CAPITAL UNIVERSITY OF SCIENCE AND TECHNOLOGY, ISLAMABAD

# ECG Signal Analysis to Detect Arrhythmia using Deep Neural Networks

by

Amina Ashfaq

A thesis submitted in partial fulfillment for the degree of Master of Science

in the

Faculty of Computing
Department of Computer Science

2021

*My work is dedicated, firstly to the Almighty Allah, for blessing me with this opportunity, health and ability to complete this. After Allah, I would like to devote my work to My Family, My Teacher and My Friends. Special thanks to my supervisor whose uncountable confidence enabled me to reach this milestone.*

# CERTIFICATE OF APPROVAL

## ECG Signal Analysis to Detect Arrhythmia using Deep Neural Networks

by

Amina Ashfaq

(MCS191003)

### THESIS EXAMINING COMMITTEE

| S. No. | Examiner | Name | Organization |
|---|---|---|---|
| (a) | External Examiner | Dr. Asim Munir | IIU, Islamabad |
| (b) | Internal Examiner | Dr. Mohammad Masroor Ahmed | CUST, Islamabad |
| (c) | Supervisor | Dr. Nadeem Anjum | CUST, Islamabad |

Dr. Nadeem Anjum
Thesis Supervisor
December, 2021

Dr. Nayyer Masood
Head
Dept. of Computer Science
December, 2021

Dr. Muhammad Abdul Qadir
Dean
Faculty of Computing
December, 2021

# *Author's Declaration*

I, **Amina Ashfaq** hereby state that my MS thesis titled "**ECG Signal Analysis to Detect Arrhythmia using Deep Neural Networks**" is my own work and has not been submitted previously by me for taking any degree from Capital University of Science and Technology, Islamabad or anywhere else in the country/abroad.

At any time if my statement is found to be incorrect even after my graduation, the University has the right to withdraw my MS Degree.

**(Amina Ashfaq)**

Registration No: MCS191003

# *Plagiarism Undertaking*

I solemnly declare that research work presented in this thesis titled "**ECG Signal Analysis to Detect Arrhythmia using Deep Neural Networks**" is solely my research work with no significant contribution from any other person. Small contribution/help wherever taken has been duly acknowledged and that complete thesis has been written by me.

I understand the zero tolerance policy of the HEC and Capital University of Science and Technology towards plagiarism. Therefore, I as an author of the above titled thesis declare that no portion of my thesis has been plagiarized and any material used as reference is properly referred/cited.

I undertake that if I am found guilty of any formal plagiarism in the above titled thesis even after award of MS Degree, the University reserves the right to withdraw/revoke my MS degree and that HEC and the University have the right to publish my name on the HEC/University website on which names of students are placed who submitted plagiarized work.

**(Amina Ashfaq)**

Registration No: MCS191003

# *Acknowledgement*

"And whoever puts all his trust in Allah, He will be enough for him." Al-Quran [65:1]. I would like to say Alhamdulillah for everything Allah has blessed me with that enabled me to reach here.

I would like to express my gratitude to my supervisor Dr. Nadeem Anjum who guided me and helped me with his valuable suggestions throughout this work. And gave his valuable time, May Allah keep him in his blessings.

My heart felt thanks to my parents, my phupo for their love, prayers and everything what I needed. And to both of my brothers who keep on pushing me for higher education.

Lastly, I would like to thank my cousins, my friends for motivating me and supporting me whenever I needed their help.

**(Amina Ashfaq)**

# *Abstract*

Identifying Arrhythmia from ECG modalities that are traditionally carried out by a careful observation by the health experts, can be automated using AI techniques to assist the doctor with a computer aided diagnostic (CAD) in identifying cardiovascular diseases such as arrhythmia. Arrhythmia is one of the leading cause of heart related complications. The advance in auto detection and self monitoring devices have increased the requirement of proper ECG classification. In this work a novel approach is proposed for ECG classifications and evaluated using MIT-BIH arrhythmia database. Proposed approach is based on hybrid model CNN(convolutional neural network) and LSTM(long short term memory). ECG signals are fed into CNN module where the features are extracted and then LSTM are used for temporal information analysis. Life threatening groups SVEB(supraventricular beat) and VEB(ventricular beat) are targeted along with other arrhythmia groups as well. For Experimental purpose three models CNN1-LSTM, CNN2-LSTM, CNN3-LSTM are proposed and evaluated. Compared with two relevant models and state of art methods this model outperformed for SVEB and VEB arrhythmia achieving an accuracy of 96%.

# Contents

# List of Figures

# List of Tables

# Abbreviations

| | |
|---|---|
| **CNN** | Convolutional Neural Network |
| **DNNs** | Deep Neural networks |
| **LSTM** | Long Short Term Memory |
| **ReLu** | Rectified Linear Unit |
| **SVEB** | Supraventricular beat |
| **VEB** | Ventricular beat |

# Symbols

| | |
|---|---|
| $f_t$ | Forget Gate |
| $i_t$ | Input Gate |
| $O_t$ | Output Gate |
| $C_t$ | New Cell state |
| $C_{t-1}$ | Old Cell State |
| $h_{t-1}$ | Output from previous time stamps |
| $\sigma$ | Sigmoid Layer |
| $W_f$ | Weight |
| $x_t$ | New Input |
| $b_f$ | Bias Value |

# Chapter 1

# Introduction

Cardiovascular disease is one of the leading causes of death around the globe, 17 million people die every year due to heart disease as shown in figure 1.1 [1], [2]. The most common causes are blocked blood vessels, hearts wall gets thickened, arrhyhthmia (rate/rhythm of the heart), irregular heart beat etc [3]. The most common test used by the healthcare experts to diagnose these cardiovascular problems is through the use of is electrocardiograms (ECG).

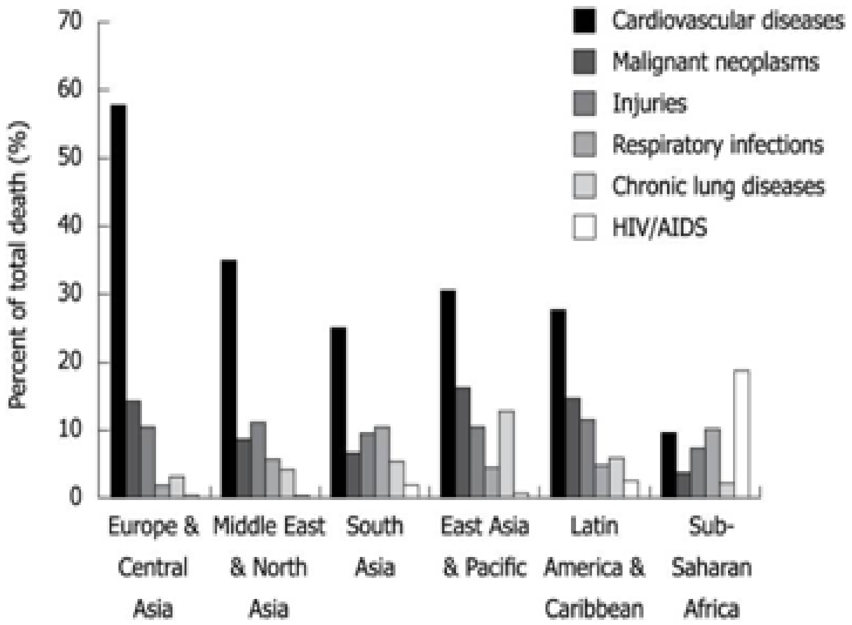



FIGURE 1.1: Cardiovascular(heart) disease death rate.

The procedure involved in these tests is through attaching electrodes (sensors) to different parts of the patients body to tap out magnitude and direction of the impulses of the patients heartbeat. This captures various irregularities of different conditions and symptoms of diseases that the medical experts try to analyze for diagnosing various diseases. These impulses consist of P, QRS complex, and T waves as shown in figure 1.2, out of which the irregular sequence of QRS complex is the most important part in the ECG that reflects the presence of abnormal heart beats called arrhythmias [4], [5]. This pattern is usually converted to Heart Rate Variability (HRV) based on difference in time between two heartbeats and is used for analyzing autonomic function to reliably classify patients having cardiovascular diseases.

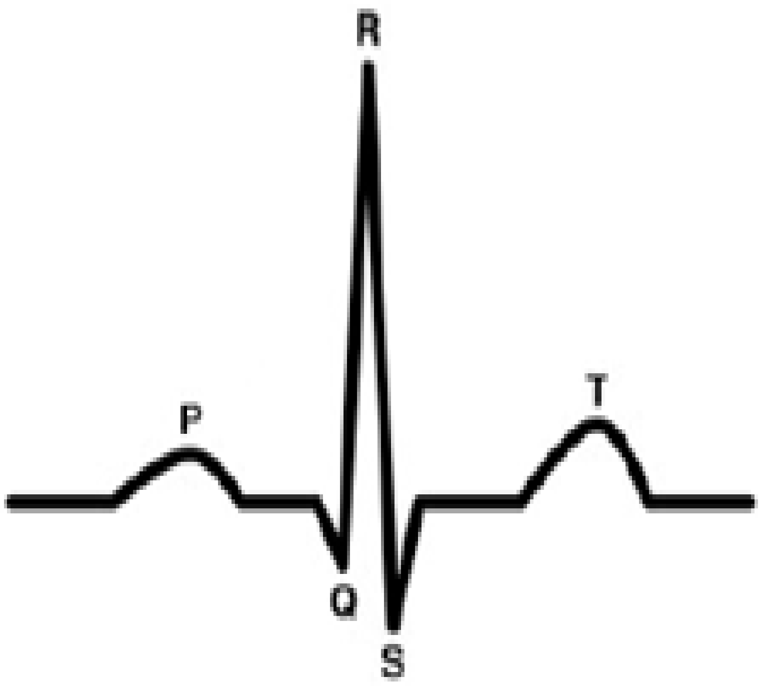



FIGURE 1.2: Basics of ECG Wave.

Recent advances in technology have resulted in more powerful architectures that has proliferated state-of-the-art AI devices that are increasingly being employed in the field of medical sciences to pave the road towards invasive and/or noninvasive health modalities. Wearable and Self-monitoring health devices are one such examples that signify and accelerate automatic detection and self-diagnosis applications. Over the last decade, an increase in wearable ECG devices has surfaced in the market which has generated huge datasets that can potentially be used for early detection of cardiovascular diseases [6].

This increase in data has also increased the challenge of problems for IoT and cloud based applications that requires to manage this data without loss of to manage such a large data without any loss is challenging.

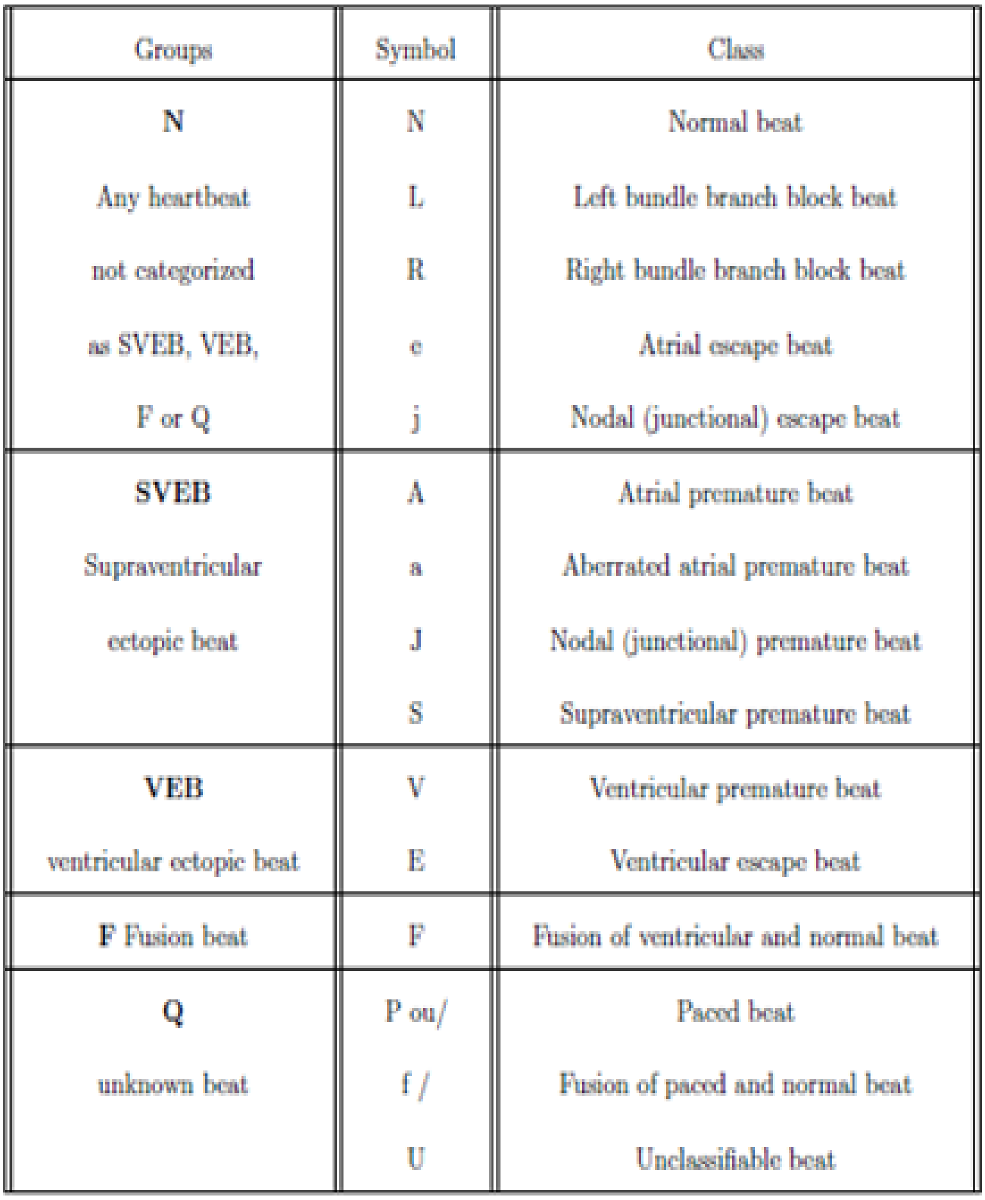
CNN applications became popular after the success in ImageNet competition in 2012 [7]. CNN is trending in the field of arrhythmia and if used with the combination of LSTM could give more accurate results. As CNNs are good in image recognition, object detection and LSTM is well suited to classify and process those extracted features.

When a hybrid model CNN-LSTM is used it can surely give good accuracy for life threatening arrhythmia like SVEB(supraventricular beat) and VEB(ventricular beat). The CNN layer will take ECG signals no need to extract the features as the CNN are good in extracting the spatial features. The features extracted from the process of convolution and pooling are further fed to the LSTM. Then softmax layer is used for output. Hence this hybrid model has increased the accuracy for life threatening arrhythmias.

If arrhythmia types are not properly classified public community will be effected, if someone is having life threatening arrhythmia but it is not correctly predicted because of inaccurate classification it could lead to serious problems like causing a stroke and leading to death. This model is successful in detecting life threatening arrhythmia's with improved accuracy it can save many lives and even decreases the physician workload. For better understanding different arrhythmia groups and their classes should be understood.

## 1.1 Classes of Arrhythmia

There exists various types of cardiac arrhythmias but only specific types are recommended by Advancement of medical Instrumentation (AAMI) to be detected by different approaches. "There are 15 recommended classes for arrhythmia that are classified into 5 superclasses: Normal (N), Supraventricular ectopic beat (SVEB), Ventricular ectopic beat (VEB), Fusion beat (F) and Unknown beat (Q)" these groups and classes of arrhythmia are shown in figure 1.3 [8].



| Groups | Symbol | Class |
|---|---|---|
| **N** | N | Normal beat |
| Any heartbeat | L | Left bundle branch block beat |
| not categorized | R | Right bundle branch block beat |
| as SVEB, VEB, | e | Atrial escape beat |
| F or Q | j | Nodal (junctional) escape beat |
| **SVEB** | A | Atrial premature beat |
| Supraventricular | a | Aberrated atrial premature beat |
| ectopic beat | J | Nodal (junctional) premature beat |
| | S | Supraventricular premature beat |
| **VEB** | V | Ventricular premature beat |
| ventricular ectopic beat | E | Ventricular escape beat |
| **F** Fusion beat | F | Fusion of ventricular and normal beat |
| **Q** | P ou/ | Paced beat |
| unknown beat | f / | Fusion of paced and normal beat |
| | U | Unclassifiable beat |

FIGURE 1.3: Arrhythmia Groups and their Classes.

