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A Novel Approach For Ecg Anomaly Detection Using Cnn

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Cardiovascular arrhythmias pose a significant challenge to global cardiac health. Thisstudy aims to develop an automated system for detecting and classifying arrhythmias us-ing the MIT-BIH database, employing three deep learning algorithms. Our investigation reveals that the Convolutional Neural Network achieved the highest accuracy of 99%, com- parable to state-of-the-art methods. Specifically, in the implementation of ECG anomaly detection using CNN, we compared CNN with Artificial Neural Network and Long Short- Term Memory models, highlighting CNN's superior performance. The accuracy of ANN 97.10 %, and LSTM is 98.97%. This research underscores the potential of CNN in im- proving the accuracy of arrhythmia detection, offering promising prospects for enhancingclinical diagnosis and treatment outcomes.

I. Introduction

The landscape of cardiovascular healthcare is characterized by a critical need for efficient and reliable methods of detecting electrocardiogram signal abnormalities. Cardiac abnormalities pose significant health risks and complications, necessitating accurate monitoring systems. However, resource-constrained medical environments, coupled with limited access to skilled practitioners, amplify the challenge of timely detection of cardiac abnormalities in ECG readings. Traditional manual interpretation of ECG readings, while effective, is labor-intensive and prone to human error. In such contexts, automated solu- tions offer promise for addressing these limitations, with Convolutional Neural Networks emerging as a potent tool for analyzing ECG signals and predicting abnormalities.

2. Background

The current landscape of cardiovascular healthcare underscores the pressing need for efficient and reliable methods of arrhythmia detection. With cardiac abnoramality posing significant health risks and complications, the demand for accurate monitoring systems has never been greater. However, the reality of resource-constrained medical environments, where access to skilled practitioners is limited, exacerbates the challenge of timely cardiac abnormality detection. Traditional manual interpretation of electrocardiogram readings, while effective, is labor-intensive and prone to human error. In such contexts, automated solutions offer a promising avenue for addressing these limitations, with Convolutional Neural Networks emerging as a potent tool for analysis of ECG signals.

The development of automated cardiac anomaly detection systems holds profound implications for improving patient care and healthcare efficiency. By leveraging CNNs and other deep learning techniques, this project seeks to bridge the gap between the critical need for continuous cardiac abnormality monitoring and the constraints of available resources. Through the implementation of a CNN-based anomaly detection system for ECG signals, project aim to empower healthcare practitioners with a reliable tool for early identification and intervention of cardiovascular irregularities. By automating the detection process, this solution not only enhances the speed and accuracy of diagnosis but also mitigates the burden on healthcare resources, ultimately advancing the quality of cardiovascular care and improving patient outcomes.

3.Electrocardiogram

An electrocardiogram (ECG) is a diagnostic tool used to measure the electrical activity of the heart over a period of time. It's commonly employed to assess heart rhythm abnormalities and to detect various cardiac conditions like arrhythmias, myocardial infarction (heart attack), and heart enlargement.[2] During an ECG, electrodes are placed on the skin of the chest, arms, and legs, which then detect the electrical impulses generated by the heart. These impulses are recorded as waves on a graph, providing valuable information about the heart's health and function.[3] ECGs are routinely used in medical settings, including hospitals, clinics, and doctor's offices, as part of cardiac evaluations and monitoring.

ECG Signal Preprocessing

During the process of capturing ECG data, the signal often gets distorted by different noises and physiological artifacts. Hence, it's essential to apply a pre-processing algorithmto refine the data.[4]In order to remove baseline wander, electromyographic (EMG) noise, and power line interference contained in the ECG signal, numerous methods have been proposed, such as bandpass filters, wavelet transform based methods[5], empirical mode decompo sition[6], and independent component analysis.

