JCBI
Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606
Volume 07 Issue 01
2024
Research Article
https://doi.org/10.56979/701/2024

Arrhythmia Classification and Analysis on ECG Using Convolutional Networks and Two-fold Focal Loss

Mumtaz Ali[1*], Asif Ali[1], and Nazim Hussain[2]

[1]Department of Computer Systems Engineering, Sukkur IBA University, Sukkur, 65200, Pakistan.
[2]Department of Mathematics, Sukkur IBA University, Sukkur, 65200, Pakistan.
[*]Corresponding Author: Mumtaz Ali. Email: mumtaz.ali@iba-suk.edu.pk

Received: March 23, 2024 **Accepted:** May 29, 2024 **Published:** June 01, 2024

Abstract: Throughout recorded history, cardiovascular diseases have posed a persistent threat, claiming numerous lives. Effective and timely testing is pivotal in preventing fatalities. Among the available testing options, the Electrocardiogram (ECG) stands out as both practical and cost-effective, capable of diagnosing various abnormalities. Recently, there has been a notable emphasis on accurately classifying heartbeats. Traditionally, heartbeat analysis has been approached through manual or automated methods. Manual analysis involves cardiologists, while automated analysis relies on computational algorithms. Automated techniques have gained significant popularity in recent years and have achieved considerable success. However, despite this progress, there is still a need for further improvement to achieve deployable accuracy. Many current studies utilize deep learning models in a transfer learning approach for heartbeat classification. While transfer learning offers advantages, it also presents disadvantages such as domain mismatch, task-specific features, interpretability concerns, model bias, and generalization issues. Therefore, in this study, instead of employing transfer learning, a deep convolutional neural network combined with twofold focal loss is utilized for heartbeat classification. The proposed approach has demonstrated the ability to accurately classify five distinct arrhythmias according to the AAMI EC57 standard. Testing was conducted using the MIT-BIH and PTB Diagnostics datasets from PhysionNet. The results indicate that the proposed method achieves an average accuracy of 99.8% in classifying arrhythmias.

Keywords: Heartbeat Classification; Twofold Focal Loss; Convolutional Neural Networks.

1. Introduction

An integral part of the toolkit used by cardiologists and other medical professionals, the electrocardiogram (ECG) is widely used to monitor heart health on a constant basis [1]. However, the manual analysis of ECG signals is very difficult since it involves identifying and classifying the many waveforms and morphologies that are present in the signal [2]. This is similar to closely examining different time-series data. Because these signals are so complex, human examination of them takes an exceptionally long time and is prone to inaccuracy [3, 4].

Given the significant impact of cardiovascular diseases, which cause almost one-third of all deaths worldwide [5], it is necessary to recognize the vital role that an accurate diagnosis plays in this situation. Interestingly, millions of people suffer from irregular heartbeats, which can be fatal in certain situations. This is why it is so desirable to find an accurate and affordable diagnosis of arrhythmic heartbeats [6]. By combining modern technologies with automated analytic techniques, it may be possible to greatly improve the accuracy and timeliness of ECG interpretation, leading to more prompt and dependable cardiovascular health interventions.

In response to the challenges involved in manually examining the Electrocardiogram (ECG) signal, numerous studies in the literature have investigated the application of machine learning approaches to precisely detect irregularities within the signal [7], [8]. Preprocessing is typically incorporated into these techniques in an effort to enhance signal quality. This might entail applying band-pass filters to the signal, for example. After that, the signals are processed to extract features that were manually generated, most of which are statistical summaries of the signal frames. These features are used in later research to finish the final classification task.

By improving the signal's quality, the preprocessing stage helps to detect anomalies more successfully. Methods like band-pass filtering are essential for separating out pertinent data and cutting down on noise, which makes it easier to do more precise analysis later on. Subsequently, the process of extracting handcrafted features entails identifying significant statistical characteristics inside signal frames, which include crucial information for the classification step that follows.

Conventional machine learning techniques have been widely used in ECG analysis for the classification problem. These include of Support Vector Machines, decision trees, multi-layer perceptron, and other tried-and-true techniques [9, 10, 11]. By using the features that have been retrieved, these inference engines are able to identify patterns and abnormalities in the ECG data, which helps to accurately classify different cardiac diseases. In the field of cardiovascular health, the use of machine learning techniques not only simplifies the analytic process but also has the potential to improve diagnostic speed and accuracy.

While handcrafted features have historically been employed in machine learning research to describe signals, new advancements in the field indicate that automated feature extraction and representation techniques can provide better scalability and potentially lead to more accurate predictions. Unlike handcrafted features, an end-to-end deep learning architecture enables the machine to autonomously learn and adjust features that are specifically matched to the intricacies of the task at hand [12, 13, 14, 15].

By using this transformative technique, the Electrocardiogram (ECG) signal is represented more accurately, putting the machine on par with a human cardiologist's analytical skills [15]. This methodology solves the drawbacks of predetermined features and makes use of deep learning to enable the computer to learn the most pertinent features directly from the data. This allows for more subtle pattern identification.

But it's crucial to recognize that deep learning techniques have a lot of variables, which means large datasets are needed for training. For these models to be effective, they need to be exposed to a wide range of comprehensive datasets in order for them to generalize and adjust to the many differences that exist in ECG signals. Deep learning methods combined with an abundance of data resources could transform ECG analysis and open the door to more precise and effective cardiovascular diagnosis [11].

