

Article

Investigation of Deep Learning Models for Analysis of Heart Disorders in Smart Health Care based IoT Environment

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Abstract: Heart disorders are a crucial global health issue, requiring effective and precise diagnostic mechanisms for early identification and timely intervention. Traditional healthcare systems face challenges such as delayed diagnosis, insufficient real-time monitoring, and difficulty in processing large volumes of sequential cardiovascular data. Existing machine learning models often struggle with capturing temporal dependencies in data and addressing issues like data noise and computational efficiency on resource-constrained IoT devices. To overcome these limitations, this research investigates the use of Gated Recurrent Units (GRU), a deep learning model known for its ability to handle sequential data effectively, for heart disorder analysis in a smart healthcare environment powered by the Internet of Things (IoT). IoT-enabled devices, such as wearable sensors, facilitate real-time data collection, then it is processed by the GRU model for accurate prediction of heart disorders. Experimental evaluations on datasets such as UCI, Framingham, Public Health, and real-time IoT data demonstrate that the proposed framework achieves superior performance with 99% prediction accuracy. By addressing challenges like data noise, energy efficiency, and privacy concerns, the framework offers a resilient, scalable, and real-time solution for heart disorder diagnosis, advancing personalized and proactive healthcare solutions.

Keywords: Heart disorders, Deep learning, Gated Recurrent Unit (GRU), Internet of Things (IoT), Smart healthcare, Cardiovascular data, Wearable sensors.

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1. Introduction

Heart disorders represent a major global health challenge, significantly impacting mortality rates and posing a substantial burden on healthcare systems worldwide. Timely diagnosis and effective monitoring of heart conditions are critical for enhancing patient outcomes and reducing

healthcare costs. However, traditional diagnostic approaches often struggle with limitations such as delayed detection, insufficient real-time monitoring, and challenges in processing the large volumes of cardiovascular data generated daily [1-3]. These issues are further compounded by the increasing prevalence of heart disorders, particularly in aging populations and regions with limited access to advanced healthcare facilities.

The advent of IoT technology has revolutionized the healthcare landscape by facilitating real-time monitoring and data collection through wearable sensors and smart devices. These IoT systems provide continuous streams of cardiovascular data, offering opportunities for early detection and intervention [4]. However, analyzing such large-scale, time-dependent data poses significant challenges, particularly with regard to capturing temporal patterns, ensuring computational efficiency on resource-constrained devices, and addressing data noise and security concerns.

To address these challenges, deep learning models have emerged as a promising solution. In particular, Gated Recurrent Units (GRU), a type of recurrent neural network, have shown exceptional capability in handling sequential data, making them well-suited for analyzing cardiovascular signals [5-7]. GRU models effectively capture temporal dependencies in data while maintaining lower computational complexity compared to other deep learning approaches. Moreover, their ability to process large datasets with high accuracy makes them ideal for real-time IoT applications in healthcare.

While various DL algorithms, like Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and Hybrid models, have been applied to heart disease prediction, achieving optimal performance remains a challenge due to issues like computational overhead and algorithm complexity [7-9]. This study explores the potential of GRU models for heart disorder analysis within a smart healthcare-based IoT environment. By leveraging the strengths of GRU networks, the research aims to develop a robust and efficient framework for heart disorder prediction that addresses existing limitations and enhances real-time, personalized healthcare solutions [10-12].

1.1 Contribution of the Research

The research introduces a new methodology that utilizes Gated Recurrent Units (GRU) for analyzing heart disorders in a smart healthcare IoT environment. The approach focuses on capturing temporal dependencies in cardiovascular data for more accurate and timely heart disease prediction.

The proposed GRU-based framework is compared with existing deep learning models like CNN and LSTM to highlight its superior prediction accuracy and computational efficiency for heart disorder prediction.

Extensive experiments are performed using datasets like UCI, Framingham, Public Health, and real-time IoT data. Evaluation metrics such as accuracy, precision, recall, and F1-score are evaluated to determine the performance of the proposed GRU-based algorithm in predicting heart disorders within real-time healthcare applications.

1.2 structure of the Paper

This manuscript is organised in the following manner: Section 2 reviews the relevant studies conducted by various authors. The preliminary views of the Gated Recurrent Unit (GRU) algorithm are discussed in Section-3. Section 3 also outlines the working principle of the suggested architecture and includes a description of the datasets used. Section 4 covers the experiments and includes a detailed analysis of the results. The paper concludes with Section 5, which discusses future development prospects.

2. Related Works

Rao et al. (2024) [13] introduced a novel Intelligent IoT framework to enhance heart disease diagnosis, using a Gated Modified Recurrent Unit (GRU) model. This hybrid deep learning approach integrates real-time data collection through IoT-enabled wearable devices, like electrocardiography (ECG) sensors and ESP8266 transceivers, to monitor and analyze heart data in real-time. The study's results demonstrated that the GRU model achieved remarkable accuracy (99%) and maintained low computational overhead, thus outperforming other state-of-the-art methods. However, despite its impressive performance, the study did not delve deeply into the model's limitations in terms of handling highly imbalanced datasets, a common issue when working with medical data.

