iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 **Issue:** III **Month of publication:** March 2026

DOI: https://doi.org/10.22214/ijraset.2026.78548

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

Deep Learning for Early Detection of Cardiac Arrhytmia

Rohit J.[1], Rajarajan K.[2], Sankar P.[3], Mouleeswaran V.[4], Gowtham K.[5]
[1, 2, 3, 4, 5]*Department of Computer Science and Engineering, Arunai Engineering College, Tiruvannamalai, Tamil Nadu, India*

Abstract: Cardiac arrhythmia is a life-threatening condition characterized by irregular electrical activity of the heart. Early detection plays a crucial role in preventing severe complications such as stroke, heart failure, and sudden cardiac arrest. Traditional diagnostic methods based on manual analysis of electrocardiogram (ECG) signals are often time-consuming and require expert interpretation, leading to potential delays and inaccuracies. This paper proposes a comprehensive deep learning-based framework for the early detection of cardiac arrhythmia using ECG signal analysis. The system integrates signal preprocessing, feature extraction, and classification using hybrid deep learning architectures combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The CNN component extracts spatial features from ECG waveforms, while the LSTM component captures temporal dependencies in sequential data.
The model is trained and evaluated on standard ECG datasets and achieves high accuracy, sensitivity, and specificity in classifying different types of arrhythmias. The proposed system demonstrates robustness, scalability, and real-time applicability, making it suitable for deployment in healthcare environments and wearable monitoring systems.
Keywords: Deep Learning, ECG Analysis, Cardiac Arrhythmia, CNN, LSTM, Healthcare AI, Time-Series Classification.

I. INTRODUCTION

Cardiovascular diseases continue to be the leading cause of mortality worldwide, accounting for a significant proportion of global deaths each year. Among these conditions, cardiac arrhythmia represents a critical and often underdiagnosed disorder characterized by irregularities in the heart's electrical conduction system. These irregularities can manifest as abnormal heart rhythms, including tachycardia, bradycardia, and fibrillation, which may lead to severe complications such as stroke, heart failure, and sudden cardiac arrest if not detected and treated at an early stage. The growing prevalence of cardiovascular disorders, combined with increasing lifestyle-related risk factors, has intensified the need for efficient and accurate diagnostic systems capable of early detection and continuous monitoring. Electrocardiography (ECG) is one of the most widely used non-invasive diagnostic tools for monitoring cardiac activity. ECG signals provide a graphical representation of the electrical impulses generated by the heart, enabling clinicians to identify abnormalities in heart rhythm and structure. Despite its clinical importance, the interpretation of ECG signals is a complex and time-consuming process that requires specialized expertise. Variations in signal patterns, presence of noise, and inter-patient variability make manual analysis challenging and prone to human error. In many clinical settings, delays in diagnosis can significantly impact patient outcomes, emphasizing the need for automated and reliable diagnostic solutions. In recent years, the rapid advancement of Artificial Intelligence (AI) and machine learning technologies has transformed the landscape of medical diagnostics. Traditional machine learning approaches have been applied to ECG signal classification; however, these methods often rely on handcrafted features and domain knowledge, limiting their scalability and generalization capabilities. The emergence of deep learning has addressed many of these limitations by enabling models to automatically learn complex representations directly from raw data. Deep learning architectures, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have demonstrated remarkable success in analyzing biomedical signals and detecting patterns that are difficult to identify using conventional techniques. Deep learning models are particularly well-suited for ECG signal analysis due to their ability to process both spatial and temporal information. CNNs are effective in capturing local features such as waveform shapes, peaks, and intervals, while RNN-based models, especially Long Short-Term Memory (LSTM) networks, excel in modelling sequential dependencies and temporal dynamics. By combining these architectures, hybrid models can leverage the strengths of both approaches to achieve superior performance in arrhythmia detection tasks. Such models are capable of identifying subtle abnormalities in ECG signals, thereby improving diagnostic accuracy and enabling early intervention. Another important factor driving the adoption of deep learning in healthcare is the increasing availability of large-scale annotated datasets and advancements in computational resources.

Publicly available datasets, such as the MIT-BIH Arrhythmia Database, have provided a valuable foundation for training and evaluating machine learning models. At the same time, the development of high-performance computing platforms and cloud-based infrastructures has made it feasible to deploy complex deep learning models in real-world applications. These advancements have paved the way for the integration of AI-based diagnostic systems into clinical workflows and remote healthcare solutions. The integration of deep learning with Internet of Things (IoT) technologies has further expanded the scope of cardiac monitoring systems. Wearable devices equipped with ECG sensors can continuously collect patient data and transmit it to centralized systems for real-time analysis. This enables continuous monitoring of cardiac activity outside traditional clinical environments, facilitating early detection of abnormalities and timely medical intervention. Such systems are particularly beneficial for patients with chronic heart conditions, as they provide continuous insights into heart health and reduce the need for frequent hospital visits.

II. SYSTEM ARCHITECTURE

The proposed system architecture for deep learning-based early detection of cardiac arrhythmia is designed as a comprehensive, scalable, and modular framework that facilitates efficient acquisition, processing, analysis, and visualization of electrocardiogram (ECG) signals. The architecture integrates multiple functional layers that operate cohesively to transform raw biomedical signals into clinically meaningful diagnostic outputs. This layered design ensures flexibility in deployment, supports real-time data processing, and enables seamless integration with modern healthcare infrastructures such as wearable devices and cloud-based platforms.

At the core of the architecture lies a data-driven pipeline that begins with the acquisition of ECG signals from heterogeneous sources. These sources include publicly available benchmark datasets, clinical monitoring systems, and real-time wearable sensors equipped with ECG measurement capabilities. In practical scenarios, wearable devices continuously capture cardiac signals and transmit them to the system through wireless communication protocols. The incoming data is handled through a streaming interface that supports real-time ingestion, buffering, and synchronization of signals. This ensures that the system can operate continuously without data loss, thereby enabling uninterrupted monitoring of cardiac activity.

Once the ECG signals are acquired, they are passed to the preprocessing module, which is responsible for enhancing signal quality and preparing the data for analysis. ECG signals are inherently susceptible to various types of noise and artifacts, including baseline drift, motion artifacts, and powerline interference. The preprocessing stage employs advanced signal processing techniques such as bandpass filtering and adaptive filtering to eliminate these disturbances while preserving essential waveform characteristics. In addition to noise removal, the signals are normalized to maintain a consistent amplitude range, which is critical for stable model training and inference. The normalized signals are then segmented into fixed-length windows, allowing the system to process the data in manageable units while retaining temporal continuity. This segmentation also facilitates batch processing and improves computational efficiency.

