Journal of Theoretical and Applied Information Technology
30th April 2023. Vol.101. No 8

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

ENSEMBLE OF DEEP LEARNING MODELS FOR CLASSIFICATION OF HEART BEATS ARRHYTHMIAS DETECTION

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ABSTRACT

Arrhythmias are one of the top causes of death worldwide, and due to changing lifestyles, their prevalence is rising dramatically. Due to their non-invasive nature, ECG signals have often been used to detect arrhythmias. The manual technique, however, takes a long time and is prone to error. Utilizing deep learning models for early automatic identification of cardiac arrhythmias is a preferred alternative to improve diagnosis and management. This paper proposes a unique ensemble deep structured learning model for categorizing arrhythmias that integrates attention mechanisms, bi-directional long short-term memory, and a convolutional neural network. It classifies beats into five categories: non-ectopic (N), supraventricular ectopic (S), ventricular ectopic (V), fusion (F), and unknown (Q). MIT-BIH and St. Petersburg data sets are integrated as multi-model datasets for training, validating, and testing the suggested model. The model's performance was also tested with the f1-score, recall, accuracy, and precision. Based on the ensemble of all of these approaches, this model is 99% accurate.

Keywords: *Artificial Neural Networks, Deep Structured Learning Models, Arrhythmia Detection, Ensemble Models*

1. INTRODUCTION

According to the WHO, more than 18.9 million people [1] in the country have atrial fibrillation (AFib), an arrhythmia that affects the heart. The risk for such cardiovascular disease is raised by factors such as elevated lipid profiles, high triglycerides, hypertension, obesity, video games, COVID, and others [2]. Clinical experts can detect AF by analyzing ECG beat signals recorded by the Holter system. Recent years have seen an increase in the [3] use of computer-based automatic heart arrhythmia detection systems by cardiologists and physicians, highlighting the importance of automatic detection of arrhythmia in facilitating prompt and accurate treatment. The computer-based ECG signals follow the steps of pre-processing, feature extraction, and classification of abnormal signals and are detected automatically. In order to proceed with feature extraction and classification, it is necessary to first remove any existing noise components. Major sources of noise in an electrocardiogram are baseline drift, power line interference, and moving artifacts [4]. Pre-processing methods that include filtering techniques aid in the elimination of noise components, allowing for rapid processing, while various signal compression procedures reduce the computational load by favoring effective signal characteristics. ECG feature extraction [5] is the primary method for diagnosing arrhythmias through the classification of the resulting feature vectors. Feature classification is the second factor that employs various different methods for classifying ECG patterns, such as neural networks, statistical methods, machine learning algorithm classifiers, and fuzzy interference [6]. Using a one-of-a-kind selection model that makes use of the best data distribution mechanism, the ECG pattern is classified statistically. Here, a neural network approach is taken for ECG data classification, taking into account a large learning ECG dataset with a lengthy learning time and a substantial computational burden. In order to improve ECG feature extraction and classification accuracy, dimension reduction is used Deep learning methods are well known and can be used for automatic feature extraction and dimensioning techniques for large volumes of data. There are several deep-learning techniques for arrhythmia detection, including CNN, LSTM, BI-LSTM, and the advanced attention model mechanism. Recently, it has come to light that ensemble learning is a significant factor in improving the effectiveness of deep learning models. In summary, the goal of deep ensemble models is to build a model that combines the best qualities of both ensemble and deep-structured learning models. The second phase of ECG arrhythmia detection includes the accuracy of the classification, which is determined by the quality of the ECG signal processing and the features extracted [7]. Several of the currently available works utilize a classical signal processing approach based on morphological characteristics, wherein an old-fashioned signal processing algorithm is implemented. Since there is a great deal of variation in the shapes of P waves and the QRS complex, Mitta et al. [8] proposed working with the morphological characteristics of the ECG signal. A perfect signal classification accuracy for arrhythmia detection cannot be achieved with just this feature. The authors of this study address this issue by taking into account morphological, temporal, and statistical features, which together will result in maximum effectiveness for all heart patients. Kachuee et al. [9] are considered one example of prior works in the field of deep learning, and both of them are computationally intensive, requiring a great deal of processing power. Thus, in this paper, various deep, structured, related learning models for ECG signals are reviewed. Bringing constant monitoring to individual wearable devices is central to the solution we propose here: an efficient classification method, which improves computational efficiency, and a long-time series monitoring deep learning technique are introduced.

The essential contributions of this study are as follows:

1. The dataset used for this work has been taken from multiple datasets provided by PhysioNet.org, MIT-BIH AD, and the PTB Diagnostic ECG database, which contains a total of 597 patient records.

2. This work generated a new combined deep structured learning model based on CNN, Bi-LSTM, and attention approaches to identify arrhythmias from long-term follow-up ECG data.

