HEART BEAT CLASSIFICATION IN MIT-BIH ARRHYTHMIA ECG DATASET USING DOUBLE LAYER BI-LSTM MODEL

J.Rexy[1], P.Velmani[2], T.C.Rajakumar[3]

[1]Research Scholar (RegNo: 11980), Department of Computer Science,

St.Xavier's College, Manonmanium Sundaranar University, Abishekapatti,

[2]Research Supervisor, Department of Computer Science, The M.D.T Hindu College,

Tamil Nadu, India

[3]Research Co-Guide, Department of Computer Science, St.Xavier's College,

Tamil Nadu, India

Abstract— Heart serves as the primary organ for human survival by bumping the blood through the cardiovascular system. World is experiencing rapid increase in heart disease. Primary checkup will save many precious lives from severe heart attack. ElectroCardioGram (ECG) is one of the primary test which will detect basic heart problems. This paper is a novel attempt to use ECG signals as the primary source for detecting and classifying various heart diseases. Raw ECG signals are retrieved from MIT-BIH Arrhythmia Dataset and are preprocessed. Heart beats are located, segmented and labeled. The proposed methodology applies double layer Bi-Directional Long Term Memory(Bi-LSTM) algorithm to classify the heart beats based on Association of Advancement of Medical Instrumentation(AAMI) standard classes. The proposed methodology's performance metrics depicts good classification result. In future this proposed methodology can be applied to real time ECG signals, which will lead to rapid diagnosis of heart disease. The implementation process was carried out using Matlab software environment.

Keywords— ECG; heart beats; Bi-LSTM; MIT-BIH; AAMI.

I.INTRODUCTION

Heart is a human organ which serves as the primary source for blood circulation. Heart disease serves as the major cause of death in past two decades. Heart's electrical activity can be recorded by using a basic test called Electrocardiogram(ECG). ECG plays a vital role as a basic and painless test to diagnose the heart disease. The electrocardiography (ECG) provides physicians with temporal and anatomic data about the heart reflected by the electric vector [1]. Hence research regarding ECG signals will be a great contribution to increase the level of initial stage diagnosis of cardiovascular disease. Initial level diagnosis will pave way for saving many precious lives. In cardiovascular disease, Arrhythmia is major set of diseases. The diagnosis of arrhythmia mainly depends on the ECG [2]. Single heart beat signal is composed of fiducial points such as P, Q, R, S and T, the interval between these components such as RR interval, QRS complex etc., serve as the features of the ECG Signal. The focus of this paper is to classify the ECG signals based on Arrhythmia ECG dataset. The MIT-BIH arrhythmia database is publicly available dataset which provides standard investigation material for the detection of heart arrhythmia [3]. This research utilizes the ECG signals from MIT-BIH Arrhythmia Dataset. The retrieved signals are preprocessed to remove the unwanted noise, which may be generated during the recording process or the noise may also be occurred due to mechanical faults of the ECG recording machine. After removing the noise, the ECG signals Peaks are identified and heart beats are segmented for retrieving the features from the heart beats. Classification of the heart beats will result with the types of Arrhythmia present in the heat beats. Various classification algorithms are available based on Convolutional Neural Network(CNN) and Recurrent Neural Network(RNN). In RNN, the feedback and the present value is fed again into the network and as result, the output contains the traces of values present in the memory as well it increases the classification performance which provides better results than the conventional feed-forward networks [4]. RNN faces vanishing gradient problem [5] and cannot remember Long Term dependencies. So this work is carried out using advanced RNN algorithm called Bi-LSTM which solves the vanishing gradient problem. Double layer Bi-LSTM Recurrent Neural Network Model is applied for classifying the ECG signals based on the standard AAMI classes. Performance metrics such as Accuracy, Specificity and Sensitivity are measured to analyze the performance of the proposed model.

II.RELATED WORKS

Xin Liu et al [6], have adopted two staked LSTM models and applied in heart disease database as hidden layers in the neural network and softmax layer as classification layer. The experimental result had reflected better performance and the robustness of the LSTM classification model is verified.

Peng Lu et al [7], have proposed a LSTM-CNN hybrid model to complete short-term ECG positive anomaly classification tasks. It had been proved experimentally that LSTM-CNN model had produced an efficient and accurate classification performance on large scale clinical ECG data.

Hilmy Associdiky et al [8], implemented LSTM method and the performance was boosted using AdaDelta as the adaptive learning rate method. It was depicted that LSTM with AdaDelta presented high accuracy while compared to LSTM without adaptive learning rate.

Siti Nurmaini A et al [9], proposed an automated delineation algorithm for ECG waveform signals that utilizes recurrent neural networks (RNNs) with bidirectional long short-term memory (LSTM) architecture. Time duration and each waveform is considered for classification purpose and the classification is done based on the annotations of the database. It has been stated that the proposed model had produced satisfactory performance.

Jiacheng Wang et al [10], proposed a framework of the combination of convolutional neural network (CNN) and Long-Short Term Memory (LSTM) for classifying normal sinus signals, atrial fibrillation, and other noisy signals. The cascading of CNN and LSTM had achieved satisfactory performance on discriminating ECG signals.

Manoj Kumar Ojha et al [11], proposed an end-to-end (E2E) deep learning model that uses a combination of convolution neural network (CNN) and a Bi-Directional long-short term memory network (Bi-LSTM) to classify. The CNN extracts features from ECG signals, and Bi-LSTM learns information. It had been stated that the proposed CNN-Bi-LSTM deep learning model outperforms existing state-of-the-art methods.

Runnan He et al [12] proposed two Deep Neural Network models of residual convolutional modules and Bi-Directional Long Short Term Memory (LSTM). The proposed DNNs has an end-to-end classification structure composed of three parts, called local features learning, global features leaning and classification. Classification results showed that DNNs significantly increases the classification accuracy for various arrhythmia types.

Yilin Wang et al [13], proposes a Generative Adversarial Network (GAN)-based deep learning framework called CAB for heart arrhythmia classification. Augmenting ECG data by a GAN model eliminates the impact of data scarcity. After data augmentation, Experiment results showed a better performance of CAB compared with state-of-the-art methods.

FeiZhu et al [14], proposed a Generative Adversarial Network (GAN), which is implemented using bidirectional long short term memory(LSTM) and convolutional neural network(CNN). The model applies a generator and a discriminator, the generator employs two layers of the BiLSTM networks and the discriminator is based on convolutional neural networks. The results indicated high morphological similarity to real ECG recordings.

Ozal Yildirim [15], a new model for deep bidirectional LSTM network-based wavelet sequences called DBLSTM-WS was proposed for classifying ECG signals. A new wavelet-based layer is implemented and the ECG signals were decomposed into frequency sub-bands at different scales. These sub-bands are used as sequences for the input of LSTM networks. The result represented the DBLSTM-WS model with high recognition performance.

III.MATERIALS AND METHODS

This section presents the details about the database used, preprocessing stage and identifying the heat beats, matching and labeling the classes and about the classification method.

*A. **ECG Database Description***

Massachusetts Institute of Technology-Beth Israel Hospital(MIT-BIH) Arrhythmia database is used for this research work and it is retrieved from PhysioBank. PhysioBank is a large and growing archive of well-characterized digital recordings of physiological signals and related data for use by the biomedical research community [16]. The MIT-BIH arrhythmia database is publicly available standard dataset and is commonly employed to study arrhythmia. MIT-BIH Arrhythmia Database, contains 48 half-hour excerpts of two-channels, 24-hour, ECG recordings [17]. Each recording contains an annotation.atr file where each heartbeat is labeled with its type. According to the ANSI/AAMI EC57:1998/(R) 2008, [18] the original 18 heartbeat types from the MIT-BIH arrhythmia data are grouped into several classes: normal (N), supraventricular ectopic beat (S), ventricular ectopic beat (V), fusion beat (F), and unknown beat(Q). The data size used in this study is represented in Table I.

TABLE I. **HEART BEAT CLASSES AND BEATS COUNT**

AAMI Heartbeat Classes	MIT-BIH Heartbeat Classes	No of Beats Available
Non-ectopic beats(N)	N (Normal beat)	74776
	L (Left Bundle Branch Block)	8052
	R (Right Bundle Branch Block)	7239
	j (Nodal (junctional) escape beat)	229
	e (Atrial escape beat)	16
Supraventricular ectopic Beats (S)	A (Atrial premature beat)	2528
	a (Aberrated atrial premature beat)	149
	S (Supraventricular premature beat)	2
	J (Nodal (junctional) premature Beat)	83
Ventricular ectopic Beats (V)	! (Ventricular flutter beat)	472
	V (Premature Ventricular Contraction)	7115
	E (Ventricular escape Beat)	106
	[(Start of ventricular flutter fibrillation)	6
	] (End of ventricular flutter fibrillation)	149
Fusion Beats(F)	F (Fusion of Ventricular and Normal beats)	106
Unknown beats (Q)	f (Fusion of paced and normal beats)	979
	/ (Paced beat)	7001
	Q (Unclassifiable beats)	33
	Total	1,09,041

*B. **Preprocessing :Reducing the noise***

Filtering techniques such as Butterworth, Chebyshev I, Chebyshev II and Elliptic are applied and it was found that Butterworth and Chebyshev Type I excelled in Performance. Hence for better and fine-tuned de-noising, the lower and upper level boundary values of Butterworth and Chebyshev Type I are concatenated [19] and a novel de-noising Algorithm named as ButterCheb was applied. The de-noised ECG signals were used for heart beat identification. The de-noised ECG signals will result in good feature extraction and arrhythmia diagnosis process. Figure 1 depicts the original raw ECG signal and the de-noised ECG Signal Version.

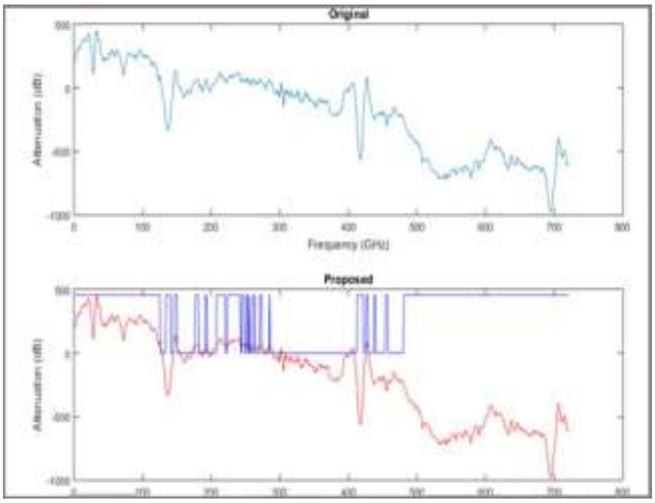

Fig. 1. Original and Preprocessed ECG Signal

*C. **Iidentifying R Peaks and Individual Heart Beats based on the annotation File***

The annotation file is used to locate the position of the R wave. A single heart beat consist of P-QRS-T wave. The R peak position is used as the base to locate the complete P-QRS-T wave in the basis of front and rear position. Individual heart beats are extracted based on the R peak by selecting one hundred and twenty-eight sample points before and one hundred and eight sample points after the R peak. Figure 2 depicts the R peak based retrieval of complete individual heart beat which comprises of P-QRS-T complete wave. Record wise heart beats are extracted and stored for further processing. Once the complete heart beat is located ,it can be used to classify according to AAMI standard classes.

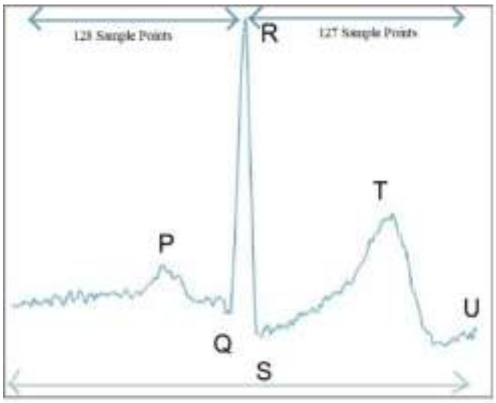

Fig. 2. R Peak based Heart beat location

D. *Mapping and Labeling the extracted Heart Beats*

The AAMI provides guidelines to classify heart beats of BIT-MIH Arrhythmia into normal beats (N), supraventricular beats (S), ventricular beats (V), fusion beats (F), and unclassified beats (Q). Based on the subclass annotations such as 'N','L','R', 'j', 'e', 'A', 'a', 'S', 'J', '!', 'V', 'E','[',']','F', 'f','/','Q', the heart beats are labelled into five primary classes. The record wise labelled records are stored for classification purpose. Figure 3 depicts the ECG class labelling using AAMI standard.

AAMI class	MIT-BIH heart beat types				
Normal beat (N)	Normal beat (N)	Left bundle branch block beat (L)	Right bundle branch block beat (R)	Atrial escape beat (e)	Nodal (junctional) escape beat (j)
Supraventricular ectopic beat (S)	Atrial premature beat (A)	Aberrated atrial premature beat (a)	Nodal (junctional) premature beat (J)	Supraventricular premature beat (S)	
Ventricular ectopic beat (V)	Premature ventricular contraction (V)	Ventricular escape beat (E)	Ventricular flutter beat (!)	Start of ventricular flutter fibrillation ([)	End of ventricular flutter fibrillation( ])
Fusion beat (F)	Fusion of ventricular and normal beat (F)				
Unknown beats(Q)	Fusion of paced and normal beats(f)	Paced beat(/)	Unclassifiable beats(Q)		

Fig. 3. ECG class Labels based on AAMI Standard

E. *Feature Extraction from the extracted heart beats*

Feature extraction is the main feature to extract the key factors of the extracted heart beats. The records were digitized with three hundred and sixty samples per second, so the frequency level is set as three hundred and sixty. Instantaneous *frequency* and *Spectral* entropy features are extracted for classification purpose. Instantaneous frequency describes the characteristic frequency bands of the heart beats extracted. The instantaneous frequency describes the time-varying spectral contents of the characteristic frequency bands which serves as the base for classification of signals. Spectral power distribution based features are also extracted for classification purpose. Feature vectors composed of instantaneous frequency and spectral frequency serves as the input parameters for classification model.

F. *Classification of Extracted Heart Beats*

Classification of the ECG signals will pave way to diagnose different Arrhythmia heart disease. If applied to the preliminary ECG test all types of Arrhythmia Diseases can be identified which will be helpful to take measures in the initial stage to save the life. Double Layer Bi-Directional Long Short Term Memory (Bi-LSTM) Recurrent Neural Network is applied to classify the signals. Long Short Term Memory (LSTM) is an advanced Recurrent Neural Network which overcomes vanishing gradient problem and remember long term dependencies. Two independent RNNs are joined in Bi-LSTM. The input Units run from past to future and from future to past. As it trains two models, first learning based on sequence of the input takes place and second reverse of that sequence is learnt. Figure 4 depicts the architecture of double Layer Bi-LSTM.

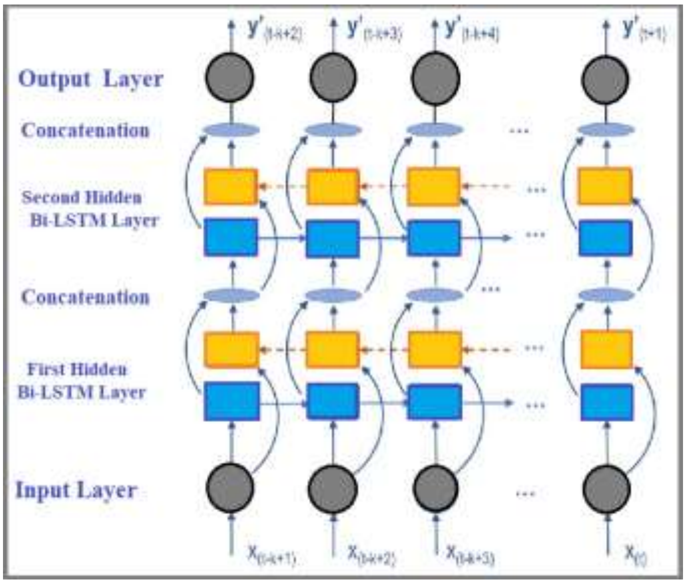

Fig. 4. Overall architecture of Double Layer Bi-LSTM

IV.PROPOSED METHODOLOGY

The Proposed Methodology for classifying the extracted signals are implemented using double layer Bi-LSTM Model. The proposed methodology will reflect improved performance metrics, as the model is well trained with double layers of Bi-LSTM and the dropout layers with twenty percent twice will tune the process of classification more clearly than single layer Bi-LSTM model. The input for the model is selected in random basis. Here sequence Input Layer represents the input layer with two dimensions representing instantaneous *frequency* and spectral *entropy*. The first Bi-LSTM layer consist of hundred hidden layers. Next to the hidden Bi-LSTM layer, a dropout Layer of twenty percent is applied. The role of the dropout layer is to forget the unrelated and unwanted units. Another Bi-LSTM hidden Layer is used with seventy-five hidden Layers. A dropout Layer of twenty percent is applied once again to tune the classification output, by once again dropping the unwanted units. Then a fully connected layer representing the five classes of AAMI standard is applied. Softmax layer normalizes the results in real values. Classification output Layer represents the output unit. Figure 5 depicts the architecture of the proposed methodology. Raw ECG signals are retrieved as input and pre-processed. After pre-processing individual heart beats are retrieved using the R peak as the base. The individual heart beats are selected in random basis and classified using double layer Bi-LSTM model. The training and testing data is divided in ninety to ten ratio. Training option called adaptive moment estimation(adam) is used and the maximum epochs is set to thirty. The minimum batch size was set as hundred and gradient threshold is used. The database is trained and tested to check the performance of the classification. The classified output is measured using various performance metrics.

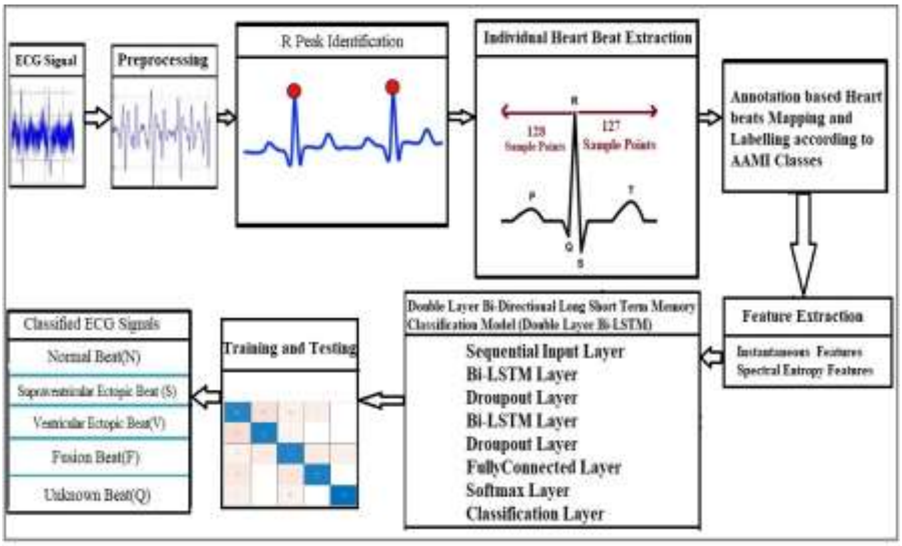

Fig. 5. Architecture of the Proposed Methodology

V.RESULT AND PERFORMACE EVALUATION

The dataset is divided into ninety to ten ratio for training and testing purpose. The heart beats are randomly selected and executed in thirty epochs. As the heart beats are selected randomly the best among the execution is considered as best performance. Figure 6 depicts the training and testing model.

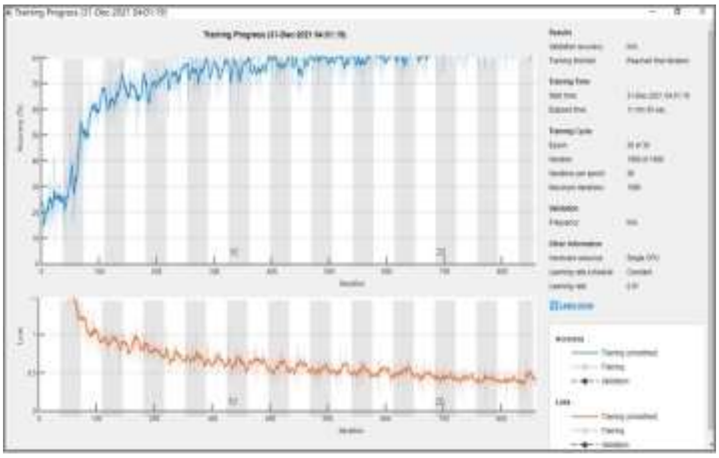

Fig. 6. Training and Testing Model

Performance metrics such as Accuracy, Specificity and Sensitivity are calculated for measuring the performance.

Accuracy   = (TP+TN)/(TP+FP+FN+TN) --------------- (1)

Specificity = TN/(TN+FP) --------------------------------- (2)

Sensitivity = TP/(TP+FN) --------------------------------- (3)

Where TP represents True Positive, TN represents True Negative, FP represents False Positive and FN represents False Negative. Figure 7 depicts the confusion Matrix of the training Model and Figure 8 depicts the confusion matrix of testing Model.

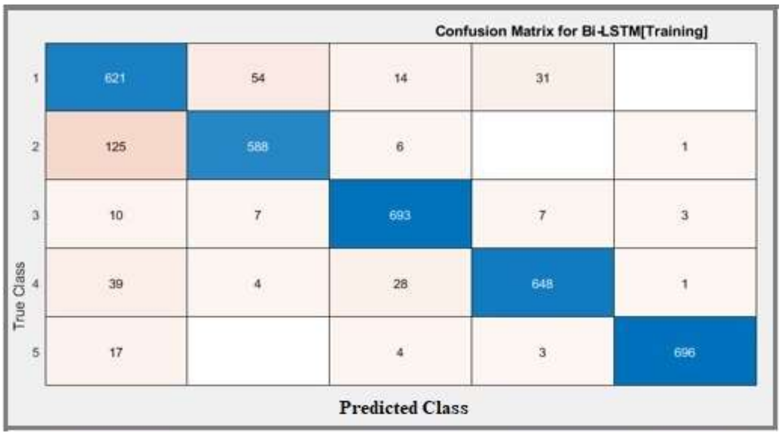

Fig. 7. Confusion Matrix of Training Model

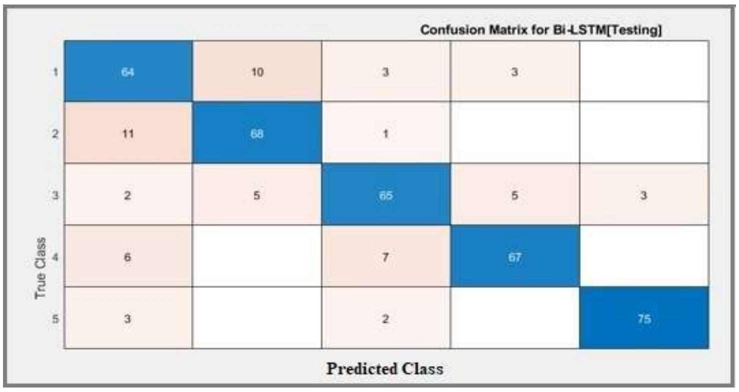

Fig. 8. Confusion Matrix of Testing Model

Table II represents the overall performance of the double Layer Bi-LSTM Model based on Accuracy, Specificity and Sensitivity. The accuracy ,sensitivity and specificity of double Layer Bi-LSTM model is 93.9%, 96.19 and 90.16%. This performance clearly depicts that the proposed methodology well suits for BIT-MIH Arrthymia ECG dataset.

TABLE II. **PERFORMANCE METRICS OF DOUBLE LAYER BI-LSTM**

Double Layer Bi-LSTM Model		
Accuracy %	**Specificity %**	**Sensitivity%**
93.9	96.19	90.16

Figure 9 depicts the performance view of Bi-LSTM Model.

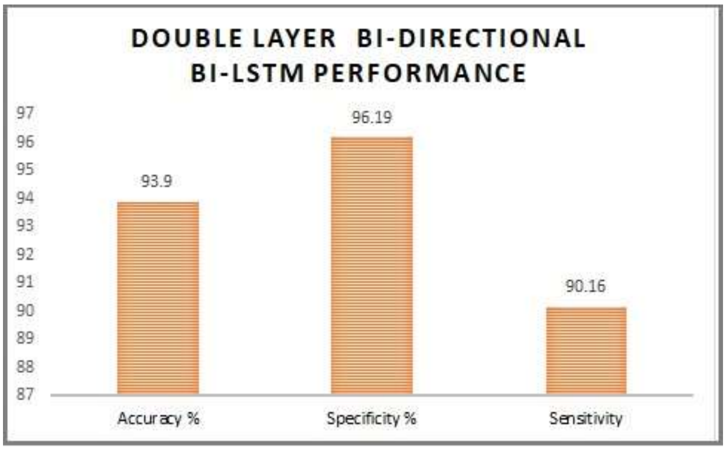

Fig. 9. Performance View of Double Layer Bi-LSTM

VI .CONCLUSION AND FUTURE WORK

This paper presents the Classification process of MIT-BIH ECG signals based on AAMI standard. This classification process will serve as an important role in identifying the heat diseases in preliminary stage itself. The raw ECG signals are preprocessed and the ECG basic components are identified. The R peak is identified and individual heart beats are extracted. Instantaneous *frequency* and Spectral *entropy* features are extracted and given as input units to the classification model. Double Layer Bi-LSTM classification model is applied for the classification purpose. As double layer of Bi-LSTM is used, the classification process is well tuned and produces good result based on performance metrics such as accuracy, specificity and sensitivity. In further this classification model can be applied to real time Sensor based ECG signals as we can witness a rapid growth of sensor based Internet of Things health devices.

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