### 1.1.1 N

Bundle branch block is a type of arrhythmia condition in which there is a blockage or delay along the pathway that electrical signals travel to make heart beat, which further makes harder for the heart to pump blood efficiently through the body. The postponement or blockage can happen on the pathway that sends electrical signals either to right or the left side of the bottom chambers of the heart. Left bundle branch block (LBBB) in this condition, actuation of the left ventricle of the heart is delayed, which makes the left ventricle contract later than the right ventricle. In a right bundle branch block (RBBB) the right ventricle isn't straightforwardly initiated by electrical signals going through the right bundle branch. Whereas an atrial escape beat is a type of beat which happens after a long sinus pause because of sinus node exit block or sinus node arrest. Atrial escape beats can turn into a supported atrial rythm when at least three beats happen in succession at a rate over 60 bpm. A junctional escape beat is a postponed heartbeat beginning not from the chamber but rather from an ectopic concentrate some place in the atrioventricular intersection. It happens when the pace of depolarization of the sinoatrial node falls beneath the pace of the atrioventricular node [8].

### 1.1.2 SVEB

An ectopic rhythm is an unpredictable heart musicality because of a premature heartbeat. Ectopic beat is otherwise called premature atrial contraction, premature ventricular contraction and extrasystole. Supraventricular premature beats are atrial contractions set off by ectopic foci as opposed to the sinoatrial hub. The emergence inside atria is through retrograde conduction in the junctional premature beats. Premature beat might not only be found in heart disease patients but also in healthy people as well. Premature beats do not fundamentally weaken cardiovascular yield all alone, they may prompt more serious types of arrhythmia like atrial fibrillation. An atrial premature beat is an additional heartbeat brought about by electrical enactment of the atria from an abnormal site before a typical heartbeat would happen. Abberated atrial premature beat is a typical electrocardiographic indication that happens when the supraventricular electrical impulse is led unusually through the ventricular directing framework, which outcomes in a wide QRS complex that might be mistaken for a ventricular ectopic beat. Whereas, an Nodal( junctional) premature beat is an anomaly found within the sight of a fundamental sinus rhythm. It is a deviant impulse that begins in the junctional tissue and happens early or rashly before the following expected P wave. This prematurity can make the beat irregularity [9].

### 1.1.3 VEB

Ventricular ectopics beats are that type of arrhythmia whose electrical signals starts at different place and they travel towards different way through heart. Premature ventricular contractions are a sort of irregular heartbeat, heart has 4 chambers: 2 upper atria and 2 lower ventricles. A unique group of cells which is in the sinoatrial (SA) in the right chamber starts the signal for heartbeat. It goes to left and right ventricle. As the signal moves they triggers close by parts of heart to contract. This permits the heart to squeeze in a planned manner. With a PVC( premature ventricular contraction), the sign to begin pulse comes from one of the ventricles.

This sign is untimely, which means it occurs before the SA has gotten an opportunity to fire. The signals spread through the heart and can cause a heartbeat that is not the same as would be expected. PVCs that happen just a single time in some expected time are normal in individuals, yet they are a more normal in elderly people. PVCs can occur in individuals with no coronary illness, yet they are more common in individuals with some sort of coronary illness. PVCs has issues if they happen over and over throughout a significant stretch of time but if happens once in a while causes no issue. Excessive number of PVCs could weaken heart muscle. Whereas, a self generated ventricular escape beat is a electrical signal of the ventricles of the heart causing contraction; regularly the heart beat is started in the atria of heart and is further transmitted to ventricles [9].

### 1.1.4 Q

Paced beats are those beats sent from a pacemaker; is a gadget that sends little electrical motivations to the heart muscle to keep a reasonable pulse. Pacemakers fundamentally keep the heart from pulsating too gradually. The pacemaker has a heartbeat generator (which houses the battery and a small PC) and leads (wires) that send driving forces from the beat generator to the heart muscle. More up to date pacemakers have many refined highlights that are intended to help oversee arrhythmias and enhance pulse related capacity however much as could be expected. Fusion of paced and normal beats is a combination beat which occurs when the normal beat and pacemaker upgrade beat somewhat depolarize the ventricles, causing a hybrid QRS complex [9].

### 1.1.5 F

A fusion beat happens when electrical signals from various sources follow up on a similar locale of the heart at the equivalent time. If it follows up on the ventricular chambers it is known as a ventricular fusion beat, while impacting flows in the atrial chambers produce atrial fusion beat [9].

In this work group N,SVEB,VEB,F would be targeted in which thirteen classes would be considered(E,F,f,N,L,R,A,a,J,S,e,j,V). Our main focus would be on life threatening groups SVEB and VEB.

## 1.2 Purpose

Automated detection of arrhythmia is still a problem. The goal of this work is to properly classify life threatening arrhythmias.The purpose of this work was not only to classify but to improve the accuracy up to 95% for life threatening arrhythmias SVEB and VEB using hybrid approach. There are some hybrid models which have been proposed. Wang et al. [10] presented a CNN-MENN achieving 97.4% accuracy and detected only Atrial fibrillation. Li et al. [11] proposed model based on CNN-GRU achieving accuracy 93.61% for SVEB and 93.71% for VEB. Xiaomao et al.[12] implemented a MS-CNN model to detect AF giving accuracy of 97.19%. Philip et al. [13] introduced CNN-LSTM model detecting AF giving 83.10% accuracy. This work helps in developing an effective and efficient deep learning method, which further leads to accurate classification.

## 1.3 Problem Statement

Accurate arrhythmia classification is still an open issue for research if some arrhythmia are not properly classified it could have deadly consequences including heart failure, stroke or certain cardiac death. Therefore there is need of a method to classify all arrhythmia groups instead of a specific class with a good accuracy.

## 1.4 Research Questions

Critical analysis led us to following questions:
**Research Question 1:** Can we develop fully automated model for classification of life threatening arrhythmia groups?
**Research Question 2:** Can all arrhythmia groups including their sub classes could be targeted by hybrid approach?
**Research Question 3:** Will hybrid approach increase accuracy for life threatening groups?

## 1.5 Significance of the Solution

In everyday life huge amount of data is produced and used in various fields. The rise in E-health data has created many problems. Likewise, the data of arrhythmia is also an issue; the problems of extracting and processing correct information. Therefore the outcome of this study will benefit the community, detection of life threatening arrhythmia with improved accuracy it could save many lives and would decrease the physician workload.

## 1.6 Objectives Achieved

**(i)** Arrhythmia data is of complex nature and becomes difficult to handle proposed hybrid approach recognized these complex features and made them very helpful in detecting the heart abnormalities.

**(ii)** The ability of CNN to extract features and when combined with LSTM to increase the capability to recognize long term dependences between the extracted features has shown satisfying results.

**(iii)** The proposed hybrid model targeted SVEB and VEB achieving an accuracy of 96%.

**(iv)** Model CNN3-LSTM outperformed the-state-of-art performance for SVEB and VEB.

# Chapter 2

# Literature Review

Deep learning has gained massive popularity and is been used in different fields to solve complex problems. Deep learning is part of machine learning family of artificial intelligence. There are different Deep learning algorithms, in order to see which is more suitable we should have better understanding of each type. This chapter provides a detail overview of the different models which have been used up-till now for arrhythmia detection. This chapter goes into detail of some ML methods. Followed by deep learning models and in the last section hybrid models are explained.

## 2.1 Machine Learning Approaches

Traditionally, Machine Learning (ML) algorithms and data mining techniques have been used to learn patterns from these datasets to identify cardiovascular diseases, consequently, these computational sciences reinforce doctors in identifying heart diseases with higher accuracy and ease. ML domain has a plethora of different algorithms in the category of supervised, unsupervised and reinforcement learning. A volume of has been reported to diagnose problems related to cardiovascular diseases, such as detecting arrhythmia, using ML based algorithms such as

Bayesian Networks (BN), Support Vector Machines (SVM), Discrete wavelet transform (DWT), Random Forest (RF), Decision Trees (DT), K-nearest neighborhood (kNN) etc.

Plawiak et al [14] has analyzed ML algorithms for detecting heart disorders from longer ECG signal modality. This research analysis considers SVM, kNN, Probabilistic Neural Network (PNN), and Radial Basis Function Neural Network (RBFNN). This research aims to design and implement a mobile base d medicine system for patient self-control and prevention.

Arun et al. developed a three phase approach that removes the noise, then further decomposes it into six phases to extract/select features and finally the features are given into the Hidden Markov Model (HMM) for ECG classification [15]. The paper has further studied the feasibility and benefits of combing cardiac arrhythmia with Internet of Medical Things (IoMT), which would enable users to monitor their health in activities of daily routines like running, walking, and other exercise and sports related activities.This research has waived off the HMM model, limitations of precise definition of model parameters, evaluation of probabilities for every specific HMM, and observed signal parameter adjustment.

Ch et al. [16] have utilized DWT for feature extraction and then SVM technique is applied for the classification of arrhythmia for identifying three different classes of normal sinus rhythm, congestive heart failure and cardiac arrhythmia. The ECG samples were collected from MIT-BIH and BIDMC databanks. Leandro et al. evaluated different feature extractions techniques using Structural Co-Occurrence Matrix (SCM) as feature extractor [17]. The obtained features were used to train SVM, BN, Optimum-Path RF, and Multi-Layer Perceptron.

However, traditional ML methods consist of a pipeline of preprocessing phases from preparing datasets to classifying the disease. **i)** Removal of power-line inference sound, a 50 Hz signal, which could potentially degrade the ECG signal quality and glut smaller features that are critical for diagnosis of cardiovascular problems. **ii)** Manual feature selection/extraction that are more discriminant for the problem at hand. **iii)** These features are used for training the ML algorithms to classify/detect the disease based on any symptoms that are learned from these datasets. The available datasets lack quality due to the costly labeling process as it needs domain knowledge to be acquired from experts. Moreover, selection/extraction of features is a very error prone phase in the ML development cycle as it is impossible to hand-craft the best features without loss of useful information and this process always carries some margin of error that might introduce biasness in the model, which would not generalize good enough on unseen data. All features, which can lead to loss of useful data.

This is due to the fact that not all features are discriminant enough to represent the problem in the context of various applications. Out of the large available feature space, only a smaller dimension is required to solve specific tasks. This is the reason why humans are best at performing many tasks of recognition and classification better than the machines that has at their disposal a huge memory and power processing capabilities. This is because the human brain is best at adaptively selecting features that suits the situation at hand from among the huge space available. Furthermore, the ML based processing techniques utilize shallow-structured hierarchy for different feature transformations that mostly involve linear modeling. Consequent upon the proliferation of a large volume of datasets over the recent years and the available computational power has given rise to deep learning structures. These computational models have gained an extraordinary level of popularity due its automatic features selection process that resulted in high accuracy in clinical health applications.

This has waived off the limitations of ML based methods, as now multiple levels of hierarchies are utilized to learn features to take into account both low level and high level attributes of the problem. One downside of deep learning computational structures is their high cost of training, which is however worth in applications that require high classification accuracy because human life and health is involved. Therefore, we can conclude that ML based approaches are not considered very useful practice due to the curse of dimensionality i.e. fewer samples and a high dimension of features. So ML based computations requires good quality and massive data sets to train on [18]. In contrast to ML based approaches that utilize a pipelined setup, we propose a hybrid approach based on Deep Learning (DL) to take a three-fold benefit from its simultaneous training process, automatic feature selection at multiple levels, and linear as well as non-linear feature transformations.

## 2.2 Deep Learning Approaches

DL technology has a great ability to learn from videos, images and unstructured data in a way that ML based approaches cannot easily do. DL based approaches has a higher capability of finding useful patterns and have great potential to produce results with high accuracy, which is key to applications in the domain of medicine and healthcare. Next we present the literature review on some successful DL structures and implementations of identifying patterns in ECG modality for diagnosing cardiovascular diseases.

### 2.2.1 CNN

Rahhal et al [19] proposed a model which used AL(active learning) which allows to select most convenient samples that can enhance the model. It minimize the training sample and ambiguous samples are given to expert for labeling, and for ranking purpose the method relies on DNN. They evaluated their model on three database data MIT-BIH ,INCART and SVDB arrhythmia database. The arrhythmia groups they considered were N,S,V,F and Q, but increasing the number of hidden layers in their proposed model gave less accurate results and AL technique is not considered resourceful for complex architectures with few training samples.

Serkan et al. [20] proposed an approach which is a ECG heartbeat classifier for specific patients, it is a novel approach based on 1-D CNNs. The CNNs were trained on every patient data. But the problem with this approach is that for specific patients or random group of patients data on which CNNs were trained does not have promising results for crucial anomaly as S beat and if it is not included while training, the model will fail to classify them.

Ali Isina and Selen Ozdali [21] proposed a productive moved profound learning based ECG arrangement framework , which is acknowledged to do programmed ECG arrhythmia diagnostics by ordering patient ECG's into relating three distinctive cardiovascular conditions; normal(N), paced(P) or right bundle branch block(RBBB). After the ECG records are gained from the online MIT-BIH arrhythmia information base, they are separated from commotions and QRS waves are identified to extricate R-T portions of the ECG. Pre-prepared AlexNet, is moved and utilized as an element extractor for the ECG grouping task close by. The extricated highlights are taken care of into a basic back spread neural organization to group the information ECG R-T portions into one of the three heart conditions(N,RBBB,P). Though the proposed framework achieved their main focus; to implement a deep learning technique that is easy and reliable but it is only classifying three classes.

Weifang et al. [22] presented a CNN using GLCM(gray-level co-occurrence matrix) to automat diagnosis method. ECG signal amplitude is mapped into fixed gray-level matrix, GLCM is employed to describe the wave shape change and wave shape description. Then CNN approach is used to automate the classification created from 3D multi-scale GLCM. Results show that this strategy can viably recognize distinctive morphological arrhythmia classes with more accuracy. The proposed technique can suppress noise coming from non stationary objects. Gray level co-occurrence matrix can easily extract the features vector from different groups of arrhythmias from lead ECGs with more performance of diagnostic. The problem with GLCM is that calculation process is little complex.

Xin et al. [23] proposed two convolutional neural network models. One is FDResNet(the fast down-sampling residual convolutional neural network). The other is MSResNet(a multi-scale decomposition enhanced fast down-sampling residual convolutional neural network). The fast down-sampled residual convolutional neural networks are trained using different scales of reconstructed datasets. Whereas multi-scale residual convolutional neural networks are trained using transfer learning. The multi-scale residual neural network consists of three parallel FDResNets coupled by a small neural network. The three FDResNets have the same structure, but are independently trained by reconstructed samples of different scales.

The dataset they used is from the PhysioNet Challenge 2017 and targeted AF(atrial fibrillation) achieving an accuracy of 87.12% by FDResNet and 92.1% by Multi FDResNet. The problem with FDResNet is that loss value is more in fast down module whereas in multi fast down module though good but it is not stable when increasing FDResNet. The results get scattered which leads the model unstable and obviously decreasing the accuracy of classification.

Hamido Fujita and Dalibor Cimr [24] proposed a CNN approach; 8 layer convolutional neural network for the detection of fibrillation and flutters (A fib, A fl, V fib ).They used data from MIT-BIH arrhythmia database for evaluations of their model. The limitation of introduced approach is that too much big batch can lead with low model performance. During normalization, the normalized signals represents voltage difference after 4ms which could lead to losing necessary information from raw input, the proposed model does not have the capability of artifact recognition.

Acharya et al. [25] proposed a model consisting of eleven-layer CNN and a output layer of four neurons. The four neurons represents the normal (Nsr), Afib(Atrial Fibrillation), Afl(Atrial Flutter), and Vfib(Ventricular Fibrillation) ECG class. Requires a lot of data (big data) for training and while training of data takes much time. If compared to other models performance is slow.

Acharya et al. [26] used a convolutional neural network as mentioned in previous study but in this work they are classifying them into shockable and non-shockable ventricular arrhythmia. Acharya et al. [27] then proposed a model of CNN comprising of nine layers to automatically identify 5 different categories(N, S, V, F, and Q) of heartbeats in ECG signals. Their introduced models includes 3 convolution layers, 3 max-pooling layers, and 3 fully-connected layers. But the problem with there proposed model was that it required more number of training hours, to efficiently train GPUs specialized hardware is required, and its training is computationally expensive. While training more number of images are required so it can reliably recognize multiple patterns.

### 2.2.2 DBN

Mathews et al. [28] presented a novel approach which is based on deep learning methodology for ventricular and supra-ventricular heartbeats classification. The application of Restricted Boltzmann Machines and deep belief networks is considered to automate classification of single-lead ECG signals. The RBM is a bidirectionally associated networks of stochastic handling units that learns signicant highlights of an obscure likelihood dissemination dependent on examples from that appropriation.

A RBM can be depicted as a bipartite chart having a visible layer and a hidden layer. DBNs are a sort of multi layer generative neural network that is perceived for its capacity to demonstrate and imagine significant level learned highlights. It is made out of stacked, calculated RBMs wherein the most reduced level RBM learns a shallow model of the information. Their work focused on five classes but classification is higher only for the SVEB and VEB class.

### 2.2.3 LSTM

Yildirim [29] used structure named DBLSTM-WS and DULSTM-WS in his work for the classification of ECG signals. In DBLSTM-WS two Bi-directional LSTM were used one for forward propagation and other for backward propagation along with two dense (fully connected) layers. While in DULSTM-WS unidirectional LSTM layer with two sense(fully connected) layers is used to classify five different types of heartbeats which are obtained from the MIT-BIH arrhythmia database. Those five types are NSR(normal sinus rhythm), VPC(ventricular premature contraction), PB(paced beat), LBBB(left bundle branch block) and RBBB(right bundle branch block).

