Cardiac Arrhythmia Detection by ECG Feature Extraction: A Machine Learning Based Approach

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Declaration of Authorship

We, Sadri Islam (190021301), Auhona Ahsan (190021306) and Tanvir Ahmad (190021308), declare that the thesis titled, "**Cardiac Arrhythmia Detection by ECG Feature Extraction: A Machine Learning Based Approach**" and the works presented in it are our own. We verify that this study has been done for the partial fulfillment of the requirements for the degree of Bachelor of Science in Electrical and Electronic Engineering at the Islamic University of Technology (IUT). Neither this thesis report nor any part of it has not been submitted elsewhere for any Degree or Diploma. We have always clearly attributed the sources when we have consulted the published work of others.

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List of Acronyms

BLSTM	Bidirectional Long Short-Term Memory
CVD	Cardiovascular Disease
CNN	Convolutional Neural Network
COs	Course Outcomes
DWT	Discrete Wavelet Transform
ECG	Electrocardiogram
ELU	Exponential Linear Unit
GSMD	Group Sparse Mode Decomposition
IMF	Intrinsic Mode Functions
LSTM	Long Short Term Memory
POs	Program Outcomes
PPV	Positive Predictive Value
OBE	Outcome Based Education
ReLU	Rectified Linear Unit
RNN	Recurrent Neural Network
SLT	Superlet Transform
SMOTE	Synthetic Minority Over-sampling Technique

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Sadri Islam

Auhona Ahsan

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Abstract

ECG beats are vital for reducing fatalities from CVDs by enabling arrhythmia detection through intelligent systems, which provide crucial cardiac insights to specialists. However, challenges such as noise, heartbeat instability, and imbalance affect the accuracy and speed of these systems. Accurate diagnosis in quick time is essential for proper treatment and patient recovery. This study focuses on enhancing the precise diagnosis of various CVD types by analyzing arrhythmias in ECG signals of the heartbeats. We developed a deep learning based arrhythmia detection system that utilizes discrete wavelet transformation during pre-processing of the signals and the SMOTE oversampling algorithm to deal with the class imbalance problem. Our classifier integrates a Convolutional Neural Network (CNN) for spatial pattern detection with a Bidirectional Long Short-Term Memory (BLSTM) network for temporal dependency identification. We trained and evaluated our system using the MIT-BIH Arrhythmia Dataset.The evaluation results demonstrate that our method, after 50 training epochs, achieves high accuracy in different categories: 99.65% for class F, 99.37% for class V, 98.45% for class N, 99.10% for class S, and 99.82% for class Q. This proposed deep learning based system can be employed for the automatic diagnosis of arrhythmia and assist the CVD specialists in accurate diagnosis.

Chapter 1

Introduction

1.1 Background

Cardiovascular diseases (CVDs) are one of the major causes of death globally and are considered almost fatal for people who are older. In general, CVD can be grouped into three forms: electrical disorders (arrhythmia), circulatory disorders (blood vessel issues), and structural dysfunctions (heart muscle diseases) [1]. Arrhythmia represents electrical disturbances in the heart’s rhythm which can be life threatening if not properly diagnosed or treated.

ECG is used to monitor cardiac activity and diagnose abnormalities. Traditional techniques for examining ECG data rely on human interpretation, which can be difficult and prone to errors. Researchers have been attempting to automate diagnostic systems by using machine learning techniques in order to overcome these problems [1],[2].

Convolutional neural networks (CNNs) have made a step towards automating heartbeat classification from the ECG signals. In this model, the necessity of having manual feature extraction is not there because CNN can learn the complex patterns very well and thus improving its classification accuracy. U R Acharya et al. demonstrated a 9 layer CNN model for automatic classification of heartbeats from ECG signal using MIT-BIH arrhythmia dataset, achieving an overall accuracy of 94.3% [1]. Kachuee et al. used a 3 layer convolutional network with ReLU activation function and 2 fully-connected layers, achieving accuracy of 93.4% [3]. SL Oh et al. demonstrated an heartbeat classification system with 6 convolutional layers, pooling, 1 layer of LSTM, and 2 fully-connected layers, achieving an accuracy of 96.1%.

The aforementioned deep learning models are expected to become useful tools in arrhythmia detection and classification at early stages which would help in prompt and precise diagnosis of cardiovascular diseases. By doing so it improves diagnostic accuracy as well as addressing difficulties that arise through manual analysis of ECG signals [1], [2].

1.2 Limitations in Current Research

Despite the advancements in utilizing deep convolutional neural networks (CNNs) for classifying heartbeats and diagnosing arrhythmias, several challenges need to be addressed to ensure its successful implementation. Firstly, the quality and diversity of the training dataset have a great effect on the system's performance. Though the MIT-BIH dataset is one of the most commonly used dataset in ECG analysis, it does not contain all possible types of ECG signals observed at clinical settings.

Another significant problem is the imbalanced class distribution where some classes like normal heartbeats have many more samples than others like fusion beats. The imbalance problem of different arrhythmias in real-world data still affects the performance of our model even SMOTE is used to cure this issue.

Due to noise and artifacts, ECG data quality range can be very wide. Even though CNNs are able to learn necessary filters efficiently to remove noise from the inputs, still handling degradation in the quality of data is an issue. In general, Discrete wavelet transformation (DWT) is used to reduce noise, but in the process, all distortions may not be removed and may delete important signal components. Because clinical data often have more noise variability compared to controlled datasets.

1.3 Research Objectives

Preprocessing: To prepare a dataset for an ECG classifier we need to deal with noisy and unbalanced data which involves denoising through discrete wavelet transform (DWT) and balancing using Synthetic Minority Over-sampling Technique (SMOTE).

Develop and Implement a Classification System: Create a classification model using the combination of Convolutional Neural Network (CNN) with Bidirectional Long Short-Term Memory (BLSTM) networks [3]. The BLSTM will capture long term relationships and trends in the data and the CNN will focus on local features and transient patterns from ECG signals.

Standard Dataset Evaluation: The performance of the developed classification system on MIT-BIH arrhythmia dataset, which is widely recognized as a benchmark in ECG classification research, will be evaluated using various performance metrics. This system will be evaluated in accordance with the standards of Association for the Advancement of Medical Instrumentation (AAMI), which enable comparison of results with other state-of-the-art methods [3].

Chapter 2

Background Studies

2.1 Electrocardiogram (ECG)

Electrocardiogram or ECG signal is the graphical representation of the electrical activity of the heart over time. The ECG signal represents the depolarization and repolarization of the heart muscle during each heartbeat [4].

Each wave and complex in an ECG signal has characteristic morphology that reflects different aspects of the heart's electrical activity. Morphology, in the context of ECG signals, refers to the shape, size, and duration of the waves and complexes observed in the electrocardiogram.

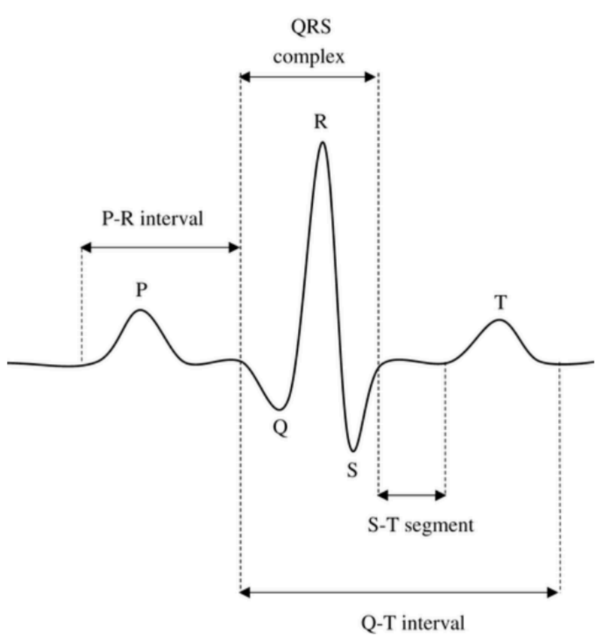


Figure 2.1 : ECG of a normal heartbeat

The P wave signifies atrial depolarization, the QRS complex indicates ventricular depolarization, and the T wave reflects ventricular repolarization [4].

2.2 Cardiac Arrhythmia

Cardiac arrhythmia refers to the irregularity in the heart's rhythm. The heart rate can be too fast too slow when arrhythmia occurs. Arrhythmia is usually caused by blocked arteries or damaged heart tissues [5].

By carefully examining the morphology of ECG signals patterns indicative of specific arrhythmias can be identified.

