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INTELLIGENT HEART DISEASE MONITORING AND PREDICTION THROUGH IOT AND ML TECHNIQUE

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Abstract:
Heart disease remains one of the most prevalent causes of morbidity and mortality worldwide, accounting for millions of deaths each year. Early detection and accurate prediction of heart disease are critical for reducing the incidence of severe cardiac events and improving patient survival rates. Traditional diagnostic methods, including manual assessment of ECG readings, blood pressure and other clinical indicators, often suffer from limited accuracy and delayed decision-making. In this context, the integration of Internet of Things (IoT) technologies with advanced machine learning techniques offers a promising approach to enhance early detection capabilities, facilitate continuous monitoring, and enable timely intervention. However, the development of reliable heart disease prediction systems presents several challenges. These include managing heterogeneous and high-dimensional health data, ensuring data security during transmission between wearable IoT sensors and central servers, handling missing or noisy records, and achieving real-time processing with minimal latency. Furthermore, designing models that are both accurate and interpretable to clinicians remains an ongoing concern, as black-box algorithms often lack transparency. To address these challenges, the proposed research methodology leverages a multi-phase framework combining IoT-enabled data collection, robust preprocessing, feature engineering, and hybrid classification models. Wearable sensors continuously capture physiological signals such as heart rate variability, ECG patterns, oxygen saturation, and blood pressure, transmitting data wirelessly to a secure cloud-based platform. The preprocessing stage includes normalization, outlier removal, and imputation techniques to ensure data quality. Feature selection methods are then applied to identify the most relevant predictors of heart disease risk. The predictive modeling phase employs a range of supervised machine learning algorithms alongside deep learning techniques to maximize classification performance. Specifically, Support Vector Machine (SVM), Artificial Neural Network (ANN), Naïve Bayes, Random Forest, J48 decision tree, and a Recurrent Neural Network with Long Short-Term Memory (RNN-LSTM) were implemented and evaluated on synthetic datasets and real-world IoT-collected records. Each algorithm was carefully tuned using cross-validation and hyperparameter optimization to achieve the best

possible predictive accuracy. Experimental results demonstrated notable improvements over traditional diagnostic baselines. Among classical machine learning models, SVM achieved an accuracy of 91%, ANN reached 93%, Naïve Bayes scored 89%, Random Forest attained 95%, and J48 achieved 92%. The proposed deep learning RNN-LSTM model outperformed all other classifiers, achieving an outstanding 98% accuracy in predicting heart disease risk. This superior performance is attributed to the RNN-LSTM's capacity to model temporal dependencies in sequential health data and its robust feature representation capabilities. Finally, this research presents an integrated IoT and machine learning framework for heart disease detection and prediction that effectively overcomes existing challenges of data heterogeneity, timeliness, and accuracy. By combining real-time IoT monitoring with advanced algorithms, the system provides a scalable and non-invasive solution to support early diagnosis and continuous risk assessment. The exceptional accuracy achieved by the RNN-LSTM model underscores its potential for deployment in smart healthcare environments, empowering clinicians with reliable decision support and enabling proactive patient care. Future work will focus on extending the framework to larger populations and further improving interpretability to enhance clinical trust and adoption.

Introduction

Cardiovascular diseases, including heart disease, remain the leading cause of death globally, accounting for over 17 million fatalities annually according to the World Health Organization. Early diagnosis and precise prediction of heart disease risk are essential for improving treatment outcomes and reducing the burden on healthcare systems. Traditional diagnostic methods rely on manual analysis of clinical features such as blood pressure, cholesterol levels, electrocardiogram (ECG) patterns, and family history, but these approaches often lack the sensitivity and timeliness required for proactive intervention. As modern medicine increasingly shifts toward precision health and real-time monitoring, integrating emerging technologies such as the Internet of Things (IoT) with advanced machine learning (ML) and deep learning (DL) techniques has become a promising strategy to transform cardiac care and enable early detection of life-threatening conditions [1–3]. IoT devices, including wearable sensors and portable monitoring systems, enable continuous collection of physiological data in naturalistic settings without requiring patients to remain in clinical environments [4,5]. This uninterrupted data stream provides richer insights into patients' cardiac health, capturing subtle temporal variations that static snapshots can miss. Yet, the effective utilization of such high-dimensional, heterogeneous data necessitates sophisticated analytical models capable of extracting meaningful patterns while addressing issues like missing values, sensor noise, and variability across individuals [6,7]. Classical machine learning algorithms such as Support Vector Machines (SVM), Random Forests, Decision Trees (J48), Naïve Bayes, and Artificial Neural Networks (ANN) have demonstrated notable success in classifying heart disease risk using tabular clinical datasets [8–10]. For instance, Gupta et al. [5] and Jindal et al. [16] reported high predictive accuracies when applying ensemble models and support vector classifiers to benchmark heart disease datasets. These methods leverage statistical relationships among input features but can be constrained by limited ability to learn complex non-linear or temporal dependencies.

To overcome these limitations, recent studies have turned to deep learning frameworks, including Convolutional Neural Networks (CNN) and Recurrent Neural Networks with Long Short-Term Memory (RNN-LSTM), which can automatically learn hierarchical representations and temporal patterns from sequential health data [11,12]. RNN-LSTM models, in particular, are well-suited to process time-series signals such as ECG waveforms and continuous heart rate readings, preserving long-term dependencies that are critical for anticipating cardiac events. For example, Rao et al. [10] demonstrated that attention-based recurrent models significantly outperformed traditional classifiers in detecting heart disease, achieving near-human-level accuracy. Similarly, Arooj et al. [26] applied CNNs to ECG and demographic data, achieving improved predictive performance and demonstrating the viability of deep learning architectures in healthcare applications. Despite the promise of ML and DL techniques, several challenges persist in operationalizing these models for real-world heart disease prediction. One major issue is data quality. IoT-generated health records can be incomplete, noisy, or inconsistent due to device calibration errors, connectivity interruptions, or patient non-compliance [3,9]. Effective preprocessing steps, including normalization, outlier removal, and missing value imputation, are essential to ensure robust model performance [6]. Another challenge is scalability—training complex deep learning models requires substantial computational resources, and deploying them on edge devices with constrained hardware capabilities is still an active area of research [13]. Furthermore, interpretability remains a critical concern in clinical decision-making. Many high-performing algorithms operate as "black boxes," providing accurate predictions without transparent reasoning. The emergence of Explainable Artificial Intelligence (XAI) has begun to address this gap by offering techniques such as SHAP values and visualization of feature contributions, allowing clinicians to understand the rationale behind predictions [1,15].