3. This work contributes to two distinct mechanisms: a hybrid CNN + Bi-LSTM model and an ensemble of CNN + Bi-LSTM + RNN-based attention.

4. First, the dataset was normalized, and then heart rate segmentation was performed using the annotation files.

5. The dataset is divided into three parts: training, validation, and testing. First, the balanced dataset is used to train the newly implemented ensemble deep-structured learning model. After training, the models were evaluated on an indeterminate dataset (the test dataset) to quantify heart rate in five groups.

2. RECENT DEEP STRUCTURED ECG SIGNALS LEARNING:

This section looked at a comprehensive survey of deep, structured learning methods for processing and classifying ECG arrhythmia signals. The ECG arrhythmia detection based on deep structured learning has been organized into two parts: feature extraction and classification and time-series classification. Each classification has a different algorithmic methodology. Also, the limitations of various deep structured learning methods incorporated in this survey paper are discussed and tabulated in Table [1], and some of them are listed below.

2.1 Convolutional Neural Network (CNN):

In the case of ECG arrhythmia detection, the CNN technique is widely used as a feature extraction and classification technique. Mishra et al. [10] present a comparison of different ECG filters and classifications with customized CNNs (CCNNs). The dataset includes electrocardiogram (ECG) signals, which are used to conduct one-hot encoding. After the Z-score is applied to these readings, heartbeats can be separated. Several filters, including the wavelet transform, the low-pass Butterworth filter, the Savitzky-Golay filter, the moving average filter, the median filter, and the Gaussian filter, are used to deny the data. After the data has been cleaned up and separated into training and testing sets, CCNNs are used to classify the heartbeats. This system achieves 94.90% accuracy in the classification of normal and abnormal signals. The system's implementation of the CCNN framework, which enables feature extraction, selection, and classification, is its greatest strength.

Limitations:

1. CCNN has a far better training period.
2. The training requirements can only be met with a massive database.
3. Since CCNN requires a static ECG signal, the length of the ECG signal must be kept constant during both the training and testing phases.

2.2 Recurrent Neural Network (RNN):

The RNN is a type of neural network with its own specific architecture. Using an RNN, data can be stored in loops between layers. One of the variants used in the RNN model is LSTM (Long Short-Term Memory). Neurons in a feed-forward network only have forward connections, but LSTM uses reversal feedback. LSTM may process individual data points, such as pictures, or it can handle data sequences, such as ongoing video or audio streams. LSTM can also decode ECG signals and hear heart sounds. In this paper [Kaya et al.] [11], ECG signals were classified using a hybrid of the long short-term memory (LSTM) and angle transform (AT) neural network architectures. When classifying ECG signals, the AT considers the angular information of signals on both sides of the target signal. The range of the resulting signals after AT conversion is 0-359. The LSTM technique takes its inputs from a histogram of recent signals. LSTM utilizes histograms to differentiate between atrial refractory rhythm (ARR), ventricular fibrillation (CHF), and normal sinus rhythm (NSR). The strength of this paper lies in achieving the best combination of signal-processing techniques and deep-learning models.

Limitations:

1. In order to achieve greater accuracy, the model is tested with a test split range of 70–30, which will generally give higher accuracy output.
2. High Computational cost.

2.3 Auto Encoders :

Autoencoders are a type of artificial neural network (ANN)-based architecture that can be used to learn unsupervised data encoding efficiently. They are commonly used to discover commonalities among data sets with the same characteristics. In addition to reducing the number of dimensions, an auto-encoder will attempt to produce a new class that is analogous to the one it is being fed. In the previous investigations, the author presented several variants of auto-encoder-based architecture.[Ojha et al. 2022] [13] This paper suggests using a CAD system to identify and categorize arrhythmias from ECG data automatically. To begin, an auto-encoder convolutional network (ACN) model is implemented. The ACN is founded on a one-dimensional convolutional neural network (1D-CNN) that can be trained to discover the optimal features from raw ECG signals. The ACN model's learned features are then used as input to a support vector machine (SVM) classifier, which aids in the detection of irregular heartbeats.

Limitations:

1. Auto encoder's classification fails to classify different types of arrhythmia diseases.

2.4 Transformer-Based Deep Neural Networks:

Transformer, in the context of deep learning, refers to a sequence-to-sequence design of neural networks that uses the self-attention process to capture global dependencies [15]. Since the transformer was made to accept sequence data as input, it piqued the interest of many scientists working in the field of natural language processing (NLP). Bidirectional Encoder Representations from Transformers (BERT) [16] is one of the most popular transformer-based models that has attained state-of-the-art performance in several NLP tasks. The transformer has become an increasingly beautiful standard in the field of computer vision recently. Dosovitskiy et al. [17] suggested a method for picture classification using a transformer that accepts image patches as input. The detection transformer (DETR) is

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

the result of one of the successful projects for an end-to-end object detection framework based on the transformer. By eliminating spatial anchoring and non-maximal suppression, two examples of manually created components that contain past knowledge, DETR streamlines the object detection pipeline. As a result, the transformer-based deep neural network is another viable mechanism for managing AI tasks, including natural language processing and computer vision.