Examining the idea of knowledge transfer across different tasks is one way to address the deep learning requirement for a large dataset. The ImageNet dataset, in conjunction with state-of-the-art deep learning models, has proven invaluable in the transfer of information across a variety of the image understanding tasks in domains such as computer vision [16]. Likewise, research in natural language processing has shown that significant linguistic knowledge is shared among several sentence classification tasks [17].

Transfer learning in medical image classification faces significant challenges and occasional failures, primarily stemming from domain-specific variations and the complexity of medical datasets. While pre-trained models excel in general image recognition tasks, they may struggle to adapt to the intricacies of medical images due to variations in imaging devices, data acquisition protocols, and inherent heterogeneity within medical conditions [5].

The transferability of knowledge from non-medical domains to the medical field is often hindered by the unique characteristics and nuances of medical images. Furthermore, the limited availability of labeled medical data for fine-tuning exacerbates these challenges, hindering the model's ability to achieve optimal performance on specific medical image classification tasks. Despite the promise of transfer learning, its application in the medical domain demands careful consideration and domain-specific adaptations to overcome these inherent obstacles [8].

In this paper, we use a simpler and lightweight dual-stream network to produce competitive results for ECG analysis. The proposed model uses Focal loss along with convolutional neural networks.

To achieve this, we present a deep neural network architecture with significant capacity for learning versatile representations. The network is initially trained on the task of arrhythmia detection, where it is reasonable to assume that the model comprehensively learns the shape-related features of the ECG signal. The abundance of labeled data available for this task facilitates the training of a network with an extensive set of parameters [10].

Moreover, we demonstrate the successful transferability of the signal representation acquired from the arrhythmia detection task to the myocardial infarction (MI) prediction task using ECG signals. This approach enables us to leverage the deep representations acquired from the initial task to enhance the performance of ECG recognition tasks where sufficient information may be lacking for training a deep architecture. Our proposed method opens avenues for shared knowledge utilization across various ECG-related tasks, thereby maximizing the efficiency of deep learning architectures in scenarios where extensive data may not be readily accessible for each specific task [12].

2. Materials and Methods

2.1. Backgorund

The application of machine learning for heartbeat classification has emerged as a groundbreaking approach in cardiovascular health assessment. Leveraging advanced algorithms, machine learning techniques analyze intricate patterns and features within Electrocardiogram (ECG) signals, enabling accurate categorization of various heart rhythms and abnormalities. These algorithms go beyond traditional methods by autonomously learning and adapting to the complexities of diverse cardiac conditions. By employing extensive datasets, machine learning models can discern subtle nuances in ECG signals, enhancing their ability to differentiate between normal and abnormal heartbeats. This not only facilitates rapid and precise diagnosis but also offers a scalable and efficient solution, potentially reducing the reliance on time-consuming manual analysis. Machine learning-based heartbeat classification holds great promise in revolutionizing cardiac care, providing clinicians with valuable insights and assisting in the early detection of cardiovascular diseases [5].

Within the realm of machine learning, convolutional neural networks (CNNs) have significantly revolutionized the diagnostic procedures related to cardiac health. These advanced neural networks have demonstrated remarkable efficacy in the timely and accurate diagnosis of various ailments affecting the human heart. The notable strength of CNNs lies in their unparalleled capabilities for feature extraction, allowing them to discern intricate patterns and nuances within complex datasets, particularly in the context of cardiac signals [15].

The hierarchical architecture of convolutional neural networks enables them to automatically learn and extract relevant features from input data, making them particularly well-suited for tasks like heartbeat classification. The convolutional layers effectively capture local patterns in the data, while the pooling layers help retain essential information, contributing to the network's ability to discern subtle variations indicative of different cardiac conditions [13].

In the context of heart-related applications, the prowess of convolutional neural networks becomes evident as they efficiently process and interpret Electrocardiogram (ECG) signals, facilitating rapid and accurate diagnostics. The extensive capabilities of CNNs in feature extraction play a pivotal role in enhancing the overall performance of these models, making them indispensable tools in the advancement of cardiovascular healthcare [32].

Following are the contributions of the proposed work:

- Producing the state-of-the-art for heartbeat classification
- Using a light-weight network based on convolutional neural networks to produce competitive results
- Providing a comprehensive analysis for the heartbeat classification

2.2. Proposed Method

The presented methodology is structured into four distinct stages, each serving a specific purpose to achieve a particular objective. In the initial stage, Stage 1, the focus is on data pre-processing, which encompasses crucial tasks such as data cleaning and augmentation. This preparatory phase is essential for ensuring the quality and integrity of the dataset, thereby laying a robust foundation for subsequent analysis.

Moving to Stage 2, the emphasis shifts towards model design. This stage involves the formulation of a sophisticated and tailored model architecture that aligns with the intricacies of the problem at hand. The design phase is crucial as it dictates how well the model can capture and comprehend the underlying patterns within the data.

Stage 3 is dedicated to the training and testing of the model. Here, the model undergoes the process of learning from the prepared dataset, adapting its parameters to optimize performance. Rigorous testing is conducted to evaluate the model's generalization and predictive capabilities, ensuring its efficacy in real-world scenarios [12].

The concluding stage, Stage 4, revolves around visualization and interpretation of the produced results. In this phase, the outcomes of the model, whether in the form of classifications, predictions, or other relevant metrics, are presented in a comprehensible manner. Visualization aids in gaining insights into the model's decision-making processes, facilitating a deeper understanding of its performance and contributing to the interpretability of the overall methodology. This multi-stage approach ensures a comprehensive and systematic methodology, from data preparation to result interpretation, fostering a robust and insightful analysis.