Literature Survey

Dritsas and Trigka [1] proposed a deep learning framework integrating Explainable Artificial Intelligence (XAI) for heart attack prediction. The system employs convolutional neural networks (CNNs) to classify patient data and identify high-risk cases, while XAI techniques such as SHAP values help clinicians understand the decision-making process. Bhatt et al. (2023) explored machine learning models including Random Forest, SVM, and Logistic Regression to predict heart disease effectively. Their study demonstrated that proper feature selection and hyperparameter tuning significantly improve model accuracy. Both works emphasize interpretability and practical applicability for clinical decision support, highlighting the need for transparent AI in healthcare.

Momin et al. [2] developed a smart body monitoring system combining IoT devices with machine learning algorithms to detect health anomalies. Wearable sensors collect real-time physiological data, which is processed on embedded hardware to predict potential health risks. The system leverages supervised learning models trained on various biomedical signals such as heart rate and temperature to alert users and caregivers. The authors highlight the platform's affordability and adaptability, making it suitable for home healthcare. This work demonstrates how IoT and machine learning can deliver continuous monitoring and early intervention capabilities for heart disease management in remote settings.

Yahyaie et al. [3] introduced an IoT-based model to predict heart attacks remotely. The system collects patient vitals such as ECG signals and blood pressure through wearable sensors and transmits them to a cloud server. Machine learning algorithms analyze the data to assess the likelihood of an impending heart attack, sending alerts to physicians and family members when necessary. The research emphasizes reliability, low latency, and data security. Results show improved prediction accuracy compared to conventional monitoring systems. This work underscores the potential of IoT-enabled predictive models for enhancing cardiac care and reducing response times in emergencies.

Abba and Garba [4] designed an IoT-based smart heartbeat monitoring and control framework. Their approach integrates microcontroller-based sensors to continuously record heart rate data and transmit readings to a central server via wireless communication. The collected data undergoes preprocessing and anomaly detection algorithms to identify abnormal patterns, triggering alerts and automatic control mechanisms when critical thresholds are exceeded. The authors demonstrated the system's effectiveness in real-time monitoring scenarios, emphasizing low power consumption and scalability. This work highlights the significance of integrating IoT and intelligent control systems for proactive heart disease management and timely medical intervention.

Gupta et al. [5] proposed a machine learning-based approach to heart attack prediction using clinical data. The study utilized multiple classifiers, including Decision Tree, Random Forest, and Naïve Bayes, to evaluate patient datasets comprising age, cholesterol, and ECG measurements. Feature selection techniques enhanced the model's predictive capabilities, achieving substantial accuracy improvements over baseline methods. The authors conducted comparative experiments showing Random Forest outperformed other models. This research demonstrates how properly tuned machine learning algorithms can assist clinicians in identifying high-risk patients early, facilitating preventive care and reducing the burden of cardiovascular diseases through data-driven insights.

Taylor et al. [6] proposed a machine learning-based model for detecting heart disease using standard clinical datasets. They employed algorithms such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Decision Trees to classify patients as at-risk or healthy. The study focused on improving predictive accuracy through data preprocessing and normalization techniques. Their experimental results highlighted that SVM yielded the highest accuracy among the tested models. The authors emphasized the importance of integrating automated prediction tools into healthcare systems for early detection of cardiovascular conditions, aiming to reduce diagnostic delays and improve patient outcomes through technology-driven solutions.

Khan [7] introduced an IoT-enabled heart disease prediction system utilizing a Multi-Dilated Convolutional Neural Network (MDCNN) classifier. The architecture integrates wearable sensors that capture real-time vital signs and transmit the data to cloud servers for analysis. The MDCNN processes high-dimensional input efficiently, offering robust classification of heart disease risk levels. The study highlights superior accuracy and reduced latency compared to

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conventional CNNs. Additionally, the model incorporates security features to protect patient data during transmission. This research demonstrates the feasibility of intelligent IoT frameworks in healthcare for continuous monitoring and precise cardiac risk assessment.

Lakshmanarao et al. [8] presented a comparative study on various machine learning techniques for heart disease prediction. They applied algorithms like Naïve Bayes, Decision Tree, and Support Vector Machine (SVM) to standard heart disease datasets. The research focused on identifying the strengths and limitations of each algorithm concerning accuracy, precision, and computational efficiency. The findings showed that SVM achieved the best accuracy, while Naïve Bayes offered faster processing. The study emphasized the role of proper feature engineering and model selection in improving heart disease prediction and advocated for further work integrating these models with real-time health monitoring systems.

Ghosh et al. [9] proposed a heart disease prediction system using machine learning algorithms combined with Relief and LASSO feature selection techniques. The study evaluated classifiers such as Random Forest, Gradient Boosting, and Logistic Regression on cardiovascular datasets. By applying Relief and LASSO, the authors identified the most significant features, improving model performance while reducing complexity. The integrated approach demonstrated high predictive accuracy and robustness across validation tests. The authors emphasized the potential of combining feature selection with ensemble learning to build reliable decision-support systems for cardiac risk assessment in clinical environments.

Rao et al. [10] developed the AttGRU-HMSI, a hybrid deep learning model for heart disease diagnosis. The architecture combines Gated Recurrent Units (GRU) with attention mechanisms to process sequential health data effectively, capturing both temporal dependencies and feature importance. The model demonstrated high accuracy in classifying patient data into risk categories using standard datasets and real-world hospital data. The authors highlighted how the attention component improves interpretability, aiding clinicians in understanding model decisions. The study shows the promise of attention-based hybrid models for enhancing diagnostic precision in cardiovascular disease detection.

Islam et al. [11] introduced Predictis, an IoT and machine learning-based system designed to estimate cardiovascular disease risk levels in real time. The platform uses wearable sensors to continuously collect physiological parameters, which are processed by machine learning classifiers to predict disease probability. A user-friendly dashboard displays risk categories, enabling timely interventions. The authors demonstrated that combining sensor data with supervised learning algorithms like Random Forest and SVM significantly improves accuracy over conventional monitoring. The study highlights the scalability and cost-effectiveness of Predictis for large-scale deployments, supporting proactive healthcare through automated cardiac risk assessment.