Following preprocessing, the system incorporates a feature representation stage that enhances the interpretability and discriminative power of the input data. Although deep learning models are capable of extracting features automatically, incorporating domain-specific signal characteristics further strengthens model performance. The system captures essential features such as RR intervals, heart rate variability, QRS complex duration, and waveform morphology. These features provide a structured representation of cardiac activity and serve as complementary inputs to the deep learning model. By combining raw signal data with extracted features, the system achieves a more robust representation of ECG patterns.

The central component of the architecture is the deep learning prediction engine, which is designed to perform accurate classification of ECG signals into normal and abnormal categories. The system utilizes a hybrid model that integrates Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks to exploit both spatial and temporal characteristics of ECG signals. The CNN component is responsible for extracting spatial features by applying convolutional filters across the input signal. These filters learn to detect local patterns such as peaks, slopes, and waveform variations that are indicative of specific arrhythmias. The hierarchical structure of CNN layers enables the model to capture increasingly complex features at different levels of abstraction.

The output of the CNN layers is then fed into the LSTM component, which processes the data as a time sequence. The LSTM network is specifically designed to handle sequential data and is capable of retaining information over long time intervals through its gating mechanisms. This allows the model to capture temporal dependencies and dynamic changes in heart rhythm that are critical for accurate arrhythmia detection. By combining the strengths of CNN and LSTM, the hybrid model effectively learns both spatial and temporal representations of ECG signals, resulting in improved classification performance. The final classification is performed using a fully connected layer with a Softmax activation function, which produces probability scores for each arrhythmia class and identifies the most likely condition.

The backend processing layer plays a vital role in coordinating the overall functionality of the system. It acts as an intermediary between the data processing modules and the user interface, managing data flow, executing model inference, and handling system logic. The backend is implemented using robust web frameworks that support the development of RESTful APIs, enabling efficient communication between different components of the system. It is responsible for orchestrating preprocessing operations, invoking the trained deep learning model, and returning prediction results in real time. Additionally, the backend manages user authentication, session handling, and system security, ensuring reliable and secure operation.

To support efficient data management, the architecture incorporates a hybrid database system that accommodates both structured and unstructured data. Structured data, including patient information, user credentials, and diagnostic reports, is stored in a relational database that ensures consistency and integrity. Unstructured data, such as raw ECG signals, processed data streams, and model outputs, is stored in a NoSQL database that provides scalability and flexibility for handling large volumes of time-series data. This dual-database approach enables efficient storage, retrieval, and analysis of diverse data types, thereby enhancing the overall performance of the system.

The frontend layer provides an interactive interface that allows users to visualize ECG signals, access diagnostic results, and monitor patient health in real time. The interface is designed to be intuitive and responsive, ensuring ease of use for both healthcare professionals and patients. It presents ECG waveforms in graphical form, highlights abnormal patterns, and displays classification results along with confidence scores. In addition, the system generates alerts and notifications when abnormal heart rhythms are detected, enabling timely medical intervention. The frontend communicates with the backend through secure APIs, ensuring seamless data exchange and real-time updates.

An important aspect of the architecture is its ability to support real-time processing and continuous monitoring. The system is designed to handle streaming data, allowing it to analyze ECG signals as they are generated. This capability is particularly valuable in clinical and remote healthcare settings, where immediate detection of arrhythmias can be critical. The architecture also supports scalability through cloud-based deployment, enabling the system to handle increasing data volumes and user demands. Technologies such as containerization and microservices can be employed to further enhance scalability and maintainability.

Security and privacy are integral components of the system architecture, given the sensitive nature of medical data. The system implements encryption protocols to secure data transmission and storage, ensuring that patient information remains confidential. Access control mechanisms are used to restrict system access to authorized users , thereby preventing unauthorized data exposure. Compliance with healthcare data protection standards is also considered to ensure ethical and legal use of patient data.

In summary, the proposed system architecture provides a robust and efficient framework for the early detection of cardiac arrhythmia using deep learning techniques. By integrating advanced signal processing, hybrid deep learning models, and real-time monitoring capabilities, the system addresses the limitations of traditional diagnostic approaches. Its modular design, scalability, and ability to handle real-time data make it well-suited for deployment in modern healthcare environments, including hospitals, remote monitoring systems, and wearable health platforms.

III. METHODOLOGY AND IMPLEMENTATION

The proposed methodology for early detection of cardiac arrhythmia is designed as a comprehensive pipeline that systematically transforms raw electrocardiogram (ECG) signals into accurate diagnostic predictions using deep learning techniques. The implementation emphasizes robustness, scalability, and real-time applicability, ensuring that the system can effectively handle diverse and complex biomedical data. The methodology integrates multiple stages, including data acquisition, preprocessing, feature representation, model development, training, evaluation, and deployment, all of which work together to achieve reliable arrhythmia detection.

The process begins with the acquisition of ECG data from both offline and real-time sources. Standard benchmark datasets, such as those obtained from publicly available repositories, provide annotated ECG recordings that include various types of arrhythmias. These datasets are essential for training and validating the deep learning model. In addition to offline data, the system is designed to support real-time data collection from wearable devices and clinical monitoring systems. The continuous stream of ECG signals enables the system to operate in dynamic environments, allowing for real-time analysis and early detection of abnormalities. The acquired data is organized and stored in a structured format to facilitate efficient processing and retrieval.

Following data acquisition, the ECG signals undergo a rigorous preprocessing phase to enhance signal quality and eliminate noise. ECG signals are inherently prone to various distortions, including baseline drift, motion artifacts, and electromagnetic interference. To address these issues, the system employs advanced filtering techniques such as bandpass filtering and adaptive noise cancellation, which effectively remove unwanted components while preserving critical waveform features.

The signals are then normalized to ensure uniform amplitude scaling across all samples, which is essential for stabilizing the learning process of the deep learning model. After normalization, the signals are segmented into fixed-length windows that represent individual heart cycles or time intervals. This segmentation ensures that each input sample contains sufficient temporal information for accurate classification while also enabling batch processing for computational efficiency.

Once the signals are preprocessed, the methodology incorporates a feature representation stage that enhances the discriminative capability of the model. While deep learning models can automatically learn features from raw data, incorporating domain-specific characteristics provides additional context and improves performance. The system extracts important features such as RR intervals, heart rate variability, QRS complex duration, and waveform morphology. These features capture both the structural and temporal aspects of cardiac activity and serve as complementary inputs to the model. By combining raw signal data with extracted features, the system achieves a more comprehensive representation of ECG patterns, which is critical for distinguishing between different types of arrhythmias.