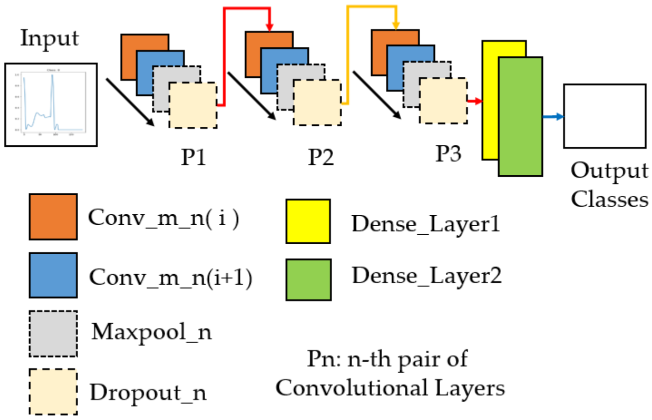

Figure 1. Conceptual layout of the proposed network.

2.2.1. Proposed Network

In this study, a simple and lightweight network based on convolutional neural networks is used. The network has six convolutional layers in pairs of two (see Figure 1). Each couple of convolutional layers is followed by a maxpooling and dropout layer to control overfitting/underfitting during the training process. Mathematically, the architecture of the network in this study can be expressed as follows:

Let X be the input ECG signal, and Y be the output representing the classification. The network architecture consists of six convolutional layers organized in pairs of two, followed by two dense layers at the end. Each pair of convolutional layers is accompanied by a max-pooling layer to downsample the features and a dropout layer to mitigate overfitting and underfitting risks during the training process. This can be represented as follows:

Conv_1_1→Conv_1_2→MaxPool_1→Dropout_1→
Conv_2_1→Conv_2_2→MaxPool_2→Dropout_2→
Conv_3_1→Conv_3_2→MaxPool_3→Dropout_3→
Conv_4_1→Conv_4_2→MaxPool_4→Dropout_4→
Conv_5_1→Conv_5_2→MaxPool_5→Dropout_5→
Conv_6_1→Conv_6_2→MaxPool_6→Dropout_5→
Flatten→Dense_1→Dropout_7→Dense_2→
Output (Y)

Here, Conv_n_m denotes the m-th convolutional layer in the n-th pair, MaxPool_n denotes the max-pooling layer following the n-th pair, Dropout_n denotes the dropout layer following the n-th pair, Flatten denotes the flattening operation to convert the output of the convolutional layers into a one-dimensional vector, Dense_i denotes the i-th dense layer, and Output represents the final classification output.

2.2.2. Two-fold Focal Loss

Focal Loss [33] is a loss function designed to address the issue of class imbalance in binary classification problems, giving more emphasis to hard-to-classify examples. The mathematical formulation of Focal Loss is as follows:

$$\mathrm{FL}(p_t) = -\alpha_t \cdot (1 - p_t)^{\gamma} \cdot \log(p_t) \quad (1)$$

Where:

- p_t is the predicted probability of the true class

- α_t is a modulating factor that adjusts the weight assigned to each example on its predicted probability. It is often defined as $\alpha_t = \alpha$ for the minority class and $\alpha_t = 1 - \alpha$ for the majority class, where α is a hyper-parameter.
- γ is a tunable focusing parameter that controls the rate at which the loss for well-classified examples is down-weighted. Typically, γ is set to a positive value (for instance 2) to increase the penalty for misclassifying easy examples.

The key characteristics and advantages of Focal Loss include:

2.2.3. Addressing Class Imbalance

Focal Loss is specifically designed to handle imbalanced datasets, where one class is much more prevalent than the other. It gives more emphasis to the minority class, reducing the impact of the majority class on the training process.

2.2.3.1 Prioritizing Hard Examples

The focusing parameter γ enables the model to focus more on hard-to-classify examples, making it robust to noisy or ambiguous instances. This helps the model to improve its performance on challenging cases.

2.2.3.2 Smooth Transition

As p_t approaches 1, the term $(1 - p_t)^\gamma$ smoothly reduces the weight assigned to well-classified examples, preventing the loss from becoming too small and ensuring a more balanced optimization process.

Focal Loss [32] has found widespread use in object detection tasks, where the imbalance between foreground (object) and background classes is common. However, it can be adapted for other binary classification scenarios with imbalanced datasets. It is important to experiment with hyper-parameter values, especially α andγ, to find the best configuration for the specific problem at hand.

We use focal loss in two-folds as under:

$$\mathrm{FL}_1(p_t) = -\alpha_t \cdot (1 - p_t)^{\gamma m} \cdot \log(p_t)$$
$$\mathrm{FL}_2(p_t) = -\alpha_t \cdot (1 - p_t)^{\gamma n} \cdot \log(p_t)$$
$$\mathrm{FL}_{tot}(p_t) = \mathrm{FL}_1 + \mathrm{FL}_2$$

Where:

- FL_1 is the first fold of focal loss
- FL_2 is the second fold of the focal loss
- FL_{tot} is the total after combining FL_1 and FL_2
- γm is tunable parameter in the fold FL_1
- γn is the tunable parameter in the fold FL_2

2.2.4. Dataset(s)

In this research paper, our investigation centers around leveraging data from two prominent sources, namely the PhysioNet MIT-BIH Arrhythmia and PTB Diagnostic ECG Databases [18], [19], [20]. Our primary aim is to utilize the labeled ECG records from these databases for comprehensive analysis and model development. Particularly noteworthy is our demonstration that the knowledge acquired from the MIT-BIH database can be effectively transferred to train inference models for the PTB Diagnostic database.