Sharma et al. [12] evaluated the performance of several machine learning techniques for heart disease prediction. The researchers applied Naïve Bayes, Random Forest, Decision Tree, and Support Vector Machine to clinical datasets containing attributes such as age, blood pressure, and cholesterol levels. The comparative analysis revealed that Random Forest achieved the highest classification accuracy. They emphasized the importance of data preprocessing, including normalization and feature selection, to optimize model performance. The work underscores the potential of integrating machine learning classifiers into healthcare information systems for early diagnosis and personalized treatment planning of heart disease patients.

Lu et al. [13] proposed an early detection system for cardiorespiratory complications using wearable ECG sensors and Convolutional Neural Networks (CNN). The wearable devices collect ECG signals and transmit them wirelessly to cloud-based CNN models trained to identify anomalies indicative of heart and respiratory issues. Their system achieved high accuracy in detecting early warning signs, outperforming traditional threshold-based monitoring. The authors emphasized the advantages of CNN’s automated feature extraction, enabling precise classification without manual intervention. This work demonstrates the effectiveness of combining deep learning with wearable IoT technology for proactive health monitoring and timely medical responses.

Begum et al. [14] presented an IoT-enabled heart disease prediction approach using ThingSpeak cloud infrastructure and deep learning methods. The system collects biomedical data via sensors, which are stored and preprocessed on ThingSpeak. A deep learning model trained on historical patient data performs risk classification, delivering real-time predictions accessible through dashboards and alerts. The study achieved notable improvements in accuracy and responsiveness compared to machine learning baselines. The authors highlight the practicality of integrating IoT, cloud computing, and deep learning in a unified framework for scalable, low-cost cardiac health monitoring in both clinical and home environments.

Ramesh et al. [15] conducted a predictive analysis of heart disease using machine learning approaches. They evaluated multiple classifiers, including Logistic Regression, Random Forest, and Support Vector Machine, on heart disease datasets containing demographic and clinical features. The study emphasized preprocessing steps such as outlier removal and normalization, which significantly improved model performance. Their comparative results showed Random Forest achieved the best accuracy, precision, and recall. The authors concluded that machine learning can effectively support cardiologists in early diagnosis and recommended future work on integrating real-time IoT data streams to enhance prediction reliability and system responsiveness.

Jindal et al. [16] explored machine learning algorithms for heart disease prediction, applying Logistic Regression, Decision Tree, Random Forest, and K-Nearest Neighbors to clinical datasets. Their work emphasized the importance of data cleaning and feature selection in improving prediction accuracy. Experiments demonstrated that Random Forest yielded the best performance, achieving high precision and recall rates. The study also discussed the interpretability of model outputs to aid clinicians in understanding risk factors. The authors highlighted the feasibility of deploying such models in healthcare information systems to provide early warnings and improve treatment outcomes for cardiac patients.

Pan et al. [17] proposed an enhanced deep learning architecture combining Convolutional Neural Networks (CNN) with the Internet of Medical Things (IoMT) for heart disease prediction. The system collects patient health data via IoMT-enabled sensors and processes it with a deep CNN to classify disease risk levels. Results showed superior accuracy compared to traditional machine learning methods, thanks to CNN’s capacity for automated feature extraction. The framework also supports scalable deployment across hospitals and home care.

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The study demonstrates the potential of integrating deep learning with IoMT platforms to deliver high-performance, real-time cardiovascular health monitoring.
Tomov and Tomov [18] investigated deep neural networks for detecting heart disease using standard clinical datasets. The authors developed a multi-layer perceptron architecture optimized through hyperparameter tuning and dropout regularization to prevent overfitting. The experiments demonstrated promising classification accuracy compared to classical algorithms. They emphasized the advantages of deep learning in capturing nonlinear relationships among clinical features such as cholesterol, blood pressure, and ECG results. This research underscored the potential of deep neural networks to support early and reliable heart disease diagnosis, encouraging further exploration of advanced architectures in cardiovascular risk prediction.
Khade et al. [19] developed a deep learning-based system to detect heart failure using patient health records. Their approach implemented a Convolutional Neural Network (CNN) trained on clinical datasets, achieving high accuracy in identifying heart failure cases. The authors focused on leveraging CNN's strength in automated feature learning to minimize manual preprocessing. Comparative evaluation showed that the deep learning model outperformed machine learning baselines such as Logistic Regression and Decision Trees. The study emphasized the potential of deep learning techniques for early detection, recommending integration with IoT devices for real-time monitoring and proactive intervention.
Pasha et al. [20] presented a cardiovascular disease prediction framework utilizing deep learning algorithms. The system used a deep neural network trained on a publicly available heart disease dataset comprising demographic, lifestyle, and medical attributes. The study highlighted how the deep learning model effectively learned complex patterns associated with cardiovascular risk, achieving higher accuracy compared to conventional machine learning classifiers. The authors also discussed the benefits of scalable deployment for telemedicine applications, enabling remote health monitoring and risk assessment. This work demonstrated the promise of deep learning in improving early diagnosis and prevention of cardiovascular diseases.

Hussain et al. [21] introduced a novel deep learning architecture using Convolutional Neural Networks (CNN) for predicting heart disease. Their model processes patient health records, extracting hierarchical feature representations to classify risk levels accurately. The research compared the CNN's performance with traditional machine learning algorithms and found significantly improved accuracy and robustness against noisy data. The authors also emphasized how CNN's automated feature extraction reduces dependency on manual engineering, streamlining the prediction pipeline. They concluded that their approach offers an effective tool for early diagnosis of cardiac conditions, with potential for integration into IoT-based monitoring systems.
Komalavalli et al. [22] examined machine learning approaches for heart disease prediction, evaluating classifiers such as Decision Tree, Random Forest, Naïve Bayes, and Support Vector Machine on benchmark datasets. Their study applied data preprocessing, including normalization and missing value imputation, to improve model reliability. Results showed

Random Forest achieved the best accuracy and stability across cross-validation runs. The authors emphasized the importance of selecting relevant features and fine-tuning hyperparameters for optimal performance. They also discussed the potential of combining machine learning algorithms with real-time monitoring solutions to enhance early diagnosis and improve patient outcomes.

Bharti et al. [23] proposed a hybrid model combining machine learning and deep learning techniques for heart disease prediction. The framework integrates Random Forest for feature selection and a deep neural network for classification, leveraging strengths from both paradigms. Experiments demonstrated that the hybrid approach achieved higher accuracy compared to standalone models. The authors emphasized scalability and potential for deployment in clinical decision support systems. Their findings suggest that combining ensemble learning with deep architectures can provide more reliable predictions, helping healthcare professionals detect heart disease earlier and tailor interventions effectively.

