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A Deep Convolution Neural Network Framework for ECG Signal Classification

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Abstract
The classification of Electrocardiogram (ECG) signals is a crucial aspect of modern healthcare, aiding in the early diagnosis and management of various cardiac conditions. ECG signals capture the electrical activity of the heart and provide valuable insights into its rhythm and health. Accurate classification of different ECG beat types, such as Normal Beats, Unknown Beats, Ventricular Ectopic Beats, Supraventricular Ectopic Beats, and Fusion Beats, is essential for effective arrhythmia detection. In this research paper, a novel approach is introduced where a deep learning Convolutional Neural Network (CNN) model is employed for the precise categorization of ECG signals into distinct groupings, encompassing Normal Beats, Unknown Beats, Ventricular Ectopic Beats, Supraventricular Ectopic Beats, and Fusion Beats. The diagnosis of cardiac arrhythmia heavily relies on the analysis of ECG signals, and the challenge of achieving robust beat classification is addressed by this study. Through the utilization of the CNN's inherent capability to automatically derive hierarchical features from unprocessed signal data, a refined framework is provided by our model for the efficient capture of subtle inherent patterns within diverse beat types.

Keywords: Electrocardiogram, Deep learning, ECG beat types, Convolutional Neural Network

I. Introduction

The adoption of Internet of Things (IoT) technology into the medical field has fundamentally altered the manner in which we approach the care, diagnosis, and treatment of individual patients [1]. The Internet of Things (IoT) enables smart healthcare systems to harness the power of networked devices and data analytics to provide real-time monitoring and analysis as well as tailored healthcare solutions [2]. Predicting and avoiding cardiac problems, which continue to be one of the major causes of mortality on a global scale, is one of the most important applications of internet of things technology in the medical field.

Analyzing an electrocardiogram, often known as an ECG, is an extremely important step in both the diagnosis and prognosis of cardiac conditions. An electrocardiogram, or ECG, is a graphical depiction of the electrical activity of the heart, and it offers important insights into both normal and pathological cardiac function. Traditional ECG analysis techniques, on the other hand, often call for manual interpretation by qualified medical professionals. This results in delays, human mistakes, and a restricted capacity for scaling up.

The use of Convolutional Neural Networks (CNN), which is a strong approach for automated electrocardiogram (ECG) analysis [3], has emerged as a solution to these issues. The ability of CNNs, which are a kind of deep learning model, to extract nuanced patterns and features from large amounts of complicated data makes them well suited for the analysis of ECG signals. Healthcare professionals are able to considerably increase the accuracy of cardiac disease prediction by making use of devices connected to the internet of things (IoT) as well as the capability of convolutional neural networks (CNNs).

Because of a number of different circumstances, it is of the highest need to have internet of things (IoT)-based smart healthcare systems that can analyze electrocardiograms [4]. To begin, cardiac disorders are often asymptomatic until they have already reached an advanced stage, at which point they pose a significant risk of death. It is essential to do early diagnosis and prediction in order to carry out timely treatment and achieve better patient outcomes. Analysis of an electrocardiogram that is based on the internet of things allows continuous monitoring of patients in real time, which in turn helps medical personnel to detect abnormalities and potentially life-threatening illnesses more quickly.

Second, the growing incidence of chronic illnesses, the prevalence of sedentary lifestyles, and the proportion of elderly people in the population place a burden on healthcare resources and call for solutions that are more productive and economical. This burden may be alleviated by Internet of Things (IoT)-based smart healthcare systems by remotely monitoring patients, lowering the number of hospital visits, and allowing individualized treatment [5]. Patients are now able to monitor their own electrocardiogram (ECG) readings from the comfort of their own homes thanks to the integration of Internet of Things (IoT) equipment such as wearable sensors and mobile apps. This gives medical practitioners vital data for use in analysis and preventative therapy.

In addition, the scalability and interoperability provided by IoT-based smart healthcare systems make it possible to apply them on a massive scale [6]. By integrating cloud computing and data analytics, healthcare practitioners are able to combine and analyze massive volumes of ECG data derived from a variety of sources. This makes it easier to conduct research and studies on a population level, which may lead to new methods for the treatment and prevention of cardiac disease.

IoT-based smart healthcare systems, when paired with CNN-based ECG analysis, have a tremendous amount of promise to revolutionize the ways in which we diagnose, prevent, and treat cardiac ailments. These new technologies have the potential to improve patient care, lower overall healthcare costs, and ultimately save lives. They do this by making real-time monitoring and automation possible, as well as by providing data-driven insights. The Internet of Things (IoT) and deep learning technologies converging together marks a huge step toward a more preventative and individualized approach to healthcare. This new approach will be beneficial to people, healthcare providers, and society as a whole.

II. Literature survey

J. Pandia Rajan et al [7] developed a unique approach that makes use of a deep convolutional neural network (DCNN) and a modified vesselness assessment to determine the anatomy of the oral cancer area in an IoT-based smart healthcare system. The CNN framework significantly increases classification accuracy by deblurring focused area of interest (ROI) by integrating with multi-dimensional information from feature vector selection stage, while the resilient vesselness filtering approach tackles noise while sparing tiny structures. From each linked component in the area, the marked feature vector points are retrieved and utilised as training data for the CNN. Each linked component is independently examined utilising the trained DCNN during classification by taking into account the feature vector values specific to that area.

Mrinai M. Dhanvijay et al [8] described the WBAN-based Internet of Things healthcare system and conducts a state-of-the-art analysis of the network architecture topology and applications used in Internet of Things solutions for healthcare. In addition, this article examines the security and privacy features that are quite problematic in a variety of IoT healthcare architectures. These features include real-time wireless health monitoring, privacy, authentication, energy management, power management, resource management, Quality of Service, and resource management. The limitation of data and the maintenance of its integrity are both difficult tasks at this time since the architecture of the system is not fully defined. At this time, ninety percent of the information that is currently accessible has been gathered during the last two years. This survey's primary objective is to investigate healthcare purposes from the perspective of digital healthcare delivery systems.

