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Enhancing Cardiovascular Health Diagnosis: A Deep Learning Approach Utilizing ECG Signals for Accurate Heart Attack Detection and Arrhythmia Identification

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Abstract. The World Health Organization reports that approximately 17 million individuals succumb to cardiovascular disorders, a consequence of detrimental lifestyle choices such as excessive alcohol and tobacco con- sumption, obesity, heightened stress levels, and alterations in dietary habits. These factors present formidable challenges for timely heart fail- ure diagnosis, complicating surgical interventions. A heart attack tran- spires when the blood flow supplying oxygen to the heart muscle is severely restricted or completely obstructed. The Electrocardiogram (ECG) serves as a precise, reliable, swift, and uncomplicated method for detect- ing heart attacks, measuring heart rates. An ECG signal encapsulates

a single heart cycle, with the QRS complex being a pivotal component. Utilizing the MIT-BIH Arrhythmia Dataset, which encompasses heart- beat signals, this study employs a 1-D Convolutional Neural Network model achieving an impressive 95% accuracy. The discernment of heart rate facilitates the identification of various arrhythmias, demonstrating the potential of deep neural networks in leveraging extensive datasets for improved diagnostic capabilities.

Keywords: *ECG signals · Cardiovascular disorders · Heart attack de- tection · Deep learning · Arrhythmia identification.*

1 Introduction

The dynamic electrical activity of the cardiac muscle is effectively captured and conveyed by the Electrocardiogram (ECG) as it undergoes temporal fluctua- tions. Comprising essential components, the ECG signal encompasses the QRS complex, P wave, and T wave, serving as a fundamental tool for understanding cardiac function [1]. A baseline heart rate of 72 beats per minute is consid- ered optimal for an individual's cardiovascular well-being. Any deviation from this rhythmic norm is classified as arrhythmia, representing irregularities in the heart rate that may lead to severe consequences, including cardiac arrest.

Within the intricate ECG signal, specific waves—P, Q, R, S, and T—along with designated segments or intervals such as PQ and ST segments, contribute to a comprehensive representation of the heart's electrical activity [14]. Distortions in these waves can give rise to arrhythmias, posing a significant risk of cardiac arrest.

The PQ segment plays a crucial role in influencing the time taken for a signal to travel from the sinoatrial (SA) node to the atrioventricular (AV) node, providing a key indicator of cardiac coordination. The Q wave signifies the depolarization of the interventricular septum, while the S wave represents the final phase of ventricular depolarization. The R-wave indicates the mass of the ventricles and their active contraction during the cardiac cycle, while the ST segment reflects cardiac contraction and blood pumping. The T-wave corresponds to ventricular repolarization and relaxation [5].

An intriguing aspect of ECG interpretation involves assessing the number of large squares between each QRS complex [3]. This metric serves as a valuable indicator of heart rate, where two squares denote a heart rate of 150 beats per minute, three squares indicate 100 beats per minute, and five squares signify a heart rate of 60 beats per minute.

In recent times, Deep Neural Networks (DNNs) have garnered substantial interest, particularly in the realm of biomedical signal processing. Specifically, Convolutional Neural Networks (CNNs) are applied directly to raw ECG signals without pre-filtering, or feature extraction. This approach addresses classifica- tion challenges by extracting transient features inherent in the ECG signal [10]. The study employs a 1-D CNN algorithm for classification techniques, suggesting the incorporation of a SoftMax regression layer over the hidden representation layer in the deep neural network. This enhancement aids in describing the most relevant and uncertain ECG beats during testing iterations, utilizing this information to iteratively update DNN weights. Additionally, a nine-layer deep CNN architecture is developed for the classification of 1-D ECG arrhythmias, drawing inspiration from diverse CNN structures reported in the literature. The study contributes to the growing body of knowledge on the application of deep learning in solving varied ECG signal classification and arrhythmia detection challenges.

The goal of this study is to segment an Electrocardiogram (ECG) signal into specific anomalies, identifying both instances of distortion, such as noise, and pathological events. The primary objective involves implementing a deep learning algorithm on ECG signals. A secondary aim is to categorize and identify irregular or abnormal patterns within ECG biosignals. The analysis focuses on low-level frequency artifacts, specifically baseline wandering noise, as well as the impact of movement-induced muscle artifacts on the ECG signal.

