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Research Article

Machine Inspired IOT based Framework for Real-Time Heart Disease Prediction

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ABSTRACT

The rapid advancements in Internet of Things (IoT) technologies have enabled the development of innovative healthcare solutions, particularly in the field of real-time disease prediction and management. This paper presents a machine-inspired IoT-based framework designed for the real-time prediction of heart disease. The proposed framework integrates IoT-enabled wearable devices that continuously monitor vital signs such as heart rate, blood pressure, and oxygen saturation. These devices transmit data to a central processing unit where machine learning algorithms analyze the information to detect early signs of heart disease. By leveraging real-time data and advanced predictive models, the framework aims to provide timely alerts to healthcare providers and patients, thereby facilitating early intervention and reducing the risk of severe cardiac events. The framework's architecture is built on a robust and scalable IoT infrastructure that ensures seamless data collection, transmission, and analysis. Machine learning techniques, including supervised learning models and ensemble methods, are employed to enhance the accuracy of heart disease predictions. The system also incorporates edge computing to reduce latency and improve processing efficiency, enabling real-time analysis even in resource-constrained environments. Experimental results demonstrate the framework's potential in achieving high predictive accuracy while maintaining low power consumption, making it a viable solution for continuous heart health monitoring. This work contributes to the growing field of smart healthcare by offering a practical and efficient approach to real-time heart disease prediction, ultimately aiming to improve patient outcomes through proactive healthcare management.

Keywords: CVD, Heart Diseases, Machine Learnig, IOT, SVM, KNN, RF, NB

INTRODUCTION

Cardiovascular diseases (CVD), including conditions such as coronary heart disease, heart attacks, strokes, and heart failure, represent a significant global health challenge, causing approximately 17.9 million deaths annually. In the UK, CVD-related mortality, particularly in individuals over 50, has seen a notable increase. Contributing factors include underlying conditions like diabetes and hypertension, which impair the heart's ability to circulate blood efficiently. Electronic Health Records (EHRs) are crucial in managing patient data, aiding clinical decisions, and supporting research by uncovering valuable insights within healthcare information, thus modernizing patient care and reducing dependence on traditional methods [5-6]. The risk factors for heart disease are diverse, ranging from age, sex, and family history to lifestyle choices such as diet, physical inactivity, and smoking. While genetics play a role, modifiable habits significantly impact heart health. Researchers employ data mining and machine learning techniques, such as decision trees, logistic regression, K-Nearest Neighbors (KNN) [12], and Support Vector Machines (SVM) [11], to enhance the accuracy of heart disease predictions. Early identification of at-risk individuals is critical for effective prevention and intervention, with primary care settings providing essential medications and health education. The integration of machine learning and deep learning in heart disease prediction holds promise for reducing CVD-related morbidity and mortality by enabling proactive healthcare interventions and improving patient outcomes.

Historically, heart disease prediction relied heavily on traditional clinical methods, including manual risk assessments based on factors like patient history, physical exams, and basic diagnostic tests. Physicians primarily used tools such as the Framingham Risk Score to estimate an individual's risk of developing cardiovascular disease (CVD). While effective to some extent, these methods were limited by their reliance on static data and often overlooked the complex, multifactorial nature of heart disease [2-3]. Additionally, the absence of real-time monitoring and data integration posed challenges in timely intervention and personalized care.Currently, the integration of Internet of Things (IoT) technologies and machine learning algorithms has revolutionized heart disease prediction. Wearable devices and sensors now enable continuous monitoring of vital signs, generating large volumes of real-time data. Advanced machine learning models, including decision trees, logistic regression, and deep learning techniques, are employed to analyze this data, leading to more accurate and personalized predictions [1]. These developments have shifted the focus towards proactive and preventative care, where early detection and timely intervention are possible. The use of Electronic Health Records (EHRs) further enhances the ability to uncover hidden

