Engineering Applications of Artificial Intelligence 152 (2025) 110754

Contents lists available at ScienceDirect

Engineering Applications of Artificial Intelligence

journal homepage: www.elsevier.com/locate/engappai

Research paper

A lightweight deep learning approach for patient-specific electrocardiogram beat classification using local and long-term dependencies

Allam Jaya Prakash, Mohamed Atef *

Electrical and Communication Engineering Department, College of Engineering, United Arab Emirates University, Al Ain 15551, Abu Dhabi, United Arab Emirates

ARTICLE INFO

Keywords:
Bi-directional Long Short Term Memory
Convolution Neural Network
Deep learning
Electrocardiogram
Heart rate

ABSTRACT

An electrocardiogram (ECG) is a graphical tool used to assess patients' cardiac activity. Long-term ECG recordings, typically spanning 24 to 48 h, are crucial for detecting cardiac disorders. This paper introduces a novel, lightweight deep-learning architecture for classifying ECG beats as per the AAMI (Association for the Advancement of Medical Instrumentation) standard. The model integrates the advantages of Convolutional Neural Networks (CNN) and Bi-directional Long Short-Term Memory (Bi-LSTM) mechanisms in a single network to effectively capture local, temporal, and sequential patterns in ECG signals. Unlike conventional training, which often relies on fixed learning rates or predefined epochs, the proposed method dynamically adjusts learning parameters based on validation performance. Two Bi-LSTM layers effectively capture rich temporal dependencies, without requiring additional depth. The proposed method concatenates extracted CNN and BiLSTM features before the compact, dense layer, which will reduce the number of parameters significantly. This lightweight model ensures fast inference and low computational costs. Experimental results show that the proposed method achieves an accuracy of 99.21%, sensitivity of 98.66%, precision of 99.19%, and an F-score of 0.987. Additionally, the model demonstrates strong generalization capabilities, achieving high accuracies of 96.17% over different databases. The model's robustness and reliability in classifying ECG beats make it a practical and efficient tool for real-time monitoring applications.

1. Introduction

An Electrocardiogram (ECG) is a widely used, non-invasive diagnostic tool that records the electrical activity of the heart over time (Strik et al., 2023; Whitaker et al., 2023; Rege et al., 2015; Suganyadevi et al., 2022; Orphanidou and Drobnjak, 2017). ECG provides critical insights into the heart's rhythm, rate, and overall functionality by measuring the electrical signals generated during the heart's contraction and relaxation phases. The typical ECG waveform consists of distinct components, such as the P-wave, QRS complex, and T-wave are shown in Fig. 1, which correspond to specific cardiac events like atrial depolarization, ventricular depolarization, and ventricular re-polarization, respectively. These waveforms serve as key indicators in identifying normal cardiac function as well as a range of pathological conditions, including arrhythmias, ischemia, and myocardial infarction (Acharya et al., 2017). In the context of cardiac health monitoring, ECG plays a vital role in the early management of cardiovascular diseases, which remain a leading cause of mortality worldwide.

Continuous or periodic ECG monitoring is essential for identifying irregularities in heart activity, enabling timely intervention and reducing the risk of severe cardiac events. With advancements in wearable devices and telemedicine, ECG monitoring has become more accessible, facilitating patient-specific diagnosis and real-time healthcare delivery. This makes ECG a cornerstone in both clinical and ambulatory settings for improving patient outcomes. The early significant abnormal ECG beats are a critical focus of research within the cardiac healthcare system (Zeng et al., 2024). Cardiologists often recommend ECG tests to monitor the impact of drugs or medical devices, such as pacemakers, on heart function. These tests enable the measurement of the locations and sizes of the heart chambers, providing valuable information to assess cardiac health (Rege et al., 2015; Phong and Thien, 2009; Aphale et al., 2021; Bartolo et al., 2001; Whitaker et al., 2023). Abnormal ECG results can be due to various factors, such as heart muscle damage, inflammation, swelling, or inadequate blood flow to the heart. Previous or current heart attacks can also contribute to abnormal ECG findings (Smith and Edelman, 2023). A prevalent cardiovascular ailment is arrhythmia, characterized by an irregular heartbeat, which can manifest itself as a fast or slow heart rate. This condition alters the electrical system of the heart or creates a short circuit within the heart, leading to compromised blood circulation throughout the body.

* Corresponding author.
E-mail address: moh_atef@uaeu.ac.ae (M. Atef).

https://doi.org/10.1016/j.engappai.2025.110754
Received 14 November 2024; Received in revised form 17 March 2025; Accepted 31 March 2025
Available online 12 April 2025

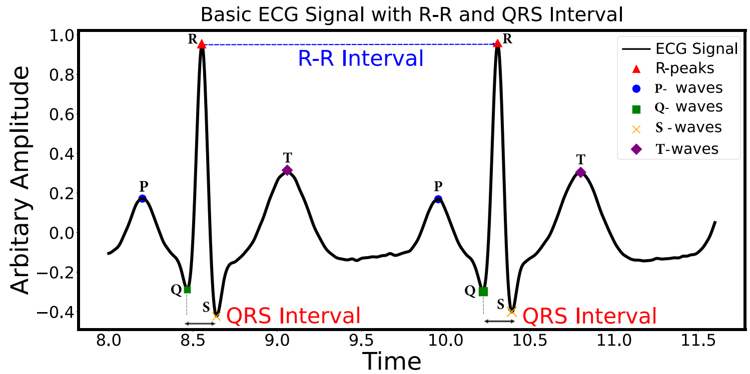


Fig. 1. The basic ECG signal and characteristic waves.

Table 1
Mapping of AAMI standard classes and corresponding MIT-BIH arrhythmia labels (Prakash and Ari, 2019a).

AAMI standard class	MIT-BIH label	Description
N	n	Normal sinus rhythm beat, indicating regular heart activity.
	L	Left bundle branch block beat, caused by delayed electrical impulses in the left ventricle.
	R	Right bundle branch block beat, due to conduction delay in the right ventricle.
	e	Nodal (junctional) escape beat, occurring when the AV node initiates a beat.
	j	Nodal (junctional) beat, an atrioventricular junctional beat with no preceding P-wave.
S	A	Atrial premature beat, occurring earlier than expected due to ectopic atrial activation.
	a	Aberrated atrial premature beat, an abnormal atrial beat with a wide QRS complex.
	J	Junctional premature beat, originating from the AV junction before the expected sinus beat.
	S	Supraventricular premature beat, arising from above the ventricles with abnormal morphology.
V	V	Premature ventricular contraction (PVC), an extra beat originating from the ventricles.
	E	Ventricular escape beat, occurring when the ventricles initiate a beat due to slow sinus node activity.
	!	Ventricular flutter wave, indicating rapid and abnormal ventricular activity.
	[	Start of ventricular flutter/fibrillation episode, marking the beginning of an arrhythmic event.
F	F	Fusion of normal and ventricular beat, appearing as a hybrid of both.
Q	Q	Unclassifiable beat due to noise, artifacts, or undefined morphology.
	/	Paced beat, an artificial beat induced by a pacemaker.
	f	Fusion of paced and normal beat, combining both paced and natural electrical activity.
	]	End of ventricular flutter/fibrillation episode, marking the termination of the event.

Inadequate blood flow poses an increased risk of heart failure and stroke.

The Association for the Advancement of Medical Instrumentation (AAMI) standard plays a crucial role in ensuring consistency, reliability, and clinical relevance in automated ECG beat classification (Prakash and Ari, 2019a). The AAMI standard categorizes heartbeats into five primary classes to standardize the evaluation of arrhythmias across different databases, making it easier for researchers and clinicians to compare models and results (Patil and Mohite-Patil, 2023). This classification is essential for ensuring that automated ECG diagnosis aligns with medical guidelines, improving clinical adoption and real-world applicability. AAMI-compliant classification addresses challenges such as class imbalance, misclassification of rare arrhythmic beats, and reducing model bias towards frequent beat types. By adhering to AAMI standards, our study ensures that the proposed Convolutional Neural Network (CNN) and Bi-directional Long-Short-Term Memory (Bi-LSTM) combination model can generalize well across multiple datasets and provide interpretable results for healthcare professionals. The Massachusetts Institute of Technology - Beth Israel Hospital (MIT-BIH) Arrhythmia database contains 17 heartbeat types, which are further grouped into five AAMI standard classes: Non-ectopic beat (N), Supraventricular (S), Ventricular (V), Fusion (F), and Unknown (Q). The mapping between AAMI standard categories and their corresponding MIT-BIH beat labels are shown in Table 1.

Early detection of arrhythmias plays a pivotal role in improving patient outcomes and preventing life-threatening complications. Arrhythmias, which are disruptions in the heart's electrical rhythm, can lead to severe conditions such as stroke and heart failure (or) sudden cardiac death if left untreated (An et al., 2023). Identifying these irregularities in their early stages allows healthcare providers to implement timely interventions, ranging from pharmacological treatments and lifestyle modifications to advanced therapies such as catheter ablation or pacemaker implantation (Orphanidou and Drobnjak, 2017). Early detection of arrhythmias before progress can significantly reduce the risk of debilitating outcomes and enhance overall patient survival. Moreover, early diagnosis can contribute to better resource management within healthcare systems by reducing the need for emergency interventions and hospitalizations. The detailed arrhythmias and the advantage in early detecting of these are summarized in Table 2. With the rise of wearable ECG devices, continuous monitoring technologies, and artificial intelligence-based diagnostic tools, arrhythmias can now be identified with greater accuracy and efficiency (Iijima et al., 2023). This proactive approach not only enables personalized care but also empowers patients to take greater control of their health. By leveraging these advancements, early can transform cardiac care, ensuring timely treatment, improved quality of life, and long-term health benefits for individuals at risk of arrhythmias (Jambukia et al., 2015). Consequently, developing an effective early arrhythmia system is essential to prevent and manage potential complications (Banerjee and Mitra, 2014). In the realm of cardiac health, extensive research has been undertaken to advance the automatic classification of ECG beats, as in numerous studies (Deevi et al., 2021; Kiranyaz et al., 2015; Sannino and De Pietro, 2018; Yildirim, 2018). Despite the availability of numerous state-of-the-art techniques for ECG beat classification, they each exhibit one or more limitations, as outlined in Table 3.

The key contributions of the proposed work aim to address these limitations effectively:

Table 2
Significance of early detection of arrhythmias in cardiac disorders.