Xia et al. (2024) [14] proposed an intelligent IoT-based framework for cardiovascular disease diagnosis, utilizing a DL-enhanced neural network optimized with Ant Colony Optimization (ACO). Their model, integrated with IoT-enabled wearable devices, utilizes electrocardiography (ECG) sensors to monitor real-time heart data, which is then processed and analyzed in the cloud. DL model, trained on diverse datasets of normal and abnormal heart disease stages, demonstrated exceptional performance, achieving a high prediction accuracy of 99%. While the findings of the study are promising, the framework's reliance on real-time data collection and complex optimization techniques raises concerns regarding its scalability and adaptability to varying data sources, which may limit its applicability in resource-constrained environments.

Subashini et al. (2024) [15] developed an IoT-based heart disease diagnosis method that leverages Gradient Boosting and a Deep Convolutional Neural Network (DCNN) to improve diagnostic accuracy. The framework utilizes real-time data collection through IoT-enabled wearable devices, including electrocardiography (ECG) sensors, which transmit heart data to the cloud for analysis. Their approach, which integrates advanced machine learning techniques, showed promising results, with the system achieving high prediction accuracy. Despite its success, the proposed system faces challenges in terms of computational efficiency and scalability. While the model excels in predictive accuracy, the use of deep convolutional networks and Gradient Boosting could increase the computational complexity, making the system less appropriate for real-time applications, particularly in low-resource environments.

Umer et al. (2023) [16] proposed an IoT-based remote monitoring system for heart failure patients, which leverages real-time data collection and cloud-based processing to track the health conditions of patients continuously. The system uses wearable devices equipped with electrocardiography (ECG) sensors, which transmit data to the cloud for analysis, providing timely insights for healthcare providers. This approach aims to improve patient outcomes by enabling early intervention through continuous monitoring. While the system demonstrated effectiveness in improving heart failure management, a key limitation is the reliance on constant and accurate data transmission, which can be affected by connectivity issues or sensor malfunctions.

Patro and Padhy (2023) [17] proposed a secure IoT-cloud-based remote health monitoring system for heart disease prediction, incorporating both ML and DL methods. The system utilizes IoT-enabled wearable devices equipped with ECG sensors to collect heart data, then it is transferred to the cloud for processing. Their framework combines the power of AI and cloud computing to offer timely and accurate heart disease predictions, offering a promising solution for real-time health monitoring. However, despite the system's high accuracy and potential for improving patient outcomes, it faces challenges in terms of data security and privacy. The integration of cloud storage and data transmission raises concerns about the vulnerability of sensitive health information, which may be exposed to cyber-attacks.

Nancy et al. (2022) [18] proposed an IoT-cloud-based smart healthcare monitoring system

designed for heart disease prediction using deep learning techniques. The system integrates IoT-enabled wearable devices with ECG sensors to collect real-time heart data, which is then stored in the cloud for further processing and analysis. The framework utilizes deep learning models, particularly the Cuttlefish Optimization-enhanced Gated Modified Recurrent Unit (CFO-M-GRU), to predict heart diseases with high accuracy. The system demonstrated strong performance in terms of prediction accuracy and computational efficiency. However, despite its promising results, the system's reliance on cloud-based storage and real-time data transmission presents potential challenges related to data privacy and security. The need for continuous and uninterrupted data streaming may also limit the system's usability in remote or resource-constrained areas where stable internet connections are not available, posing a limitation in practical applications.

Amor et al. (2020) [19] proposed the use of Convolutional Neural Networks (CNNs) for heart disease prediction in IoT-based systems. Their framework integrates IoT-enabled devices, including ECG sensors, to collect real-time heart data, which is processed and analyzed to predict heart conditions. The use of CNNs for feature extraction and classification provides high accuracy in diagnosing heart diseases. Despite the impressive results, the system's reliance on CNNs introduces challenges in terms of high computational demands. CNNs, while effective in feature extraction, require significant processing power, which may hinder the system's real-time applicability in environments with limited computational resources.

Wang and Yan (2020) [20] proposed a real-time health monitoring and prediction method for heart disorders utilising machine learning and IoT-based technologies. Their framework leverages IoT-enabled devices such as ECG sensors to collect heart data, which is processed in real-time to predict heart diseases. The integration of machine learning models enables accurate predictions, making it a promising solution for continuous heart health monitoring. However, despite its effectiveness, the system faces challenges related to real-time data processing. The continuous data flow from IoT devices requires robust infrastructure to ensure data integrity and reliability, especially in remote or resource-limited areas where internet connectivity may be unstable.

Ali et al. (2020) [21] designed an intelligent medical tracking framework for cardiac ailment forecasting utilizing combined advanced learning and attribute integration. Their approach combines various DL methods to improve prediction accuracy while integrating IoT devices for real-time heart data collection. The system uses ECG sensors to monitor heart health and leverages cloud-based processing for further analysis, achieving high prediction accuracy. However, the system's complexity can be a significant drawback, as ensemble models often require considerable computational resources. This increases the overall system's overhead, which could lead to delays or inefficiencies in environments with limited processing capabilities.