A new wavelet transform based layer WS for feature extraction was placed at the top of the model, this layer was introduced because both of the above structure were not giving accurate result while classifying ECG signals into classes. The problem with introduced approaches is that because of limited resources all arrhythmia data in MIT-BIH is not used and the time cost of the training phase.

### 2.2.4 Autoencoders

Ozal et al. [30] presented with a compression scheme which uses CAE(AE structure with many hidden layers) instead of traditional AES. In encoder phase signals are reduced and encoded whereas in decoder section reconstruction is performed on low features, 27 layers were used 14 layers in encoding phase and 13 layers in decoding phase. In the encoder segment of this model, the signs are diminished to low-dimensional vectors; and in the decoder segment, the signs are remade. The profound learning approach gives the portrayals of the low and undeniable degrees of signs in the hidden layers of the model.

With insignificant loss the original signal is constructed, different from conventional straight change techniques, a profound pressure approach infers that it can figure out how to utilize diverse ECG records automatically. The model is assessed on an informational set including 4800 ECG sections from 48 extraordinary clinical patients. The pressure rate (CR) of the proposed model was 32.25, and the normal PRD esteem was 2.73%. Their main focus was an approach that can be used/embedded in wearable, other hardware devices and a model that can permit secure information transfer with a low dimensional structure to far off clinics.

The approaches which were used before needed an expert to manage long duration ECG beat recording. So to overcome this problem Ozal et al. [31] introduced a novel approach(CAE-LSTM) which first compresses the signals and then classify them. CAE(Convolutional Autoencoders) model which is used to compress the

ECG signals with minimum data loss and then LSTM is used to recognize these compressed signals. Deep CAE model consist of 16 layers whereas LSTM consist of 5 layers. The problem with the proposed approach is it requires a complex deep learning model for compression, during compression some features are lost and process on raw data, required to obtain coded features took time.

### 2.2.5 ANN

Sarah et al. [32] presented with an exceptionally encouraging appraisal apparatus for wellbeing; Heart RateVariability (HRV) using ANN. HRV is the distinction on schedule between one heartbeat and the following. HRV estimation is simple and non-obtrusive; it is gotten from recording of ECG on free moving subjects. The fundamental point of this work is to research the elements in the autonomic guideline of the pulse by using recurrence and fleeting examination to correspond between the HRV and these physiological patterns.

The framework comprises four stages: information obtaining, preprocessing stage, highlight extraction stage and characterization stage. Preprocessing of the HRV data was an urgent advance to have the option to remove precisely the features. Time and recurrence area proportions of HRV were calculated from the RR span tachogram. Different neural networks designs were executed and investigated in this work. Then the detection of the rest/alert states is accomplished, finally a multi-classification of various sorts of activities such as resting, strolling, practicing and eating is performed with an accuracy of 88.7%.

Sannino and De Pietro [33] proposed deep learning approach for ECG classification of normal and abnormal beats. For experiment purpose they used data of MITBIH Arrhythmia Database. Then they developed DNN by performing trials. In each experiment they manually configured deep neural network by changing parameters like: how many hidden layers would be there and for each layer how many neurons are needed, the activation function. The accuracy of the testing set was evaluated for each configuration. After manual phase, then finally a good classification performance was obtained with a DNN composed of seven hidden layers, with 5, 10, 30, 50, 30, 10 and 5 neurons. The accuracy of the proposed DNN is the highest with values greater than 99% but it is only classifying normal and abnormal not targeting type of arrhythmia.

### 2.2.6 RBFN

Muqing et al. [34] proposed a dynamical neural learning mechanism for human ID and cardiovascular illnesses classification. The proposed technique comprises of two steps: first step is the preparation stage and the second step is to test. In the first step, heart elements inside ECG signals is separated (approximated) precisely by utilizing spiral premise work (RBF) neural networks through deterministic learning. The acquired heart framework elements is addressed and put away in steady RBF networks. An ECG mark is then gotten from the removed heart elements along the intermittent ECG state directions. A bank of assessors is developed utilizing the extricated heart elements to address the prepared stride designs. In the test stage, acknowledgment mistakes are produced and taken as the likeness measure by looking at the cardiovascular elements of the prepared ECG designs and the elements of the test ECG design.

A test ECG design starts with estimating the condition of test design, and consequently continues with the advancement of the acknowledgment mistake framework. As per the littlest blunder rule, the test ECG example can be quickly perceived. This sort of cardiovascular elements data addresses the beat to beat worldly difference in ECG alterations and the transient/dynamical nature of ECG designs. Along these lines, the measure of discriminability given by the cardiovascular elements is bigger than the first signals. The developed acknowledgment framework can recognize and allocate dynamical ECG examples to predefined classes, analyses are done on the FuWai and PTB ECG information bases to show the adequacy of the proposed technique. But the size of the PTB Diagnostic

ECG Database is little, which restricts the capacity of the proposed ECG design acknowledgment strategy for regular cardiovascular illnesses.

## 2.3 Hybrid Approaches

In this section some hybrid approaches of DNNs are been presented.

Wang Jibin [10] proposed a CNN-MENN structure for the detection of Atrial fibrillation(leads to serious heart disease) achieving 97% accuracy. It was based on 11 layers with modified elman neural network to increase the performance. CNN-MENN, CNN-ENN and CNN-MLP models were compared to see the performance and accuracy. They used MIT-BIH arrhythmia database data. Drawback of the proposed model is it only focused on AF detection and it still requires larger, diverse data set for learning and training.

Li et al. [11] proposed a deep model; they used the densely connected convolutional neural network(DenseNet) and gated recurrent unit network(GRU) for the classification of supraventricular (SVEB) and ventricular (VEB) accuracy 93%. In DenseNet at each conventional layer low and high-level features are concatenated together whereas GRU receives output from previous step which is a dense block and analyses them step by step for learning of temporal features. Both GRU and LSTM have same results in some cases and their design were also similar. Proposed deep learning model architecture is evaluated using the MIT-BIH arrhythmia and supraventricular databases. But a model that is accurately able to label all types of classes would undoubtedly help but introduced model is only classifying SVEB and VEB.

Xiaomao et al. [12] presented with a multi-scaled fusion of deep convolutional neural network(MS-CNN) is proposed to detect AF signals based on ECG recordings. The technique MS-CNN mainly focuses on VisualGeometry group network(VGGNet), which is kind on neural network which is considered to be efficient in solving computer field problems. It mainly has two stages, first stage comprises of 13 layer convolutional neural network and the second stage comprise of 3 fully connected layers, it can take input beat of 20 seconds and more than that. The proposed model is giving 97% accuracy. There introduced model performs good for 20 second beat but classification accuracy is not good for less; 5 second beat.

Qihang et al. [35] presented with model which is a attention based, time gradual convolutional neural network (AT-CNN), the model separated data from ECG signals in two stages, in the first stage the spatial data is dependent on CNN and in second stage temporal data is dependent on LSTM cells. These modules with various capacities were consolidated into a uniform DNN to finish the model. There attention module has applied a tangent function to each feature followed by two fully connected layers.

The data set used for training is obtained from the 1st China physio- logical signal challenge. For classification purpose the classes which were considered are 8; Left bundle branch block (LBBB), Right bundle branch block (RBBB), Premature atrial contraction (PAC), Premature ventricular contraction (PVC), Normal (N), ST-segment elevation (STE), Atrial fibrillation (AF). The accuracy achieved by introduced model is 81%. There model results were not satisfactory for classes PAC and PVC. Jen et al. [36] presented a model LSTM-CNN to detect CAD(computer-aided diagnosis) ECG signals accurately. Accuracy is 95%. There model showed low results in diagnostic of specific person data. Warric et al. [13] proposed a CNN-LSTM model using the raw ECG input for the detection of arrhythmia class AF giving accuracy of 83%. Dataset from Physionet Challenge 2017 was considered for training of their proposed model.

## 2.4 Critical Review of Techniques

The brief overview of techniques is described in table 2.1 below. Hybrid model analysis is also presented in table 2.2 below along with their data,methodology used and targeted classes with accuracy.

TABLE 2.1: Critical Analysis of Literature

| Reference | Year | Method | Limitation |
|---|---|---|---|
| Sannino et al. [33] | 2018 | DNN composed of seven hidden layers. | KStar classifier is worst in terms of sensitivity |
| Ozal et al. [31] | 2019 | CAE model is used to compress the ECG signals then LSTM model is used to classify them. | A complex deep learning model for compression and during compression some features are lost. |
| Rahhal et al [19] | 2016 | Used the concept of active learning with DNN. | Not fully automatic (expert interaction involved). |
| Ozal et al. [30] | 2018 | Presented with a compression scheme that can be used in wearable and other hardware devices. | No training phase used for training of data direct compression methods are applied. |
| Yildirim [29] | 2018 | Structure named DBLSTM-WS was used in this paper for the classification of ECG signals. | Complex structure and took too much time. |

Continued on next page –

Table 2.1: Critical Analysis of Literature

| Reference | Year | Method | Limitation |
| --- | --- | --- | --- |
| Xin et al. [23] | 2019 | Proposed two convolutional neural network model (FDResNet) and (MSResNet). | Loss value is more in fast down module. Multi fast down module though good but it is not stable when increasing FDResNet;results get scattered which leads the model unstable and obviously decreasing the accuracy of classification |
| Jibin Wang [10] | 2020 | Proposed a CNN-MENN structure, It was based on 11 layers with modified elman neural network. | This model system only focused on AF detection, CNN-MENN model often requires sufficient learning processes of data or relevant information in the early stage. It still requires more larger and diverse data set for learning and training. |

Continued on next page

Table 2.1: Critical Analysis of Literature

| Reference | Year | Method | Limitation |
|---|---|---|---|
| Li et al. [11] | 2019 | Proposed densely connected convolutional neural network and gated recurrent unit network for the classification of arrhythmia. | Not performing classification for multi-classes of arrhythmia. |
| Xiaomao et al. [12] | 2018 | A multi-scaled fusion of deep convolutional neural network is proposed,it is designed and built drawing on the experiences of VGGNet. | There introduced model performs good for 20 second beat but classification accuracy is not good for less; 5 second beat. |
| Philip et al. [13] | 2017 | Used a combination of Convolution Neural Networks and a sequence of Long Short-Term Memory. | Classifying AF only with 83% accuracy. |

Continued on next page

Table 2.1: Critical Analysis of Literature

| Reference | Year | Method | Limitation |
|---|---|---|---|
| Acharya et al. [27] | 2017 | Work consists of an eleven-layer deep CNN. | Requires a lot of data (big data) for training and takes more time to train the data. If compared to other models performance is slow. |
| Jen et al. [36] | 2017 | They presented a model LSTM-CNN to detect CAD(computer-aided diagnosis). | Requires huge dataset and takes more training time. |
| Acharya et al. [26] | 2018 | This work also used a convolutional neural network based on 11 layers. | Model have performed badly in the classification of APB(Artrial Premature Beat) segments. Model is computationally intensive and learning is slow. |
| Serkan et al. [20] | 2016 | 1-D convolutional neural networks was used for each patient,an individual and simple CNN was trained by using relatively small common and patient-specific training data. | hinders the ability to adapt to the changes of the patients heartbeat patterns and doenot guarantees to represent crucial anomaly as S beats properly. |

Table 2.1: Critical Analysis of Literature

| Reference | Year | Method | Limitation |
|---|---|---|---|
| Weifang et al [22] | 2019 | Proposed a gray-level co-occurrence matrix (GLCM) to enhanced the convolutional neural network. | GLCM calculation process is little complex. |
| Acharya et al. [25] | 2017 | They proposed a 9-layer deep convolutional neural network (CNN). | Long training hours are required with specialized hardware to efficiently train (GPU);training is computationally expensive and large number of images is required to train the model that can reliably recognize multiple patterns. |
| Ali et al. [21] | 2018 | Proposed a deep learning technique Artificial Neural Network (ANN), for the classification. | Only classifying three classes N,RBBB, P |
| Sarah et al. [32] | 2018 | Presented with a assessment tool for HRV using ANN. | Assessment tool having 83% accuracy |

TABLE 2.2: Critical Analysis Table of Literature for Hybrid Approaches

| Reference | Year | Data | Classes | Technique | Accuracy |
|---|---|---|---|---|---|
| [11] | 2019 | MIT-BIH Arrhythmia Database | SVEB,VEB | CNN-GRU | 93% |
| [13] | 2017 | PhysioNet Challenge 2017 dataset | AF | CNN-LSTM | 83% |
| [10] | 2019 | MIT-BIH Arrhythmia Database | AF | CNN-MENN | 97% |
| [12] | 2018 | PhysioNet Challenge 2017 dataset | AF | MS-CNN | 97% |

After the critical analysis of above mentioned papers we can say that deep learning techniques are far better on unstructured and large data. ECG data which are of complex nature could be handled better by deep learning techniques as compared to ML. ML are good in supervised, unsupervised, reinforcement same as DL but when comes to feature extraction firstly we need to extract then move on further. But in DL we are not worried about feature extraction as neural networks do both feature extraction, feature selection and classification.

Convolutional neural network is superior to a feed-forward network since CNN has highlights boundary sharing and dimensionality decrease. In view of boundary partaking in CNN, the quantity of boundaries is diminished subsequently the calculations likewise diminished. The fundamental instinct is the gaining from one piece of the picture is likewise valuable in one more piece of the picture. Due to the dimensionality decrease in CNN, the computational force required is diminished.

CNN learns the channels consequently without referencing it expressly. These channels help in separating the right and important components from the information data.CNN catches the spatial elements from a ECG. Spatial components allude to the course of action of pixels and the connection between them. They help us in recognizing the article precisely, the area of an item, just as its connection with different items in a ECG. While tackling a picture characterization issue utilizing ANN, the initial step is to change over a 2-dimensional picture into a 1-dimensional vector before preparing the model. This has disadvantages, The quantity of teachable boundaries increments definitely with an expansion in the size of the picture. ANN loses the spatial provisions of a picture. One normal issue in this load of neural network is the Vanishing and Exploding Gradient. This issue is related with the backpropagation.

Therefore LSTM networks are appropriate to handle problems like that they are good at making expectations dependent on time series information, since there can be loose of uncertain term between significant occasions in a period series. LSTMs were created to overcome the problems of RNNs so we can say LSTMs are variation of RNNs. LSTMs are good at handling time series data as arrhythmia are time series 1D data.

As for DBNs, while training of the data lower bound decreases by adding additional layer while the number of neurons in those layers does not decrease. Generally DBNs models requires enumeration over number of terms therefore these kind of models are quit difficult. Auto encoders on the other hand focus on compression rather than feature learning. Auto encoders did not work very well at recognizing objects compared to latest approaches

# Chapter 3

# Methodology

This section describes the proposed methodology. We will be discussing different modules of our technique and architecture of our module.

## 3.1 Overview of Architecture

In this work proposed deep neural networks have two modules CNN and LSTM. The CNN layer is taking ECG signals to extract the features as CNN are good at extracting. The features extracted from the process of convolution and pooling are further fed into the LSTM. Then LSTM are used for temporal information analysis and then the softmax layer is displaying the output. Architecture of CNN-LSTM hybrid model is shown in figure 3.1.
Block diagram of hybrid model is shown in figure 3.6. In which Raw ECG signals are fed into the hybrid model, which enters the first block of CNN. It goes through convolutional process followed by max pool. Batch normalization layer is used to normalize the output of previous layer. The output of the first block of CNN-1 is fed into second Block CNN-2 going through the same steps convolutional, batch normalization and max pool the resultant output is fed into third block CNN-3. The output of CNN blocks is flatten down to be fed into LSTM. Then in the end Softmax layer is giving us final classification results.

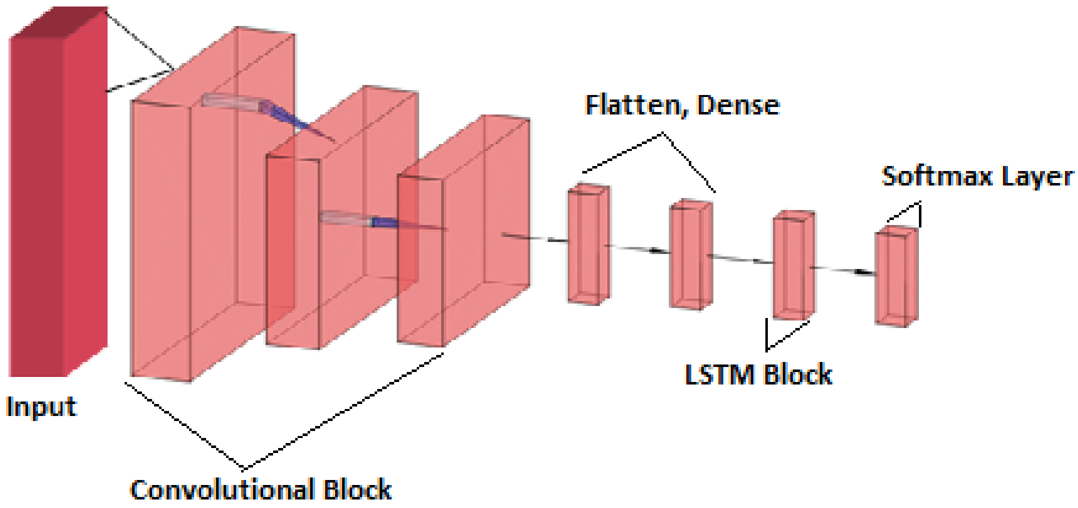



FIGURE 3.1: Overview of Architecture.