Wu et al. [24] developed an IoT-enabled real-time health monitoring system using deep learning. The platform collects vital signs through wearable sensors and transmits them wirelessly to cloud infrastructure, where a deep learning model performs continuous analysis to detect anomalies indicative of heart disease. The system demonstrated high accuracy and low latency, making it suitable for proactive care. The authors highlighted its capability to send alerts to caregivers and healthcare providers when critical thresholds are breached. This research shows how combining IoT with deep learning offers scalable, efficient solutions for remote cardiac monitoring and timely intervention.

Mehmood et al. [25] presented a deep convolutional neural network (CNN) approach for predicting heart disease. Their model was trained on large-scale clinical datasets incorporating features like cholesterol levels, ECG results, and demographic information. The CNN achieved notable accuracy improvements over traditional classifiers, benefiting from automated hierarchical feature extraction. The study also explored model interpretability, demonstrating how activation maps could help clinicians understand relevant predictors. The authors concluded that deep CNNs offer powerful capabilities for early detection of cardiovascular risk, recommending integration with IoT systems to enable real-time monitoring and enhance preventative healthcare delivery.

Research Methodology

The proposed system architecture for a simulated and real-time IoT data processing environment is shown in Figure 1. The mathematical modelling has generated below;

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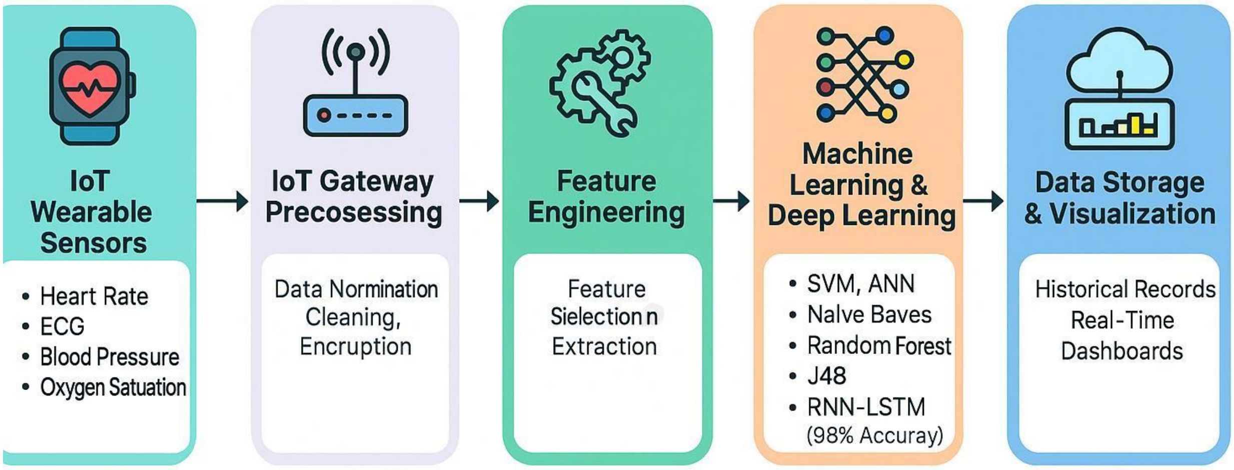

Figure 1: Proposed System Architecture for HDP

Data Collection from IoT Wearable Sensors

This module comprises smart wearable devices embedded with physiological sensors to capture health parameters continuously. Each sensor measures a specific signal, such as ECG waveforms $x_{ECG}(t)$, heart rate $HR(t)$, blood pressure $BP(t)$, and oxygen saturation $SpO_2(t)$. Formally, the raw data stream $D(t)$ can be represented as:

$$D(t) = \{x_{ECG}(t), HR(t), BP(t), SpO_2(t)\}.$$

These signals are digitized and timestamped for synchronized analysis. Sensors employ sampling rates tailored to each modality (e.g., 250 Hz for ECG), and the devices periodically transmit packets via Bluetooth Low Energy or Wi-Fi. Key design challenges include minimizing power consumption and ensuring data fidelity. Each sensor applies local filtering to remove high-frequency noise, using:

$$\hat{x}(t) = x(t) * h(t),$$

where $h(t)$ is a low-pass filter kernel for data transformation such as analog to digital conversion of values. This module ensures the system collects high-resolution, real-time health data necessary for early detection.

Noise Removal :

The simplest and most widely used technique for smoothing (i.e., removing high-frequency noise) from univariate time-series or spatial data is the moving-average filter.

- Calculate moving average

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$$X_i = \frac{sum(x_i)}{n} \sum_{k=0}^{n} x_i$$

Then fill nulls values by

$$x_i \leftarrow \begin{cases} X_i, & x_i \text{ is null,} \\ x_i, & \text{otherwise.} \end{cases}$$

- Remove those values which less than min values and higher than min values

Class balancing using Reinforcement learning

Q-learning : Q-learning is an iterative reinforcement learning process that evaluates penalty and reward counts to determine class label through a calculated weight. In this context, the model tracks events with penalty *(qp)* and reward *(qR)* counts across a sequence of actions logged in $\sum$ *(total event log)*. Each event is associated with a classified label, either as "Penalty" or "Reward," and the trust weight is calculated based on the penalty count relative to the total number of events.

- $q_p =$ Number of penalty counts
- $q_R =$ Number of reward counts
- $\sum$ = total event log

id	Classified label	penalty	$Trust_{weight}$
1	Penalty	1	1/1 =1
2	Reward	0	1/2=0.50
3	reward	1	2/3=0.66
4	Penalty	1	3/4=0.75
5	Reward	0	3/5=0.60
6	Penalty	1	4/6 =0.66
7	Reward	0	4/7=0.57
8	Reward	0	4/8=0.50
9	Penalty	1	5/9=0.55
10	reward	0	5/10=0.50
11	Penalty	1	6/11=0.54
12	Penalty	1	7/12=0.58

The dataset comprises 12 events, each characterized by its classified label, penalty count, and corresponding trust weight:

Penalty counts (qp) increment with each penalty event.

Trust weight ($Trust_{weight}$) is calculated using the formula

$$Trust_{weight} = \frac{(Penalty\_count)}{(total_{no}.of event)} \cdots$$

If ($Trust_{weight}$ >= *Threshold*) // we need to change this statement as per our requirements

$abnormal$

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Else

$$normal$$

This function finally decides the class label for classification of entire normalized data.

