AI-Driven IoT Framework for Advanced Cardiac Monitoring and Analysis

Shreedevi S Ronihal*[ID], G Nandini[ID], N L Kavya[ID], H Jagruthi[ID], V Laxmi[ID], S R Divyashree[ID]

Department of Information Science and Engineering, B N M Institute of Technology, Bengaluru 560070, India

Corresponding Author Email: shreedevisr@bnmit.in

ABSTRACT

The integration of Internet of Things (IoT) and Artificial Intelligence (AI) offers significant opportunities for proactive cardiac healthcare. However, existing solutions often struggle with noisy ECG data, lack real-time IoT adaptability, and provide limited deployment strategies. This study introduces a novel IoT-enabled hybrid framework that combines Empirical Mode Decomposition (EMD)-based signal denoising with a CNN-LSTM deep learning model for robust and real-time ECG analysis. Unlike prior works, the proposed approach emphasizes adaptive preprocessing, cloud-based deployment with EHR interoperability, and strong security protocols for clinical integration. Experimental results on the MIT-BIH dataset demonstrate 96.5% accuracy, 95.2% precision, and an F1-score of 94.9%, outperforming conventional CNN and LSTM models. Statistical tests confirm significance ($p < 0.05$). This research bridges the gap between algorithmic accuracy and practical IoT deployment, paving the way for intelligent, secure, and real-time cardiac monitoring systems.

1. INTRODUCTION

Cardiovascular diseases (CVDs) remain one of the leading causes of mortality worldwide, posing a critical challenge to healthcare systems. Traditional cardiac monitoring methods, which rely on periodic clinical evaluations, often fail to detect early signs of cardiac abnormalities, resulting in delayed diagnosis and treatment. Recent advancements in the Internet of Things (IoT) and Artificial Intelligence (AI), particularly Deep Learning techniques, offer a promising solution for continuous and intelligent cardiac monitoring.

IoT-enabled wearable and implantable devices allow real-time acquisition of physiological signals such as ECG, heart rate, and oxygen saturation in patients' daily environments. This continuous stream of high-resolution data provides an opportunity for proactive and remote monitoring. However, the large volume and complexity of ECG signals require advanced AI models capable of extracting clinically relevant features and predicting potential abnormalities accurately.

Existing research primarily focuses on either Convolutional Neural Networks (CNNs) for spatial feature extraction or Long Short-Term Memory (LSTM) networks for temporal pattern analysis. While these models perform well individually, limited work has explored an optimized combination of both approaches in a real-time IoT framework. Moreover, issues such as interoperability with Electronic Health Records (EHR), data security, and deployment scalability are often overlooked in current studies.

To address these gaps, this paper proposes an IoT-enabled hybrid deep learning framework that integrates CNN and LSTM to leverage their complementary strengths. The CNN component effectively captures morphological features of ECG signals, such as QRS complex and ST-segment variations, while the LSTM component models temporal dependencies for accurate prediction of rhythm irregularities. This end-to-end architecture supports real-time data acquisition, cloud-based analytics, secure communication protocols, and integration with EHR systems. The proposed solution aims to enable early detection of cardiac anomalies, timely alerts, and improved patient outcomes, particularly for individuals with chronic cardiovascular conditions or those in remote locations.

2. LITERATURE REVIEW

This work [1] proposes an AIoT-based crowd counting system using deep learning and edge-cloud integration for accurate, real-time estimation, validated on benchmark datasets. As urbanization grows, cities struggle to ensure secure, sustainable living. IoT and AI together enable smarter, more efficient cities by connecting devices and analyzing data. This review [2] covers smart city concepts, IoT architecture, communication technologies, AI algorithms, and their integration with 5G, highlighting their role in improving urban sustainability and quality of life. This study [3] analyzes the rise of AI, IoT, and Big Data in enabling environmentally sustainable smart cities, highlighting rapid growth, evolving challenges, and implications for policy and practice. This paper [4] presents a data fusion and dynamic load balancing approach to reduce redundancy and optimize edge server use in dense IoT networks, improving QoS and energy efficiency. This paper [5] reviews the edge–fog–cloud computing paradigm, highlighting its role in enhancing IoT by addressing

latency, bandwidth, and scalability challenges through distributed AI and analytics.

