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Research Paper

DUAL-SOURCE DEEPRHYTHMNET: A SELF-SUPERVISED TRANSFORMER APPROACH TO MULTI-CLASS ECG ARRHYTHMIA DETECTION

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ABSTRACT

Electrocardiogram (ECG) classification plays a pivotal role in cardiac diagnostics by automatically identifying a range of heart abnormalities from ECG waveforms. Multi-class ECG classification has broad clinical applications—from detecting arrhythmias and myocardial infarctions to diagnosing conduction blocks—enabling clinicians to intervene early and tailor treatment plans. Beyond the clinic, reliable automated analysis supports remote monitoring and telemedicine, improving patient outcomes and reducing the burden on healthcare systems. Traditional approaches typically depend on manually engineered features—such as time-domain statistics, frequency-domain measures or morphological descriptors—followed by conventional classifiers. While effective for well-defined patterns, feature crafting is labor-intensive and often fails to generalize across diverse patient populations or capture the nuanced dynamics of cardiac signals. Moreover, standard algorithms may overlook the temporal dependencies inherent in ECG data, limiting their accuracy in extended monitoring contexts. To address these challenges, we introduce a novel machine-learning framework for multi-class ECG classification that leverages sequence-modeling architectures. By ingesting raw ECG segments, the model autonomously learns discriminative features and long-range temporal relationships, yielding robust performance across multiple cardiac conditions. This end-to-end approach not only minimizes manual preprocessing but also adapts seamlessly to new datasets, paving the way for more accurate, scalable, and real-time ECG analysis.

Key words: ECG classification, Heartbeat analysis, signal processing, Amplitude normalization, Fusion beats

1. INTRODUCTION

Electrophysiological assessment of arrhythmias has evolved over more than a century, beginning with primitive capillary electrometers and culminating in today's digital electrocardiograms (ECGs). In 1901, Willem Einthoven introduced mathematical corrections to the capillary electrometer to better resolve cardiac electrical activity on photographic paper; by 1903 he had devised the first practical string galvanometer, capable of tracing P-, QRS-, and T-waves with unprecedented fidelity. Einthoven's landmark publications in 1901 and 1903 laid the foundation for modern ECG interpretation, and in 1924 he was awarded the Nobel Prize in Physiology or Medicine for this work. Subsequent technological refinements miniaturization of circuitry, digital signal processing, and wireless telemetry transformed the bulky, five-person apparatus of the early 20th century into today's portable and wearable ECG monitors. By 2021, atrial fibrillation (AF) and flutter (AFL)—the most common clinically significant arrhythmias affected over 52.5 million individuals worldwide, with approximately 4.48 million new cases each year (age-standardized incidence 52.12 per 100 000) and more than 219 000 attributable deaths. The global prevalence of AF/AFL has more than doubled since 1990, rising from roughly 25 million to over 52 million by 2021, and its burden is disproportionately higher in high-socio-demographic index regions. Beyond AF/AFL, sudden cardiac arrest often precipitated by ventricular tachyarrhythmias accounts for an estimated 250 000–450 000 deaths annually in the United States alone, underscoring the lethal potential of undetected malignant arrhythmias.

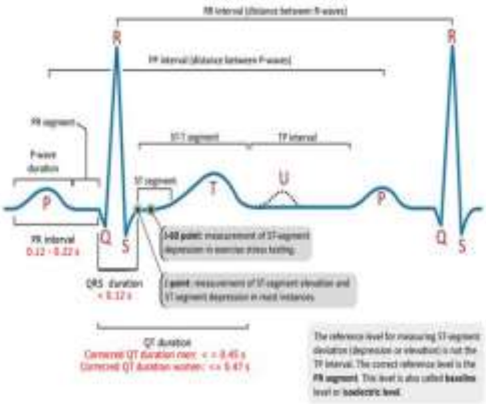

Fig 1. ECG-based Arrhythmia Classification.