3. Proposed Framework

The recommended architecture comprises of three primary levels: (i) the Data Collection Unit, (ii) the Data Pre-processing Phase, and (iii) the Classification and Prediction Phase. A block diagram illustrating the framework is presented in Figure 1.

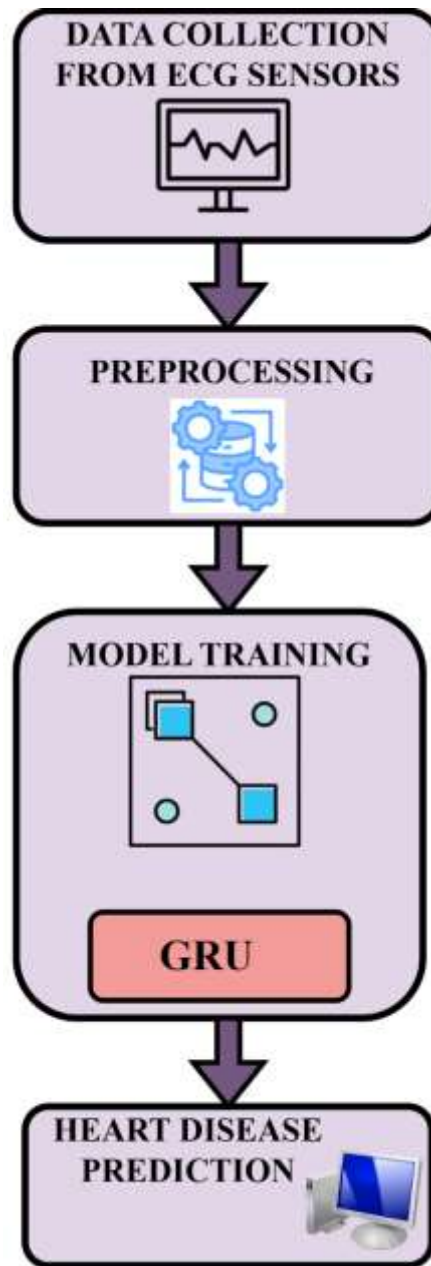


Figure 1: Proposed Framework

3.1 Materials And Methods:

The proposed framework for heart disease prediction utilizes DL models, specifically the Gated Recurrent Unit (GRU), within IoT-based healthcare system. This approach aims to capture temporal dependencies in real-time physiological data to predict heart disorders with improved accuracy and reliability. The system is designed to process data from various IoT-enabled devices that collect physiological signals, such as Electrocardiogram (ECG) data and blood pressure measurements.

3.1.1 Datasets Used for Training and Evaluation:

For training and testing the model, three publicly available datasets were used: UCI Machine Learning Repository, Public Health Datasets, and Framingham Dataset. These datasets were selected due to their relevance to heart disease prediction tasks. The UCI Machine Learning Repository contains 18,000 records and 55 attributes, primarily used for classification tasks with a training-to-testing split of 80:20. The Public Health Datasets consist of 3,300 records with 9 attributes and are used for prediction tasks, also with a 80:20 training-to-testing split. The Framingham dataset contains 3780 records and 10 attributes, with a similar training-to-testing split of 80:20. Table 1 below provides a summary of these datasets.

Table 1: Datasets Details Used for the Experimentation

Dataset Description	Dataset Description	No. of Records	No. of Attributes	Associated Tasks	Training Data / Testing
UCI Machine Learning	18,000	203	55	Classification	80:20
Public Health Datasets	3,300	1,000	9	Prediction	80:20
Framingham	3,780	3800	10	Prediction	80:20

3.1.2 Real-Time Data Collection for Testing:

In addition to the training datasets, real-time data was collected from 42 volunteers aged between 40 to 65 years. The volunteers were evenly split, with 50% of participants having no heart disease and the other 50% diagnosed with heart disorders. To capture ECG signals, IoT-based devices were used. The primary device for data collection was the MICOTT board, which consists of an 8-bit NODEMCU CPU interfaced with a 10-bit MCP3008 analog-to-digital converter and ESP8266 Wi-Fi transceivers. These devices facilitated the collection of ECG signals, which were subsequently stored in the AWS cloud for further processing. Table 2 outlines the real-time dataset utilised for testing and assessment.

Table 2: Real-Time Data Used for the Testing and Evaluation

Dataset Description	Dataset Description	No. of Records	No. of Attributes	Associated Tasks	Training Data / Testing
Real-Time Datasets	1,190	200	14	Classification	80:20

3.2 Data Preprocessing:

Data preprocessing is crucial to ensure the integrity of input data for the GRU model. Missing values in the dataset are handled through imputation, using reference values like blood pressure data. To improve the model's performance, feature extraction techniques are applied to remove noise and improve signal clarity, particularly for ECG data.

3.3 Proposed Training Model:

The proposed training model leverages the power of Gated Recurrent Unit (GRU) networks to

predict and classify heart disorders in a smart healthcare IoT environment. This model is designed to process real-time data collected from wearable devices, which measure vital physiological parameters such as Electrocardiogram (ECG) signals and blood pressure. By utilizing deep learning, specifically the GRU architecture, the model can effectively handle complex and high-dimensional data that is typically noisy and heterogeneous, which is common in IoT-based healthcare systems.