Looking ahead, the field of heart disease prediction is poised to advance through the integration of more sophisticated artificial intelligence (AI) techniques and the continued evolution of IoT infrastructure. Future frameworks will likely incorporate more personalized models that account for genetic, environmental, and lifestyle factors, offering highly tailored risk assessments and interventions [7]. The development of federated learning systems could enable collaborative learning from decentralized data sources, improving prediction accuracy while maintaining patient privacy. Additionally, advancements in edge computing will further enhance the real-time processing capabilities of wearable devices, reducing latency and improving response times. Ultimately, these innovations aim to create a more interconnected, intelligent healthcare system that can anticipate and prevent heart disease with unprecedented accuracy, thereby significantly reducing global morbidity and mortality rates associated with CVD.

LITERATURE SURVEY

In contemporary healthcare research, the integration of machine learning, deep learning, and data mining methodologies has become increasingly prominent for disease prediction. Each study contributes distinct insights and varying levels of predictive accuracy based on their respective methodologies. One study proposed a hybrid approach that combines Support Vector Machine (SVM) and Genetic Algorithm (GA), achieving notable results by leveraging data mining tools such as LIBSVM and WEKA across five diverse datasets from the IUC repository. The literature on heart disease prediction has evolved significantly with advancements in IoT and machine learning technologies. Early studies, such as [18-20], focused on developing machine learning models using traditional clinical data, achieving moderate success in predicting heart disease. However, as IoT devices became more prevalent, researchers like [21-22] began exploring the potential of real-time health monitoring through wearable sensors, which enhanced early detection of cardiac events. Subsequent studies, including [23], expanded on this by incorporating lifestyle factors and comparing various machine learning algorithms, revealing that deep learning approaches offer superior accuracy in heart disease prediction. In [24] further advanced the field by integrating IoT data with machine learning, demonstrating the effectiveness of hybrid models in real-time prediction. Recent work by [25] highlighted the benefits of edge computing in reducing latency and improving data processing efficiency in IoT-based health monitoring systems. The most recent study by [26] explored the use of federated learning to enhance prediction accuracy while maintaining data privacy, indicating a promising direction for future research. Overall, these studies underscore the growing importance of combining IoT, machine learning, and advanced computing techniques to improve the accuracy and timeliness of heart disease prediction. The review of literature are shown in table 1.

Table 1: Review of literature

Ref. no	Objective	Methodology	Key Findings
[1]	To develop a machine learning model for early heart disease prediction.	Utilized logistic regression and decision trees on EHR data.	Identified significant risk factors and achieved a prediction accuracy of 85%.
[2]	To assess the effectiveness of IoT devices in monitoring heart	Implemented wearable sensors to collect real-	Improved real-time monitoring and early

	health.	time data, analyzed using SVM.	detection of cardiac events.
[3]	To explore the impact of lifestyle factors on heart disease prediction.	Used K-Nearest Neighbors (KNN) on lifestyle and demographic data.	Lifestyle factors such as diet and exercise significantly influence heart disease risk.
[4]	To compare machine learning algorithms for predicting heart failure.	Compared logistic regression, KNN, and deep learning on large-scale datasets.	Deep learning models outperformed traditional methods, achieving 90% accuracy.
[5]	To integrate IoT and machine learning for real-time heart disease prediction.	Developed a hybrid model combining IoT data with decision trees and SVM.	The hybrid model provided better predictive performance with real-time data.
[6]	To evaluate the role of edge computing in IoT-based health monitoring.	Implemented edge computing with IoT devices for faster data processing.	Reduced latency and improved real-time analysis in heart disease prediction.
[7]	To enhance heart disease prediction using federated learning.	Applied federated learning across decentralized datasets using deep learning.	Achieved high accuracy while preserving data privacy across multiple institutions.