Limitations:

1. Coming to real time for arrhythmia detection the transformer model is still lack to compute .
2. An automated transformer model for a hybrid combination-based pipeline model is one of the gaps to be designed.

2.5 CNN and LSTM:

The hybrid combination of CNN and LSTM leads to a time series classification category. In this technique, CNN is used for ECG feature extraction and LSTM for time series classification. [Ullah et.al 2021][12], in this paper, intends to use deep learning on the available dataset to identify and categorize arrhythmias. The MIT-BIH arrhythmia database contains 1,09,446 ECG beats sampled at a rate of 125 Hz. This initial data collection consists of five different types: N, S, V, F, and Q. PTB Diagnostic ECG Database are the other database. There are two groups in the secondary data source. Both datasets employ the CNN model, the CNN + LSTM, and the CNN + LSTM + Attention Model. The greatest advantage of this system is that it makes use of a multimodal database for the analysis of various ECG signal formats.

Limitations:

1. When it comes to CNN models, the biggest drawback is the high computational cost of neural networks.
2. Another drawback is that they demand a big training sample to be effective.

2.6 LSTM and Auto-Encoder :

Most of the time the combination of LSTM and Auto encoder acts as feature extraction and dimensionality reduction techniques in time series analysis of ECG Signals.[Evangelin et al., 2021] [14] In this paper, a convolutional denoising autoencoder (CDAE) and long short-term memory (LSTM) are combined in this research to present an edge-based innovative technique for ECG signal reduction. Instead of including numerous convolutional filters and pooling layers at the conclusion of the encoder section of the CDAE, a single-layered LSTM network is added. It results in a decrease in the model's trainable parameters, which in turn speeds up computation. Additionally, the LSTM network learns the order dependencies between the data, which aids in decompressing and reassembling the data. The suggested algorithm, which makes use of a denoising autoencoder architecture, denoises the signal in the interim. The greatest strength of this paper's usage of the LSTM network is its ability to increase computational efficiency.

Limitations :

1. Not applicable for real time datasets.
2. Lacks of joint compression of multiple ECG signals.

3. MATERIALS AND METHODOLOGY :

In this section, details on the database used, balanced sampling, matching and labeling the classes, and the feature extraction and classification procedure are presented.

3.1 Dataset:

This study makes use of the combination of the MIT-BIH (Massachusetts Institute of Technology-Beth Israel Hospital) arrhythmia database and Physio Bank is a sizable and expanding collection of high-quality digital recordings of the biomedical research community that can employ physiological signals and related data. The arrhythmia database at MIT-BIH is a widely used standard dataset that is available to the public for the study of arrhythmia. contains the MIT-BIH Arrhythmia Database. Two-channel, 24-hour ECG recordings were cut into 48 half-hour segments. Each recording includes a file called an annotation.atr in which the type of heartbeat is identified. The original 18 heartbeat kinds from ANSI/AAMI EC57:1998/(R) 2008 are divided into many categories, including normal (N), supraventricular ectopic beat (S), ventricular ectopic beat (V), fusion beat (F), and unknown beat (Q). The secondary data from the ECG database on the physio bank A PTB diagnostic ECG was used to construct the MI detection system. ECGs were taken from 148 patients with MI and 52 healthy participants. In order to build rules based on the data feature, data was used as a reference. The figure [1] shows the dataset classes and

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

their labels. The drawbacks of arrhythmia detection require computing the ECG signals as soon as possible. Thus, the suggested framework consists of locating the heart beats ,labeling of classed and classify using ensemble model which reduces the time of pre-processing .Figure [2] shows the schematic diagram of the proposed methodology.

3.2 Balanced Sampling Technique :

The main aim of this work is to enable the reduction of pre-processing steps so that data has to be balanced. Figure 3 represents the before and after of classifying imbalanced arrhythmias. As shown in the figure, the fusion of ventricular and normal data seems to be as low as 0.73%. The data has to be balanced at or above 1.00%. Thus, the technique used is sampling methods for imbalance methods from synthetic ECG datasets. Sampling-based strategies seek to "rebalance" the data by ensuring that each outcome is fairly represented. The most straightforward strategy is to arbitrarily under sample the majority result or oversample the minority. Here, the majority class (Normal) is under sampled and reduced to 79.9%. Such that the minority class comes in at 2.06%.