Cardiac disorder	Significance of early detection	Clinical implications
Atrial Fibrillation (AF) (European Heart Rhythm Association (EHRA) et al., 2010)	Early detection can identify AF before it leads to thromboembolic events like strokes.	Reduces stroke risk by initiating anticoagulation therapy and rhythm control strategies early.
Ventricular Tachycardia (VT) (Whitaker et al., 2023)	Detecting VT early prevents its progression to life-threatening ventricular fibrillation (VF).	Enables timely intervention with antiarrhythmic drugs, implantable cardioverter defibrillators (ICDs), or ablation therapy.
Supraventricular Tachycardia (SVT) (Roston et al., 2017)	Early diagnosis allow management of abnormal electrical pathways before symptoms worsen.	Prevents symptoms such as palpitations, dizziness, and syncope, improving quality of life.
Bradyarrhythmias (e.g., Heart Block) (Dreifus et al., 1983)	Identifying conduction delays or complete blocks early prevent severe bradycardia and syncope.	Allows implantation of pacemakers to avoid fainting, fatigue, or sudden cardiac arrest.
Long QT Syndrome (LQTS) (Khan, 2002)	Early detection of prolonged QT intervals help prevent torsades de pointes, a potentially fatal arrhythmia.	Facilitates lifestyle modifications, beta-blocker therapy, or ICD placement to reduce sudden cardiac death risk.
Wolff-Parkinson-White (WPW) Syndrome (Kim and Knight, 2017)	Early detection identifies accessory pathways responsible for arrhythmias, even in asymptomatic patients.	Enables preventive catheter ablation to eliminate pathways and avoid future tachycardia episodes.
Premature Ventricular Contractions (PVCs) (Abadir et al., 2016)	Frequent PVCs, if detected early, can be monitored to prevent the development of cardiomyopathy.	Allows treatment with lifestyle modifications or ablation to preserve heart function.
Heart Failure (HF) (Ariyaratnam et al., 2021)	Detecting arrhythmias like atrial fibrillation or VT in heart failure patients reduce exacerbations.	Improves patient management with synchronized pacing and arrhythmia control, reducing hospitalization rates.
Sudden Cardiac Death (SCD) (Arntz, 2015)	Early detection of high-risk arrhythmias in predisposed individuals (e.g., hypertrophic cardiomyopathy and LQTS) is critical.	Provides life-saving interventions such as ICD implantation or preventive medications.
Post-myocardial infraction (MI) (Moss et al., 2002)	Monitoring for arrhythmias after an MI detects VT or VF that could lead to cardiac arrest.	Improves survival by initiating antiarrhythmic therapy or ICD placement as secondary prevention.

Table 3
Limitations of current machine and deep learning techniques in ECG beat classification.

Limitation	Explanation
Class imbalance (Vadillo-Valderrama et al., 2024)	ECG datasets often have an inherent imbalance in the distribution of heartbeat types, leading to biased models that perform well on dominant classes but poorly on minority classes.
Noise interference (Vadillo-Valderrama et al., 2024)	ECG signals are susceptible to noise from various sources, such as muscle activity and electrode motion, reducing model accuracy.
Lack of interpretability (Verma, 2022)	Many deep learning models operate as "black boxes", making it difficult to understand how predictions are made, which limits clinical trust and adoption.
Feature engineering dependency (Pyakillya et al., 2017)	Traditional machine learning approaches often rely on hand-crafted features, which may not fully capture the complexities of ECG signals.
Computational complexity (Ahmad et al., 2021)	Deep learning models, especially those involving recurrent or convolutional layers, require significant computational resources, which can be a barrier for real-time or resource-constrained environments.
Generalization issues (Xu et al., 2019)	Models trained on specific datasets (e.g., MIT-BIH) may not generalize well to other datasets or real-world settings due to differences in patient populations and recording conditions.
Requirement for fixed-length inputs (Chen et al., 2019; Sattar et al., 2024)	Many models require ECG signals to be segmented into fixed-length samples, which may not accurately capture varying heartbeat durations.

- A hybrid deep learning model combining CNN with Bi-LSTM is proposed to classify ECG beats, efficiently capturing both local features and temporal dependencies in one-dimensional ECG signals.
- The proposed method classifies ECG beats in line with the Association for the Advancement of Medical Instrumentation (AAMI) standards, ensuring compatibility with clinical applications and reliable performance for real-world cardiac diagnosis.
- Achieves State-of-the-Art Accuracy with Only ∼634K Parameters — Significantly reduces computational burden while maintaining a classification accuracy of 99.21%.
- Uses Lightweight CNN with Efficient Pooling — Instead of deep CNN stacks, only two convolutional layers are combined with BiLSTM layers for sequential processing, ensuring faster training and inference.
- In conventional training, which often relies on fixed learning rates or predefined epochs, but the proposed method dynamically adjusts learning parameters based on validation performance, leading to an adaptive training process.
- The proposed method achieves faster training (320 min) and inference (0.1787 s per ECG beat) compared to other high-parameter models that typically require >600 min for training.
- By eliminating the need for computationally expensive ECG signal-to-image transformations, the model directly processes raw one-dimensional ECG signals, significantly reducing the complexity and resource requirements, making it ideal for deployment in real-time and portable health monitoring devices.
- The combination of CNN for spatial feature extraction and Bi-LSTM for temporal feature learning in a parallel architecture results in superior classification performance, achieving high accuracy and efficiency across multiple ECG databases.
- Testing and validating of the model performed on the wide range of databases, i.e., MIT-BIH (Moody and Mark, 2001), St. Petersburg Institute of Cardiological Technics (INCART) (Goldberger et al., 2000), and supraventricular (PhysioNet, 2000) databases, demonstrating robustness and adaptability to diverse population and signal characteristics.

– Focusing on patient-specific ECG beat classification by dynamically adapting the model's parameters to individual patients' ECG signal variations, enhancing personalized cardiac monitoring.

These contributions highlight the innovative aspects of the proposed work, focusing on applying a robust, lightweight model for ECG beat classification. The rest of the manuscript is structured as follows: The comprehensive literature survey on ECG beat classification is elaborated in Section 2. The proposed Bi-LSTM-based deep CNN network is explained thoroughly in Section 3. The algorithm is validated by conducting experiments on publicly available datasets, and the results are given in Section 4. Finally, Section 5 concludes the proposed work.

2. Related work

In recent years, automated arrhythmia detection has become a focal point in cardiac monitoring, especially with advancements in computational methods (Liu et al., 2021). Machine learning and deep learning techniques have significantly improved the ability to analyze ECG signals for arrhythmias with greater speed and accuracy (Liu et al., 2021). These algorithms are capable of processing large datasets, identifying subtle abnormalities, and providing patient-specific insights that may not be evident through manual inspection (Ong et al., 2008). Wearable ECG devices equipped with these intelligent systems have enabled continuous, real-time monitoring, which is particularly beneficial for detecting transient or sporadic arrhythmias like atrial fibrillation or ventricular tachycardia (Rege et al., 2015). This innovation has greatly enhanced the potential for early intervention and improved patient outcomes. Despite these advancements, challenges remain in the accurate detection of arrhythmias. Variations in ECG signals caused by noise, motion artifacts, or physiological differences among patients can complicate the process. Moreover, some arrhythmias closely resemble normal ECG patterns, necessitating the development of robust and precise detection systems (Strik et al., 2023). Lightweight and efficient methods that consider local and long-term dependencies in ECG signals are particularly valuable in addressing these challenges, especially in resource-constrained environments or for wearable applications. Enhancing the reliability and accessibility of arrhythmia detection remains a critical area of research in cardiac health monitoring. Current research trends focus on developing beat classification techniques using both traditional machine learning and more recent deep learning methods (Sahoo et al., 2020; Liu et al., 2021). Typically, machine learning methodologies involve pre-processing, feature extraction, and classification stages. Pre-processing is essential for removing noise from ECG signals, a common step in machine and deep learning techniques (Prakash and Ari, 2019b). In machine learning, manual feature extraction is required to derive features from ECG signals, known as hand-made features. Additional optimization techniques might enhance their effectiveness if these features are not inherently optimal. These optimized features are then applied in machine learning algorithms for classification purposes (Alvarado et al., 2012). In contrast, deep learning algorithms are increasingly recognized for their ability to automate feature extraction and classification, eliminating the need for manual intervention in traditional machine learning methods.

Traditional ECG beat classification techniques rely on handcrafted feature extraction, such as wavelet transform (WT) (Akhtar et al., 2017) and Fourier transform (FFT) (Kheirati Roonizi and Sassi, 2024), which poses several limitations. These limitations include feature selection bias, fixed feature representations that fail to adapt to patient-specific variations, and loss of temporal dependencies in ECG signals (Jambukia et al., 2015). Wavelet transform, despite its popularity, has several disadvantages. First, it requires manual selection of wavelet functions, which may not be optimal for all ECG patterns, leading to potential biases in classification (Stephane, 1999). Second, WT suffers from sensitivity to noise and baseline wander, which can significantly impact classification accuracy (Thakor et al., 2006). Third, WT provides a fixed-resolution analysis that may not effectively capture the complex morphologies of ECG signals, limiting its ability to generalize across diverse datasets (Heil, 1993). Additionally, while WT decomposes signals into frequency components, it does not fully retain the sequential dependencies necessary for accurate classification, reducing its effectiveness in capturing dynamic cardiac variations. Similarly, the Fourier transform, which decomposes signals into sinusoidal components, assumes stationarity and lacks temporal resolution, making it unsuitable for ECG signals that exhibit non-stationary characteristics. The loss of time-domain information makes FFT less effective in detecting subtle variations in ECG beats, further limiting its utility in real-world applications. In contrast, deep learning models, particularly CNN combined with BiLSTM, overcome these challenges by automatically learning robust and adaptable features from raw ECG signals. CNN enables adaptive feature learning, eliminating the need for manual feature engineering and improving generalization across diverse datasets (Acharya et al., 2017). Furthermore, CNN enhances noise handling by extracting local features while preserving signal integrity (Kiranyaz et al., 2015). When combined with BiLSTM, CNN efficiently processes spatial features before BiLSTM captures long-term dependencies, leading to improved classification performance (Yıldırım et al., 2018). The ability of BiLSTM to retain sequential dependencies is particularly beneficial for ECG analysis, as it allows for the detection of complex cardiac patterns that traditional methods may overlook (Zhou et al., 2018). Although CNN-based models have a slightly higher computational cost, they provide optimized feature extraction, ensuring superior accuracy and adaptability compared to traditional methods (Kandala et al., 2019).