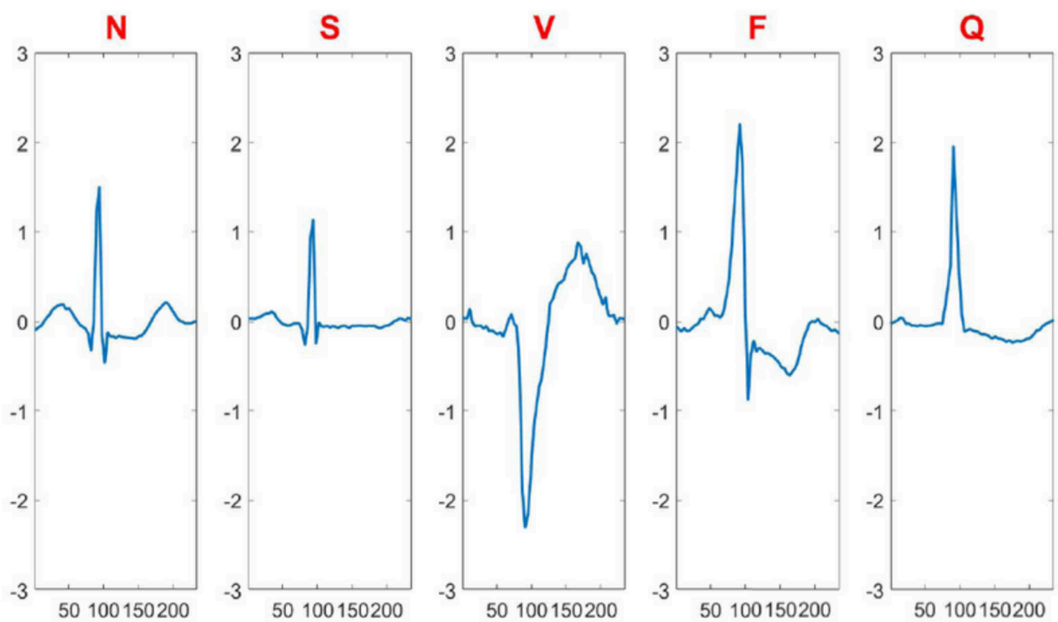


Figure 2.2 : ECG of different classes of heart beat

Here, N denotes normal heartbeat and S, V, F and Q represents irregular heartbeat.

AAMI Classes	**Heartbeat Type**
Normal beats **(N)**	Normal beats (N) Left bundle branch block (L) Right bundle branch block (R) Atrial escape beat (e) Nodal (junctional) escape beat (j)
Supraventricular ectopic Beats **(S)**	Atrial premature contraction (A) Aberrated atrial premature beat (a) Nodal (junctional)premature beat (J) Supraventricular premature beat (S)
Ventricular ectopic beats **(V)**	Ventricular premature contraction (V) Ventricular escape beat (E)
Fusion beats **(F)**	The fusion of ventricular and normal beat (F)
Unclassifiable beats **(Q)**	Paced beat (/) Fusion of paced and normal beat (f) Unclassified beat (Q)

Table 2.1 : Classification of Heartbeats in the MIT-BIH Database by AAMI [6]

Chapter 3

Methodology

The methodology consists of preprocessing the raw ecg signal, noise removal, addressing the class imbalance and finally building and evaluating the neural network model.

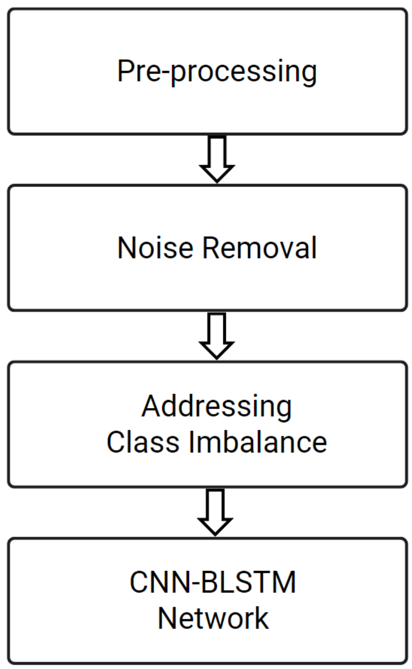


Figure 3.1 : Flow diagram of our proposed method

3.1 Preprocessing

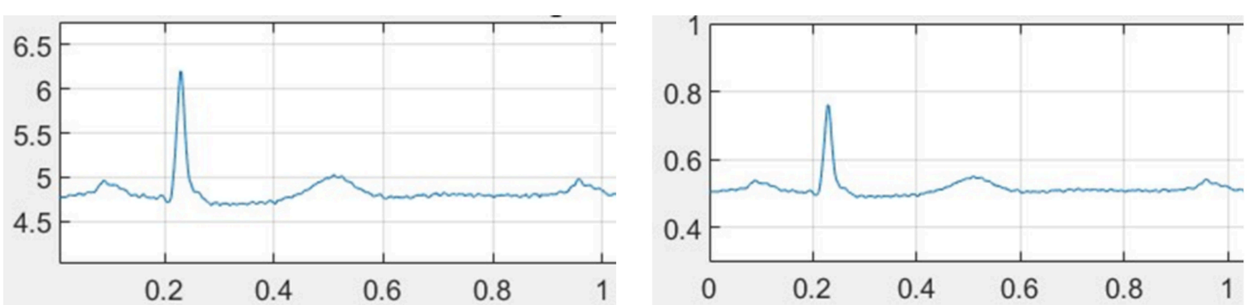
The ECG signals collected from the MIT-BIH arrhythmia dataset consists of 48 signals each having a 30 minutes duration [9]. In order to specify each heart beat and label them according to the annotation file, the signals are first normalized and then segmented into individual beats.

3.1.1 Normalizing the ECG Signal

Different signals have different ranges of amplitude. In order to make the ranges similar, all the signals are normalized to the amplitude range of 0 to 1. The formula used for normalizing the signal is -

$$X_{normalized} = \frac{[\, X - X_{minimum} \,]}{[\, X_{maximum} - X_{minimum} \,]}$$

Here X is the value of each sample, $X_{minimum}$ is the minimum value of X, $X_{maximum}$ is the maximum value of X and $X_{normalized}$ is the normalized value [8].



(a) (b)

Figure 3.2 : (a) ECG signal before normalizing and (b) ECG signal after normalizing

3.1.2 Segmenting Each Heartbeat

After normalizing the signals, these are segmented into each individual heat beat. Using MATLAB, the set of T waves are identified from the ECG signal. The T waves are extracted according to the information of R peaks from the annotation files [7]. Then the signal is splitted into segments based on the T waves. As the T wave signifies the end of a heartbeat, the splitting can be done easily.

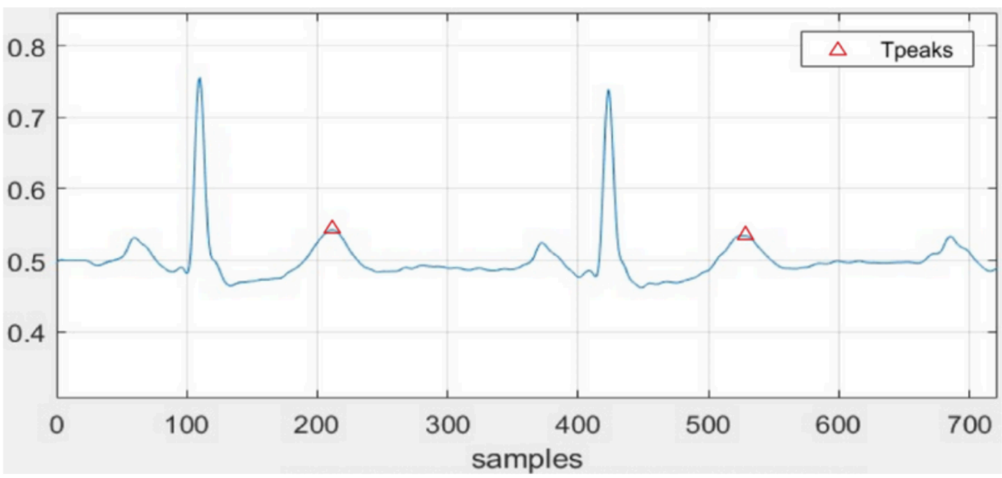


Figure 3.3 : Extracting T waves

Following the segmentation of the beats, labels are assigned to each beat based on the annotation file. These labels are F, N, S, V, Q - which are the five classes of heartbeats that are to our interest in the arrhythmia detection task.