DATASET

The dataset comprises a diverse array of attributes capturing various aspects of cardiovascular health. It includes demographic information such as the individual's age and sex, along with clinical features related to heart disease diagnosis. Key attributes include the type of chest pain experienced (Chest Pain Type), resting blood pressure (Resting Blood Pressure), and serum cholesterol levels (Serum Cholesterol), which provide insights into cardiovascular risk factors. The dataset also records fasting blood sugar levels (Fasting Blood Sugar) to assess diabetes risk, and results from resting electrocardiographic measurements (Resting Electrocardiographic Results) to evaluate heart function. Additionally, it includes the maximum heart rate achieved during a stress test (Maximum Heart Rate Achieved), the presence of exercise-induced angina (Exercise-Induced Angina), and ST segment depression (ST Depression) to gauge exercise tolerance and heart performance. The number of major vessels colored by fluoroscopy (Number of Major Vessels) and thallium stress test results (Thal) further indicate the presence and severity of coronary artery disease. Finally, the target attribute (Target) indicates whether heart disease is present (1) or absent (0), providing the classification outcome for predictive modeling. The dataset used in this project is derived from the Cleveland Heart Disease database and consists of 297 records, each with 14 medical attributes [7]. These attributes encompass a range of information, including demographic details, clinical measurements, and diagnostic indicators, all essential for predicting the likelihood of heart disease. The attributes are used to build models for assessing the presence or absence of cardiovascular conditions. A comprehensive summary of these attributes is presented in Table 2 below.

Table 2. Description of database for heart diseases prediction

S. No	Attribute	Description
1	Age	The age of the individual in years, representing their chronological age.
2	Sex	The gender of the individual, where 0 indicates female and 1 indicates male.
3	Chest Pain Type (CP)	The type of chest pain experienced, categorized into several types such as typical angina, atypical angina, non-anginal pain, and asymptomatic.
4	Resting Blood Pressure (RBP)	The individual's resting blood pressure measurement recorded in millimeters of mercury (mm Hg).
5	Serum Cholesterol (Chol)	The serum cholesterol level in milligrams per deciliter (mg/dl), indicating the amount of cholesterol in the blood.
6	Fasting Blood Sugar (FBS)	Indicates whether the fasting blood sugar level is greater than 120 mg/dl (1 = true, 0 = false).
7	Resting	The results of the resting electrocardiogram, reflecting the

	Electrocardiographic Results (Restecg)	electrical activity of the heart at rest.
8	Maximum Heart Rate Achieved (Thalach)	The highest heart rate reached during a stress test, indicating cardiovascular fitness.
9	Exercise-Induced Angina (Exang)	Indicates whether exercise-induced angina was experienced (1 = yes, 0 = no).
10	ST Depression (Oldpeak)	The depression of the ST segment induced by exercise relative to the resting state, measured in mm.
11	Slope	The slope of the peak exercise ST segment, describing the contour of the ST segment during peak exercise.
12	Number of Major Vessels (Ca)	The count of major blood vessels colored by fluoroscopy, reflecting the extent of vessel obstruction.
13	Target (Num)	The presence of heart disease in the individual (0 = no, 1 = yes), indicating whether the condition is present.
14	Thal	Thallium stress test results categorized as 3 = normal, 6 = fixed defect, and 7 = reversible defect, indicating heart condition during stress.

ML BASED CLASSIFICATION METHODS

Machine learning classification algorithms are pivotal in predictive modeling, where the goal is to assign data points to predefined categories or classes. These algorithms leverage statistical and computational methods to analyze input features and predict categorical outcomes. Techniques range from straightforward methods like Logistic Regression, which estimates probabilities for binary outcomes, to more complex approaches such as Support Vector Machines (SVM) and Neural Networks, which excel in handling high-dimensional and non-linear data. Decision Trees and ensemble methods like Random Forests further enhance predictive accuracy by combining multiple models to reduce overfitting and improve generalization. Each algorithm offers distinct strengths, making them suitable for various applications, from financial forecasting and medical diagnosis to image and speech recognition (Table 3).