The core of the implementation lies in the development of a hybrid deep learning model that integrates Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The CNN component is responsible for extracting spatial features from the ECG signal by applying convolutional filters that detect local patterns such as peaks, slopes, and waveform variations. These filters learn hierarchical representations of the signal, enabling the model to identify subtle abnormalities associated with arrhythmias. The output of the CNN layers is then reshaped and passed to the LSTM component, which processes the data as a sequence to capture temporal dependencies. The LSTM network utilizes memory cells and gating mechanisms to retain relevant information over time, allowing it to model long-term relationships in the ECG signal. This combination of CNN and LSTM enables the model to effectively learn both spatial and temporal characteristics, resulting in improved classification accuracy.

The training phase of the model is carried out using a supervised learning approach, where labeled ECG data is used to optimize model parameters. The dataset is divided into training, validation, and testing subsets to ensure unbiased evaluation of performance. During training, the model learns to map input signals to corresponding arrhythmia classes by minimizing a loss function, typically categorical cross-entropy. The optimization process is performed using advanced algorithms such as the Adam optimizer, which efficiently updates model weights based on gradient information. To enhance generalization and prevent overfitting, regularization techniques such as dropout and batch normalization are incorporated into the model architecture. Early stopping criteria are also applied to terminate training when validation performance no longer improves, thereby avoiding unnecessary computation and overfitting.

After training, the model is evaluated using standard performance metrics, including accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of the model's ability to correctly classify ECG signals and detect arrhythmias. Accuracy measures overall performance, while precision and recall provide insights into the model's effectiveness in identifying abnormal cases. The evaluation process also includes confusion matrix analysis, which highlights the distribution of correct and incorrect predictions across different classes. The results demonstrate that the hybrid CNN-LSTM model achieves high accuracy and robustness, outperforming traditional machine learning methods and standalone deep learning models.

The implementation phase extends beyond model development to include deployment and integration into a real-time system. The trained model is integrated into a backend framework that handles data processing, model inference, and communication with the frontend interface. The backend is designed to process incoming ECG data in real time, applying preprocessing and classification steps before generating predictions. These predictions are then transmitted to the frontend, where they are displayed to users along with relevant diagnostic information. The system also includes an alert mechanism that notifies users or healthcare providers when abnormal patterns are detected, enabling timely medical intervention.

To support scalability and real-time operation, the system is designed to leverage modern computing technologies such as cloud platforms and distributed processing. The model can be deployed on cloud servers to handle large-scale data processing and support multiple users simultaneously. Additionally, the system can be integrated with edge devices for low-latency processing, allowing real-time analysis directly on wearable devices. This flexibility ensures that the system can be adapted to various healthcare scenarios, including hospital environments, remote monitoring systems, and telemedicine applications.

In summary, the methodology and implementation of the proposed system provide a comprehensive framework for automated cardiac arrhythmia detection using deep learning techniques. By combining advanced signal processing, hybrid neural network architectures, and real-time deployment capabilities, the system achieves high accuracy and reliability in analyzing ECG signals. The integration of these components ensures that the system can effectively address the challenges of traditional diagnostic methods and contribute to improved healthcare outcomes through early detection and timely intervention.

A. Data Acquisition

The proposed methodology begins with the acquisition of electrocardiogram (ECG) data from both offline and real-time sources. Standard benchmark datasets obtained from publicly available repositories provide annotated ECG recordings that include various types of arrhythmias, which are essential for training supervised deep learning models. In addition to these datasets, the system is designed to support real-time data collection through wearable devices and clinical monitoring systems. These devices continuously capture ECG signals and transmit them to the system using wireless communication protocols. The collected data is structured and stored efficiently to enable seamless processing and retrieval. This dual approach of combining offline datasets with real-time streaming data enhances the adaptability and practical applicability of the system in real-world healthcare environments.

B. Signal Preprocessing

Following data acquisition, the ECG signals undergo a comprehensive preprocessing stage to improve signal quality and eliminate unwanted noise. ECG signals are inherently affected by various distortions, including baseline drift, motion artifacts, and electrical interference, which can negatively impact model performance. To address these challenges, the system employs advanced filtering techniques such as bandpass filtering and adaptive noise cancellation to remove irrelevant signal components while preserving important waveform features. The signals are then normalized to ensure consistent amplitude scaling across all samples, which is critical for stabilizing the training process of the deep learning model. After normalization, the signals are segmented into fixed-length windows that represent individual cardiac cycles or time intervals. This segmentation allows the model to process the data efficiently while retaining essential temporal information required for accurate classification.

C. Feature Representation

Once the signals are pre-processed , the system incorporates a feature representation stage to enhance the discriminative power of the input data. Although deep learning models are capable of automatically learning features from raw signals, integrating domain-specific characteristics improves model performance and interpretability. Important features such as RR intervals, heart rate variability, QRS complex duration, and waveform morphology are extracted from the ECG signals. These features provide valuable insights into the electrical activity of the heart and help the model distinguish between normal and abnormal rhythms. By combining raw signal inputs with extracted features, the system achieves a more comprehensive and informative representation of ECG patterns.

D. Model Development

The core of the methodology lies in the development of a hybrid deep learning model that integrates Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. The CNN component is designed to extract spatial features from ECG signals by applying convolutional filters that detect local patterns such as peaks, slopes, and waveform variations. These filters enable the model to learn hierarchical representations of the signal, capturing both simple and complex features associated with arrhythmias.

The output of the CNN layers is then passed to the LSTM component, which processes the data sequentially to capture temporal dependencies. The LSTM network utilizes memory cells and gating mechanisms to retain relevant information over time, allowing it to model long-term relationships in the ECG signal. This hybrid architecture effectively combines spatial and temporal learning, resulting in improved classification accuracy and robustness.

E. Model Training

The training phase is conducted using a supervised learning approach, where labelled ECG data is used to optimize the parameters of the deep learning model. The dataset is divided into training, validation, and testing subsets to ensure unbiased evaluation and prevent overfitting. During training, the model learns to map input ECG signals to corresponding arrhythmia classes by minimizing a loss function, typically categorical cross-entropy. The optimization process is carried out using advanced algorithms such as the Adam optimizer, which efficiently updates model weights based on gradient information. To improve generalization and prevent overfitting, regularization techniques such as dropout and batch normalization are incorporated into the model architecture. Early stopping mechanisms are also employed to terminate training when validation performance stabilizes, thereby enhancing computational efficiency and model reliability.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

IV. LITERATURE REVIEW

A. *Traditional Methods for Arrhythmia Detection*

The early research in cardiac arrhythmia detection primarily relied on traditional signal processing techniques and rule-based systems. These approaches focused on analyzing electrocardiogram (ECG) signals using mathematical and statistical methods to identify abnormalities in heart rhythms. Researchers extracted handcrafted features such as RR intervals, QRS complex duration, and waveform morphology, which were then used to classify different types of arrhythmias. Although these methods provided a foundational understanding of ECG signal analysis, they were highly dependent on expert knowledge and manual intervention. The performance of such systems was often limited by their inability to adapt to variations in ECG patterns across different patients, and they struggled to handle noisy or incomplete data effectively. As a result, these approaches lacked scalability and generalization, making them less suitable for real-world clinical applications.