3.2 Noise Removal

The ECG signal often includes various types of noise, such as baseline wander, high-frequency noise, and power line interference [10]. To minimize the impact of these noises, discrete wavelet transform is employed in this task.

3.2.1 Discrete Wavelet Transform

The wavelet transform breaks down the original signal waveform into a collection of basis waveforms called wavelets, much like the Fourier transform does. A wide variety of "mother" wavelets are accessible for study, such as Symmlet, Coiflet, and Daubechies wavelets.

Daubechies wavelets are sold in a series, often represented by the notation dbN, where N is the wavelet's order. In this work, we processed electrocardiogram (ECG) signals using the Daubechies wavelet and the order is taken as 2 (db2). The db2 wavelet provides sufficient frequency resolution and time localization required for ECG analysis, striking a balance between simplicity and efficacy.

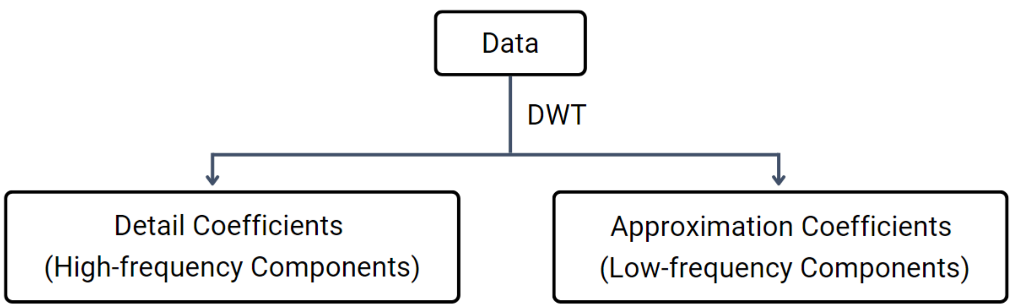


Figure 3.4 : Working principle of DWT

After applying the Discrete Wavelet Transform, the signal is separated into two components, one having low frequency components and the other consisting of high frequency components. The low frequency component is the general trend of the signal that is called Approximation Coefficients. And the high frequency component is called Detailed Coefficients which represents the high frequency noise which is then discarded [11].

```
data1, data2 = pywt.dwt(data, "db2")
data = data1
```

Before applying the Discrete Wavelet Transform, each heartbeat consisted of 280 samples. After the removal of noise components, each heartbeat became of 141 samples.

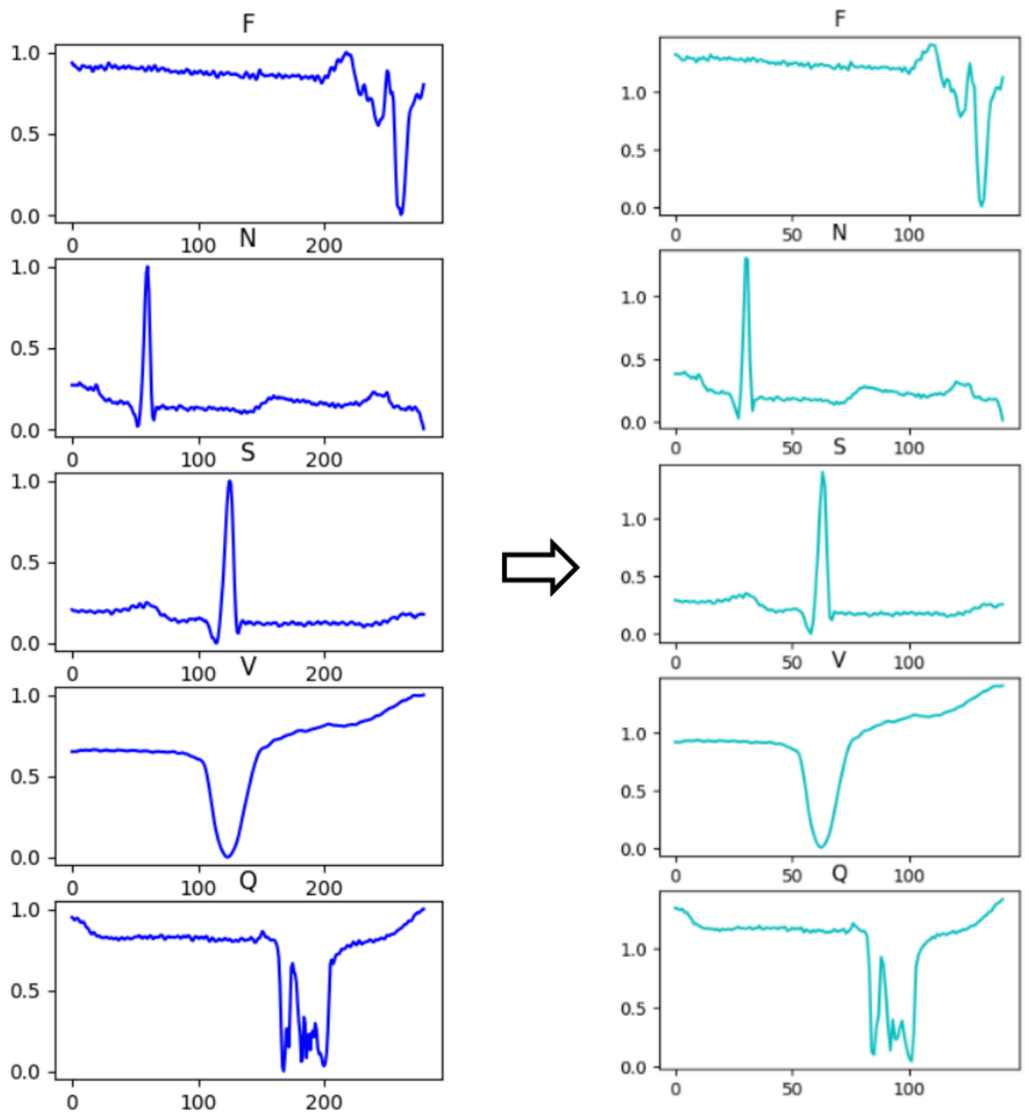


Figure 3.5 : Before and after noise removal

3.3 Fixing Class Imbalance

The MIT-BIH arrhythmia dataset is highly imbalance which can be understandable from the following pie chart -

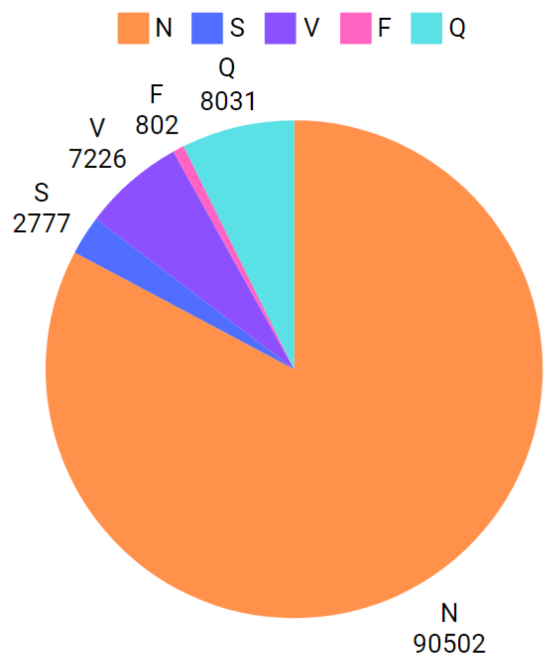


Figure 3.6 : Pie chart of the number of beats in each classes

We had extracted a total number of 1,09,338 beats among which F class has only 802 samples and S class has only 2,777 samples. This imbalance might cause overfitting of the model. In order to solve this issue we first split the dataset into training sets and testing sets at a ratio of 9:1 and then applied SMOTE oversampling technique to increase the number of samples of F and S class in the training set. After the oversampling, the number of samples in F and S class increased to 2,083 and 5,289 respectively.

3.3.1 Synthetic Minority Over-sampling Technique (SMOTE)

SMOTE starts by identifying the samples of minority classes in the dataset. For each sample of the minority class, it selects several of its nearest points. It then randomly selects one of these points and creates a synthetic sample. This is done by interpolating between the feature values of the original sample and the selected point. The interpolation is controlled by a number randomly chosen between 0 and 1, creating a point that is somewhere along the line segment connecting the two samples. The generated synthetic samples are added to the dataset, and thus it increases the number of samples in the minority class and balances the class.