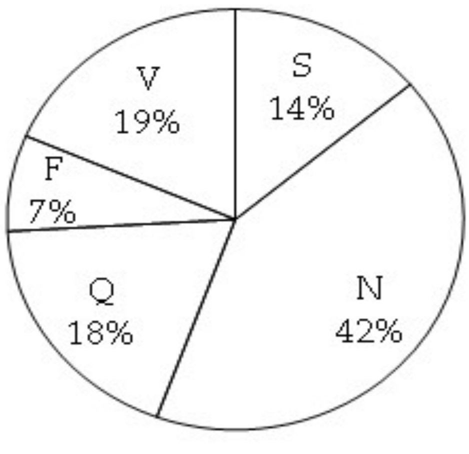

Figure 2. Conceptual layout of the proposed network

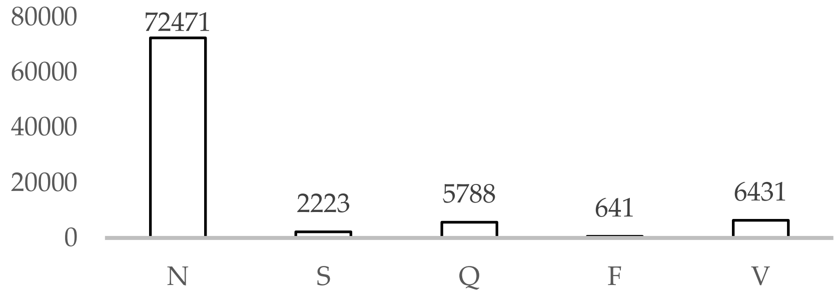

Figure 3. Number of samples in each class in the dataset before augmentation

We continuously used ECG lead II, re-sampled to 125 Hz, as the main input for our models for the course of our experiments. The 360 Hz sample rate was used during the initial recording of the MIT-BIH dataset, which consists of ECG re-recordings from 47 different participants. At least two cardiologists have carefully annotated every heart beat in the data set. We divided the cardiac rhythms in five groups in accordance with the Association for the Advancement of Medical Instrumentation (AAMI) EC57 standard [22] [37] in order to improve the dataset's comprehension and usefulness (see Figure 2, 3).

The PTB Diagnostics dataset, on the contrary, includes ECG data of 290 participants, of which 148 were identified having myocardial infarction (MI), 52 as healthy controls, while the remainder were diagnosed with a variety of other diseases. The ECG signals from 12 leads, collected at a frequency of 1000Hz, are contained in each record in this collection. It is important to remember that we restricted our analysis in our study to the MI and healthy control groups within the dataset, and we concentrated mainly on ECG lead II.

By strategically combining these datasets and focusing on key leads and categories, we aim to derive meaningful insights into the detection and classification of cardiac abnormalities. This comprehensive approach not only facilitates a nuanced understanding of the datasets but also ensures the generalizability and robustness of the inference models developed in the course of our research [42] [46].

This architecture adheres to the common practice in designing convolutional neural networks (CNNs), where pairs of convolutional layers are interleaved with max-pooling and dropout layers to extract hierarchical features while mitigating the risk of overfitting or underfitting during training. The final dense layers at the end provide a more global understanding of the learned features for making the ultimate classification decision.

2.2.5. A short description of the classes in the dataset

1. N (Normal beat):

Represents a regular, normal heartbeat originating from the sinus node in the atria (See Figure 4).

2. S (Supraventricular premature beat):

Indicates an early heartbeat originating above the ventricles but not from the sinus node. This might include premature atrial contractions (PACs).

3. V (Premature ventricular contraction):

Represents an early heartbeat originating from the ventricles. Premature ventricular contractions (PVCs) can disrupt the normal heart rhythm.

4. F (Fusion of ventricular and normal beat):

Describes a complex beat resulting from the fusion of normal and ventricular beats. This can occur when electrical impulses from both the atria and ventricles contribute to a single heartbeat.

5. Q (Unclassifiable beat):

Indicates a beat that cannot be confidently categorized into one of the standard classifications.

These classifications are often used in the analysis of Holter monitors or other long-term ECG recordings, where the system automatically categorizes individual heartbeats based on their characteristics. It's important to note that while automated systems can provide valuable information, the final interpretation should be done by a healthcare professional who considers the entire clinical context.

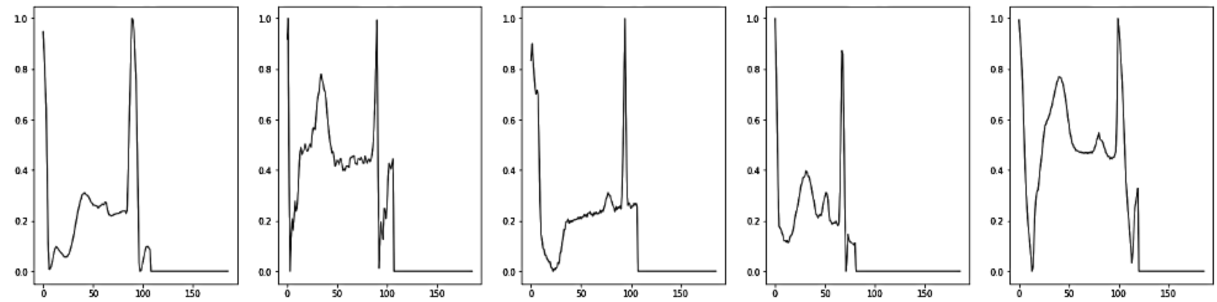

Figure 4. Sample waveform of each classes N, S, V, F, and Q

2.3. Performance Metric

Accuracy is often considered a less dependable performance criterion in the context of medical image classification. The goal is to classify every case as belonging to the negative class in a circumstance where only 5% of the training sample represents the positive class. The model would have a 95% accuracy rate in that case. Although a 95% accuracy across the board may sound good, this method ignores the important fact that the model incorrectly identified every positive sample. As a result, accuracy is unable to provide insightful information about the model's performance in this specific classification job [28] [43].