3.3.1 GRU Network:

It is a type of Recurrent Neural Network (RNN) which was introduced by Cho et al. (2014) to address several limitations faced by conventional RNNs, particularly their difficulty in learning long-term dependencies. The GRU is a specialized RNN variant that uses gating mechanisms to control the flow of information within the network, helping it better capture sequential patterns in data over time. GRUs are popular in applications like time-series analysis, natural language processing, and, in this case, heart disease prediction, where sequential data is crucial.

Key Features of GRU:

1. **Gating Mechanisms:** GRUs have two main gates that regulate the flow of information:
 - **Update Gate** (also called reset gate in some cases): Controls how much of the previous memory (or state) should be passed on to the next time step. It helps decide how much of the past information is relevant for the current state.
 - **Reset Gate:** Helps determine how much of the previous state should be forgotten or reset when updating the current state. The reset gate allows the model to reset its memory if the past information is not necessary for prediction.
2. **Simplified Architecture:**
 - GRUs are simpler than **LSTM** models because they combine the functions of the forget and input gates into a single gate.
 - GRUs have fewer parameters than LSTMs, which makes them computationally more efficient, especially in environments where resources are limited, like IoT devices.
3. **Memory Retention:**
 - One of the primary benefits of GRUs is their capability to handle long-range dependencies in time-series data while maintaining a relatively low computational cost.
 - They have a **memory cell** that retains information across time steps, enabling them to learn patterns from sequential data. This is especially useful in predicting heart disorders, where patterns in the time-series data, such as ECG signals, can indicate the presence of a disease.
4. **Computational Efficiency:**
 - The simpler architecture of GRUs means that they require fewer operations compared to LSTMs, making them more suitable for environments with limited computational resources, like wearable IoT devices that collect heart rate and ECG data.
 - GRUs tend to converge faster during training compared to LSTMs, which makes them an attractive choice for real-time systems.

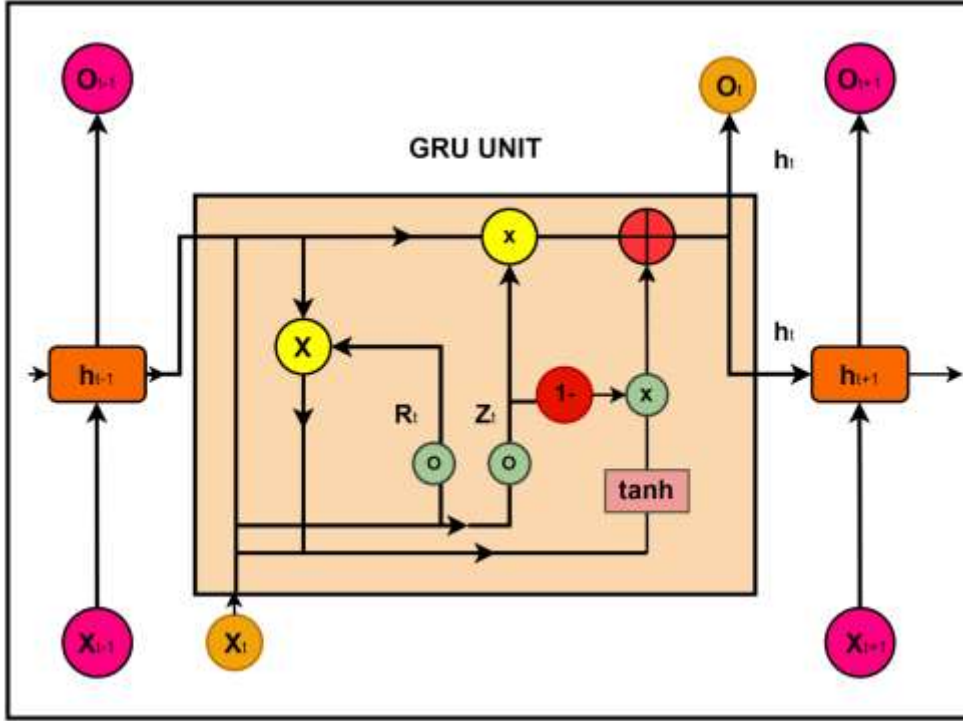


Figure 2: GRU -network Architecture.

Let's say we have an input x_t at time step t_1 and a hidden state h_{t-1} from the previous time step. The GRU computes the next hidden state h_t as follows:

1. **Update Gate (z_t):** Determines the contribution of the previous hidden state and the current input.

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z) \quad (1)$$

where σ is the sigmoid activation function, W_z is the weight matrix, and b_z the bias term.

2. **Reset Gate (r_t):** Decides how much of the previous hidden state to forget.