Class	**Without Oversampling**			**After Oversampling**		
	Train Data Samples	**Test Data Samples**	**Total Samples**	**Train Data Samples**	**Test Data Samples**	**Total Samples**
F	722	80	802	2,000	80	2,083
N	81,430	9,072	90,502	81,464	9,072	90,502
S	2,515	262	2,777	5000	262	5,289
V	6,526	700	7,226	6,478	700	7,226
Q	7,211	820	8,031	7,255	820	8,031

Table 3.1 : Number of samples in each class before and after oversampling

3.4 Model Architecture

The neural network used for this task consists of 3 sets of convolution layer, batch normalization layer, ELU and MaxPool layer followed by 2 Bi-LSTM layers.

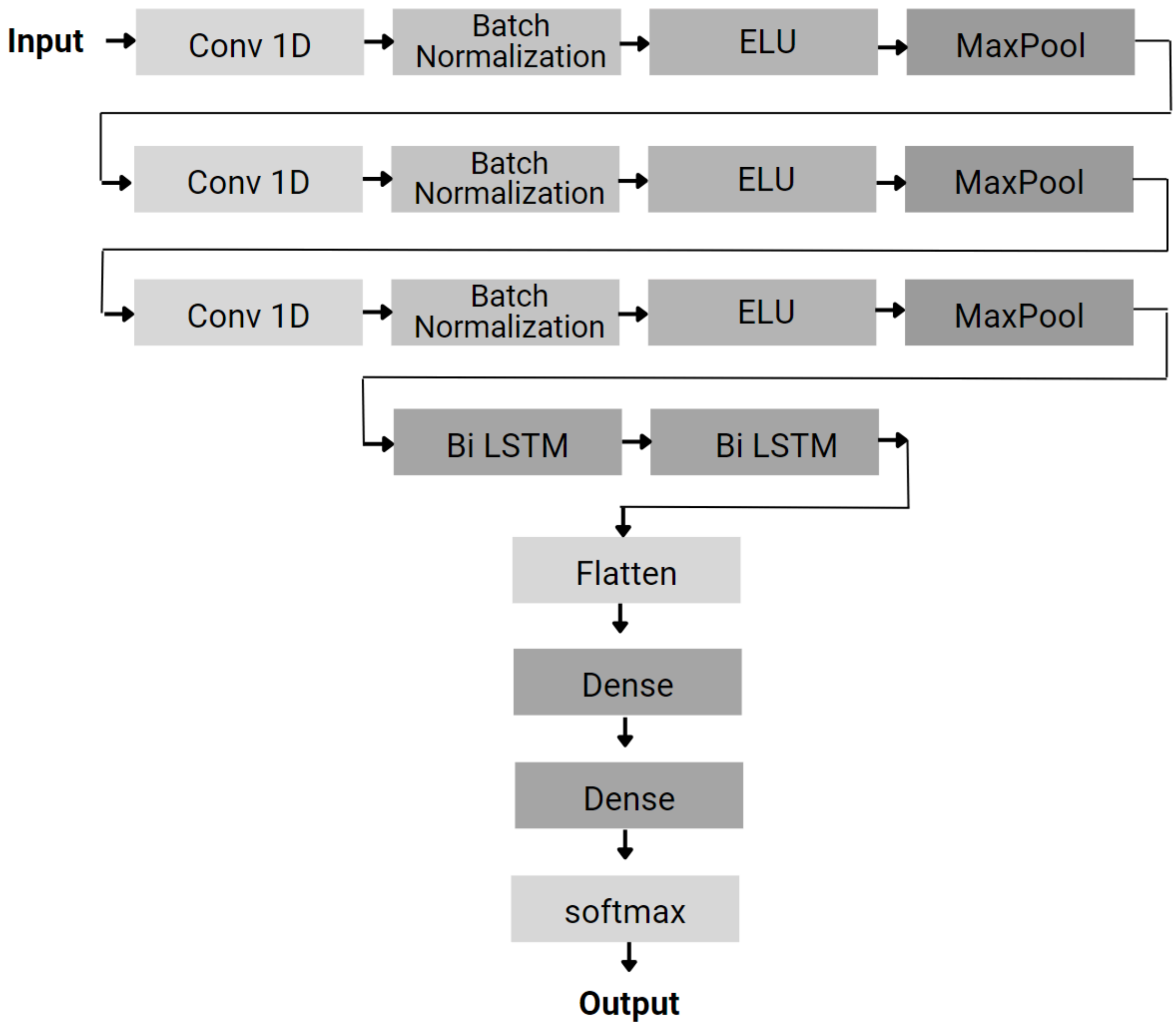


Figure 3.7 : CNN-BLSTM Model Architecture

3.4.1 Convolution Layer

We used the convolution layer to extract the spatial patterns from the ECG signal. Spatial pattern in context of ECG signal refers to the size, shape, duration, amplitude of different parts such as P wave, QRS complex, T wave etc in a heartbeat.

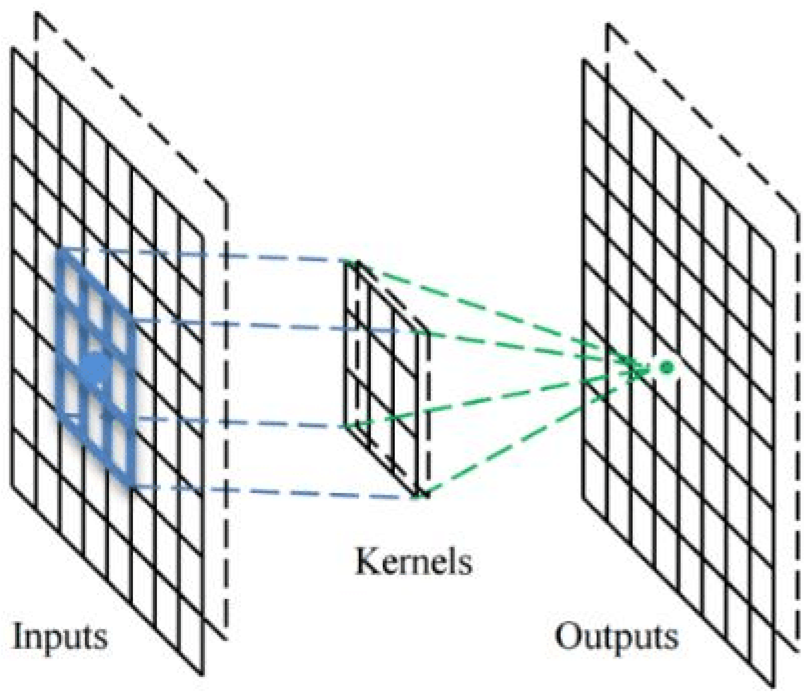


Figure 3.8 : Convolution operation

3.4.2 Batch Normalization

We used batch normalization to reduce the chances of overfitting in the network. Overfitting occurs when the training accuracy is much higher compared to testing accuracy. It can also eliminate the issues of exploding or vanishing gradient problems.

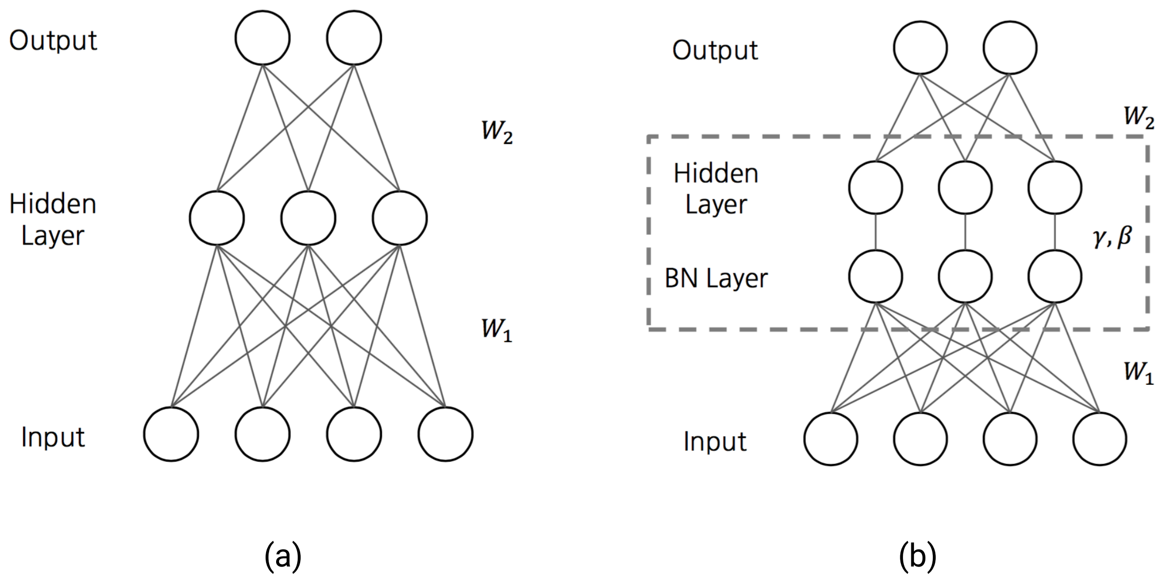


Figure 3.9 : (a) Neural network without batch normalization; (b) Neural network with batch normalization

3.4.3 ELU (Exponential Linear Unit)

We used ELU activation function in the neural network for better performance. It provides better results compared to other activation functions such as ReLU (Rectified Linear Unit). It combines the advantageous characteristics of the Sigmoid function and the ReLU activation function.

