ECG SIGNAL CLASSIFICATION USING DEEP LEARNING

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***Abstract*—**
ECG interpretation is crucial in the diagnosis of cardiac diseases. The main goal is classification, and methods based on machine learning are becoming more helpful in this setting. In this research, a deep neural network-based automatic classification method for primary ECG data was developed. Data from a PTB-XL database was used for the study. A comparative study and implementation was done using three different architectures. First one is convolution network , second one using SincNet architecture, and the third one using convolutional neural network with enhanced entropy-based properties. Seventy percent of the data was used for training, fifteen percent for validation, and fifteen percent for testing. The proposed algorithms were implemented on 3 different disease groups consisting of 2, 5, and 20 people. A convolution network trained using entropy features produced the most accurate categorization. The original convolution network though not a successful classifier but resulted as computationally efficient due to its decreased neuron count.

***Keywords*:**
ECG, convolution network, PTB-XL database.

I. Introduction:

Major reason for worldwide mortality rate is cardio vascular diseases according to public reports [1]. Heart diseases are caused by cardiac arrhythmia, or an irregular heartbeat [2]. However, there are a few unique categories that irregular heartbeats might be placed into. Correctly categorizing the various forms of cardiac disease may facilitate better diagnosis and treatment [3]. Electrocardiograms (ECGs) are a common, non-invasive method of diagnosing heart problems. Twelve leads are used in a typical electrocardiogram [4]. ECG recordings have historically been evaluated by cardiologists manually, utilizing a wide range of diagnostic criteria and their own clinical expertise. However, human interpretation is complex and needs a high level of expertise. Electrocardiogram (ECG) misinterpretation might have serious consequences. Since there are not enough cardiologists to meet the growing demand for ECG technology, many researchers are currently interested in developing methods for the automated and precise interpretation of ECG data. Over the last decade, several efforts have been made to enhance the 12-lead clinical ECG, many of which have been motivated by the availability of vast quantities of open-source ECG data. It has been shown in previous work using ECG datasets [5, 6] that signal processing and machine learning use quite different methodologies. Low-pass and high-pass filters, the rapid Fourier transform, and the wavelet transform are all examples of algorithms used in digital signal processing [7]. Feature extraction, feature selection, and classification form the backbone of many algorithms in this field [8]. However, one might also resort to the use of machine learning techniques. The use of automated pattern recognition for the purpose of detecting disease entities would be the primary focus of such an application, since this method is gaining popularity in clinical settings. Over the last five years, "deep neural network" techniques have received a lot of attention. It has been shown that ECG-based diagnostics for cardiovascular illness may benefit from the deployment of deep learning models. As increasingly complicated characteristics are recovered through a hierarchy of heterogeneous layers, the quality of neural networks continuously rises. In many AI algorithmic applications, the full potential of deep neural networks has already been achieved. Medical applications, video games, and image processing are just a few of the fields that have benefited greatly from machine learning models [9]. Lack of data, unclear evaluation criteria, and unclear signal labeling have all slowed the progress of creating an automated interpretation system for