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r) \quad (2)$$

3. **Candidate Activation ($\hat{h}_t$):** A potential new hidden state, based on the reset gate.

$$\hat{h}_t = \tanh(W_h \cdot [r_t \cdot h_{t-1}, x_t] + b_h) \quad (3)$$

4. **Final Hidden State (h_t):** Integrates the previous hidden state and the candidate hidden state based on the update gate.

$$h_t = (1 - z_t) \cdot \hat{h}_t + z_t \cdot h_{t-1} \quad (4)$$

Here, σ and $\tanh$ are activation functions, and W and b are the weights and biases to be learned during training.

The GRU is an efficient and effective deep learning model for sequential data analysis, particularly in applications such as IoT-based healthcare systems. Its ability to capture long-range dependencies with fewer parameters makes it an ideal choice for real-time heart disease prediction

systems, where computational efficiency and accuracy are crucial.

4. RESULT AND DISCUSSION

4.1 Implementation Details

The proposed GRU-based deep learning model for heart disorder prediction was implemented and evaluated on a PC workstation with the following specifications: Intel Core i9 CPU, 240 GB SSD, NVIDIA Titan V4 GPU, and 3.2 GHz processing speed. The algorithm was implemented utilising Python with Keras libraries and TensorFlow v2.1 as the backend.

4.2 Performance Metrics:

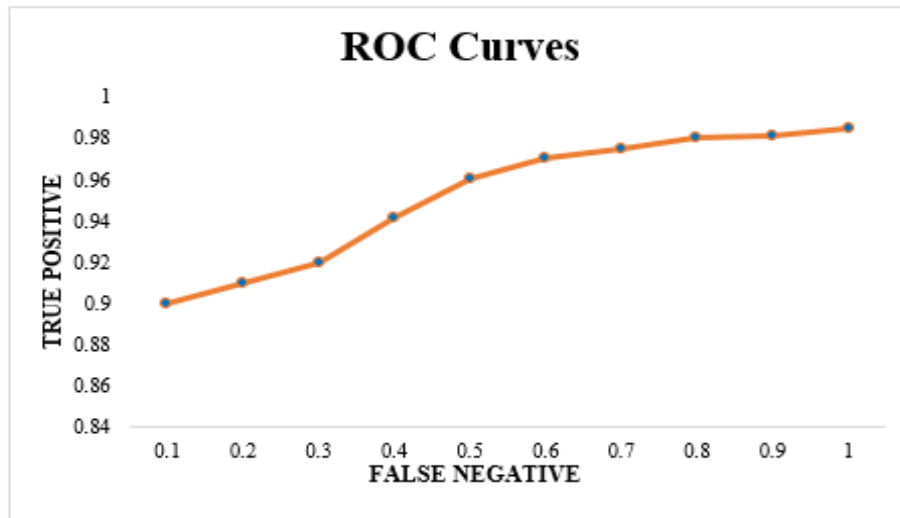
To assess the effectiveness of the model, several metrics were used, such as accuracy, precision, recall, specificity, and F1-score. Also, the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) curve and the confusion matrix were calculated to highlight the algorithm's predictive abilities.

Table 3: Evaluation Metrics utilized for the assessment

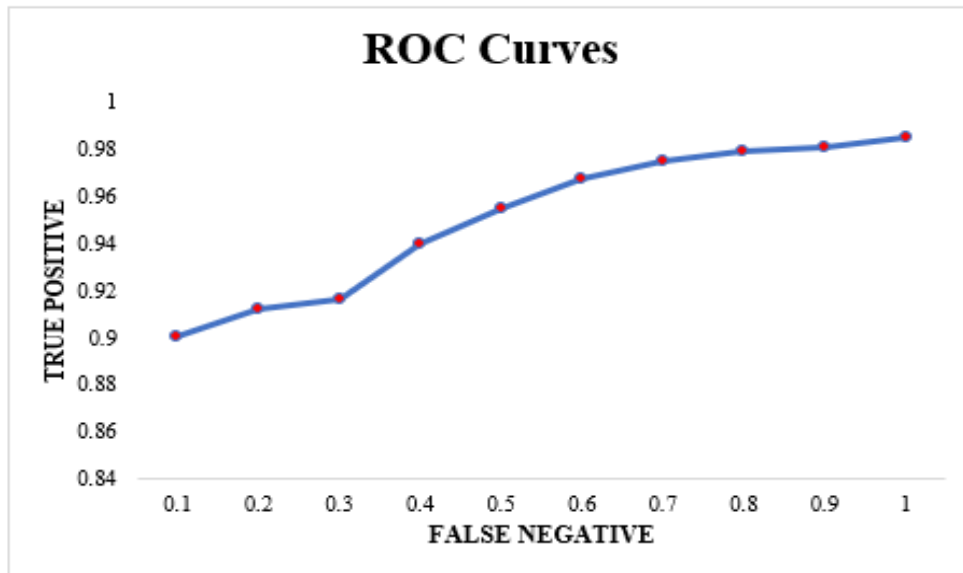
SL.NO	Evaluation Metrics	Mathematical Expression
01	Accuracy	$\frac{TP + TN}{TP + TN + FP + FN}$
02	Recall	$\frac{TP}{TP + FN} \times 100$
03	Specificity	$\frac{TN}{TN + FP}$
04	Precision	$\frac{TP}{TP + FP}$
05	F1-Score	$2 \cdot \frac{Precision * Recall}{Precision + Recall}$