The output of this activation function is as such -

$$f(x) = \begin{cases} a(e^x - 1), & x < 0 \\ x, & x \geq 0 \end{cases}$$

Where x is the input and f(x) is the output. α is the hyperparameter that represents how the function saturates for negative value of input. The value of α ranges from 0 to 1.

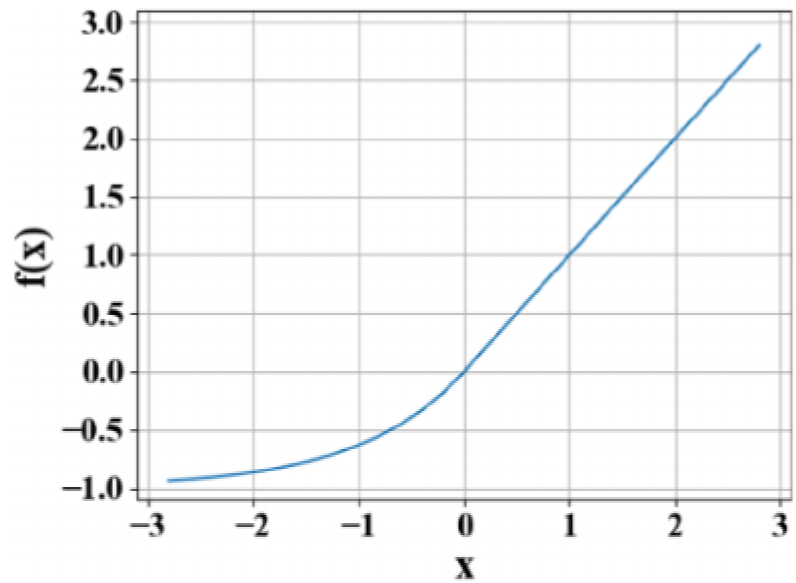


Figure 3.10 : Graph of f(x) against input x in ELU activation function

3.4.4 Pooling Layer

Pooling layer reduces the number of spatial dimensions of the input. Thus computational complexity is reduced and higher efficiency is achieved. MaxPool is the operation where the pooling window goes over the input map by sliding and the maximum value of that window is taken as output. Thus it reduces the spatial dimension from the input.

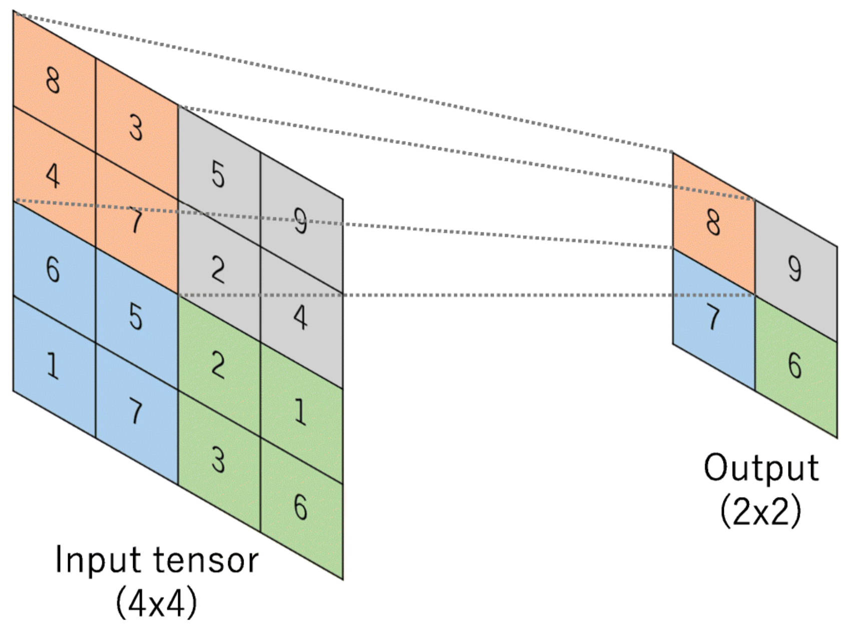


Figure 3.11 : MaxPool operation

3.4.5 Bi-LSTM Layer

The Bidirectional Long Short Term Memory (Bi-LSTM) is used to recognize temporal dependencies and sequential patterns from ECG signals. As ECG signal is a time series data, Recurrent Neural Network (RNN) is very suitable to work with this type of data. Bi-LSTM is a function of RNN that holds the properties of LSTM and works in both directions.

LSTM or Long Short Term Memory is a type of RNN. We used BLSTM to capture long term dependencies in time series data. An LSTM unit consists of 3 gates - Input Gate, Forget Gate and Output Gate. Cell state is the memory of the network [13]. Input gate determines which new information to be added to the cell state. Forget gate determines which portion of the information to be discarded. Output gate determines which information to be the output of the LSTM.

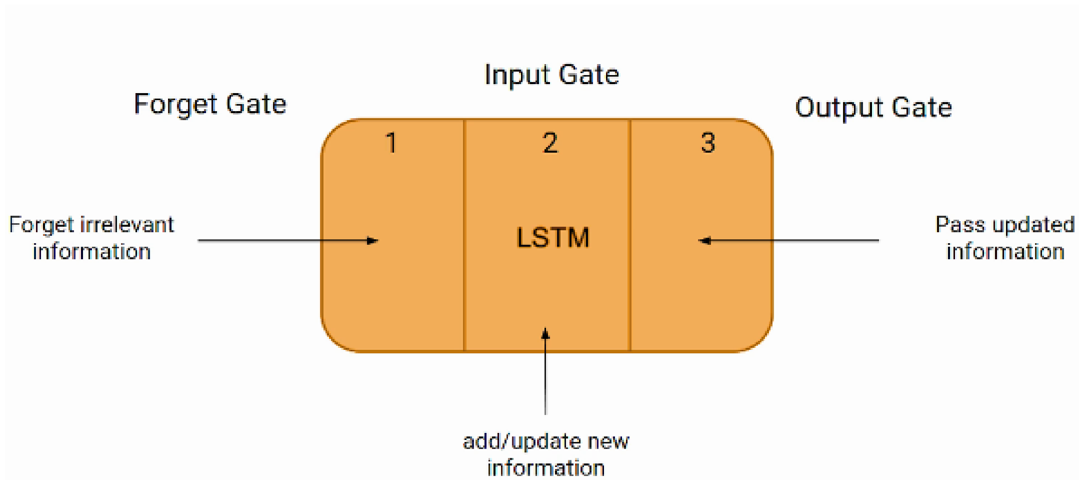


Figure 3.12 : Working principle of LSTM

Forward LSTM uses information from previous inputs to predict future outputs by processing the input sequence from the start to the end.

Backward LSTM uses information from future inputs to predict past outputs by processing the input sequence from the end to the start.

A Bidirectional LSTM (BiLSTM) combines the characteristics of both forward and backward LSTMs. This allows the model to understand the full context of the ECG of a heartbeat by considering both past and future information at each time step. Therefore, it provides better performance compared to LSTM.