Deep learning mimics brain functions to analyze medical data for disease diagnosis and management. This paper [6] reviews DL applications in healthcare, compares key studies, and highlights challenges and future research. 5G-IoT is vital for e-health applications, where securing patient data is crucial. This paper [7] proposes CNN-DMA, a deep learning model using CNN layers to detect malware attacks in cloud-stored health data. Tested on the Malimg dataset, CNN-DMA achieved 99% accuracy, outperforming existing methods. Accurate brain tumor classification is vital for brain cancer diagnosis in IoT healthcare. This study [8] proposes an improved CNN model using MRI data, enhanced by data augmentation and transfer learning, achieving higher accuracy than existing methods, making it suitable for IoT-based diagnosis. This study [9] presents a lightweight CNN for cardiovascular disease classification from ECG images that runs efficiently on a single CPU and improves traditional machine learning performance through feature extraction. This study [10] presents a 1D CNN model for early heart disease detection using balanced data and clinical parameters, overcoming limitations of traditional machine learning and improving diagnostic accuracy.

This paper [11] analyzes LSTM-based deep learning models for ECG heartbeat classification using the MIT-BIH dataset. The bi-directional LSTM variant performs best, showing strong accuracy and reliability, confirming LSTM's suitability for heart disease diagnosis. This study [12] presents a hybrid method combining PCA and LSTM for classifying 16 types of cardiac arrhythmias from ECG data. It improves accuracy by reducing noise and handling ECG signal variability more effectively than traditional approaches. This study [13] proposes a smart healthcare system for heart disease diagnosis using ECG signals by combining CNN and LSTM to extract signal features. It addresses data imbalance with SMOTE and uses gated pooling for feature reduction, showing strong performance on standard ECG datasets. This study [14] enhances remote cardiac care by combining IoT data and clinical records, using XGBoost and Bi-LSTM for accurate heart disease prediction, outperforming traditional models. IoT combined [15] with cloud computing enables proactive healthcare through deep learning. Using Bi-LSTM on IoT and health record data, the system predicts heart disease risk with high accuracy, outperforming existing methods.

The literature reveals three main gaps:

(1) limited critique of hybrid approaches in real-world IoT deployments,

(2) inadequate focus on preprocessing strategies tailored for ECG noise reduction, and

(3) absence of an end-to-end architecture addressing data acquisition, AI-driven analytics, and secure integration with healthcare systems.

The proposed CNN-LSTM-based IoT framework aims to fill these gaps by combining morphological and temporal feature learning, implementing robust preprocessing pipelines and ensuring cloud-based scalability with secure EHR integration for continuous cardiac health monitoring.

Table 1 presents a comparative analysis of various deep learning architectures applied to cardiac signal processing, while Table 2 summarizes key research studies focusing on CNN-LSTM and hybrid deep learning frameworks in healthcare applications.

Table 1. Comparison of deep learning models for cardiac signal analysis

Model	Strengths	Suitable Tasks
CNN	Spatial feature extraction	Beat classification, waveform analysis
LSTM	Temporal sequence modeling	Rhythm prediction, temporal pattern recognition
CNN + LSTM	Combined spatial and temporal learning	Complex heartbeat classification, predictive modeling
Transformer	Long-range dependency and attention	Long sequence analysis, multi-modal data
Autoencoder	Unsupervised anomaly detection	Detecting unknown or rare anomalies

**Table 2.** Key studies on CNN-LSTM and hybrid deep learning models in healthcare

No.	Authors	Application Domain	Dataset/Platform	Key Contributions/Findings
1	Rayan et al. [16]	Medical systems enhancement	Not specified	Improved medical system performance using CNN-LSTM hybrid
2	Rai and Chatterjee [17]	Myocardial infarction detection	Large ECG datasets	Automated MI detection with high accuracy using ensemble approach
3	Elbagoury et al. [18]	Stroke prediction	Mobile AI smart hospital platform	Novel hybrid deep learning model for stroke prediction on mobile platform
4	Begum et al. [19]	Breast cancer diagnosis	Not specified	Combined CNN-LSTM with RF for improved breast cancer diagnosis
5	Amin et al. [6]	Healthcare broadly	N/A	Discusses issues, challenges, and opportunities in DL healthcare
6	Ayus and Gupta [20]	Alzheimer's identification	Biomedical signal datasets	Novel hybrid DL system for Alzheimer's detection
7	Hiriyannaiah et al. [11]	Heartbeat classification	MIT-BIH arrhythmia dataset	Comparative analysis of LSTM models for ECG heartbeat classification
8	Sowmya and Jose [21]	Arrhythmia signal classification	ECG signals datasets	CNN-LSTM based model for arrhythmia classification