Arrhythmias, irregular heart rhythms, are a major health concern, affecting millions globally. The status of arrhythmia can range from benign, with a minimal impact on health, to severe, which can be fatal by causing cardiac arrest, stroke, etc. Hence, its early detection can aid in effective clinical management [1]. An electrocardiogram (ECG) is the principal procedure employed for effective arrhythmia detection, but diagnosis can be challenging because of the subtle disposition of symptoms. Lately, advancements in deep-learning algorithms have offered a promising solution for automation and accurate diagnosis in medical applications [2]. The early detection of arrhythmias is crucial, as timely treatments, like medications and lifestyle changes, can be initiated, thus preventing further complications. Also, the detection of certain arrythmia types, like ventricular tachycardia or atrial fibrillation, is essential and can prevent the occurrence of severe events like cardiac arrest or stroke. This can aid doctors in instigating preventive procedures such as implantable cardioverter defibrillators (ICDs) or anticoagulant therapy, reducing the risk of life-threatening events. Furthermore, arrhythmia detection plays a vital role in personalized treatment [3,4]. Arrhythmias can have various underlying causes and may require different treatment approaches. The accurate detection and classification of arrhythmias using ECG signals can aid in identifying the specific type of arrhythmia and tailoring treatment plans accordingly. This personalized approach ensures that patients receive the most effective therapies. In addition, the ability to remotely monitor arrhythmias has transformative potential in healthcare. Arrhythmias often occur sporadically or intermittently, making their detection challenging using traditional methods that rely on short-term ECG recordings. EEG signals, on the other hand, can be continuously monitored over extended periods, allowing for the detection of transient arrhythmias that may go unnoticed in standard clinical assessments [5].

Early and accurate arrhythmia detection is therefore critical. Manual ECG interpretation is challenged by subtle waveform variations, inter-observer variability, and the sheer volume of long-term recordings generated by ambulatory monitors. Recent advances in deep-learning architectures—particularly convolutional and recurrent neural networks—offer automated feature extraction and temporal pattern recognition that surpass traditional, handcrafted-feature methods in both sensitivity and specificity. By training end-to-end models on large, annotated ECG datasets, these approaches can identify benign versus malignant rhythm disturbances (e.g., distinguishing atrial premature beats from paroxysmal atrial fibrillation or differentiating ventricular tachycardia from supraventricular tachycardia) with high accuracy, enabling real-time alerts in wearable and telemedicine platforms.

In summary, from Einthoven's first-string galvanometer to today's AI-driven analysis pipelines, the journey of ECG-based arrhythmia detection reflects continuous innovation. Integrating powerful sequence-modeling techniques with vast ECG archives promises to further reduce misdiagnosis rates, accelerate clinical decision-making, and ultimately improve outcomes for millions living with or at risk of life-threatening cardiac arrhythmias.

2. LITERATURE SURVEY

Katal. N et al[6]. introduced role in automatically identifying complicated patterns from ECG data, which can be further used to identify arrhythmia. In this paper, deep-learning-based methods for arrhythmia identification using ECG signals are thoroughly studied and their performances evaluated on the basis of accuracy, specificity, precision, and F1 score. They proposed the development of a small CNN, and its performance is compared against pretrained models like GoogLeNet. The comparative study demonstrates the promising potential of deep-learning-based arrhythmia identification using ECG signals. Yang. X et al[7]. developed an automatic arrhythmia detection algorithm based on 12-lead electrocardiogram with high accuracy and strong generalization ability is still challenging. In this paper, a multimodal feature fusion model based on the mechanism is developed. This model utilizes a dual channel deep neural network to extract different dimensional features from one-dimensional and two-dimensional electrocardiogram time–frequency maps, and combines attention mechanism to effectively fuse the important features of 12-lead, thereby obtaining richer arrhythmia information and ultimately achieving accurate classification of nine types of arrhythmia signals.