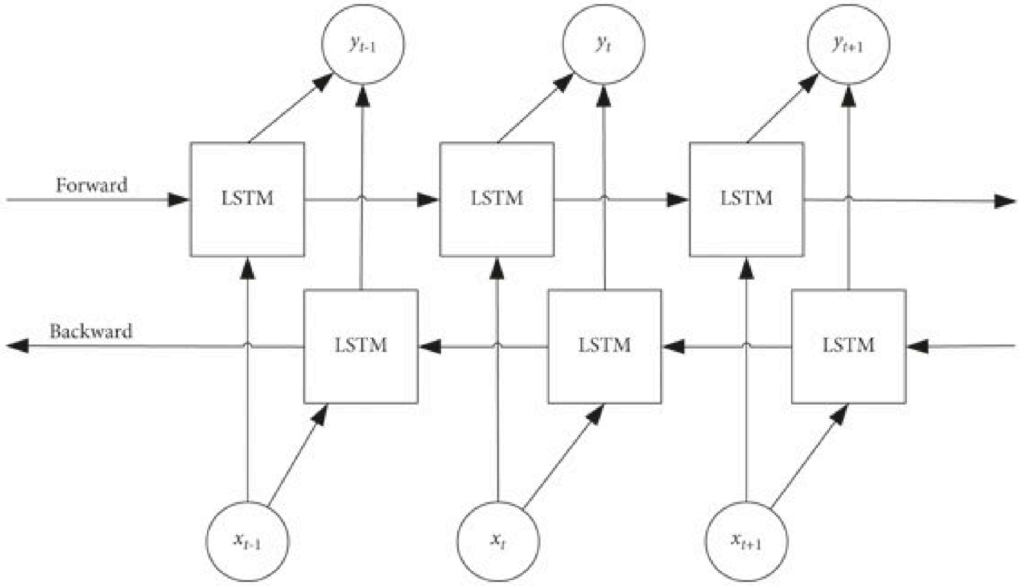


Figure 3.13 : Schematic diagram of Bi-LSTM structure

3.5 Building the model

The CNN-BLSTM is built in python by the following code -

```
import tensorflow as tf
# Define the model
model = tf.keras.models.Sequential()


model.add(
    tf.keras.layers.Conv1D(
        filters=100,
        input_shape=(input_length, 1),
        kernel_size=5,
        strides=2,
        activation=None,
    )
)
```

```
model.add(tf.keras.layers.BatchNormalization())
model.add(tf.keras.layers.ELU(alpha=0.1))

model.add(tf.keras.layers.MaxPool1D(pool_size=3))

model.add(
    tf.keras.layers.Conv1D(
        filters=90,
        kernel_size=5,
        strides=2,
        activation=None,
    )
)
model.add(tf.keras.layers.BatchNormalization())
model.add(tf.keras.layers.ELU(alpha=0.1))

model.add(tf.keras.layers.MaxPool1D(pool_size=3))

model.add(
    tf.keras.layers.Conv1D(
        filters=80,
        kernel_size=3,
        strides=2,
        activation=None,
    )
)
model.add(tf.keras.layers.BatchNormalization())
model.add(tf.keras.layers.ELU(alpha=0.1))

model.add(tf.keras.layers.MaxPool1D(pool_size=1))

# Adding BiLSTM layers
model.add(tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(60, return_sequences=True)))
model.add(tf.keras.layers.Bidirectional(tf.keras.layers.LSTM(60, return_sequences=True)))

# Flatten the output
model.add(tf.keras.layers.Flatten())

# Adding Dense layers
model.add(tf.keras.layers.Dense(30, activation=None))
model.add(tf.keras.layers.ELU(alpha=0.1))
model.add(tf.keras.layers.Dense(5, activation="softmax"))

# Print model summary
model.summary()
```

3.6 Model Parameters:

Layer (Type)	Output Shape	Number of Parameters
Conv1D	(None, 69, 100)	600
Batch Normalization	(None, 69, 100)	400
ELU	(None, 69, 100)	0
MaxPooling1D	(None, 23, 100)	0
Conv1D	(None, 10, 90)	45090
Batch Normalization	(None, 10, 90)	360
ELU	(None, 10, 90)	0
MaxPooling1D	(None, 3, 90)	0
Conv1D	(None, 1, 80)	21680
Batch Normalization	(None, 1, 80)	320
ELU	(None, 1, 80)	0
MaxPooling1D	(None, 1, 80)	0
BLSTM	(None, 1, 120)	67680
BLSTM	(None, 1, 120)	86880
Flatten	(None, 120)	0
Dense	(None, 30)	3630
ELU	(None, 30)	0
Dense	(None, 5)	155

Table 3.2 : Parameters of each layer in the model

Total Parameters	Trainable Parameters	Non-trainable Parameters
226795	226255	540

Table 3.3 : Total trainable and non-trainable parameters

Chapter 4

Results and Discussion

4.1 Accuracy and Loss

Running the model for 50 epochs and taking batch size of 20, the accuracy and loss measured for testing and training are as such -

Training Accuracy	Training Loss	Testing Accuracy	Testing Loss
99.27 %	2.25 %	95.17 %	18.12 %

Table 4.1 : Accuracy and loss of the model

4.1.1 Training Accuracy

Training accuracy refers to the accuracy of the model on the training dataset. It is a measure of how well the model has learned for classification. Higher training accuracy means the model can fit the data well enough. But in the case of higher training accuracy but getting lower testing accuracy, it indicates overfitting problem.

4.1.2 Testing Accuracy

Testing accuracy refers to the accuracy of the model on the testing dataset. It is a measure of how well the model can perform on unforeseen data. Higher testing accuracy means the model can accurately predict from new data. Significance difference between testing accuracy and training accuracy indicates overfitting of the model.

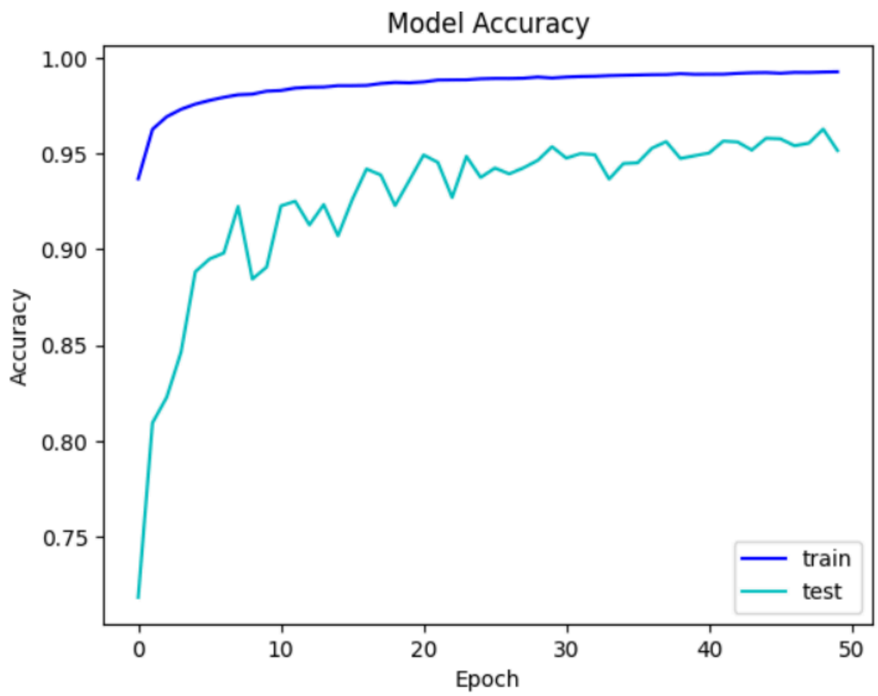


Figure 4.1 : Graph of train and test accuracy for 50 epochs

4.1.3 Training Loss

Training loss is the measure of the model's performance on the training dataset. A low training loss indicates good fitting of the classification model on the training data.

4.1.4 Testing Loss

Testing loss is the measure of the model’s performance on the testing dataset. A low testing loss indicates the model can predict well for new data.

In case the training loss is low but the testing loss is high, the classification model might be overfitting. If both losses are high, the classification model might be underfitting.