Numerous studies have shown that the classification precision with conventional methods is generally lower compared to that achieved with deep learning techniques (Liu et al., 2021; Deevi et al., 2021; Kiranyaz et al., 2015; Sannino and De Pietro, 2018; Yildirim, 2018). The application of deep learning for the classification of ECG beats has become widespread due to its effectiveness and efficiency. Deep learning approaches generally follow pre-processing and classification steps to classify the type of ECG beats. Deep learning approaches do not require a separate manual feature extraction technique, which reduces the system‘s complexity. Most researchers implemented deep learning architectures based on CNN to efficiently classify ECG beats (Kiranyaz et al., 2015). Arrhythmias demand accurate diagnosis, emphasizing the importance of ECG interpretation. Our research introduces image-based ECG representations and cascading deep neural networks (CDNNs) for arrhythmia detection, achieving 100% accuracy on the Shaoxing–Chapman ECG database (Zeng et al., 2024). The inclusion of SHapley Additive explanations (SHAP) and Gradient-weighted Class Activation Mapping (Grad-CAM) enhances model interpretability, advancing both performance and transparency in ECG classification (Zeng et al., 2024). A novel deep learning method designed for real-time ECG image detection and classification, integrating feature extraction, attention mechanisms, and feature fusion (Ma and Zhang, 2024a). Saeed et al. developed wavelet transform (WT) and multiple LSTM recurrent neural networks (RNNs) based architecture to classify ECG beats (Yildirim, 2018). LSTM-RNN automatically extracts features, and standard features are extracted using WT, which helps to capture specific patterns in the ECG signal. In Kuila et al. (2024), employs Differential Evolution Algorithm (DEA) with LSTM for arrhythmia classification. Using the Massachusetts Institute of Technology-Boston's Beth Israel Hospital (MIT-BIH) arrhythmia database, the model achieves 98.23% accuracy by optimizing focal loss to address ECG data imbalance, enhancing classification performance.

In Deevi et al. (2021), two blocks are framed for de-noising and classification. Different up and down samplings are used to denoise the ECG signal, and the denoised ECG signal is applied to the HeartNetEC (Customized CNN architecture) for ECG beat classification. DNN with seven hidden layers is developed to classify ECG beats using raw ECG

Table 4
Comparison of literature review for ECG beat classification techniques.

Literature	Method	Database	Metrics	No. of parameters	Advantages	Disadvantages
Jaya Prakash and Ari (2020)	ST-based 2D ResNet	MIT-BIH	Accuracy (Acc): 99.73%	13.6M	High accuracy, robust features.	High computational cost, low generalization, and more parameters.
Islam et al. (2024a)	Cat-net	MIT-BIH, INCART	Acc: 99.14%	1.18M	Generalizes well across databases.	Requires large training data and high-complexity.
Wang et al. (2020b)	CNN-MLP with Focal Loss	MIT-BIH	Acc: 92.53%	30K	Handles class imbalance	Lower accuracy than CNN-simple BiLSTM
Deevi et al. (2021)	HeartNetEC (Customized CNN)	MIT-BIH	Acc: 97.11%	–	Optimized for ECG beats.	Not suitable for real-time as only tested with single database.
Kim et al. (2023)	Deep Learning with CNN	MIT-BIH	Acc: 91.40%	–	Effective for arrhythmia detection.	Low specificity and Accuracy.
Huang et al. (2023)	Hybrid CNN-LSTM	MIT-BIH	Acc: 98.95%	–	Captures temporal dependencies	Higher training time
Mogili and Narsimha (2022)	BiLSTM	MIT-BIH	Acc: 94.63%	–	Efficient for time-series.	Sensitive to hyperparameters and less accuracy.
Hu et al. (2022)	Transformer-based Model	MIT-BIH	Acc: 95.47%	–	Effective on imbalanced data.	Computationally expensive transformers.
Xu (2024)	Hybrid CNN-GRU	MIT-BIH	Acc: 94.19%	–	Low latency model.	Not robust for noisy ECG and less generalization.
Zabihi et al. (2024)	CNN with Attention	MIT-BIH	Acc: 95.96%	–	Improves feature learning	No generalization
Islam et al. (2023)	RNN with Dilated CNN	MIT-BIH	Acc: 99.60%	142K	High precision.	Higher computational cost and No generalization.
Ma and Zhang (2024b)	Bi-Level Routing Attention	Private	Precision (Pre): 94.70%	56.49M	Improved classification performance.	Requires high memory.

signal in Sannino and De Pietro (2018). In Jaya Prakash and Ari (2020), at first, ECG beats are segmented based on R-peak location, further transformed these beats into spectrograms, and finally, these spectrograms are applied to the deep residual network (ResNet) to classify five types of ECG beats in a patient-specific way. Xie et al. implemented an ECG beat classification system using the Combination of bi-directional RNN and CNN named Bi-RCNN (Xie et al., 2018). Two dimensional (2D) gray-scale ECG beat images are applied as input to the 2D-CNN for ECG beat classification and achieved 99.05% performance accuracy in Jun et al. (2018). In Nurmaini et al. (2019), a different combination of auto-encoders (AEs) and deep neural networks (DNNs) is developed to classify ten types of ECG beats. In Wang et al. (2021), continuous WT and CNN architecture were designed to classify ECG beats based on AAMI standards. Continuous WT is utilized in this design to convert ECG beats into scalograms applied to the CNN for automatic beat identification. Different deep learning techniques such as CNN (Jun et al., 2018), LSTM (Yildirim, 2018), CNN-LSTM (Petmezas et al., 2021), GreyART (adaptive resonant theory) (Wen et al., 2007), and deep belief network (DBN) (Springenberg et al., 2014) are also popular in ECG beat classification. The 12-lead ECG is vital for diagnosing cardiovascular conditions like arrhythmia, and DNNs such as CNNs and Transformers have enhanced classification accuracy. In Zhang et al. (2024), a multi-scale convolutional Transformer network (MCTnet) combines CNN and Transformer encoder mechanisms, achieving superior performance by capturing multi-scale features and reducing redundant information. The detailed literature with different advantages and disadvantages of the existing approaches are summarized in Table 4. A key limitation observed in existing literature is the large parameter size and computational complexity of deep learning models. The ST-based 2D ResNet model (Jaya Prakash and Ari, 2020) achieves 99.73% accuracy but requires 13.6M parameters, leading to high memory usage and computational demand, making it impractical for real-time or embedded ECG classification tasks. Similarly, the Bi-Level Routing Attention model (Ma and Zhang, 2024b) shows a good precision of 94.70%, but with 56.49M parameters, making it memory-intensive and unsuitable for edge devices. Transformer-based models (Hu et al., 2022) are computationally expensive, limiting their applicability in resource-constrained environments. The HeartNetEC model (Deevi et al., 2021) is optimized for ECG beats but is only tested on a single database, reducing its generalization capabilities. Similarly, RNN with Dilated CNN (Islam et al., 2023) and CNN with Attention (Zabihi et al., 2024) achieve high precision but fail to generalize across multiple datasets. While CNN-MLP with Focal Loss (Wang et al., 2020b) is an efficient model (only 30 K parameters), its accuracy (92.53%) is significantly lower than hybrid architectures. Neither computational complexity, excessive model weight, nor lack of generalization is the primary issue in existing approaches. Many ECG monitoring systems operate on wearable devices (smartwatches, fitness bands, portable ECG monitors) that have limited memory, battery life, and processing power. Heavy deep-learning models with billions of parameters require high computational resources, making them unsuitable for embedded medical applications. Therefore, lightweight models are essential for many real-time applications, as they reduce inference latency and enable continuous health monitoring without the need to offload data to cloud servers.

In addition, the above review provides a comprehensive overview of ECG beat classification systems, it is important to acknowledge several limitations inherent in the current ECG beat classification approaches. The ECG beat as images (Mandal et al., 2021), spectrograms (Jaya Prakash and Ari, 2020), and scalograms (Yanık et al., 2020) generally require higher computational resources, making their deployment challenging in real-time or resource-constrained environments like wearable devices. More complex, multi-stream deep learning architectures — such as those incorporating numerous convolutional and recurrent layers — may achieve high accuracy but also introduce substantial computational overhead, which is impractical for real-time applications and low-power devices (Allam et al., 2024). High computational complexity often increases the demand for more advanced hardware, including high-performance graphical processing units (GPUs), and can result in longer processing times, higher power consumption, and increased latency (Jaya Prakash and Ari, 2020). The overview of the possible limitations is summarized in Table 3. These limitations make complex models less suitable for real-time monitoring, especially in wearable or mobile health applications where the hardware resources are restricted (Acharya et al., 2017). Reducing model complexity ensures that the network can be implemented on low-power, resource-constrained devices like wearables, which are increasingly being used in continuous health monitoring applications (Wechsler and Wernovsky, 2008). By eliminating the need to convert ECG signals into higher-dimensional representations such as images, the model can directly process raw one-dimensional (1D) signals, making it more suitable for real-time, continuous monitoring of cardiac health. A lightweight model decreases inference time, which is crucial for real-time applications. In scenarios such as arrhythmia detection, where timely intervention is critical, the ability to provide rapid results without sacrificing accuracy is essential (Jaya Prakash and Ari, 2020).

The proposed CNN and Bi-LSTM architecture processes 1D ECG signals directly, leading to a reduced number of trainable parameters and faster computational times compared to models that rely on 2D images or spectrograms. By using a simpler network structure with fewer parameters, the demand for high-end GPUs is minimized, making the model more accessible for deployment in everyday clinical settings or on portable devices (Mandal et al., 2021). This reduction in hardware requirements also leads to lower power consumption, which is critical for battery-powered devices used in long-term monitoring. Despite the low complexity, our model achieves high accuracy and performance metrics across multiple datasets such as MIT-BIH arrhythmia, St. Petersburg Institute of Cardiological Technics (INCART), and the MIT-BIH supraventricular. This demonstrates that the proposed architecture can maintain excellent generalization capabilities while reducing the computational burden. By focusing on the essential features of 1D ECG signals and using a parallel combination of CNN for local feature extraction and Bi-LSTM for temporal dependencies, we can efficiently capture both spatial and temporal patterns with fewer layers and parameters. Testing the model on multiple publicly available datasets ensures that it can handle diverse ECG signals from different populations, which is crucial for real-world deployment. By targeting a low-complexity network, this work seeks to strike a balance between achieving high classification accuracy and ensuring the model can be practically implemented in real-time, resource-constrained environments, such as wearable devices and mobile health platforms.