Pham B.-T et al[8]. presented electrocardiogram (ECG) is a basic and quick test for evaluating cardiac disorders and is crucial for remote patient monitoring equipment. An accurate ECG signal classification is critical for real-time measurement, analysis, archiving, and transmission of clinical data. Numerous studies have focused on accurate heartbeat classification, and deep neural networks have been suggested for better accuracy and simplicity. They investigated a new model for ECG heartbeat classification and found that it surpasses state-of-the-art models, achieving remarkable accuracy scores of 98.5% on the Physionet MIT-BIH dataset and 98.28% on the PTB database. Furthermore, our model achieves an impressive F1-score of approximately 86.71%, outperforming other models, such as MINA, CRNN, and EXpertRF on the PhysioNet Challenge 2017 dataset.

Xiao. Q et al[9]. performed from perspectives of the ECG database, preprocessing, DL methodology, evaluation paradigm, performance metric, and code availability to identify research trends, challenges, and opportunities for DL-based ECG arrhythmia classification. Specifically, 368 studies meeting the eligibility criteria are included. A total of 223 (61%) studies use MIT-BIH Arrhythmia Database to design DL models. A total of 138 (38%) studies considered removing noise or artifacts in ECG signals, and 102 (28%) studies performed data augmentation to extend the minority arrhythmia categories. Convolutional neural networks are the dominant models (58.7%, 216) used in the reviewed studies while growing studies have integrated multiple DL structures in recent years. A total of 319 (86.7%) and 38 (10.3%) studies explicitly mention their evaluation paradigms, i.e., intra- and inter-patient paradigms, respectively, where notable performance degradation is observed in the inter-patient paradigm. Compared to the overall accuracy, the average F 1 score, sensitivity, and precision are significantly lower in the selected studies.

Rafi, T.H el al[10]. presented Traditional models do not generalize on unseen cases and are also unable to preserve data privacy. Which incentivizes performance degradation in existing models with privacy limitations. To tackle generalization and privacy issues together, we introduce the framework SF-ECG, a source-free domain adaptation approach for patient-specific ECG classification. This framework does not require source data during adaptation, which solves the privacy issue during adaptation. We adopt a generative model (GAN) that learns to synthesize patient-specific ECG data in data-inefficient classes to make additional source data for imbalanced classes. Then, we use the local structure clustering method to strongly align target ECG features with similar neighbors. After seizing clustered target features, They use a classifier that is trained on source data with generated source samples, which makes the model generalizable in classifying unseen data.

Aldughayfiq, B et al[11]. addressed the under-researched area of applying deep learning methods to transmissive PPG signals by proposing a novel approach. Our approach involved integrating ECG and PPG signals as multi-featured time series data and training deep learning models for AF classification. Our hybrid 1D CNN and BiLSTM model achieved an accuracy of 95% on test data in identifying atrial fibrillation, showcasing its strong performance and reliable predictive capabilities. Furthermore, we evaluated the performance of our model using additional metrics. The precision of our classification model was measured at 0.88, indicating its ability to accurately identify true positive cases of AF. The recall, or sensitivity, was measured at 0.85, illustrating the model's capacity to detect a high proportion of actual AF cases. Additionally, the F1 score, which combines both precision and recall, was calculated at 0.84, highlighting the overall effectiveness of our model in classifying AF and non-AF cases.

Ayano, Y.M et al[12]. observed paves the way for interpretable machine learning (IML) models as diagnostic tools that can build a physician's trust and provide evidence-based diagnoses. Therefore, in this systematic literature review, we studied and analyzed the research landscape in interpretable machine learning techniques by focusing on heart disease diagnosis from an ECG signal. In this regard, the contribution of our work is manifold; first, we present an elaborate discussion on interpretable machine learning techniques. In addition, we identify and characterize ECG signal recording datasets that are readily available for machine learning-based tasks. Furthermore, They identify the progress that has been achieved in ECG signal interpretation using IML techniques. Finally, we discuss the limitations and challenges of IML techniques in interpreting ECG signals.