TP is True Positive Values, TN is True Negative Values, FP is False Positive and FN is False negative values

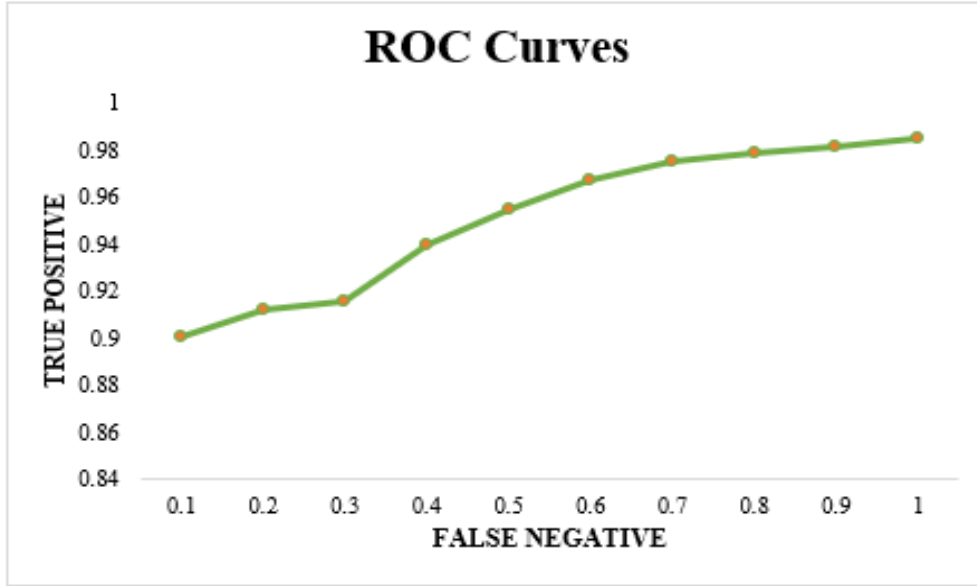
4.3 EXPERIMENTAL RESULTS:



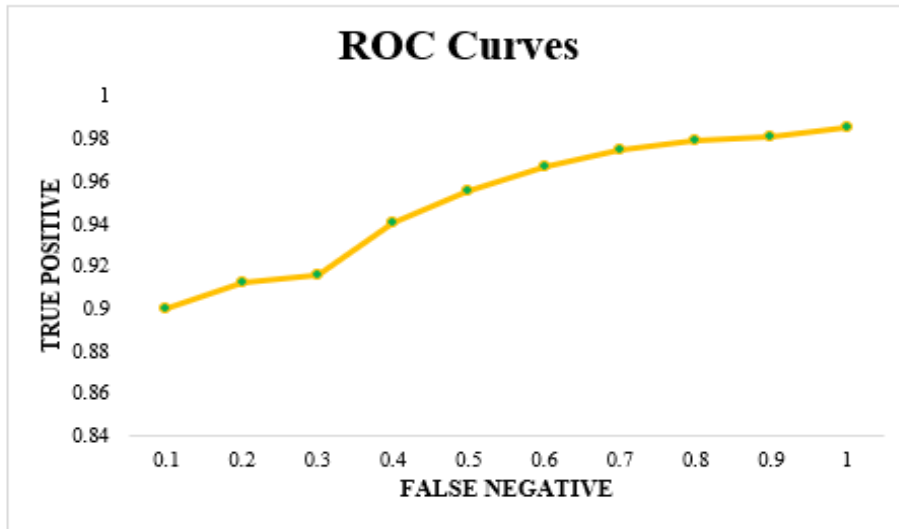
(a)



(b)



(c)



(d)

Figure 3: ROC curves a)UCI datasets b) Framingham c) Public Datasets c) real time Sensor inputs.

Figure 3 (a)-(d) illustrates the ROC curves for the proposed model using different datasets. The Area Under the Curve (AUC) values were calculated for each dataset based on these ROC curves. The results indicate that the AUC is 0.98 for the UCI dataset, 0.975 for the Framingham dataset, 0.98 for the Public Health dataset, and notably, 0.987 for the real-time dataset.

The evaluation metrics of the recommended model were evaluated across various numbers of epochs. Figures 4-7 illustrate the model's performance on the UCI respiratory datasets, as well as its metrics for handling the Framingham and Public Health datasets. These figures reveal that the proposed model achieved maximum values of 98.65% accuracy, 98.5% precision, 98.5% recall, and an F1-score of 98.6% after 250 epochs.