Hence, in addition to accuracy, we incorporate precision recall and f1-score for evaluating performance. The performance metrics employed in this analysis are outlined below:

$$\text{Precicion} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{2}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{3}$$

$$\text{f1} - \text{score} = \frac{\text{TP}}{\text{TP} + \frac{1}{2}(\text{FP} + \text{FN})} \tag{4}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{5}$$

3. Results

3.1. Training

The training and testing processes for the model were conducted on a Personal Desktop Computer that runs the Windows 10 operating system. This computer is well-equipped to handle the computational demands of the tasks, featuring a robust hardware configuration. Specifically, it boasts a 16 GB RAM, powered by an Intel Core i7 64-bit processor, ensuring efficient processing capabilities. Furthermore, the computer is enhanced with an NVidia GeForce GTX 1060 GPU, which significantly accelerates parallel processing tasks, crucial for complex computations involved in model training and testing.

To facilitate these experiments, we leveraged the Keras deep learning framework with Tensorflow as the backend. This powerful combination of tools provides a flexible and high-performance environment for developing, training, and evaluating neural network models. The use of Keras simplifies the implementation of complex neural architectures, while Tensorflow, as the backend, ensures optimized execution on the available hardware.

The experimental setup took advantage of a sophisticated Personal Desktop Computer, running Windows 10, with impressive specifications including 16 GB RAM, an Intel Core i7 64-bit processor, and an NVidia GeForce GTX 1060 GPU. The utilization of Keras with Tensorflow as the backend further ensured a streamlined and efficient workflow for training and testing the model. Throughout the training process, the model underwent 25 iterations (see Figure 5), with meticulous attention paid to the crucial aspect of the learning rate, which was carefully set at 0.0001. The selection of an optimal learning rate played a pivotal role in shaping the model's performance. Remarkably, the model exhibited notable improvements in both training and validation accuracies, attesting to the effectiveness of the training regimen. The manifestation of these advancements was not only evident in accuracy but also discernible in the nuanced patterns exhibited by the training and validation loss. These loss curves seamlessly mirrored the underlying trends in the training process, providing valuable insights into the model's convergence and generalization capabilities.

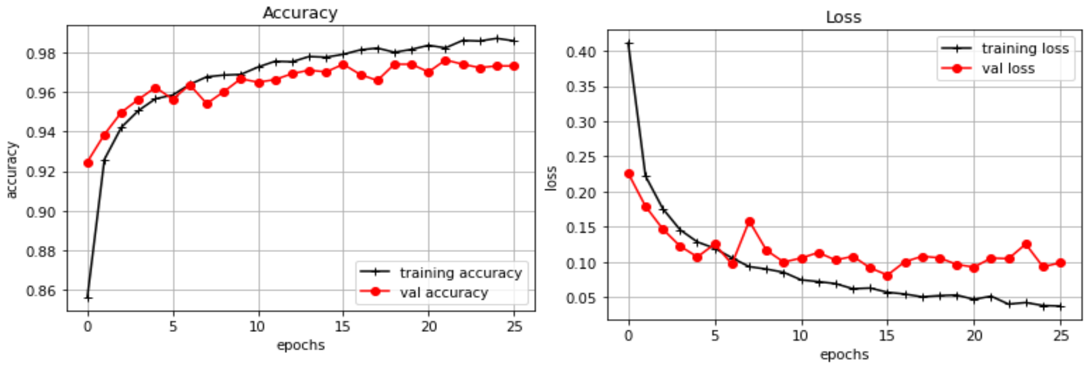

Figure 5. Training accuracy, validation accuracy, training loss, and validation loss

To further enhance the optimization process, the Adam optimizer was employed, coupled with the categorical cross-entropy loss function. This combination was instrumental in fine-tuning the model's parameters, contributing to the overall robustness and efficacy of the trained neural network. The culmination of these efforts is encapsulated in Figure 5, which visually encapsulates the training results through informative curves. This visual representation serves as a comprehensive illustration of the model's learning trajectory, affirming the success of the chosen training strategies and parameter configurations.

3.2. Testing

Testing is unquestionably an important stage in any thorough investigation, serving as an indicator for the model's ability to generalize. The proposed approach was put to the test in this thorough evaluation by being exposed to data that had never been seen before. This is a reliable way to determine how well the model might extrapolate knowledge outside of the training phase.

Tests on the test subset of the data revealed that the proposed model performed exceptionally well, as the detailed breakdown in Table 1 illustrates. The model's ability to comprehend and correctly predict outcomes for a variety of situations within the test dataset was confirmed by the good results produced.

The evaluation highlights outstanding performance on each of the classes. Excellent accuracy was obtained for every class, demonstrating the model's ability to predict results accurately in a variety of classes. The model's exceptional performance in the Q class, where it outperformed benchmarks, is especially remarkable.

