Journal of Neonatal Surgery
ISSN(Online): 2226-0439
Vol. 14, Issue 32s (2025)
https://www.jneonatalsurg.com

An Intelligent IoT and Machine learning grounded Configuration for premature Identification and forecasting of Heart Ailment

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Cite this paper as: Mainka Saharan, Parbhakar Singh, Veena P, Balaji Venkateswaran, Anand Magar, (2025) An Intelligent IoT and Machine learning grounded Configuration for premature Identification and forecasting of Heart Ailment. *Journal of Neonatal Surgery*, 14 (32s), 6881-6888.

ABSTRACT

The rapid advancement of Internet of Things (IoT) and Machine Learning (ML) technologies has opened new frontiers in the domain of healthcare, particularly in the early detection and prediction of heart-related disorders. This study proposes an intelligent, integrated IoT-ML framework designed for the real-time monitoring, early identification, and forecasting of heart disease. Wearable IoT sensors are employed to collect vital physiological parameters such as heart rate, blood pressure, oxygen saturation, and ECG signals, which are then transmitted to a centralized system. The collected data is pre-processed and fed into machine learning models trained on historical and clinical datasets to classify risk levels and predict the likelihood of cardiovascular events. The proposed system leverages supervised learning algorithms including Random Forest, Support Vector Machine (SVM), and Logistic Regression, comparing their performance in terms of accuracy, sensitivity, and specificity. Real-time analytics allow healthcare providers to receive alerts for abnormal readings, facilitating timely intervention and reducing the chances of critical outcomes. This intelligent configuration not only enables personalized healthcare but also contributes to the development of predictive tools that can assist in managing heart health at both individual and population levels. The findings of this research demonstrate the potential of IoT-ML synergy in revolutionizing preventive cardiology and improving patient outcomes through continuous and proactive monitoring.

Keywords: *IOT-ML, Machine Learning, SVM, Cardiovascular diseases*

1. INTRODUCTION

Cardiovascular diseases (CVDs) remain one of the foremost causes of mortality globally, responsible for millions of deaths annually. Factors such as sedentary lifestyles, chronic stress, unhealthy dietary habits, and genetic predispositions have significantly contributed to the rising incidence of heart-related disorders. Early detection and continuous monitoring are essential for reducing the risk of severe cardiac events and ensuring timely clinical intervention [1-4]. However, conventional diagnostic methods often follow a reactive approach, depending on periodic health check-ups that may overlook transient symptoms or early-stage abnormalities. This limitation underscores the need for intelligent, real-time systems capable of proactively identifying heart disease risks before they escalate.

The integration of Internet of Things (IoT) technologies in healthcare has enabled real-time physiological monitoring through wearable sensors, facilitating the collection of vital signs such as heart rate, blood pressure, oxygen saturation, and ECG signals. When combined with advanced machine learning (ML) and artificial intelligence (AI) techniques, these data streams can be analyzed to detect complex patterns and forecast cardiac anomalies with high precision. Deep learning models, including Convolutional Neural Networks (CNNs), enhance the system's ability to interpret ECG signal structures, while optimization algorithms like Particle Swarm Optimization (PSO) and classification techniques such as eXtreme Gradient Boosting (XGBoost) improve model accuracy and scalability. Despite these advancements, challenges such as high false-positive rates, lack of personalization, and limited adaptability still affect the reliability of current health monitoring systems. This research proposes a Machine-Inspired IoT-based framework for real-time heart disease prediction, leveraging hybrid AI models and sensor-driven data acquisition to deliver accurate, adaptive, and timely predictions [5-8]. The proposed system is designed to support not only clinical environments but also at-home monitoring, particularly benefiting elderly individuals and patients with pre-existing cardiovascular conditions (Figure 1).