## 3.2 Convolutional Block

The first part of the proposed model consists of 1D convolutional layer, which extracts the features from ECG segments. As time series data are one dimension and have spatial properties so 1D convolutional is good choice as kernel slides along one dimension. While implementing the model different models are analyzed which will be discussed further in chapter 4. Firstly data is generated for the model(as for keras CNN model data is needed to be reshaped just a bit), the batch size is 2048 which is a number of samples processed before the model is updated whereas epochs is 15 which means that it is a complete pass on the data being trained on neural network. If consider the first input( record 101 ) which is fed into first CNN block whose figure is shown in figure 3.2.

With CNN we take small patches of a ECG picture as shown in figure 3.3, 3.4 and compare the image piece by piece, we can refer piece as features. A Keras convolutional neural network is utilizing a numerical method to extricate just the most significant pixels. This numerical activity is called convolution. This strategy permits the network to adapt progressively complex highlights at each layer. The convolution isolates the grid into little pieces as to figure out the most fundamental components inside each piece. Then align the features and for each

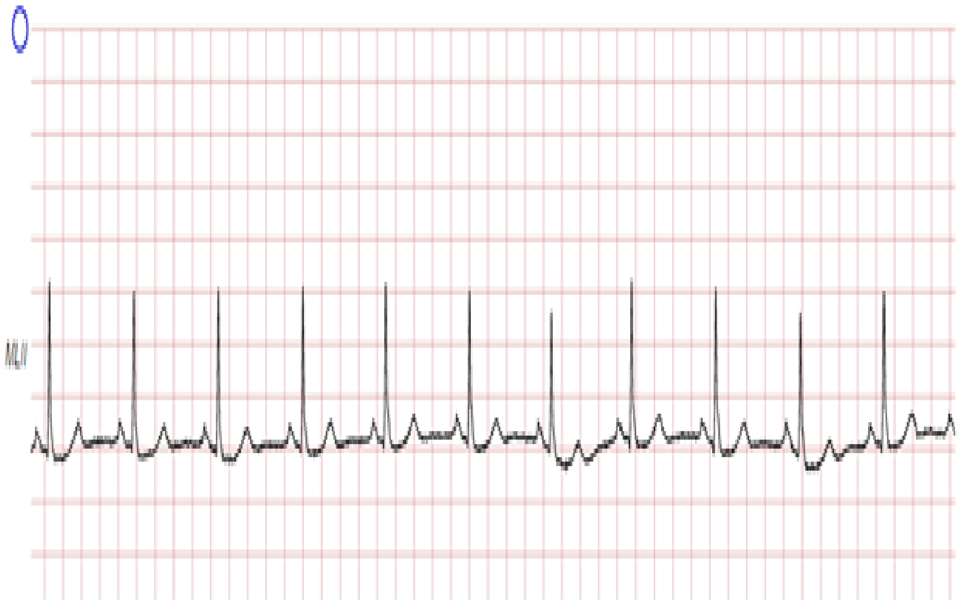


FIGURE 3.2: ECG of Arrhythmia.

pixel of the image multiply by the corresponding feature pixel. First block has 1D convolutional layer with filter 32, kernel size 5 and used ReLu (which is considered best so far).

Then align the features and for each pixel of the image multiply by the corresponding feature pixel. First block has 1D convolutional layer with filter 32, kernel size 5 and used ReLu (which is considered best so far). For the input shape we needed to convert the dimensions before feeding into CNN, the detail of models each layer is shown in table 3.1.

The 1D convolution layer takes the filter and multiplies with every component against the first kernel size time steps. These products are then added for the first cell in the next layer. Computer understands an image by using number(1,0,-1) at each pixel let us take black pixel 1 and white -1. The size of the output layer of CNN is calculated as (n-(f-1)) where n is the input size, f is the filter size. Taking input size 10*10 and filter size 5*5 the resultant will be 6*6.

Then batch normalization layer is applied which allows every layer to do the learning more independently by normalizing the output of the previous layer. Then max pooling 1D layer is applied having pool size 8 and stride is set to 1. The pooling layer is used to reduce the learned features by keeping only the essential elements.


FIGURE 3.3: Convolution operation is used with some filters for detecting edges.

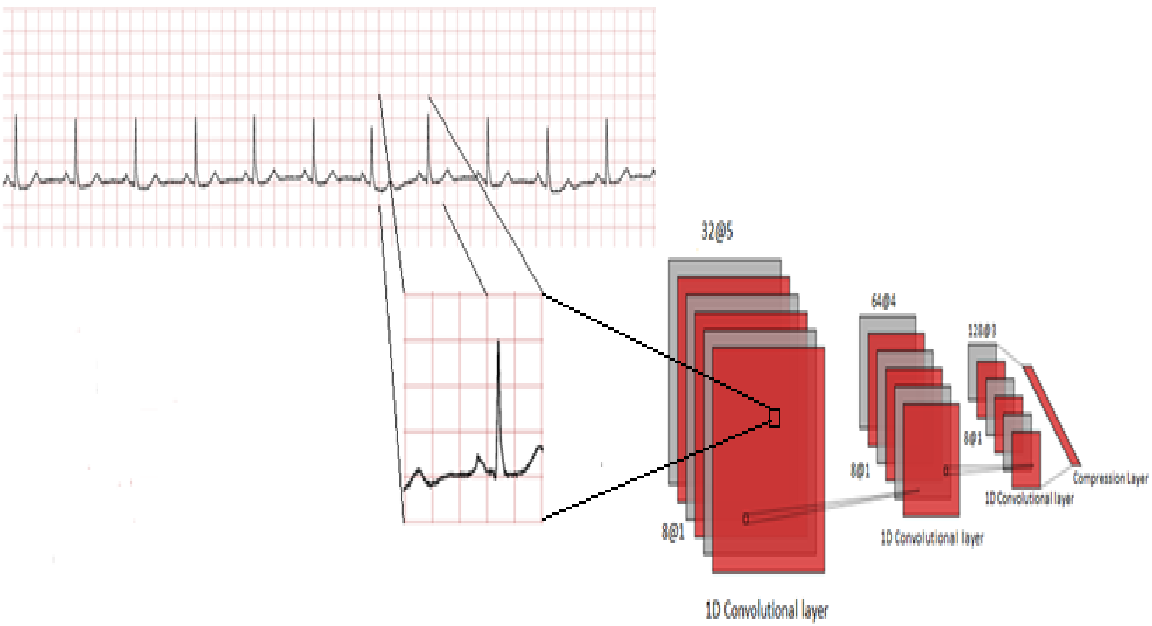



FIGURE 3.4: CNN Feature Extraction.

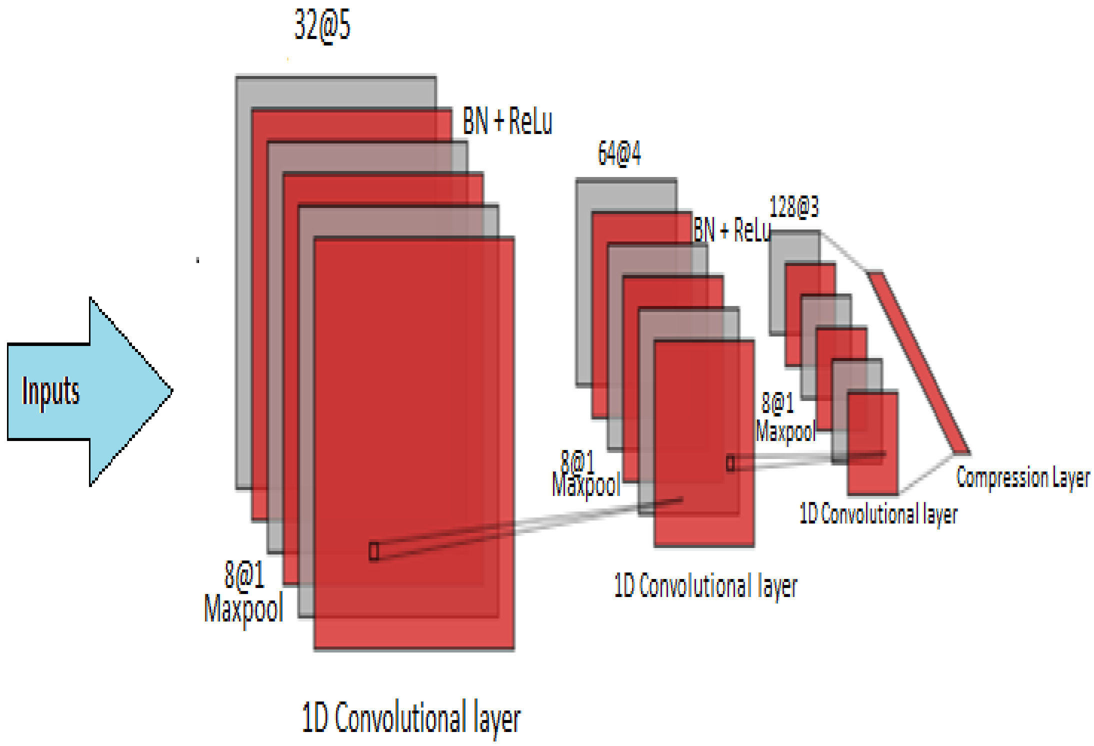



FIGURE 3.5: CNN block having 32@5 annotation; 32 is the filter number and 5 is the filter size. Whereas in the left annotation 8@1, 8 represents maxpool size and 1 represents the stride.

Then comes the next convolutional block in each block we used 2 convolutional layers followed by maxpool and batch normalization as shown in figure 3.5. The number of filters and size of filter varied with each increasing layer. The same steps would be repeated for second convolutional block and as well as for the third convolutional block.

After CNN and pooling step it is then flatten down into a single one dimensional vector to be used as input to the LSTM. After flattening, the flattened feature map is passed to compression layer or we can say fully connected layer; Dense adds the fully connected layer to the neural network. Then the output coming from fully connected it is fed into LSTM. In this model used CNN layers in form of two groups to ensure that the model has a good chance of learning features, from the input data. Further after CNN module processing it is passed into LSTM module.

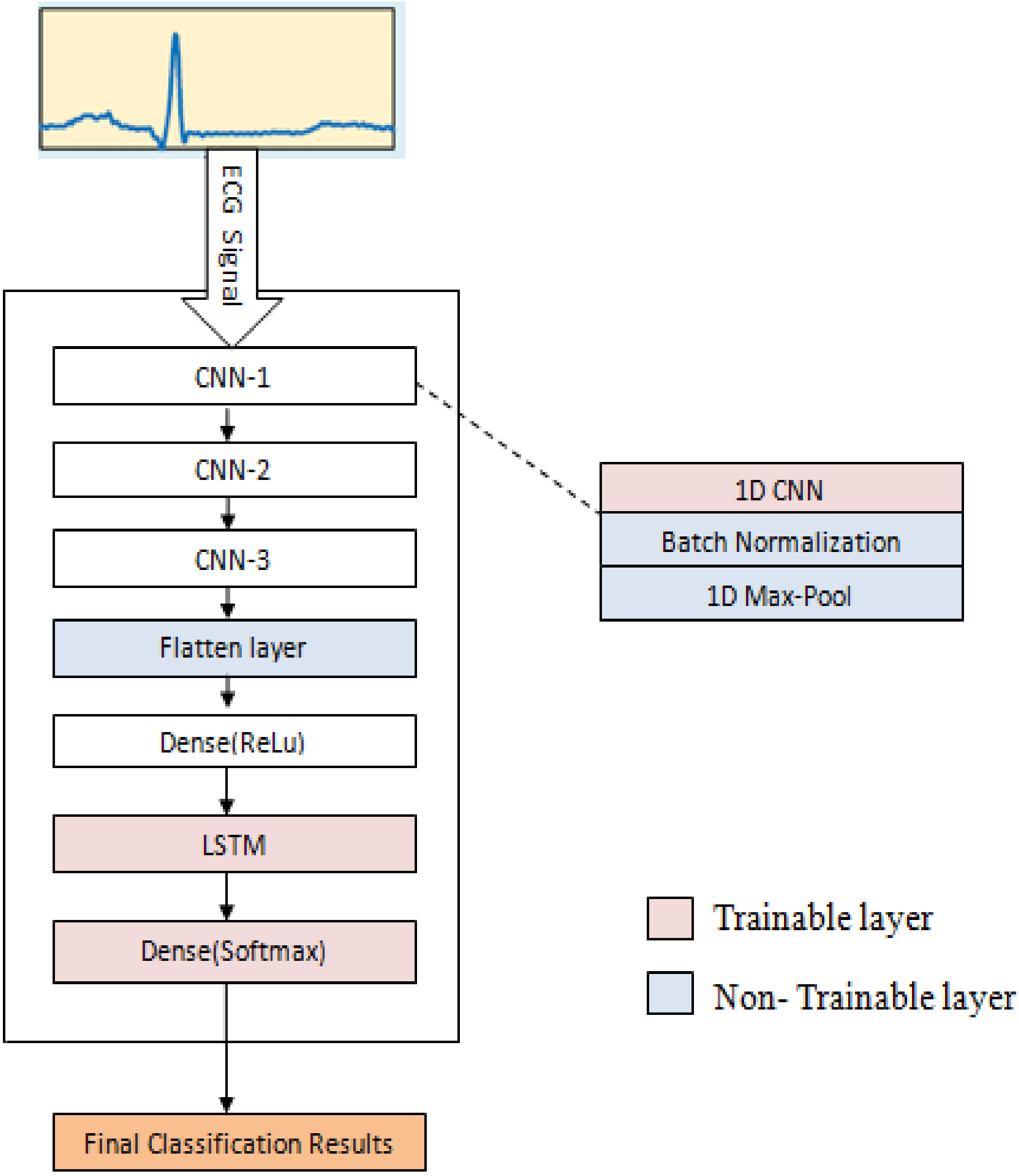



FIGURE 3.6: Block Diagram of Proposed Model.

In above block diagram Raw ECG signals are fed into the hybrid model, which enters the first block of CNN. It goes through convolutional process followed by max pool. Batch normalization layer is used to normalize the output of previous layer. The output of the first block of CNN-1 is fed into second Block CNN-2 going through the same steps convolutional, batch normalization and max pool the resultant output is fed into third block CNN-3. The output of CNN blocks is flatten down to be fed into LSTM. Then in the end Softmax layer is giving us final classification results.

## 3.3 LSTM Block

The second part of the proposed model consists of LSTM. CNN model works as a feature extraction and LSTM to interpret the sequence of subsequences. Recurrent Neural Networks are designed in such a way that are suitable for working with time series data and are capable of learning dependencies in sequential information and LSTM are special type of RNNs. LSTM are those neural networks that have neurons, gates, multipliers and threshold as shown in figure 3.7. In this LSTM block the module receives input(activations) from the previous block and further it analyses them sequentially for learning of temporal features from the inputs.

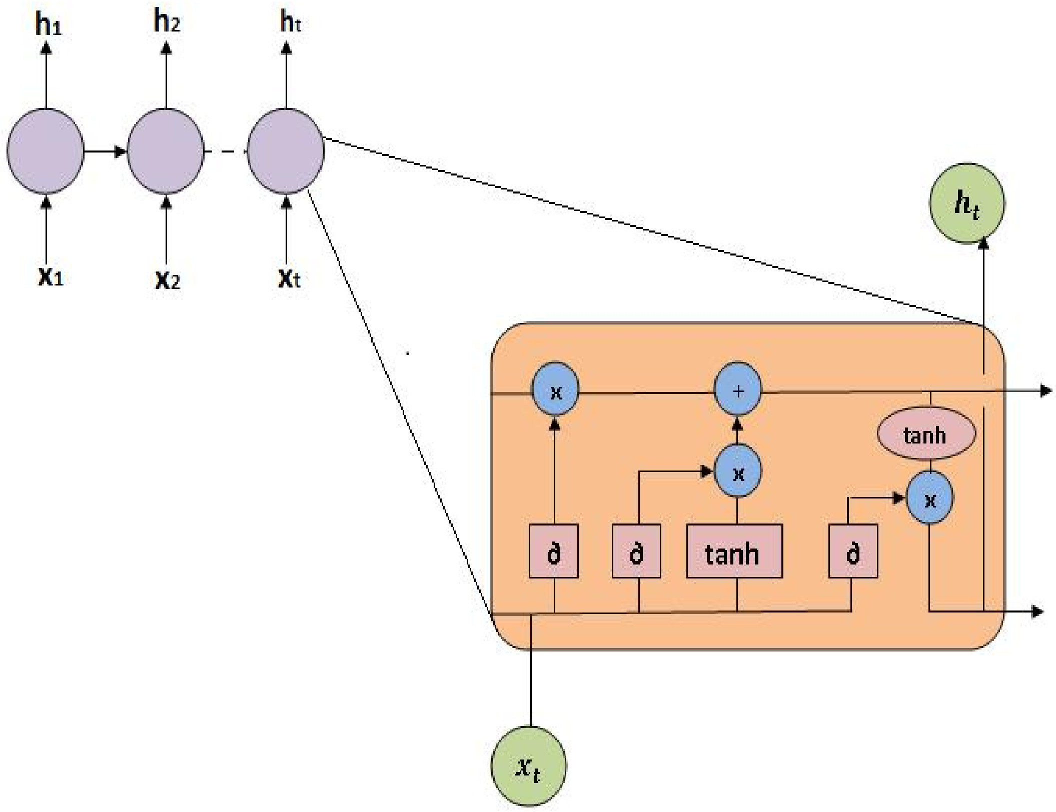



FIGURE 3.7: Overview of LSTM Module.