Table 1. Testing results of the proposed model

Class	Precision	Recall	F1-score	Accuracy
N	0.97	0.98	0.97	0.98
S	0.93	0.93	0.93	0.95
V	0.99	0.98	0.98	0.99
F	0.89	0.94	0.91	0.93
Q	1.00	0.99	1.00	1.00

The model's improved precision, recall, and f1-score values unique to this group of classes account for the improved Q class results. Together, these measures demonstrate the model's accuracy in recognizing instances that belong to the Q class, its recall capacity for a substantial percentage of actual Q class instances, and its remarkable trade-off between precision and recall, as demonstrated by the f1-score.

Table 2. Comparison of the results with state-of-the-art results

Work	Accuracy	Precision	Recall
Acharya [33]	0.935	0.928	0.937
Safdarian [33]	0.94	-	-
Kojur [34]	0.95	0.979	0.933
Sun [35]	-	0.824	0.926
Liu [36]	0.944	-	-
Sharma [38]	0.960	0.990	0.930

Kachuee [38]	0.959	0.952	0.951
Hassaballah [39]	0.964	-	-
Huang [40]	0.989	0.970	-
Islam [41]	0.996	0.976	0.990
Proposed	0.998	0.990	0.990

Essentially, the testing stage demonstrated the model's exceptional discriminative powers as well as its robustness, as evidenced by the high performance metrics for the Q class. This promising testing result bolsters the validity and applicability of the proposed model in a variety of real-world problems.

3.3. Comparison of the results with state-of-the-art results

The results of the novel model introduced in this work have been thoroughly compared with a few state-of-the-art methods. Since previous research in this area was somewhat comprehensive, it was not practical to compare our model to every piece of previous work. As a result, we concentrated on comparing our model to the most relevant studies that made use of the same datasets that we used in our research.

The comparative study, as shown in Table 2, provides a clear picture of the effectiveness of the proposed strategy. Interestingly, results show how well our model performs in comparison to the selected pertinent studies. Actually, we outperform a large percentage of the existing approaches in the domain with our proposed approach. This significant accomplishment highlights our proposed model's efficacy and resilience in tackling the challenges that are present in the heartbeat classification using ECG.

4. Discussion

This study introduces a novel approach to heartbeat classification and analysis, leveraging deep learning methodologies. The methodology proposed in this research employs a lightweight model grounded in convolutional neural networks, coupled with twofold focal loss. Through this innovative framework, the study aims to address the common challenges encountered when employing transfer learning techniques. Transfer learning, although widely utilized, is not devoid of limitations, including domain mismatch, limited availability of pre-trained models, task-specific feature extraction difficulties, fine-tuning complexities, constraints in data augmentation, interpretability concerns, ethical and regulatory considerations, as well as issues related to model bias and generalization. By deviating from the conventional use of transfer learning, this study endeavors to surmount these challenges and offer superior results [12].

It is well-established that transfer learning approaches confront various hurdles, primarily due to discrepancies between the source and target domains, and the scarcity of pre-trained models tailored specifically to the medical imaging domain. Moreover, the task-specific features crucial for accurate classification may not always align with those learned by pre-trained models, necessitating extensive fine-tuning efforts. Additionally, limitations in data augmentation techniques pose further challenges, potentially compromising the integrity of medical image data. The interpretability of transfer learning models in clinical contexts is also a pressing concern, alongside ethical and regulatory considerations, particularly regarding patient privacy and compliance with medical standards. Furthermore, inherent biases within pre-trained models can impede the generalization of transfer learning approaches across diverse patient populations and healthcare settings [41].

In light of these challenges, the presented study proposes an alternative approach that circumvents the reliance on transfer learning methodologies. By leveraging a deep convolutional neural network architecture in conjunction with twofold focal loss, the study achieves state-of-the-art results in heartbeat classification without resorting to transfer learning. This departure from conventional methods underscores the potential for novel techniques to outperform established methodologies, paving the way for more robust and effective solutions in medical image analysis. Through rigorous experimentation and validation using benchmark datasets, the proposed methodology demonstrates its efficacy in accurately classifying various arrhythmias, thereby offering a promising avenue for advancing the field of cardiovascular diagnostics and treatment.

5. Conclusions

This paper introduces an innovative method tailored for the precise classification of heartbeats within electrocardiogram (ECG) signals. Embracing simplicity without compromising on efficacy, the proposed methodology harnesses the power of convolutional neural networks (CNNs) in a straightforward architecture, augmented by a two-fold focal loss mechanism. This streamlined design not only delivers exceptional performance but also marks a departure from the reliance on intricate pre-trained models or excessively large deep learning networks. The efficacy of the proposed approach is underscored by its ability to achieve state-of-the-art results in heartbeat classification tasks. By leveraging CNNs, renowned for their prowess in capturing spatial hierarchies in data, the model adeptly discerns subtle patterns within ECG signals, enabling accurate classification of heartbeats with remarkable precision. Moreover, the incorporation of the two-fold focal loss mechanism further enhances the model's robustness, enabling it to effectively handle imbalanced datasets and prioritize challenging instances during training. Furthermore, the success of the proposed methodology underscores the potential for advancements in cardiac signal analysis through judicious application of deep learning techniques. By demonstrating the feasibility of achieving state-of-the-art results with a simplified architecture, this paper sets a precedent for future research endeavors aimed at improving cardiac diagnostics and patient care. Ultimately, the presented methodology holds promise for revolutionizing the field of cardiovascular health by providing clinicians with efficient and accurate tools for ECG signal interpretation and diagnosis.