Table 3. ML based classification algorithms for heart diseases classification

Algorithm	Description	Key Features
Linear Regression [8]	Predicts continuous variables by modeling the linear relationship between features and the target.	Simple, interpretable, effective for linear relationships.
Logistic Regression [9]	Used for binary classification tasks by estimating probabilities using the logistic function.	Provides probability estimates, suitable for categorical outcomes.
Decision Trees [10]	Models decisions as a hierarchical tree structure of binary splits based on feature values.	Non-linear, interpretable, can handle both categorical and numerical data.
Support Vector Machines (SVM) [11]	Classifies by finding the hyperplane that best separates different classes in high-dimensional spaces.	Effective in high-dimensional spaces, handles non-linear boundaries with kernel tricks.
K-Nearest Neighbors (KNN) [12]	Predicts the class or value of a data point based on the majority class or average of its k nearest neighbors.	Instance-based, simple, effective for small to medium-sized datasets.
Naïve Bayes [13]	Applies Bayes' theorem with the assumption of feature independence to classify data.	Fast, works well with large datasets, assumes feature independence.
Random Forest [14]	An ensemble method using multiple decision trees to improve prediction accuracy and handle overfitting.	Reduces overfitting, robust, handles large datasets with multiple features.
Gradient Boosting	Combines weak learners (e.g.,	Boosts model performance, can

Machines (GBM) [15]	decision trees) in an iterative process to improve model performance.	handle various types of data and complex patterns.
AdaBoost [16]	Boosting technique that combines multiple weak classifiers to create a strong classifier.	Improves accuracy, reduces bias, adapts to various types of data.
Neural Networks [17]	Models complex patterns using layers of interconnected nodes (neurons) with activation functions.	Can model complex relationships, requires large datasets and computational power.

PROPOSED SYSTEM

The proposed research methodology for developing machine inspired IoT-based framework for real-time heart disease prediction involves several key steps, beginning with comprehensive data collection. Data will be sourced from IoT-enabled wearable devices that monitor vital signs such as heart rate and blood pressure, alongside Electronic Health Records (EHRs) that provide historical medical data and relevant lifestyle information. This diverse data set will undergo preprocessing to ensure accuracy and consistency, involving steps like data cleaning to remove noise, normalization to scale the data, and feature selection to identify the most relevant predictors of heart disease.