2 Literature Review

In a study by Mayank Chourasia et al., the authors emphasized the crucial role of Electrocardiogram (ECG) data in cardiovascular disease (CVD) detection [6]. Recognizing the significance of classifying heartbeats into five categories, they utilized the MIT-BIH Arrhythmia Dataset and implemented a 1-D Convolutional Neural Network (CNN) with a 5-fold cross-validation method. Their approach achieved an impressive accuracy of 97.36

Ç ağla SARVAN and Nalan Ö ZKURT addressed the issue of imbalanced data in their dataset across five different classes [12]. To tackle this imbalance, they employed statistical performance metrics and data mining techniques, particu- larly focusing on the recall of data. This strategic application of methodologies contributed to a more balanced and informative dataset.

In another study by Rajkumar. A et al., the authors employed a Deep Learn- ing (DL) algorithm, specifically a Convolutional Neural Network (CNN), for the identification of various arrhythmias [11]. Using the MIT-BIH Database from Physiobank.com, they harnessed the capability of CNN to automatically learn features from time-domain ECG signals. Successfully classifying seven types of arrhythmias, their model achieved a low loss value of 0.2.

The exploration of heart failure susceptibility detection was undertaken by authors who developed a system employing a two-class boosted decision tree [8]. Utilizing a dataset consisting of approximately 10,000 patients and incorporat- ing parameters like exercise habits, heart rate, cholesterol levels, age, gender, body mass index, family history, and smoking habits, the authors demonstrated a comprehensive approach. If the probability of heart vulnerability exceeded 50%, the ECG data was fed into a CNN model. Support vector machines were employed for heart attack type identification, achieving an 84% accuracy, while artificial neural networks demonstrated an accuracy of 88.30%.

Authors also integrated Internet of Things (IoT) devices, specifically pulse sensors, for pulse rate detection alongside other health parameters [13]. Employ- ing multiple regression for heart problem prediction, the pulse sensor connected to an Arduino board facilitated data collection. Following prediction, health sta- tus notifications were conveyed to individuals via messages, providing a real-time health monitoring solution.

Furthermore, researchers utilized the Heart Disease Dataset from Kaggle in their study, considering 14 attributes essential for heart disease identification [2]. Models such as Support Vector Machine, Na¨ıve Bayes, Random Forest, Decision Tree, and Logistic Regression were applied, with Decision Tree exhibiting high accuracy. The authors opted for RapidMiner, a data mining tool, to enhance accuracy in their study, highlighting the versatility of tools in the domain of heart disease prediction.

Collectively, these literature survey findings underscore the diverse method- ologies and technologies applied in the pursuit of advancing ECG signal anal- ysis, arrhythmia detection, and heart disease prediction. The studies showcase the significance of leveraging deep learning algorithms, data mining techniques, and IoT devices to enhance the accuracy and efficiency of cardiovascular health monitoring systems.

3 Proposed System

3.1 Pre-processing

The dataset exhibited an imbalance in the number of samples across different classes, with a notably higher number of samples in normal beats compared to fusion beats. To address this imbalance, we conducted resampling on the minor- ity class of data. A visual representation of the data distribution through a bar chart highlighted the significant imbalance, with over 80% of the data belonging to class 0. To enhance the accuracy of predictions, the first step involved balancing the data. Through resampling, we adjusted the number of rows in the dataset for class 0 to align more closely with the quantities present in the other classes as shown in Figure 1.

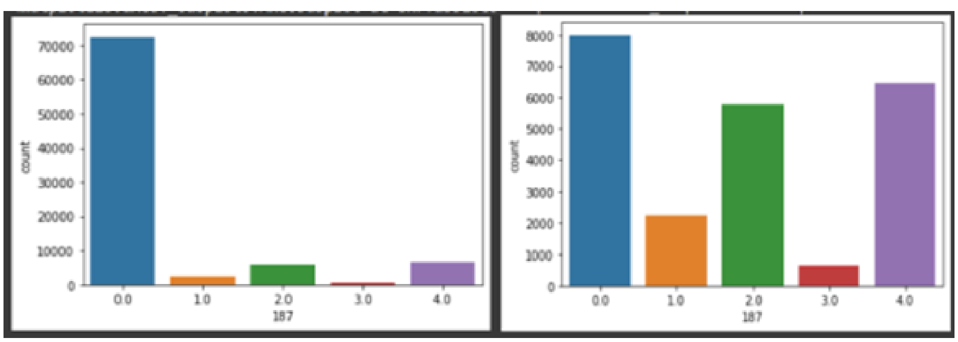

Fig. 1. Pre-processing of imbalanced data.