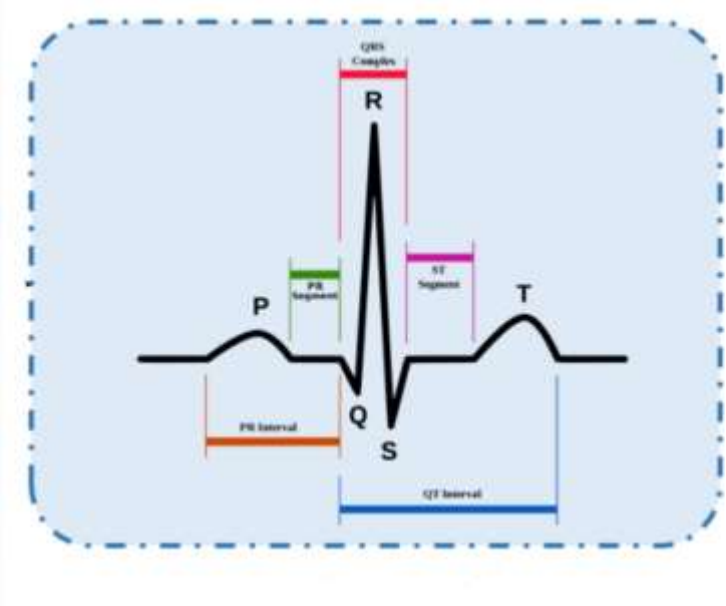


Figure 2.1: Components of ECG Signal.[1]

3.2 Segmentation

Segmentation of ECG signals begins with the crucial task of R-peak detection, which serves as the cornerstone for subsequent analysis. R-peaks denote the onset of ventricular depolarization and are pivotal in delineating various components of the ECG waveform. Several methodologies exist for accurate R-peak detection, each tailored to handle the challenges posed by ECG signals, such as noise, baseline wander, and varying morphologies. Traditional approaches like thresholding algorithms establish a predefined threshold to identify R-peaks based on signal amplitude, often coupled with criteria to mitigate false detections caused by noise. Template matching techniques correlate the ECG sig- nal with a predefined template resembling the R-wave morphology to locate R-peaks accurately. Wavelet-based methods leverage the multi-resolution analysis capabilities of wavelet transform to detect R-peaks across different frequency bands, offering robustness against noise and baseline drift. The Pan-Tompkins algorithm[8] stands as a seminal contribution, providing a real-time QRS detection method widely adopted for its efficiency and reliability. These diverse approaches offer flexibility in addressing the complexities of ECG signals and play a pivotal role in the accurate segmentation of ECG waveforms, facilitating subsequent cardiac analysis tasks with enhanced precision and reliability.

3.3 Deep Learning Models

Deep learning has emerged as a powerful tool across various domains, including bioinformatics, particularly in the analysis of bioinformatics signals. Ubeyli introduced a recurrent neural network (RNN) classifier[9] with an eigenvector-based feature extraction method, achieving 98.06% average accuracy across four different arrhythmias. Kumar and

Kumaraswamy utilized a random forest tree (RFT) classifier with only RR intervals as features, while Park et al. proposed a K-nearest neighbor (K-NN) classifier for detecting different types of ECG beats.Similarly, Jun et al. introduced a parallel K-NN classifier for rapid arrhythmia detection[10].

In related works, Kiranyaz et al. employed a one-dimensional (1D) convolutional neural network (CNN) for ECG classification,[2] although their accuracy did not surpass subsequent methods. They likely employed standard CNN architectures, including convolutional layers followed by pooling layers and fully connected layers, for feature extraction and classification.

Furthermore, Chauhan and Vig leveraged deep long short-term memory (LSTM) networks[11] to detect abnormal signals with high accuracy. LSTMs are well-suited for modeling temporal dependencies in sequential data, allowing them to effectively capture long-range dependencies in ECG signals. Tan et al. combined LSTM with CNN[12] to accurately diagnose coronary artery disease, leveraging the strengths of both architectures for feature extraction and temporal modeling. Hwang et al. proposed an optimal deep learning framework for monitoring mental stress using ECG signals. These diverse deep learning architectures demonstrate their efficacy in advancing arrhythmia detection and analysis in bioinformatics applications.

3.4 Beat Classification

Normal Beat: The normal ECG waveform consists of a P wave (atrial depolarization), a QRS complex (ventricular depolarization), and a T wave (ventricular repolarization).This pattern indicates regular electrical activity within the heart

Left Bundle Branch Block (LBBB): LBBB appears as widened QRS complexes (>0.12 seconds) due to delayed depolarization of the left ventricle. This delay results from block-age or impairment in the left bundle branch conduction system. LBBB often presents with broad, slurred S waves in lateral leads and broad R waves in right precordial leads.