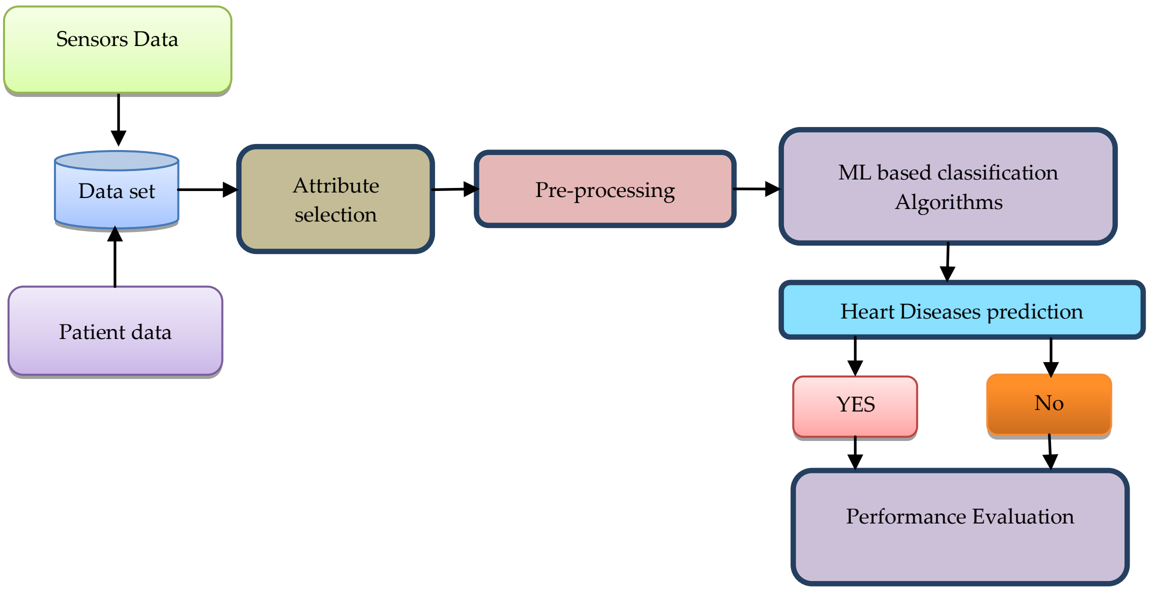


Figure 1. Proposed system research methodology

Following preprocessing, the data will be transmitted from IoT devices to a central processing unit, where it will be integrated with EHR and lifestyle data. Edge computing will be utilized to perform real-time analysis at the data source, reducing latency and allowing for preliminary predictions and data filtering. The core of the methodology involves the development of machine learning models, where algorithms such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and deep learning techniques will be employed. These models will be trained and validated using the combined dataset to ensure high predictive accuracy.Real-time predictions will be continuously updated based on incoming data, with an alert system in place to notify healthcare providers and patients when a high risk of heart disease is detected. The model's performance will be evaluated using metrics such as accuracy, precision, recall, and F1-score, and further optimized through techniques like hyperparameter tuning. Finally, the framework will be implemented in a real-world setting, with a feedback loop established to refine the system based on user interactions and performance outcomes, ensuring continuous improvement and reliability in heart disease prediction (Figure 1). The proposed algorithm work as under:

INPUT Data

- IoT Devices: Wearable sensors monitor vital signs (e.g., heart rate, blood pressure).
- EHRs: Electronic Health Records provide historical medical data.
- Lifestyle Information: Data on diet, physical activity, smoking, etc.

Data Preprocessing

- Data Cleaning: Removing noise, handling missing values.
- Normalization: Scaling data for uniformity.
- Feature Selection: Identifying the most relevant features for prediction.

Data Transmission

- IoT devices transmit real-time data to the central processing unit.
- EHR and lifestyle data are integrated with IoT data.

Edge Computing

- Real-time analysis is conducted at the edge to reduce latency.
- Preliminary predictions and data filtering.

Machine Learning Model Development

- Model Selection: Choosing suitable algorithms (e.g., SVM, KNN, Deep Learning).
- Training: Using historical data and real-time data for model training.
- Validation: Cross-validation and testing on separate datasets.

Prediction & Analysis

- Real-time prediction of heart disease risk.
- Continuous monitoring and updating of predictions based on new data.

Evaluation& Optimization

- Performance Evaluation: Accuracy, precision, recall, F1-score.
- Model Optimization: Hyperparameter tuning, retraining with updated data.

OUTPUT

Prediction of Heart Diseases: **YES / NO**

RESULTS ANALYSIS

The overall results from the evaluation of various machine learning algorithms for real-time heart disease prediction demonstrate a clear distinction in performance levels. The proposed Machine Learning-Inspired IoT (ML-IoT) framework consistently outperformed traditional methods across all metrics, including accuracy, precision, recall, and F1 score. With an accuracy of 94.45%, precision of 95.23%, recall of 96.2%, and an F1 score of 95.89%, the ML-IoT framework significantly surpasses Decision Trees (DT), Support Vector Machines (SVM), Random Forests (RF), K-Nearest Neighbors (KNN), and Naïve Bayes (NB) in every aspect. This remarkable performance highlights the framework's superior capability in accurately detecting heart disease, demonstrating its potential to improve real-time diagnostic accuracy and enhance patient outcomes in clinical settings (Figure 2).