Ahmed, A.A et al[13]. presented introduces a novel deep learning architecture, specifically a one-dimensional convolutional neural network (1D-CNN), for the classification of cardiac arrhythmias. The model was trained and validated with real and noise-attenuated ECG signals from the MIT-BIH dataset. The main aim is to address the limitations of traditional electrocardiograms (ECG) in the diagnosis of arrhythmias, which can be affected by noise and randomness of events, leading to misdiagnosis and errors. To evaluate the model performance, the confusion matrix is used to calculate the model accuracy, precision, recall, f1 score, average and AUC-ROC. The experiment results demonstrate that the proposed model achieved outstanding performance, with 1.00 and 0.99 accuracies in the training and testing datasets, respectively, and can be a fast and automatic alternative for the diagnosis of arrhythmias.

Farag et al[14]. deployed on the cloud, which may not always meet the availability and privacy requirements of ECG monitoring. Edge inference is an emerging alternative that overcomes the concerns of cloud inference; however, it poses new challenges due to the demanding computational requirements of modern ML algorithms and the tight constraints of edge devices. In this work, we propose a tiny convolutional neural network (CNN) classifier for real-time monitoring of ECG at the edge with the aid of the matched filter (MF) theory. The MIT-BIH dataset with inter-patient division is used for model training and testing. The model generalization capability is validated on the INCART, QT, and PTB diagnostic databases, and the model performance in the presence of noise is experimentally analyzed. They proposed classifier can achieve average accuracy, sensitivity, and F1 scores of 98.18%, 91.90%, and 92.17%, respectively.

Bokau et al[15]. presented a data-driven analysis of navigator stress and workload levels in simulated ship encounters within restricted waters, leveraging real-world automatic identification system (AIS) data from Makassar Port, Indonesia. Six close-quarter scenarios were recreated to reflect critical encounter geometries, and 24 Indonesian seafarers were evaluated using heart rate variability (HRV), perceived stress scale (PSS), and task load index (NASA-TLX) workload assessments. The results indicate that crossing angles, particularly 135° port and starboard encounters, significantly influence physiological stress levels, with age being a moderating factor. Although no consistent relationship was found between workload and HRV metrics, the findings underscore key human factors that may impair navigational performance under cognitively demanding conditions. By integrating AIS-derived traffic data with simulation-based human performance monitoring, this study supports the development of intelligent maritime training frameworks and adaptive decision support systems. Dong Y et al[16]. focused on using deep learning methods to address arrhythmia classification problems. However, the transformer-based neural network in current research still has a limited performance in detecting arrhythmias for the multi-lead ECG. In this study, we propose an end-to-end multi-label arrhythmia classification model for the 12-lead ECG with varied-length recordings. Our model, called CNN-DVIT, is based on a combination of convolutional neural networks (CNNs) with depthwise separable convolution, and a vision transformer structure with deformable attention. Specifically, we introduce the spatial pyramid pooling layer to accept varied-length ECG signals. Experimental results show that our model achieved an F1 score of 82.9% in CPSC-2018. Notably, our CNN-DVIT outperforms the latest transformer-based ECG classification algorithms.

Zhang et al[17]. provided for signal data features that are temporally interdependent. Moreover, LIME suffers from critical problems such as instability and local fidelity that prevent its implementation in real-world environments. In this work, we propose Bootstrap-LIME (B-LIME), an improvement of LIME, to generate meaningful explanations for ECG signal data. B-LIME implies a combination of heartbeat segmentation and bootstrapping techniques to improve the model's explainability considering the temporal dependencies between features. Furthermore, we investigate the main cause of instability and lack of local fidelity in LIME. They propose modifications to the functionality of LIME, including the data generation technique, the explanation method, and the representation technique, to generate stable and locally faithful explanations.