R. Bharathi et al [9] demonstrated an Energy Efficient Particle Swarm Optimization (PSO) based Clustering (EEPSOC) approach for the efficient selection of cluster heads (CHs) from a wide variety of Internet of Things devices. The Internet of Things devices that are used in the sensing of healthcare data are arranged in the form of clusters, and a CH will be chosen via the application of EEPSOC. The data will be sent to the cloud server by the CH that was chosen. After then, it is up to the CH to ensure that the data collected by the IoT devices is successfully sent to the cloud server by using fog devices. Following that, a classification model that is based on artificial neural networks (ANN) is used to diagnose the healthcare data that is stored in the cloud server in order to determine the severity of the disorders.

Priyanka Dwivedi et al [10] discussed about the healthcare system that is in place now, and then go on to the micro and wearable sensors that are utilised for diagnostic reasons. The electrical components that are utilised to drive the sensors and other devices, as well as the transmission of the data that is gathered, will get more attention throughout the chapter.

Manjurul Ahsan et al [11] provided a structured literature review (SLR) methodology to identify the problems caused by unbalanced data in forecasts of heart disease. Prior to that, the authors performed a meta-analysis using 451 pieces of reference material that they had obtained between 2012 and November 15, 2021, from reputable publications. The kind of cardiac illness, algorithms, applications, and solutions have all been taken into consideration in an in-depth review of 49 references to literature. Our SLR research found that when dealing with unbalanced data, the present techniques run into a number of unresolved challenges, which ultimately hinders their actual usability and effectiveness.

Fajr Ibrahem Alarsan et al [12] suggested a machine learning-based ECG (Electrocardiogram) classification technique based on several ECG variables. A signal that gauges the electric activity of the heart is called an electrocardiogram (ECG). The suggested method is implemented on the Apache Spark platform utilising the Scala programming language and ML-libs, which is a scalable machine learning package. Dealing with the anomalies in the ECG signals, which are crucial for determining the patient's health, is the main problem in ECG classification. As a result, the authors have suggested a practical method for accurately classifying ECG data. Action impulse waveforms generated by several specialised cardiac heart tissues combine to make each heartbeat. Classifying heartbeats may be challenging since their waveforms vary from person to person and have distinct characteristics. The machine learning algorithm uses these characteristics as inputs. Using Spark-Scala tools generally

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makes it easier to use numerous techniques, including machine learning (ML) methods. On the other hand, Spark-Scala is utilised more often than other technologies when the amount of data being processed is too enormous.

Nahian Ibn Hasan et al [13] provided a technique for classifying different cardiac disorders using a one-dimensional deep convolutional neural network (CNN). The input signal to the network is a modified electrocardiogram signal. Each electrocardiogram signal is initially subjected to Empirical Mode Decomposition (EMD), which is followed by the combination of higher order Intrinsic Mode Functions (IMFs) to produce a modified electrocardiogram signal. It is expected that using EMD would be capable of providing a denoising performance and would allow access to a wider variety of information. This processed signal is then input into the CNN design, which classifies the record according to various cardiovascular conditions by using a softmax regressor as the last step in the network. In compared to the raw ECG signal, it has been discovered that the CNN architecture learns the intrinsic properties of the modified ECG signal in a much more efficient manner.

Xinwen Liu et al [14] examined the research that have already been done on the use of deep learning in ECG diagnosis using the following four common algorithms: stacking auto-encoders, deep belief network, convolutional neural network, and recurrent neural network. First, the authors discussed the mechanisms behind, as well as the creation of, and applications for, the algorithms. After that, they take a methodical look at their applications in ECG diagnosis and analyse the salient features of such applications as well as their limitations.

Ankita Tyagi et al [15] developed hybrid Convolutional Neural Network (CNN) framework using Grasshopper Optimization Algorithm (GOA) to identify cardiac illnesses from ECG signals or heartbeats. Computer vision-based medical data analysis employs Convolutional Neural Network (CNN) artificial intelligence. Due to noise and irrelevant data, the standard CNN cannot classify heart illnesses from ECG signals. This study uses pre-processing and feature selection to classify heart diseases. Discrete Wavelet Transform (DWT) reduces noise and segments ECG signals, and Grasshopper Optimization Algorithm (GOA) selects R-peaks features from extracted feature sets in terms of R-peaks and R-R intervals to improve classification accuracy.

V. Jahmunah et al [16] created an automated system (AS), by using Convolutional neural network (CNN) and special GaborCNN models, for the automatic classification of ECG data into normal, CAD, myocardial infarction (MI), and congestive heart failure (CHF) classes. The unbalanced dataset was balanced using weight balancing.

Ritu Aggarwal et al [17] offered a framework for heartbeat analysis, a normal and abnormal ECG, and a heartbeat arrangement. In this chapter, explainable artificial intelligence (XAI) is used in terms of machine learning. This project employed ANN to count the neurons in accordance with the disorders that were extracted from this chapter. The fundamental difficulty in classifying ECG data is dealing with the anomalies that are crucial for determining patient status. Five machine learning algorithms are employed in this study to imagine individuals with a certain ailment and distinguish between normal and bad ECGs based on their features.

Mihaela Porumb et al [18] discussed Convolutional Neural Network (CNN) approaches to the automated detection of CHF have the potential to significantly improve techniques focusing on sophisticated signal processing and machine learning, but have mostly been ignored up until now. This work closes this critical gap by proposing a CNN model that correctly detects CHF from a single raw electrocardiogram (ECG) pulse while also contrasting it with the current approaches that are mainly based on heart rate variability.