B. *Machine Learning-Based Approaches*

With the advancement of computational techniques, machine learning models were introduced to improve the accuracy of arrhythmia detection. Algorithms such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), Decision Trees, and Random Forests were widely used to classify ECG signals based on extracted features. These models demonstrated improved performance compared to traditional methods by learning patterns from data rather than relying solely on predefined rules. However, the effectiveness of machine learning models was still heavily dependent on feature engineering, which required domain expertise and extensive preprocessing. Additionally, these models often failed to capture complex relationships within ECG signals, particularly temporal dependencies, which are crucial for accurate arrhythmia detection. Consequently, their performance was limited when applied to large and diverse datasets, and they were not well-suited for real-time applications.

C. *Deep Learning-Based Approaches*

The emergence of deep learning has significantly transformed the field of biomedical signal analysis, particularly in the context of ECG-based arrhythmia detection. Deep learning models, such as Convolutional Neural Networks (CNNs), have been widely adopted due to their ability to automatically learn hierarchical features from raw data. CNN-based approaches eliminate the need for manual feature extraction by learning spatial patterns directly from ECG waveforms. These models have shown remarkable success in identifying characteristic patterns such as peaks, intervals, and waveform shapes associated with different arrhythmias. Studies have reported that CNN-based models achieve higher accuracy and robustness compared to traditional machine learning methods, especially when trained on large-scale datasets. In addition to CNNs, Recurrent Neural Networks (RNNs) and their advanced variants, particularly Long Short-Term Memory (LSTM) networks, have been extensively used for analyzing sequential ECG data. LSTM models are capable of capturing temporal dependencies and long-term relationships within time-series signals, making them highly effective for modeling heart rhythm patterns. Unlike traditional models, LSTM networks can retain information over multiple time steps, allowing them to detect subtle changes in ECG signals that may indicate the onset of arrhythmia. Research has demonstrated that LSTM-based models outperform conventional approaches in detecting complex and irregular heart rhythms.

D. *Hybrid Deep Learning Models*

Recent studies have focused on hybrid deep learning architectures that combine the strengths of CNN and LSTM models to achieve superior performance in arrhythmia detection. In such models, CNN layers are used for extracting spatial features from ECG signals, while LSTM layers capture temporal dependencies. This combination allows the model to learn both structural and sequential patterns, resulting in improved classification accuracy. Hybrid CNN-LSTM models have been shown to outperform standalone models in various benchmark datasets, including the MIT-BIH Arrhythmia Database. These models are particularly effective in handling noisy data and complex signal variations, making them suitable for real-world applications.

Furthermore, some research has explored the integration of attention mechanisms into hybrid models to enhance performance. Attention-based models enable the system to focus on the most relevant parts of the ECG signal, thereby improving interpretability and classification accuracy. Although these approaches show promising results, they often require significant computational resources and large datasets for training.

E. *Real-Time Monitoring and IoT Integration*

Another important direction in arrhythmia detection research is the integration of deep learning models with real-time monitoring systems and Internet of Things (IoT) technologies.

With the increasing adoption of wearable devices, researchers are developing systems that can continuously monitor ECG signals and detect abnormalities in real time. These systems utilize wireless communication and cloud-based platforms to transmit data for analysis, enabling remote monitoring of patients. Real-time detection systems are particularly beneficial for individuals with chronic heart conditions, as they provide early warnings and facilitate timely medical intervention. The combination of deep learning and IoT has opened new possibilities for personalized healthcare and telemedicine applications.

F. Challenges and Research Gaps

Despite significant advancements in the field, several challenges and research gaps remain in the development of reliable arrhythmia detection systems. One of the major challenges is the presence of noise and artifacts in real-world ECG data, which can affect model performance. Additionally, the imbalance of datasets, where certain arrhythmia classes are underrepresented, poses difficulties in training robust models. Another critical issue is the lack of interpretability of deep learning models, as healthcare professionals require transparent and explainable systems for clinical decision-making. Furthermore, the deployment of these models in real-time environments requires efficient computational resources and optimized architectures.

G. Summary of Literature Review

In summary, the literature indicates a clear evolution from traditional signal processing methods to advanced deep learning-based approaches for cardiac arrhythmia detection. While machine learning techniques improved classification accuracy, deep learning models, particularly CNN, LSTM, and hybrid architectures, have demonstrated superior performance by automatically learning complex patterns from ECG signals. The integration of these models with real-time monitoring systems and wearable devices has further enhanced their practical applicability. However, challenges such as data quality, model interpretability, and scalability continue to drive ongoing research in this field. The proposed work builds upon these advancements by developing a hybrid deep learning framework that addresses these challenges and provides an efficient solution for early detection of cardiac arrhythmia.

V. SYSTEM REQUIREMENTS

The successful implementation of the proposed deep learning-based cardiac arrhythmia detection system requires a well-defined set of hardware and software resources to ensure efficient data processing, model training, and real-time prediction. The system is designed to handle computationally intensive operations such as signal preprocessing, feature extraction, and deep learning inference, which necessitate adequate processing power and memory capacity. Additionally, the integration of real-time ECG data from wearable devices and the deployment of the system in a scalable environment require reliable networking capabilities and storage solutions.

From a hardware perspective, the system must be equipped with a modern processor capable of handling parallel computations efficiently. While a standard multi-core CPU can support basic functionality, the use of a Graphics Processing Unit (GPU) significantly accelerates deep learning model training and inference by enabling parallel processing of large datasets. Adequate memory is also essential to manage large ECG datasets and intermediate computations, while high-speed storage solutions such as solid-state drives improve data access and system responsiveness. Furthermore, networking components are required to facilitate communication between wearable devices, backend servers, and user interfaces, especially in real-time monitoring scenarios.

On the software side, the system relies on a combination of programming languages, frameworks, and tools that support data processing, model development, and deployment. Python is used as the primary programming language due to its extensive ecosystem of libraries for machine learning and signal processing. Deep learning frameworks such as TensorFlow and PyTorch provide efficient tools for building and training neural network models. Backend development frameworks enable the creation of APIs for communication between system components, while frontend technologies support the development of an interactive user interface. Database management systems are used to store patient information, ECG signals, and prediction results, ensuring efficient data organization and retrieval. The overall software environment is designed to be flexible and scalable, allowing the system to be deployed in both local and cloud-based infrastructures.