Right Bundle Branch Block (RBBB): RBBB displays widened QRS complexes (>0.12 seconds) due to delayed depolarization of the right ventricle. This occurs when the right bundle branch conduction system is impaired or blocked. RBBB typically features broad, slurred S waves in right precordial leads and broad R waves in lateral leads.

Premature Ventricular Contraction (PVC): PVCs are ectopic heartbeats originating from the ventricles rather than the sinoatrial (SA) node. They appear as premature QRS complexes with abnormal morphology and are not preceded by P waves. PVCs disrupt the normal cardiac rhythm and can manifest as single, couplet, or triplet beats.

Paced Rhythm: Paced rhythms occur when an artificial pacemaker stimulates the heartto contract, bypassing the heart's intrinsic electrical conduction system. Paced ECGs show consistent pacing spikes followed by QRS complexes. The morphology of the QRS complexes may vary depending on the pacing site and mode.

4. Methodology

The analysis and interpretation of electrocardiogram signals are vital for diagnosing cardiac abnormalities. Preprocessing techniques such as lead extraction, noise removal, and digital filtering optimize ECG data quality, preparing it for accurate analysis. Segmentation techniques isolate individual heartbeats, enabling detailed analysis of cardiac activity. Deep learning models like artificial neural networks, Long Short-Term Memory networks, and convolutional neural networks offer advanced approaches for ECG signal analysis, leveraging sequential and spatial features to achieve high accuracy.

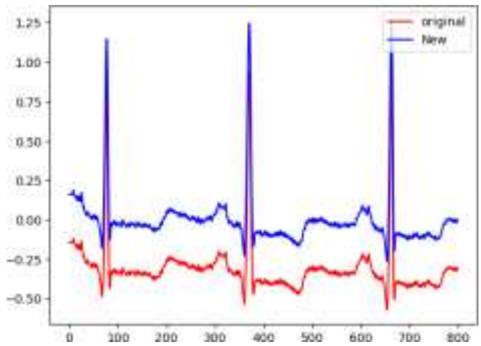
4.1 Dataset

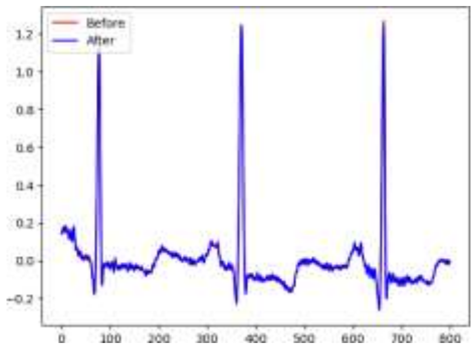
The dataset comprising 48 records, each 30 minutes in duration, was obtained from the Beth Israel Hospital Arrhythmia Laboratory. It includes ECG data from 25 men (aged 32 to 89 years) and 22 women (aged 23 to 89 years). Two signals, recorded as two leads sampled at 360 Hz, form the basis of this dataset.[13] Typically, the Modified Limb Lead II (MLII) signal is the primary signal observed in most ECG records, revealing QRS complexes exclusively within this lead. However, Record 114 deviates from this norm. Notably, Records 102 and 104 lack the MLII signal and were consequently excluded from analysis, with a modified lead V5 substituted for the upper signal in these instances.

4.2 Preprocessing

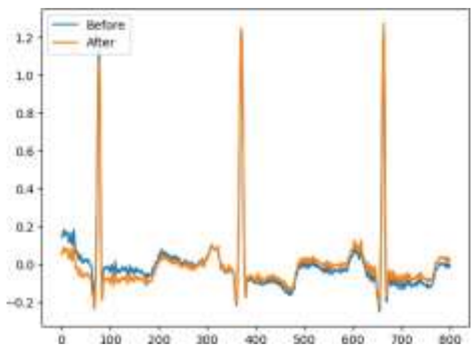
Preprocessing plays a pivotal role in optimizing the quality and reliability of electrocardiogram signals before their analysis. The first crucial step involves extracting lead information, where specific leads are selected from multi-lead ECG recordings to ensure consistency and relevance in subsequent analysis. Subsequently, measures are taken to eliminate potential sources of noise and artifacts that could distort the signals. This in cludes the removal of baseline wandering, which involves correcting gradual shifts in the baseline caused by factors such as electrode motion or skin impedance variations. Additionally, preprocessing entails the removal of powerline interference, which eliminates unwanted electrical noise originating from the power supply network, ensuring cleanerECG signals.