3.2 Feature Extraction

The CNN’s convolutional layer plays a crucial role in capturing spatiotemporal features from the ECG data, while the utilization of RELU aids in extracting non-linear features. The CNN model encompasses layers such as convolutional, Max Pooling, dense, Dropout, and Flatten, each contributing to the overall architecture. The incorporation of a max pooling layer specifically contributes to dimensionality reduction within the model.

Classification The Electrocardiogram (ECG) is a diagnostic tool that records the heart's electrical activity over time by placing electrodes on the skin. Widely utilized by physicians, it provides valuable insights into the analysis and diagnosis of cardiac diseases. Numerous elements of the heart's operation, such as rhythm, electrical conduction, architecture, and possible ischemia sites, can be identified and quantified using signal analysis. Electrical impulses from specialized myocardial cells cause the cardiac muscles to polarize and depolarize, which results in the cardiac signal. The heart's ability to contract and pump blood to various regions of the body is made possible by this depolarization.

As seen in Figure 2, the cardiac signal displays a cyclic pattern due to the sequential nature of the heart's pumping action. The neurological system also controls the circulatory system, which adds an unpredictable element to the signal's behaviour. It is important to understand that an adequate ECG signal is a sequence of sequential events. Examining the presence, amplitude, and form of the waves as well as their interactions with one another, different segments, and intervals are all part of the analysis process of the ECG signal. The letters P, Q, R, S, and T [15] are used to represent waves; T is not always present and is frequently connected to the QRS complex in ventricular contraction. Intervals include pertinent time intervals involving consecutive waves and segments, while segments show the millisecond intervals between consecutive waves [9].

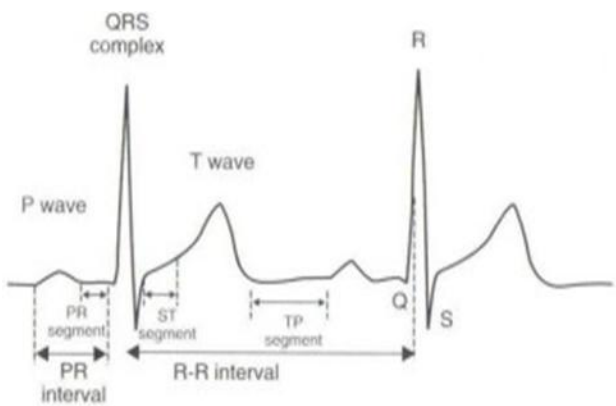

Fig. 2. Two cardiac cycles, with their phases, waves, and intervals

3.3 Architecture Description

Two distinct architectures were carefully chosen and fine-tuned for the specific tasks at hand in ECG classification—namely, the classification of segments affected by noise and the classification of various types of arrhythmias and normal sinus rhythms (NSRs). A crucial component of the process is choosing the right models for each task. Both algorithms were implemented using an autoencoder, and Figure 3 highlights the coding features of this model in particular. This chapter provides a comprehensive overview of the implemented autoencoder and the model employed for the classification tasks.

The methodology adopted for this endeavor involves leveraging an autoen- coder to comprehend the characteristics inherent in a standard ECG signal de- void of noise and pathological events. By presenting an ECG signal containing diverse types of noise or pathological events to the algorithm, equipped with the correct structure of a healthy, noise-free ECG signal, a function is created to classify the ECG signal and discern the disparities between normal and abnormal signals. The signal data is organized into 64-sample windows during classifica- tion, allowing for effective training for each algorithm. This training is conducted in batches of 256 to enhance overall generalization. Each window, based on the data utilized, encapsulates approximately one cycle of ECG signals.

Pooling layers play a pivotal role in diminishing the dimensions of feature maps, facilitating a reduction in the computational load required for network training. Two widely used pooling functions include Max-Pooling, which iden- tifies the maximum value within each feature map, and Average Pooling, which calculates the average value of each feature map. In this context, Average Pooling is employed to optimize the network's performance.