3. Proposed methodology

This work's generalized block diagram for ECG beat is represented in Fig. 2. In the proposed methodology section, the major steps for ECG beat classification: (i) pre-processing of the ECG signals, (ii) data separation for training and testing of the proposed deep learning model, and (iii) ECG beat classification using CNN-Bi-LSTM architecture are discussed. The effectiveness of the proposed deep learning architecture is verified using publicly available ECG databases such as MIT-BIH arrhythmia (Moody and Mark, 2001; Goldberger et al., 2000), INCART (Berrahou et al., 2024; Goldberger et al., 2000), and MIT-BIH supraventricular (PhysioNet, 2000; Goldberger et al., 2000). The proposed methodology is trained on MIT-BIH arrhythmia (Moody and Mark, 2001; Goldberger et al., 2000), and the remaining INCART (Berrahou et al., 2024; Goldberger et al., 2000), and MIT-BIH supraventricular (PhysioNet, 2000; Goldberger et al., 2000) databases are utilized for testing. During the training phase of the network, the first five minutes of data from each patient in the MIT-BIH arrhythmia database were considered. As a result, we treated this model as patient-specific, and a total of 8672 ECG beats were considered. The detailed description of the databases is discussed as follows.

3.1. Database

The effectiveness of the proposed deep learning architecture is verified using publicly available ECG databases such as MIT-BIH arrhythmia (Moody and Mark, 2001), INCART (Moody and Mark, 2001), and MIT-BIH supraventricular (PhysioNet, 2000).

- **MIT-BIH Arrhythmia Database** (Goldberger et al., 2000; Moody and Mark, 2001) This database, often considered the gold standard for heartbeat and its classification, includes normal and abnormal cardiac rhythms (Moody and Mark, 2001). It contains 48 ambulatory ECG recordings, each 30 min long, collected from 47 subjects. Among these, 23 recordings represent typical clinical ECG recordings, while the remaining ones involve subjects with potentially life-threatening arrhythmias. Each recording has a sampling rate of 360 Hz, and there are two information streams, with the MLII lead offering higher signal quality than the V5 lead (Moody and Mark, 2001). The database comprises approximately 109,000 annotated heartbeats with 17 different labels. However, four records (102, 104, 107, and 217) have poor quality and are excluded from the final classification efficiency calculations. The variability in ECG signals between different patients, and even within the same patient over time, poses challenges for developing robust classification systems.
- **St. Petersburg INCART Arrhythmia Database** (Berrahou et al., 2024; Goldberger et al., 2000): This dataset provides 75 ECG recordings, each 15 min long, collected from 25 patients with a diverse range of cardiac conditions. The ECGs were recorded using 12 leads and included more than 175,000 annotated heartbeats, manually labeled by two cardiologists. Although the dataset captures a broad range of conditions, the limited sample size may not fully represent the broader population. Nonetheless, it remains a valuable resource for testing ECG classification algorithms.
- **MIT-BIH Supraventricular Arrhythmia Database** (PhysioNet, 2000; Goldberger et al., 2000): This database consists of 78 two-lead ECG recordings, each 30 min long, collected from 14 patients. The patients include 11 males and 3 females, and the dataset covers a range of supraventricular arrhythmias, including normal, ventricular, fusion, and unknown beats. It has been extensively used in clinical and research settings to develop and test arrhythmia algorithms. The database has also served as a benchmark in studies comparing the performance of different machine learning and deep learning techniques.

The datasets utilized in this work were chosen based on their relevance, diversity, and widespread use in ECG classification research. Specifically, the following publicly available datasets were selected based on the following critical nature as shown in Table 5. The proposed model was chosen wisely as per the database challenges. The proposed CNN-BiLSTM model effectively mitigates the identified challenges through a combination of noise robustness, class imbalance handling, and improved generalization. To enhance noise robustness, the CNN component extracts spatial features that remain less sensitive to noise, while the Bi-LSTM layer captures long-term dependencies, minimizing misclassifications caused by signal distortions. To address class imbalance, the model employs weighted loss functions, ensuring that minority classes receive adequate attention, along with data augmentation techniques that enhance representation for underrepresented classes. Furthermore, to improve generalization, the model was trained on the MIT-BIH Arrhythmia Database and tested on the INCART and MIT-BIH Supraventricular Arrhythmia Databases, demonstrating its adaptability across datasets. The parallel CNN-BiLSTM architecture efficiently captures both local and sequential features, thereby improving classification accuracy across diverse ECG datasets.

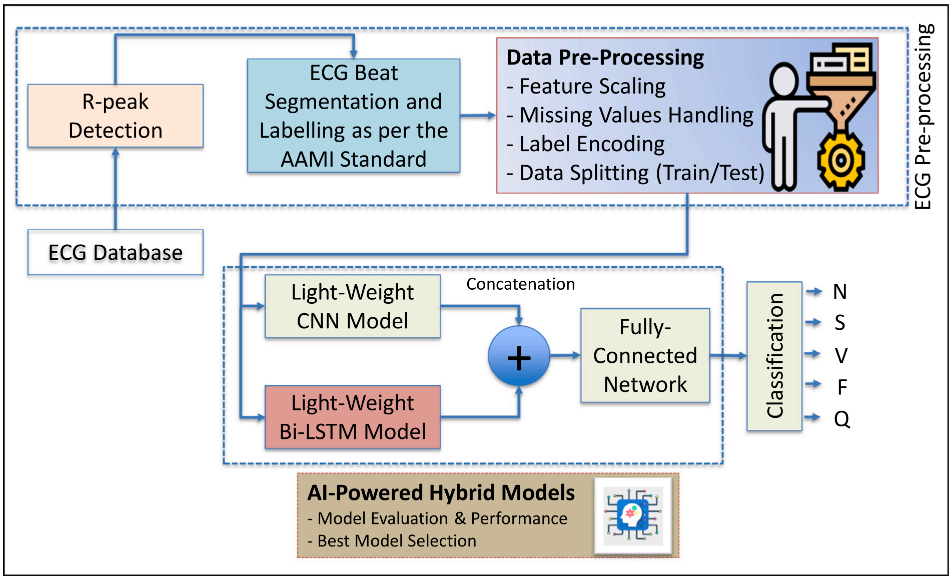


Fig. 2. Proposed methodology for ECG beat Classification.

Table 5
Challenges in ECG classification for selected datasets.

Dataset	Challenges
MIT-BIH Arrhythmia Database (Goldberger et al., 2000; Moody and Mark, 2001)	Variations in ECG lead quality and differences in recording conditions.
	Certain arrhythmia classes have fewer samples, leading to imbalanced data.
INCART Database (Berrahou et al., 2024)	Multi-lead configurations introduce variability affecting classification consistency.
	Some beats exhibit overlapping characteristics, making distinction difficult.
MIT-BIH Supraventricular Arrhythmia Database (PhysioNet, 2000)	High noise levels make classification more challenging.
	Certain supraventricular classes are underrepresented, impacting recall rates.

3.2. Pre-processing of the ECG signals

Pre-processing is the basic step for further beat classification. The ECG signal exhibits non-stationary characteristics, leading to rapid amplitude and instantaneous frequency changes. To mitigate these effects, a normalization process is employed, adjusting the signal to have zero mean and a standard deviation of one. Additionally, a band-pass filter with a range of 0.1 to 100 Hz is applied to eliminate unwanted noise. The Pan–Tompkins algorithm is utilized to accurately identify the locations of the R-peaks in the ECG signal. Based on these R-peak locations, individual beats are segmented by considering a window of −64 samples to the left and +64 samples to the right of each R-peak. This approach is effective since the QRS complex, which contains vital beat information, encompasses the majority of the relevant ECG signal content. After successful segmentation of the individual ECG beats, respective labels as per the AAMI standard are added.

3.3. ECG beat classification using CNN-Bi-LSTM architecture

In this work, the parallel combination of CNN and Bi-LSTM is utilized to extract the more meaningful features from the ECG beats. The benefits of CNN and Bi-LSTM are combined in this work to get better performance. The network architecture consists of convolutional layers, pooling layers, Bi-LSTM layers, flatten layers, dense layers, dropout layers, and a softmax layer. These layers combine to extract features from the input data, capture temporal dependencies, reduce dimensionality, and produce the final output probabilities. The detailed input layers, output shape, and number of parameters required in the implementation of the network are depicted in Table 6. The CNN layers are responsible for learning local patterns within the ECG beats. In contrast, the Bi-LSTM layers capture temporal and long-range dependencies in both forward and backward directions. This combination helps improve the network's performance in classifying ECG signals accurately.

Initially, a one-dimensional convolutional layer extracts features from the input signal, which are then processed by the Bi-LSTM layers. The Bi-LSTM consists of two LSTMs, which take input from both forward and backward directions, effectively allowing it to learn from past and future data. This combination works better than the regular LSTM. The two-layer Bi-LSTM model is utilized inside the framework of this architecture. The first and second layers are made up of Bi-LSTM, with the first layer having 90 units and the second layer having 180 units. A fully connected layer consists of flattening, dropout, and dense layers, just like in the traditional CNN model, followed by preceding layers. The proposed architecture for ECG beat classification is shown in Fig. 3. In the first stream, a conv1D layer employing rectified linear unit (ReLU) activation and a kernel size of 13 or 16 filters are employed. An average pooling of 3 and 2 strides follows this layer. There are 15 and 32 filters in the second conv1D layer. The second Conv1D employs

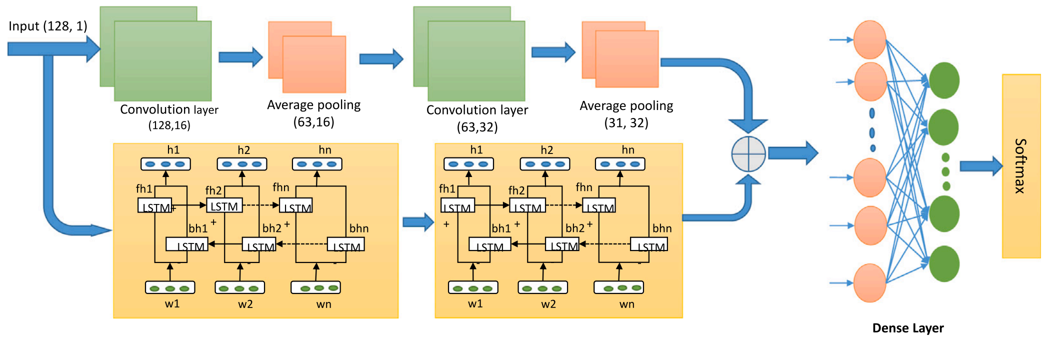


Fig. 3. Block diagram of proposed deep learning architecture.