3. SYSTEM ARCHITECTURE

The proposed IoT-enabled cardiac monitoring system consists of three interconnected layers: IoT Layer, Data Processing Layer, and AI/Deep Learning Layer. These layers collaboratively enable secure, real-time data acquisition, analysis, and integration with clinical systems such as Electronic Health Records (EHR). The components of the IoT

architecture layer are depicted in Figure 1.
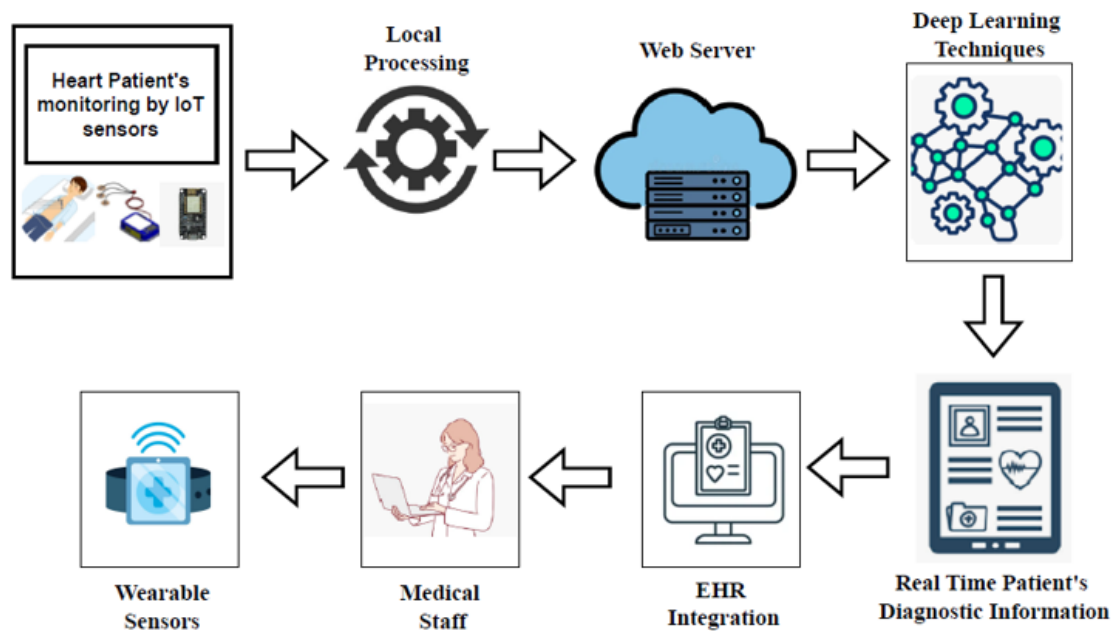
Figure 1. IoT layer components

3.1 IoT layer

(1) Wearable Sensors: Wearable biosensors play a crucial role in physiological data acquisition for health monitoring systems. Key devices utilized include the AD8232 ECG sensor, which captures real-time electrocardiogram (ECG) signals to assess cardiac activity; the MAX30100 Pulse Oximeter, which measures both heart rate and blood oxygen saturation (SpO_2) levels; and the MLX90614 Infrared Temperature Sensor, which enables non-contact monitoring of body temperature. These sensors collectively provide comprehensive vital signs data essential for continuous heart health observation, as highlighted in recent studies published by MDPI.

(2) Microcontroller Unit (NodeMCU): Serves as the central control component responsible for acquiring sensor data and enabling wireless communication. It transmits the collected data to the processing unit using built-in Wi-Fi or Bluetooth capabilities, thereby facilitating seamless integration between the sensing environment and the data analysis system.