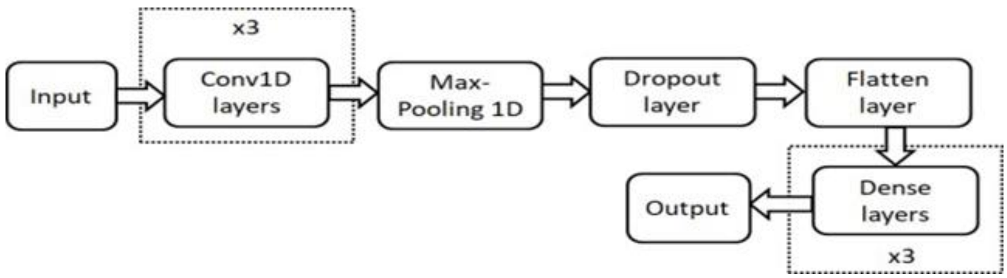

Fig. 3. Architectural block diagram for 1D-CNN Model.

3.4 Arrhythmia detection using neural network

Convolutional Neural Networks (CNNs) are a type of feedforward neural network that often comprises up to twenty or thirty layers. The distinctive strength of CNNs lies in the inclusion of a specialized layer known as the convolutional layer. The architecture of a CNN is structured as a multi-layer feedforward neural net- work, stacking numerous hidden layers sequentially. This sequential arrangement allows CNNs to grasp hierarchical features, with hidden layers typically incorporating a convolution layer followed by an activation layer, and some layers followed by a pooling layer.

These models excel in learning to extract features from sequences of obser- vations and mapping these internal features to various activity types. A notable advantage of using CNNs for sequence classification is their ability to learn di- rectly from raw statistical data, eliminating the need for manual feature engi- neering by domain experts. The model can internally represent the statistical data and ideally achieve performance comparable to models trained on datasets with engineered features. Given the one-dimensional nature of ECG signals, a 1-D CNN was implemented for automated heart disease classification.

The convolutional, max pooling, dropout, flatten, and thick layers make up our CNN model. There are three convolution layers in it, each with 32, 64, and 128 filters. The activation functions Softmax and ReLU are used. In a neural network, the activation function converts each node's total weighted input into the activation of that node. A piece-wise linear function, the ReLU activation function outputs the input directly if it is positive and zero otherwise. The neural network's output layer makes use of the Softmax activation function. Twenty-one,892 heartbeats are used to validate the CNN model after it was trained on 100,000 sample heartbeats. We designate 10 epochs with a batch size of 650 samples in order to train the model.

3.5 Optimization Algorithm

Adam estimation is an optimisation approach algorithm. When dealing with large problems with lots of information or parameters, the technique is essentially efficient. It's efficient and needs minimal memory. Adam is a computationally efficient, low-memory optimisation solver for the Neural Network technique that can handle problems with many parameters, information, or both. The adaptive estimation of first- and second-order moments is supported by this favoured modification of the stochastic gradient descent approach. The decay rate for the first moment estimates. Adam Optimizer (used for optimizing the loss function for neural networks) consists of three free parameters: η, step size/learning rate. $\beta 1$ forgetting factor for gradients, $\beta 2$ forgetting factor for second moments of gradients.

4 Experimental Results and Discussion

4.1 Dataset Experimented

Dataset consist series of csv files from the MIT-BIH which was used to study heart rate classification using deep neural network architecture. The signal cor- responds to an electrocardiographic (ECG) style heartbeat in normal and affected by various arrhythmias and cardiac infarction. These signals are preprocessed and segmented, with each segment corresponding to a heartbeat. There are 109446 samples split into 5 classes namely N, S, V, F, Q shown in Fig 4

4.2 Result analysis

During 10 epochs, the input data is divided into batches of 650, meaning that during the training phase, the internal model parameters are changed for each batch. In order to prevent overfitting and help the models achieve greater generalizations, these batches are additionally mixed. Confusion Matrix aids in evaluating and assessing machine learning model performance [4]. This square matrix will help you to predict the performance of the model based on the test data. Positive and negative target classes, or variables, will be employed [7]. As seen