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the ECG signal. PhysioNet's reliance on preexisting data sources was found wanting [10, 11]. These included the MIT-BIH Arrhythmia Database and the PTB Diagnostic ECG Database. Algorithm development in machine learning models was stymied by the availability of data from single, tiny, or usually homogenous datasets due to the small number of patients and rhythm events. The PhysioNet/Computing in Cardiology Challenge 2020 project offered a chance to train an automated ECG classifier using data from many sources in order to solve this issue. The creation of a deep neural network model that can extract up to 27 clinical diagnoses from an EKG is an example of this kind of research. The ResNet model was utilized in one of these experiments [12], which found an AUC of 0.967 and an ACC of 0.43. The serenest model [13] was suggested to enhance the effectiveness of ECG abnormalities categorization. Others have evaluated convolution neural networks by contrasting their results on the newly published PTB-XL dataset [14], namely those based on the Resent and Inception architectures. The detection of QRS complexes, T and P waves, and the outlines of these waves' borders were proposed as a unique method for categorizing cardiovascular illnesses in [15]. The method used to categorize ECGs was divided into 19 categories. The average QRS and the distances between the detected places were used to determine the restored features. When discussing automated cardiac arrhythmia classification using ECG diagnostics, the 12-lead ECG deep learning model is most often cited. We used a deep neural network [16] based on 1D CNN and a deep learning model trained on a large ECG dataset to automatically detect multi-label arrhythmias with an accuracy of ACC = 0.94 0.97. The authors also examined and analyzed single-lead electrocardiograms. Other researchers [17] have created a model with an LSTM score of 0.6 for classifying arrhythmias. Recent study [18] utilized electrocardiograms to identify four potentially fatal arrhythmias automatically. To calculate the entropy of the electrocardiogram, these 13 nonlinear characteristics were used. ANOVA was used to classify the collected attributes, and then K-nearest neighbor and decision tree classifiers were used for automated classification. Results showed that KNN achieved an accuracy of 93.3%, whereas DT achieved an accuracy of 96.3%. With an ACC = 0.992 [19], atria fibrillation has been the subject of several deep learning ECG analysis model publications. Tests employing numerous ECG signals confirmed that the provided model accurately detected atrial fibrillation. We also used a novel convolution neural network [9] with a nonlocal convolution block attention module (NCBAM) to hone in on representative qualities spanning space, time, and channels, which helped us gain a deeper knowledge of cardiac arrhythmias and cardiovascular illnesses. The AUC that the authors saw while attempting to detect potentially hazardous arrhythmias on an ECG was 0.93. In addition to being praised in previous research [20], the potential and use of technology and the analysis of biological data have also received praise. In this study, we developed a hierarchical classification scheme using a machine learning strategy based on convolutional neural networks (CNNs). The paper included a comprehensive summary of the essential reconstruction method, including its caveats and recommendations for improvement. An alternative method for assessing ECG signals was provided by the authors of which included signal processing, data sampling, feature extraction, and classification. To interpret the ECG data, they used a deep learning class model comprised of gated recursive complexes (GRUs) and extreme learning machines (ELMs). The purpose of this research was to evaluate and contrast several neural network designs for multiclass categorization of electrocardiogram (ECG) data. The feasibility of ultra-thin categorization nets was also investigated. In this study, researchers use an innovative approach by integrating a neural network with entropy-based metrics.

II. Literature survey:

Electrocardiograms (ECGs) are a frequent non-invasive diagnostic procedure, and algorithms are being developed to aid in their interpretation. A dearth of suitable datasets for training and a lack of well-defined assessment methodologies have slowed the development of automated ECG interpretation, making it difficult to directly compare various algorithms. Our initial benchmarking findings for PTB-XL, a newly released public clinical 12-lead ECG dataset featuring a wide range of

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workloads such as ECG statement prediction, age prediction, and sex prediction, aim to address these concerns. We discover that convolution neural networks, especially those with resent- and inception-based designs, outperform other deep-learning based time series classification systems. Using classifiers retrained on PTB-XL, we achieve stable performance on the ICBEB2018 challenge ECG dataset, highlighting the potential for transfer learning. The benchmarking findings serve as a starting point for further investigation of the dataset, and are augmented with information on the hidden stratification, the model's uncertainty, and an exploratory review of the dataset's interpretability. Our findings show the potential of deep learning-based algorithms for ECG analysis, both quantitatively and in terms of additional quality criteria like uncertainty quantification and interpretability, which are of critical importance in the context of therapeutic applications. By publishing our results, we aim to inspire other scientists to conduct their own structured benchmarking of ECG analysis algorithms using the PTB-XL dataset.

Automatic analysis of electrocardiograms (ECGs) for the aim of finding and diagnosing cardiac problems is a hotly contested topic in [15]. This research aims to standardize the categorization of electrocardiograms (ECGs) into one of nineteen different categories. The HITTING team developed this algorithm for the PhysioNet/Cinch Challenge 2020. Using the collected data and custom criteria, our program can identify certain diseases. There were six different data signals gathered. It is possible to use the same apparatus to detect the QRS complex, the T wave, and the P wave, as well as their start and offset. The frequency of each QRS shape within each record was then tallied. The average and most common values for these QRS intervals were calculated. Information such as the median QRS and detection intervals were used to extract features. Using classification trees, the most useful traits and rules were isolated. We received an overall test score of 0.354 and a challenge validation score of 0.435, placing us in the middle of the pack. The simplicity of our approach is one of its main benefits. How obvious it is relies on the features algorithm used and the criteria chosen.

