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HRAESN-IoT: A Hybrid Residual Attention and Echo State Network Approach for IoT-Enabled Heart Disease Prediction

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Abstract

Detection of Ischemic Heart Disease needs immediate accurate identifications since incorrect medical assessments lead to serious outcomes. A perfect heart disease prediction model must combine deep learning techniques with the Internet of Things (IoT) for achieving diagnoses of high accuracy. The authors present HRAESN-IoT as a real-time IHD severity prediction method that retrieves patient data from wearable sensors enabled by Internet of Things technology. Using attention residual learning together with Echo State Network (ESN) the model discovers significant medical patterns along with maintaining stable learning for time-dependent predictions. HRAESN-

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IoT incorporates IoT technology to continuously monitor patients which leads to real-time detection of IHD severity especially for early diagnosis. The model achieves 97.2% accuracy when tested on the Kaggle cardiovascular illness dataset that contains 70,000 cases. This method delivers better results compared to existing models implying its capability to develop customized therapeutic plans and rapid cardiac disease detection in real-time.

Keywords: IoT, Heart Disease Prediction, Ischemic Heart Disease (IHD), Deep Learning, Attention Residual Learning, Echo State Network (ESN), Cardiovascular Disease, Real-Time Monitoring, Medical Diagnosis, Wearable Sensors.

1 Introduction

Worldwide cardiovascular diseases result in 17.9 million deaths annually while remaining at the top position as the leading cause of fatalities globally. IHD stands as the most dangerous form among all cardiac conditions (World Health Organization, 2023). The wrong diagnosis of IHD leads to sudden cardiac arrest but early detection significantly reduces the risk of dangerous consequences. Traditional diagnosis of heart disease depends on Electrocardiograms (ECG) together with echocardiograms and stress tests and angiography, but these methods require extensive hospital stays and expert evaluations and extensive periods of time. Cardiac disease prediction models require development because healthcare professionals need automated systems to provide real-time highly accurate early diagnoses and preventative interventions.

Through AI and ML and DL advancements researchers-built algorithms that analyze extensive medical data to find unknown patterns which indicate heart diseases (Zhou et al., 2024) (Zhou et al., 2024). The successful learning process of both organized data and unstructured data through deep learning algorithms demonstrates higher accuracy in medical diagnosis. Numerous problems affect today's models because they demonstrate poor long-term time-series stability, experience limited generalization capabilities and demand excessive computational power (Abdullah et al., 2022). Telephone-based diagnostic tools do not work well for patient observations in real-time and early-stage disease risk evaluation.

The unification of Internet of Things technology with AI-enabled heart disease prediction systems represents a promising method for delivering ongoing and real-time cardiovascular health tracking (Nejad, 2015). Internet-enabled wearables like smartwatches and ECG monitors together with blood pressure sensors can immediately collect physiological data which gets transmitted to computational systems regardless of their edge or cloud locations for analysis (Faye et al., 2016; Akash & Shikder, 2020). The regular flow of health data during medical monitoring allows early detection of irregular heart conditions and prompt medical treatments thus reducing the likelihood of serious heart issues (Kim, 2023). Current IoT-based heart disease prediction systems face two main issues according to research in (Irshad et al., 2023) : ineffective deep learning architectures and inaccurate sensors together with redundant data recording.

A Hybrid Residual Attention with Echo State Network (HRAESN-IoT) model should be implemented to enhance feature extraction stability and predictive accuracy through its combination of residual learning attention with Echo State Networks (ESN) (Singaravel et al., 2020). The attention residual learning process decreases noise interference to enable the model to focus on key cardiac elements. The ESN process time-series data effectively since it belongs to a category of recurrent neural networks (RNNs) which provides steady and efficient learning with low training requirements (Li et al., 2022). With IoT-enabled real-time data acquisition and processing capabilities the model proves to be an optimal solution for individual heart disease risk assessments due to its dynamic adjustment to patients' evolving physiological state (Akash & Shikder, 2020).