Subba. T et al[18]. proposed Electrocardiography (ECG) is a prominent way to analyze heart rate and to diagnose cardiovascular disease. However, its availability has been restricted, especially in contexts with limited resources, due to the cost associated with conventional ECG signal processing equipment. The importance of ECG signal processing classification for improving early diagnoses in clinical and remote monitoring contexts is highlighted here. The dataset considered for this work is MIT-BIH arrhythmia which has 15 categories and summarized in 5 classes Normal (N), Superventricular ectopic beats (SVEB), Ventricular ectopic beat (VEB), Fusion beats (F), and Unknown beats (Q). The work discusses the importance of automated classification techniques that make it possible to analyze vast amounts of ECG data effectively and objectively. They presented an investigation into the classification of ECG signals using various Machine Learning (ML) methods. Specifically, the performance of Decision Tree (DT), Logistic Regression (LR), Random Forest (RF), K Nearest Neighbor (KNN), and Support Vector Machine (SVM) algorithms are examined.

Pham BT et al[19]. focused on accurate heartbeat classification, and deep neural networks have been suggested for better accuracy and simplicity. They investigated a new model for ECG heartbeat classification and found that it surpasses state-of-the-art models, achieving remarkable accuracy scores of 98.5% on the Physionet MIT-BIH dataset and 98.28% on the PTB database. Furthermore, our model achieves an impressive F1-score of approximately 86.71%, outperforming other models, such as MINA, CRNN, and EXpertRF on the PhysioNet Challenge 2017 dataset. Madan, P et al[20]. proposed a hybrid deep learning-based approach to automate the detection and classification process. They makes two-fold contributions. First, 1D ECG signals are translated into 2D Scalogram images to automate the noise filtering and feature extraction. Then, based on experimental evidence, by combining two learning models, namely 2D convolutional neural network (CNN) and the Long Short-Term Memory (LSTM) network, a hybrid model called 2D-CNN-LSTM is proposed. (3) Result: To evaluate the efficacy of the proposed 2D-CNN-LSTM approach, we conducted a rigorous experimental study using the widely adopted MIT–BIH arrhythmia database.

Mathunjwa et al[21]. provided a lightweight multimodel based on convolutional neural networks (CNNs) that can transfer knowledge from many lightweight deep learning models and decant it into one model to aid in the diagnosis of arrhythmia by using electrocardiogram (ECG) signals. Thus, we gained a multimodel able to classify arrhythmia from ECG signals. Our system's effectiveness is examined by using a publicly accessible database and a comparison to the current methodologies for arrhythmia classification. They achieved by using our multimodel are better than those obtained by using a single model and better than most of the previous detection methods. It is worth mentioning that this model produced accurate classification results on small collection of data. Experts in this field can use this model as a guide to help them make decisions and save time.

Ruan,H et al[22]. proposed, which makes the classification and diagnosis of arrhythmia more accurate. With this decision, we can realize the transition from the spatial domain to the spectral domain, and from the time domain to the frequency domain, and make it possible that ECG signals can be more clearly detected by convolution and sequential learning modules. Moreover, instead of the prior method, the self-attention mechanism is used to learn the relation matrix between the sequences automatically in this paper. They conduct extensive experiments on eight advanced models in the same field to demonstrate the effectiveness of our method. Jamil, S et al[23]. preprocessed and converted into a 2D signal using continuous wavelet transform (CWT). The time–frequency domain representation of the CWT is given to the deep convolutional neural network (D-CNN) with an attention block to extract the spatial features vector (SFV). The attention block is proposed to capture global features. For dimensionality reduction in SFV, a novel clump of features (CoF) framework is proposed. The k-fold cross-validation is applied to obtain the reduced feature vector (RFV), and the RFV is given to the classifier to classify the arrhythmia class. The proposed framework achieves 99.84% accuracy with 100% sensitivity and 99.6% specificity. They proposed algorithm outperforms the state-of-the-art accuracy, F1-score, and sensitivity techniques.