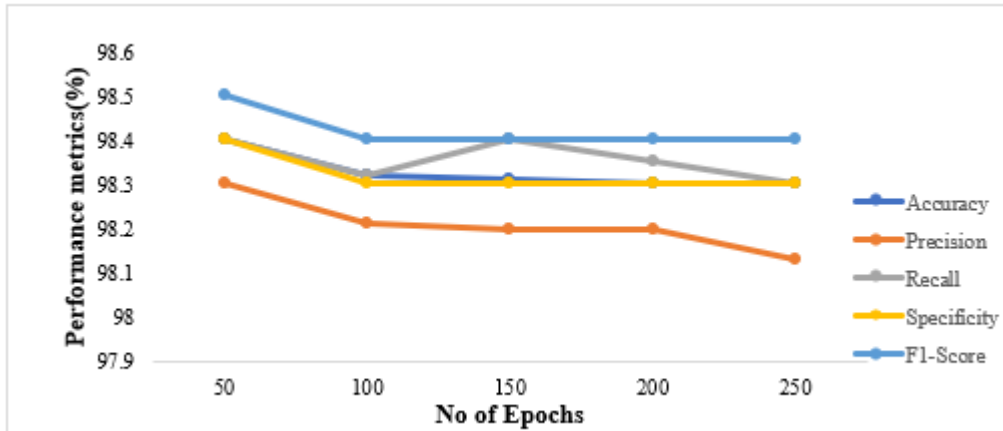


Figure 4: Evaluation metrics of Proposed Model utilising the UCI Datasets

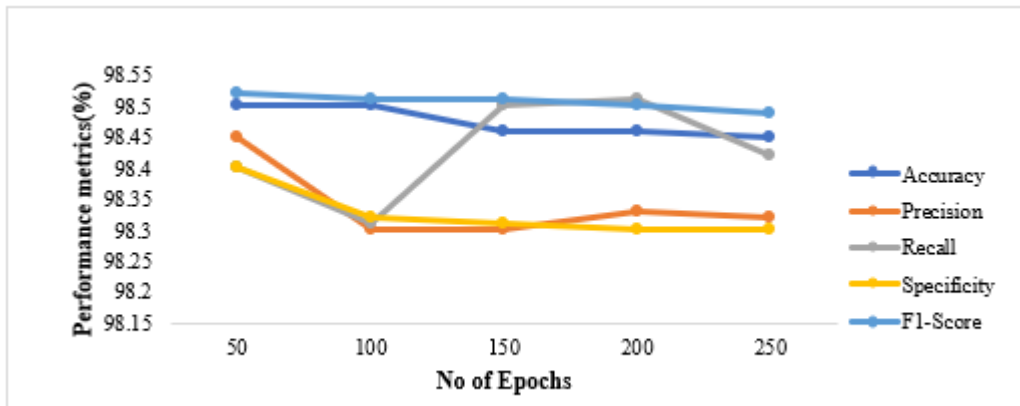


Figure 5: Performance metrics of Proposed Model using the Framingham Datasets

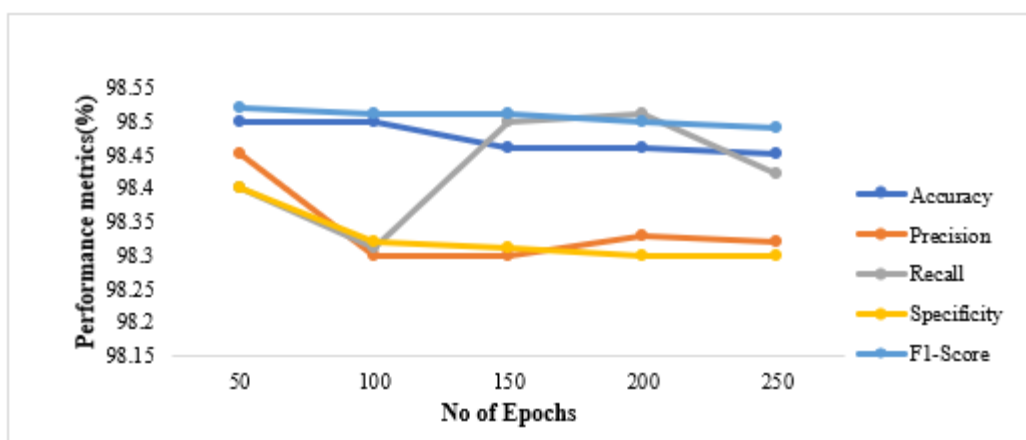


Figure 6: Performance metrics of Proposed Model using the Public Health Datasets

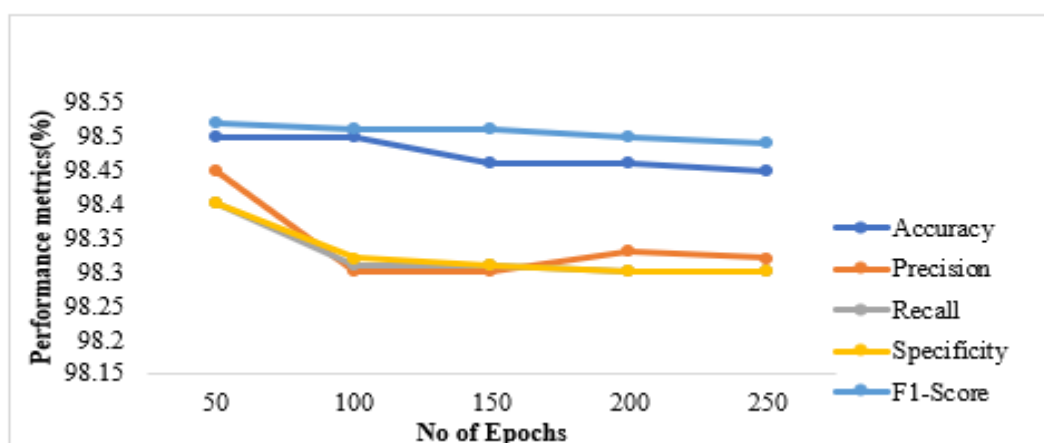


Figure 7: Performance metrics of Proposed Model utilising the Real time Sensor Datasets