In addition to hardware and software requirements, the system also requires a stable operating environment and supporting tools for development and deployment. Integrated development environments, version control systems, and containerization tools contribute to efficient development workflows and system scalability. These requirements collectively ensure that the proposed system operates reliably and meets the performance demands of real-time cardiac arrhythmia detection.

Table 1: Hardware Requirements

Component	Specification	Description
Processor	Intel Core i5 / i7 or higher	Required for efficient computation and data processing
GPU (Optional)	NVIDIA GPU (CUDA enabled)	Accelerates deep learning model training and inference
RAM	8 GB minimum (16 GB recommended)	Supports handling of large ECG datasets and model operations
Storage	256 GB SSD or higher	Ensures fast data access and system responsiveness
Network	High-speed internet connection	Required for real-time data transmission and cloud integration

Table 2: Software Requirements

Component	Specification	Description
Programming Language	Python	Used for model development and data processing
Deep Learning Framework	TensorFlow / PyTorch	Used for building and training neural networks
Backend Framework	Flask / Django	Enables API development and server-side processing
Frontend Technologies	HTML, CSS, JavaScript	Used for developing user interface
Database	MySQL / MongoDB	Stores structured and unstructured data
Development Tools	Jupyter Notebook / VS Code	Supports coding, testing, and experimentation
Operating System	Windows / Linux	Provides environment for system execution

Table 3: Deployment and Environment Requirements

Component	Specification	Description
Cloud Platform	AWS / Azure / Google Cloud	Supports scalable deployment and data storage
Containerization	Docker	Enables portability and easy deployment
Version Control	Git / GitHub	Manages source code and collaboration
API Communication	RESTful APIs	Facilitates interaction between frontend and backend
Security	HTTPS, SSL/TLS	Ensures secure data transmission and privacy

VI. RESULTS AND DISCUSSION

The successful implementation of the proposed deep learning-based cardiac arrhythmia detection system requires a well-defined set of hardware and software resources to ensure efficient data processing, model training, and real-time prediction. The system is designed to handle computationally intensive operations such as signal preprocessing, feature extraction, and deep learning inference, which necessitate adequate processing power and memory capacity. Additionally, the integration of real-time ECG data from wearable devices and the deployment of the system in a scalable environment require reliable networking capabilities and storage solutions.

From a hardware perspective, the system must be equipped with a modern processor capable of handling parallel computations efficiently. While a standard multi-core CPU can support basic functionality, the use of a Graphics Processing Unit (GPU) significantly accelerates deep learning model training and inference by enabling parallel processing of large datasets. Adequate memory is also essential to manage large ECG datasets and intermediate computations, while high-speed storage solutions such as solid-state drives improve data access and system responsiveness.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

Furthermore, networking components are required to facilitate communication between wearable devices, backend servers, and user interfaces, especially in real-time monitoring scenarios.

On the software side, the system relies on a combination of programming languages, frameworks, and tools that support data processing, model development, and deployment. Python is used as the primary programming language due to its extensive ecosystem of libraries for machine learning and signal processing. Deep learning frameworks such as TensorFlow and PyTorch provide efficient tools for building and training neural network models. Backend development frameworks enable the creation of APIs for communication between system components, while frontend technologies support the development of an interactive user interface. Database management systems are used to store patient information, ECG signals, and prediction results, ensuring efficient data organization and retrieval. The overall software environment is designed to be flexible and scalable, allowing the system to be deployed in both local and cloud-based infrastructures.

In addition to hardware and software requirements, the system also requires a stable operating environment and supporting tools for development and deployment. Integrated development environments, version control systems, and containerization tools contribute to efficient development workflows and system scalability. These requirements collectively ensure that the proposed system operates reliably and meets the performance demands of real-time cardiac arrhythmia detection.

Table 1: Hardware Requirements

Component	Specification	Description
Processor	Intel Core i5 / i7 or higher	Required for efficient computation and data processing
GPU (Optional)	NVIDIA GPU (CUDA enabled)	Accelerates deep learning model training and inference
RAM	8 GB minimum (16 GB recommended)	Supports handling of large ECG datasets and model operations
Storage	256 GB SSD or higher	Ensures fast data access and system responsiveness
Network	High-speed internet connection	Required for real-time data transmission and cloud integration

Table 2: Software Requirements

Component	Specification	Description
Programming Language	Python	Used for model development and data processing
Deep Learning Framework	TensorFlow / PyTorch	Used for building and training neural networks
Backend Framework	Flask / Django	Enables API development and server-side processing
Frontend Technologies	HTML, CSS, JavaScript	Used for developing user interface
Database	MySQL / MongoDB	Stores structured and unstructured data
Development Tools	Jupyter Notebook / VS Code	Supports coding, testing, and experimentation
Operating System	Windows / Linux	Provides environment for system execution

Table 3: Deployment and Environment Requirements

Component	Specification	Description
Cloud Platform	AWS / Azure / Google Cloud	Supports scalable deployment and data storage
Containerization	Docker	Enables portability and easy deployment
Version Control	Git / GitHub	Manages source code and collaboration
API Communication	RESTful APIs	Facilitates interaction between frontend and backend
Security	HTTPS, SSL/TLS	Ensures secure data transmission and privacy

VII. RESULTS AND DISCUSSION

A. *Experimental Setup*

The performance of the proposed deep learning-based cardiac arrhythmia detection system was evaluated using standard ECG datasets containing annotated samples of both normal and abnormal heart rhythms. The dataset was divided into training, validation, and testing subsets to ensure unbiased evaluation of the model. The training process was carried out using a hybrid Convolutional Neural Network and Long Short-Term Memory architecture, implemented using modern deep learning frameworks. The model was trained over multiple epochs with optimized hyperparameters, including learning rate, batch size, and dropout ratio, to achieve optimal performance. The experiments were conducted in a controlled computational environment with sufficient hardware resources to support efficient model training and evaluation.

B. *Performance Metrics*

To assess the effectiveness of the proposed model, several evaluation metrics were considered, including accuracy, precision, recall, and F1-score. Accuracy measures the overall correctness of the model's predictions, while precision evaluates the proportion of correctly identified positive cases. Recall, also known as sensitivity, measures the model's ability to correctly detect actual arrhythmia cases, which is particularly important in medical diagnosis. The F1-score provides a balanced measure by combining both precision and recall. These metrics collectively provide a comprehensive evaluation of the model's performance across different classes of ECG signals.