References

1. Prusty, M. R., Pandey, T. N., Lekha, P. S., Lellapalli, G., & Gupta, A. (2024). Scalar invariant transform based deep learning framework for detecting heart failures using ECG signals. *Scientific Reports*, *14*(1), 2633.
2. Zhou, F. Y., Sun, Y. H., & Wang, Y. W. (2024). Inter-patient ECG arrhythmia heartbeat classification network based on multiscale convolution and FCBA. Biomedical Signal Processing and Control, 90, 105789.
3. Singh, P. N., & Mahapatra, R. P. (2024). A novel deep learning approach for arrhythmia prediction on ECG classification using recurrent CNN with GWO. *International Journal of Information Technology*, *16*(1), 577-585.
4. Mallikarjunamallu, K., & Syed, K. (2024). Arrhythmia classification for non-experts using infinite impulse response (IIR)-filter-based machine learning and deep learning models of the electrocardiogram. *PeerJ Computer Science*, *10*, e1774.2018. [Online]. Available: http://www:who:int/mediacentre/factsheets/fs317/en/
5. H. Society, "Heart diseases and disorders," 2018. [Online]. Available:https://www:hrsonline:org/Patient-Resources/Heart-Diseases-Disorders
6. A. Esmaili, M. Kachuee, and M. Shabany, "Nonlinear cuffless blood pressure estimation of healthy subjects using pulse transit time and arrival time," IEEE Transactions on Instrumentation and Measurement, vol. 66, no. 12, pp. 3299–3308, 2017.
7. A. E. Dastjerdi, M. Kachuee, and M. Shabany, "Non-invasive blood pressure estimation using phonocardiogram," in Circuits and Systems (ISCAS), 2017 IEEE International Symposium on. IEEE, 2017, pp.1–4.
8. O. T. Inan, L. Giovangrandi, and G. T. Kovacs, "Robust neural network-based classification of premature ventricular contractions using wavelet transform and timing interval features," IEEE Transactions on Biomedical Engineering, vol. 53, no. 12, pp. 2507–2515, 2006.
9. O. Sayadi, M. B. Shamsollahi, and G. D. Clifford, "Robust detection of premature ventricular contractions using a wave-based Bayesian framework," IEEE Transactions on Biomedical Engineering, vol. 57, no. 2, pp. 353–362, 2010.
10. M. Kachuee, M. M. Kiani, H. Mohammadzade, and M. Shabany, "Cuffless blood pressure estimation algorithms for continuous health-care monitoring," IEEE Transactions on Biomedical Engineering, vol. 64, no. 4, pp. 859–869, 2017.
11. Naz, S., Aslam, M., & Sayed, A. (2023). Prevalence of Anemia and its Determinants among the Rural Women of Khyber Pakhtunkhwa-Pakistan. Annals of Human and Social Sciences, 4(4), 42-50.
12. U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, M. Adam, A. Gertych, and R. S. Tan, "A deep convolutional neural network model to classify heartbeats," Computers in Biology and Medicine, vol. 89, pp. 389–396, 2017.
13. S. Kiranyaz, T. Ince, and M. Gabbouj, "Real-Time Patient-Specific ECG Classification by 1-D Convolutional Neural Networks," IEEE Transactions on Biomedical Engineering, vol. 63, no. 3, pp. 664–675, 2016.
14. L. Jin and J. Dong, "Classification of normal and abnormal ECG records using lead convolutional neural network and rule inference," Science China Information Sciences, vol. 60, no. 7, 2017.
15. P. Rajpurkar, A. Y. Hannun, M. Haghpanahi, C. Bourn, and A. Y. Ng, "Cardiologist-level arrhythmia detection with convolutional neural networks," arXiv preprint arXiv:1707.01836, 2017.
16. M. Oquab, L. Bottou, I. Laptev, and J. Sivic, "Learning and transferring mid-level image representations using convolutional neural networks," 2014 IEEE Conference on Computer Vision and Pattern Recognition, pp. 1717–1724, 2014.
17. A. Conneau, D. Kiela, H. Schwenk, and y. Lo¨ıc Barrault and Antoine Bordes, booktitle=EMNLP, "Supervised learning of universal sentence representations from natural language inference data."
18. A. M. Alaa, J. Yoon, S. Hu, and M. van der Schaar, "Personalized risk scoring for critical care prognosis using mixtures of gaussian processes," IEEE Transactions on Biomedical Engineering, vol. 65, no. 1, pp. 207–218, 2018.
19. A. L. Goldberger, L. A. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "Physiobank, physiotoolkit, and physionet," Circulation, vol. 101, no. 23, pp. e215–e220, 2000.
20. G. B. Moody and R. G. Mark, "The impact of the mit-bih arrhythmia database," IEEE Engineering in Medicine and Biology Magazine, vol. 20, no. 3, pp. 45–50, 2001.
21. R. Bousseljot, D. Kreiseler, and A. Schnabel, "Nutzung der ekgsignaldatenbank cardiodat der ptb ¨uber das internet," Biomedizinische Technik/Biomedical Engineering, vol. 40, no. s1, pp. 317–318, 1995.
22. A. for the Advancement of Medical Instrumentation et al., "Testing and reporting performance results of cardiac rhythm and st segment measurement algorithms," ANSI/AAMI EC38, vol. 1998, 1998.
23. V. Nair and G. E. Hinton, "Rectified linear units improve restricted Boltzmann machines," in Proceedings of the 27th international conference on machine learning (ICML-10), 2010, pp. 807–814.