3.2 Data processing layer

(1) Edge Computing Unit: This component is responsible for conducting preliminary processing of the raw signals collected from sensors. It applies noise reduction techniques and other preprocessing methods at the edge of the network—closer to the data source—before the data is transmitted to central systems. This ensures that the information sent onward is cleaner, more accurate, and of higher quality, thereby enhancing the reliability of subsequent analysis and reducing the burden on downstream processing units.

(2) Cloud Integration: Enables the seamless storage of processed data on cloud platforms, providing scalable infrastructure for advanced analytics, real-time data access, and secure long-term archival. It supports integration with analytical tools and services to derive meaningful insights from large datasets

3.3 AI/Deep learning layer

(1) Model: The proposed model adopts a hybrid CNN-LSTM architecture to process ECG (Electrocardiogram) signals, aiming to extract both spatial and temporal features from the input data. This is crucial in the context of biomedical signal analysis, where the morphological structure of the ECG waveform and the temporal dynamics between heartbeats are both vital for accurate diagnosis and classification.

The architecture's first phase for extracting spatial features is the Convolutional Neural Network (CNN) component. This involves identifying significant localized signal features, such as peaks, slopes, and durations within the waveform—more particularly, elements like the P-wave, QRS complex, and T-wave that are involved in the processing of ECG signals. To find these local features, 1D convolutional layers typically employed, in which filters traverse across the ECG signal. Activation functions (such as ReLU), pooling layers (like MaxPooling1D) to reduce dimensionality, and batch normalization to enhance training stability may also be included in this step. Once the CNN has extracted the spatial features, the output is passed through a Flatten or Reshape layer to prepare the data for temporal modeling. This transformation reshapes the data into a format compatible with the Long Short-Term Memory (LSTM) network, converting the multi-channel spatial outputs into a time-series-like sequence of feature vectors.

The model's temporal learning stage is depicted by the LSTM component, which appears next. A specific type of Recurrent Neural Network (RNN), LSTMs are exceptionally good at discovering sequential patterns and long-term dependencies in time-series data. The LSTM learns to recognize irregular intervals, rhythmic patterns, and temporal anomalies between heartbeats in ECG signals by recording how features shift over time. This is particularly critical for

identifying diseases like arrhythmias, which are characterized by erratic heartbeat patterns and temporal spacing.

The outcome is passed into a number of Dense (fully connected) layers for final feature integration and decision-making after passing through the LSTM layers. Depending on the task, the output layer, which is the last layer, utilizes the proper activation function. For instance, a sigmoid is used for binary classification tasks (such as normal vs. abnormal), whereas a softmax activation is used for multi-class classification (such as distinguishing between different cardiac conditions).

(2) Function: Using ECG signal data, the proposed CNN-LSTM model's primary objectives involve categorizing various heartbeat types and forecasting possible cardiovascular risk patterns. Given that precise classification of cardiac rhythms aids in the early identification of cardiac disorders like arrhythmias, atrial fibrillation, and other abnormal heart conditions, this task is crucial for clinical diagnostics.

Using the CNN and LSTM components, the model first investigates the provided ECG signal to extract crucial features, both temporally and spatially. The form of heartbeat found in each ECG segment is then determined using these features that have been extracted. For instance, it may differentiate between different kinds of arrhythmic patterns, including bundle branch blocks, supraventricular ectopic beats, and premature ventricular contractions (PVCs), and a typical sinus rhythm. This classification aids doctors in determining whether the heart is beating normally or if there are anomalies that call for additional research or medical attention.

The model can be trained to predict possible risk patterns in addition to classification. Learning from a wide range of structured ECG signals, including those linked to previous cardiac events, the model is able to identify minute irregularities or shifts from normal patterns that could point to a higher risk of cardiac problems in subsequent years. Potential warning indicators could include, for example, persistent irregularities in heartbeat intervals or a gradual lowering of specific ECG components.

IoT-based wearable devices and remote health monitoring systems, which regularly gather and evaluate real-time ECG data, benefit greatly from these predictive features. The CNN-LSTM model can be used in these systems to continuously track patients and notify medical professionals of possible risks before clinical signs appear.