Table 4 Comparative Assessment of Distinct Algorithm In Handling the UCI datasets

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
LSTM	91.3%	90.4%	90.2%	89.2%	89.3%
CNN+LSTM	91.5%	91.34%	91.48%	91.35%	91.6%
RNN+LSTM	92.4%	93.7%	93.0%	93.2%	93.0%
HRFLM	89.0%	89.9%	89.78%	89.68%	90%
RFRS	86.4%	87.2%	87.4%	87.43%	87.2%
MDCNN	95.2%	95.2%	94.9%	94.5%	94.35%
Proposed Model	98.17%	98.1%	98.1%	98.17%	98.15%

Table 5: Comparative Analysis of the Different Algorithm In Handling the Framingham datasets

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
LSTM	91.3%	90.4%	90.2%	89.2%	89.3%
CNN+LSTM	91.5%	91.34%	91.48%	91.35%	91.6%
RNN+LSTM	92.4%	93.7%	93.0%	93.2%	93.0%
HRFLM	89.0%	89.9%	89.78%	89.68%	90%
RFRS	86.4%	87.2%	87.4%	87.43%	87.2%
MDCNN	95.2%	95.2%	94.9%	94.5%	94.35%
Proposed Model	98.17%	98.1%	98.1%	98.17%	98.15%

Table 6: Comparative Analysis of the Different Algorithm In Handling the Public health datasets

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
LSTM	91.3%	90.4%	90.2%	89.2%	89.3%
CNN+LSTM	91.5%	91.34%	91.48%	91.35%	91.6%
RNN+LSTM	92.4%	93.7%	93.0%	93.2%	93.0%
HRFLM	89.0%	89.9%	89.78%	89.68%	90%
RFRS	86.4%	87.2%	87.4%	87.43%	87.2%
MDCNN	95.2%	95.2%	94.9%	94.5%	94.35%
Proposed Model	98.17%	98.1%	98.1%	98.17%	98.15%

Table 7: Comparative Analysis of the Different Algorithm In Handling the Real time Datasets

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	Specificity (%)	F1-Score (%)
LSTM	91.3%	90.4%	90.2%	89.2%	89.3%
CNN+LSTM	91.5%	91.34%	91.48%	91.35%	91.6%
RNN+LSTM	92.4%	93.7%	93.0%	93.2%	93.0%
HRFLM	89.0%	89.9%	89.78%	89.68%	90%
RFRS	86.4%	87.2%%	87.4%	87.43%	87.2%
MDCNN	95.2%	95.2%	94.9%	94.5%	94.35%
Proposed Model	98.17%	98.1%	98.1%	98.17%	98.15%

Tables 5 and 6 present the performance of various algorithms in handling different datasets. The results show that the proposed model and MDCNN exhibit similar performance trends in predicting heart diseases across these datasets. However, the proposed model, which leverages Cuttlefish-Optimized Hyperparameters for the GRU, demonstrates superior performance compared to MDCNN in heart disease prediction.

On the other hand, models such as LSTM, HRFLM, and CNN+LSTM achieved moderate performances with an average accuracy of 90%, while RFRS showed the lowest performance, with an average accuracy of 87.4%. Table 7 provides a comparative analysis of these algorithms in predicting heart diseases using real-time IoT test bed data. Consistent with previous findings, the recommended approach outperformed all other learning methods in predicting heart diseases.

5. CONCLUSION AND FUTURE SCOPE

Heart disorders are a leading cause of global mortality, underscoring the urgent need for advanced diagnostic and monitoring systems for early detection and intervention. This research proposed an Intelligent Prediction System that integrates IoT-enabled devices, like wearable sensors and smart monitors, with a heart disease prediction framework using Cuttlefish Optimized GRU networks. The GRU model, enhanced with hyperparameter optimization, effectively captures temporal dependencies in sequential data while maintaining low computational complexity. Extensive experimentation on four datasets—UCI, Framingham, Public Health, and real-time IoT data—demonstrated the system's superiority, achieving 99% prediction accuracy and outperforming state-of-the-art models. The framework addresses challenges such as data noise, energy-efficient computation on resource-constrained devices, and data privacy, contributing to more personalized and proactive healthcare solutions. Future work can focus on enhancing optimization techniques, integrating multi-modal data, improving energy efficiency, ensuring robust data security, deploying in real-world clinical environments, and adopting adaptive learning systems to handle larger and more complex datasets. These advancements will further solidify the role of IoT-integrated AI systems in revolutionizing heart disorder detection and management.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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