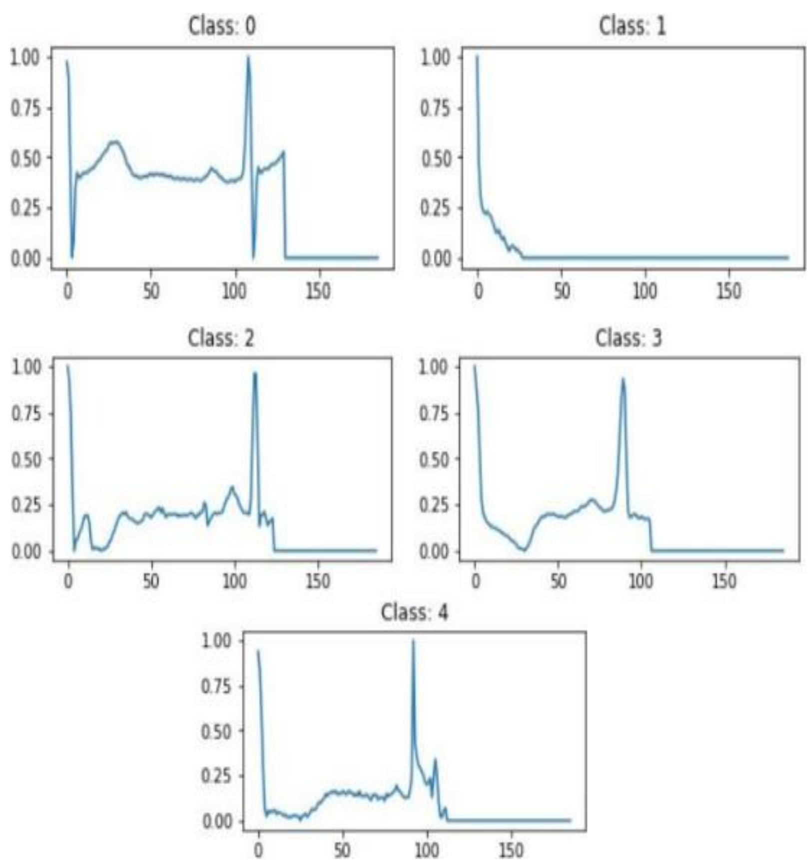

Fig. 4. Plots of different classes of ECG.

in Figure 5, the actual values are defined as rows, and the anticipated values are defined as columns.

The accuracy is about 96.44% and the plot is shown in Figure 6.

5 Conclusion

This dissertation's main goal was to develop a framework for identifying changes from the ECG signal's typical pattern. This was accomplished by creating a model that picks up on the key elements of an average ECG cycle. The model was then applied to build classification algorithms that could recognize and classify differences in terms of the existence of noise and the incidence of diseased activities.

An autoencoder was especially created, with an emphasis on its encoder component that captures progressively learnt characteristics, to implement de- signs for noise and arrhythmia detection. Through mimicking the morphology of the signals in the test dataset, the programme was able to correctly recreate ECG signals. This proved that the autoencoder could comprehend the essential elements of a typical ECG cycle.

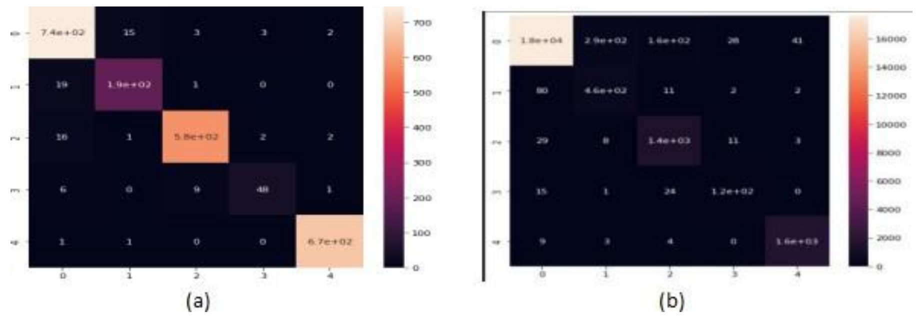

Fig. 5. Confusion Matrix for (a) Training Data (b) Testing Data.

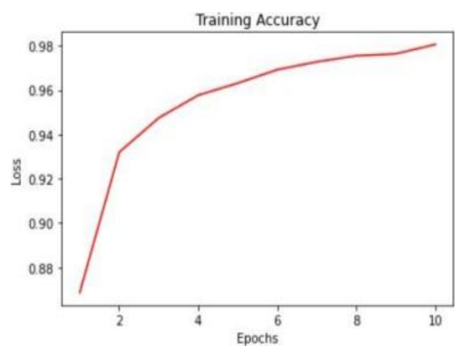

Fig. 6. Accuracy plot.

The combined performance of these algorithms validates the suggested archi- tectures' capacity to identify anomalous events in ECGs. However, it has become increasingly challenging to accurately identify the sort of abnormalities found on these signals due to the requirement for larger volumes of training data. But because it teaches important aspects of signals, the use of encoders for classification algorithms has shown to be a helpful tool in detecting illicit activity.

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