3.3 Matching and Labeling the data :

According to the AAMI, the heart rhythms associated with BIT-MIH arrhythmias can be divided into five categories: normal (N), supraventricular (S), ventricular (V), fused (F) and unknown rhythm (Q). Heartbeat is divided into five main classes based on subclass annotations, including 'N', 'L', 'R', 'j', 'e', 'A', 'a', ' S', 'J', '!', 'V', 'E', '[',']', 'F', 'f', '/' and 'Q' Records labeled with each record are retained for classification purposes.

Table 1: Deep Arrhythmia structured learning methods and its research gaps

R.NO	Input Dataset	Pre-processing Technique	Feature Extraction(Deep Learning Models) and Classification	Accuracy	Research Gaps
17	Physio-Bank ATM MIT-BIH(2022)	1. Z-Score ECG Signal Normalization 2. Imbalanced with Balanced Processing Using SMOTE	Deep CNN-BLSTM Model	CNN – BLSTM : 98.36 CNN – GRU : 96.63	Model can be trained with different activation layers among different layers to reduce the time and space complexity.
18	Physio-Bank ATM MIT-BIH(2018)	CNN Technique	CNN-LSTM model	98.10%	This model is not focussed on elimination of noise
19	MIT-BIH Atrial Fibrillation(2021)	Butterworth Filter Wavelet Transform	Hybrid CNN-LSTM Model	97.87%	Computation time is high.
20	MIT-BIH Atrial Fibrillation Database(2020)	Signal Processing	CNN - LSTM model	97.21%	Not suitable for non scale fixed inputs
21	(CPSC) dataset (2019)	Unify to 30sec by normalization	Deep residual network - BiLSTM	80.60%	New methods based on feature learning from the related leads of certain pathological conditions are expected.
22	MIT-BIT Arrhythmia Physio net(2020)	1.Normalization 2.Peak Detection	1.CNN -concatenate - BiLSTM 2. CNN - Feed - BiLSTM	82%	The performance of the result still could not capture the variation of different types of patients.
23	Physio Net 2017(2021)	-	hybrid attention-based deep learning network	86%	Takes more memory to compute.
25	4th China Physiological Signal Challenge-2021.(2023)	-	convolutional long short-term memory	97.88%	Signal processing is not done .