Each LSTM node consists of forget gate, input gate and output gate. xt is represented as the new input whereas ht is presented as output in above figure.

In this proposed model used dropout value 0.5, it is a technique for reducing over-fitting problem by randomly removing some nodes. The first step in the LSTM is to identify the information that is needed and what information will be taken away from the cell state, sigmoid layer makes this decision which is called as forget gate ($f_t$) layer figure 3.8. Then next the input gate ($i_t$) decides which new information is to be kept and what new values are to be updated 3.9. Further a new vector is created by the tanh which is a squashing function for new values, so it could be added to the state.

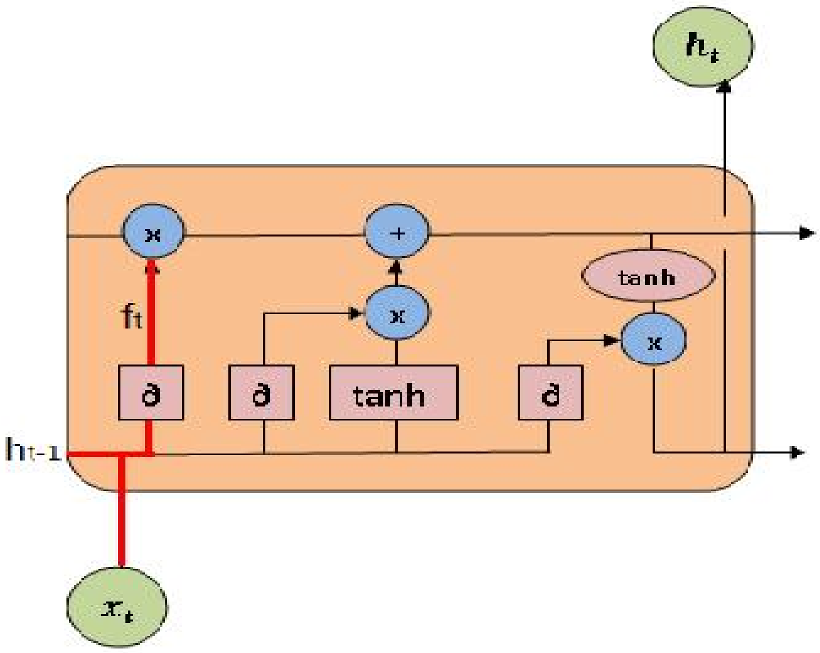



FIGURE 3.8: LSTM Forget Gate Processing.

In above figure the information which should be thrown away is decided by forget gate, it takes under consideration $h_(t-1)$ and $x_t$ giving a output of 0 and 1. One means keep the information whereas zero means forget it.

$$\text{f}_t\text{=}\sigma(W_f\ [h_(t-1)\text{,}x_t]\ +b_f)\ (3.1)$$

$$\text{i}_t\text{=}\sigma(W_i\ [h_(t-1)\text{,}x_t]\ +b_i)\ (3.2)$$

$$\text{C`}_t\text{=tanh}(W_c\ [h_(t-1)\text{,}x_t]\ +b_c)\ (3.3)$$

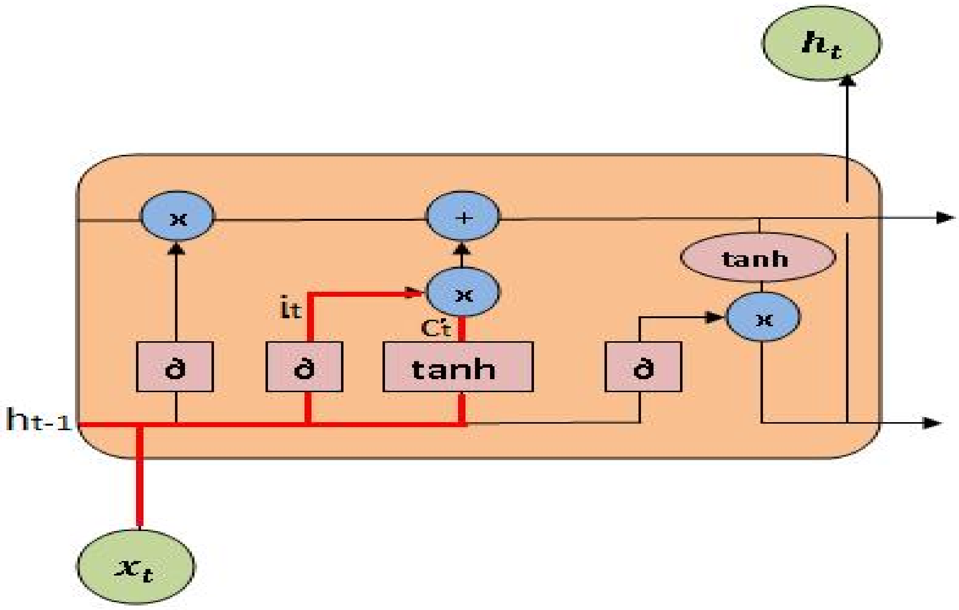



FIGURE 3.9: LSTM Input Gate Processing Step 1.

In above Figure the new information that is going to be stored in cell state is decided by input gate and squashing function tanh which is further combined to update the state. In below figure the old cell state $C_(t-1)$ is updated to new cell state $C_t$ by multiplying with $f_t$ and then adding it with the resultant of $i_t$, $C`_t$.

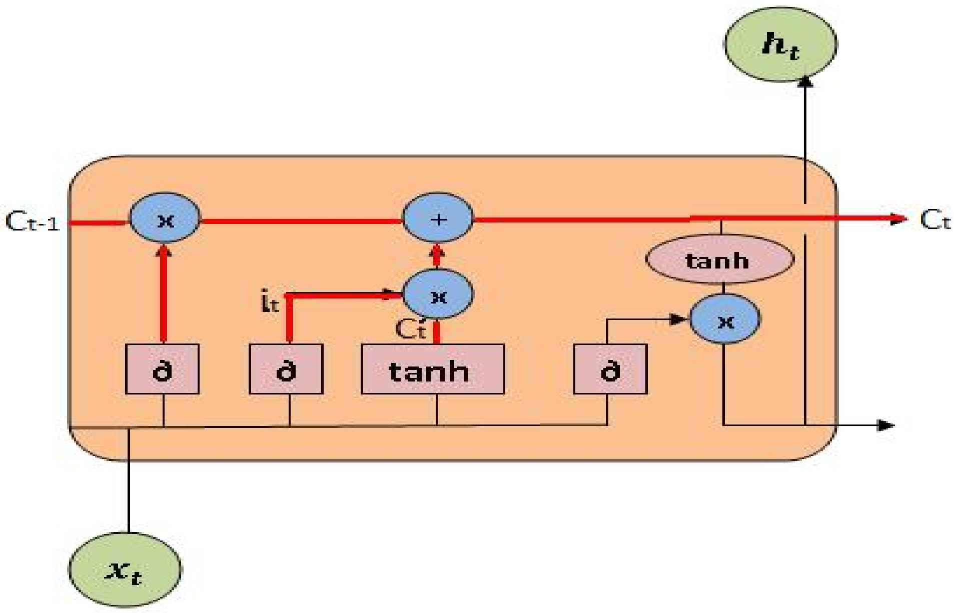



FIGURE 3.10: LSTM Input Gate Processing Step 2.

Old cell ($C_(t-1)$) state will be updated into new cell state ($C_t$) figure 3.10. By multiplying the old state, forgetting and adding.

$$C_t = f_t * C_(t-1) + i_t * C`_t \quad (3.4)$$

Then comes the output gate ($O_t$) figure 3.11 which decides what will be the output. The sigmoid layer will decide what part of the cell state is going to be the output. The cell state goes through tanh, multiplies by the output of sigmoid gate.

$$O_t = \sigma(W_o\ [h_(t-1), x_t]\ + b_o) \quad (3.5)$$
$$h_t = O_t * \tanh(C_t) \quad (3.6)$$

In above equations $W_f$, $W_i$,$W_o$ of gates represents weights and $b_f$, $b_i$, $b_o$ presents the bias value. After going through the above mentioned steps a dense layer also known as the final layer in this model passes through softmax function displaying the output.

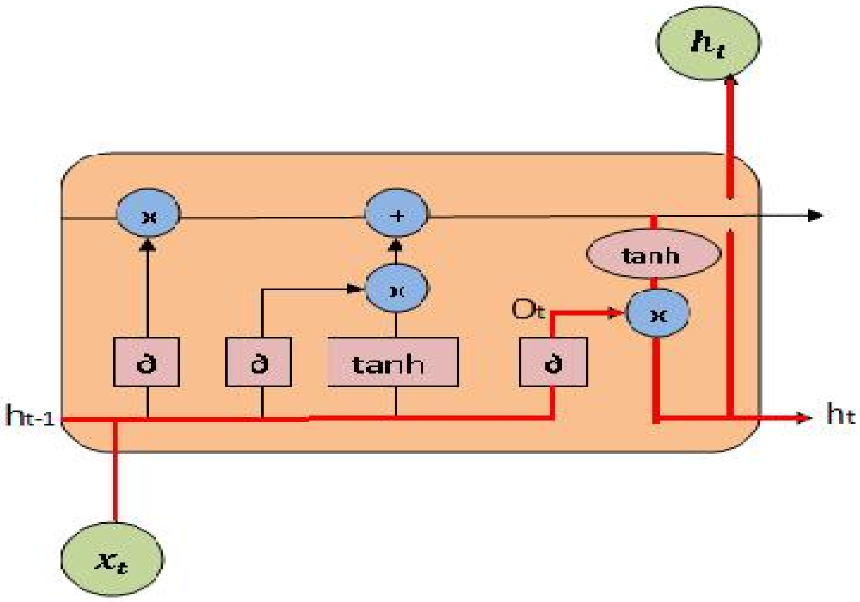



FIGURE 3.11: LSTM Output Gate Processing.

In above figure the information which is going to be output is decide by sigmoid layer and squashing function tanh whose values is between 1 and -1.

## 3.4 Softmax layer

At the end of LSTM we are getting values which are called raw outputs. In order to understand, these raw values they are converted into probabilities using softmax function. To classify the training data softmax activation layer comes into action. Following is the softmax equation:

$$softmax(z_j) = \frac{e^{z_j}}{\sum_{k=1}^{k} e^{z_k}}$$

for j=1,..,k(3.7)

When calculating the value of softmax $z_1$ cannot be considered alone we have to consider $z_1$, $z_2$, $z_3$ and $z_4$ as well.

$$softmax(z_1) = \frac{e^{z_1}}{\sum_{k=1}^{k} e^{z_k}}$$

$$= \frac{e^{z_1}}{e^{z_1} + e^{z_2} + e^{z_3} + e^{z_4}}$$

$$= \frac{e^{z-0.5}}{e^{z-0.5} + e^{z-0.1} + e^{z2.4} + e^{z1.2}}$$

Table 3.1: Detail of Model

| **Layers** | **Type** | **Output Shape** | **kernel size** | **Param** |
|---|---|---|---|---|
| 1-2 | convolutional | 96, 32 | 5 | 192 |
| 3 | max-pool | 89, 32 | 8 | 0 |
| 4-5 | convolutional | 85, 32 | 5 | 5152 |
| 6 | max-pool | 78, 32 | 8 | 0 |
| 7-8 | convolutional | 75, 64 | 4 | 8256 |
| 9 | max-pool | 68, 64 | 8 | 0 |
| 10-11 | convolutional | 65, 64 | 4 | 16448 |
| 12 | max-pool | 58, 64 | 8 | 0 |
| 13-14 | convolutional | 56, 128 | 3 | 24704 |
| 15 | max-pool | 49, 128 | 8 | 0 |
| 16-17 | convolutional | 47, 128 | 3 | 49280 |
| 18 | max-pool | 40, 128 | 8 | 0 |
| 19 | flatten | 5120 | - | 0 |
| 20 | dense(relu) | 256 | - | 1310976 |
| 21 | LSTM | 256 | - | 525312 |
| 22 | dense(softmax) | 4 | - | 1028 |

# Chapter 4

# Experimental Results

This section describes required tools and how experimental setup is done.This chapter explains from where the data was obtained, which datasets are been used. This section also tells about the tools used and how evaluation is done. Last parts consist of discussion and results.

## 4.1 Experimental Setup

### 4.1.1 Programming Language

For the implementation of this experiment, Python programming language is used. It is a powerful language as it contains built-in libraries. It is most suitable because along with the useful libraries it is also very easy to implement and run with minimum system requirements.

### 4.1.2 Libraries

The profound model was actualized in Python utilizing the Keras library with a TensorFlow backend, which gives effective usefulness on CPUs and GPUs. Python interface for neural networks is provided by Keras which is an open source software.

In just a few lines of code our neural network model could be trained and defined by using the library tensorflow; Keras wraps this efficient library. The reason we are using Keras is as it is a high level interface which uses tensorflow to support all kind of neural networks; convolutional, pooling etc which could be further combined to build complex models as we are proposing hybrid model CNN-LSTM which is of complex nature.

### 4.1.3 Tools Used

Tools used for implementation of this experiment is Anaconda and Jupyter. Anaconda is used as it is a conveyance of the Python programming language for scientific computing (information science, AI applications, enormous scope information preparing, prescient investigation, and so forth). The anaconda incorporates information reasonable for Windows, Linux, and macOS. Whereas Jupyter can be called as presentation layer it runs the python code. Jupyter attempts to tackle the issue of reproducibility in investigation by empowering an iterative and involved way to deal with clarifying and picturing code; by utilizing rich content documentations joined with visual portrayals, in a solitary arrangement.

## 4.2 MIT-BIH Arrhythmia Database

The MIT-BIH arrhythmia data set is freely accessible dataset which gives standard examination material to the identification of heart arrhythmia. Since 1980, it is utilized for reason for central exploration and clinical gadget improvement on heart mood and related illnesses. The target to construct the data set is to make mechanized arrhythmia identifiers that read the variety of the sign and dependent on that computerized heart conclusion should be possible. The various intricacies of the electrocardiogram like the assortment of the waveform of the heartbeat and relating cardiovascular thump, and the bewildering force of the relics and clamor, join to build investigation of the sign interesting. So robotization of the account of the Electrocardiograms (ECG) signal is clear and diverse openly accessible information bases are there which contain the recorded ECG signal for future clinical use.

MIT-BIH arrhythmia data set is for the most part utilized for clinical and research reason for various heart arrhythmia identifications and investigations. This data set attempts to give a completely robotized climate to give accurate data to the location of arrhythmias. ECGs remembered for the MIT-BIH Arrhythmia Database is a bunch of more than 4000 long haul Holter accounts that were under the control of Beth Israel Hospital Arrhythmia Laboratory. It lies in the range of 1975 and 1979. Among all the patients they are 25 men between the range of 32 to 89 years, and 22 ladies between the range of 23 to 89 years (Records 201 and 202 came from a same male patient). Every one of the 48 records is marginally more than 30 minutes in length. Four of the 48 records (102, 104, 107, and 217) incorporate paced beats.