Cutting-edge machine learning technique Deep Neural Networks (DNNs) show promise in analyzing electrocardiographic data [13]. There is a severe lack of research towards optimizing or testing DNNs using ECG datasets. Encoding a single QRS complex using a convolutional neural network and enhancing ECG identification with entropy-based features are shown in this research. The goal of this research is to identify the optimal set of signal features for categorization. The investigated data set included the raw ECG signal, features calculated from the raw ECG signal using entropy, extracted QRS complexes, and features computed from the extracted QRS complexes using entropy. Diagnostic groups (often 2–20) were created from the cardiac examinations. The research relied on information culled from a PTB-XL database. By synthesizing the findings of several existing methods for extracting QRS from multi-lead signals, we provide a novel strategy for QRS complex extraction. Incorporating derived QRS complexes and entropy-based characteristics into the original signal improves its quality, as shown by the findings. The performance reduction was striking when compared to raw signals utilizing entropy-based features without removing QRS complexes.

The research of Maseru et al.One of the most common cardiac disorders is atrial fibrillation (AF). Most of the currently available methods for automatically classifying AF rely on qualities created by humans. The goal of this study is to automate the feature-identification process normally performed by humans using a deep learning-based approach. For our pre-trained convolution neural network (CNN), we utilized 5,655 single-lead ECG recordings. We named this network Alex Net. First, we used Continuous Wavelet Transform (CWT) to convert 30-second signal spectrograms into RGB pictures, which we then fed into Alex Net and trained with a wide range of hyper parameters. With an F1 score of 98.82 percent, an accuracy of 97.9 percent, a sensitivity of 98.1 percent, and a specificity of 90.7 percent, our method clearly beats the state-of-the-art. [4]. In [5], we zero in on Obstructive sleep apnea (OSA), defined by periodic pauses of more than 10 seconds in breathing during sleep, is the most common and serious respiratory condition. The most reliable method for diagnosing OSA is polysomnography (PSG). However, this method does need a major investment of time and money. Researchers are developing a novel method of analyzing ECG data for signs of sleep apnea to solve

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this problem. There has been much investigation on ECG-based methods for diagnosing OSA. Attribute extraction, which requires human knowledge, was the primary focus of early studies. In this study, we investigate the feasibility of predicting sleep apnea using a convolutional neural network (CNN) and a previously trained model (Alex Net).[5] Those in the group led by Dr. Z. Ibrahim [2020]Since DL is being studied in many other industries, including healthcare, it is important to be able to identify any abnormalities in the patient's electrocardiogram as soon as possible. This study provides a review of the state-of-the-art DL methods for categorizing ECG data. Convolutional neural networks, deep belief networks, recurrent neural networks, long short-term memory, and gated recurrent units are just some of the DL methods we examine here.

III. Implementation:

- **Alex Net:**

Here, we provide a refined variant of Alex Net, an FFT-based convolution neural network technique. From the user's ECG data, a more efficient sequence of activities may be determined. The ECG data was placed into Alex Net, a neural network classifier, for analysis. Fast Fourier Transform (FFT) analysis might be used to determine an item's identity. Electrocardiogram wave transformation methods allow for the detection of RR intervals, QRS complexes, T-waves, and P-waves, as seen in Fig. 1. The initial step of preprocessing is to clean up the signal by removing any unwanted noise. A deep learning-based detection approach is implemented once the functions have been obtained. Then, the vocabulary of the recommended technique is expounded upon.

We employed a convolution neural network (CNN) that has already been trained, in this case Alex Net, and gave it 5,655 single-lead ECG data. Before feeding the Alex Net for training, we built a spectrogram of all 30-second signals and transformed them to RGB pictures using Continuous Wavelet Transform (CWT). We observed that our technique not only has higher sensitivity (98.1%) and specificity (90.7%), but also higher accuracy (97.9%) and F1 score (98.82%) compared to the state-of-the-art methods.

According to the ECG theory,Electrical abnormalities of the heart may sometimes be detected by use of an electrocardiogram (ECG). Electrodes are implanted on the skin to record the electrical activity of the heart over a prolonged period of time, and the proper answer changes based on the inquirer's heart health condition. Electrocardiogram (ECG) waves during a heartbeat are in perpetual motion.