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

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

Figure 1: Heartbeat Classes and its class labels

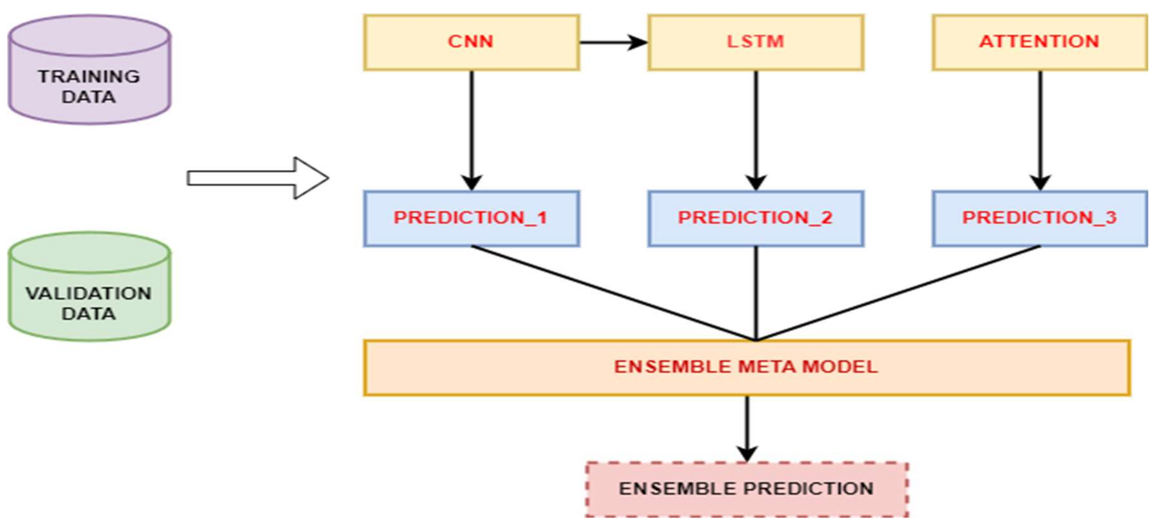

Figure 2: Proposed Ensemble Methods

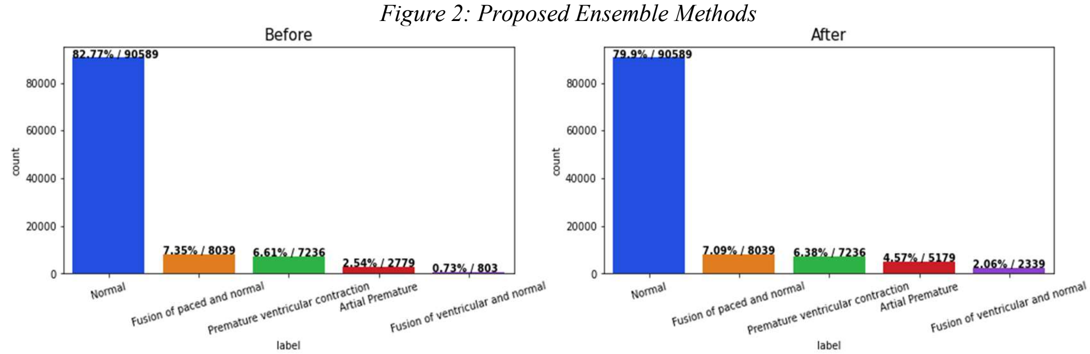

Figure 3: Before and after of Balanced Data

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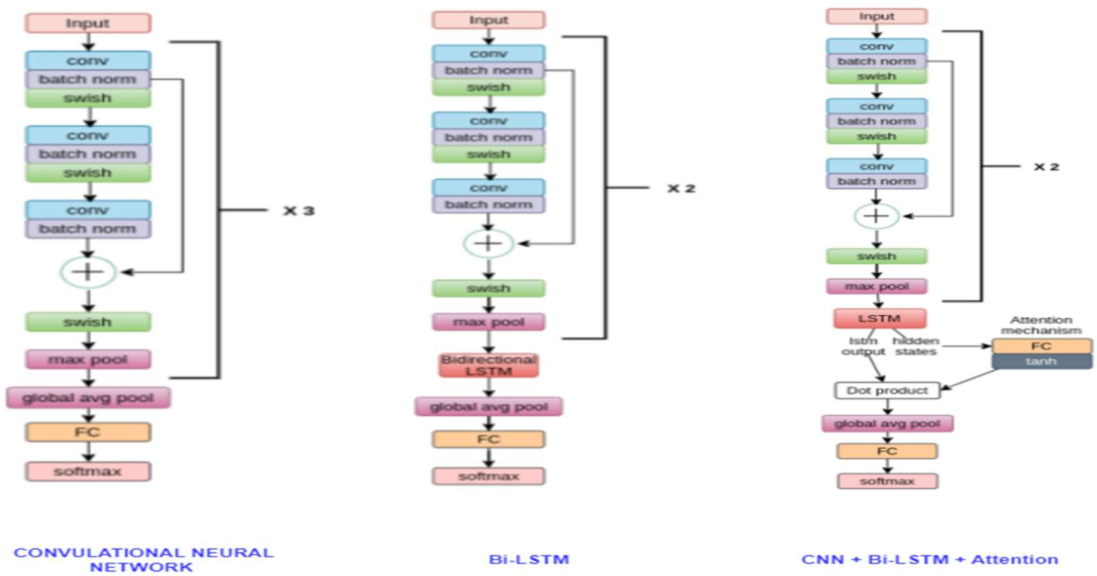


Figure 4 : Proposed Layers Description

3.4 Feature Extraction And Classification :

The proposed methodology consists of three pipelines methods, such as :

Pipeline 1 : Convolutional Neural Network (CNN)

Pipeline 2 : Bidirectional - Long short term memory (Bi-LSTM)

Pipeline 3 : Ensemble models (CNN + Bi-LSTM + Attention) for time series ECG classification

The steps involved to create those ensemble models are given below :

Step 1: Import all necessary packages .

Step 2: Set up the automatic hyper parameters to understand the problem .

Step 3: Setup the algorithm for balancing the data.

Step 4: Divide the dataset into train(z) ,validation(z) and test(z) data.

Step 5: Create a custom, three hybrid ensemble algorithm pipeline :

Level 1 : Develop a class named Convolutional Neural Network algorithm on one pipeline.

Level 2: Call a class called Bi-LSTM consisting of a series of RNN modules in a bidirectional way.

Level 3 : Call a class called ensemble that includes the functions of CNN,Bi-LSTM and attention mechanism.

Step 6: The custom deep learning set model is created and predicts the value of the test data .

As a result, by following this procedure, we can get a high degree of accuracy with little computational effort.

The figure [4] shows the neural schema of each pipelines and the detailed of each procedure is explained below

3.4.1 CNN methods :

Layers of neurons using weights make up neural networks in general. After each neuron calculates a scalar product using the inputs it has received, it performs a non-linear operation. Every layer up to the output layer, when the network produces predictions for the input data, goes through this procedure again. A unique class of deep learning algorithms called CNN is frequently applied in research work. The proposed CNN model consists of three layers of convulational and three layers of batch normalisation, and this model especially uses swish activation functions and adaptive average pooling. Convulational layers take the input of ECG signals and perform convulation operations so that important features are extracted. On-batch normalisation allows for the processing of small batches of data rather than the entire dataset. Generally, the swish function works better than ReLu because of its better and quicker convergence. The figure [5] shows the swish function curve and its convergence. The mathematical representation of swish activation and its derivatives is given in equations [1] and [2].

swish(conv) = Conv(x) * sigmoid(Conv(x)) --- (1)

Where Conv(x) = output from normalized convoluted features

swish(conv) = output of activated features

Derivative of Swish :

swish(conv)’ = swish(conv)+ sigmoid(Conv(x)) * (1- swish(conv)) --(2)

The equation () gives the final outcomes of activated ECG signals .