Table 6
The input flow and output shapes of the proposed network.

S.No	Input layer	Output shape	Number of parameters
1	Input	(128,1)	0
2	Convolution Average-Pooling Convolution Average-pooling	(126,16) (63,16) (63,32) (31,32)	7936
3	Flatten	(992)	0
4	Bi-LSTM	(128,180)	66 240
5	Bi-LSTM	(360)	519 840
6	Flatten	(360)	0
7	Concatenation	(1352)	0
8	Dropout	(1352)	0
9	Dense	(35)	47 355
10	Dense	(5)	144
11	Soft-max	5	0
15	Trainable parameters Non-trainable parameters		634 621 6894

the same average pooling layer as the first one. Bi-LSTM also extracts the features from the ECG signal in the second stream. The features extracted from the 1D-CNN and the features extracted by the Bi-LSTM are concatenated to form a deep feature set. The proposed deep learning architecture, as outlined in Table 6, presents a comprehensive overview of its structural components and parameter details. Understanding the size of the trained network is crucial for assessing its computational efficiency and potential deployment scenarios. The model comprises convolutional layers, average-pooling operations, bidirectional LSTM layers, flattening, concatenation, dropout, and dense layers, culminating in a softmax output layer. The input layer accepts data with a shape of (128, 1), corresponding to ECG signals. The total number of trainable parameters is 634,621, while non-trainable parameters are 6894. Notably, the convolutional and LSTM layers contribute significantly to the overall parameter count, with 7936 parameters for the initial convolutional layers and 519,840 parameters for the second Bi-LSTM layer.

3.3.1. Feature extraction using 1D-CNN

A 1D-CNN is a deep-learning architecture commonly used for processing 1D sequential data, such as ECG signals. It is designed to capture local patterns and extract relevant features from the input data. The CNN architecture for one-dimensional signals consists of three main components: convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply filters to the input data, allowing the network to learn local patterns and features. Each filter convolves across the input sequence, capturing different patterns. The output of the convolutional layer is obtained by applying the filters to the input data using the convolution operation (Cheikhrouhou et al., 2021).

$$Output[i] = \sigma\left(\sum_{j=0}^{k-1} Filter[j] \cdot Input[i+j] + Bias\right) \tag{1}$$

where, Output[i] represents the output value at position i in the output feature map, $\sigma(\cdot)$ is the activation function, such as ReLU (Rectified Linear Unit), applied element-wise to introduce non-linearity, Filter[j] represents the filter values or weights, Input[$i + j$] denotes the input values at position $i+j$ in the input sequence, Bias is the bias term added to the convolutional operation (Cheikhrouhou et al., 2021).

Pooling layers down-sample the feature maps generated by the convolutional layers, reducing the spatial dimensions and retaining the most important information. The most common pooling operation is max pooling, which selects the maximum value within each window. The equation for max pooling in one-dimensional CNN can be represented as:

$$Output[i] = \max(Input[i \cdot stride : i \cdot stride + pool\_size]) \tag{2}$$

Fully connected layers are responsible for making predictions based on the extracted features from the previous layers. These layers connect every neuron in the previous layer to every neuron in the current layer, allowing the network to learn complex relationships and make high-level abstractions.

$$Output = \sigma(W \cdot Input + b) \tag{3}$$

where Output represents the output of the fully connected layer, $\sigma(\cdot)$ is the activation function applied element-wise, $\mathbf{W}$ represents the weight matrix connecting the input to the fully connected layer, Input denotes the input from the previous layer, $\mathbf{b}$ is the bias vector added to the fully connected operation.

By combining these convolutional, pooling, and fully connected layers, a one-dimensional CNN can effectively extract local patterns and relevant features from ECG signals. The network learns to recognize distinctive patterns in the ECG signal that are important for classification or other tasks.

3.3.2. Feature extraction using Bi-LSTM

The Bi-LSTM is one kind of RNN architecture widely used for modeling and processing sequential data, including ECG signals. It is particularly effective in capturing temporal dependencies in ECG data due to its ability to consider both past and future information. The Bi-LSTM consists of two LSTMs, one processing the input sequence in the forward direction and the other in the backward direction. Let us denote the input ECG signal sequence as $\mathbf{X} = (x_1, x_2, \dots, x_T)$, where T represents the length of the sequence. The LSTM cell comprises a memory cell, denoted as $\mathbf{c}_t$, and three gating mechanisms: the input gate, denoted as $\mathbf{i}_t$, the forget gate, denoted as $\mathbf{f}_t$, and the output gate, denoted as $\mathbf{o}_t$. These gates control the flow of information within the LSTM cell, allowing it to remember or forget information based on its relevance selectively. At each time step t, the forward LSTM updates its hidden state, denoted as $\mathbf{h}_t^f$, and memory cell $\mathbf{c}_t^f$ based on the input ECG signal x_t and the previously hidden state and memory cell (Forward pass) (Dey et al., 2021):

$$\mathbf{i}_t^f = \sigma(\mathbf{W}_i^f \cdot [\mathbf{h}_{t-1}^f, x_t] + \mathbf{b}_i^f) \tag{4}$$

Table 7
Computational complexity of the proposed CNN-Bi-LSTM method.

Layer name	Complexity	Total operations
Convolution layers	$16 \times 1 \times 2 \times 128$	4096
Average pooling (Stride = 3)	$128/3$	43
Total CNN complexity	$13 \times (4096 + 43)$	53,807
Bi-LSTM layer 1	$2 \times (4 \times 90) \times 2 \times 128$	$1,84,320$
Bi-LSTM layer 2	$2 \times (4 \times 180) \times 2 \times 128$	$3,68,640$
Total complexity	$O(\cdot) = 53{,}807 + 1{,}84{,}320 + 3{,}68{,}640$	**6,06,767**

$$\mathbf{f}_t^f = \sigma(\mathbf{W}_f^f \cdot [\mathbf{h}_{t-1}^f, x_t] + \mathbf{b}_f^f) \tag{5}$$

$$\mathbf{o}_t^f = \sigma(\mathbf{W}_o^f \cdot [\mathbf{h}_{t-1}^f, x_t] + \mathbf{b}_o^f) \tag{6}$$

$$\mathbf{g}_t^f = \tanh(\mathbf{W}_g^f \cdot [\mathbf{h}_{t-1}^f, x_t] + \mathbf{b}_g^f) \tag{7}$$

$$\mathbf{c}_t^f = \mathbf{f}_t^f \odot \mathbf{c}_{t-1}^f + \mathbf{i}_t^f \odot \mathbf{g}_t^f \tag{8}$$

$$\mathbf{h}_t^f = \mathbf{o}_t^f \odot \tanh(\mathbf{c}_t^f) \tag{9}$$

This combined representation $[\mathbf{h}_t^f, \mathbf{h}_t^b]$ allows the network to incorporate information from both previous and future time steps, making it more effective in capturing temporal dependencies in ECG signals.

3.3.3. Feature concatenation

The outputs of the forward and backward LSTMs are concatenated with the features extracted from the 1D-CNN to obtain the final feature representation:

$$\mathbf{H}_t = [\mathbf{h}_t^f, \mathbf{h}_t^b, \mathbf{F}_t] \tag{10}$$

where $\mathbf{F}_t$ represents the feature extracted from the 1D-CNN at time step t. The combined feature representation is then used for classification or further processing. The Adam Optimizer is used in this work to replace random gradients and cross-entropy for the loss function, as shown below.

$$\text{Loss} = -\sum_{b \in B} \sum_{c=1}^{C} \hat{p}_c(b) \cdot \log\left(p_c(b)\right) \tag{11}$$

where $p_c(b)$ is the probability that beat b is from class c and $\hat{p}_c(b)$ either 1 or 0 based on the softmax output, which says whether class c is the correct class or not respectively. The input size in the proposed method, the kernel size, and the average pooling are (128,1), 16, and 3, respectively. The Table 7, summarizes the computational complexity of the proposed CNN-BiLSTM method by breaking it down into different layers. The CNN layer performs 53,807 operations, including convolution and average pooling. The first Bi-LSTM layer, with 90 units, requires 1,84,320 operations, while the second Bi-LSTM layer, with 180 units, demands 368,640 operations. The total computational cost of the entire model is 606,767 operations, with the Bi-LSTM layers contributing the most. This tabular representation provides a concise and clear view of the model's complexity.

4. Experimental results and discussion

A complete experimental investigation for the identification of beats has been described in this section. In this work, the classification was made possible using a hybrid architecture that suitably extracts the features of different beats. The experiment results were conducted on a well-known, publicly accessible ECG five-class dataset (obtained from 47 patients). A detailed parametric study to validate our hyper-parameter choices, including their impact on accuracy and network training time, is conducted. We observed the accuracy of the model with different possible combinations. Table 8 presents the impact of increasing the number of epochs while keeping the learning rate fixed at 0.01 and the batch size at 16. As observed, accuracy improves slightly with an increasing number of epochs, but the gains diminish beyond 150 epochs. Additionally, training time increases significantly, suggesting that further training may not be optimal beyond 100–150 epochs. Table 9 shows the impact of varying the learning rate while keeping the number of epochs fixed at 60 and the batch size at 16. The results indicate that a learning rate of 0.001 provides the highest accuracy, whereas values that are too high (0.01) or too low (0.0001) lead to reduced accuracy and inefficient training. Table 10 analyzes the impact of different batch sizes while keeping the learning rate fixed at 0.001 and epochs fixed at 60. The results show that a batch size of 32 achieves the highest accuracy of 0.9921, while increasing the batch size beyond this point reduces accuracy due to poorer generalization. From the above experiments, we concluded that the optimized parameters of the proposed method as shown in Table 11. The performance of the proposed deep learning model is assessed based on the following parameters, such as accuracy (Acc), sensitivity (Sen), specificity (Spe), positive-predictivity (Ppr), and F-Score (F) (Das and Ari, 2014).

Table 8
Performance of the proposed method with the fixed learning rate of 0.01 and batch size of 16 by a varying number of epochs.