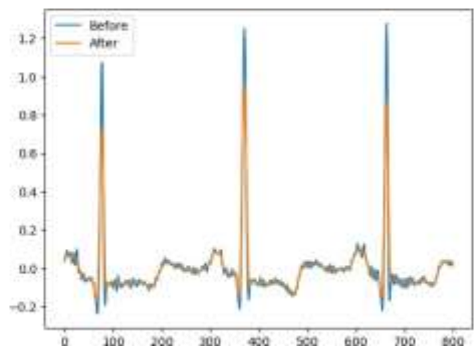
Further refinement is achieved through the application of digital filtering techniques. A high-pass filter with a cutoff frequency of 0.5 Hz is employed to attenuate low-frequency noise and baseline drift, effectively sharpening the ECG waveform. Conversely, a low-pass filter is utilized to smooth the signals and remove high-frequency noise, enhancing the clarity of the underlying cardiac activity. In particular, convolution-based filtering techniques are applied to preserve the integrity of the ECG signals while effectively suppressing noise components. Through these preprocessing steps, the ECG signals are meticulously pre-pared, ensuring that subsequent analysis, such as beat classification, can be performedaccurately and reliably. Overall, preprocessing serves as a critical foundation for enhanc-ing the quality and interpretability of ECG data, ultimately facilitating more accurate diagnosis and treatment of cardiac abnormalities.





(a) Baseline wander removal. (b)
Powerline interference removal.





(c) High-pass filtering. (d)
Hanning window smoothing.

Figure 3.1: Preprocessing.

4.3 Segmentation

The segmentation process in the project involves the precise extraction of individual heart-beats from the continuous electrocardiogram signals, facilitating subsequent analysis and classification. This is achieved through the implementation of the Pan-Tompkins algorithm, a widely used method for QRS complex detection in ECG signals. The algorithm detects the characteristic QRS complexes, which represent the electrical activity associated with ventricular depolarization, thus delineating individual heartbeats within the signal.

Once the heartbeats are segmented, relevant information including the record IDs, segment start and end times, and annotation classes are extracted and stored in separate lists for further analysis. This information provides crucial context for each segmented heartbeat, allowing for comprehensive characterization and interpretation of cardiac activity. By systematically organizing the segmented heartbeats along with their associated metadata, the segmentation process facilitates efficient data management and enables subsequent steps such as feature extraction and classification.

Overall, the segmentation process plays a pivotal role in breaking down the continuous ECG signals into discrete units, enabling detailed analysis and interpretation of cardiac activity. Through the precise extraction and organization of individual heartbeats, the segmentation process forms a foundational step in the accurate characterization and classification of cardiac abnormalities, ultimately contributing to improved diagnostic accuracy and patient care.

	Record ID	Segment Start	Segment End	0	1	...	196	197	198	199	Annotation Class
0	100	13	213	0.059449	0.055308	...	0.034166	0.033702	0.033134	0.032648	N
1	100	307	507	0.084239	0.087566	...	0.020971	0.020866	0.020622	0.020434	N
2	100	563	763	-0.006937	-0.005690	...	-0.082953	-0.080644	-0.077424	-0.073181	N
3	100	883	1083	0.072086	0.073128	...	0.038051	0.036671	0.035565	0.034817	N
4	100	1168	1368	0.084762	0.083995	...	0.031715	0.034364	0.036462	0.037443	N
...	...	...	...	...	...	...	...	...	...	...	...
99169	234	648712	648912	-0.023666	-0.022070	...	-0.032065	-0.033554	-0.035425	-0.038141	N
99170	234	648940	649140	-0.049222	-0.047622	...	-0.041381	-0.040224	-0.038717	-0.036685	N
99171	234	649207	649407	-0.046435	-0.044558	...	-0.075501	-0.082202	-0.089518	-0.096355	N
99172	234	649451	649651	-0.091740	-0.094112	...	0.018187	0.014254	0.010847	0.008183	N
99173	234	649688	649888	0.075938	0.077890	...	0.061765	0.054254	0.047195	0.041080	N