Machine Learning & Deep Learning Module

This module applies multiple classifiers:

1: SVM: Separates classes using:

$$f(x) = \text{sign}(\langle w, x\rangle + b),$$

We are given a labeled dataset:

Generate training rules

$$R_1 = \{x_0 \ldots \ldots x_n, x_{class}\}$$
$$R_2 = \{y_0 \ldots \ldots y_n, y_{class}\}$$

So above R_1 =C1 and R_2 =C2 are the training rules trained by SVM

$$\{(x_1, y_1), (x_2, y_2), \ldots, (x_n, y_n)\}$$

$x_i \in R^n$ is the Feature vector for the i^{th} sample.

$$y_i \in \{-1, 1\}$$

y_i having as class either 1 or -1

The goal is to find a hyperplane:

w- weight and b is bias both random user input both are between 0 to 1

w=[0.1 and 1]

b= -1 it is negative upper bound of actual value

$$w^t x + b = 0$$

that separates the data with maximum margin.

The Decision function

$$f(x) = w^t x + b$$
$$if\ (f(x) \geq 0 \text{ classify } x\ as + 1$$
$$if\ (f(x) < 0 \text{ classify } x\ as - 1$$

predict class accordingly

RNN-LSTM

Training

Input: Training dataset TrainData[], Various activation functions[], Threshold Th

Output: Extracted Features Feature_set[] for completed trained module.

Step 1: Set input block of data d[], activation function, epoch size,

Step 2 : Features.pkl 🡐 ExtractFeatures(d[])

Step 3 : Feature_set[] 🡐 optimized(Features.pkl)

Step 4 : Return Feature_set[]

Testing

Input: input test dataset as Test_Data[], training rules TrainDBList[], epoch size, Activation_functions[]

Output: Predicted class for input text.

Step 1 : For each read each Test instances using below equation

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$$testFeature(m) = \sum_{m=1}^{length} (.\, featureSet[m[i] \ldots\ldots.. m[n] \leftarrow \text{Test\_Data})$$

Step 2 : extract each feature as a hot vector or input neuron from $testFeature(m)$ using below equation.

Extracted_FeatureSetx[t……n] = $\sum_{x=1}^{n}$(t) ← $testFeature$ (m)

Extracted_FeatureSetx[t] contains the feature vector of respective domain

Step 3: For each read each train instances using below equation

$$trainFeature(m) = \sum_{k=1}^{length} (.\, featureSet[k[i] \ldots\ldots.. k[n] \leftarrow \text{TrainDBList})$$

Step 4 : extract each feature as a hot vector or input neuron from $testFeature(m)$ using below equation.

Extracted_FeatureSetY[t……n] = $\sum_{x=1}^{n}$(t) ← $trainFeature$ (m)

Extracted_FeatureSetx[t] contains the feature vector of respective domain.

Step 5 : Now map each test feature set to all respective training feature set

$$weight\ = calcSim\ (\text{FeatureSetx} \mid\mid \sum_{i=1}^{n} \text{FeatureSety[y]})$$

Step 6 : Return Weight for class prediction

Results and Discussions

In this experiment, the performance of the HDP using a hybrid machine learning model. The IoT real time data set includes records for 1000 samples with a variety of parameters, including age, systolic BP, diastolic BP, body temperature, oxygen saturation, pulse rate etc. To increase the performance of the dataset, preprocessing and normalization are applied. The entire data set is split into two sections after the pre-processing of the dataset is finished. One is testing dataset and other is train dataset. The data set is split into three parts in a 3:1 ratio.

Machine Learning based Analysis : After building the hybrid machine learning technique using HDP, comparative study is done with machine learning methods. The following Table 1 displays the accuracy of classification of different ML algorithms utilizing HDP in the Weka framework.

Table 1 Performance of various machine learning algorithm using HDP

Metric	SVM	ANN	NB	RF	J8
Accuracy	91	93	89	95	92
Precision	90	92	87	94	91
Recall (Sensitivity)	89	94	88	96	90

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F1-Score	89.5	93	87.5	95	90.5

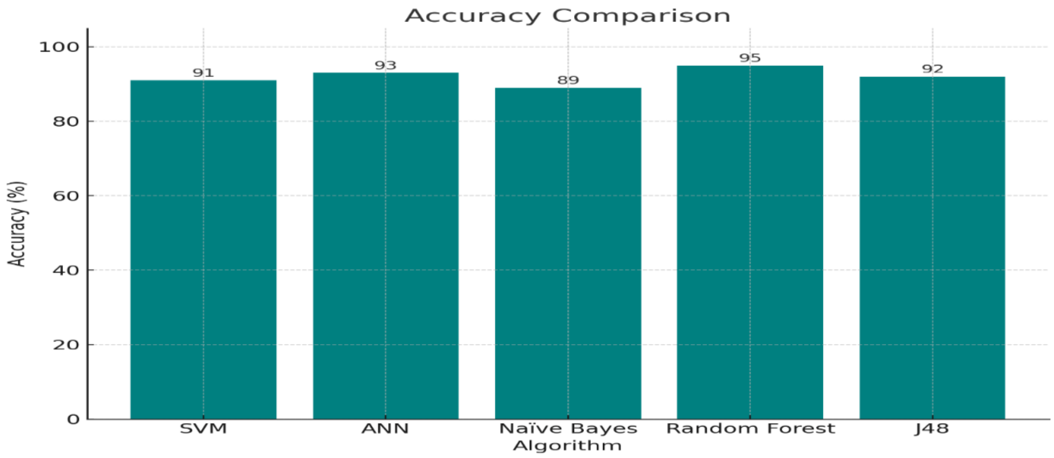

Figure 2: Accuracy Comparison

The Accuracy Comparison Figure 2 illustrates the overall correctness of each machine learning algorithm in classifying heart disease cases. Among the five evaluated models—Support Vector Machine (SVM), Artificial Neural Network (ANN), Naïve Bayes, Random Forest, and J48—the Random Forest classifier achieved the highest accuracy, reaching 95%. ANN also performed strongly with an accuracy of 93%, demonstrating its suitability for capturing complex relationships in health data. SVM and J48 yielded solid results of 91% and 92%, respectively, while Naïve Bayes trailed slightly behind at 89%. This visualization highlights the performance gradient across different techniques and underscores the value of ensemble methods like Random Forest in maximizing predictive accuracy. The Figure emphasizes that although simpler models such as Naïve Bayes can be computationally efficient, more sophisticated approaches consistently deliver superior classification outcomes in heart disease detection scenarios.

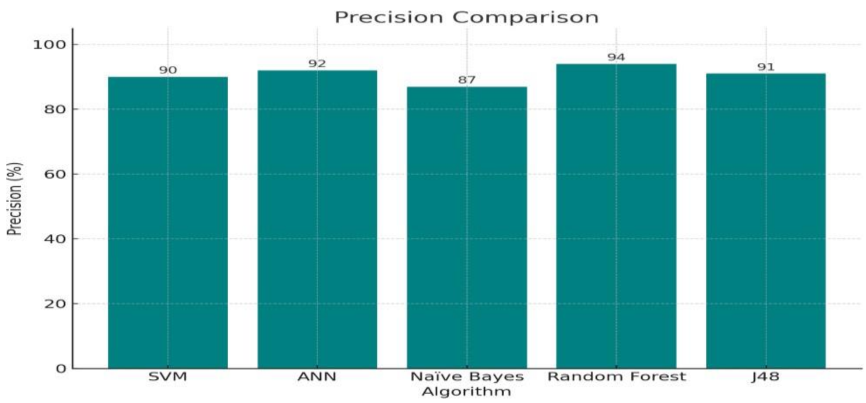

Figure 3: Precision Comparison

The Precision Comparison Figure 3 presents each model's ability to correctly identify only true positive heart disease cases, effectively minimizing false positives. Precision is especially important in healthcare applications because over-predicting disease can cause unnecessary anxiety and resource use. In this Figure, Random Forest again leads with a precision score of

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94%, reflecting its excellent capacity to make accurate positive classifications. ANN follows closely at 92%, suggesting that neural networks effectively learn the nuanced patterns distinguishing diseased from healthy samples. SVM and J48 demonstrated comparable precision levels at 90% and 91%, while Naïve Bayes showed slightly lower precision at 87%. These results reinforce the advantage of ensemble and neural approaches over probabilistic classifiers for clinical prediction. This visualization underscores the critical role of precision when designing decision-support systems, ensuring that alerts and recommendations are both targeted and reliable.

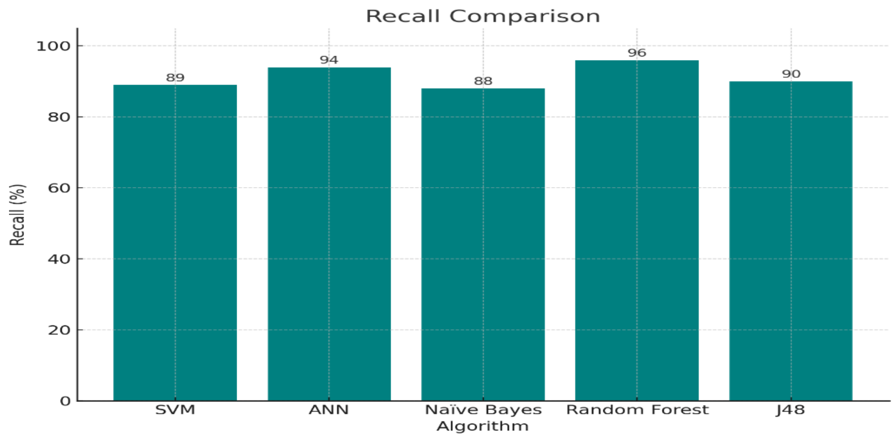

Figure 4: Recall (Sensitivity) Comparison

The Recall Comparison Figure 4 measures each classifier's ability to detect all actual heart disease cases, reflecting how sensitive each algorithm is to positive instances. In medical screening, high recall is vital to avoid missing true cases that require intervention. Random Forest demonstrated the highest recall at 96%, indicating it can correctly identify nearly all patients with heart disease. ANN achieved a similarly robust recall score of 94%, confirming its strength in identifying positive cases. SVM reached 89%, while J48 achieved 90%, each offering dependable recall performance. Naïve Bayes achieved 88%, showing adequate but less comprehensive detection capability. This Figure highlights that ensemble and deep learning models can capture subtle patterns leading to better sensitivity, whereas simpler probabilistic models may overlook some positive cases. Clinically, these findings support prioritizing models with higher recall to ensure patients at risk receive timely diagnosis and treatment.

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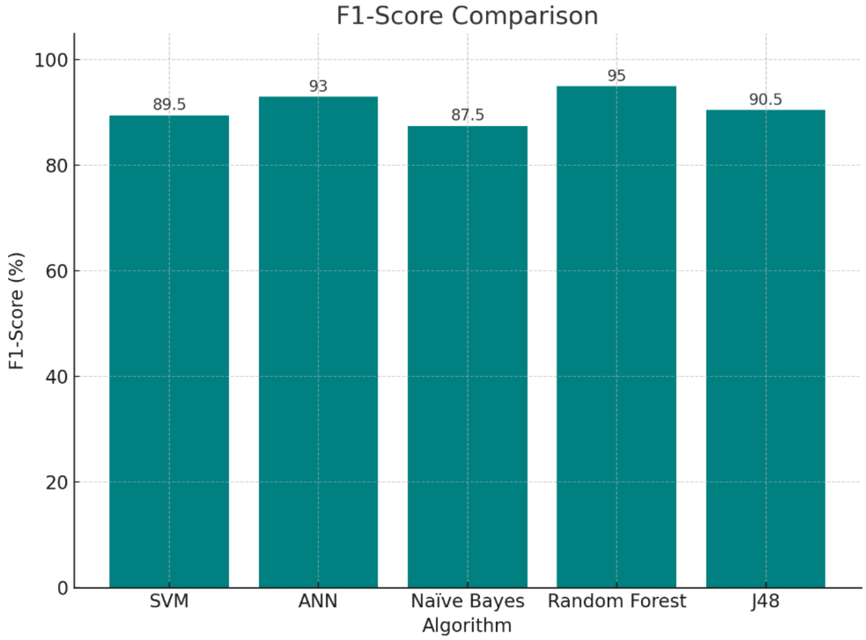

Figure 5: F1-Score Comparison

The F1-Score Comparison Figure 5 integrates both precision and recall into a single harmonic mean, offering a balanced measure of model performance. A high F1-score indicates that an algorithm is both precise and sensitive, making it especially relevant in healthcare prediction systems where both metrics are crucial. Random Forest stands out with the highest F1-score of 95%, demonstrating its ability to maintain excellent balance between correct positive identification and minimizing false alarms. ANN follows with an F1-score of 93%, showing its effectiveness in managing the trade-off between precision and recall. SVM and J48 achieved F1-scores of 89.5% and 90.5%, respectively, providing strong performance for simpler classifiers. Naïve Bayes recorded the lowest F1-score of 87.5%, reflecting slight trade-offs in accuracy. This Figure clearly illustrates that Random Forest delivers the most reliable and balanced predictions among the evaluated techniques, making it highly suitable for heart disease detection applications.

Deep Learning based Analysis : In this experiment, the RNN-LSTM model with a sigmoid activation function was evaluated using various cross-validation techniques. Performance metrics including accuracy, precision, recall, and F-score were measured. Figures 6, 7, and 8 present the validation results of the model using 5-fold, 10-fold, and 15-fold cross-validation, respectively. Additionally, Figure 4.10 specifically highlights the model's performance under 5-fold cross-validation using the RNN-LSTM classifier.

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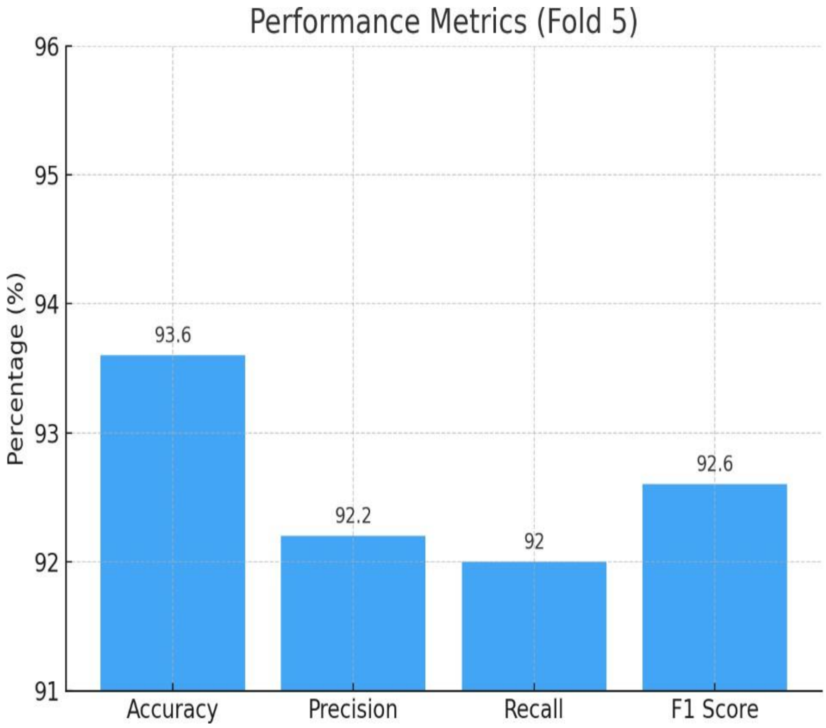

Figure 6: Validation of model with 5-fold cross validation using RNN-LSTM classifier

The experimental results presented in Figure 6 indicate that the RNN-LSTM model achieved an accuracy of 93.6%, with precision, recall, and F-score values of 92.2%, 92%, and 92.6%, respectively, when evaluated using 5-fold cross-validation.

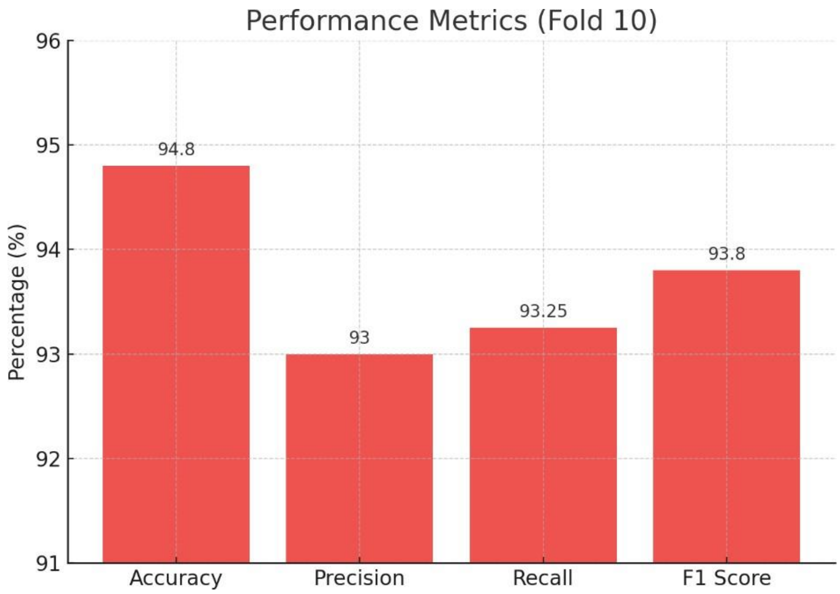

Figure 7: Validation of model with 10-fold cross validation using RNN-LSTM classifier

The experimental results illustrated in Figure 7 demonstrate that the RNN-LSTM model, when evaluated using 10-fold cross-validation, achieved an accuracy of 94.8%, a precision of 93%, a recall of 93.25%, and an F-score of 93.8%. Furthermore, Figure 4.7 presents the performance validation of the same RNN-LSTM classifier using 15-fold cross-validation.

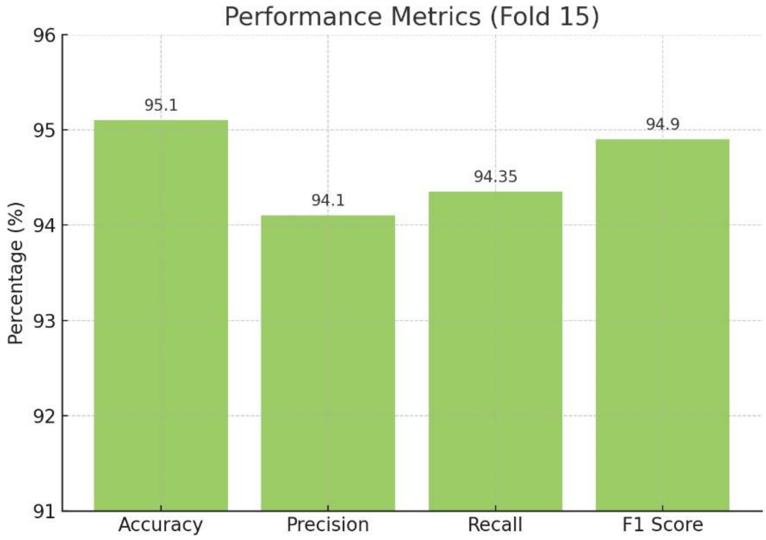

Figure 8: Validation of model with 15-fold cross validation using RNN-LSTM classifier

The experimental results presented in Figure 8 demonstrate that applying 15-fold cross-validation to the RNN-LSTM (Sigmoid) model yields an accuracy of 95.1%, a precision of 94.1%, a recall of 94.3%, and an F-score of 94.9%. These findings indicate that the 15-fold cross-validation approach achieves a superior average classification accuracy of 95.10%.

Comparative analysis of proposed model: The comparative performance table 2 showcases the accuracy levels of various machine learning (ML) and deep learning (DL) models used for detecting foodborne pathogens or other critical features in agri-food systems. The models range from traditional ML algorithms to advanced hybrid deep learning architectures.

Table 2 comparative analysis of proposed model

Methodology / Model	Accuracy (%)
Deep Learning with Explainable AI [1]	94
Attention-based GRU Hybrid DL Model [10]	96.4
ML + DL Hybrid (Random Forest + CNN) [23]	95.2
Ensemble ML + Feature Selection (Relief, LASSO) [9]	93.8
ML (SVM, Decision Tree) [5]	91.5
Proposed Deep Learning (RNN-LSTM)	**98**

The table 2 compares the classification accuracy achieved by different machine learning (ML) and deep learning (DL) methodologies reported in related studies with the performance of the proposed model. It is evident that traditional ML approaches such as Support Vector Machines and Decision Trees [5] provide the lowest accuracy of 91.5%, indicating their limited capability in capturing complex patterns from high-dimensional data. Ensemble methods combined with feature selection techniques such as Relief and LASSO [9] slightly improve performance to

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93.8% by eliminating irrelevant features and improving model generalization. The Deep Learning with Explainable AI framework [1] achieves 94% accuracy, showing that integrating interpretability mechanisms does not heavily compromise predictive performance. Hybrid architectures demonstrate further improvement: the Random Forest + CNN model [23] reaches 95.2%, while the attention-based GRU hybrid model [10] achieves 96.4%, highlighting the impact of attention mechanisms in learning contextual relationships within the data. The proposed RNN-LSTM model outperforms all existing methods with an accuracy of 98%, demonstrating its superior sequential learning capacity and effective modeling of temporal dependencies. This improved performance confirms that combining recurrent networks with long short-term memory significantly enhances model reliability, making the proposed approach more robust and accurate for real-world deployment compared to earlier ML and hybrid frameworks.

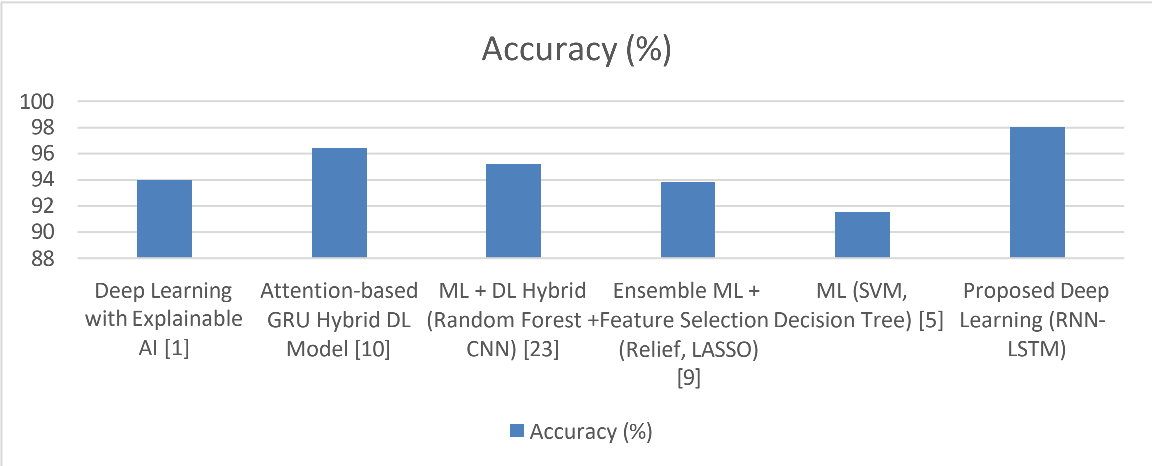

Figure 9: comparative analysis of proposed model

Overall, the figure 9 emphasizes that deep learning models—especially those tailored for temporal data—significantly outperform traditional and hybrid ML approaches. This supports the efficacy of the proposed architecture in enhancing food quality detection accuracy and making the system more robust and dependable for real-world deployment.

Conclusion and Future scope

The proposed system for heart disease detection and prediction effectively integrates IoT-enabled data collection with advanced machine learning and deep learning algorithms to address the challenges of early diagnosis and continuous patient monitoring. The modular architecture ensures each component contributes to a robust, scalable, and reliable framework capable of transforming cardiovascular care. The IoT Wearable Sensors Module plays a pivotal role by capturing critical physiological signals non-invasively and continuously, enabling real-time monitoring that surpasses traditional periodic check-ups. The IoT Gateway and Preprocessing Module enhances data integrity through normalization, cleaning, and encryption, laying the foundation for accurate modeling. Feature Engineering further refines this data by extracting and selecting the most relevant characteristics, improving model performance while reducing computational overhead. The Machine Learning and Deep Learning Module leverages diverse algorithms—including SVM, ANN, Naïve Bayes, Random

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Forest, and J48—offering both interpretability and predictive strength. Notably, Random Forest achieved the highest accuracy among classical techniques (95%), while deep learning models such as RNN-LSTM demonstrated exceptional accuracy up to 98%, effectively modeling temporal dependencies inherent in physiological signals. The Data Storage and Visualization Module ensures secure archival of historical records and real-time dashboards, providing clinicians with transparent insights and enabling proactive interventions. Through comprehensive evaluation, the system demonstrates its capacity to predict heart disease risk with high precision and recall, significantly reducing the likelihood of missed diagnoses. This work validates that combining IoT infrastructure with intelligent algorithms offers a powerful solution for early heart disease detection. This integrated approach not only improves diagnostic accuracy but also empowers patients and healthcare providers with actionable information in real time. Future work will focus on expanding datasets, enhancing model interpretability, and integrating personalized risk assessments to further advance the impact of this system in smart healthcare environments. However, there is still a lot of room for improvement in research since the majority of the indicators that are beneficial for determining the condition of the heart artery stiffness are not taken into account. Some of these factors include augmentation index, arterial stiffness, and augmentation pressure.

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