4. METHODOLOGY

The model is divided following phases:
- Data Acquisition
- Preprocessing
- Input Representation
- CNN-based Feature Extraction
- LSTM-based Temporal modelling
- Model Training
- Deployment

4.1 Data acquisition

To assure complete representation and generalization, cardiovascular signals from multiple sources are gathered and aggregated during the data gathering phase. The MIT-BIH Arrhythmia Database, which provides comprehensive ECG recordings with appropriate diagnostic labels, is one example of an annotated dataset. Furthermore, IoT-enabled biomedical sensors—such as wearable and implantable devices—provide real-time data streams by gathering physiological signals from patients in clinical or mobile settings. The dataset is robust for training and testing intelligent models due to the integration of these sources, which assures that it reflects both typical and unconventional cardiac behavior under various conditions.

4.2 Preprocessing

In addition to technical constraints, patient movement, and environmental disturbances, raw cardiac signals from sensors are vulnerable to noise and irregularities. Preprocessing is therefore required for transforming noisy, unstructured inputs into clean, standardized data that can be used to train models.

4.2.1 Signal denoising

In an attempt to reduce unwanted noise while retaining clinically significant features, denoising is used. Baseline wander, powerline disruption, and muscle distortions are removed, and the frequency factors of interest are distinguished using methods like bandpass filtering, wavelet decomposition, and Empirical Mode Decomposition (EMD).

4.2.2 Normalization

Normalization methods like min-max scaling or z-score standardization are used to remove bias brought on by variances in signal amplitudes among sensors or subjects. This enhances efficiency and reliability during training by ensuring that the input signals received by the deep learning model fall within a consistent range.

4.2.3 Segmentation

In addition to the persistent nature of ECG signals, temporal analysis is made simpler by segmenting the data into distinct windows or cardiac cycles. Individual heartbeat segments can be extracted with the aid of techniques like peak detection-driven segmentation and predetermined-length windowing. Deep learning models then use these segments as units of input.

4.2.4 Artifact removal

Noise removal methods like threshold-based filters or Independent Component Analysis (ICA) are used to reduce non-cardiac noise and improve signal quality even more. Cleaner signal inputs enhance model precision and lower false alarms as a result.

These preprocessing methods work together to convert noisy, unstructured raw data into clean, standardized, and well-segmented inputs, which help deep learning algorithms detect and anticipate cardiac abnormalities. Therefore, the success of the intelligent IoT-enabled heart monitoring system recommended in this study depends critically on efficient preprocessing.

4.3 Input representation

After preprocessing, each ECG segment is formatted as a one-dimensional time-series vector:

$$x = [x_1, x_2, \ldots, x_T], \quad x \in R^T \tag{1}$$

where, T denotes the number of time steps in a single segment. This representation serves as the input to the convolutional

layers, capturing both local and global morphological features necessary for downstream classification.

4.4 CNN-based feature extraction

The initial stage of the deep learning pipeline involves Convolutional Neural Networks (CNNs) that extract spatial features from the input signal. CNNs are particularly effective in identifying morphological patterns in ECG signals, such as QRS complexes, P waves, and T wave irregularities.

4.4.1 Convolution operation
Convolutional filters slide across the input signal to detect local patterns:

$$y_i = \sum_{j=1}^{k} w_j * x_{i+j} + b \qquad (2)$$

where, k is the kernel size, w_j are the filter weights, and b is the bias.

4.4.2 Batch normalization and ReLU
Batch normalization is applied to stabilize learning, followed by a ReLU activation function:

$$f(x) = \max(0, x) \qquad (3)$$

These steps improve model convergence and address vanishing gradient problems.

4.4.3 Max pooling and dropout
Max pooling downsamples the feature map, reducing computational load and emphasizing dominant features:

$$y_i = \max(x_i, x_{i+1}, \dots, x_{i+p}) \qquad (4)$$

Dropout regularization prevents overfitting by randomly disabling a fraction of neurons during training.

4.4.4 Fully connected layer
Extracted features are passed through a dense layer to consolidate local patterns into higher-order representations:

$$y = w_x + b \qquad (5)$$

4.5 LSTM-based temporal modeling

The output of the CNN block is fed into Long Short-Term Memory (LSTM) layers to model the temporal dependencies between heartbeats across segments.