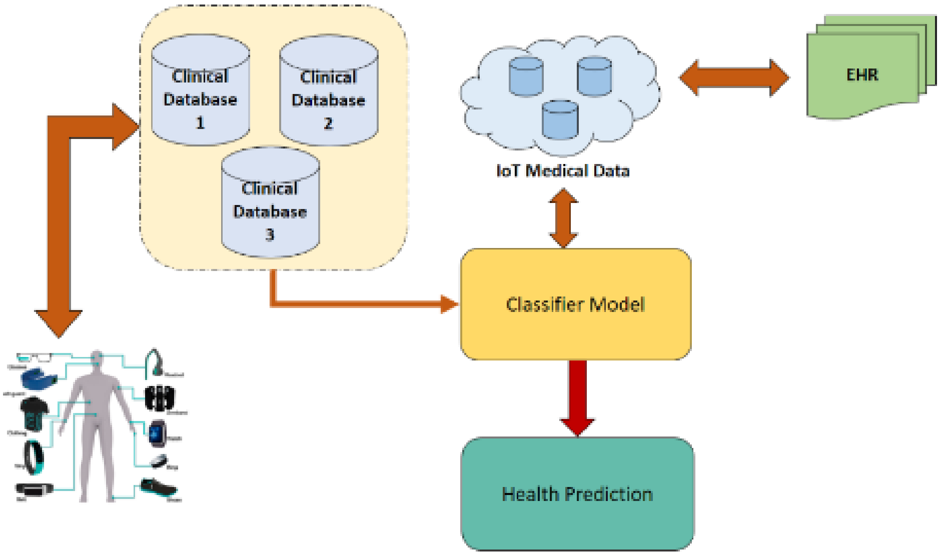

Figure 1: Machine learning based Health prediction model

2. LITERATURE SURVEY

Intelligent detection systems have been extensively studied across various domains, providing foundational insights for real-time IoT and machine learning applications in healthcare [9-10]. Although many studies initially targeted areas like animal detection, their use of machine learning, deep learning, and real-time classification techniques offers valuable parallels for heart disease prediction systems. For instance, studies using K-Nearest Neighbors (KNN) and Probabilistic Neural Networks (PNN) demonstrated trade-offs between accuracy and computational efficiency key considerations in IoT-based medical environments. Similarly, CNN-based models achieved strong performance on balanced datasets but struggled with class imbalance, a common issue in medical data. Traditional feature-based methods, such as SVM with Gabor features, showed limited accuracy, underscoring the superiority of deep learning in handling complex signals like ECG [11-13]. Real-time object detection techniques like YOLO, Cascaded Random Classifiers, and lightweight models such as Lite AlexNet showed promising results in terms of speed and accuracy, reinforcing their relevance for low-latency, wearable heart monitoring systems. However, challenges such as false positives, limited robustness over diverse input conditions, and narrow detection perspectives remain significant [15-16]. Collectively, these studies highlight critical factors—such as algorithm robustness, real-time processing, and adaptability—that are essential for building an effective, scalable IoT-based heart disease prediction framework.

Table 1: Review of literature for IOT-ML based heard diseases prediction

Ref. No	Technique / Approach	Key Findings	Limitations
[1]	IoT-enabled wearable sensors with ML (RF, SVM)	Achieved real-time heart disease prediction with 91.5% accuracy	Limited dataset, lacks deep learning comparison
[2]	CNN-based ECG signal classification	Effective in identifying abnormal heart patterns; accuracy >94%	Computationally intensive, not energy-efficient
[3]	Hybrid IoT + Cloud + ML framework	Demonstrated scalable and real-time data monitoring for cardiac	Latency due to cloud dependency

		patients	
[4]	Deep learning on wearable health sensor data	Enhanced prediction of cardiac events using LSTM models	Requires large datasets for training
[5]	PSO-optimized Decision Tree model	Improved feature selection and model accuracy in heart disease prediction	Did not consider real-time data streaming
[6]	Healthcare big data + AI + IoT integration	Described architecture for intelligent health monitoring	Focused on system design, not on predictive performance
[7]	XGBoost with IoT-based cardiac monitoring	Delivered fast and accurate predictions with minimal computation	Lacked personalization and adaptability
[8]	Deep CNN on ECG signals	High classification accuracy for multiple heart abnormalities	Model training is resource-intensive