99174 rows × 204 columns

Figure 3.2: Segmentation

4.4 Deep Learning Models

In this project, three distinct deep learning models—LSTM, CNN, and ANN—to tackle the challenges of ECG signal analysis and classification. Each model offers unique strengths in capturing temporal and spatial patterns within the data, enhancing our ability to ex- tract meaningful insights.

3.4.1 Artificial Neural Network

In the project, a feedforward neural network with a directional data flow, meaning information moves only from the input to the output layer without any loops. This network follows a layered structure, comprising an input layer, one or more hidden layers , and an output layer. The number of layers in the ECGANNModel can be determined by examining the length of the layers list provided during the model's initialization. The model is initialized with a list of 3 elements for the layers parameter, it indicates the presence of 3 hidden layers in addition to the input and output layers. Throughout training, the network learns by adjusting the weights associated with each connection between neurons to minimize the error between predicted and actual outputs. Activation functions playa crucial role by introducing non-linearity, enabling the network to capture complex pat-terns within the data and enhancing its ability to learn and make accurate predictions.In the model, the training accuracy is 97.10%, while the test accuracy is 98.88%.

	Precision	Recall	F1 Score
0	1.00	1.00	1.00
1	0.98	0.99	0.98
2	1.00	0.99	1.00
3	0.99	1.00	0.99
4	0.94	0.96	0.95

Table 3.1: Classification Report for ANN model

3.4.2 Long Short-Term Memory

The neural network configuration utilized for the task comprises a single Long Short-Term Memory layer with an input size of 200 and a hidden size of 50. LSTMs are a type of recurrent neural network designed to effectively capture and learn from sequential data, making them particularly suitable for tasks involving time-series analysis or sequential modeling. In this setup, the LSTM layer processes input sequences of length 200, leverag-ing its memory cells to retain important temporal information and learn intricate patterns within the data.

Following the LSTM layer, the network incorporates two linear layers. The first linear layer applies a Rectified Linear Unit activation function, which introduces non-linearity into the model, enabling it to learn complex relationships in the data. Additionally, dropout regularization is applied within this layer to prevent overfitting by randomly deactivating a portion of the neurons during training, promoting generalization. The second linear layer functions as the final output layer responsible for producing predictions based on the learned representations from the preceding layers.

The model achieved a train accuracy of 98.97% , highlighting its capability to effectively learn and generalize from the provided data. The training process spanned 10 epochs and required a total training time of 50 seconds , demonstrating the efficiency ofthe model's training procedure. Despite its high accuracy, the model maintains a rela-tively compact parameter count, totaling 72.2 thousand parameters, which contributes toits efficiency and scalability.

	Precision	Recall	F1 Score
0	1.00	1.00	1.00
1	0.99	0.98	0.98
2	1.00	0.99	1.00
3	0.99	0.99	0.99
4	0.94	0.98	0.96

Table 3.2: Classification Report for LSTM model

3.4.3 Convolutional Neural Network

The convolutional neural network model architecture utilized for this task exhibits a structured design aimed at extracting and transforming features from input data to pro-duce meaningful predictions. The CNN begins with a convolutional layer comprising two consecutive 1-dimensional convolutional layers, each followed by a Rectified Linear Unit (ReLU) activation function to introduce non-linearity. Subsequently, a max-pooling layer is employed to downsample the feature maps, followed by a batch normalization layer to enhance the stability and efficiency of the training process.

This series of operations is repeated twice within the network, allowing for deeperfeature extraction and representation learning. Following the final convolutional block, the feature maps are flattened into a 1-dimensional array using a flatten layer, prepar-ing the data for processing through fully connected layers. The linear layers consist ofthree sequential layers, each incorporating a dropout layer for regularization and a ReLU activation function to introduce non-linearity and improve the model's generalization ca- pabilities.