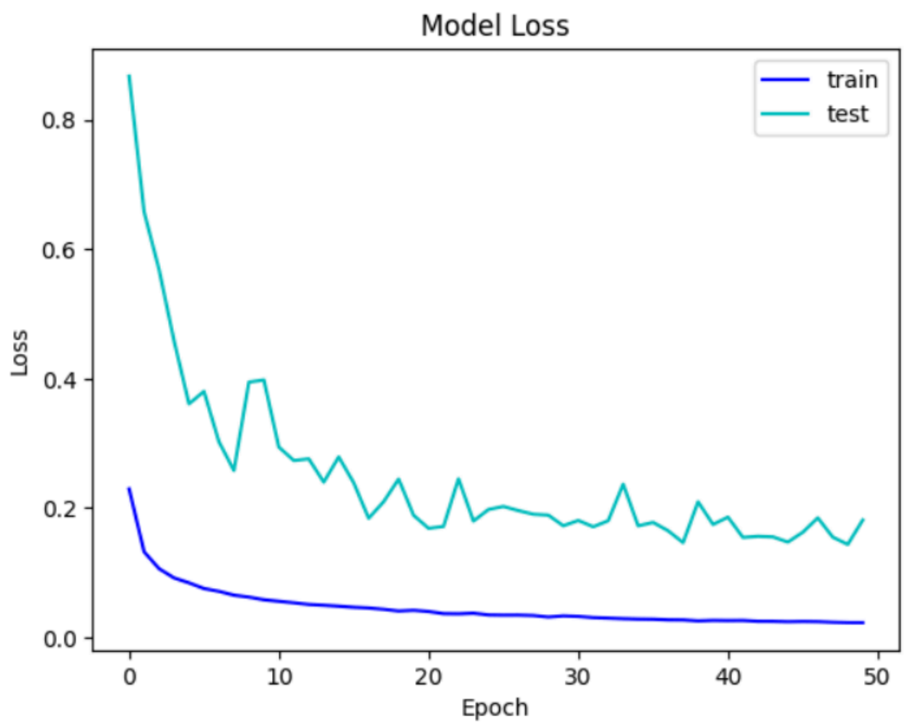


Figure 4.2 : Graph of train and test loss for 50 epochs

4.2 Confusion Matrix

We used a confusion matrix to evaluate the performance of a classification model by relating the actual cases versus predicted classes [12]. It provides a detailed breakdown of the correct and incorrect predictions. Thus confusion matrix makes it easier to understand the model's performance for different classes.

		True Label				
	Class	F	N	S	V	Q
Predicteed Label	F	61	7	0	6	1
	N	15	8971	43	23	8
	S	1	43	244	2	0
	V	8	21	8	638	1
	Q	0	9	1	0	823

Table 4.2 : Confusion matrix

4.3 Performance Parameters

Accuracy, sensitivity, specificity and PPV of the model are-

Class	Acc (%)	Sen (%)	Spec (%)	PPV (%)
F	99.65	81.33	99.78	71.76
N	98.45	99.02	95.73	99.12
S	99.1	84.14	99.51	82.43
V	99.37	94.38	99.7	95.37
Q	99.82	98.8	99.9	98.8

Table 4.3 : Different parameters of performance for the model

4.3.1 Accuracy

Accuracy is the measure of how much correct the prediction is compared to all predictions [12].

Accuracy is denoted by -

$$\text{Accuracy} = \frac{Number\ of\ correct\ prediction}{Total\ number\ of\ prediction} = \frac{TN + TP}{TP + TN + FP + FN}$$

Here TP, TN, FP, FN denotes True Positive, True Negative, False positive and False Negative respectively [13].

True Positive: Positive cases predicted which are actually positive.

True Negative: Negative cases predicted which are actually negative.

False Positive: Positive cases predicted which are actually negative.

False Negative: Negative cases predicted which are actually positive.

4.3.2 Sensitivity

Sensitivity is the parameter of performance that measures the ratio of actual positive cases that are predicted correctly to all the positive cases predicted by the model.

Sensitivity is denoted by -

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

Sensitivity is also known as Recall or True Positive Rate.

4.3.3 Specificity

Specificity is the parameter of performance that measures the ratio of actual negative cases that are predicted correctly to all the negative cases predicted by the model.

Specificity is denoted by -

$$\text{Specificity} = \frac{TN}{TN + FP}$$

Specificity is also known as True Negative Rate.

4.3.4 Positive Predictive Value (PPV)

Positive Predictive Value (PPV) is the parameter of performance that measures the proportion of positive predictions that are actually correct.
PPV is denoted by -

$$\text{PPV} = \frac{TP}{TP + FP}$$

Positive Predictive Value (PPV) is also known as Precision.

Chapter 5

Future Works

5.1 Group Sparse Mode Decomposition (GSMD)

ECG signals nonstationary signals as they are time series data. By using Group Sparse Mode Decomposition (GSMD) these signals can be decomposed into Intrinsic Mode Functions (IMF). The bandwidth of IMF is finite and it has disjoint frequency bands.

The GSMD algorithm can create several decomposition levels. Different combinations of these decomposition levels can be utilized to get noiseless data.

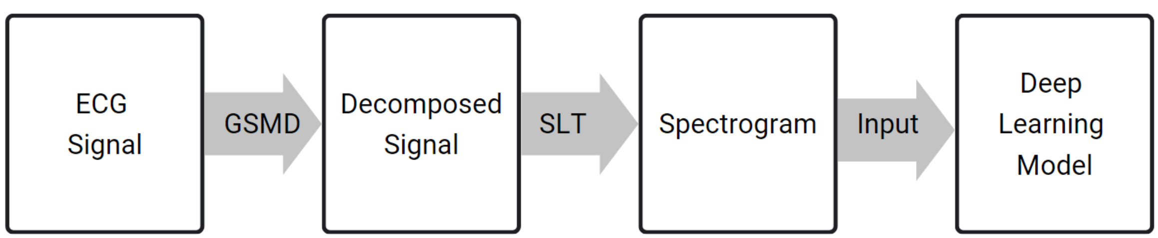


Figure 5.1 : Workflow of the proposed method

5.2 Superlet Transform

Superlet transform can convert the one dimensional ECG data into two dimensional format in time and frequency domain. This way spectrograms can be generated from the ECG signal and can be used as input from the CNN-BLSTM model.

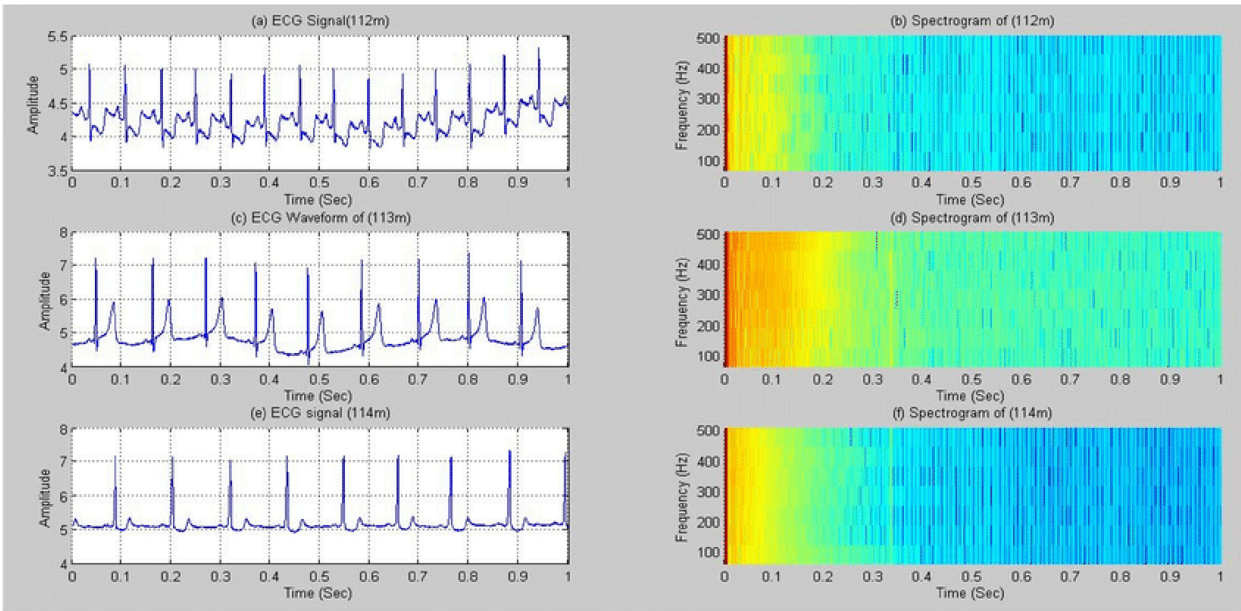


Figure 5.2 : Spectrogram of ECG signal

Chapter 6

Conclusion

6.1 Overall Summary

In order to build a machine learning system that can predict arrhythmia cases, a Convolutional Neural Network and Bidirectional Long Short Term Memory based model has been created and evaluated. The dataset used for training the model is collected from MIT-BIH arrhythmia database. After preprocessing the signals to reduce noise and separating into single beats, an oversampling process has been utilized to mitigate the issue of imbalanced data. The model has been trained on 90% of the data, and evaluated on the rest 10%. The CNN-BLSTM model provided good enough results in different performance parameters.

6.2 Significance

Arrhythmia is the abnormality of the heart which can be life threatening in many cases. Early and accurate detection of this abnormality is vital for the diagnosis and patient care. While the conventional methods take much time and the possibility of getting false results is higher, an automated system built using the advancement of machine learning technologies can be useful in case of detecting different types of arrhythmia quickly and more accurately.