4.5.1 LSTM mechanics
LSTM networks capture long-term dependencies using gates and memory cells. The core operations include:
Forget gate:

$$f_t = \sigma(W_{f[h_{t-1}, x_t]} + b_f) \qquad (6)$$

Input gate:

$$i_t = \sigma(W_{i[h_{t-1}, x_t]} + b_i), \qquad \tilde{C_t} = \tanh(W_c[h_{t-1}, x_t] + b_c \qquad (7)$$

Cell state update:

$$C_t = f_t * C_{t-1} + i_t * \tilde{C_t} \qquad (8)$$

These mechanisms allow the model to retain clinically important temporal dynamics that span across multiple cardiac cycles.

4.5.2 Final dense and softmax layers
The LSTM output is passed through one or more fully connected layers, followed by a softmax layer:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}, y = argmax \, P(y_i) \qquad (9)$$

This produces the class probabilities, allowing the model to predict heart conditions such as normal rhythm, arrhythmia, or other cardiac abnormalities.

4.6 Customized CNN–LSTM for ECG signal processing

To address ECG-specific characteristics and ensure robust detection of arrhythmias and related anomalies, we introduce a customized CNN–LSTM model that combines spatial and temporal feature learning with physiological constraints. Unlike generic CNN and LSTM formulations, this design incorporates beat-synchronous segmentation, multi-scale convolutions matched to ECG wave durations, morphology-aware regularization, RR-interval conditioning, and a temporally consistent early-alarm loss. The proposed model processes ECG signals as follows:

4.6.1 Beat-synchronous input representation
Each ECG segment is extracted around R-peak positions to ensure alignment with cardiac cycles:

$$x_t = \Pi(X, [r_t - \lfloor W/2 \rfloor, r_t + \lfloor W/2 \rfloor]) \in \mathbb{R}^{L \times W} \qquad (10)$$

where, X is the multi-lead ECG input, rtr_trt is the R-peak index for beat t, L is the number of leads, and W is the window length in samples.

4.6.2 Lead-attention fusion
Physiologically important leads (e.g., V1, V2 for QRS morphology) are adaptively weighted:

$$\tilde{x_t}(\tau) = \sum_{l=1}^{L} x_t^{(l)}(T), \qquad \alpha_\ell = \frac{\exp(\alpha_\ell)}{\sum_{j=1}^{L} \exp(\alpha_j)} \qquad (11)$$

where, α_ℓ are attention scores for each lead.

4.6.3 Multi-scale dilated convolutions
To capture P-wave, QRS, and T-wave patterns, we use multiple convolution kernels with physiologically tuned receptive fields:

$$f_t^{(m)}(T) = \sigma\left(b_m + \sum_{k=0}^{K_m-1} w_k^{(m)} \tilde{x_t}(T + d_m k)\right), \qquad m = 1, \dots, M \qquad (12)$$

where, d_m controls dilation (spacing) and K_m is the kernel size.

4.6.4 Morphology regularization for QRS complex

To enforce sharp, near-symmetric QRS detection, we regularize CNN kernels:

$$R_{morph} = \lambda_{sym} \sum_{m \in Q} \sum_k \left(w_k^{(m)} + w_{K_m - 1 - k}^m \right)^2 \\ + \lambda_{tv} \sum_{m \in Q} \sum_k \left(w_{k+1}^{(m)} - w_{K_{m+1}}^{(m)} \\ - w_k^{(m)} \right)^2 \qquad (13)$$

where, Q is the set of QRS-focused kernels.

4.6.5 RR-interval conditioning

Rhythm variability is encoded by concatenating RR intervals with CNN features:

$$s_t = \varphi(GAP(f_t) \parallel z_t) \qquad (14)$$

where, z_t represents a short RR history and GAP is global average pooling.