The last linear layer in the architecture is used for making predictions and does not incorporate dropout or an activation function, which is typical for the output layer of classification models. Despite the sophisticated architecture, the model achieved a train accuracy of 99% and a test accuracy of 99.19% on the target task. This level of perfor-mance is achieved with a substantial number of parameters, totaling approximately 2.47 million, reflecting the complexity and depth of the network.During training, the CNN was trained over 6 epochs, which required a training duration of 840 seconds.

	Precision	Recall	F1 Score
0	1.00	0.99	1.00
1	0.98	0.99	0.99
2	1.00	0.99	0.99
3	0.99	0.99	0.99
4	0.92	0.98	0.95

Table 3.3: Classification Report for CNN model

4.5 Modal Evaluation

In evaluating deep learning models, precision, recall, and F1 score serve as fundamental metrics to gauge their performance in classification tasks. Precision measures the accuracy of positive predictions, while recall evaluates the model's capability to identify all relevant positive instances. The F1 score harmonizes precision and recall into a comprehensive measure, offering crucial insights into the model's effectiveness in accurate prediction-making while managing trade-offs between false positives and false negatives. Leveraging precision, recall, and F1 score enables optimization of models for superior performance across diverse datasets and real-world applications, ensuring robust and reliable outcomes in various machine learning tasks.[6]

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

The preprocessing of ECG signals involves several key steps to enhance signal qual- ity. Baseline wander removal centers the signal by subtracting its mean, while powerline interference removal targets and nullifies frequency components associated with power-line noise. High-pass filtering refines the signal by attenuating low-frequency components below a specified cutoff frequency. Additionally, Hanning window smoothing is applied to reduce abrupt transitions. In machine learning applications, various models are employed for training tasks based on these processed signals. An LSTM model trained over 10 epochs achieves an accuracy of 99.16%, whereas an ANN, trained over 100 epochs, attains a slightly higher accuracy of 98.88%. Notably, a CNN surpasses both with remarkable accuracy, reaching 99.19% after just 6 epochs. In conclusion, among the models evaluated, the CNN exhibits the highest accuracy.

5.Results

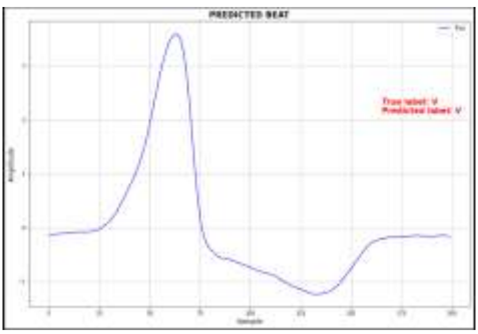
5.1 Model Performance

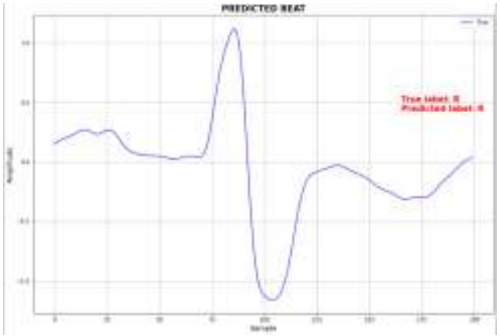
In this project, three deep learning models were compared, each yielding different test and train accuracy metrics. Among them, the CNN demonstrated the highest levels of both test and train accuracy. Consequently, the CNN was selected for subsequent classification tasks.

Models	Train Accuracy	Test Accuracy
ANN	97.10	98.88
LSTM	98.97	99.16
CNN	99	99.19

Table 4.1: Accuracy Comparison

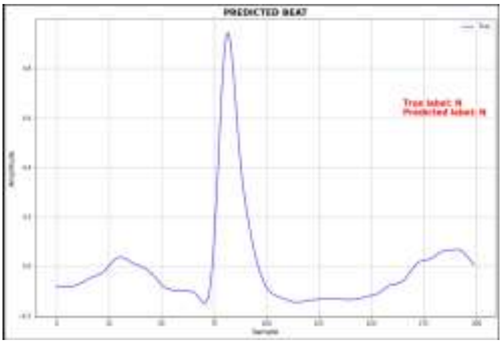
Additionally, accuracy versus epochs and loss versus epochs plots were generated forthe trained CNN model.Accuracy versus epochs illustrates how well the model is learning over time, showing improvements in performance. On the other hand, loss versus epochs demonstrates the convergence of the model during training, indicating how effectively it is minimizing errors and optimizing its parameters.