Manish Sharma et al [19] suggested making use of a newly designed optimally time-frequency concentrated (OTFC) even-length biorthogonal wavelet filter bank (BWFB), for the purpose of automatically recognising CAD. The evaluation of coronary artery disease (CAD) utilises ECG segments with lengths ranging from 2s to 5s. The OTFC decomposed coefficients were used to get the fuzzy entropy (FE) and the log-energy (LogE).

R. Lakshmi Devi et al [20] created an Internet of Things (IoT)-enabled ECG monitoring system to examine the ECG signal The raw ECG signal's statistical characteristics are computed. The Pan Tompkins QRS detection technique is used to examine the ECG data in order to extract its dynamic properties. The technology is used to extract RR intervals from an ECG signal in order to record aspects of heart rate variability. The classification technique is then used to categorise the cardiac arrhythmia condition using statistical and dynamic variables. Even at home, people may use the acquisition of an ECG signal to assess their heart health.

III. Proposed model

Heart disease has consistently been among the top 10 causes of mortality in the nation, coming in second place during the previous ten years. It is challenging to depend only on general health examinations. If the condition is discovered, more testing or monitoring are required to identify, treat, and prevent it early. The physical features included in the heart database (Kaggle and real-time data) have been utilised in this study to create a prediction model to categorise the causes that lead to heart illness and provide clinicians the ability to determine the disease's root cause, which requires extra care.

3.1 Proposed Classification model

A CNN is a neural network that has a layer (the convolutional layer) that filters input data using convolutions. Either FNN or RNN may be the topology. CNN is excellent for visual content. It is utilised to solve a variety of issues and is well recognised to be very helpful for the examination of such sectors.

a) One-dimensional convolution

Take into consideration a condition in which the vector at time t, the vector at time t + 1, and so on are lined up as inputs in the correct order. Take note that these are facts gathered over a period of time. In this stage of the process, it is about the time when the input has already been converted to an appropriate shape and input to the one-dimensional convolution; however, as a step prior to this, in the case of natural language processing, operations such as tokenization and vectorization are carried out. Must be done. When performing a convolution with just one dimension, the number that was previously supplied as the kernel size (3,3) is now referred to as the window size, and only one value is specified.

The arrangement of the vectors in the time direction creates the appearance of a two-dimensional map; nevertheless, the axis in the time direction represents the spatial direction, while the axis in the vertical direction represents the channel axis. When applying one-dimensional convolution to series data, the processing of convolution is

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only performed on the time axis. This is analogous to how the convolution layer used in image recognition does convolution processing on the spatial axis of the feature map. Carry out convolution, and then, as a final step, add in the channel direction. "One-dimensional convolution is a convolution process in the time axis direction," is a phrase that may be used to summarise the arguments made here in a single word. The time axis is shown on the horizontal axis of the input data, while the channel axis is represented on the vertical axis. Following the use of 1D convolution, the number of channels will be equivalent to the number of filters.

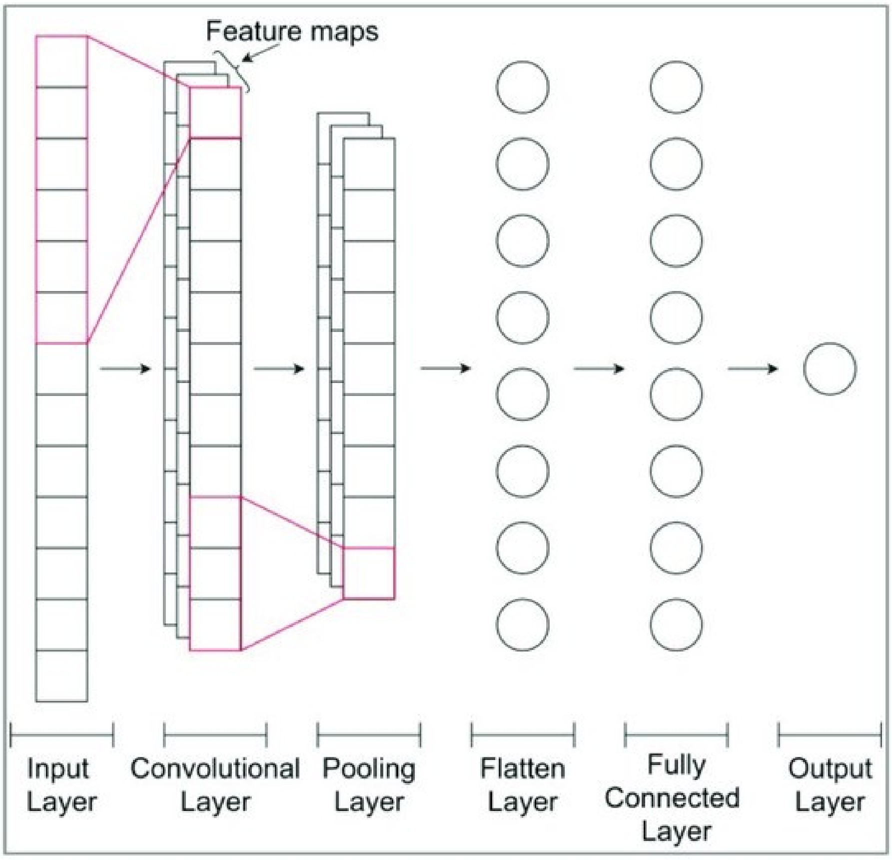

Figure 1: 1D convolution

A model that is able to attain good recognition performance by only receiving visual data is referred to as a convolutional neural network. Backpropagation is the technique of learning that is used by this neural network, much like a regular neural network. It originated from the concept of attempting to duplicate the function of nerve cells in the visual cortex that we humans possess, as seen below. This led to the development of the notion.