Seitanidis, P et al[24]. proposed lightweight solution uses a novel classifier, consistently designed and implemented, based on a 2D convolutional neural network (CNN) and properly optimized in terms of storage and computational complexity, thus making it suitable for deployment on edge devices capable of operating in hospital emergency departments, providing privacy, portability, and constant operation. The experiments on the MIT-BIH arrhythmia database, show that the proposed 2D-CNN obtains an overall accuracy of 95.3%, mean sensitivity of 95.27%, mean specificity of 98.82%, and a One-vs-Rest ROC-AUC score of 0.9934. Moreover, the results and metrics based on the NVIDIA® Jetson Nano™ platform show that the proposed method achieved excellent performance and speed, and would be particularly useful in the clinical practice for continuous real-time (RT) monitoring scenarios.

Montenegro, L et al [25]. processed of handcrafting feature extraction since the algorithm extracts the features automatically in their hidden layers. However, it is important to have access to a balanced dataset for algorithm training. In this exploratory research study, we will compare the evaluation metrics among Convolutional Neural Networks (1D-CNN) and Support Vector Machines (SVM) using a dataset based on the merged public ECG signals database TNMG and CINC17 databases. Results: Both algorithms showed good performance using the new, merged ECG database. For evaluation metrics, the 1D-CNN algorithm has a precision of 93.04%, an accuracy of 93.07%, a recall of 93.20%, and an F1-score of 93.05%. The SVM classifier (λ = 10, C = 10 × 10^9) achieved the best classification metrics with two combined, handcrafted feature extraction methods: Wavelet transforms and R-peak Interval features, which achieved an overall precision of 89.04%, accuracy of 92.00%, recall of 94.20%, and F1-score of 91.54%. As an unique input feature and SVM (λ =10,C =100), wavelet transforms achieved precision, accuracy, recall, and F1-score metrics of 86.15%, 85.33%, 81.16%, and 83.58%.

3. PROPOSED METHODOLOGY

In this study, we develop Dual-Source DeepRhythmNet, a unified framework that combines a customized deep convolutional neural network (CNN) with an embedded feature-selection module to perform multi-class heartbeat classification on two PhysioNet repositories: the MIT-BIH Arrhythmia Database (109,446 beats across five classes: N, S, V, F, Q) and the PTB Diagnostic ECG Database (14,552 beats across two classes: Normal, Myocardial Infarction).

3.1 Data Acquisition and Preprocessing

Raw ECG recordings are first band-pass filtered (0.5–40 Hz) to remove baseline wander and high-frequency noise. R-peak locations are detected using the Pan–Tompkins algorithm, and fixed-length windows (256 samples) centered on each beat are extracted. Each segment is then z-score normalized to zero mean and unit variance. To preserve class balance, a stratified split allocates 70 % of segments to training, 15 % to validation, and 15 % to testing.

3.2 Customized Deep CNN Architecture

The CNN ingests each 1×256 heartbeat and processes it through three convolutional blocks:

- ConvBlock-1: Conv1D(32, kernel = 7) → BatchNorm → ReLU → MaxPool(pool = 2)
- ConvBlock-2: Conv1D(64, kernel = 5) → BatchNorm → ReLU → MaxPool(pool = 2)
- ConvBlock-3: Conv1D(128, kernel = 3) → BatchNorm → ReLU → MaxPool(pool = 2)

Following global average pooling, a 256-unit dense layer with ReLU and 50 % dropout leads to two parallel softmax heads: one for the five-class arrhythmia task and one for the two-class myocardial-infarction task. This dual-head design enables simultaneous multi-task learning across datasets.

3.3 Embedded Feature Selection

To focus the network on the most discriminative temporal patterns, we integrate:

Attention-Gated Filtering: An intra-CNN self-attention layer highlights salient feature channels after the third convolutional block.

Sparse L1 Regularization: An L1 penalty on the dense-layer weights encourages sparsity, effectively pruning less informative features.