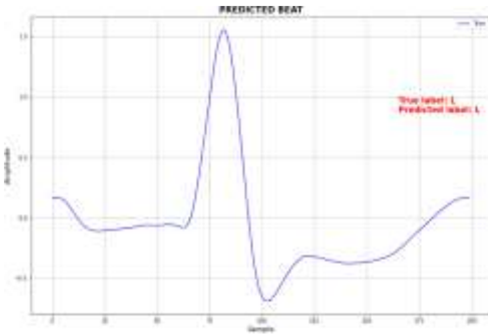


(a) PVC Beat.

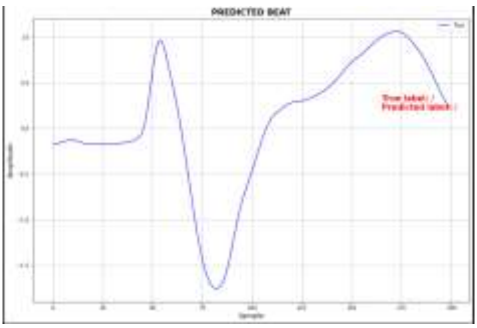
(b) RBBB Beat.



(c) Normal Beat.



(d) LBBB Beat.



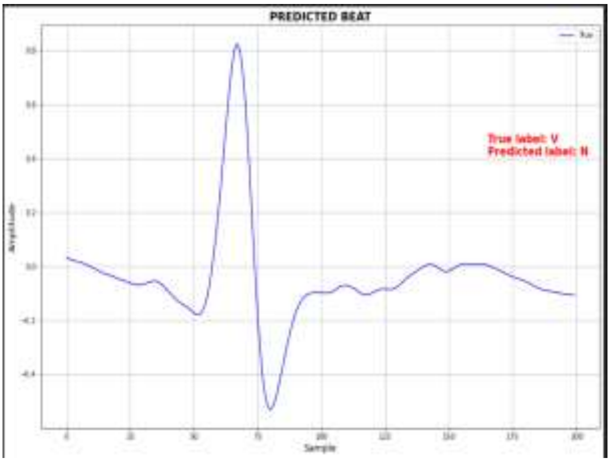
(e) Paced Beat.

Figure 4.3: Illustration of generated beat segments with corresponding true labels and predicted labels.

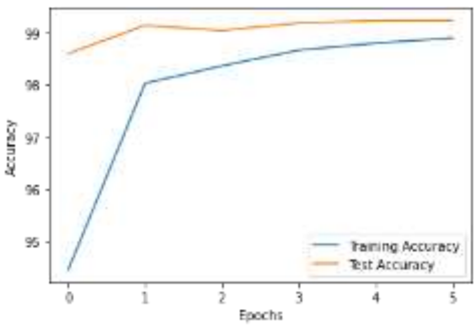
The model's success rate is determined by comparing its predictions with the true classes of the test data. Out of a total of 19,835 cases, the model makes 162 incorrect predictions, resulting in an impressive success rate of 99.18%.

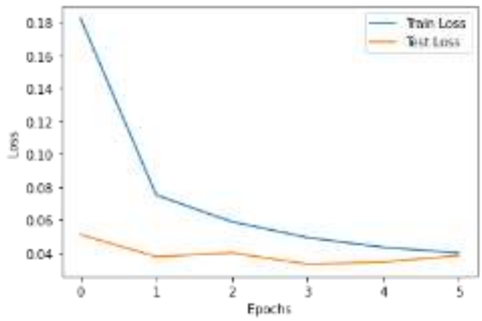
Below is the representation of one such segment where the true label does not matchthe predicted label.