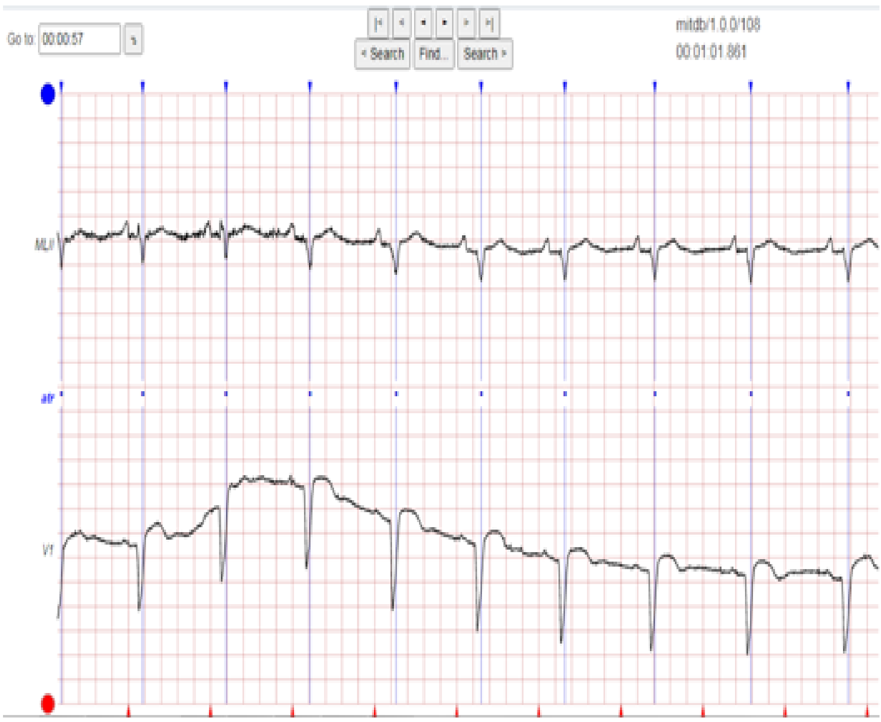



Figure 4.1: ECG recording of 87 year old female

## 4.3 Preprocessing and DataSet

Dataset from the MIT-BIH arrhythmia database is used in this work; 48 recordings, each containing two 30-min ECG lead signals acquired at 360 Hz. Basic preprocessing such as band pass filtering was already performed on these records prior to their availability for research usage. QRS complex detection was performed to show markings of R peaks and the subsequent segmentation processes to separate beats individually as images. Further arrhythmia types are selected the beats of our interest are S and V their mapping and types are shown in Figure **??** . Though we were targeting S and V but we considered 'N', 'L', 'R', 'A', 'a', 'J', 'F', 'e', 'j', 'E', 'F' for analysis also. 50 sequences from both sides of the sample were generated. Non beat annotations ' [ ', '!', ' ] ', 'x', ' ( ', ' ) ', 'p', 't', 'u', '‘', '”', '^', '—', '~', '+', 's', 'T', '*', 'D', '=', ”, '@' also known as unknown beats are not considered. Using the one hot encoding vector specific patient data is encoded. During the training of data the annotations which has occurred the most determines the class label of that specific patient data.


FIGURE 4.2: ECG recording of 51 year old male

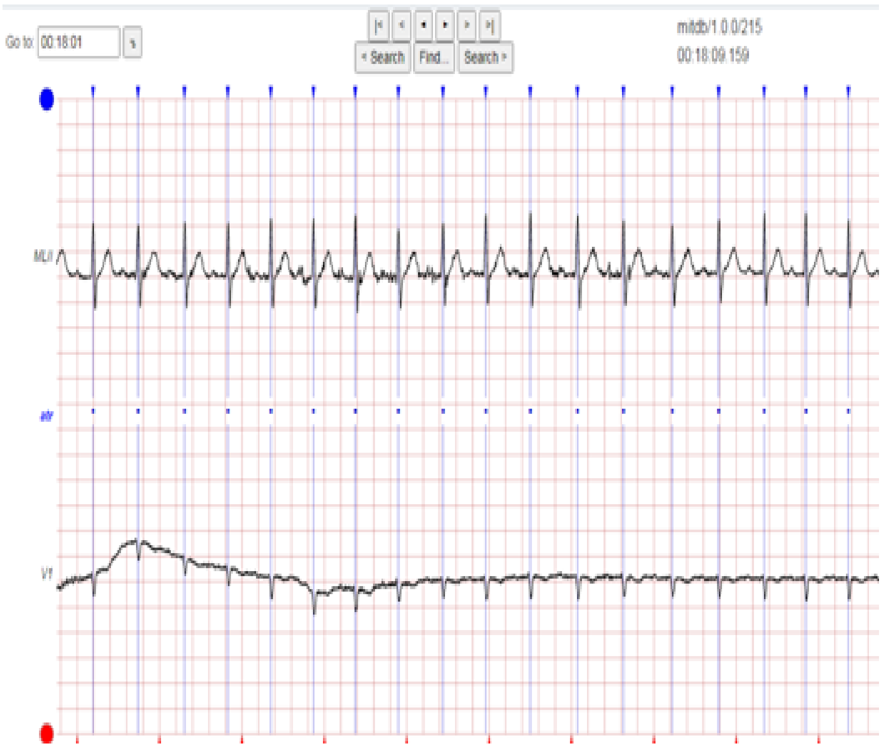



FIGURE 4.3: ECG recording of 81 year old male

Information sections from a 22 patients subset is picked; each individual patient record is 30 minutes long, as the preparing set(training data): DS = 101, 106, 108, 109, 112, 114, 115, 116, 118, 119, 122, 124, 201, 203, 205, 207, 208, 209, 215, 220, 223, 230, some signals like 108,122,215 and 230 with different time stamp are shown in figure 4.1, 4.2, 4.3, 4.4.

While sections from another subset of 22 patients are picked as the testing set(testing data): TS = 100, 103, 105, 111, 113, 117, 121, 123, 200, 202, 210, 212, 213, 214, 219, 221, 222, 228, 231, 232, 233, 234. The staying 4 patient chronicles from the mitdb are definitely not considered as they are on pacemakers and are comprised of just paced, (obscure sort) pulses.Table 4.3 4.1 shows the number of training data, validating data and testing data.

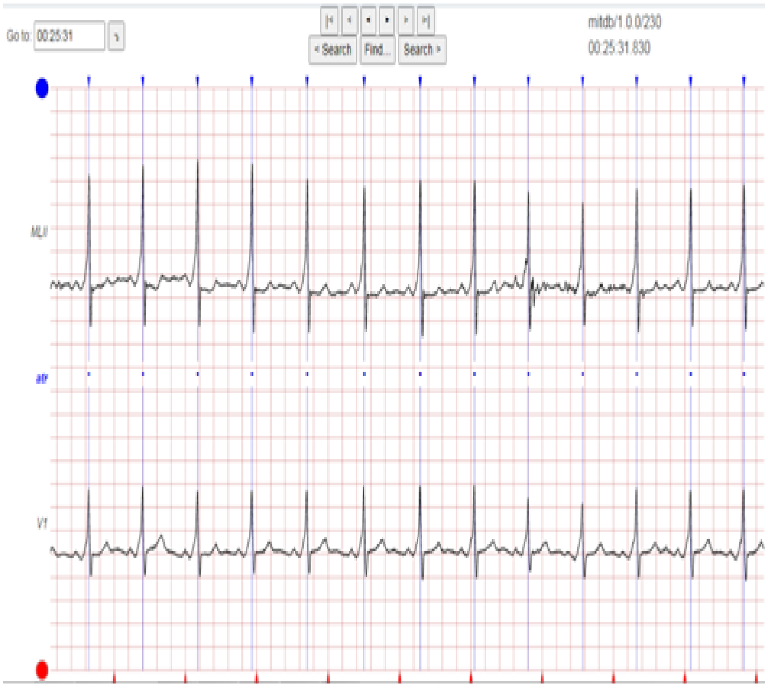



FIGURE 4.4: ECG recording of 32 year old male

TABLE 4.1: Data Set for validation purpose 37% data is used whereas for testing 23% data is used.

| **Training Data** | **Validation Data** | **Testing Data** |
| --- | --- | --- |
| 102016 | 76214 | 23186 |

## 4.4 Performance and Evaluation

In order to evaluate the proposed methodology, some standard metrics are applied. In this Work, accuracy, precision, recall, and F1 score are the measurements for evaluating the performance of the hybrid model CNN-LSTM. In view of true positive (TP), true negative (TN), false positive (FP) and false negative (FN), the meaning of these four measurements can be characterized as following whereas f1 score is for performance comparison used as the combined metric .

**True Positive:** How many times the actual positive value will be equal to the predicted positive value will give us the TP.

**False Positive:** How many times our model will give us negative values lies in FP.

**False Negative:** How many times our model will foretell positive values as negative lies in FN.

**True Negative:** The number of times our model gives us actual negative values which are same as foretell negative values lies in TN.

### 4.4.1 Accuracy

> "The accuracy is used to find the portion of correctly classified values. It tells us how often our model is right" [37].

$$Accuracy = \frac{TP + TN}{TP + TN + Fp + FN} \tag{4.1}$$

### 4.4.2 Precision

> "It is used to calculate the models ability to classify positive values correctly. We can say the model predicts a positive value how often it is right" [38].

$$Precision = \frac{TP}{TP + FP} \tag{4.2}$$

### 4.4.3 Recall

> "It is used to calculate the models ability to predict positive values, how often the model actually predicts the correct values" [38].

$$Recall = \frac{TP}{TP + FN} \tag{4.3}$$

### 4.4.4 F1 score

"It is the harmonic mean of recall and Precision. It is useful when we need to take both precision and recall into account" [37].

$$F1score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4.4}$$

## 4.5 Results and Discussion

The model was experimented with different range values of filters;32,64,128,256. Further the model was also tested for different kernel size;5,4,3,2 and the results suggested kernel size of odd number 5 and 3 is a good choice. The number of layers were increased and compared with previous results having one layer of 1D CNN. Further, results of two layers of 1D CNN was compared with three layers of 1D CNN, results were increasing by increasing the number of layers. In order to evaluate the model results of three models were analyzed CNN1-LSTM, CNN2-LSTM and CNN3-LSTM.The combined results of three different models are shown below in table 4.3 and 4.4 for SVEB and VEB.

The first CNN1-LSTM model consists of one group of 1D convolutional layers with filter size 32, kernel size 5 and Relu. Then batch normalization layer is applied, in the end max pooling layer with pool size 8 and stride 1 is applied. Further it is flatten down to be used for LSTM. CNN1-LSTM model accuracy and model loss are shown in figure 4.5 and 4.6.

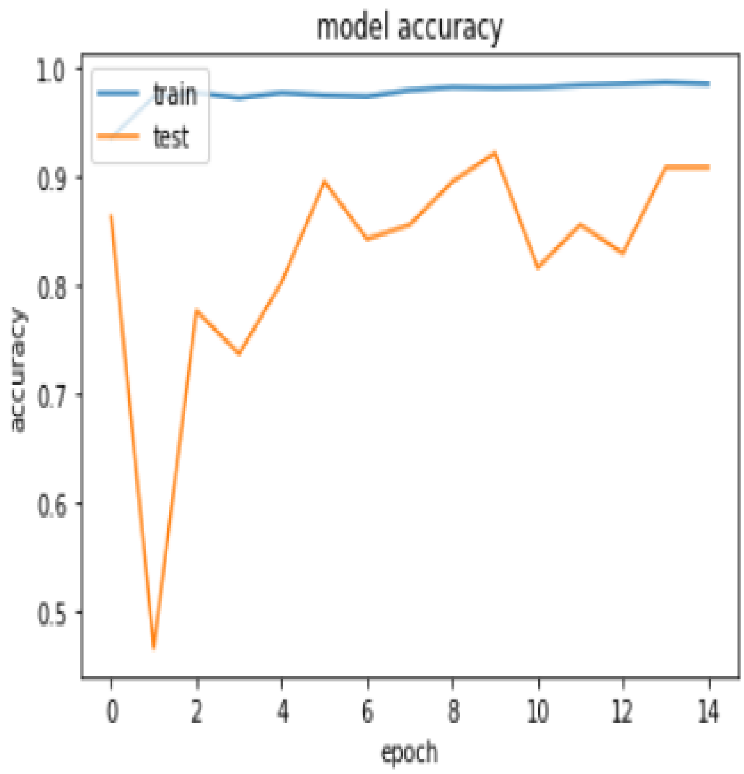



Figure 4.5: CNN1-LSTM Model Accuracy Graph.

In this above graph accuracy is the number of classifications a model correctly predicts divided by the total number of predictions made whereas epoch 15(0-14) refers to a complete pass on the data being trained on neural networks. The blue line in graph shows that model was trained perfectly, whereas while testing the model on unseen data which is represented as orange line there is fall in curve at epoch 1/15 showing model didnot performed well at this time stamp while there is rise in slope at 2/15 with categorical accuracy 0.0764 with little decrease of slope at 3/15 epoch. Then the testing of model on unseen data is increasing with little slight ignorable fall not going below 0.8 categorical accuracy and not going above 0.9 with a straight line between 13/15 and 14/15 showing model accuracy is good.

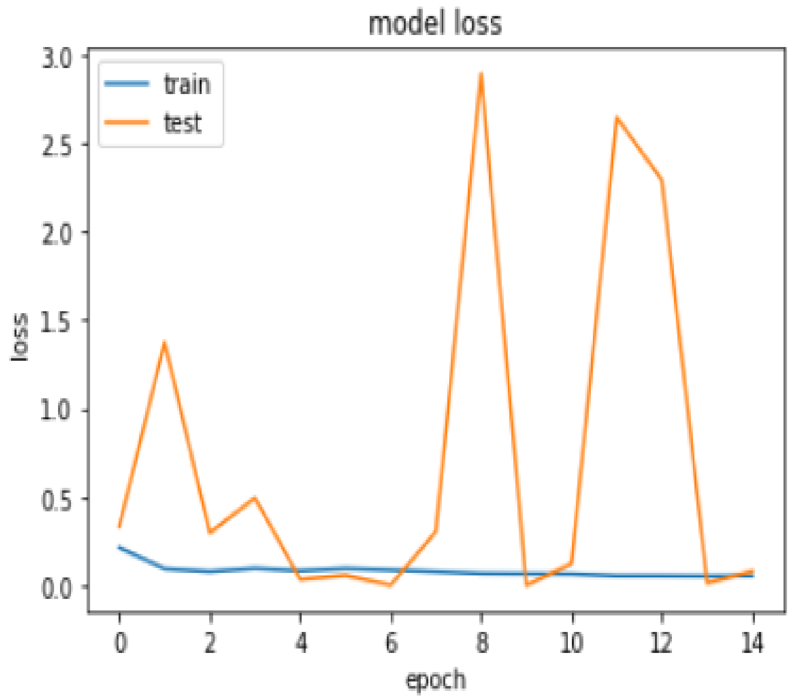



FIGURE 4.6: CNN1-LSTM Model Loss Graph.

Model Loss implies how poorly or well a model behaves after each epoch. While training the model the blue line represents there is minimal loss but while testing on unknown data there is a huge increase of slope at epoch 8/15 and 11/15 indicating there is a overfitting problem, model is not performing well for testing of data but then drop in curve at 13/15 and straight line afterwards shows model loss is reduced.

Then the second CNN2-LSTM model consists of two groups of 1D convolutional layers. The first group has filter size 32, kernel size 5 and Relu. Whereas the second group has filter size 64, kernel size 4. Further batch normalization layer is applied, and then the max pooling layer with pool size 8 and stride 1 is applied. Further it is flatten down to be used as input for LSTM. This model compared to previous CNN1-LSTM model showed better result with increased accuracy. CNN2-LSTM model accuracy and model loss are shown in figure 4.7 and 4.8

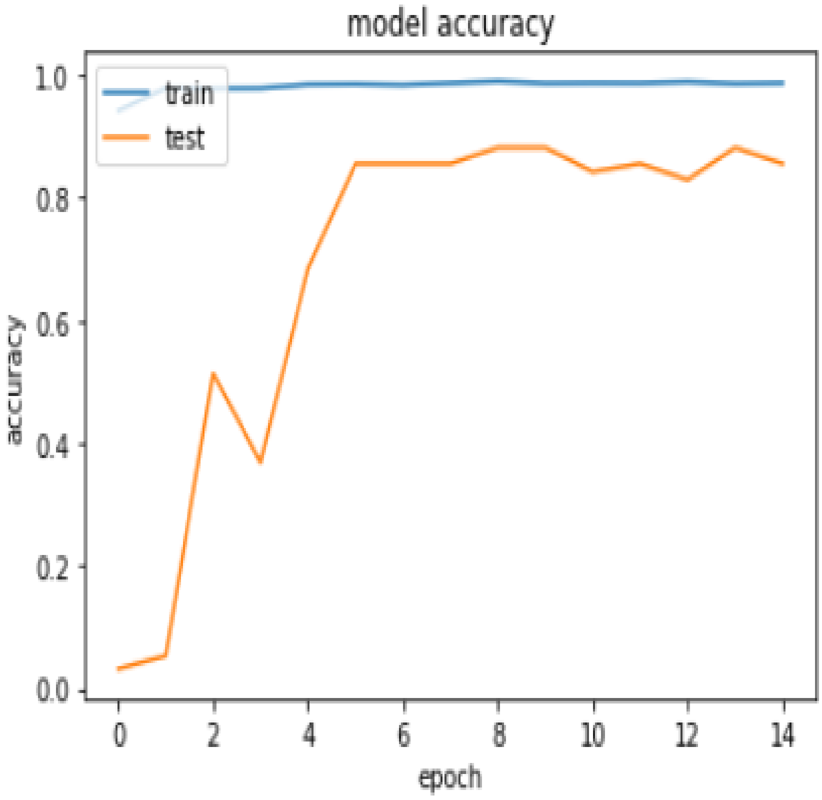



FIGURE 4.7: CNN2-LSTM Model Accuracy Graph.