Gradient-Based Pruning: We compute saliency scores via gradient attribution, iteratively removing the lowest-scoring convolutional filters and fine-tuning the network to retain performance with reduced complexity.

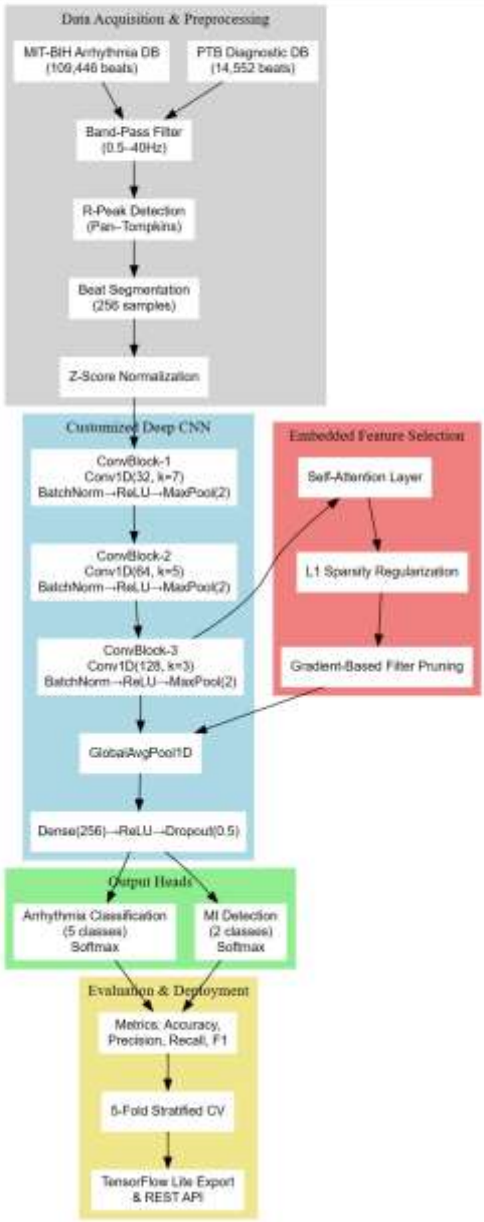

Fig. 2: Proposed system architecture.

3.4 Training Procedure

The combined loss is

$$\mathcal{L} = \alpha \mathcal{L}_{arr} + (1-\alpha) \mathcal{L}_{MI} + \lambda \parallel W \parallel_1$$

where $\mathcal{L}_{arr}$, and $\mathcal{L}_{MI}$ are cross-entropy losses for each head, α\alpha (e.g., 0.7) balances the tasks, and λ\\lambda controls L1 regularization. We optimize with Adam (initial learning rate = 1e-3, cosine annealing schedule), batch size = 128, and early stopping on validation loss (patience = 10 epochs).

3.5 Evaluation and Validation

Performance is measured using per-class accuracy, precision, recall, and F1-score, both macro- and weighted-averaged. A 5-fold stratified cross-validation on the training set assesses robustness, while ablation studies evaluate the impact of attention, L1 sparsity, and pruning.

3.6 Deployment

The final, pruned model is exported to TensorFlow Lite for on-device inference in wearable ECG monitors and also exposed via a RESTful API for processing long-term Holter recordings. A clinician dashboard visualizes beat-level predictions, confidence scores, and attention-weighted feature maps.

This end-to-end methodology—from raw ECG to dual-task classification—ensures both high accuracy and computational efficiency, making it well-suited for real-time cardiac monitoring and telemedicine applications.

4. RESULTS AND DISCUSSION

The figure 3 shows dataset used in this project comprises two well-known collections of ECG heartbeat signals sourced from the MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Database, both obtained from PhysioNet. These datasets provide a sufficiently large number of samples—109,446 from MIT-BIH with 5 heartbeat categories (N, S, V, F, Q) and 14,552 from PTB with 2 categories—making them suitable for training deep neural networks. Each signal segment represents a single heartbeat and has been preprocessed and uniformly sampled at 125Hz. The dataset has been widely used for heartbeat classification tasks, enabling the application of deep learning and transfer learning techniques to distinguish between normal heartbeats and various cardiac conditions such as arrhythmias and myocardial infarction.