Number of epochs	Learning rate	Batch size	Accuracy	Training time (in Min)
60	0.01	16	0.9579	298
100	0.01	16	0.9601	359
150	0.01	16	0.9627	432
200	0.01	16	0.9634	516

Table 9
Performance of the proposed method with the fixed number of epochs of 60 and batch size of 16 by a varying learning rate.

Learning rate	Number of epochs	Batch size	Accuracy	Training time (in Min)
0.01	60	16	0.9532	263
0.001	60	16	0.9685	310
0.0001	60	16	0.9324	372
0.005	60	16	0.8962	295

Table 10
Performance of the proposed method with the fixed number of epochs of 60 and batch size of 16 by a varying learning rate.

Batch size	Learning rate	Number of epochs	Accuracy	Training time (in Min)
16	0.001	60	0.9685	340
32	0.001	60	0.9921	320
64	0.001	60	0.9415	293
128	0.001	60	0.9085	279

Table 11
Final Hyper-parameters of the proposed model after tuning.

Parameter	Value
Learning rate (η)	0.001
Batch size	32
Epochs	60

Table 12
Ablation study of the proposed CNN-Bi-LSTM for ECG beat classification.

CNN1 & 2 and LSTM1 & 2		CNN1 & 2 and Bi-LSTM1 & 2		Bi-LSTM1 & Bi-LSTM 2	Acc (in %)	Sen (in %)	Spe (in %)	Ppr (in %)	F-score
Serial	Parallel	Serial	Parallel	Serial					
✓	–	–	–	–	94.98	94.01	93.89	90.58	0.931
–	✓	–	–	–	95.97	95.33	95.48	94.32	0.950
–	–	–	–	✓	91.36	89.26	88.68	91.01	0.905
–	–	✓	–	–	97.11	95.93	95.41	95.86	0.956
–	–	–	✓	–	99.21	98.66	99.16	99.19	0.987

4.1. Performance analysis

The performance analysis of the proposed method is analyzed using an Ablation study and computational time requirement for the classification of ECG beats. The detailed ablation study and relative mean performance metrics of the proposed method are depicted in Table 12. The above ablation study investigates the impact of different configurations of CNN, Bi-LSTM and LSTM layers on the performance of arrhythmia classification. The study aims to identify each component's contribution and determine the parallel processing's effectiveness. The table presents five different configurations, each varying in the presence or absence of CNN and LSTM layers in a serial or parallel manner. The results highlight the importance of parallel processing and the inclusion of both CNN and Bi-LSTM layers. The findings indicate that the configuration with CN-1 & 2 and BiLSTM-1 and 2 in parallel processing achieved the highest performance accuracy of 99.21% and F-score of 0.987 on three databases, indicating its superior performance in ECG beat classification. From the Ablation studies, it is observed that the CNN extracts local features from the QRS complex. The CNN still plays a crucial role in extracting local morphological features within the QRS segment. The QRS complex varies significantly due to different arrhythmias, noise, patient variability, and signal distortions. CNN helps in capturing fine-grained variations (e.g., sharpness of peaks, QRS width, amplitude changes). Detecting waveform distortions due to noise or lead placement variations. Identifying subtle ECG features that differentiate arrhythmias have different QRS morphologies compared to normal beats). BiLSTM captures sequential dependencies (long-term temporal patterns). Bi-LSTM captures long-term dependencies, but it does not efficiently extract local features (such as QRS complex morphology). This hybrid model balances feature extraction (using CNN) and temporal learning (using Bi-LSTM), outperforming models that rely solely on one architecture.

4.2. The effectiveness of the proposed approach on the MIT-BIH Arrhythmia, INCART, and supraventricular databases

The effectiveness of the proposed approach is evaluated using different metrics as in Jaya Prakash and Ari (2020). Table 13 indicates that the proposed model outperforms other ECG beat classification models. The proposed model has an accuracy of 99.78% when it is being trained, 99.56% when it is being validated, and 99.21% when it is being tested. The proposed CNN-Bi-LSTM model has a Sen of 98.66%, Spe of 99.16%, Ppr of 99.19%, and F-score of 0.987. The detailed performance of the proposed method on different databases and the number of parameters required during implementation is described in Table 13. From the table, it is observed that the proposed method requires a minimum number of parameters for the implementation compared to the state-of-the-art techniques. Fig. 4 represents the training cum validation performance and loss curve of the proposed CNN-Bi-LSTM architecture. we extend the experiments up to 200 epochs with a learning rate of 0.001 and batch size 32, as shown in Fig. 4. From the experiment, the validation loss exhibits fluctuations and remains relatively stable without a clear decreasing trend after approximately 50–60 epochs. This suggests that additional training epochs might not lead to significant improvements in model generalization and may risk over-fitting. There is no significant improvement in accuracy in 60 and 100 epochs, as training time is crucial in decision-making; we selected 60 as the optimal parameter. The validation curve smoothly followed the training curve, which means that the network is perfectly trained without over-fitting. The network reached a steady state for 50 epochs. The obtained confusion matrix of the proposed deep learning architecture is shown in Fig. 5 with the test dataset. The elements that have been successfully categorized can be found on the diagonal of the matrix confusion matrix. From Fig. 5, it is observed that very few beats are misclassified as N-83, S-7, V-2, F-8, and Q-1, respectively, by the proposed method. It is observed that the proposed method detected S and V beats decently, which are very important in cardiac clinical diagnosis. The proposed model is also validated with the remaining two publicly available test datasets. The model's performance found in the INCART and MIT-BIH supraventricular ECG database is presented in Table 13. The proposed technique can classify five ECG beats on INCART and MIT-BIH supraventricular ECG databases with the performance of 96.17% and 97.20%, respectively. Fig. 6 illustrates the confusion matrices for the proposed method on the INCART and MIT-BIH supraventricular ECG databases. From the confusion matrices, it is observed that very few ECG beats are misclassified. In a comparison of MIT-BIH arrhythmia, more beats are misclassified due to the large and noisy data. The average Sen, Spe, Ppr, and F-score of these two databases are 93.96%, 96.59%, 93.65%, and 95.87%, respectively. The overall patient-specific ECG beat classification accuracies of the proposed CNN-Bi-LSTM technique for three different databases, namely MIT-BIH arrhythmia, INCART, and MIT-BIH supraventricular, are 99.21%, 96.17%, and 97.20%, respectively. The proposed method's trainable and non-trainable parameters are 6,34,621 and 6894, respectively. The same hyperparameters are used to implement CNN and Bi-LSTM independently. The trainable and non-trainable parameters in implementing those architectures are approximately the same as the combination of CNN-Bi-LSTM. The proposed system shows the best performance with fewer trainable parameters. Hence, the method is called the lightweight hybrid deep learning algorithm.

4.3. Ten-fold cross-validation for stability analysis

To ensure that our model's reported performance is not dataset-specific, we employ 10-fold cross-validation and report mean and standard deviation values. Table 14 presents the cross-validation results of our CNN-BiLSTM model. The low standard deviation in accuracy, sensitivity, and specificity confirms that our model's performance remains consistent across different data partitions, reducing the likelihood of over-fitting. Our proposed CNN-BiLSTM model demonstrates a high accuracy of 99.21% on the MIT-BIH arrhythmia dataset, reducing diagnostic errors and ensuring reliable arrhythmia detection for timely clinical interventions. With a sensitivity of 98.66%, it effectively identifies true arrhythmia cases, minimizing false negatives and enabling early detection of critical events. The model's specificity of 99.16% ensures a low false alarm rate, making it ideal for real-time applications in wearable devices and clinical monitoring. Achieving an F-score of 0.987 reflects a balanced performance between precision and recall, supporting accurate classification across diverse arrhythmia types. Designed for efficiency, the model processes 1D ECG signals without

Table 13
The comparison of size of the network (arranged by number of parameters).

Literature	Number of parameters	Size	Database	Performance metrics
Bi-Level Routing Attention (BRA) mechanism, 2024 (Ma and Zhang, 2024a)	56.49 Million	–	MIT-BIH Arrhythmia	Precision: 96.10 Recall: 01.00 Accuracy: 99.50
Yolo V7, 2020 (Hwang et al., 2020)	51.60 Million	–	MIT-BIH Arrhythmia	Precision: 83.20 Recall: 91.20 Accuracy: 94.26
ST-based 2D ResNet, 2020 (Jaya Prakash and Ari, 2020)	13.6 Million	340 MB	MIT-BIH Arrhythmia	Precision: 98.20 Recall: 98.84 Accuracy: 99.73
Cat-net, 2024 (Islam et al., 2024b)	1,189,637	–	MIT-BIH Arrhythmia INCART	Overall Acc: 99.14 Overall F1: 94.69
Cardiac Net (Vavekanand et al., 2024)	67,169	–	MIT-BIH Arrhythmia	Acc : 94.60 F1 score: 85.36
RNN with dilated CNN (Islam et al., 2023)	142,725	–	MIT-BIH Arrhythmia	Acc : 99.60 F1 score: 98.21
CNN-MLP with Focul loss (Wang et al., 2020b)	30,276	–	MIT-BIH Arrhythmia	Acc : 92.53 F1 score: 66.09
Proposed CNN-Bi-LSTM	**634,621**	**72 MB**	**MIT-BIH A** **INCART** **MIT-BIH Supraventricular**	**MIT-BIH A**: Acc: 99.21 F1: 98.70 **INCART**: Acc: 96.17 F1: 96.00 **MIT-BIH Supra** Acc: 97.20 F1: 98.70

(a) (b)

Fig. 4. A curves of (a) Training and validation loss, (b) Training and validation accuracy.

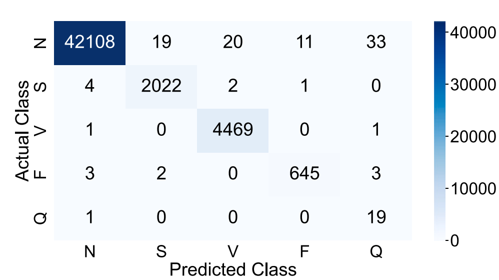
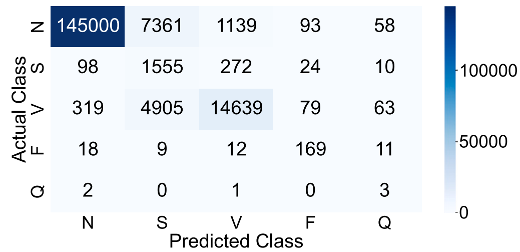


Fig. 5. The confusion matrix of the CNN-Bi-LSTM model on MIT-BIH arrhythmia Database.