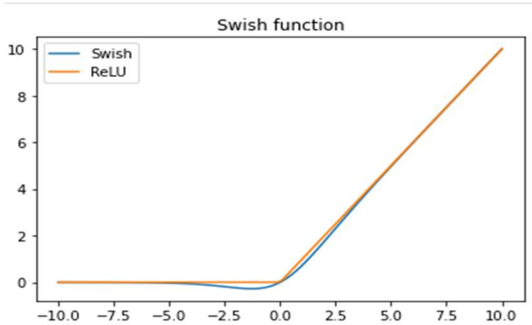


Figure 5 : swish function curve(x-axis = sigmoid values & y-axis = Number of epochs)

```
CLASS CNN(X)
do
X = Reshape (ecg data training data)
      Conv1 = convolution (x,hidden_size)
       Conv1 = batch_normalization(conv1)
       Conv1 = swish(Conv1)’
Conv2 = convolution (x,hidden_size)
Conv2 = batch_normalization(conv2)
Conv2 = swish(Conv2)’
Conv3 = convolution (x,hidden_size)
Conv3 = batch_normalization(conv3)
Conv3 = swish(Conv3)’
Xout = Adaptive average pool(Conv3)
Output = softmax(fully_connect ( Xout))
End
```

Finally, the fully connected layers take the average weight of the features and give the final outcomes.

3.4.2 CNN and Bi-LSTM model :

RNNs are the foundation of the LSTM method. The bi-LSTM consists of two independent LSTMs that can integrate and summarise data coming from both forward and backward directions. It is helpful to have access to both past and future contexts while performing activities involving sequence labelling. To obtain information about the future and the past, Bi-LSTM suggests advancing and backwarding each sequence to two different hidden states and then concatenating the two hidden states to produce the result. The output of the CNN layers serves as the input to the LSTM in this combination of CNN and Bi-LSTM modeling.Model The bi-LSTM model cycles through a set of RNN values that include all three gates. The cell in every gate is in charge of retaining the values throughout particular time intervals, while the gates control the communication between the cells. Finally, the fully connected layers give the outcomes of every labelled class.

3.4.3 Attention Mechanism :

The encoder-decoder model for machine translation was given a performance boost by the addition of the attention mechanism. The purpose of the attention mechanism was to allow the decoder to use the most pertinent portions of the input sequence in a flexible way by combining all of the encoded input vectors in a weighted manner, with the most pertinent vectors receiving the highest weights. Thus, the decoding part is considered important for attention. The steps to compute the decoding of attention are given as follows:

Step 1 : Accepts attention input from all encoder states (enc_state_1, enc_state_2,....enc_state_k etc.) and a decoder state (decode(ht)).

Step 2 : Evaluate Attention scores.

Att_score = score(decode(ht),.enc_state_k),k

Step 3 : For each encoder state enc_state_k, attention computes its "relevance" for this decoder state (decode(ht)).

Step 4: Perform attention weights, which are probabilistic distributions based on softmax that are applied to attention scores.

Attention weights = softmax(Att_score)

Step 5 : computes attention output, which is the weighted sum of encoder states with attention weights.

These steps are followed to give attention to

Journal of Theoretical and Applied Information Technology
30th April 2023. Vol.101. No 8

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

important features and classify the ECG abnormal signals outputs.

3.4.4 Ensemble of models :

Ensemble of deep structured learning model that combines the various different algorithms for predictions. On this proposed model, the ensemble works based on the combination of CNN, BI-LSTM, and the attention mechanism. The working mechanism of the proposed model is given in the algorithm [1].

Algorithm 1: Ensemble of deep ECG ensemble classifier

Input : Training ECG signals data (ECG_DATA)

Base Level classifiers (BL1-CNN and BL2 - LSTM)

Meta Level classifiers(Attention mechanism)

Output : Trained deep ensemble model (Trained_ECG_DATA)

BEGIN

Step 1 : Train the base learners model by applying classifiers CNN and LSTM to the ECG_DATA

for i = 1…..n do

Base_Learners = BL $_{(ECG\_DATA\_n)}$

End for

Step 2 : Construct new dataset for predictions ECG_DATA

Step 3 : Train a meta level classifier (Attention mechanism) from constructed new dataset

Return attended values

END

Thus by using the attention will find the important features that the features may be from recurrent layers or convoluted .