In this graph the accuracy is increasing rapidly in the first two epochs, indicating that the model is learning fast there is minimal downfall at 3/15 then increase but afterwards the curve flattens indicating that not too many epochs are required to train the model further.

TABLE 4.2: Trainable and Non-Trainable Parameters

| **Trainable params** | **Non-trainable params** | **Total Params** |
|---|---|---|
| 1,942,244 | 896 | 1,943,140 |

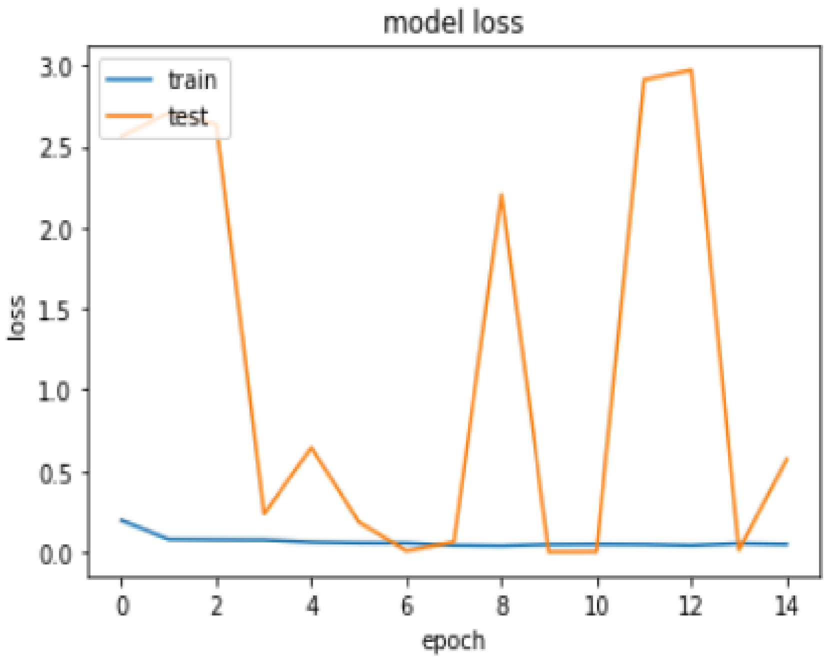



FIGURE 4.8: CNN2-LSTM Model Loss Graph.

The training loss vs testing loss over a number of epochs is a good way to determine if the model has been sufficiently trained as testing loss is increasing at 1/15, 2/15, 8/15, 11/15, 12/15 and 14/15 indicating model will predict training data with high accuracy but not the testing data.

Then finally CNN3-LSTM with three groups of 1D convolutional layers is selected having different filter and kernel size. The first group of 1D convolutional layer has filter size=32 and kernel size=5. Second group 1D convolutional layer has filter size=64 and kernel size=4. Third group 1D convolutional layer has filter size=128 and kernel size=3. Whereas the max pooling layer pool size is set to 8 with stride 1.Model loss and model accuracy are shown in figure 4.9 and 4.10. CNN4-LSTM is also evaluated but results were not satisfying as the accuracy dropped to 95% so the CNN4-LSTM model is ignored.The trainable and non trainable parameters are shown in table 4.2.

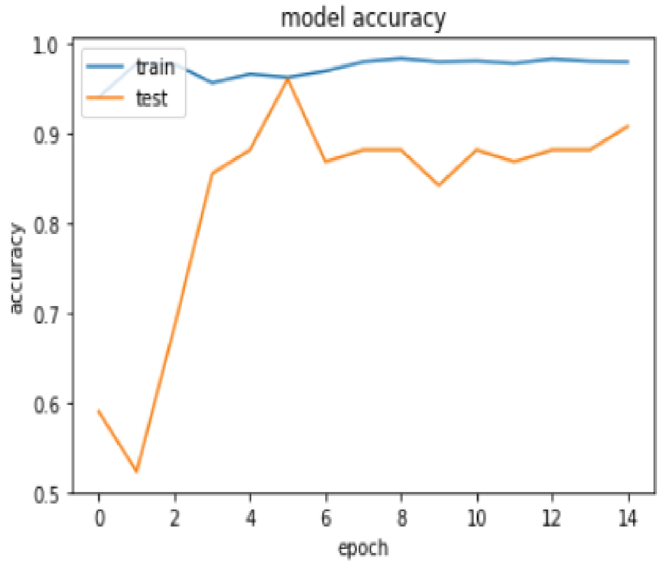



FIGURE 4.9: CNN3-LSTM Model Accuracy Graph.

When the training and testing accuracy is increasing and loss graph is decreasing it means model is been trained in a good way. There is slight fall at 1/15 with categorical accuracy 0.056 but then rise afterwards and reaching categorical accuracy of 0.988 at 5/15 indicating that the proposed model is performing well.

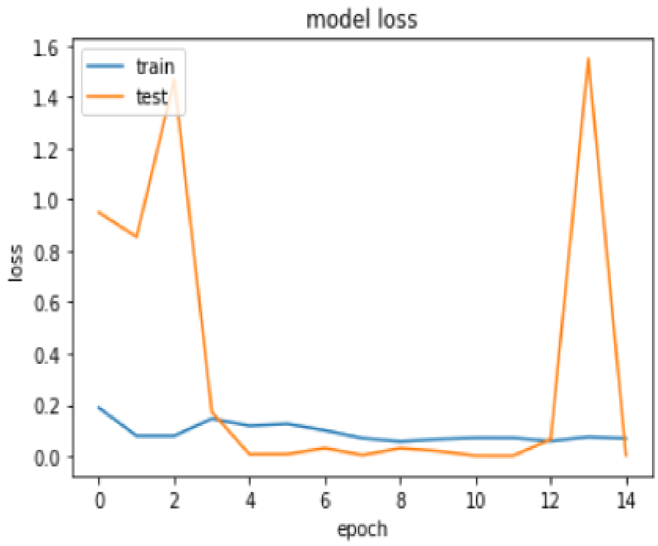



FIGURE 4.10: CNN3-LSTM Model Loss Graph.

Table 4.3: Models Result for SVEB.

| **SVEB** | **Recall** | **Precision** | **F1 score** | **Accuracy** |
|---|---|---|---|---|
| CNN1-LSTM | 95% | 94% | 94% | 90% |
| CNN2-LSTM | 98% | 95% | 97% | 94% |
| CNN3-LSTM | 99% | 96% | 98% | 96% |

Three proposed models CNN1-LSTM, CNN2-LSTM and CNN3-LSTM are evaluated to see the results for SVEB and VEB. First model CNN1-LSTM consists of one block of CNN. Second model CNN2-LSTM consists of two blocks of CNN with different filter and kernal size. Third model CNN3-LSTM consisting of three blocks of CNN with different filter and kernal size is evaluated to see the results for SVEB and VEB.

Table 4.4: Models Result for VEB.

| **VEB** | **Recall** | **Precision** | **F1 score** | **Accuracy** |
|---|---|---|---|---|
| CNN1-LSTM | 63% | 68% | 65% | 90% |
| CNN2-LSTM | 72% | 84% | 77% | 94% |
| CNN3-LSTM | 72% | 97% | 83% | 96% |

For comparison purpose the work in Li et al. used four blocks of dense whereas our work used three dense blocks. We first checked the results with one dense block which were not satisfactory we increased the dense block, trained the model and saw the results which was increased by 1% . Then added one more dense block to see the results and expectedly the result was increased by 32%. As the accuracy was increasing one more dense block was added to see the results but the result was not according to our expectations it decreased to 1%.

One of the reason could be while choosing the number of layers Li et al in their work used four number of layers in each dense block whereas our work consisted of two convolutional layers in each dense block. With this proposed model accuracy was increased upto 3%. Table 4.5 and 4.6 presents the results of Li et al work and our proposed model results.

Table 4.5: SVEB results of Li et al and this work

| **SVEB** | **Recall** | **Precision** | **F1 score** | **Accuracy** |
|---|---|---|---|---|
| Li et al | 62% | 61% | 61% | 93% |
| This Work | 99% | 96% | 98% | 96% |

Table 4.6: VEB results of Li et al and this work

| **VEB** | **Recall** | **Precision** | **F1 score** | **Accuracy** |
|---|---|---|---|---|
| Li et al | 91% | 88% | 89% | 93% |
| This Work | 72% | 97% | 83% | 96% |

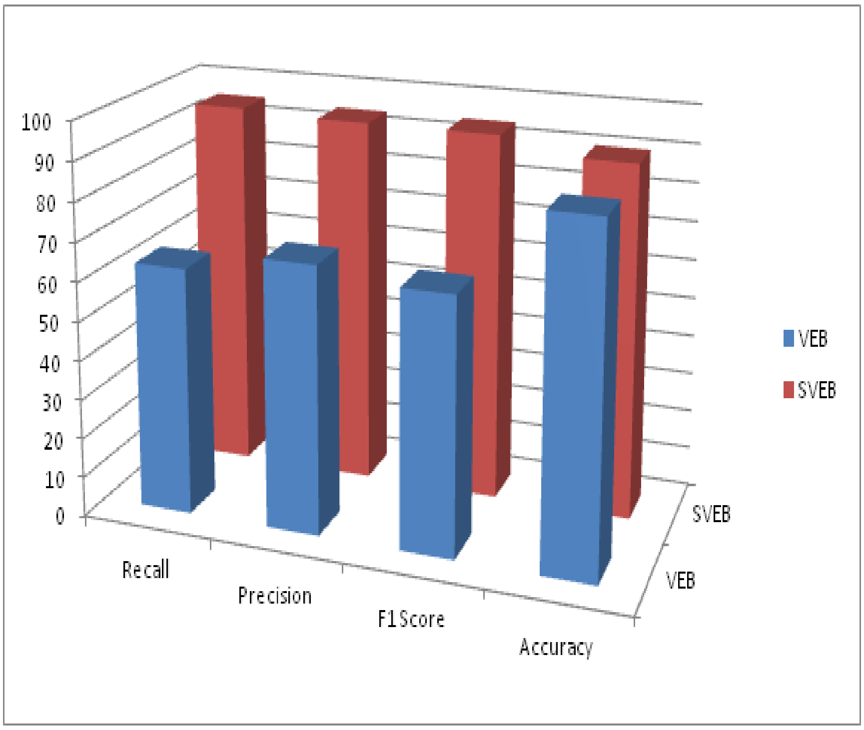



FIGURE 4.11: CNN1-LSTM Model Evaluation Graph.

Figure 4.11 shows the performance and evaluation graph of CNN1-LSTM model. Blue bars presents the VEB performance measures labeled as recall, precision, F1-Score and then giving accuracy. The Red bars present SVEB standard measures recall, precision, F1-score and accuracy. This graph in depth explains the measures for VEB and SVEB. When compared with one another this model CNN1-LSTM performed better incase of SVEB class. It can be clearly seen in the graph that results for SVEB are much better when compared with VEB group results.

Figure 4.12 shows the performance and evaluation graph of CNN2-LSTM model. Blue bars presents the VEB performance measures labeled as recall, precision, F1-Score and then giving accuracy. The Red bars present SVEB standard measures recall, precision, F1-score and accuracy. This graph in depth explains the measures for VEB and SVEB. When compared with one another the model CNN2-LSTM showed that both VEB and SVEB had slight difference in there measures. Showing that this model performed better than the previous model with a slight difference of f1-score.

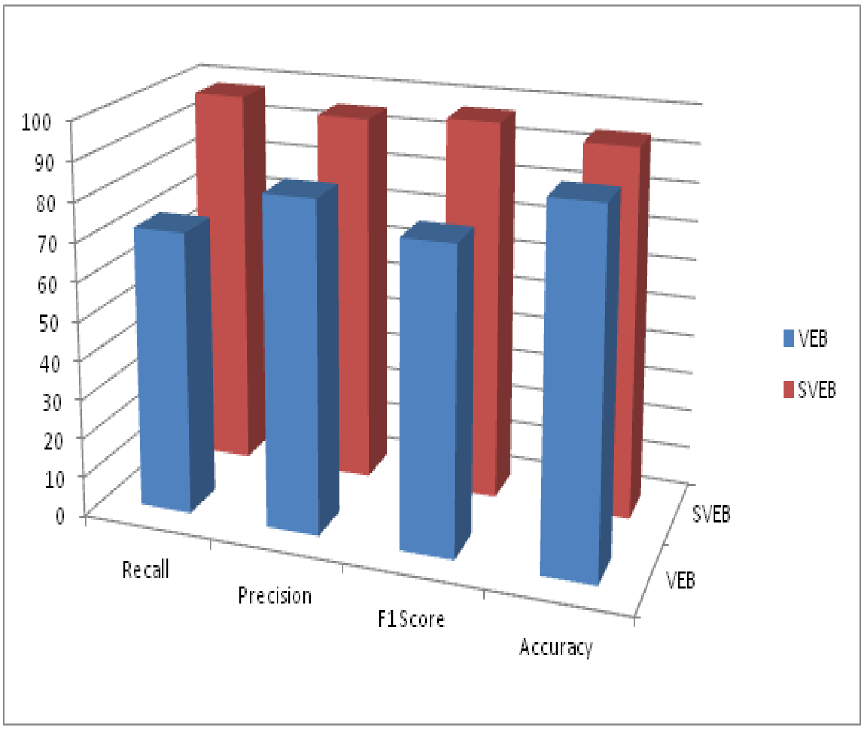



FIGURE 4.12: CNN2-LSTM Model Evaluation Graph.

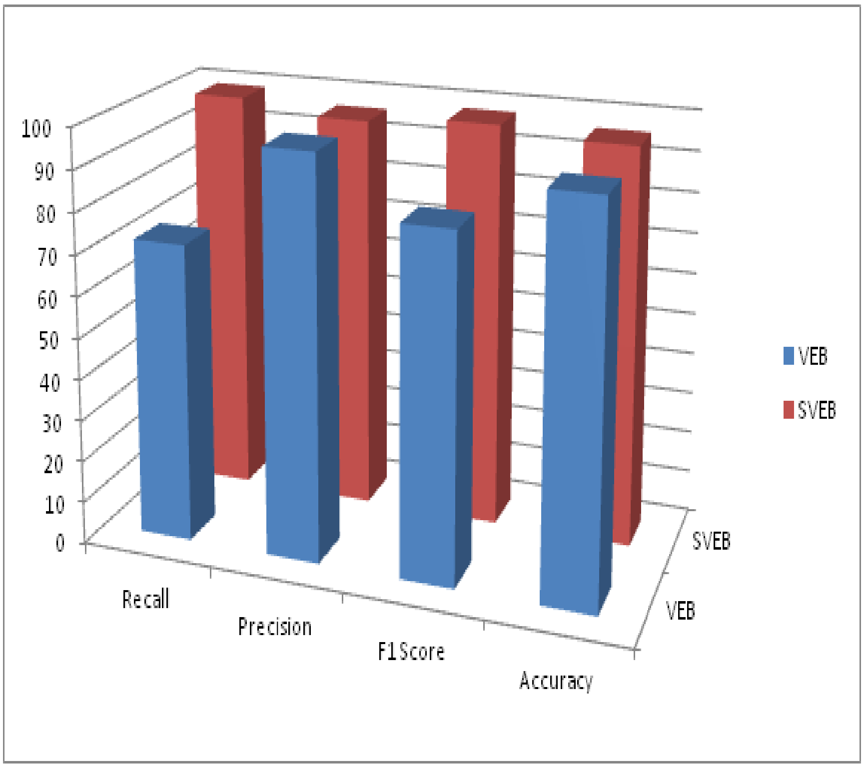



FIGURE 4.13: CNN3-LSTM Model Evaluation Graph.

Figure 4.13 shows the performance and evaluation graph of CNN3-LSTM model. Blue bars presents the VEB performance measures labeled as recall, precision, F1-Score and then giving accuracy. The Red bars present SVEB standard measures recall, precision, F1-score and accuracy. This graph in depth explains the measures for VEB and SVEB. When compared with other proposed models the model CNN3-LSTM showed that somehow this model showed equal results for VEB and SVEB, a slight difference in the recall could be ignored as in the end accuracy for both were same.This model CNN3-LSTM outperformed the other two models.

