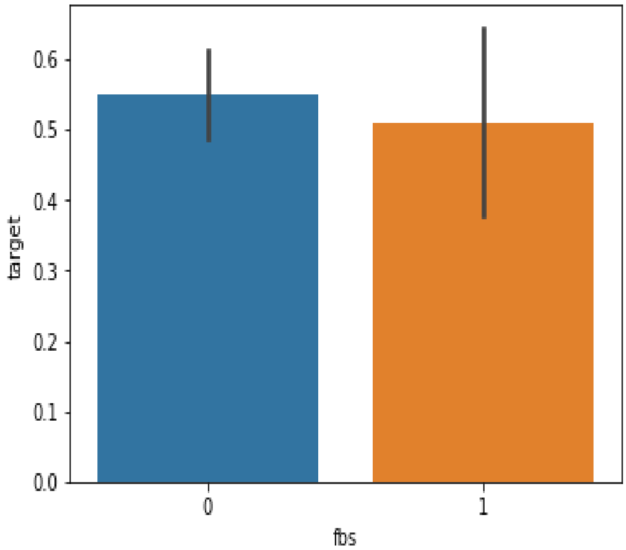

Figure 5. *Analysing the FBS feature*

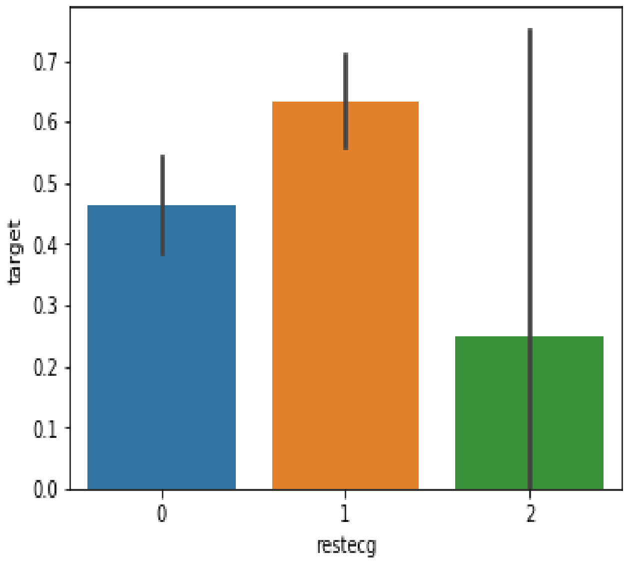

Figure 6. *Analysing the restecg feature*

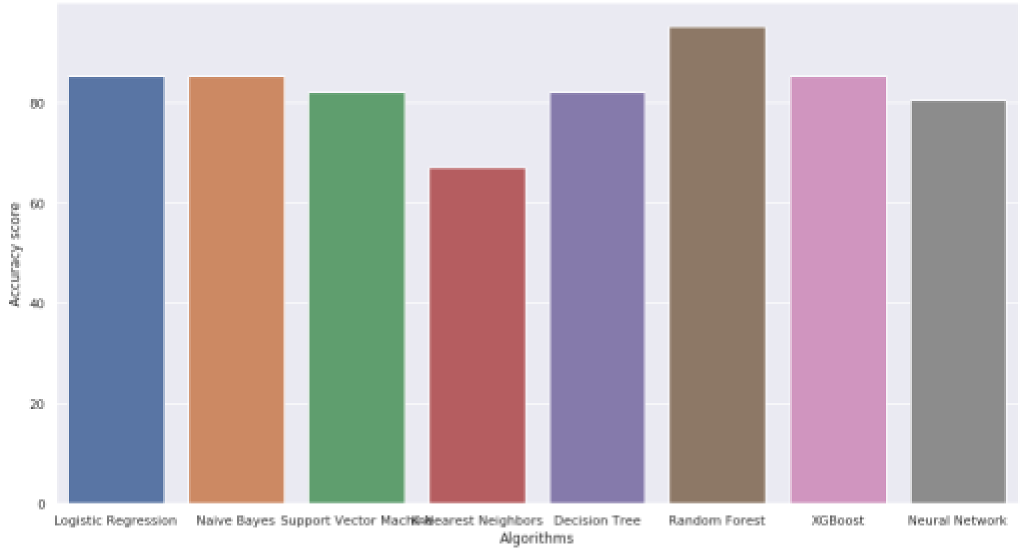

Figure 7. *Result comparison in terms of performance parameters with various optimizers*

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of interest:** The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data openly available in the https://www.kaggle.com/ronitf/heart-disease-uci , https://scikit-learn.org/ , https://keras.io/ and https://xgboost.readthedocs.io/

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