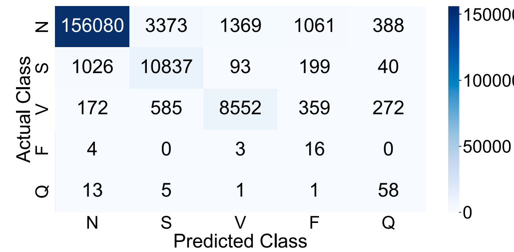
requiring complex transformations, making it suitable for resource-constrained environments such as wearable and remote monitoring devices. Its robust generalization across multiple datasets (e.g., MIT-BIH arrhythmia, INCART, and MIT-BIH supraventricular) confirms its adaptability to real-world variations in patient demographics and signal quality. Furthermore, its compliance with AAMI standards enhances clinical trust and facilitates integration into diagnostic workflows. Ultimately, by enabling rapid and accurate arrhythmia detection, the model supports early interventions, potentially preventing severe cardiac events like stroke or sudden cardiac arrest, thereby improving patient outcomes.

4.4. Computational time requirement

In this section, the computational time (s) for the proposed ECG beat classification system are evaluated and shown in Table 15. The time taken for pre-processing an input beat is 0.073 (s). The classification time of the proposed method to detect input ECG test beat image is 0.1787 (s). Therefore, the average time to classify input ECG beat is 0.2217 (s). The ST-based ResNet method reported pre-processing and classification times of 0.1291 s and 0.2365 s, respectively, leading to an average classification time of 0.1828 s. Conversely, the proposed CNN-Bi-LSTM method demonstrated notably improved efficiency, with pre-processing and classification times reduced to 0.073 s



(a)



(b)

Fig. 6. Confusion matrices for ECG beat classification with the proposed method are displayed for the test databases: (a) INCART and (b) MIT-BIH Supraventricular.

Table 14
10-fold cross-validation results for CNN-BiLSTM model.

Fold	Accuracy (%)	Sensitivity (%)	Specificity (%)
Fold 1	98.12	98.55	99.05
Fold 2	98.20	98.60	99.10
Fold 3	99.18	98.65	99.08
Fold 4	98.25	98.70	99.15
Fold 5	99.22	98.68	99.12
Fold 6	99.28	98.75	99.20
Fold 7	99.17	98.62	99.09
Fold 8	99.21	98.67	99.14
Fold 9	99.24	98.72	99.18
Fold 10	99.26	98.74	99.19
Mean ± Std	**99.21 ± 0.29**	**98.67 ± 0.07**	**99.13 ± 0.06**

and 0.1787 s, respectively. Consequently, the average classification time for the proposed CNN-Bi-LSTM method is 0.2217 s.

4.5. Performance comparison of the proposed method classification of S and V beats

The proposed CNN-Bi-LSTM technique presented in this work demonstrates a highly effective performance in the classification of Supraventricular ectopic (S) and ventricular ectopic (V) beats. S and V beats classification are essential for early arrhythmia detection, risk assessment, and improving ECG-based automated diagnosis systems (Al-Mousa et al., 2023; Aphale et al., 2021). Proper differentiation enhances clinical decision-making, patient monitoring, and emergency interventions, ultimately reducing mortality rates associated with cardiac disorders. The performance of the proposed method in detecting S and V beats is compared with other state-of-the-art techniques, and the detailed mean accuracy results are summarized in Table 16. The proposed CNN-Bi-LSTM technique presented in this work demonstrates a highly effective performance in the S and V beats. The performance of the proposed method is compared with other state-of-the-art techniques, and the detailed mean accuracy results are summarized in Table 16. The effectiveness of the proposed technique stems from its utilization of a two-stream architecture, which combines the strengths of CNN and Bi-LSTM. This architecture allows for the effective capture of temporal dependencies and the extraction of discriminative features from the ECG signal. The results presented in Table 16 demonstrate the superior performance of the proposed CNN-Bi-LSTM technique compared to other state-of-the-art methods. The combination of its high accuracy, sensitivity, and robustness across different databases establishes its potential as an effective approach for beat classification.

4.6. Performance comparison of the proposed method with earlier reported techniques

Table 17 compares the CNN-Bi-LSTM model proposed with state-of-the-art techniques on the MIT-BIH arrhythmia database. The table includes the accuracy, sensitivity, specificity, precision, and F-Score values of each method. The ST-ResNet model achieves an accuracy of 98.78% with a standard deviation of 0.289. It also demonstrates a high sensitivity of 98. 24%, a specificity of 98. 68%, a precision of 98. 38%, and an F-Score of 0.976 (Jaya Prakash and Ari, 2020). However, the CNN-Bi-LSTM model achieves even higher precision, with a mean of 99.21% and a standard deviation of 0.004. It also achieves a competitive sensitivity of 98. 66%, a specificity of 99. 16%, a precision of 99. 19%, and an impressive F-Score of 0.987. The CNN-Bi-LSTM model, in particular, exhibits slightly higher accuracy and F-Score compared to the ST-ResNet model, showcasing its potential as a highly accurate and reliable approach for arrhythmia.

The performance of the proposed method in the INCART and MIT-BIH supraventricular databases is compared with the reported literature shown in Tables 18 and 19. In the INCART database, the proposed CNN-Bi-LSTM method achieves an accuracy of 96.17% with a standard deviation of 0.129. This shows its high precision in accurately classifying arrhythmias, outperforming other state-of-the-art techniques. The proposed CNN-Bi-LSTM model shows promising results in the MIT-BIH supraventricular database, achieving a precision of 97. 20% with a standard deviation of 0.102. This highlights its effectiveness in accurately detecting and classifying ECG beats. Overall, the CNN-Bi-LSTM model demonstrates consistent and impressive performance across the INCART and MIT-BIH Supraventricular databases, making it a promising approach for ECG beat classification. The CNN component of the model is adept at extracting local features from the ECG signal. Using multiple convolutional layers with different filter sizes, CNN can capture various levels of abstraction and learn discriminative features that represent different ECG beat patterns. The Bi-LSTM component handles the temporal dependencies present in the ECG data. The bidirectional nature of the LSTM allows the model to capture both past and future information, enabling a comprehensive understanding of the sequential patterns in the ECG signal. This is crucial for accurately classifying arrhythmias, as the timing and duration of specific patterns can vary. The combination of CNN and Bi-LSTM enables the model to learn hierarchical representations of the ECG signal. The CNN captures local features, while the Bi-LSTM integrates these features over time to form higher-level long-term dependencies representations. This hierarchical approach allows the model to effectively capture local and global information, leading to more robust and accurate classification. Therefore, CNN-Bi-LSTM is able to automatically learn discriminative feature representations from the raw ECG data, removing the need for manual feature engineering. By learning features directly from the data, the model can adapt and generalize well to different ECG beats, enhancing its ability to classify accurately in various scenarios. The discrete ROC of the proposed method in MIT-BIH arrhythmia, INCART, and the MIT-BIH supraventricular database is shown in Fig. 7. From the discrete ROC, it is observed that the proposed method shows a high TPR and less FPR compared to the state-of-the-art methods. Hence, the proposed method can provide a better ECG beat classification. The overall key advantages of the proposed method compared with the state-of-the-art techniques are elaborated in Table 20. From the table it is observed that the proposed work presents an innovative, efficient, and scalable deep

Table 15
Time and GPU usage of the proposed CNN-Bi-LSTM network.

Proposed method	GPU utilized	Time required for pre-processing (in Sec)	Total training time (in Minutes)	Time required to test one ECG beat (in Sec)
Jaya Prakash and Ari (2020)	NVIDIA Quadro M4000-8 GB Intel I7, 32GB DDR3	0.1291	600	0.2365
Islam et al. (2023)	–	–	–	0.9100
Liang et al. (2020)	–	–	–	0.5896
Proposed method	NVIDIA Quadro M4000-8 GB Intel I7, 32GB DDR3	0.0730	320	0.1787

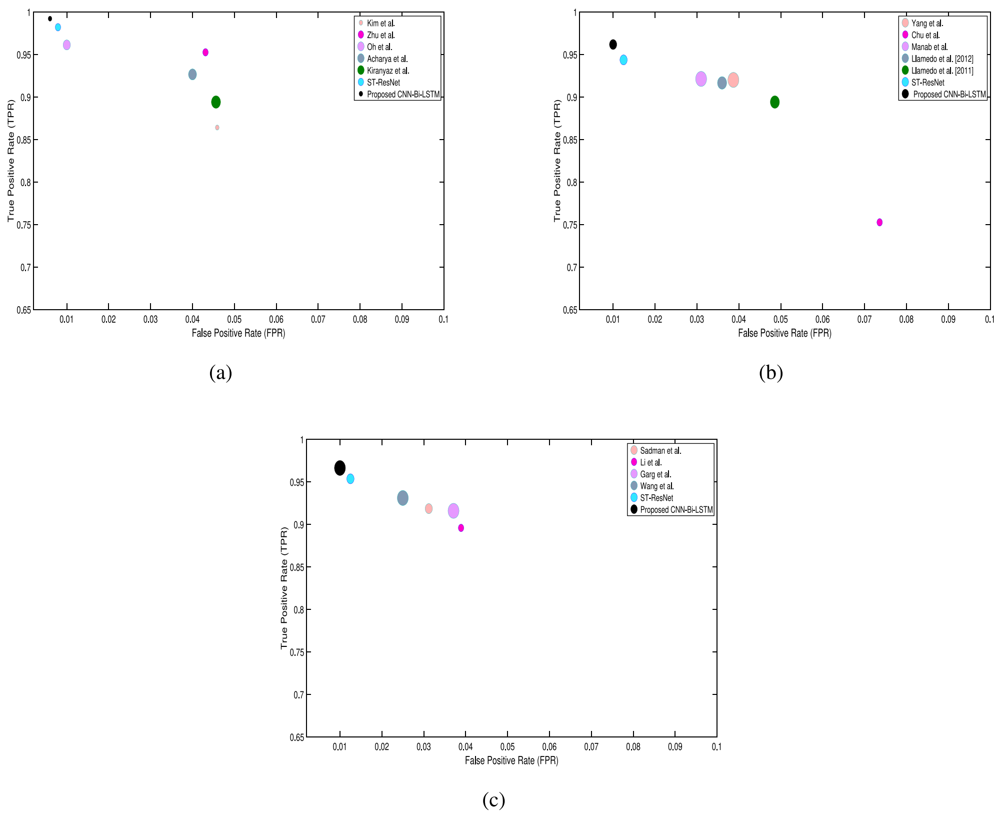


Fig. 7. Discrete ROC graphs for (a) MIT-BIH arrhythmia, (b) INCART, and (b) MIT-BIH supraventricular databases.