4.6.6 LSTM temporal modeling

$$\begin{aligned} i_t &= \sigma(W_i\, s_t + U_i\, h_{t-1} + b_i), \\ f_t &= \sigma(W_f\, s_t + U_f\, h_{t-1} + b_f), \\ \tilde{c}_t &= tanh(W_c\, s_t + U_c\, h_{t-1} + b_c), \\ o_t &= \sigma(W_o\, s_t + U_o\, h_{t-1} + b_o), \\ c_t &= f_t \odot c_{t-1} + i_t \odot \tilde{c}_t, \\ h_t &= o_t \odot tanh(c_t) \end{aligned} \qquad (15)$$

4.6.7 Early-alarm prediction & loss

To encourage early detection, predictions are made h beats ahead:

$$p_{t+h} = softmax(V\, h_t + b) \qquad (16)$$

The overall loss combines class-weighted cross-entropy, temporal consistency, early-alarm emphasis, and morphology regularization:

$$J = L_{CE} + \lambda_{temp} L_{temp} + \lambda_{early} L_{early} \\ + \lambda_{morph} R_{morph} + \lambda_2\, \Sigma \left\| \Theta \right\|^2 \qquad (17)$$

where, Θ denotes all learnable parameters.

4.7 Model training

The training process for the proposed CNN-LSTM model involves leveraging annotated cardiovascular signal datasets, where each signal segment is labeled to indicate specific heart conditions such as normal rhythm, arrhythmias, or other abnormalities. Initially, the preprocessed data—consisting of clean, normalized, and segmented heart signal windows—is fed into the Convolutional Neural Network (CNN) component. The CNN automatically extracts spatial features, such as morphological patterns in the heartbeats, by applying a series of filters across the signal. These high-level features are then passed to the Long Short-Term Memory (LSTM) layers, which are responsible for learning the temporal dependencies and sequential dynamics present in cardiac signals over time. The model undergoes supervised learning, where the predicted outputs are compared to ground truth labels, and the error is minimized through backpropagation and optimization algorithms such as Adam or RMSprop. To enhance generalization and robustness, techniques like dropout, early stopping, and batch normalization are employed during training. Furthermore, the trained model is validated using a separate set of real-time or unseen input data to evaluate its accuracy, sensitivity, specificity, and overall performance in detecting cardiac anomalies. This ensures the model's reliability and readiness for deployment in real-world, IoT-enabled heart monitoring systems.

The CNN-LSTM model was trained using the MIT-BIH Arrhythmia dataset and real-time ECG segments. The training process involved supervised learning with categorical cross-entropy as the loss function, optimized using the Adam optimizer with an initial learning rate of 0.001. Hyperparameters were tuned through a grid search over learning rates [0.0001, 0.001, 0.01][0.0001, 0.001, 0.01][0.0001,0.001,0.01], batch sizes [32,64,128][32, 64, 128][32,64,128], and dropout rates [0.2,0.5][0.2, 0.5][0.2,0.5]. The final configuration employed a batch size of 64, dropout of 0.3, and early stopping with a patience of 10 epochs to prevent overfitting. The model was trained for 50 epochs, with an 80:10:10 split for training, validation, and testing. Regularization was achieved through L2 weight decay ($\lambda = 0.0001$) and dropout layers.

4.8 Deployment

Once the deep learning model (e.g., CNN or LSTM) is trained and validated using preprocessed cardiac data, it is deployed to a cloud-based server environment. This cloud infrastructure provides the scalability, processing power, and storage capacity required to handle continuous streams of data from multiple IoT-enabled wearable or implantable sensors. The model is integrated into a backend system that supports real-time inference, allowing it to analyze incoming heart signals and detect anomalies on the fly. To ensure accessibility and usability, the system is connected to a user-facing mobile or web application. This application serves as the interface through which patients, caregivers, or healthcare professionals can monitor heart activity in real time, receive alerts about irregular patterns, and access historical health data. The deployment not only ensures 24/7 availability and seamless access but also facilitates remote healthcare by bridging the gap between real-time data acquisition and clinical decision-making. Security and privacy measures, such as encryption and authentication protocols, are implemented to safeguard sensitive health data during transmission and storage. The methodology is illustrated in Figure 2.
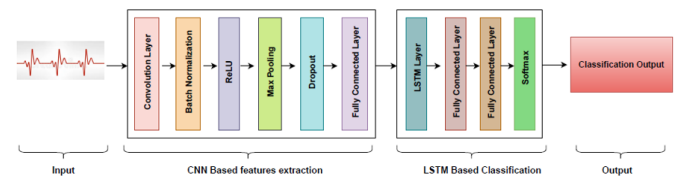