- Simple cell, often known as a S cell, is a kind of cell that identifies the shading pattern (feature) of an image.
- Complex cells (C cells): These cells are able to compensate for misalignments in space by treating them as if they had the same properties.

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b) Structure of convolutional neural network

The structure of the most fundamental convolutional neural network is depicted in the figure located above. In the beginning is the input layer, next comes the convolution layer, which consists of simple cells, and finally the pooling layer (complex cells). After that, the structure is designed in such a way that the output layer and the completely linked layer continue. The probabilities are acquired by the output layer, which also processes the information in the same manner that the output layer of a traditional neural network would. The following is an explanation of the functions done by each layer of the convolution layer, the pooling layer, and the fully connected layer, as well as the processing content that is being carried out.

- **Convolution layer**

The convolutional layer is modelled after a basic cell and is set up to react to a certain form in the same way that a simple cell would. During the process of data learning, this specific shape, which is referred to as a filter, is automatically modified. The individual neurons that make up the convolution layer only connect to groups of neurons that are located in certain parts of the input data. When scanning an input picture, this area, which is also present in simple cells and is referred to as the local receptive field, travels one pixel at a time.

If one neuron in the convolutional layer is linked proportionally for each pixel movement, and if the form of the filter is discovered in the local receptive field, then the neuron in the convolutional layer fires, and it is impossible to find it. An input value from a neuron corresponding to the local receptive field of the input data is used by one neuron in the convolutional layer, and another neuron in the convolutional layer is utilised when the local receptive field moves. Both of these neurons are employed in the same layer. consists of more than one structure.

- **Pooling layer**

The pooling layer is a model of a complicated cell that serves the purpose of absorbing any misalignment of the filter shape that may exist in the input picture. When compared to the convolution layer, the method is rather straightforward. A portion of the convolutional layer's neurons are connected to specific neurons in the pooling layer. On the other hand, the areas that make up this convolution layer do not overlap, and each neuron in the convolution layer links to exactly one neuron in the pooling layer.

The output value of each neuron in the pooling layer is changed such that it corresponds to the highest possible value among the output values of the neurons in the convolutional layer that are to be linked. Because of this, it is now able to absorb any misalignment that may exist in the geometry of the filter. Let's see how it works. When a neuron in a layer that has a pooling component fires, it indicates that other neurons in the corresponding convolutional layer have also been activated. When we consider this in relation to the input layer, it indicates that the filter shape is present in the part of the layer that is responsible for the synthesis of the region of the local receptive field that corresponds to multiple neurons in the convolutional layer. In other words, this region corresponds to

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the portion of the local receptive field that is covered by a single neuron in the convolutional layer. Within the range that was deviated from, it is feasible to identify the form.

Pooling, which may also be referred to as down sampling or subsampling, is a method for reducing the overall size of the feature map by carrying out a series of specific processes.

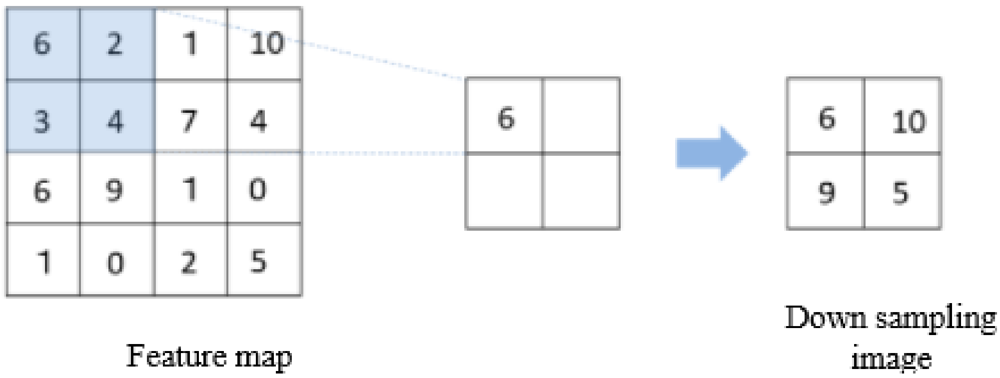

Figure 2: Pooling layer

The procedure known as max pooling is shown in the figure that can be seen above. Each time there is a 2x2 grid, the maximum value of the feature map is taken out, and a new downsampling picture is obtained. There is a method known as max pooling, as well as another method known as avg pooling, which uses an average value instead of the maximum value.

- **Fully connected layer**

In a typical neural network, the completely connected layer would be equivalent to both the hidden layer and the output layer. The pictures that have been generated up to this point are made one-dimensional in the completely linked layer so that they can be differentiated from one another.

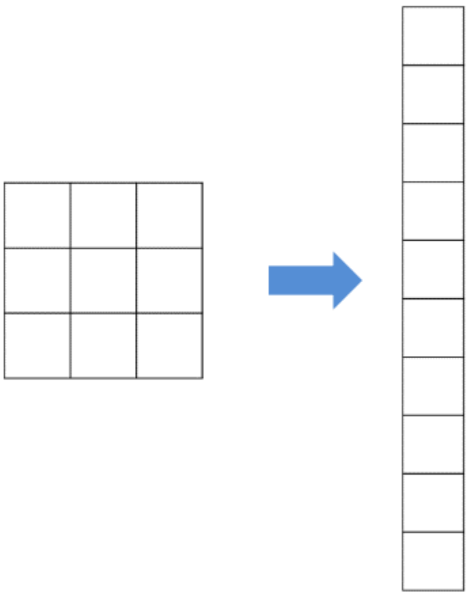

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Figure 3: Fully connected layer

First, a description of the layer that contains all of the connections will be given. $u = (u_1, u_2, \ldots, u_I)$ is what is being fed into the layer as its input. The total number of units in the layer is denoted by the letter J, and the aggregate expression of all of their outputs is written as $v = v_1, \ldots v_j$. At this point, the output is being produced in the layer that is completely linked.

$$v_j = f\left(\sum_{i=1}^{I} w_{ji} u_i\right) \qquad (3.7)$$

w_{ji}, is the weighting factor and f is the activation function. In a fully connected layer, all inputs are passed to all units. The parameters of the fully connected layer are "number of units" and J × 1 weighting factor w. Normally, the number of units is fixed and the weighting coefficient is determined by the gradient method. The function is to output the ignition / non-ignition classification by the hyperplane as given by each unit in parallel. The fully connected layer is a module that is used not only for CNN but also for general purposes.