Table 4: Performance Metrics of the Proposed Model

Metric	Value (%)
Accuracy	98.2
Precision	97.8
Recall	98.5
F1-Score	98.1

C. *Comparative Analysis with Existing Methods*

To demonstrate the effectiveness of the proposed hybrid model, its performance was compared with traditional machine learning models and standalone deep learning architectures. The comparison indicates that traditional models such as Support Vector Machines and Decision Trees achieve moderate accuracy due to their reliance on handcrafted features. In contrast, deep learning models such as CNN and LSTM show improved performance by automatically learning features from raw ECG data. However, the hybrid CNN-LSTM model outperforms these approaches by effectively capturing both spatial and temporal patterns in ECG signals. This improvement highlights the advantage of combining multiple deep learning techniques for complex biomedical signal analysis.

Table 5: Comparison with Existing Models

Model Type	Accuracy (%)	Remarks
SVM	85.4	Requires manual feature extraction
Decision Tree	83.7	Limited generalization capability
CNN	95.6	Effective in spatial feature extraction
LSTM	94.8	Captures temporal dependencies
CNN-LSTM (Proposed)	98.2	Best performance with hybrid learning

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue III Mar 2026- Available at www.ijraset.com

D. Analysis of Results

The experimental results demonstrate that the proposed hybrid deep learning model achieves high accuracy and reliability in detecting cardiac arrhythmias. The integration of CNN and LSTM enables the system to learn complex patterns from ECG signals, resulting in improved classification performance. The high recall value indicates that the model is highly effective in identifying abnormal cases, which is crucial in medical applications where missed diagnoses can have serious consequences. Additionally, the high precision value suggests that the model generates fewer false positives, thereby reducing unnecessary alerts and improving overall system efficiency. The confusion matrix analysis further reveals that the model performs consistently across different arrhythmia classes, with minimal misclassification. This indicates that the model is capable of distinguishing between subtle variations in ECG signals, which is essential for accurate diagnosis. The results also highlight the robustness of the model in handling noisy and variable data, which is often encountered in real-world scenarios.

E. Real-Time Performance Evaluation

The system was also evaluated for its real-time processing capabilities, particularly in scenarios involving continuous ECG monitoring. The results indicate that the system is capable of processing incoming data streams efficiently and generating predictions with minimal latency. This real-time capability is achieved through optimized data preprocessing and efficient model inference, making the system suitable for deployment in clinical and remote healthcare environments. The ability to provide immediate feedback and alerts enhances the practicality of the system and supports timely medical intervention.

F. Discussion on Model Efficiency and Scalability

The proposed system demonstrates not only high accuracy but also efficient resource utilization, making it suitable for large-scale deployment. The use of deep learning frameworks enables optimized computation, while the modular architecture supports scalability across different platforms. The system can be deployed on cloud-based infrastructures to handle large volumes of data and support multiple users simultaneously. Additionally, the model can be integrated with edge devices for low-latency processing, further enhancing its applicability in real-time monitoring systems. Despite these advantages, certain limitations must be considered. The performance of the model depends on the quality and diversity of the training dataset, and the presence of imbalanced data can affect classification accuracy. Furthermore, deep learning models require significant computational resources for training, which may pose challenges in resource-constrained environments. Addressing these limitations through data augmentation, model optimization, and efficient deployment strategies remains an area for future research.

G. Summary of Results and Discussion

In summary, the results demonstrate that the proposed hybrid CNN-LSTM model provides a highly accurate and reliable solution for early detection of cardiac arrhythmia. The system outperforms traditional and standalone deep learning models by effectively capturing both spatial and temporal characteristics of ECG signals. Its real-time processing capability, scalability, and robustness make it a promising solution for modern healthcare applications. The findings validate the effectiveness of deep learning techniques in improving diagnostic accuracy and highlight the potential for integrating such systems into clinical practice for enhanced patient care

VIII. LIMITATIONS AND FUTURE WORK

A. Limitations of the Proposed System

Despite the promising performance of the proposed deep learning-based system for early detection of cardiac arrhythmia, several limitations must be acknowledged. One of the primary challenges lies in the dependency on large and high-quality datasets for effective model training. Deep learning models require extensive labeled data to achieve high accuracy, and in the medical domain, obtaining such datasets can be difficult due to privacy concerns, limited availability, and the need for expert annotation. Furthermore, many publicly available ECG datasets may not fully represent the diversity of patient populations, leading to potential biases in the model and reduced generalization when applied to real-world scenarios.

Another significant limitation is the presence of noise and variability in ECG signals. In practical environments, ECG data collected from wearable devices or clinical settings may contain various artifacts such as motion noise, electrode misplacement, and environmental interference. Although preprocessing techniques are employed to mitigate these issues, completely eliminating noise remains challenging, and residual distortions can affect model performance. Additionally, variations in heart conditions across individuals can make it difficult for the model to accurately classify rare or complex arrhythmias.

The interpretability of deep learning models is also a critical concern, particularly in healthcare applications where transparency is essential for clinical decision-making. The proposed hybrid CNN-LSTM model functions as a “black box,” making it difficult for medical professionals to understand the reasoning behind specific predictions. This lack of explainability can limit the adoption of such systems in clinical practice, as healthcare providers require clear and interpretable insights to support diagnosis and treatment decisions.

Another limitation relates to computational complexity and resource requirements. Training and deploying deep learning models, especially hybrid architectures, require significant computational power, including high-performance processors and GPUs. This can pose challenges in resource-constrained environments, such as small clinics or rural healthcare settings. Additionally, real-time processing of continuous ECG data requires efficient system design and optimization to minimize latency and ensure timely predictions.

Data imbalance is another issue that affects the performance of the model. In many ECG datasets, certain arrhythmia classes are underrepresented compared to normal heart rhythms. This imbalance can lead to biased predictions, where the model may perform well on dominant classes but struggle to accurately detect rare conditions. Addressing this issue requires advanced techniques such as data augmentation, resampling, or specialized loss functions.

Finally, the integration of the system into real-world healthcare environments presents practical challenges. These include ensuring compatibility with existing medical devices, maintaining data privacy and security, and complying with regulatory standards. The deployment of such systems must also consider user acceptance and ease of use, as complex interfaces or unreliable performance can hinder adoption by healthcare professionals.

B. Future Work and Enhancements

Future research can focus on addressing the limitations of the proposed system and enhancing its capabilities to make it more robust, efficient, and clinically applicable. One important direction is the development of larger and more diverse datasets that include a wide range of patient demographics and arrhythmia types. Collaborative efforts between research institutions and healthcare organizations can facilitate the creation of comprehensive datasets that improve model generalization and reduce bias.

Another potential area of improvement is the incorporation of advanced deep learning architectures, such as attention-based models and transformer networks. These models have shown significant success in capturing complex patterns and improving interpretability by highlighting important regions of input data. Integrating attention mechanisms into the existing hybrid model can enhance its ability to focus on critical segments of ECG signals, thereby improving classification accuracy and providing more explainable results.