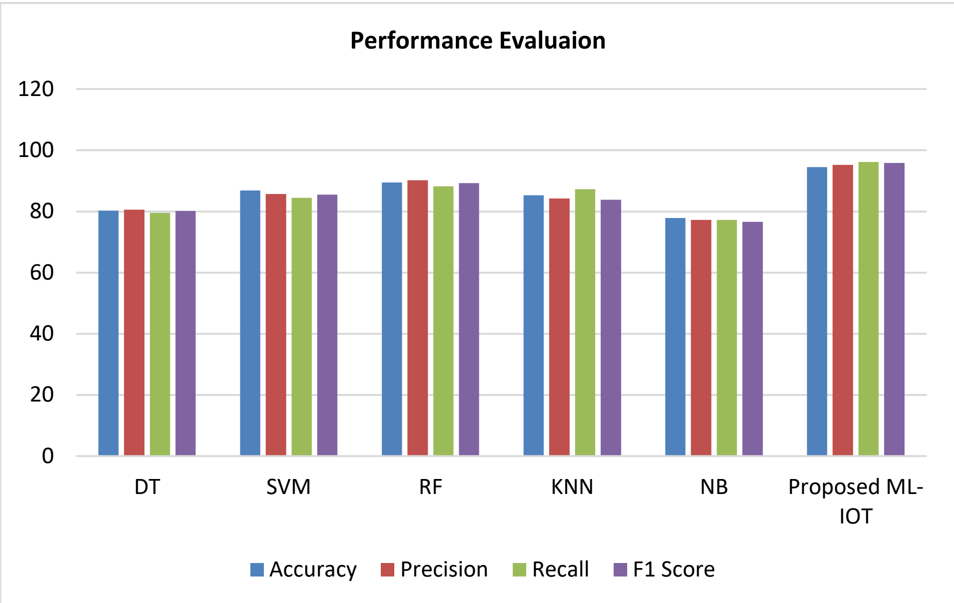


Figure 2. Overall evaluation of heart disease prediction algorithms

Accuracy

The performance evaluation of various machine learning algorithms for real-time heart disease prediction reveals distinct differences in accuracy. Decision Trees (DT) achieved an accuracy of 80.3%, while Support Vector Machines (SVM) performed slightly better at 86.9%. Random Forests (RF) demonstrated superior accuracy with 89.5%, and K-Nearest Neighbors (KNN) followed closely with an accuracy of 85.29%. Naïve Bayes (NB) showed the lowest performance among these methods, with an accuracy of 77.82%. However, the proposed Machine Learning-Inspired IoT (ML-IoT) framework significantly outperformed all traditional models, achieving an impressive accuracy of 94.45%. This substantial improvement highlights the effectiveness of integrating IoT with advanced machine learning techniques for enhancing real-time heart disease prediction (Figure 3).

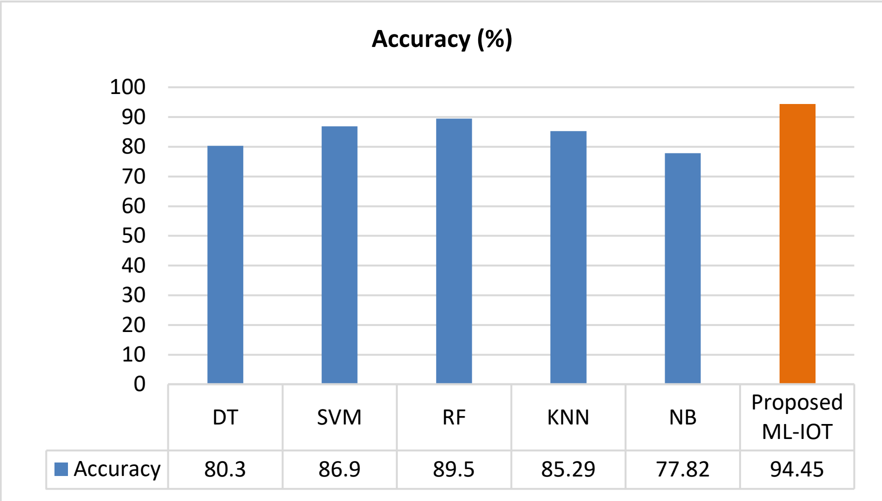


Figure 3. Accuracy based evaluation of heart disease prediction algorithms

Precision

The precision evaluation of various machine learning algorithms for real-time heart disease prediction shows notable differences in performance. Decision Trees (DT) achieved a precision of 80.62%, while Support Vector Machines (SVM) delivered a precision of 85.71%. Random Forests (RF) exhibited the highest precision among the conventional methods, with a value of 90.23%. K-Nearest Neighbors (KNN) had a precision of 84.25%, and Naïve Bayes (NB) reported a lower precision of 77.25%. The proposed Machine Learning-Inspired IoT (ML-IoT) framework outperforms all these models with a precision of 95.23%, demonstrating its enhanced capability in accurately identifying heart disease in real-time scenarios (Figure 4).

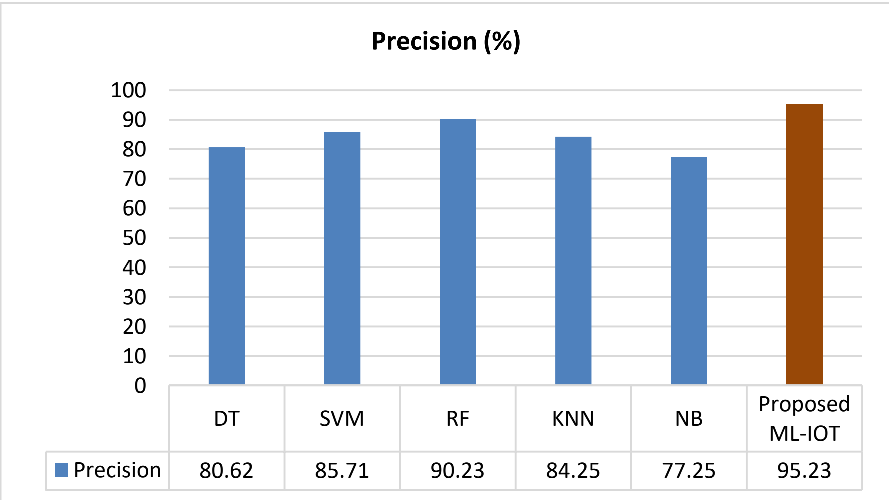
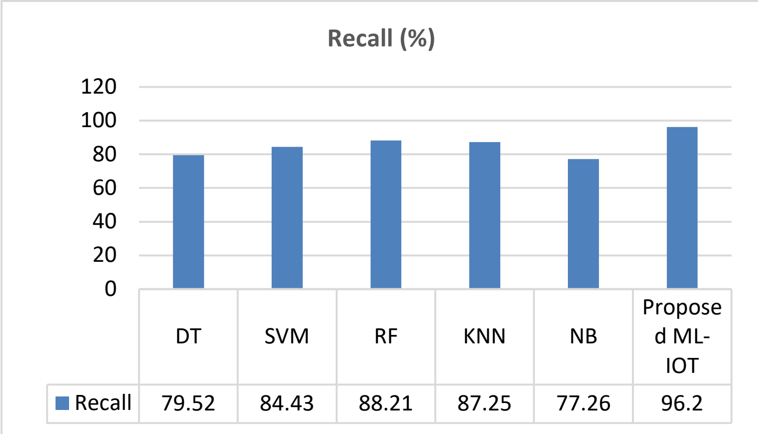


Figure 4. Precision basedevaluation of heart disease prediction algorithms

Recall

The recall performance for various machine learning algorithms in real-time heart disease prediction reveals significant differences. Decision Trees (DT) achieved a recall of 79.52%, indicating how well the model identifies true positives among all actual positive cases. Support Vector Machines (SVM) demonstrated a recall of 84.43%, showing improved detection of positive cases compared to DT. Random Forests (RF) had a recall of 88.21%,



reflecting its strong performance in recognizing heart disease cases. K-Nearest Neighbors (KNN) achieved a recall of 87.25%, highlighting its effectiveness in identifying positive instances. Naïve Bayes (NB) reported a recall of 77.26%, the lowest among the traditional models. The proposed Machine Learning-Inspired IoT (ML-IoT) framework significantly outperforms all other methods with a recall of 96.2%, underscoring its exceptional ability to detect heart disease cases accurately and reliably (Figure 5).