- **Datasets:**

The proposed method makes use of the arrhythmia database created by the Massachusetts Institute of Technology and Beth Israel Hospital (MIT-BIH). There are now 48 records in the database, with 47 active users. Each recording consists of 30 ECGs taken at random from a single 24-hour recording. The MLII and V5 channels are shown in these ECG recordings. The Continuous ECG Signal Pass Band Filter digitalizes the raw signal using a band pass filter with a pass range of 0.1 to 100 Hz.

Every single record in the aforementioned database. The annotation file contains both a heartbeat classification and a pulse occurrence time (the position of the R peak). A heartbeat may be identified by taking 100 measurements at the R peak. After excluding the four results that include rhythmic beats, the database is down to only 44rhythmic beats. Given their representativeness of the whole dataset, the first 20 records (100-124) are highly suggested for use as a generic training set in subsequent phases. From recordings 200-234, we were able to identify 24 instances of abnormal heart rates. Utilize the outcomes of the tests to gauge the performance of your system.

- **Right Bundle Branch Block (RBBB):** When the regular processes for controlling the heart's rhythm fail, the result is a QRS complex that looks aberrant and is called a bundle branch block. The RV often becomes depolarized due to right branch obstruction. The RBBB protocol does not engage the right branch block. A depolarizing pulse originates in the right ventricle (RV) and travels to the left ventricle (LV).

Both premature atrial contraction (PAC) and premature ventricular contraction (PVC) occur when a premature or early beat disrupts the heart's regular rhythm. An atria premature beat (or PAC) is a

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premature heartbeat that begins in the atrium. If the arrhythmia begins in the ventricles, doctors will diagnose it as PVC

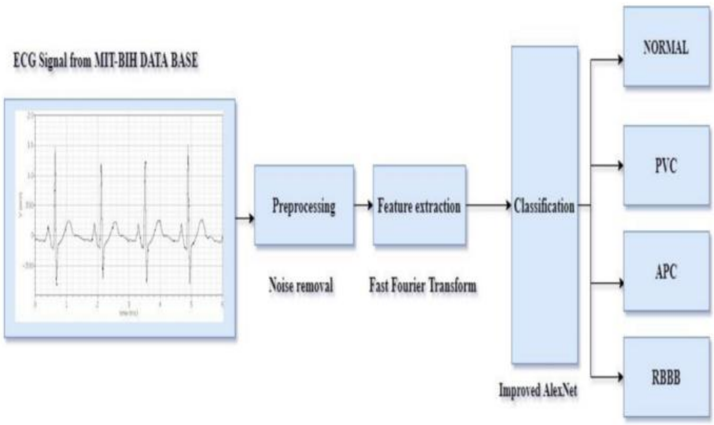

Figure 1. Block diagram for ECG data classification

Block diagram in figure. 1 shows the steps followed in classification of ECG data.

- **Pre-processing:**

Database-derived ECG data has a much lower background noise level than patient-reported data. In contrast to high-frequency noises, which may be caused by ambient stimuli, low-frequency impacts can be made by DC tones, muscular contractions, breathing motions, electrode insertion, etc. It's not hard to place some of the sounds, like those made by machines. Thus, it is necessary to do signal preprocessing in order to clean up ECG recordings. The average of 500 readings shouldn't be relied upon if the reported ECG waveform is noisy. At the end of this procedure, the amplitude of the signal's baseline will be 0. The filter is calibrated to let through low-frequency impulses while dampening higher-frequency ones, thereby reducing background noise.

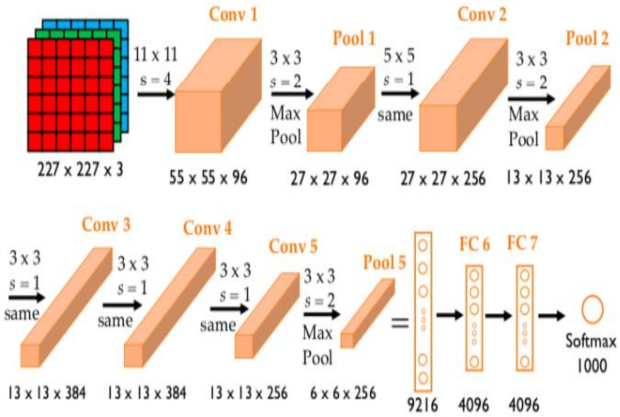

Figure.2. Preprocessing of ECG data

Deep learning's application to machine vision, and in particular the deployment of a convolution neural network dubbed Alex Net, has had far-reaching ramifications for the discipline of machine learning as a whole.