Table 16
Performance comparison of the proposed method and earlier reported methods for S and V beats classification.

Literature	Accuracy (in %)		Sensitivity (in %)	
	S	V	S	V
Jaya Prakash and Ari (2020)	98.95	98.79	97.19	97.32
Xia et al. (2023)	95.11	99.29	95.39	94.89
Wang et al. (2020b)	97.50	97.98	98.20	97.98
Mogili and Narsimha (2022)	99.63	99.71	91.84	97.48
Di Paolo and Castro (2024)	95.47	96.88	92.90	96.10
Zabihi et al. (2024)	95.96	97.89	94.56	95.34
Proposed CNN-Bi-LSTM	99.01	99.50	98.79	99.81

learning approach for automated ECG beat classification, contributing significantly to the advancement of real-time cardiac health monitoring and arrhythmia detection systems.

4.7. Limitations and future directions

The publicly available datasets used in our study, such as MIT-BIH arrhythmia, INCART, and MIT-BIH supraventricular, primarily consist of recordings from specific patient populations and environments. These datasets may not fully represent the diversity of real-world cardiac conditions, such as those seen in underrepresented demographics or patients with comorbidities. Although our model achieves high accuracy on multiple datasets, its performance may vary for patients whose ECG signals deviate significantly from those represented in the training data. For example, detecting rare arrhythmias in patients with complex cardiac conditions might require further model fine-tuning. While our model achieves high accuracy, it currently lacks interpretability tools which would help clinicians understand why a specific prediction was made. This transparency is critical for building trust and facilitating clinical adoption. To address these limitations, we propose the following future directions i.e., Dataset Expansion, Noise-Robust Training, Explainability, Adaptive Learning, Real-World Testing, and Advanced Architectures:

Table 17
Comparison of the proposed method with state-of-the-art techniques using the MIT-BIH arrhythmia database.

Literature	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F-score
Jaya Prakash and Ari (2020)	99.73	98.84	99.50	98.20	–
Begum et al. (2023) (Not as per AAMI)	99.48	98.74	–	99.73	0.987
Varalakshmi and Sankaran (2023)	98.58	98.00	99.00	–	0.991
Huang et al. (2023)	98.95	96.54	99.38	97.07	0.964
Mewada (2023)	99.52	95.12	95.64	–	0.995
Kim et al. (2023)	91.40	97.70	98.62	98.67	–
El-Ghaish and Eldele (2024)	99.35	–	–	–	94.26
Zabihi et al. (2024)	–	96.03	–	97.35	–
Wang et al. (2024)	98.50	91.00	–	92.07	91.53
Proposed CNN-Bi-LSTM	**99.21**	**98.66**	**99.16**	**99.19**	**0.987**

Table 18
Comparison of the proposed method with state-of-the-art techniques on the INCART database.

Literature	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F-score
Chu et al. (2019)	88.56	70.90	82.19	60.12	0.651
Yang et al. (2019)	94.01	93.28	93.89	92.89	0.917
Jaya Prakash and Ari (2020)	95.40	93.63	95.23	93.83	0.951
Malik et al. (2021)	–	88.90	–	95.40	92.10
Cai et al. (2022)	–	87.90	–	93.20	90.50
Berrahou et al. (2024)	97.23	–	–	–	–
Peimankar et al. (2024)	86.00	85.00	85.00	85.00	–
Imtiaz and Khan (2024)	–	61.37	–	57.35	57.29
Wang et al. (2024)	98.50	89.91	–	96.72	93.19
Proposed CNN-Bi-LSTM	**96.17**	**95.36**	**96.09**	**95.17**	**0.960**

Table 19
Comparison of the proposed method with state-of-the-art techniques on the MIT-BIH Supraventricular database.

Literature	Accuracy (%)	Sensitivity (%)	Specificity (%)	Precision (%)	F-score
Wang et al. (2020a)	96.00	70.53	95.85	74.16	0.899
Garg and Sharma (2015)	92.30	81.12	90.62	83.14	0.883
Guo et al. (2019)	90.35	75.62	95.04	82.84	0.790
Jaya Prakash and Ari (2020)	96.63	85.34	96.06	88.89	0.953
Sakib et al. (2020)	93.31	84.65	91.98	93.00	0.923
Aphale et al. (2021)	92.73	89.93	–	–	0.910
Al-Mousa et al. (2023)	97.70	–	–	–	0.956
Qi et al. (2023)	91.70	90.86	–	–	–
Proposed CNN-Bi-LSTM	**97.20**	**92.57**	**97.10**	**92.14**	**0.956**

– Incorporating diverse, large-scale, and real-world datasets (e.g., multi-lead ECG recordings from wearable devices) to improve generalizability and robustness.
– Developing noise-robust training methods and augmenting datasets with realistic noise to better simulate real-world scenarios.
– Exploring patient-specific fine-tuning methods to improve performance for individual patients with unique ECG signal characteristics.
– Deploying the model in real-world environments, such as wearable ECG devices, to validate its performance under practical conditions and constraints.
– Incorporating emerging architectures, such as attention mechanisms or transformer models, to further boost accuracy while maintaining efficiency.

We acknowledge the above limitations and believe that addressing these areas in future work will further enhance the impact and applicability of our research. Despite these limitations, the current study provides a strong foundation for lightweight, accurate ECG beat classification.

5. Conclusion

In this work, we proposed a lightweight CNN-BiLSTM deep learning model for ECG beat classification, integrating spatial and temporal feature extraction to enhance classification accuracy while maintaining computational efficiency. The model achieved 99.21% accuracy, 98.66% sensitivity, and 99.16% specificity on the MIT-BIH arrhythmia dataset, demonstrating superior performance compared to state-of-the-art methods. By directly processing raw 1D ECG signals instead of relying on computationally expensive signal-to-image transformations, the model significantly reduces inference time and hardware requirements, making it suitable for real-time applications, wearable health monitoring, and edge computing. Furthermore, its strong generalization ability, validated across multiple datasets such as INCART (96.17% accuracy) and MIT-BIH Supraventricular (97.20% accuracy), ensures robustness in diverse clinical scenarios. The proposed method adheres to AAMI standards, making it highly relevant for automated cardiac monitoring and arrhythmia detection in clinical practice. Despite its advantages, limitations such as dataset diversity, model generalizability to rare arrhythmias, and the need for interpretability in clinical applications must be addressed in future work. Future directions include incorporating larger and more diverse datasets, enhancing model explainability with techniques such as SHAP and Grad-CAM, and validating the model in real-world wearable ECG applications. Overall, this research presents a highly accurate, computationally efficient, and clinically relevant solution for ECG beat classification, contributing to automated arrhythmia detection and real-time cardiac health monitoring.

Table 20
Comparison of the proposed CNN-BiLSTM model with state-of-the-art methods for ECG beat classification.

Literature	Advantages	Disadvantages	Key advantages of proposed method
Xie et al. (2018)	Uses CNN and Bi-RNN for feature extraction. Captures both spatial and temporal dependencies.	High computational cost due to Bi-RNN. Requires powerful hardware, limiting real-time use.	Optimized BiLSTM structure reduces complexity while maintaining high accuracy. Better suited for wearable and real-time applications.
Liu et al. (2021)	Uses CNN with attention mechanisms for feature selection. Provides better interpretability using attention maps.	Computationally expensive due to attention layers. Slower inference speed, making real-time deployment challenging.	Achieves similar feature selection without attention layers, reducing the computational cost. Lightweight and optimized for edge computing and wearable devices.
Islam et al. (2023)	Uses CNN and RNN with dilated convolutions to model long-term dependencies. Improves robustness against ECG noise.	Extremely high computational cost due to complex hybrid architecture. Requires extensive training data.	Achieves similar performance with lower complexity, making it deployable on edge devices. Eliminates the need for dilated convolutions, reducing training and inference time.
Zabihi et al. (2024)	Multi-scale feature fusion improves classification performance. Handles class imbalance issues in ECG datasets.	Requires extensive hyperparameter tuning for optimal performance. Not suitable for real-time applications due to high processing latency.	Self-optimizes via adaptive learning rate scheduling. Low-latency processing, making it ideal for continuous cardiac monitoring.
Imtiaz and Khan (2024)	Implements cross-domain transfer learning, enhancing generalization across datasets. Adapts to unseen ECG recordings efficiently.	Requires large pre-trained networks, increasing memory usage. Does not scale well for resource-constrained environments.	Fully trainable from scratch, avoiding dependency on pre-trained networks. Highly scalable for low-resource and portable devices.
Qi et al. (2023)	Uses ensemble deep learning to improve classification accuracy. Learns diverse ECG patterns using multiple models.	Requires significantly more computational power due to multiple models. Not ideal for battery-powered wearable devices.	Achieves high accuracy with a single lightweight model, eliminating ensemble complexity. Consumes significantly less energy, making it ideal for continuous heart monitoring.
Proposed method (CNN-Bi-LSTM)	Lightweight and real-time, optimized for wearable applications. Combines CNN and BiLSTM for spatial and temporal feature extraction. No ECG signal-to-image transformation is required, reducing preprocessing complexity. Generalizes well across MIT-BIH, INCART, and MIT-BIH Supraventricular datasets. AAMI-compliant, clinically relevant for automated cardiac monitoring.	Requires additional explainability techniques (e.g., SHAP, Grad-CAM) for improved clinical adoption. Future work will focus on optimization for real-world wearable ECG devices.	Balances high accuracy and low computational cost, making it ideal for real-time ECG monitoring. Optimized for deployment in low-power and edge-computing environments. Faster inference than existing models, ensuring rapid arrhythmia detection. Highly scalable and adaptable for large-scale ECG datasets.

CRediT authorship contribution statement

Allam Jaya Prakash: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Mohamed Atef:** Writing – review & editing, Supervision, Investigation, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This work is supported by the KU-UAEU Joint Research Program, United Arab Emirates. Award No. KU-UAEU-2023-004 having UAEU grant code G00004680.

Data availability

No data was used for the research described in the article.

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