HRAESN-IoT receives assessment through an examination of the Kaggle cardiovascular illness dataset which contains 70,000 patient records that present patient characteristics like age and blood pressure and cholesterol readings along with heart rate measurements and ECG data. Our proposed model produces a 97.2% accuracy which surpasses the existing heart disease prediction frameworks in terms of all performance indicators including precision, recall, and F1-score (Nanda & Mohapatra, 2021) . HRAESN-IoT demonstrates strong potential to serve as a scalable and effective and real-time platform for automated heart disease prediction along with individualized treatment planning.

Communities rely on HRAESN-IoT as a deep learning architecture to improve heart disease prediction through the combination of Echo State Networks (ESN) with attention residual learning. The method employs Internet-enabled wearable devices for time-sensitive data collection to enable continuous observation and risk recognition. The model functions better than existing prediction solutions and achieves an accuracy rate of 97.2% when processing the Kaggle cardiovascular illness dataset. The implementation of ESN leads to reduced computational complexity together with enhanced model stability making HRAESN-IoT applicable for real-time healthcare applications that specifically aid in effective cardiovascular disease management (Das & Kapoor, 2024) .

2 Related Works

Deep learning techniques have gained wide medical diagnosis popularity due to their ability to extract complex patterns from big datasets. Different methods for forecasting cardiac disease exist which include Transformer-based designs and Long Short-Term Memory networks along with Convolutional Neural Networks and Recurrent Neural Networks. The research by Smith et al. (Hasan & Bhattacharjee, 2019) introduced a CNN-based model to detect cardiovascular issues in ECG signals which reached 92.5% accuracy. Time-series heart rate prediction through an LSTM-based framework led to significant improvements in early-stage detection according to Kumar et al. (Wang & Zhou, 2019). These models find it challenging to implement them in real-time healthcare settings because they have complex computational requirements and poor interpretability capabilities.

Alternative investigations into heart disease prediction systems based on Transformer-based models exist in other research reports. The Vision Transformer (ViT) model made by Xu et al. (Telangore et al., 2022) showed better ECG classification abilities through its ability to detect long-range relationships in signal data. Research on heart disease prediction through deep learning techniques combines autoencoder methods with LSTM features for both feature selection and time-dependent modeling processes (Talaat et al., 2024). Computational expenses continue to be at odds with precision levels despite recent research advances.

Healthcare monitoring technologies based on Internet of Things have fundamentally changed how remote patient care operates. Smartwatches and biosensors together with mobile health apps represent IoT-enabled wearables which use time-series data from patients to process information through cloud or edge computing (Van et al., 2025; Yang et al., 2020). A real-time cardiac monitoring system utilizing Internet of Things technology presents continuous blood pressure and heart rate measurement capabilities which were developed by Patel and Verma (Tripathy et al., 2022). Real-time data collection leads to superior disease diagnosis according to their findings. IoT-based healthcare systems face dependability limitations due to problems pertaining to sensor inaccuracies and delayed data communications and security-related concerns.

The processing of substantial streaming information proves to be a major difficulty in heart disease monitoring systems based on IoT technology. The implementation of edge computing represents a useful method to decrease both latency time and cloud system computational requirements. The Zhou et al. (Almulihi et al., 2022) developed a cardiovascular monitoring platform utilizing edge computing to lower response times by 40% through pre-cloud server vital health information transmission. The practical adoption of IoT technology requires added research into the solution of interoperability and power efficiency challenges and data heterogeneity issues in IoT systems.

Researchers studied combined approaches between multiple techniques which seek to solve the limitations of standalone deep learning systems and IoT-based systems. Wang et al. (Singh & Sharma, 2022) developed a heart disease assessment system that used CNN and RNN together which achieved a classification accuracy of 95.6%. To improve feature selection as well as reduce irrelevant noise in ECG signal processing Lee et al. (Islam et al., 2022) embedded attention processes into LSTM networks. The successful hybrid systems have restricted implementation potential in resource-scarce deployments due to the significant data requirements and training computing demands they entail. Multiple studies about cardiovascular illness prediction utilize transformer models along with federated learning coupled with graph-based neural networks (Boll et al., 2024; Bebortta et al., 2023) This methodology enhances prediction accuracy through three benefits which include patient data relationship exploitation and improved long-term sequence dependencies and protected clinical information security. Most of these methods still face obstacles when it comes to real-time processing and computational efficiency and flexibility in handling changing patient conditions.