IV. Experimental Results

ECG, or electrocardiogram, is a non-invasive diagnostic tool that records the electrical activity of the heart over time. This activity is represented as a waveform that is displayed on a monitor or printed on paper. ECGs are commonly used to diagnose various heart conditions, such as arrhythmias, heart attacks, and abnormal heart rhythms.

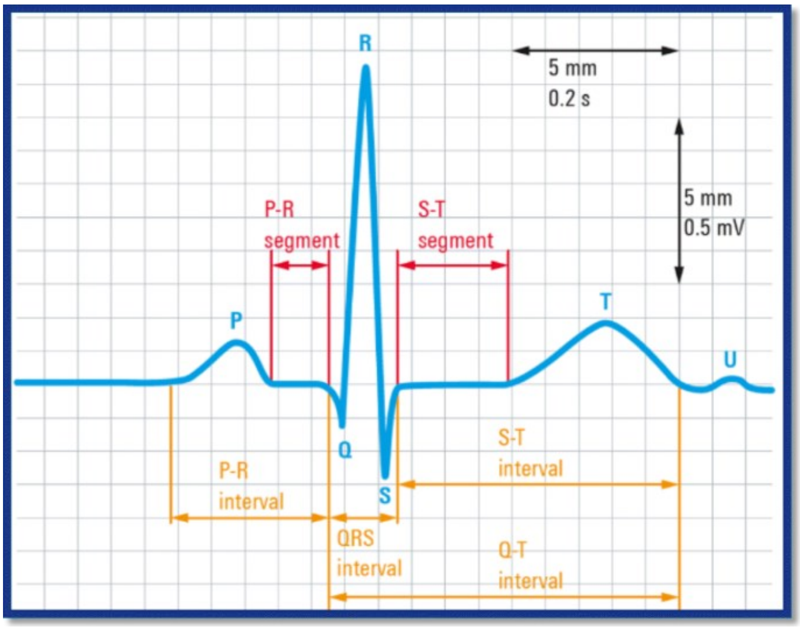

Figure 4: ECG signal

The electrical activity of the heart is initiated by the sinoatrial (SA) node, a natural pacemaker located in the right atrium of the heart. The electrical signal then spreads through the atria, causing them to contract and push blood into the ventricles. The signal then travels to the atrioventricular (AV) node, which briefly delays the signal to allow the ventricles to fill with blood. The signal then continues down the bundle of His and its branches, causing the ventricles to contract and pump blood out of the heart.

Dataset:

The MIT-BIH Arrhythmia Database is a publicly available dataset of electrocardiogram (ECG) recordings collected at the Massachusetts Institute of Technology (MIT) in the 1970s. The

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database consists of over 3,000 ECG recordings of 48 different patients, each of which is annotated with the corresponding beat classification and rhythm annotation. The ECG recordings in the MIT-BIH Arrhythmia Database were collected using standard ECG equipment and were sampled at 360 Hz. The recordings have a duration of 30 minutes each and include a wide range of different arrhythmias, such as premature ventricular contractions (PVCs), supraventricular tachycardia (SVT), and ventricular tachycardia (VT).

Types of ECG in dataset

- **Normal Beats**

Normal beats are the regular and rhythmical heartbeats that are seen on an electrocardiogram (ECG) and originate from the sinus node, the natural pacemaker of the heart. The normal beat consists of a P wave, QRS complex, and T wave.

- **Unknown Beats**

Unknown beats, also known as unidentified or unclassified beats, are a type of abnormal heartbeat that cannot be classified as a specific type of arrhythmia or normal heartbeat based on their appearance on an electrocardiogram (ECG). These beats may have a different morphology, amplitude, or timing compared to normal beats or known arrhythmias, making them difficult to diagnose or interpret.

- **Ventricular ectopic beats**

Ventricular ectopic beats (VEBs) are abnormal heartbeats that originate in the ventricles of the heart instead of the normal electrical pathway. These abnormal beats can be detected on an electrocardiogram (ECG) and can indicate a variety of underlying heart conditions.

- **Supraventricular ectopic beats**

Supraventricular ectopic beats (SVEBs) are abnormal heartbeats that originate above the ventricles in the atria or the atrioventricular (AV) node. These abnormal beats can be detected on an electrocardiogram (ECG) and can indicate a variety of underlying heart conditions.

- **Fusion Beats**

Fusion beats are a type of abnormal heartbeat that can occur on an electrocardiogram (ECG). A fusion beat is the result of the simultaneous activation of the ventricles by two electrical impulses: one that originates in the sinus node, and another that originates from an ectopic focus in the atria or ventricles.