Figure 2. CNN-LSTM model architecture

5. RESULTS AND EVALUATION

Table 3 presents a comparative analysis of the performance of three deep learning models—CNN, LSTM, and the hybrid CNN+LSTM—evaluated using four key metrics: Accuracy,

Precision, Recall, and F1-Score. This comparison highlights the strengths and weaknesses of each model in processing and interpreting cardiac signals. Correspondingly, Figure 3 illustrates these results in a graphical format, clearly showing that the CNN+LSTM hybrid model consistently outperforms both standalone models across all evaluation criteria. This superior performance underscores the hybrid model's robustness and enhanced capability in accurately detecting and classifying heart signal anomalies, making it a more effective solution for real-time cardiac monitoring applications.

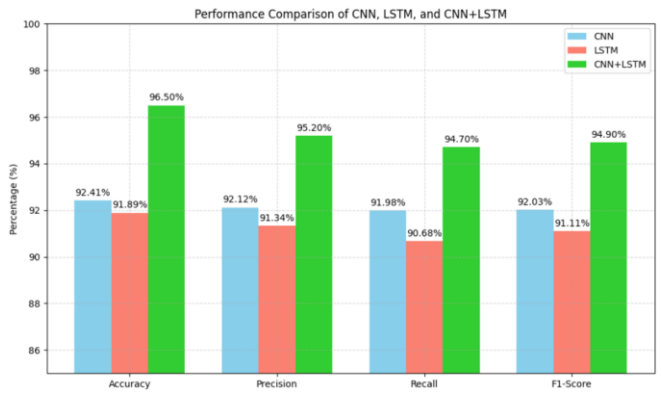**Table 3.** Performance comparison of CNN, LSTM and proposed model

Metric	CNN Value	LSTM Value	CNN+LSTM Value
Accuracy	92.41%	91.89%	96.5%
Precision	92.12%	91.34%	95.2%
Recall	91.98%	90.68%	94.7%
F1-Score	92.03%	91.11%	94.9%

These intervals indicate that the proposed CNN+LSTM model consistently outperforms standalone models with a high level of confidence, reinforcing its robustness for real-world deployment.

Statistical Significance Analysis:

To validate whether the performance improvements of the proposed CNN+LSTM model over standalone CNN and LSTM models are statistically significant, we conducted a paired t-test on cross-validation folds. The null hypothesis (H_0) assumes no significant difference between models, while the alternative hypothesis (H_1) assumes the CNN+LSTM model performs better.

Results indicate p-values < 0.05 for all metrics (Accuracy, Precision, Recall, F1-score), confirming that the performance gains of the hybrid model are statistically significant as shown in Table 4.

Figure 3. Performance comparison of CNN, LSTM and proposed model

Table 4. Statistical significance (p-values) of performance comparison between models

Comparison	Accuracy p-Value	Precision p-Value	Recall p-Value	F1-Score p-Value
CNN vs CNN+LSTM	0.002	0.004	0.003	0.005
LSTM vs CNN+LSTM	0.001	0.003	0.002	0.004

6. CONCLUSION

The integration of IoT and AI-driven deep learning provides a transformative approach for continuous, real-time cardiac monitoring. By leveraging wearable devices for data acquisition and a hybrid CNN–LSTM model for spatial and temporal feature analysis, the proposed framework enhances diagnostic accuracy and enables proactive interventions. Cloud integration further ensures scalability, secure data access, and seamless connectivity for remote healthcare applications. Experimental results validate its robustness, with the hybrid model achieving 96.5% accuracy, 95.2% precision, and an F1-score of 94.9%, outperforming standalone CNN and LSTM models. This work demonstrates a practical, intelligent solution for early detection and management of cardiac anomalies, bridging the gap between algorithmic innovation and real-world deployment.

7. LIMITATIONS AND FUTURE WORK

The proposed CNN-LSTM IoT framework, while effective on benchmark datasets, faces key limitations. First, reliance on the MIT-BIH dataset introduces demographic bias, limiting generalizability. Second, real-world deployments may encounter noise, motion artifacts, and inconsistent sensor quality.

Future work will explore bias reduction via federated learning, lightweight edge-compatible models, adaptive noise handling, and large-scale clinical trials for real-world validation.

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