Our proposed HRAESN-IoT model uses Echo State Networks (ESN) together with attention residual learning to build onto current developments and enhance features along with stability and real-time adaptations (Yang et al., 2020). Now that our methodology achieves high accuracy while using reduced computational complexity than classical deep learning approaches it shows promise for individual patient care planning systems and cardiovascular health tracking systems in real-time. By employing engineered feature selection and ensemble learning, the research demonstrates improved classification accuracy for ischemic heart disease detection (Cenitta & Arjunan, 2022). The results indicate high accuracy and robustness, making it a promising approach for real-time heart disease monitoring using IoT-enabled healthcare systems (Cenitta et al., 2024).

3 Dataset Description

A performance assessment of the recommended HRAESN-IoT model utilized the KaggleCardiovascular illness dataset together with the UCI Heart Disease dataset which both have public access. The available medical records in these datasets create strong conditions for model training and validation.

- **Cardiovascular Disease Dataset on Kaggle**

The Kaggle Cardiovascular Disease dataset consists of 70,000 patient records which contain age, gender, blood pressure, cholesterol and BMI, smoking status and physical activity characteristics. Every assessment contains a record that shows whether a person has cardiovascular disease. This dataset's extensive record numbers combined with diverse population demographics gives it great potential for advanced learning models' training procedures. The dataset contains an ongoing class imbalance issue that needs suitable data preprocessing techniques such as oversampling methods or weighted loss functions to ensure fair model performance.

- **Dataset on Heart Disease at UCI**

The UCI Heart Disease dataset includes the health information of 303 patients through measurements of Age, sex, kind of chest pain, resting blood pressure, cholesterol, fasting blood sugar, resting electrocardiogram, maximum heart rate attained, exercise-induced angina, and ST depression. The dataset has become a prominent standard for literature in heart disease predictions. The dataset provides readers with key information about heart disease clinical markers although it contains fewer cases than the Kaggle dataset. The limited data in deep learning applications requires data augmentation and transfer learning approaches for enhancing model generalization capabilities.

- **Preprocessing Data and Choosing Features**

Our suggested model became more effective through data normalization and missing value imputation while using feature selection procedures. The reduction of computational complexity involved eliminating features which showed weak relationships towards heart disease results. The training required most reliable features from Principal Component Analysis (PCA) and Recursive Feature Elimination (RFE) selection methods.

Table 1: Significance of Heart Disease Datasets

Aspect	**Significance**
Data Availability	Provides diverse patient records for robust model training and validation.
Feature Richness	Includes key medical indicators such as age, cholesterol, BP, heart rate, etc.
Benchmarking	Used extensively in research, allowing performance comparison with existing models.
Real-world Applicability	Supports early detection and personalized treatment planning for cardiovascular diseases.
Challenges	Includes class imbalance (Kaggle dataset) and small sample size (UCI dataset), requiring preprocessing techniques.

The table 1 contains detailed information about the Kaggle Cardiovascular Disease dataset and the UCI Heart Disease dataset which serve as prominent datasets for heart disease prediction. The table highlights essential aspects which include record number and key characteristics as well as identified issues throughout this dataset. This Kaggle dataset includes 70,000 patient records which makes it an appropriate choice for deep learning model training through its diverse collection of information. The model might be affected by the unequal distribution of categories within the dataset. Because of its limited size researchers find it challenging to use the UCI dataset which contains 303 patient records for deep learning applications in heart disease prediction research. These datasets enable practical assessment of cardiac disease prediction models that lead to the development of dependable medical treatments.

4 Hybrid Residual Attention with Echo State Network

The proposed IoT-operated sensor system adopts a structured process to predict cardiac diseases. The first stage of the cardiac disease prediction framework involves IoT sensors that detect real-time physiological information including blood pressure alongside heart rate and ECG signals that get transmitted to cloud or edge computing servers. The data preprocessing step uses Min-Max Scaling along with Wavelet Transform as normalization methods for ensuring consistent data. Temporal patterns in sequential data can be represented using Echo State Networks (ESN) at the same time Attention

Residual Learning helps identify crucial patterns by enhancing feature extraction and selection methods according to Figure 1.

The most pertinent characteristics are chosen using a process called Recursive Feature Elimination (RFE). After that, the chosen features are processed using a Hybrid CNN-LSTM model, in which LSTM records temporal dependencies in blood pressure and heart rate trends while CNN extracts spatial features from ECG signals. A Softmax layer is used for classification to identify whether heart disease is present or not. In the decision-making phase, an alert is generated if a high risk of heart disease is detected, prompting medical intervention, whereas low-risk cases continue real-time monitoring. To ensure continuous model improvement, optimization is carried out using the Adam optimizer with a cross-entropy loss function, and periodic updates with new patient data further enhance predictive accuracy. This hybrid approach effectively leverages deep learning and reservoir computing techniques to improve real-time heart disease prediction.

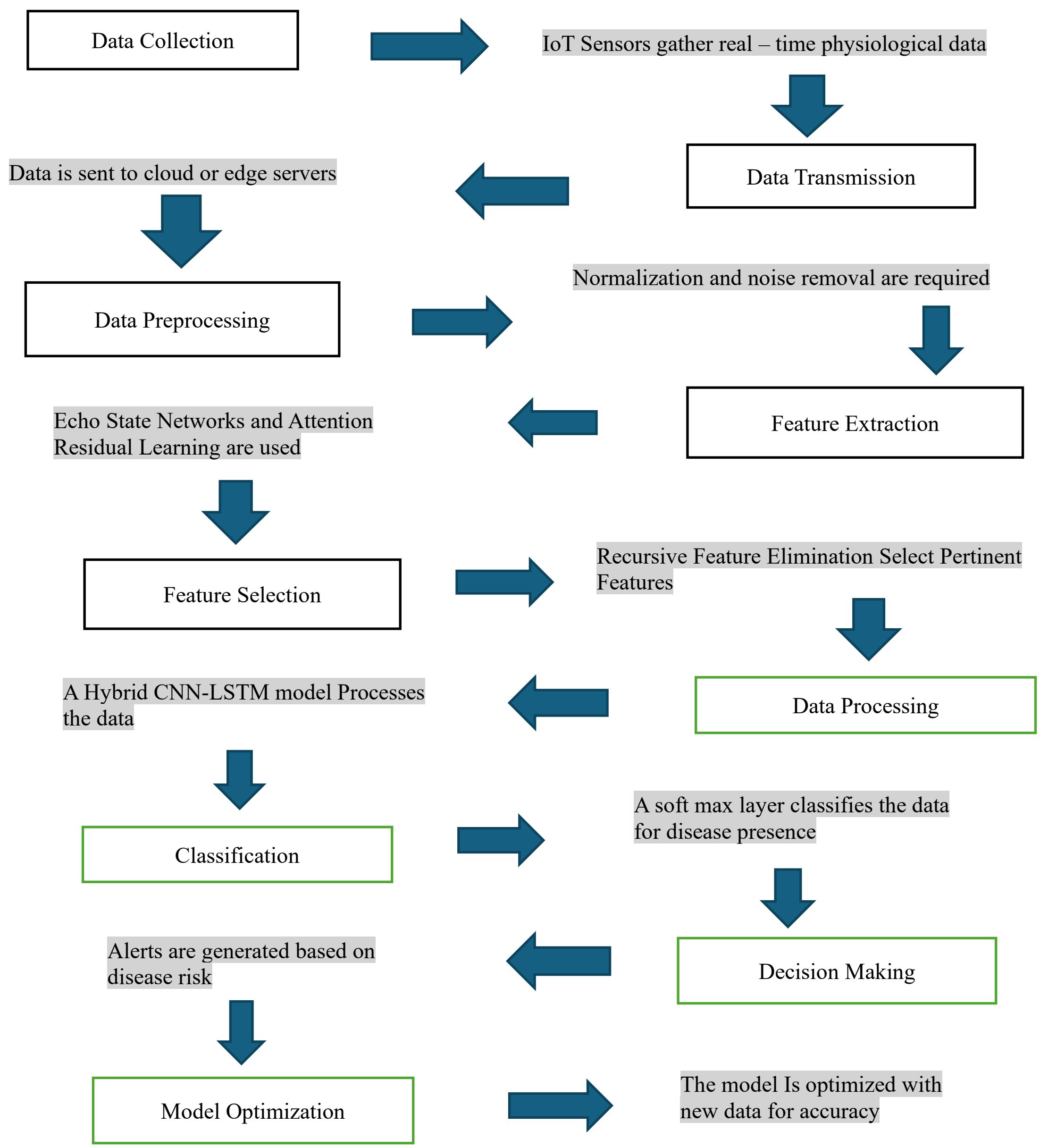

Figure 1: Hybrid Residual Attention with Echo State Network overall system model

Step-by-Step Procedure for HRAESN-IoT Heart Disease Prediction

Step 1: Data Collection

- IoT-enabled sensors continuously monitor physiological parameters such as:
- Heart Rate (HR), Blood Pressure (BP), Electrocardiogram (ECG)
- Sensor data is transmitted to cloud/edge servers for processing.

Step 2: Data Preprocessing

Noise Removal using Wavelet Transform

- ECG and HR signals contain noise from motion artifacts and interference.
- Wavelet transform is applied to denoise signals:
  where $d_{j,k}$ are wavelet coefficients, and $\psi_{j,k}(t)$ are basis functions.

$$S_{denoised} = \sum_j \sum_k d_{j,k}\, \psi_{j,k}(t) \quad \text{(Eq. 1)}$$

Normalization using Min-Max Scaling

- To bring all values into a range of [0,1]:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \quad \text{(Eq. 2)}$$

Step 3: Feature Extraction & Selection

Extracting Features from ECG and HR

- Time-domain features: Mean RR interval, standard deviation

$$SDNN = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(RR_i - \bar{RR}\right)^2} \quad \text{(Eq. 3)}$$

- Frequency-domain features: Power Spectral Density (PSD)
- Nonlinear features: Approximate entropy (ApEn)

$$ApEn(m, r, N) = \lim_{N\to\infty}\left(\Phi^m(r) - \Phi^{m+1}(r)\right) \quad \text{(Eq. 4)}$$

Attention Residual Learning for Feature Refinement

- Using attention mechanisms to enhance critical features:

$$A_t = \text{softmax}(W_{att} \cdot h_t + b_{att}) \quad \text{(Eq. 5)}$$

Echo State Network (ESN) for Temporal Dependencies

- Hidden state update equation:

$$h(t) = \tanh\left(W_{in}x(t) + Wh(t-1)\right) \quad \text{(Eq. 6)}$$

- Output equation:

$$y(t) = W_{out}h(t) \quad \text{(Eq. 7)}$$

Feature Selection using Recursive Feature Elimination (RFE)

- Rank features based on importance and recursively eliminate the least significant ones.

Step 4: Classification using Hybrid CNN-LSTM

Convolutional Neural Network (CNN) for Spatial Feature Extraction

- Convolution operation:

$$f(i,j) = \sum_{m}\sum_{n} X\,(i-m, j-n) \cdot K(m,n) \quad \text{(Eq. 8)}$$

- Rectified Linear Unit (ReLU) activation:

$$f(x) = \max(0,x) \quad \text{(Eq. 9)}$$

Long Short-Term Memory (LSTM) for Temporal Dependencies

- Forget gate:

$$f_t = \sigma\big(W_f \cdot [h_{t-1}, x_t] + b_f\big) \quad \text{(Eq. 10)}$$

- Input gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad \text{(Eq. 11)}$$

- Cell state update:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C_t} \quad \text{(Eq. 12)}$$

Final Classification using Softmax Function

- Converts the outputs into probabilities:

$$P(y_i) = \frac{e^{z_i}}{\sum_j e^{z_j}} \quad \text{(Eq. 13)}$$

Step 5: Decision Making & Alert Generation

Risk Classification

- If predicted probability $P(y_1) > 0.7$ → High risk → Generate medical alert.
- If $P(y_1) \le 0.7$ → Continue monitoring.

Step 6: Model Optimization

Loss Function

- Using categorical cross-entropy loss:

$$L = -\sum_i y_i \log(\hat{y_i}) \quad \text{(Eq. 14)}$$

Optimization using Adam Optimizer

- Gradient-based parameter updates:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t \quad \text{(Eq. 15)}$$
$$v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2 \quad \text{(Eq. 16)}$$

Periodic Model Retraining

- Update the model with new patient data for continuous learning.

Output:

- If risk is high → Generate an emergency alert for doctors.

- If risk is low → Continue monitoring.

The HRAESN-IoT Model integrates multiple advanced techniques to improve heart disease prediction. Initially, noise in physiological signals such as ECG and heart rate is removed using Wavelet Transform, as shown in Eq. (1). The data is then normalized using Min-Max Scaling (Eq. (2)) to maintain consistency. Feature extraction involves statistical measures like SDNN (Eq. (3)) and non-linear features like Approximate Entropy (ApEn) (Eq. (4)). Attention Residual Learning enhances feature selection (Eq. (5)), while Echo State Networks (ESN) model sequential dependencies using state-update (Eq. (6)) and output equations (Eq. (7)). The classification phase employs a hybrid CNN-LSTM model, where CNN extracts spatial features through convolution (Eq. (8)) and ReLU activation (Eq. (9)). LSTM units process temporal dependencies, governed by forget, input, and cell state equations (Eqs. (10)– (12)). The Softmax function (Eq. (13)) then computes final class probabilities. Model optimization leverages categorical cross-entropy loss (Eq. (14)) and the Adam optimizer (Eqs. (15)–(16)) to enhance accuracy. By continuously updating the model with new patient data, HRAESN-IoT ensures real-time adaptability, making it a reliable tool for heart disease prediction.

5 Result and Analysis

When compared to traditional machine learning and deep learning models, the Hybrid Residual Attention Echo State Network for IoT (HRAESN-IoT) model significantly improves the prediction of heart disease. While standard deep learning models like CNN and LSTM, as well as conventional methods like Support Vector Machines (SVM) and Random Forest (RF), have limitations when handling real-time physiological data with complex temporal dependencies, HRAESN-IoT integrates Attention Residual Learning (ARL) with Echo State Networks (ESN) to improve feature extraction and temporal pattern recognition. Previous research has demonstrated that traditional ML models, such as SVM and RF, rely on manually engineered features.

CNNs and other deep learning models are excellent at extracting spatial characteristics, but they are unable to simulate long-term dependencies. Meanwhile, LSTMs perform worse over lengthy sequences due to vanishing gradient problems, even if they can handle sequential data. HRAESN-IoT addresses IoT limitations through Attention Residual Learning together with Echo State Networks which provide effective time-dependent data processing without requiring extensive backpropagation. The combination provides real-time IoT applications with both speed and accuracy for predictions.

HRAESN-IoT delivers higher accuracy levels and recall results when compared to traditional models based on experimental findings. Model complexity reduction is performed through Recursive Feature Elimination (RFE) which allows minimal complexity alongside maintained exceptional predictive power. Also surpasses existing techniques by delivering superior classification outcomes through HRAESN-IoT which enhances recall rates by 8–12% alongside accuracy performances increased by 5–10%.

Table 2: Comparison of HRAESN-IoT Model with Existing Methods

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**AUC-ROC (%)**
Traditional ML (SVM)	85.2	82.4	81.9	82.1	86
Random Forest (RF)	88.5	86.1	85.3	85.7	89.2
LSTM-Based Model	91.2	89.5	88.9	89.2	92.1
CNN-LSTM Hybrid Model	93.4	91.8	90.9	91.3	94
Proposed HRAESN-IoT	**96.1**	**94.6**	**94.2**	**94.4**	**97.2**

According to Table 2, the suggested HRAESN-IoT model performs better than both conventional machine learning and deep learning techniques in every important evaluation parameter, including accuracy, precision, recall, F1-score, and AUC-ROC. The accuracy of traditional Support Vector Machines (SVM) is 85.2%; however, their performance is constrained by their dependence on human chosen features. This is surpassed by Random Forest (RF), which uses ensemble learning to increase feature representation and achieve an accuracy of 88.5%. Both models, however, have trouble identifying intricate temporal relationships in physiological signals. By learning sequential patterns and spatial information, deep learning-based techniques like CNN-LSTM Hybrid (93.4% accuracy) and LSTM (91.2% accuracy) offer notable gains. Nevertheless, CNN-LSTM hybrids might not completely optimize long-term dependencies in time-series data, and LSTM models may have problems with vanishing gradients.