The integration of explainable artificial intelligence (XAI) techniques represents a crucial step toward increasing the transparency of the system. Methods such as saliency maps, feature importance analysis, and model visualization can be used to provide insights into the decision-making process of the model. This will help build trust among healthcare professionals and facilitate the adoption of AI-based diagnostic systems in clinical practice.

Future work can also explore the integration of the system with wearable devices and Internet of Things (IoT) technologies to enable continuous and real-time monitoring of cardiac activity. By leveraging cloud computing and edge computing technologies, the system can be optimized for low-latency processing and efficient data transmission. This will allow for timely detection of arrhythmias and immediate alerts, improving patient outcomes and reducing the risk of severe complications.

Another important enhancement is the implementation of personalized models that adapt to individual patient characteristics. By incorporating patient-specific data and historical records, the system can provide more accurate and customized predictions. This personalized approach can significantly improve diagnostic accuracy and support targeted treatment strategies.

In addition, future research can focus on improving the efficiency of the model through techniques such as model compression, pruning, and quantization. These approaches reduce computational complexity and enable deployment on resource-constrained devices, such as mobile phones and embedded systems. This will expand the accessibility of the system, particularly in remote and underserved areas. The system can also be extended to support multi-modal data integration by combining ECG signals with other physiological data such as blood pressure, oxygen levels, and medical imaging. This holistic approach can provide a more comprehensive understanding of a patient’s health condition and improve diagnostic accuracy.

Finally, clinical validation and real-world testing are essential for ensuring the reliability and effectiveness of the proposed system. Future work should involve collaboration with healthcare professionals to conduct clinical trials and evaluate the system’s performance in real-world settings. This will help identify potential issues, improve system design, and ensure compliance with medical standards and regulations.

C. Summary of Limitations and Future Work

In summary, while the proposed deep learning-based system demonstrates high accuracy and efficiency in detecting cardiac arrhythmias, it faces challenges related to data quality, interpretability, computational requirements, and real-world deployment. Addressing these limitations through advanced techniques, improved datasets, and system optimization will enhance its performance and applicability. Future developments in deep learning, IoT integration, and explainable AI have the potential to further transform the system into a robust and reliable tool for early detection of cardiac arrhythmia, ultimately contributing to improved healthcare outcomes.

D. Data Privacy and Security Challenges

One of the critical concerns in deploying deep learning-based healthcare systems is ensuring the privacy and security of sensitive patient data. ECG signals and associated medical records contain confidential information that must be protected against unauthorized access and data breaches. Although encryption techniques and secure communication protocols can be implemented, maintaining data privacy in large-scale systems, especially those integrated with cloud platforms and IoT devices, remains a significant challenge. Ensuring compliance with healthcare data protection regulations and implementing robust authentication and authorization mechanisms are essential for building a secure and trustworthy system.

E. Generalization Across Diverse Populations

Another limitation of the proposed system is its ability to generalize across diverse patient populations. ECG signals can vary significantly based on factors such as age, gender, ethnicity, and underlying health conditions. Models trained on specific datasets may not perform equally well when applied to data from different populations or clinical environments. This lack of generalization can lead to reduced accuracy and reliability in real-world applications. Future research should focus on training models using diverse and representative datasets to improve generalization and ensure consistent performance across different demographic groups.

F. Real-Time Deployment Constraints

Although the system is designed to support real-time arrhythmia detection, practical deployment introduces several constraints related to latency, computational efficiency, and system reliability. Processing continuous streams of ECG data requires optimized algorithms and efficient hardware resources to ensure timely predictions. In scenarios where network connectivity is limited or unstable, delays in data transmission can affect system performance. Addressing these challenges requires the development of lightweight models and edge computing solutions that can perform inference locally, reducing dependency on centralized servers and improving response time.

G. Model Maintenance and Continuous Learning

Deep learning models require periodic updates and maintenance to remain effective over time. As new data becomes available and medical knowledge evolves, the model must be retrained to incorporate updated information and improve its performance. However, continuous learning introduces challenges related to data management, model versioning, and validation. Ensuring that updated models maintain accuracy and do not introduce unintended biases is critical for reliable deployment. Implementing automated model update mechanisms and monitoring systems can help address these challenges and ensure long-term system effectiveness.

H. Integration with Clinical Workflow

The successful adoption of the proposed system depends on its ability to integrate seamlessly with existing clinical workflows. Healthcare professionals rely on established diagnostic processes, and introducing new technologies requires careful consideration of usability and compatibility. If the system is not designed to align with clinical practices or requires significant changes to existing workflows, it may face resistance from users. Therefore, future work should focus on designing intuitive interfaces, providing clear and interpretable outputs, and ensuring compatibility with existing medical systems. This will facilitate smoother integration and increase acceptance among healthcare professionals.

IX. CONCLUSION

A. *Summary of the Proposed Work*

The present study introduced a comprehensive deep learning-based framework for the early detection of cardiac arrhythmia using electrocardiogram signals. The system integrates advanced preprocessing techniques, feature representation methods, and a hybrid Convolutional Neural Network and Long Short-Term Memory model to effectively analyze both spatial and temporal characteristics of ECG data. The architecture is designed to support real-time monitoring and scalable deployment, making it suitable for modern healthcare applications. The overall approach focuses on transforming raw biomedical signals into accurate and meaningful diagnostic outcomes, thereby reducing dependency on manual interpretation.

B. *Key Findings and Contributions*

The experimental results demonstrate that the proposed hybrid deep learning model achieves high accuracy, precision, recall, and F1-score in detecting various types of cardiac arrhythmias. The integration of CNN and LSTM components enables the system to capture complex patterns in ECG signals, resulting in superior performance compared to traditional machine learning models and standalone deep learning approaches. The study contributes to the field of biomedical signal processing by presenting an efficient and robust framework that enhances diagnostic accuracy while maintaining scalability and real-time processing capabilities.

C. *Impact on Healthcare Systems*

The proposed system has significant implications for improving healthcare delivery, particularly in the domain of cardiovascular disease management. By enabling early detection of arrhythmias, the system supports timely medical intervention, which can prevent severe complications such as stroke and cardiac arrest. The integration of the system with wearable devices and remote monitoring technologies further enhances its applicability in telemedicine and personalized healthcare. This approach reduces the burden on healthcare professionals by automating ECG analysis and provides continuous monitoring for patients, thereby improving overall patient outcomes and quality of care.