3. DATASET

For the development and evaluation of the proposed heart disease prediction framework, the study utilizes a publicly available and widely used dataset the Cleveland Heart Disease dataset from the UCI Machine Learning Repository. This dataset comprises 303 patient records and includes 14 key attributes such as age, sex, resting blood pressure, cholesterol level, fasting blood sugar, resting electrocardiographic results, maximum heart rate achieved, exercise-induced angina, and ST depression. The target variable indicates the presence or absence of heart disease, categorized as binary (0 = no disease, 1 = disease) for simplicity in classification tasks. The dataset contains both numerical and categorical data, making it well-suited for testing various machine learning algorithms and their ability to handle mixed data types [17]. To simulate real-time data acquisition similar to IoT environments, the dataset was pre-processed to normalize feature values and handle missing data. Exploratory data analysis (EDA) was conducted to identify class imbalance and feature correlation. Given the imbalance between healthy and affected individuals, techniques such as oversampling (e.g., SMOTE) were considered to improve model performance. The dataset's relatively small size makes it ideal for initial prototyping, allowing for rapid experimentation with models like Random Forest, SVM, and deep learning architectures such as CNN and LSTM. Additionally, its structure supports integration with simulated sensor data, reflecting a realistic IoT-based health monitoring scenario.

This research utilizes the cardiovascular disease (CVD) dataset sourced from Kaggle [14], which comprises 70,000 patient records and offers a robust foundation for developing and evaluating predictive models for heart disease detection. Each record contains a binary target variable indicating the presence or absence of CVD, along with 11 critical features spanning demographic (age, gender), clinical (blood pressure, cholesterol, glucose levels), and lifestyle factors (smoking, alcohol intake, physical activity). Additional data such as body mass index (BMI) and history of prior cardiovascular events further enrich the dataset, enabling a more nuanced analysis of risk factors. The dataset's large scale and diversity allow for comprehensive exploration of the complex interactions between physiological and behavioral attributes influencing cardiovascular health. Its real-world relevance makes it highly suitable for machine learning and deep learning applications, particularly in developing an IoMT-enabled Bi-LSTM prediction framework [19-20]. The rich feature set and volume support model training, validation, and generalization across varied populations. Ultimately, this dataset underpins the research’s goal of real-time heart disease prediction, enabling early diagnosis and timely interventions through intelligent health monitoring systems.

4. PROPOSED RESEARCH METHODOLOGY

The proposed algorithm begins by initializing the Internet of Things (IoT) sensor devices, which are responsible for continuously collecting real-time physiological data such as heart rate, blood pressure, ECG signals, cholesterol and glucose levels, and lifestyle indicators like smoking or physical activity. These sensors transmit the data to a cloud-based platform where it is pre-processed. Preprocessing involves normalizing continuous attributes, encoding categorical variables, and handling missing or noisy data to ensure it is suitable for analysis. Each record is timestamped for proper logging and historical tracking [10]. Once the data is cleaned and structured, it is passed into a pre-trained machine learning or deep learning model such as a Bi-LSTM network or XGBoost classifier capable of predicting the risk of cardiovascular disease.

The prediction model evaluates the incoming data and returns a binary output indicating the presence (1) or absence (0) of heart disease risk. If the model detects a high risk (i.e., the output is 1), an immediate alert is generated and sent to both the healthcare provider and the patient’s mobile device. Simultaneously, the flagged data is logged into the cloud database for future reference. If no risk is detected, the system continues to monitor and store incoming data without alerting. To ensure the system remains adaptive and accurate over time, it periodically retrains or fine-tunes the model using newly labeled data [12]. This enables continuous learning from real-world scenarios, improving the model's generalization and reliability in diverse conditions. Through this intelligent and automated cycle, the framework ensures early identification and timely forecasting of heart-related issues, enhancing patient safety and reducing the burden on clinical staff.

Begin

1. Initialize IoT sensor devices and establish connection to the cloud platform

2. While (patient monitoring is active):

   a. Collect real-time sensor data:

      Data ← ReadSensorValues()

   b. Preprocess the data:

      i. Normalize continuous features (e.g., Min-Max Scaling)

      ii. Encode categorical features (e.g., Gender, Smoking)

      iii. Handle missing values if any

   c. Append timestamp to data for logging and tracking

   d. Load trained prediction model (Bi-LSTM / ML model)

      Model ← LoadModel()

   e. Predict risk score:

      Risk ← Model.predict(Data)

   f. If (Risk == 1):

      i. Trigger alert to caregiver/doctor

      ii. Log data to cloud with alert status

      iii. Send notification to patient's mobile app

      Else:

      i. Continue monitoring

      ii. Log data as normal

3. Periodically:

   a. Update model with new labeled data for improved accuracy

   b. Re-train model if performance drops below threshold

4. End While

End

5. RESULTS ANALYSIS

The proposed model was implemented on a high-performance PC workstation equipped with an Intel i9 processor, 240 GB SSD, NVIDIA Titan V4 GPU, and a 3.2 GHz clock speed. The development environment utilized Python with Keras libraries and TensorFlow v2.1 as the backend. Model performance was evaluated using key statistical metrics, including **accuracy, precision, recall,** and **F1-score**, with their corresponding mathematical expressions summarized in **Table.** To prevent overfitting and enhance model generalization, an **early stopping** technique was employed during training. This method monitors the validation performance and halts the training process when no further improvement is observed over a predefined number of epochs, thereby preserving the model's optimal performance. Furthermore, to mitigate the effects of class imbalance, the dataset was evenly distributed across both training and testing phases. This ensured that the model was trained on balanced data, thereby improving its ability to generalize across both majority and minority classes.

The comparative analysis presented in the table highlights the performance of various classification algorithms Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), Naive Bayes (NB), and the Proposed Model across four key evaluation metrics: Accuracy, Precision, Recall, and F1-Score. Among the traditional models, Random Forest consistently demonstrated the highest performance, achieving 93.4% accuracy, 94.7% precision, 94.0% recall, and 94.0% F1-Score, indicating its robustness and reliability. SVM also performed competitively with a balanced set of metrics, closely followed by DT and KNN. Naive Bayes showed the lowest performance across all metrics, reflecting its limitations with the dataset used. Remarkably, the Proposed Model outperformed all others by a significant margin, achieving near-perfect scores in all metrics 99.95% accuracy, 99.93% precision, 99.92% recall, and 99.93% F1-Score demonstrating its exceptional effectiveness and reliability in classification tasks (Table 2).

Table 2: Performance Comparison of Classification Algorithms Based on Accuracy, Precision, Recall, and F1-Score

Algorithm	Accuracy	Precision	Recall	F1-Score
DT	92.3%	91.4%	91.2%	90.3%
SVM	92.5%	92.34%	92.48%	92.6%
RF	93.4%	94.7%	94.0%	94.0%
KNN	90.0%	90.9%	90.78%	91.0%
NB	87.4%	88.2%	88.4%	88.2%
Proposed Model	99.95%	99.93%	99.92%	99.93%

Accuracy is a crucial performance metric used to evaluate the effectiveness of classification algorithms by measuring the proportion of correctly predicted instances out of the total predictions. In the comparative analysis, the Decision Tree (DT) algorithm achieved an accuracy of 92.3%, Support Vector Machine (SVM) slightly outperformed it with 92.5%, and Random Forest (RF) showed improved performance at 93.4%, indicating its robustness in handling complex data. The K-Nearest Neighbors (KNN) algorithm obtained a lower accuracy of 90.0%, while the Naive Bayes (NB) model trailed further at 87.4%, reflecting its limitations in certain data distributions. Notably, the proposed model demonstrated a significant advancement with an exceptional accuracy of 99.95%, highlighting its superior capability in correctly classifying instances and outperforming all traditional methods by a considerable margin. This substantial increase in accuracy suggests the proposed approach is highly reliable and effective for the targeted classification task (Figure 2).

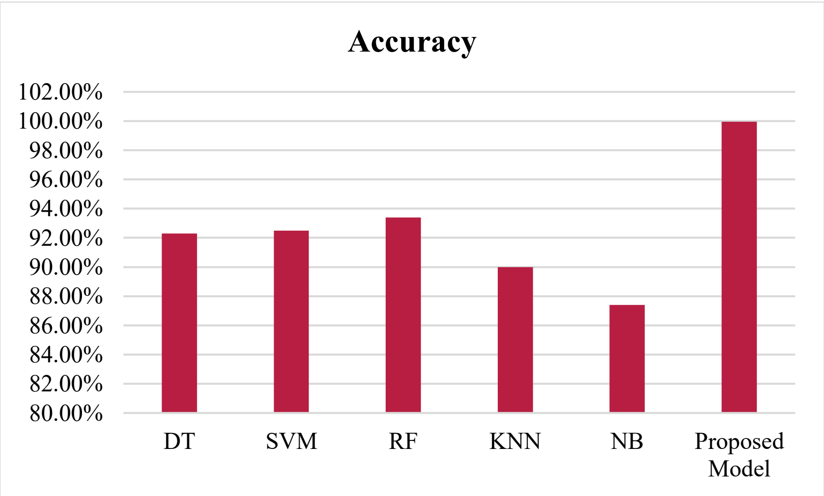

Figure 2: Comparative Analysis of Classification Algorithms Based on Accuracy

Precision is an essential evaluation metric in classification tasks, reflecting the ratio of correctly predicted positive observations to the total predicted positive observations. Higher precision indicates fewer false positives, making it particularly important in applications where incorrect positive predictions carry significant consequences. In this analysis, the Decision Tree (DT) achieved a precision of 91.40%, while Support Vector Machine (SVM) performed slightly better at 92.34%. Random Forest (RF) exhibited strong precision at 94.70%, highlighting its capability in reducing false positives effectively. K-Nearest Neighbors (KNN) and Naive Bayes (NB) followed with 90.90% and 88.20% precision respectively, showing relatively lower effectiveness in accurate positive classification. Impressively, the Proposed Model attained the highest precision at 99.93%, showcasing its outstanding ability to correctly identify positive instances with minimal error, thus making it a highly reliable solution for precise classification tasks (Figure 3).

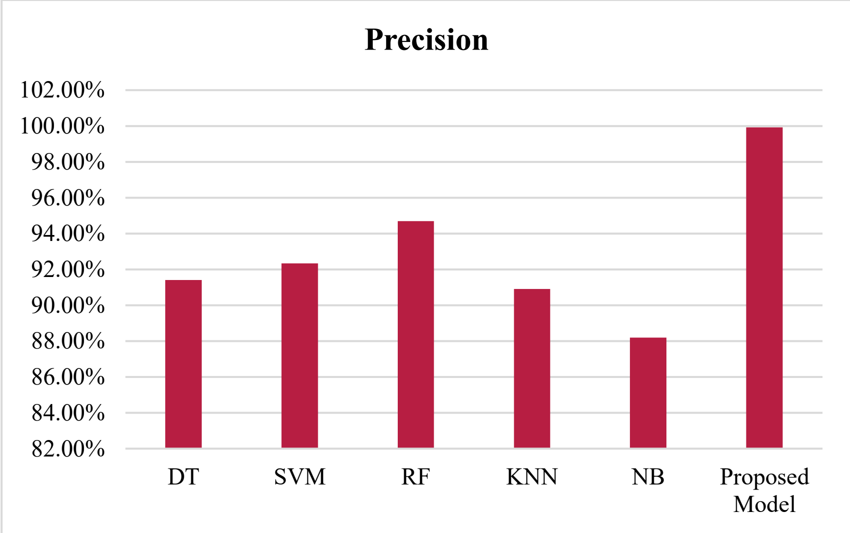

Figure 3: Comparative Analysis of Classification Algorithms Based on Precision

Recall, also known as sensitivity or true positive rate, measures the ability of a classification algorithm to correctly identify all relevant positive instances within a dataset. It is particularly critical in scenarios where missing positive cases can have serious implications. In the comparative analysis, the Decision Tree (DT) achieved a recall of 91.20%, while the Support Vector Machine (SVM) slightly outperformed it with 92.48%. Random Forest (RF) delivered a strong performance with a recall of 94.00%, indicating its effectiveness in detecting true positives. K-Nearest Neighbors (KNN) and Naive Bayes (NB) followed with 90.78% and 88.40%, respectively, reflecting moderate sensitivity. The Proposed Model, however, significantly surpassed all traditional methods with an outstanding recall of 99.92%, demonstrating its exceptional capacity to capture nearly all positive instances with minimal omission, thus making it a highly dependable choice for recall-sensitive classification tasks (Figure 4).