Figure 4.4: Incorrectly predicted beat



In conclusion, the comparison of deep learning models highlighted the superior performance of the Convolutional Neural Network (CNN), which exhibited the highest accuracy metrics on both test and train data. The subsequent analysis involved visualizing the model's learning process through accuracy versus epochs and loss versus epochs plots. The evaluation was further enhanced by employing a confusion matrix, providing com-prehensive insights into the model's predictive capabilities. The application of the CNN model in classifying heartbeat types in electrocardiogram signals demonstrated promising results, as depicted in the visual representations of true and predicted classes. Despite some minor discrepancies, the model's overall success rate of 99.18% underscores its effi- cacy in accurate classification, offering valuable implications for diagnostic and research endeavors.



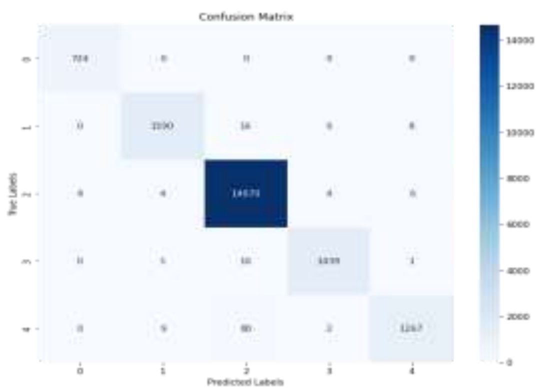


Test &Train accuracy (b) Test&Train loss

Figure 4.1: Accuracy and Loss of the CNN Model

A confusion matrix is a fundamental tool in evaluating the performance of classification models. It presents a comprehensive summary of the model's predictions by comparing them to the actual class labels. Typically organized as a grid, the confusion matrix displays four key metrics: true positives, true negatives, false positives, and false negatives. These metrics offer insights into the model's accuracy, precision, recall, and F1 score. By analyzing the distribution of predictions across the matrix, practitioners can identify areas of strength and weakness in the model's performance, aiding in fine-tuning and optimizing the classification algorithm for better results.

Figure 4.2: Confusion matrix of CNN model



4.2 Prediction

Convolutional Neural Network model trained on labeled data is employed to classify heart-beat types in unseen electrocardiogram signals. To facilitate quick assessment, plots are generated displaying the ECG signal alongside both the true and predicted classes. These visual representations allow for intuitive evaluation of the model's performance, aiding in the identification of any discrepancies or misclassifications. By observing the agreement between the actual signal and the predicted and true classes, clinicians or researchers can efficiently assess the model's efficacy in accurately classifying different types of heartbeats, providing valuable insights for diagnostic or research purposes and potentially guiding further improvements in model training or architecture.

The plots displayed below showcase the signal representation, with the true and predicted labels printed alongside. Each plot highlights the beat segment corresponding to the user input index from the test data. Additionally, the predicted classes for each seg- ment are printed alongside the true labels for comparison. Notably, when the CNN model accurately predicts the class label, mirroring the true label, it underscores the model's precise classification of the input signal, validating its effectiveness.

Conclusions & Future Scope

This project has achieved the successful development and implementation of a Convolutional Neural Network based anomaly detection system for electrocardiogram signals, aimed at accurately classifying 5 different types of heart beats. Through comprehensive testing and evaluation, here compared the performance of various deep learning models, including CNN,LSTM, and ANN. Our findings revealed that CNN exhibited superior test and train accuracy, with CNN achieving a test accuracy of 99.19% and a train accuracy of 99%. These results underscore the effectiveness of CNN in accurately classifying ECG beats, highlighting the potential of deep learning techniques in automating the detection of cardiac abnormalities and improving healthcare outcomes.

Moving forward, several avenues for future exploration and enhancement of the project emerge. Firstly, further refinement and optimization of the CNN architecture could en- hance its accuracy and efficiency in beat classification. Additionally, integrating addi- tional features or data sources, such as patient demographics or physiological parameters, may bolster the robustness of the anomaly detection system. Moreover, deploying the system in real-world clinical settings and collecting longitudinal data could offer valuable insights into its performance and effectiveness over time. Lastly, exploring the applicationof ensemble learning techniques or hybrid models combining CNN with other algorithmsmay yield further improvements in classification accuracy and generalization capabilities. Overall, the future scope of the project extends to ongoing research and developmentefforts aimed at advancing automated detection of cardiac abnormalities and enhancing cardiovascular healthcare delivery.

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