4. EXPERIMENTAL AND RESULTS:

This work is primarily focused on demonstrating the significance of not performing pre-processing on imbalance data in arrhythmia detection with an ensemble model . The result is plotted in three ways :

1. Confusion Matrix for ECG arrhythmias
2. Loss Function
3. Accuracy(ECG),Precision(ECG),Recall (ECG) and F1-score(ECG)

4.1 Confusion Matrix for ECG arrhythmias :

Confusion matrix of this method comes under four cases

Case 1 : True ECG Positive(TEP) :The abnormal ECG signal is correctly detected as an arrhythmia ECG signal.

Case 2 : False ECG Positive (FEP): The normal ECG signal is incorrectly detected as an arrhythmic ECG signal.

Case 3 : False ECG Negative (FCN):An abnormal ECG signal that is not correctly detected is an arrhythmia ECG signal.

Case 4 : True ECG Negative(TEN) : The Normal ECG signal is detected exactly as normal ECG signal.

Based on the following cases ,the figure [6] shows the classification report of the ensemble model .From the figure, the fusion of ventricular and normal ECG signals shows a high rate of having arrhythmia diseases .

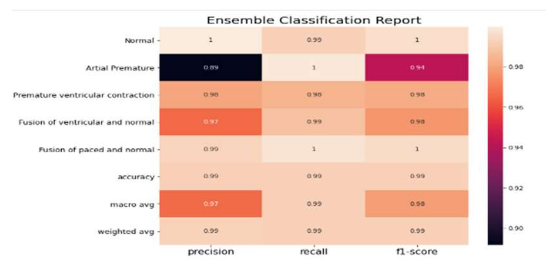
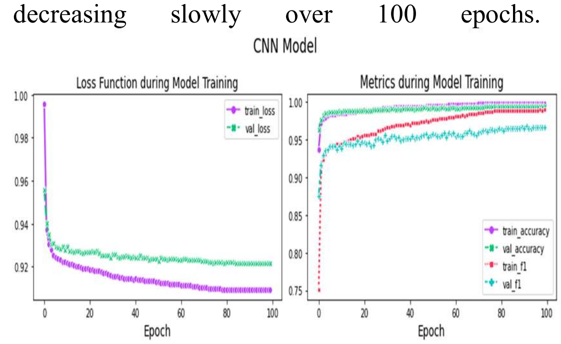


Figure 6 :Confusion Matrix Report

4.2 Loss Function :

Using the loss function, we can assess how effectively this ensemble algorithm models our balanced dataset. Cross-entropy loss is used in our work. Cross-entropy works based on adjusting the model weights during training to minimise the loss values. Our model performed better when the loss was smaller. Figure [7] shows the loss function graph of three pipelines. From the graph, we inferred that loss is decreasing slowly over 100 epochs.



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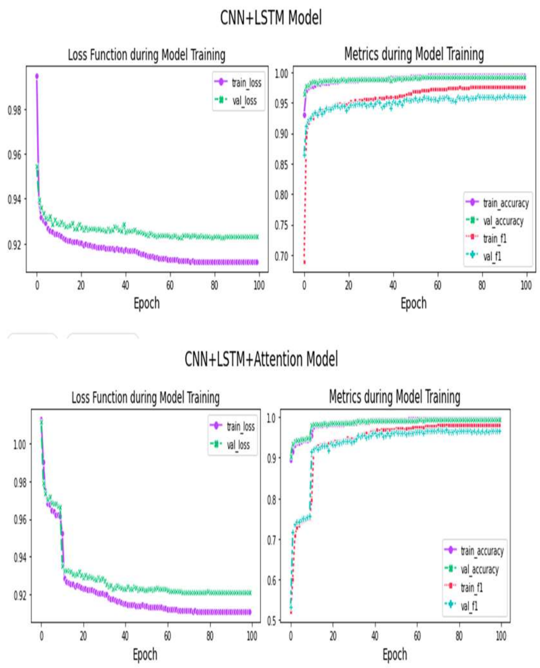

Figure 7 :Loss Function Graph

4.3 Accuracy,Precision,Recall and F1-score :

Performance metrics such as Accuracy, Precision, Recall and F1-Score are calculated for measuring the performance from equations [3] to [6].

Accuracy(ECG) = (TEP+TEN)/(TEP+FEP+FEN+TEN) --------------- (3)

Precision(ECG) = TEN/(TEN+FEP) --------------------------------- (4)

Recall(ECG) = TEP/(TEP+FEN) --------------------------------- (5)

F1-Score = 2 * Precision(ECG). Recall(ECG)/ Precision(ECG) + Recall(ECG) —-----------------------(6)

Figure [8] shows the visualized chart report for proposed three pipelines .We compare all other deep learning with the proposed ensemble technique which achieves 99% in detection using this multi-model dataset.

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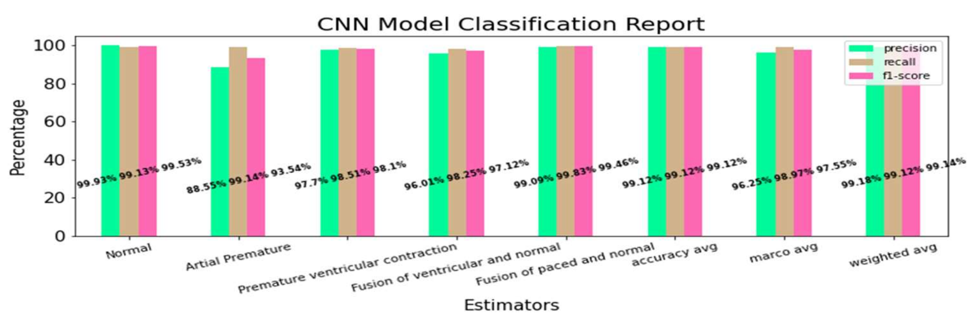

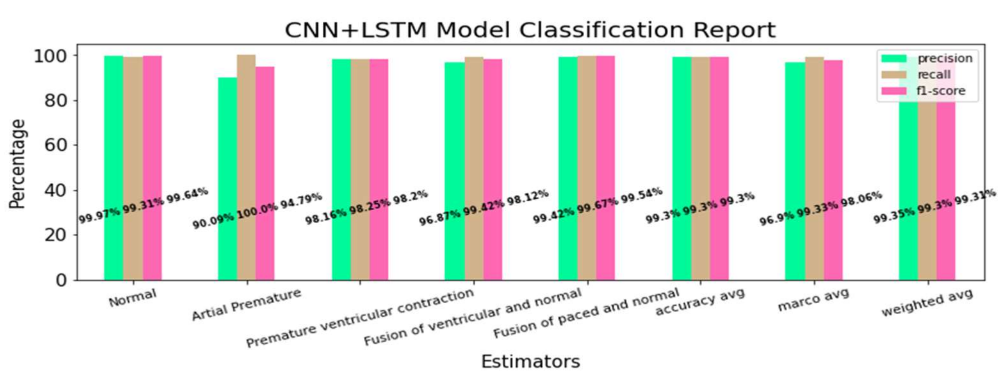

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30th April 2023. Vol.101. No 8

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

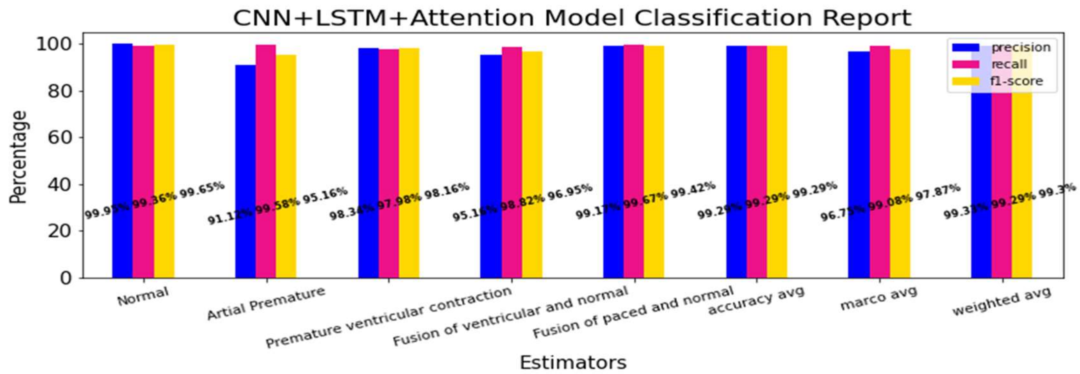

Figure 8 : Ensemble Classification Report Chart

5. CONCLUSION:

The processing of ECG segment data can be used to predict arrhythmia, a severe cardiovascular disease. To reverse heart disease, arrhythmias must be accurately recognised and prevented early. Our proposed system model achieved the primary research goal of helping physicians quickly identify the type of ECG or confirm their diagnosis in a medical setting while maintaining a high level of accuracy. High and affordable. To build an efficient and robust stand-alone computer-aided diagnostic system, a deep aggregation model is presented in this study to classify five types of ECG segments. Using a multi-model dataset for training, validation, and testing, the network achieved a maximum accuracy of 99%.

This study demonstrated a number of benefits, including its capacity to support doctors in making decisions about clinical procedures that involve ECG recordings. Additionally, it was designed to be as straightforward as possible while providing the best performance. For health professionals, the presented method is simple and does not need feature extraction or signal modification. Additionally, this study only examined one type of CVD, namely arrhythmia, despite the fact that the symptoms of cardiac disease are frequently complex and variable. Therefore, additional ECG data types will be required to increase the network'spotential

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