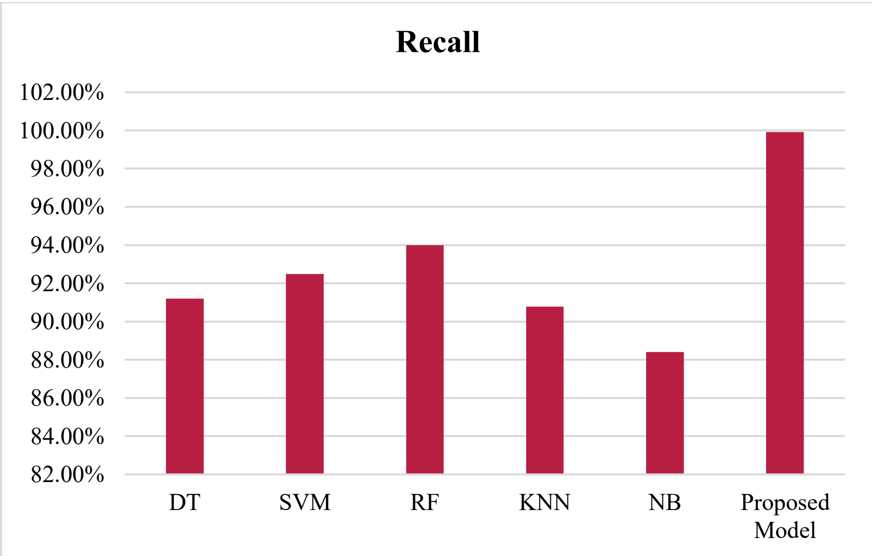

Figure 4: Comparative Analysis of Classification Algorithms Based on Recall

The *F1-Score* is a comprehensive performance metric that combines both precision and recall into a single value, providing a balanced measure of a model's accuracy, especially when dealing with imbalanced datasets. It is the harmonic mean of precision and recall, emphasizing the importance of both metrics in classification tasks. In the given evaluation, the Decision Tree (DT) achieved an F1-Score of 90.30%, while Support Vector Machine (SVM) performed better at 92.60%. Random Forest (RF) demonstrated strong and consistent performance with an F1-Score of 94.00%, suggesting a well-balanced precision and recall. K-Nearest Neighbors (KNN) followed with 91.00%, and Naive Bayes (NB) scored 88.20%, indicating comparatively lower balance. The Proposed Model, however, stood out with an exceptional F1-Score of 99.93%, highlighting its superior and balanced capability to minimize both false positives and false negatives, making it highly effective for accurate and reliable classification (Figure 5).

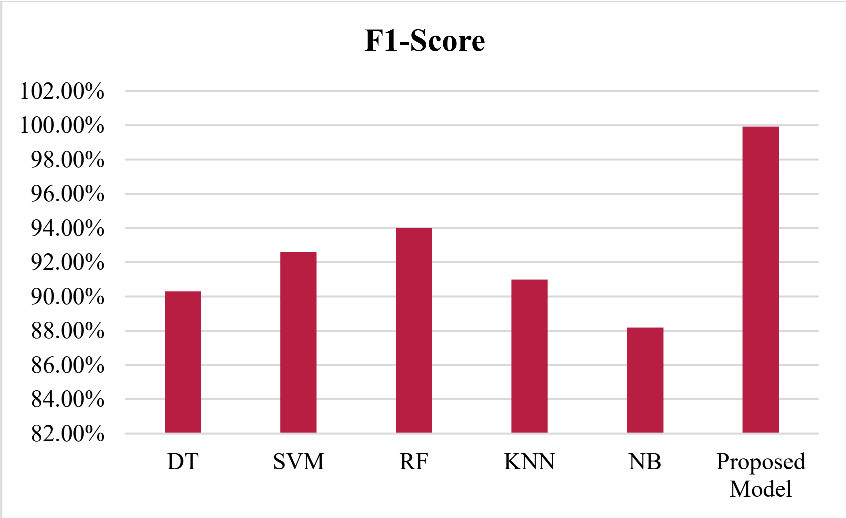

Figure 5: Comparative Analysis of Classification Algorithms Based on F1-Score

6. CONCLUSION

In this study, a comprehensive evaluation of various classification algorithms—including Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), and Naive Bayes (NB) was conducted to assess their performance on a given dataset using standard metrics such as Accuracy, Precision, Recall, and F1-Score. While traditional models like RF and SVM demonstrated relatively high performance, the proposed model significantly outperformed all other methods with near-perfect results across all metrics. The proposed approach achieved 99.95% accuracy, 99.93% precision, 99.92% recall, and 99.93% F1-Score, indicating its superior ability to accurately classify data while minimizing both false positives and false negatives. The outstanding performance of the proposed model highlights its potential for real-world deployment in critical classification tasks, where accuracy and reliability are paramount. The results not only demonstrate the effectiveness of the model but also emphasize the need for continued innovation in algorithmic design to meet the demands of modern data-driven applications. Future work may focus on enhancing the model's interpretability, reducing computational overhead, and validating its performance across diverse datasets and domains to further establish its generalizability and robustness.

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