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Chapter 7

Demonstration of Outcome Based Education (OBE)

7.1 Addressing COs and POs

The following table shows the Course Outcomes (COs), corresponding Program Outcomes (POs) and how they were achieved -

COs	CO Statement	POs	Justification
CO1	Identify a contemporary real life problem related to electrical and electronic engineering by reviewing and analyzing existing research works.	PO2	Manual detection of ECG is slow and prone to error
CO2	Determine functional requirements of the problem considering feasibility and efficiency through analysis and synthesis of information.	PO4	We checked various models and selected the feasible one
CO3	Select a suitable solution and determine its method considering professional ethics, codes and standards.	PO8	We used open-source dataset that was created with patients' consent
CO4	Adopt modern engineering resources and tools for the solution of the problem.	PO5	We chose machine learning algorithm as the solution
CO5	Prepare management plan and budgetary implications for the solution of the problem.	PO11	We implemented it with low cost and free tools
CO6	Analyze the impact of the proposed solution on health, safety, culture and society.	PO6	Fast and accurate medical diagnosis can be done
CO7	Analyze the impact of the proposed solution on environment and sustainability.	PO7	Reduced use of paper, inks and carbon emission

CO8	Develop a viable solution considering health, safety, cultural, societal and environmental aspects.	PO3	We created a proper CNN Bi-LSTM model as a viable solution
CO9	Work effectively as an individual and as a team member for the accomplishment of the solution.	PO9	All the team members were involved actively in the work
CO10	Prepare various technical reports, design documentation, and deliver effective presentations for demonstration of the solution.	PO10	We prepared proposals, presentations and Thesis books on our work
CO11	Recognize the need for continuing education and participation in professional societies and meetings.	PO12	Further research needed to adopt with the newer technologies that are evolving

Table 7.1 : CO statements, corresponding POs and justification

7.2 Addressing Knowledge Profiles (K3-K8)

The following table shows the Knowledge Profiles (K3 – K8) addressed in the project -

K	Knowledge Profile (Attribute)	Put Tick (√)
K3	A systematic, theory-based formulation of engineering fundamentals required in the engineering discipline	√
K4	Engineering specialist knowledge that provides theoretical frameworks and bodies of knowledge for the accepted practice areas in the engineering discipline; much is at the forefront of the discipline	√
K5	Knowledge that supports engineering design in a practice area	√
K6	Knowledge of engineering practice (technology) in the practice areas in the engineering discipline	
K7	Comprehension of the role of engineering in society and identified issues in engineering practice in the discipline: ethics and the engineer's professional responsibility to public safety; the impacts of engineering activity; economic, social, cultural, environmental and sustainability	√
K8	Engagement with selected knowledge in the research literature of the discipline	√

Table 7.2 : Knowledge profile attributes

The following table explains or justifies how the Knowledge Profiles (K3 – K8) have been addressed -

K	Explanation/Justification
K3	Understanding fundamental signal processing concepts like filtering, noise reduction, and feature extraction is crucial for pre-processing ECG data for accurate arrhythmia detection.
K4	Utilizing advanced deep learning techniques like Seq2Seq, LSTM, and CNN for medical data analysis, bridging the gap between electrical engineering and healthcare.
K5	Selecting a deep learning model, preprocessing ECG data, training and evaluating the model, integrating it with existing systems, optimizing and regularizing the model.
K6	
K7	Understanding of the multifaceted role of engineering in society and highlighting the potential for deep learning to improve public health while acknowledging the importance of ethical considerations, responsible resource management, and transparency in engineering practice.
K8	Reviewing existing research on arrhythmia detection methods, understanding deep learning techniques, applying them to specific problems, and citing relevant sources to strengthen claims about the effectiveness of deep learning for this purpose.

Table 7.3 : Justification of the addressed knowledge profile attributes

7.3 Addressing Attributes of Ranges of Complex Engineering Problem Solving (P1 – P7)

The following table shows the Attributes of Ranges of Complex Engineering Problem Solving addressed in the project -

P	Range of Complex Engineering Problem Solving	Put Tick (√)
Attribute	Complex Engineering Problems have characteristic P1 and some or all of P2 to P7:	
Depth of knowledge required	**P1:** Cannot be resolved without in-depth engineering knowledge at the level of one or more of K3, K4, K5, K6 or K8 which allows a fundamentals-based, first principles analytical approach	√
Range of conflicting requirements	**P2:** Involve wide-ranging or conflicting technical, engineering and other issues	√
Depth of analysis required	**P3:** Have no obvious solution and require abstract thinking, originality in analysis to formulate suitable models	√
Familiarity of issues	**P4:** Involve infrequently encountered issues	
Extent of applicable codes	**P5:** Are outside problems encompassed by standards and codes of practice for professional engineering	
Extent of stakeholder involvement and conflicting requirements	**P6:** Involve diverse groups of stakeholders with widely varying needs	√
Interdependence	**P7:** Are high level problems including many component parts or sub-problems	

Table 7.4 : Attributes of ranges of complex engineering problem solving

The following table explains or justifies how attributes of ranges of complex engineering problem solving are addressed in the project -

P	Explanation/Justification
P1	The project required a strong foundation in engineering fundamentals, machine learning, design knowledge, engineering practice, and research engagement. It required understanding signal processing, machine learning architectures, design knowledge, and computational resources.
P2	Deep learning models for arrhythmia detection face technical issues such as data quality, model selection, overfitting, engineering resources, interpretability, ethical considerations, and regulatory landscape. Large, high-quality ECG datasets, suitable deep learning architectures, and careful hyperparameter selection were crucial.
P3	Deep learning is applied to analyze complex medical data like ECG recordings for arrhythmia detection, requiring creativity and adapting existing architectures. Balancing model complexity and performance is crucial, and incorporating domain knowledge is essential. This required abstract thinking and original analysis of ECG data.
P6	The stakeholders in the development of a deep learning system for early arrhythmia detection include patients, healthcare professionals, medical device regulators, and engineers. To address these diverse needs, the project should prioritize transparency, rigorous testing, and ethical considerations, ensuring trust, safety, and efficiency.

Table 7.5 : Justification of the addressed attributes of ranges of complex engineering problem solving

7.4 Addressing Attributes of Ranges of Complex Engineering Activities (A1 – A5)

The following table shows the Attributes of Ranges of Complex Engineering Activities addressed in the project -

A	Range of Complex Engineering Activities	Put Tick (√)
Attribute	Complex activities means (engineering) activities or projects that have some or all of the following characteristics:	
Range of resources	**A1:** Involve the use of diverse resources (and for this purpose resources include people, money, equipment, materials, information and technologies)	√
Level of interaction	**A2:** Require resolution of significant problems arising from interactions between wide-ranging or conflicting technical, engineering or other issues	√
Innovation	**A3:** Involve creative use of engineering principles and research-based knowledge in novel ways	√
Consequences for society and the environment	**A4:** Have significant consequences in a range of contexts, characterized by difficulty of prediction and mitigation	√
Familiarity	**A5:** Can extend beyond previous experiences by applying principles-based approaches	

Table 7.6 : Attributes of ranges of complex engineering activities

The following table explains or justifies how attributes of ranges of complex engineering activities are addressed in the project -

A	Explanation/Justification
A1	The team consists of electrical engineers with deep learning expertise. Funding for computational resources, data acquisition, and software licenses might have been required. Powerful hardware like GPUs or TPUs is needed for training deep learning models. ECG data and relevant research literature are essential for building, training, and evaluating the model.
A2	The development of deep learning models for arrhythmia detection faces challenges such as data quality, interpretability, computational resources, model bias, and regulatory landscape. To address these issues, a holistic approach involving collaboration with medical professionals, data preprocessing and augmentation, model selection and regularization, explainable AI techniques, and collaboration with regulatory bodies is needed.
A3	The project merges electrical engineering principles with deep learning techniques for ECG data analysis, requiring creativity in adjusting architectures, improving interpretability, and leveraging diverse data sources, such as raw waveforms, to detect arrhythmias.
A4	The potential impact of deep learning systems on arrhythmia detection could improve public health outcomes and increase access to care, but also raise ethical concerns, reduce physician expertise, and strain healthcare systems. To mitigate these challenges, focus on fairness, explainability, complementary role for AI, and healthcare system readiness. Addressing these challenges is crucial for a successful project.

Table 7.7: Justification of the addressed attributes of ranges of complex engineering activities