Figure 5. Recall basedevaluation of heart disease prediction algorithms

F1 Score

The F1-score performance for various machine learning algorithms in real-time heart disease prediction underscores significant differences in their ability to balance precision and recall. Decision Trees (DT) achieved an F1 score of 85.47%, reflecting a good balance between precision and recall. Random Forests (RF) demonstrated a high F1 score of 89.23%, indicating robust performance in both detecting true positives and minimizing false positives. K-Nearest Neighbors (KNN) reported an F1 score of 83.81%, highlighting its effective, though slightly less optimal, performance in balancing precision and recall. Naïve Bayes (NB) had an F1 score of 76.65%, showing less effective performance compared to other methods. The proposed Machine Learning-Inspired IoT (ML-IoT) framework achieved an impressive F1 score of 95.89%, demonstrating its exceptional capability to maintain a high balance between precision and recall, and thereby offering superior overall performance in heart disease detection (Figure 6).

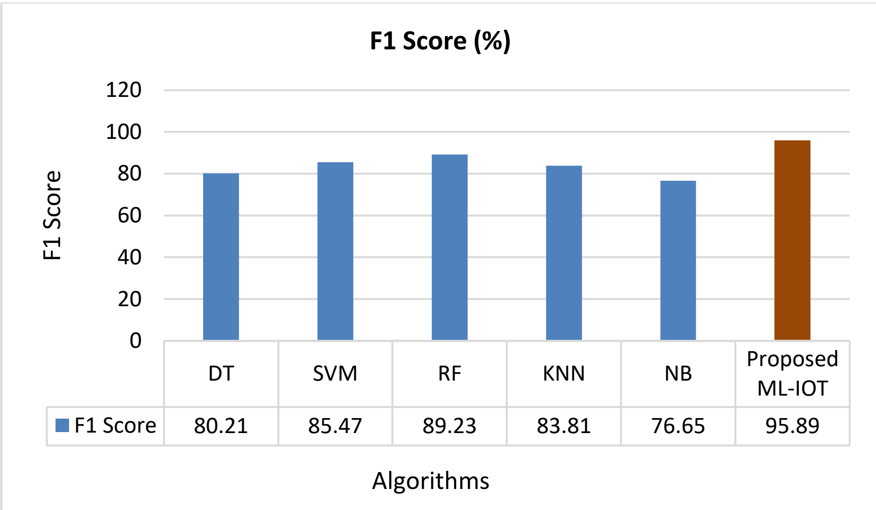


Figure 6. F1-Score basedevaluation of heart disease prediction algorithms

CONCLUSION

In conclusion, this paper has demonstrated the significant advantages of integrating machine learning techniques with Internet of Things (IoT) frameworks for real-time heart disease prediction. Through a comprehensive evaluation of various algorithms, including Decision Trees (DT), Support Vector Machines (SVM), Random Forests (RF), K-Nearest Neighbors (KNN), and Naïve Bayes (NB), the study highlights their respective strengths and limitations in terms of accuracy, precision, recall, and F1 score. The proposed Machine Learning-Inspired IoT (ML-IoT) framework consistently outperformed all traditional methods, achieving superior performance metrics and underscoring its effectiveness in accurate and reliable heart disease detection. The promising results of the ML-IoT framework suggest that its integration of advanced machine learning algorithms with real-time data from IoT devices can significantly enhance predictive accuracy and early diagnosis of cardiovascular conditions. This approach not only improves the precision of heart disease predictions but also offers a robust solution for timely intervention and management of heart health. Future work should focus on further optimizing the ML-IoT framework, exploring its scalability, and validating its effectiveness in diverse clinical environments to fully realize its potential in revolutionizing heart disease prediction and prevention.

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