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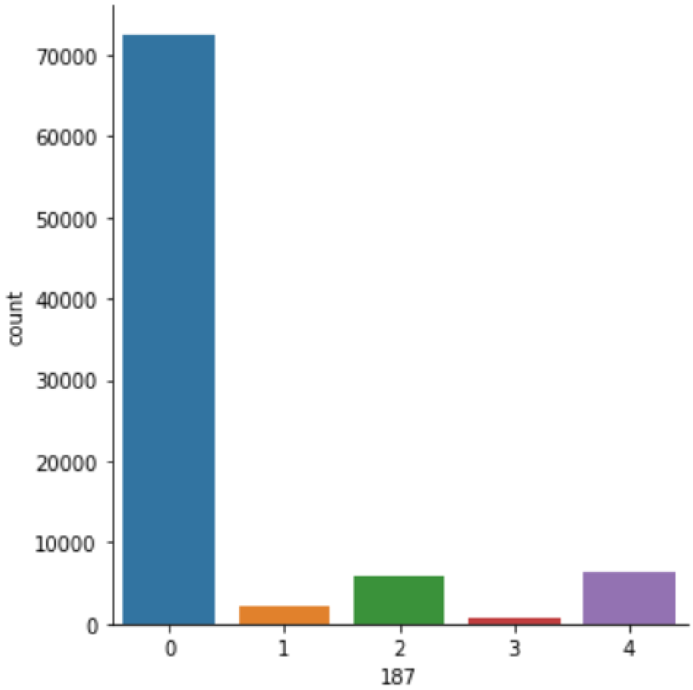