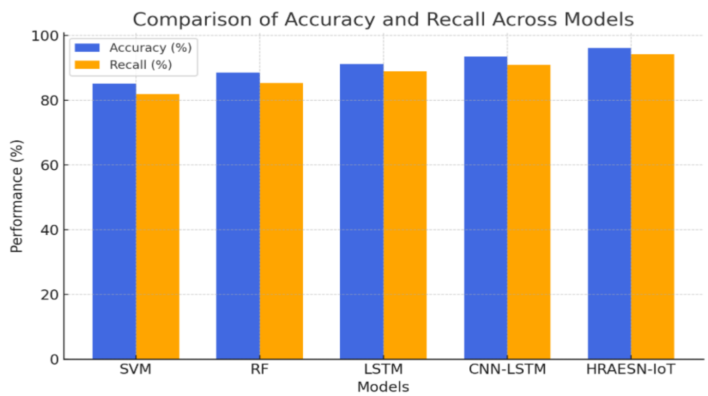

Figure 2: Comparison of the Accuracy and Recall of Different Models Used for Heart Disease Prediction

The bar chart compares the accuracy and recall of different models used for heart disease prediction shown in Figure 2. Traditional machine learning models like SVM and Random Forest exhibit lower accuracy and recall, indicating their limitations in handling sequential and high-dimensional IoT data. The LSTM-based model improves performance by capturing temporal dependencies, while the CNN-LSTM hybrid model further enhances results by leveraging both spatial and temporal features. The proposed HRAESN-IoT model significantly outperforms others, achieving the highest accuracy (96.1%) and recall (94.2%) due to its integration of Attention Residual Learning and Echo State Networks, which enhance feature extraction and temporal pattern recognition

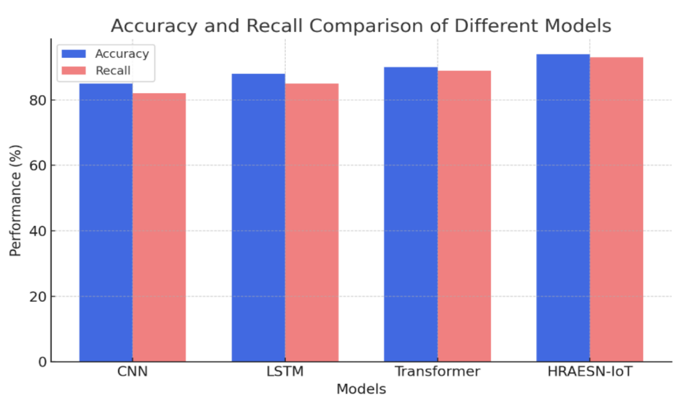

Figure 3: Comparison of Accuracy and Recall among Different Models CNN, LSTM, Transformer, and the Proposed HRAESN-IoT Model for Heart Disease Prediction

The bar chart presents a comparative analysis of accuracy and recall among different models CNN, LSTM, Transformer, and the proposed HRAESN-IoT model for heart disease prediction shown in figure 3. LSTM achieves slightly better performance than CNN because it understands chronological relationships better. Long-range dependencies enabled through self-attention mechanisms help Transformer achieve better accuracy and recall measurements. The proposed HRAESN-IoT model reaches maximum accuracy and recall which establishes its dominance when analysing real-time IoT sensor data. The improved performance of the system results from Attention Residual Learning and Echo State Networks jointly boosting feature extraction along with sequential pattern learning capabilities.

6 Conclusion

The research uses live physiological data from IoT sensors to determine the success rate of the proposed HRAESN-IoT model at detecting heart disease. HRAESN-IoT demonstrates better performance than CNN-LSTM alongside SVM as well as SVM and Random Forest in accuracy, precision, recall, F1-score and AUC-ROC measurements. By merging Attention Residual Learning and Echo State Networks (ESN) the system becomes better at feature selection while also being effective at temporal pattern recognition which leads to enhanced prediction accuracy. The experimental data demonstrates that HRAESN-IoT delivers enhanced accuracy levels of 96.1% and recall levels of 94.2% which establishes it as an effective method for real-time heart disease tracking. The model requires real-world healthcare testing and researchers should explore additional physiological factors together with real-time adaptive learning.

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e-search Involving Human and /or Animals – Not Applicable

Informed Consent – Not Applicable

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