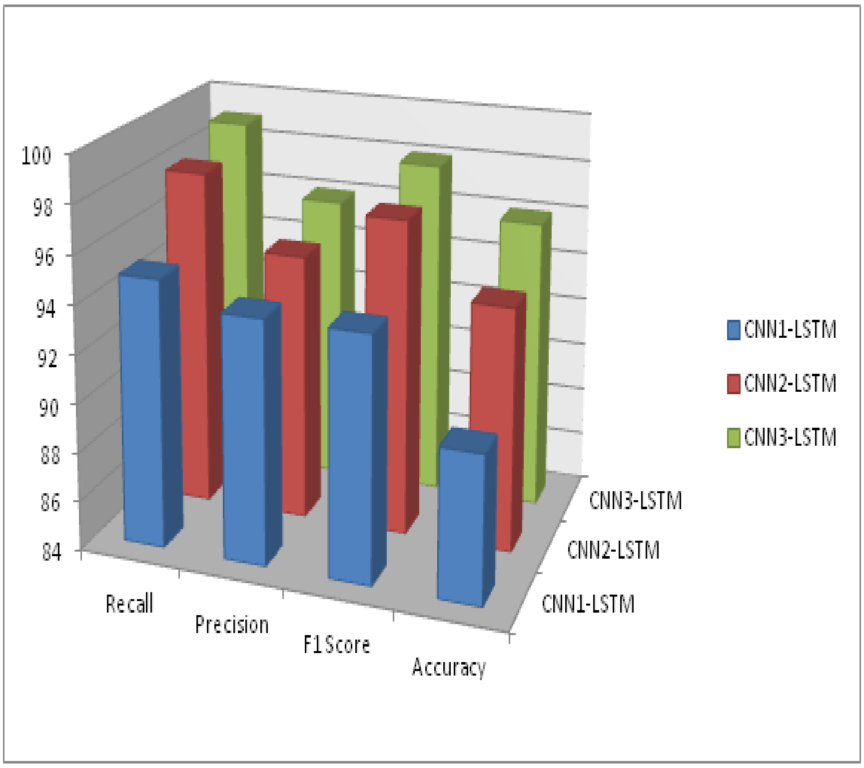



Figure 4.14: Hybrid Models Evaluation Result Graph for SVEB.

Figure 4.14 shows the performance graph of all the three models which were proposed. Blue bars presents the CNN1-LSTM model performance measures labeled as recall, precision, F1-Score and then giving accuracy. The Red bars present CNN2-LSTM standard measures recall, precision, F1-score and accuracy. Green bars presents the CNN3-LSTM model performance measures labeled as recall, precision, F1-Score and then giving accuracy. This graph in depth explains the measures for all three models. When compared with one another the model CNN3-LSTM showed that it had little difference with CNN2-LSTM model. Whereas compared to CNN1-LSTN model it had a much difference among four measures which obviously is of no match compared to CNN3-LSTM model for SVEB.

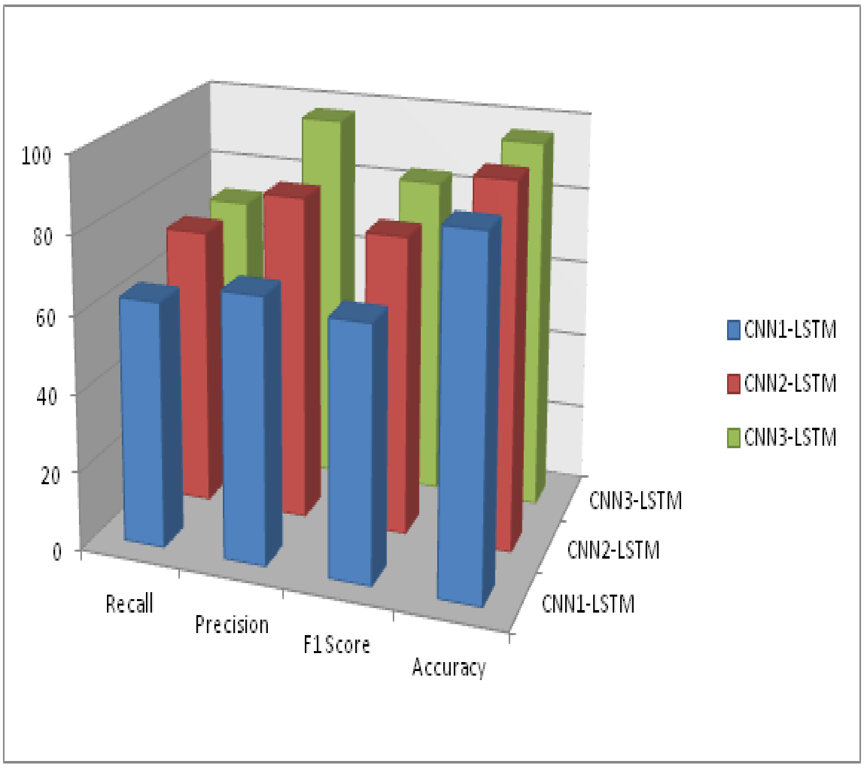



FIGURE 4.15: Hybrid Models Evaluation Result Graph for VEB.

Figure 4.15 shows the performance graph of all the three models which were proposed. Blue bars presents the CNN1-LSTM model performance measures labeled as recall, precision, F1-Score and then giving accuracy. The Red bars present CNN2-LSTM standard measures recall, precision, F1-score and accuracy. Green bars presents the CNN3-LSTM model performance measures labeled as recall, precision, F1-Score and then giving accuracy. This graph in depth explains the measures for all three models. When compared with each other the model CNN3-LSTM at first showed that it had no difference incase of recall but there is a large difference with precision measure. When compared at last with ignorable F1-score difference with a slight difference of accuracy showed that three models were performing better for VEB as compared to last SVEB graph showed huge differences among the accuracies of models.

Table 4.7: Hybrid Approaches

| Work | Data | Classes | Technique | Accuracy |
|---|---|---|---|---|
| Warric el at | PhysicoNet'17 | AF | CNN-LSTM | 83% |
| Li el at | MIT-BIH | SVEB, VEB | CNN-GRU | 93% |
| Jiban Wang | MIT-BIH | AF | CNN-MENN | 97% |
| Xiaomao el at | PhysicoNet'17 | AF | MS-CNN | 97% |
| **This Work** | **MIT-BIH** | **SVEB,VEB** | **CNN-LSTM** | **96%** |

An comparison is shown in table 4.7, the hybrid approaches which are targeting life threatening arrhythmia are been presented in this table. Xiaomo el at proposed model is achieving 97% accuracy but they are only targeting a specific class Atrial fibrillation, the dataset they have used is from PhysicoNet. Jiban Wang model also achieved 97% using MIT-BIH database but targeting same class Atrial fibrillation.

Warric el at proposed a model based on CNN-LSTM achieving accuracy of 83% only whereas our model is also based on CNN-LSTM but achieving accuracy up-to 96% though at start our goal was to present with a model having 95% but after various experiments we were able to present with a model giving 96% accuracy. Our work also targeted groups of life threatening arrhythmia's;SVEB and VEB rather than a specific class. Li el at proposed approach is also targeting groups of

SVEB and VEB but giving accuracy up-to 93%.

Table 4.8: Proposed Model Result with Different Dropout Value

| **Dropout Value** | **Model Performance** |
|---|---|
| 0.7 | 93% |
| 0.8 | 92% |
| 0.5 | 96% |
| 0.6 | 94% |

In above 4.8 proposed model further it is evaluated with different dropout values as adding more complexity(layers) can risk overfitting problem which can be avoided by adding dropout, a good value for dropout is between 0.5 and 0.8 but higher dropout results in higher variance and degrades training.

# Chapter 5

# Conclusion and Future Work

Research Work is summarized in this chapter by drawing the achievements of this work. It also highlights the areas for future work.

## 5.1 Conclusion

Cardiovascular diseases are the main source of death today. Worldwide medical experts and scientists are consistently in process of finding effective ways to control the death rates caused by these diseases. ECG is a clinical checking innovation recording for cardiovascular diseases. Searching for specialists to examine a lot of ECG is a problem. The methods of AI for distinguishing ECG have become predominant by DNNs.

In this work deep learning approach based on two kind of neural networks CNN and LSTM is used to detect the arrhythmia. The ability of CNN to extract features and when combined with LSTM to increase the capability to recognize long term dependences between the extracted features has shown satisfying results. The proposed hybrid model targeted SVEB and VEB achieving an accuracy of 96%.

Three models CNN1-LSTM, CNN2-LSTM, CNN3-LSTM were analyzed and groups N,F,Q of arrhythmia were also considered for experiment purpose. Model CNN3-LSTM outperformed the other two proposed models.

## 5.2 Future Work

As we are entering the cloud-enabled health care era the development of automatic diagnosis and early warning services has increased.AI programs are applied to practices diagnosis processes so further we will like to implement a health care band, wrist worn device for patient monitoring and care.

# Bibliography


[1] N. T. Srinivasan and R. J. Schilling, "Sudden cardiac death and arrhythmias," *Arrhythmia & electrophysiology review*, vol. 7, no. 2, p. 111, 2018.

[2] S. Sahoo, M. Dash, S. Behera, and S. Sabut, "Machine learning approach to detect cardiac arrhythmias in ecg signals: A survey," *IRBM*, vol. 41, no. 4, pp. 185–194, 2020.

[3] T. O. Aje and M. Miller, "Cardiovascular disease: a global problem extending into the developing world," *World journal of cardiology*, vol. 1, no. 1, p. 3, 2009.

[4] G. Tse, "Mechanisms of cardiac arrhythmias," *Journal of arrhythmia*, vol. 32, no. 2, pp. 75–81, 2016.

[5] S. Celin and K. Vasanth, "Survey on the methods for detecting arrhythmias using heart rate signals," *Journal of Pharmaceutical Sciences and Research*, vol. 9, no. 2, p. 183, 2017.

[6] F. Murat, O. Yildirim, M. Talo, U. B. Baloglu, Y. Demir, and U. R. Acharya, "Application of deep learning techniques for heartbeats detection using ecg signals-analysis and review," *Computers in biology and medicine*, vol. 120, p. 103726, 2020.

[7] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "Imagenet classification with deep convolutional neural networks," *Communications of the ACM*, vol. 60, pp. 84–90, 2017.

[8] E. J. da S.Luz, W. R. Schwartz, G. Cmara-Chvez, and D. Menotti, "Ecg-based heartbeat classification for arrhythmia detection: A survey," *Computer Methods and Programs in Biomedicine*, vol. 127, pp. 144–164, 2016.

[9] S. Manoj, P. Dinakarroa, A. Jantsch, and M. Shafique, "Computer-aided arrhythmia diagnosis with bio-signal processing: A survey of trends and techniques," *ACM Computing Surveys*, vol. 52, p. 37, 2019.

[10] J. Wang, "A deep learning approach for atrial fibrillation signals classification based on convolutional and modified elman neural network," *Future Generation Computer Systems*, vol. 102, p. 670679, 2020.

[11] L. Guo, G. Sim, and B. Matuszewski, "Inter-patient ecg classification with convolutional and recurrent neural networks," *Biocybernetics and Biomedical Engineering*, vol. 39, no. 3, pp. 868–879, 2019.

[12] X. Fan, Q. Yao, Y. Cai, . F. S. Fen Mia, and Y. Li, "Multiscaled fusion of deep convolutional neural networks for screening atrial fibrillation from single lead short ecg recordings," *Journal of Biomedical and Health Informatics*, vol. 22, no. 6, pp. 1744–1753, 2018.

[13] P. Warrick and M. N. Homsi, "Cardiac arrhythmia detection from ecg combining convolutional and long short-term memory networks," *Computing in Cardiology*, vol. 4, pp. 161–460, 2017.

[14] P. Plawiak, "Novel methodology of cardiac health recognition based on ecg signals and evolutionary-neural system," *Expert Systems with Applications*, vol. 92, pp. 334–349, 2018.

[15] A. K. Sangaiah, M. Arumugam, and G.-B. Bian, "An intelligent learning approach for improving ecg signal classification and arrhythmia analysis," *Artificial Intelligence in Medicine*, vol. 103, p. 101788, 2020.

[16] C. Kumari, A. D. Murthy, B. Prasanna, M. P. Reddy, and A. K. Panigrahy, "An automated detection of heart arrhythmias using machine learning technique: Svm," *Materials Today: Proceedings*, vol. 45, pp. 1393–1398, 2021.

[17] L. B. Marinho, N. de M.M. Nascimento, J. W. M. Souza, M. V. Gurgel, P. P. R. Filho, and V. H. C. de Albuquerque, “A novel electrocardiogram feature extraction approach for cardiac arrhythmia classification,” *Future Generation Computer Systems*, vol. 97, pp. 564–577, 2019.

[18] D. Anguita, A. Ghio, N. Greco, L. Oneto, and S. Ridella, “Model selection for support vector machines: Advantages and disadvantages of the machine learning theory,” *The 2010 International Joint Conference on Neural Networks (IJCNN)*, 2010.

[19] M. A. Rahhal, Y. Bazi, H. AlHichri, N. Alajlan, F. Melgani, and R.R.Yagerc, “Deep learning approach for active classification of electrocardiogram signals,” *Information Sciences*, vol. 345, pp. 340–354, 2016.

[20] S. Kiranyaz, T. Ince, and M. Gabbouj, “Real-time patient-specific ecg classification by 1-d convolutional neural networks,” *IEEE Transactions on Biomedical Engineering*, vol. 63, pp. 664 – 675, 2016.

[21] A. Isina and S. Ozdalili, “Cardiac arrhythmia detection using deep learning,” *Procedia Computer Science*, vol. 120, pp. 268–275, 2017.

[22] W. Sun, N. Zeng, and Y. He, “Morphological arrhythmia automated diagnosis method using gray-level co-occurrence matrix enhanced convolutional neural network,” *IEEE Access*, vol. 7, no. 67123, pp. 2169–3536, 2019.

[23] X.-C. Cao, B. Yao, and B.-Q. Chen, “Atrial fibrillation detection using an improved multi-scale decomposition enhanced residual convolutional neural network,” *IEEE Access*, vol. 7, pp. 89 152–89 161, 2019.

[24] H. Fujita and D. Cimr, “Computer aided detection for fibrillations and flutters using deep convolutional neural network,” *Information Sciences*, vol. 486, pp. 1231–239, 2019.

[25] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, M. Adam, A. Gertych, and R. S. Tan, “A deep convolutional neural network model to classify heartbeats,” *Computers in Biology and Medicine*, vol. 89, pp. 389–396, 2017.

[26] U. R. Acharya, H. Fujita, S. L. Oh, U.Raghavendra, J. H. Tan, M. Adam, A. Gertych, and Y. Hagiwara, "Automated identification of shockable and non-shockable life-threatening ventricular arrhythmias using convolutional neural network," *Future Generation Computer Systems*, vol. 89, pp. 952–959, 2018.

[27] U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. H. Tan, and M. Adam, "Automated detection of arrhythmias using different intervals of tachycardia ecg segments with convolutional neural network," *Informstion Science*, vol. 405, pp. 81–90, 2017.

[28] S. M.Mathews, C. Kambhamettu, and K. E.Barner, "A novel application of deep learning for single-lead ecg classification," *Computers in Biology and Medicine*, vol. 99, pp. 53–62, 2018.

[29] O. Yildirim, "A novel wavelet sequence based on deep bidirectional lstm network model for ecg signal classification," *Computers in Biology and Medicine*, vol. 96, pp. 189–202, 2018.

[30] O. Yildirim, R. S. Tan, and U. R. Acharya, "An efficient compression of ecg signals using deep convolutional autoencoders," *Cognitive System Research*, vol. 52, pp. 198–211, 2018.

[31] O. Yildirim, U. B. Baloglu, E. J. Ru-San Tan, and U. R. Acharya, "A new approach for arrhythmia classification using deep coded features and lstm networks," *Computer Methods and Programs in Biomedicine*, vol. 176, pp. 121–133, 2019.

[32] S. C. Matta, Z. Sankari, and S. Rihana, "Heart rate variability analysis using neural network models for automatic detection of lifestyle activities," *Biomedical Signal Processing and Control*, vol. 42, pp. 145–157, 2018.

[33] G.Sannino and G. Pietro, "A deep learning approach for ecg-based heartbeat classification for arrhythmia detection," *Future Generation Computer Systems*, vol. 86, no. 10, pp. 446–445, 2018.

[34] M. Deng, C. Wang, M. Tang, and T. Zheng, "Extracting cardiac dynamics within ecg signal for human identification and cardiovascular diseases classification," *Neural Networks*, vol. 100, pp. 70–83, 2018.

[35] Q. Yao, R. Wang, X. Fan, J. Liu, and YeLi, "Multi-class arrhythmia detection from 12-lead varied-length ecg using attention-based time-incremental convolutional neural network," *Information Fusion*, vol. 53, pp. 174–182, 2020.

[36] J. H. Tan, Y. Hagiwara, W. Pang, I. Lim, S. L. Oh, M. Adam, R. S. Tan, M. Chen, and U. RajendraAcharya, "Application of stacked convolutional and long short-term memory network for accurate identification of cad ecg signals," *Computers in Biology and Medicine*, vol. 94, pp. 19–26, 2018.

[37] D. M. Powers, "Evaluation: From precision, recall and f-measure to roc, informedness, markedness and correlation," *International Journal of Machine Learning Technology*, vol. 2, pp. 37–63, 2011.

[38] N. Tatbul, T. J. Lee, S. Zdonik, M. Alam, and J. Gottschlich, "Precision and recall for time series," *Conference on Neural Information Processing Systems*, vol. 32, p. 11, 2019.