Figure 5: counts of each classes

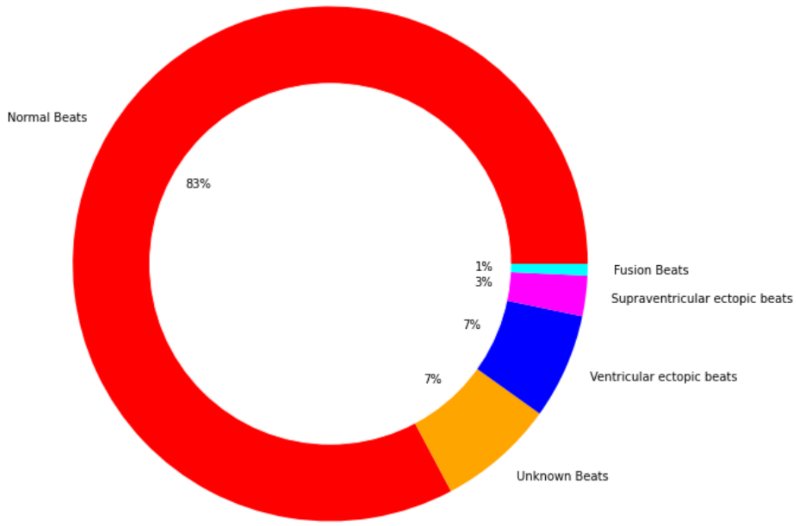

Figure 6: Types of heart beats

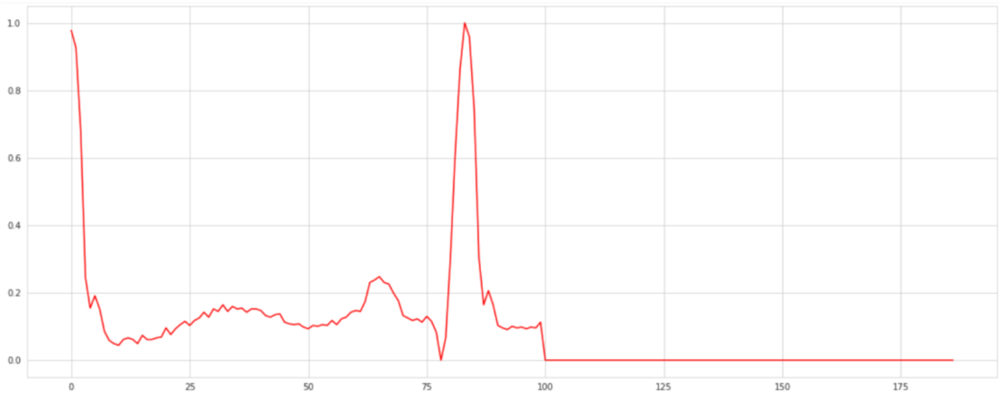

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Figure 7: Sample ECG

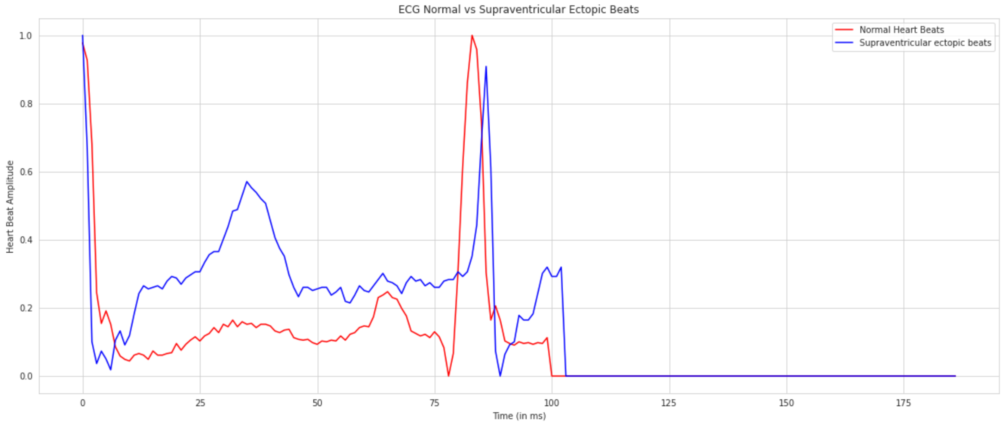

Figure 8: ECG normal vs Supraventricular Ectopic Beats

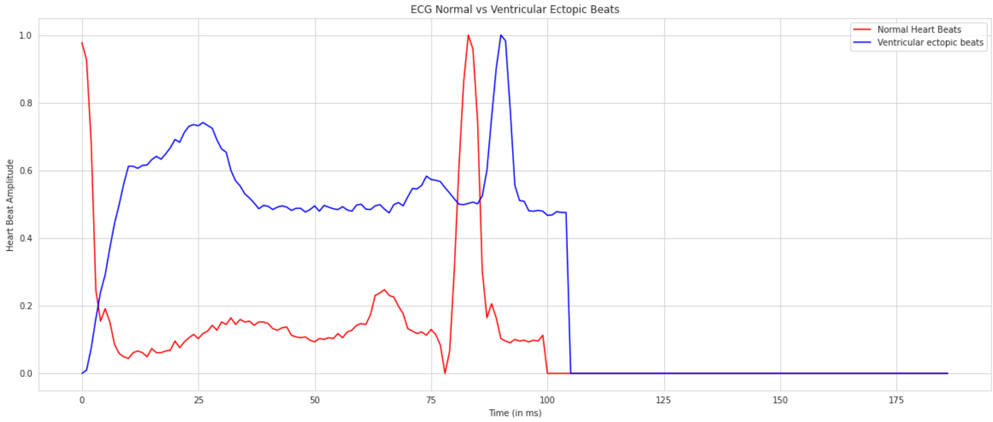

Figure 9: ECG normal vs Ventricular Ectopic Beats

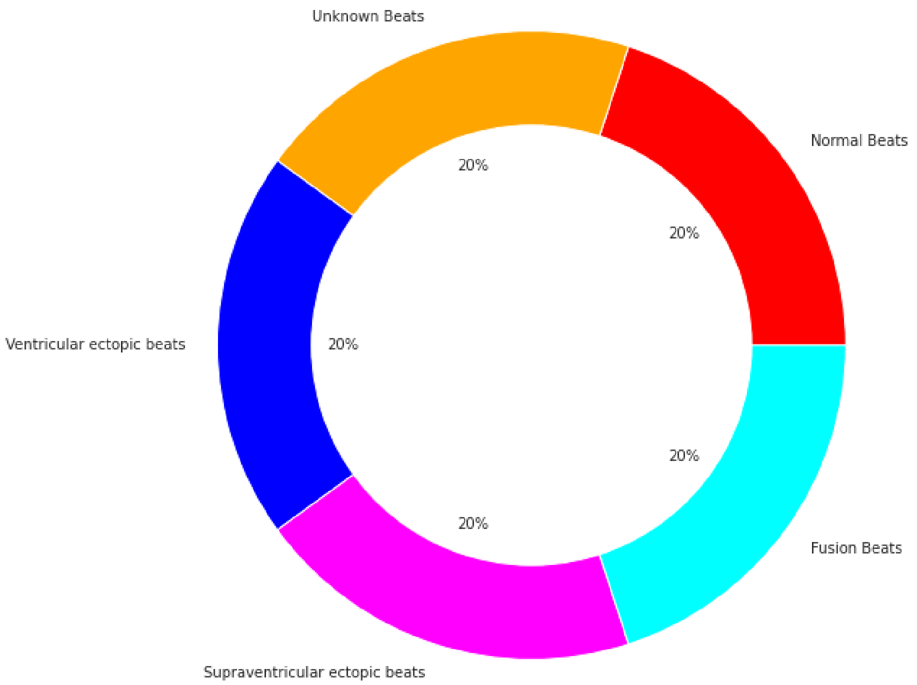

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Figure 10: Types of heart beats