Results:

All experiments were conducted on Mat lab R2021b. We evaluated the improved Alex Net's ability to detect and categorize cardiac arrhythmias using a dataset consisting of 1200 signal segments extracted from an electrocardiogram (ECG). These 1200 records are divided into two groups, with the first serving as training data and the second as test data. Standard metrics are used to assess the accuracy, sensitivity, specificity, and precision of the Alex net model with eight layers.

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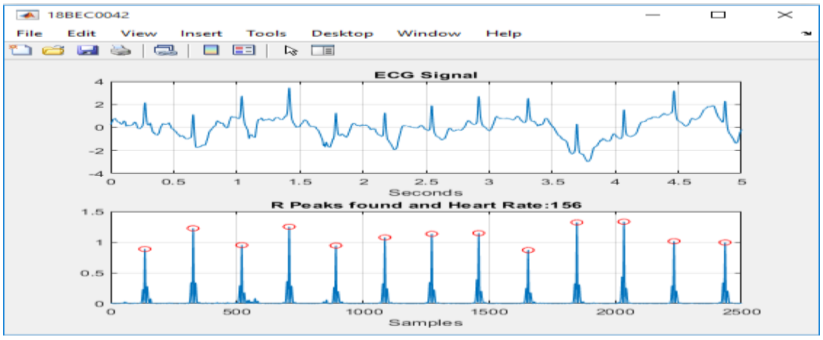

Figure 3 shows the ECG Signal and R Peaks detected

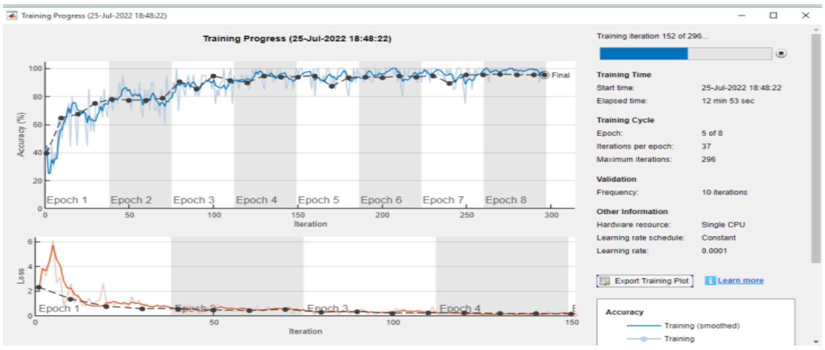

Figure 4 Shows Training Process of validating the ECG Signal using CNN

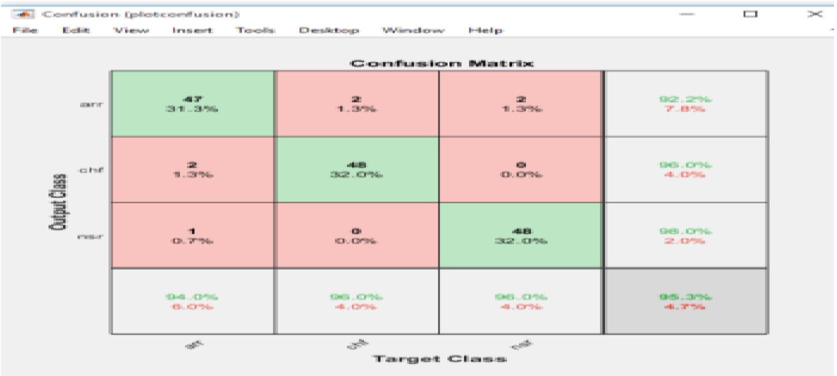

Figure 5 Shows the Confusion Matrix showing accuracy of classification

Conclusion:

While some preliminary research on ECG signals for this issue does exist, existing models are inadequate for doing in-depth analysis. Very solid evidence has been found through analyzing alpha, beta, delta, and gamma characteristics. Traditional ML-based models such as PSO, GA, RFO, and others fared poorly. The suggested Alex Net CNN deep learning technique has the potential to increase a variety of measures, including accuracy, sensitivity, Recall, F1 measure, and throughput. The results of our calculations and experiments will be revealed in forthcoming studies.

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