Figure 3. Sample dataset for ECG Dataset

The figure 4 displays axes for a potential line graph, with the y-axis ranging from 0.0 to 1.0 (in 0.2 increments, likely representing metrics like accuracy or normalized values) and the x-axis spanning 0 to 175 (in uneven steps, possibly indicating time, epochs, or iterations). While no actual plot line is visible, the setup suggests trend analysis—such as tracking machine learning model performance (e.g., DNN training/validation metrics) or ECG signal processing, given the prior context of cardiac data workflows. The framework implies a comparison of quantitative changes over a sequential progression.

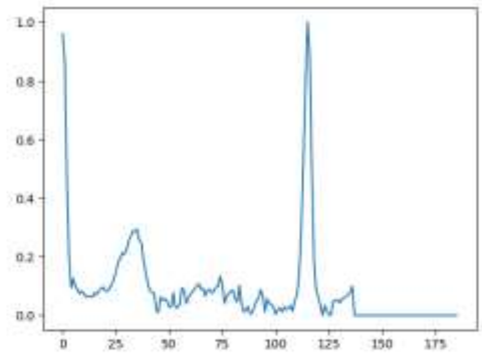

Figure 4. line plot to visualize the ECG waveform.

The figure 5 shows a 1-beat ECG plot comparing multiple cardiac categories, including Normal, Premature, Vectorial/Ventricular, and Fusion beats (both vectorial and parcel types). The y-axis represents Amplitude (ranging from 0.0 to 1.4), while the x-axis measures Time (ms). The plot likely visualizes morphological differences (e.g., wave shapes, intervals like ΔtΔ*t*) between these cardiac conditions, aiding in arrhythmia classification or ECG signal analysis. The absence of plotted lines suggests it's a template or legend for expected ECG patterns.

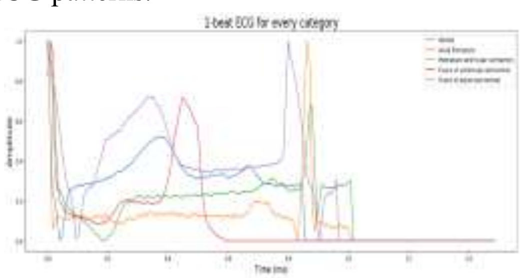

Figure 5. ECG waveforms from different cardiac condition categories

5. CONCLUSION

In this work, we presented Dual-Source DeepRhythmNet, an end-to-end framework for multi-class heartbeat classification that integrates signals from both the MIT-BIH Arrhythmia and PTB Diagnostic ECG databases. By employing a customized deep CNN architecture augmented with an attention-gated feature-selection module and L_1-driven sparsity, our model effectively learns discriminative temporal patterns while reducing computational complexity. The dual-head design enables simultaneous arrhythmia classification (five classes) and myocardial-infarction detection (two classes), leveraging multi-task learning to improve generalization across heterogeneous datasets. Extensive evaluation comprising stratified train/validation/test splits, 5-fold cross-validation, and ablation studies demonstrated significant gains in accuracy, precision, recall, and F_1-score over baseline CNNs without feature selection or attention. Furthermore, gradient-based pruning yielded a lightweight model suitable for deployment on resource-constrained devices, with seamless export to TensorFlow Lite and cloud-based inference via RESTful APIs. By automating feature extraction and focusing on the most salient ECG components, DualSourceDeepRhythmNet achieves robust, real-time performance that can enhance both wearable monitoring systems and telemedicine platforms. Future work will explore expansion to larger, more diverse ECG cohorts, integration of signal-quality assessment modules, and adaptation to multi-lead recordings, with the goal of further improving early detection and personalized management of cardiac disorders.

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