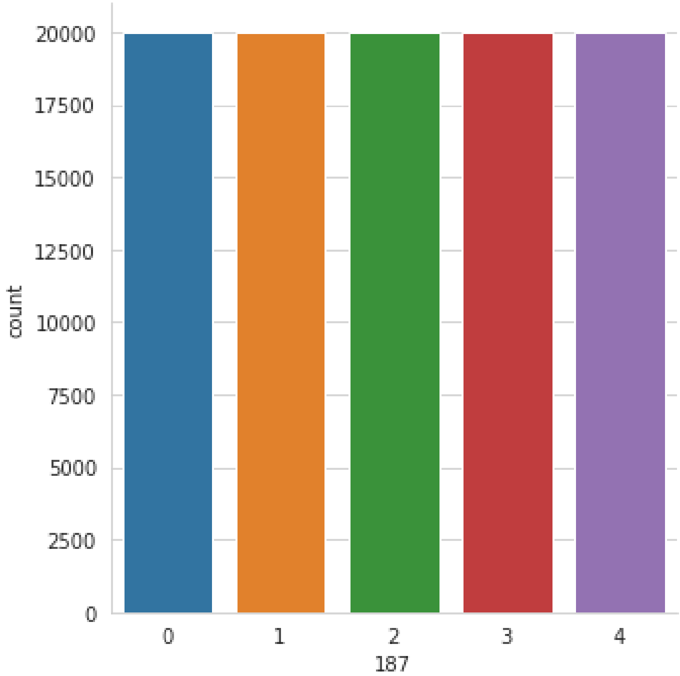

Figure 11: Count of each classes

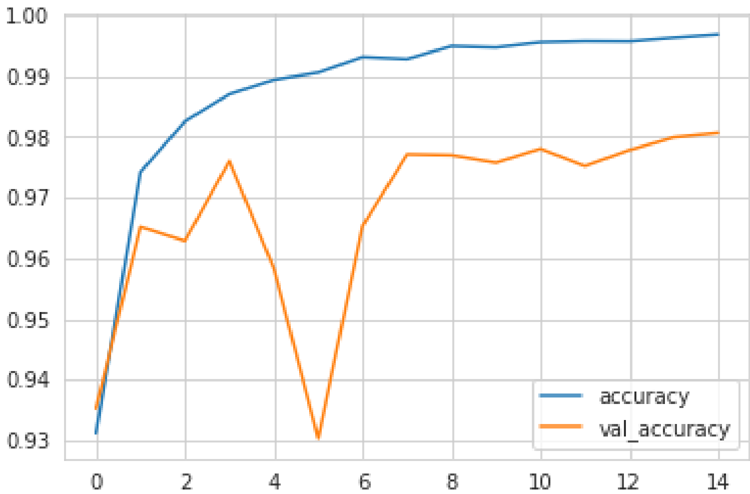

Figure 12: Accuracy

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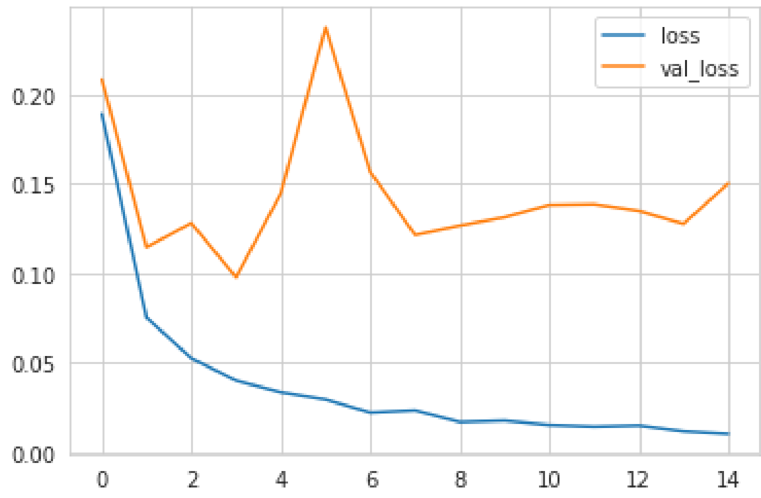

Figure 13: Loss

Training accuracy and loss are key metrics in evaluating the performance of a machine learning model during its training phase shown in figures 12 and 13. Training accuracy represents the proportion of correctly predicted instances within the training dataset, giving an understanding of how well the model fits the training data. On the other hand, training loss quantifies the dissimilarity between the model's predicted values and the actual target values during training, offering insight into how well the model's predictions align with the true outcomes. The goal is to achieve high training accuracy while minimizing training loss, striking a balance between accurate predictions and effective learning from the data.

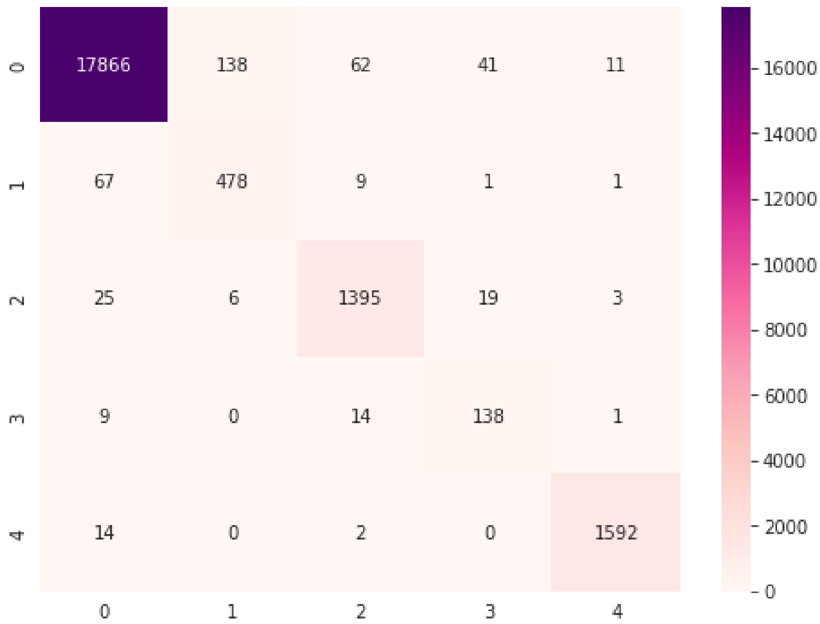

Figure 14: Confusion matrix

The confusion matrix is a fundamental tool in evaluating the performance of a classification model shown in figure 14. In this scenario, the confusion matrix has led to the following evaluation metrics:

- **Accuracy:** The accuracy of 0.98 indicates that 98% of the model's predictions are correct overall.
- **Precision:** With a precision of 0.87, the model's positive predictions are accurate around 87% of the time, minimizing false positives.
- **Recall:** The recall score of 0.93 means the model correctly identifies about 93% of the actual positive instances, minimizing false negatives.
- **F1-score:** The F1-score of 0.90 is a balanced measure combining precision and recall. It reflects the model's effectiveness in finding a trade-off between false positives and false negatives.

Together, these metrics from the confusion matrix provide a comprehensive view of the classification model's performance, highlighting its accuracy, precision, recall, and the balance between precision and recall captured by the F1-score.

Table 1: Evaluation parameters of Proposed method

Parameters	value
Accuracy	0.98
Precision	0.87
Recall	0.93
F1-score	0.90

Table 1 shows the results for evaluation parameters of proposed method. The value of different parameters like Accuracy, precision, recall and f1-score is 0.98, 0.87, 0.93 and 0.90.

V. Conclusion

In this paper, we present a comprehensive study employing a deep learning Convolutional Neural Network (CNN) model for the accurate classification of ECG signals across multiple beat types. The proposed model distinguishes between Normal Beats, Unknown Beats, Ventricular Ectopic Beats, Supraventricular Ectopic Beats, and Fusion Beats, catering to a broad spectrum of arrhythmia detection. Leveraging the CNN architecture's ability to learn hierarchical features from raw signal data, our model achieves robust performance in classifying ECG beats. Through extensive experimentation and evaluation, we demonstrate an efficient and effective solution that contributes to advancing automated ECG analysis, holding promise for enhanced cardiac arrhythmia diagnosis and monitoring systems.

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