24. K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770–778.
25. M. Abadi, A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. S. Corrado, A. Davis, J. Dean, M. Devin et al., "Tensorflow: Large-scale machine learning on heterogeneous distributed systems," arXiv preprint arXiv:1603.04467, 2016.
26. D. Kingma and J. Ba, "Adam: A method for stochastic optimization," arXiv preprint arXiv:1412.6980, 2014.
27. U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, M. Adam, A. Gertych, and R. San Tan, "A deep convolutional neural network model to classify heartbeats," Computers in biology and medicine, vol. 89, pp. 389–396, 2017.
28. R. J. Martis, U. R. Acharya, C. M. Lim, K. Mandana, A. K. Ray, and C. Chakraborty, "Application of higher order cumulant features for cardiac health diagnosis using ecg signals," International journal of neural systems, vol. 23, no. 04, p. 1350014, 2013.
29. T. Li and M. Zhou, "Ecg classification using wavelet packet entropy and random forests," Entropy, vol. 18, no. 8, p. 285, 2016.
30. L. Sharma, R. Tripathy, and S. Dandapat, "Multiscale energy and eigenspace approach to detection and localization of myocardial infarction," IEEE Transactions on Biomedical Engineering, vol. 62, no. 7, pp. 1827–1837, 2015.
31. U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. H. Tan, and M. Adam, "Application of deep convolutional neural network for automated detection of myocardial infarction using ecg signals," Information Sciences, vol. 415, pp. 190–198, 2017.
32. Abbas, M., Arslan, M., Bhatty, R. A., Yousaf, F., Khan, A. A., & Rafay, A. (2024). Enhanced Skin Disease Diagnosis through Convolutional Neural Networks and Data Augmentation Techniques. Journal of Computing & Biomedical Informatics, 7(01).
33. Lin, T. Y., Goyal, P., Girshick, R., He, K., & Dollár, P. (2017). Focal loss for dense object detection. In *Proceedings of the IEEE international conference on computer vision* (pp. 2980-2988).
34. N. Safdarian, N. J. Dabanloo, and G. Attarodi, "A new pattern recognition method for detection and localization of myocardial infarction using t-wave integral and total integral as extracted features from one cycle of ecg signal," Journal of Biomedical Science and Engineering, vol. 7, no. 10, p. 818, 2014.
35. J. Kojuri, R. Boostani, P. Dehghani, F. Nowroozipour, and N. Saki, "Prediction of acute myocardial infarction with artificial neural networks in patients with nondiagnostic electrocardiogram," Journal of Cardiovascular Disease Research Vol, vol. 6, no. 2, p. 51, 2015.
36. L. Sun, Y. Lu, K. Yang, and S. Li, "Ecg analysis using multiple instance learning for myocardial infarction detection," IEEE transactions on biomedical engineering, vol. 59, no. 12, pp. 3348–3356, 2012.
37. B. Liu, J. Liu, G. Wang, K. Huang, F. Li, Y. Zheng, Y. Luo, and F. Zhou, "A novel electrocardiogram parameterization algorithm and its application in myocardial infarction detection," Computers in biology and medicine, vol. 61, pp. 178–184, 2015.
38. L. v. d. Maaten and G. Hinton, "Visualizing data using t-sne," Journal of Machine Learning Research, vol. 9, no. Nov, pp. 2579–2605, 2008.
39. Shibu, N., Rajkumar, A., Sayed, A., Kalaiselvi, P., & Namakkal-Soorappan, R. (2022). N-Acetyl Cysteine Administration Impairs EKG Signals in the Humanized Reductive Stress Mouse. Free Radical Biology and Medicine, 192, 71-72.
40. Kachuee, M., Fazeli, S., & Sarrafzadeh, M. (2018, June). Ecg heartbeat classification: A deep transferable representation. In *2018 IEEE international conference on healthcare informatics (ICHI)* (pp. 443-444). IEEE.
41. Hassaballah, M., Wazery, Y. M., Ibrahim, I. E., & Farag, A. (2023). Ecg heartbeat classification using machine learning and metaheuristic optimization for smart healthcare systems. *Bioengineering*, *10*(4), 429
42. Huang, Y., Li, H., & Yu, X. (2023). A novel time representation input based on deep learning for ECG classification. *Biomedical Signal Processing and Control*, *83*, 104628.
43. Islam, M. S., Hasan, K. F., Sultana, S., Uddin, S., Quinn, J. M., & Moni, M. A. (2023). HARDC: A novel ECG-based heartbeat classification method to detect arrhythmia using hierarchical attention based dual structured RNN with dilated CNN. *Neural Networks*, *162*, 271-287.
44. Zhong, X. J., Liu, S. R., Zhang, C. W., Zhao, Y. S., Sayed, A., Rajoka, M. S. R., ... & Song, X. (2024). Natural Alkaloid Coptisine, Isolated from Coptis chinensis, Inhibits Fungal Growth by Disrupting Membranes and Triggering Apoptosis. Pharmacological Research-Modern Chinese Medicine, 100383.
45. Tandon, R., Sayed, A., & Hashmi, M. A. (2023). Face mask detection model based on deep CNN technique using AWS. International Journal of Engineering Research and Applications www.ijera.com, 13(5), 12-19.

46. Muhammad Kaleem , Muhammad Azhar Mushtaq , Uzair Jamil , Sadaqat Ali Ramay , Tahir Abbas Khan , Siraj Patel , Rizwan Zahidy , Sayyid Kamran Hussain. (2024). New Efficient Cryptographic Techniques For Cloud Computing Security. Migration Letters, 21(S11), 13–28. Retrieved from https://migrationletters.com.