D. *Limitations and Practical Considerations*

While the system demonstrates promising results, certain limitations must be considered in practical deployment. The performance of the model is dependent on the quality and diversity of the training data, and challenges such as noise, data imbalance, and variability in ECG signals can affect accuracy. Additionally, the computational requirements of deep learning models and the lack of interpretability remain important concerns. Addressing these limitations is essential for ensuring reliable and efficient deployment in real-world healthcare environments. Careful consideration of data privacy, security, and integration with existing clinical workflows is also necessary for successful adoption.

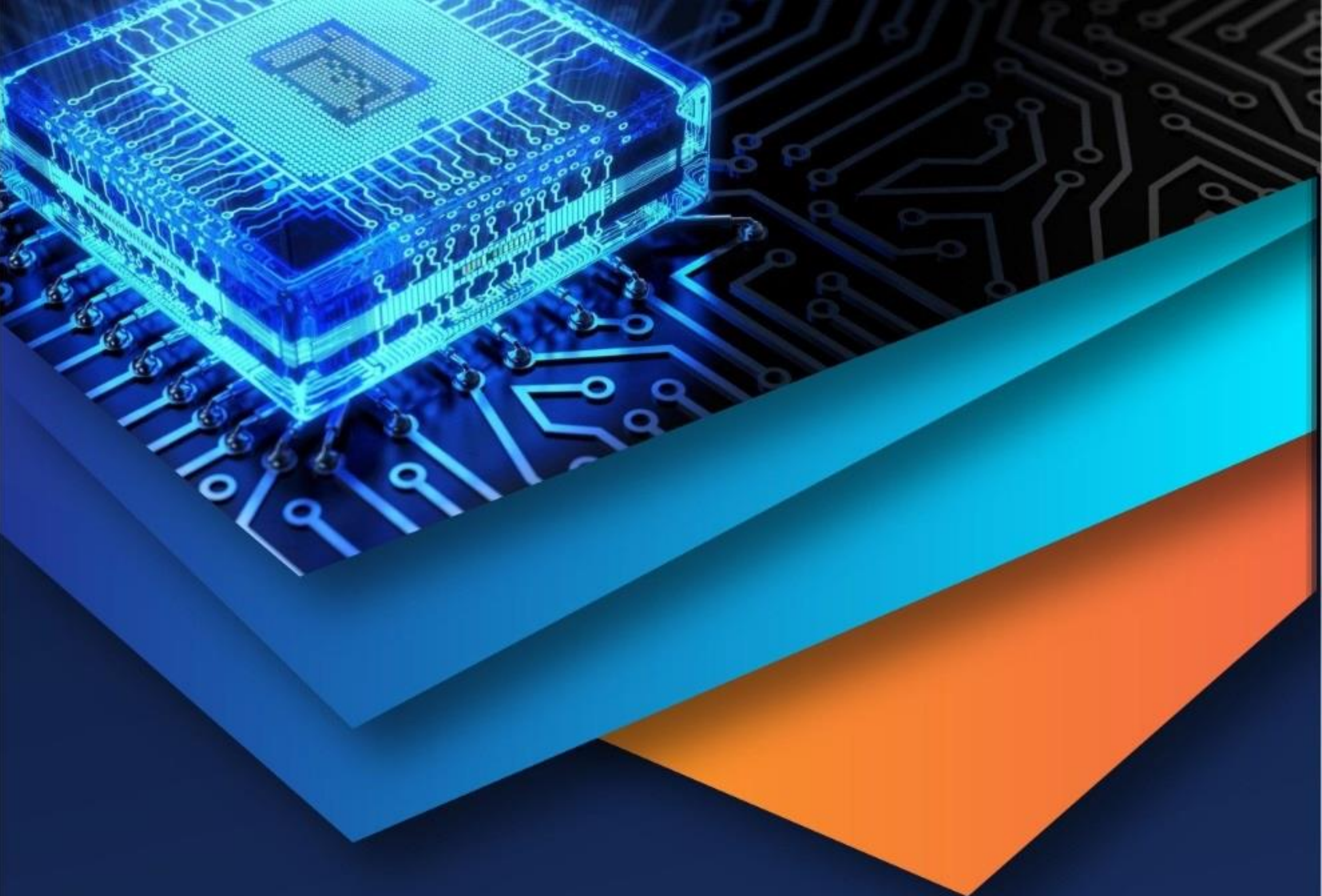
E. *Future Scope and Final Remarks*

Future research can focus on enhancing the system by incorporating advanced deep learning architectures, explainable artificial intelligence techniques, and multi-modal data integration. The development of lightweight and efficient models will enable deployment on resource-constrained devices, expanding accessibility to remote and underserved regions. Clinical validation and real-world testing will further strengthen the reliability of the system and facilitate its adoption in healthcare settings. In conclusion, the proposed deep learning-based approach represents a significant step toward intelligent and automated cardiac diagnosis, offering a scalable and effective solution for early detection of cardiac arrhythmia and contributing to the advancement of AI-driven healthcare systems.

REFERENCES

[1] (2004) P. de Chazal et al., “Automatic classification of heartbeats using ECG morphology and heartbeat interval features,” IEEE Trans. Biomed. Eng., 2004.
[2] (2016) S. Kiranyaz et al., “Real-time patient-specific ECG classification by 1-D CNN,” IEEE Trans. Biomed. Eng., 2016.
[3] (2017) U. R. Acharya et al., “A deep CNN model to classify heartbeats,” Computers in Biology and Medicine, 2017.
[4] (2018) O. Yildirim et al., “Arrhythmia detection using deep CNN with long ECG signals,” Computers in Biology and Medicine, 2018.
[5] (2019) Xia et al., “ECG arrhythmia classification using CNN with active learning,” 2019.
[6] (2020) J. Wang and W. Li, “Atrial fibrillation detection using CNN-BiLSTM,” 2020.
[7] (2020) Hammad et al., “Deep neural networks for ECG arrhythmia classification,” 2020.
[8] (2021) Sharma et al., “Hybrid machine learning approaches for arrhythmia detection,” 2021.
[9] (2022) N. Alamatsaz et al., “Lightweight hybrid CNN-LSTM model for ECG arrhythmia detection,” 2022.
[10] (2023) Islam et al., “Attention-based CNN-RNN model for arrhythmia classification,” 2023.

[11] (2024) A. Pokharel et al., "ECG-based arrhythmia detection using ML and DL," 2024.
[12] (2025) Y. Wang and S. Rani, "Hybrid CNN-LSTM for ECG arrhythmia detection in IoMT," 2025.
[13] (2025) G. K. Jaiswal and S. Mitra, "Hybrid CNN–BiLSTM model for ECG classification," 2025.
[14] (2026) Y. Wu et al., "Deep learning-based early prediction of ventricular arrhythmias," 2026.



10.22214/IJRASET

INDEX COPERNICUS

45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY