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HybDeepNet: ECG Signal Based Cardiac Arrhythmia Diagnosis Using a Hybrid Deep Learning Model

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To monitor electrical indications from the heart and assess its performance, the electrocardiogram (ECG) is the most common and routine diagnostic instrument employed. ECG records are used to diagnose an arrhythmia, an abnormal cardiac beat that can cause a stroke in extreme circumstances. However, due to the extensive data that an ECG contains, it is quite difficult to glean the necessary information through visual analysis. For decades, researchers have focused on developing methods to automatically and computationally categorize and identify cardiac arrhythmias. However, monitoring for arrhythmias in real-time is challenging. To streamline the detection and classification process, this research presents a hybrid deep learning-based technique. There are two major contributions to this study. To automate the noise reduction and feature extraction, 1D ECG data are first transformed into 2D Scalogram images. Following this, a combined approach called the Residual attention-based 2D-CNN-LSTM-CNN (RACLC) is recommended by merging multiple learning models, specifically the 2D convolutional neural network (CNN) and the Long Short-Term Memory (LSTM) system, based on research findings. The name of this model comes from a combination of the two deep learning. Both the beats themselves, which provide morphological information, and the beats paired with neighboring segments, which provide temporal information, are essential. Our suggested model simultaneously collects time-domain and morphological ECG signal data and combines them. The application of the attention block to the network helps to strengthen the valuable information, acquire the confidential message in the ECG signal, and boost the efficiency of the model when it comes to categorization. To evaluate the efficacy of the proposed RACLC method, we carried out a complete experimental investigation making use of the MIT-BIH arrhythmia database, which is used by a large number of researchers. The results of our experiments show that the automated detection method we propose is effective.

KEYWORDS: Cardiac Arrhythmias, Hybrid Deep Learning, ECG, Scalogram, LSTM, CNN, MIT-BIH Dataset.

1. Introduction

It is the primary cause of human sickness because cardiovascular disease claims the lives of more than 17 million people every year. Research conducted by the World Heart Federation found that low-income nations are home to more than 75 percent of the world's population with cardiovascular disease (CVD). Electrocardiograms, often known as ECGs, are used to record the electrical activity caused by depolarizations of the heart muscle. This activity can be measured as it goes to the surface in impulses. However, the electrical current is negligible; ECG electrodes can reliably detect it on the skin. Due to its non-invasive nature, ease of use, and ability to offer valuable heart health and pathology data, electrocardiography (ECG) is the most basic and accessible approach for identifying cardiac arrhythmia (or heart rhythm abnormalities). Arrhythmias of the heart arise as a significant sign of cardiovascular illness. The latter is a major social issue since 1) it is so common and deadly, and 2) it is so expensive to treat. These problems will get more severe as the global population ages, which could lead to a rise in mortality rates.

Arrhythmias, in which the heart beats in a way that is abnormal from its usual pattern, is one of the most frequent cardiovascular disorders. Classifying these atypical patterns into their respective subclasses is necessary for making practical treatment recommendations. In cardiology, the electrocardiogram, often known as an ECG, is widely used to diagnose and determine the likelihood of cardiac conditions characterized by irregular heartbeats. Arrhythmia analysis relies heavily on electrocardiogram (ECG) readings. It's a cutting-edge medical tool that records cardiac excitability, conduction, and recovery. The electrocardiogram (ECG) is an essential and accurate diagnostic tool in contemporary medicine, and the precise automation of the interpretation of ECG data is beneficial for clinical practice and patient security. Humans can experience problems with their heart's rhythm and activity due to a condition known as arrhythmia [35].

Machine learning (ML) approaches have been increasingly widely used in recent years for tackling issues in many different industries, including health. The reality that ML can handle challenges that are hard to solve in the traditional sense because of unclear rules is largely responsible for its popularisation. Learning and the transferability of information make these techniques effective problem-solvers. Success in many scientific domains is attributable to artificial intelligence methods. Potential benefits of ML (especially computational intellectual ability) stem from features shared with their biomedical analogs, such as the ability to learn and generalize awareness, achieve global optimization (e.g., the process of adapting), and make use of unspecific terminology (e.g. fuzzy systems). Several machine learning (ML) techniques, such as support vector machines (SVM), have been proposed in recent decades to automate the classification of heart arrhythmias based on ECG signals. However, there were drawbacks to these methods that limited their adaptability in customized healthcare systems, such as technological restrictions in the learning process.

Studies that employ deep learning (DL) approaches frequently use CNN, which executes feature mining and categorization [9, 22]. A distinctive CNN consists of several successive convolutional and pooling layers, providing a deep network that can extract a single input's underlying features while lowering the input's complexity. These features make them ideally suited for research requiring substantial computational effort, such as ECG classification [11, 26-28]. Analysis of time series [23, 31], including speaker identification [36] and speech synthesis [10], are typical applications of DL techniques like Convolutional Neural Networks [15]. One type of RNN, the long short-term memory (LSTM) network, represents a development from the original RNN. For ECG signal categorization [8], LSTM networks have proven popular due to their ability to learn the time evolution of the raw data and to preferentially recall or forget knowledge based on the present storage state.

The current research aims to classify cardiac arrhythmias by proposing a hybrid DL model architecture that blends CNNs with LSTMs with an attention mechanism. The fundamental idea behind this method is to achieve dimensionality reduction simultaneously by using the CNN component as a feature extractor and feeding the LSTM component with the most discriminatory features of the input. The suggested model uses the categorical loss function to reduce prediction errors further and deal with data imbalance. The model is trained and tested with data from the widely-used MIT-BIH atrial fibrillation database of electrocardiograms.

The remaining parts of this work are organized in the following way: In Section 2, contextual information for cardiac arrhythmias is provided, and associated state-of-the-art deep-learning approaches for ECG classification are evaluated. Both of these topics are covered under the heading "Background Knowledge." In Section 3, the research technique is broken down into its component parts, and in Section 4, the experimental designs and procedures are analyzed. The recital appraisal process of the suggested model is described in Section 5, where it is then reviewed and numerically related to current investigations that are pertinent to the topic. Section 6, a summary of the findings, is presented in the final part of this study.

2. Related Works

In the latest days, computer vision and computational intelligence network have not only made significant gains in the domains of image processing, voice recognition, and a wide variety of other sectors, but it has also become routinely utilized in the supported detection of cardiac illness based on ECG data. Kumaraswamy and colleagues have developed a novel classifier for the categorization of heartbeats, which may be helpful in the diagnosis of arrhythmias [25] after taking into consideration the MIT-BIH arrhythmia database. Precisely, to locate R-R intervals as features, they used a random forest tree predictor in conjunction with a discrete cosine transform (DCT). R-R intervals are a fundamental pattern that is utilized in the process of identifying arrhythmias. A predictor suggested by Park et al. [32] that can recognize 17 unique heartbeat variations can be used to diagnose arrhythmias. This predictor can sense the sequences. For the purpose of arrhythmia detection, Jun et al. [19] utilized a high-performance cloud system based on GPUs. In a manner analogous to [32], they identified and classified the data using the Pan-Tompkins algorithm in conjunction with KNN.

The principles that are used in machine learning are strongly affected by feature architecture, with a particular emphasis being placed on the procedure of obtaining and limiting elements. For the machine learning algorithm to be able to learn and select appropriate functions, it is necessary to incorporate all of the data that constitutes the signals into the learning process. Additionally, this theory serves as the foundation for the deep learning model, particularly CNN and its 1-D versions [24]. Researchers [1–3, 33] have begun using deep learning techniques to detect and classify a wide variety of chronic diseases. This is because deep learning techniques offer much-untapped potential and promise. In the study of Pawiak et al. [34], the long-duration ECG signal was classified using a deep genetic ensemble of classifiers. Gao et al. [13] used an efficient long short-term memory (LSTM) recurrence network model to categorize 8 different kinds of heartbeats.

To discriminate amongst five separate heartbeats, atal et al. came up with the concept of a deep convolutional neural network that could adapt its efficacy [3, 10] Deep learning networks, in contrast to typical neural networks, can routinely extract features, identify detailed data patterns, and do away with compound signal preparation. Deep learning networks also have a superior capacity for nonlinear fitting, which allows them to recognize single-lead, multi-class, and imbalanced ECG datasets with greater accuracy. CNN stands for "convolutional neural network,". CNN's have been the subject of extensive research and are being utilized in deep learning. CNNs have also been effectively helpful in the classification of arrhythmia. Because relatively little effort is put forward to categorize the ECG signal's micro-classes, the micro-classification of heartbeats, which has five types, is our primary purpose for conducting this research.

An 8CSL method for the discovery has been projected by Ping et al. [33]. This method uses shortcut interactions in CNN, which helps increase the speed at which data can be transmitted, and one layer of LSTM, which helps to decrease the degree to which data depend on one another over the long term. He contrasted the proposed method multi-scale convolutional neural network (MCNN), and he found that the 8CSL retrieved features better when contrasted to the other two approaches in terms of F1-score 84.89%, 89.55%, and 85.64% with multiple data segment lengths. This was done so that he could conduct additional testing on the research methods that had been proposed. When it comes to heartbeat intercepts, Ullah et al. [39] used three distinct techniques: CNN, CNN+LSTM, and CNN+LSTM+attention model for the categorization of five distinct types of arrhythmias in cardiac observations over two well-known datasets, MIT-BIH arrhythmias, and the PTB Clinical ECG Database. These algorithms were applied to heartbeat detection systems over 3the MIT-BIH arrhythmias dataset and the PTB Diagnostic ECG Data system.

While the article provides an overview of various techniques used in detecting cardiac illness using ECG data, it needs to discuss the limitations of these techniques or provide a comparative analysis of their effectiveness. Additionally, the article does not discuss potential ethical considerations surrounding the use of deep learning techniques in diagnosing and treating heart disease. Further research could explore these gaps to improve the understanding of the applications and limitations of computer vision and computational intelligence networks in cardiology.

3. Proposed Methodology

This part discusses the dataset employed, several data cleaning and preparation approaches, and a detailed explanation of the suggested model. There are a few different approaches to dynamically analyze an electrocardiogram (ECG), the most common of which are machine learning and deep learning. Because feature engineering is handled autonomously, deep learning techniques are more practically viable. The suggested model is educated with the assistance of K-fold cross-validation, and then hyper-parameter tweaking is carried out. Figure 1 demonstrates the overall structure of the proposed method.

3.1. Dataset

This study makes use of the MIT-BIH database, which is an ECG database provided by MIT. This database complies with global practices and has been documented by several industry experts (Moody and Mark, 2000). Researchers have extensively used the MIT-BIH database [14, 29, 38, 30] to study the categorization of arrhythmic heartbeats.

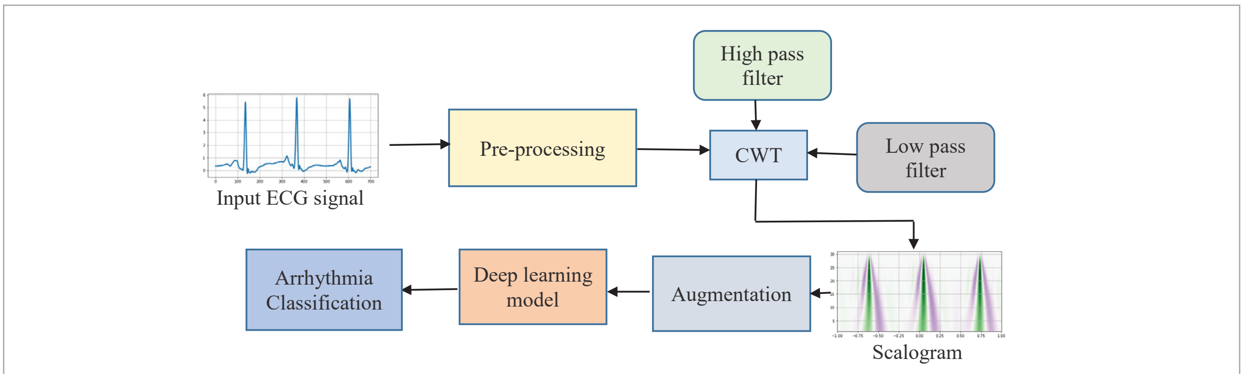
In Figure 1, the ECG signal is preprocessed and fed as input to the continuous wavelet transform. They are instrumental in detecting and analyzing signals with non-stationary features or time-varying characteristics.finally, analyzed data is augmented and a deep learning model is implemented for classifying the heart disease arrhythmia.

Each of the 48 ECG recordings in the MIT-BIH database was recorded over 30 minutes, with a sample rate of 360 hertz, and features two separate leads. Incorporating expert annotations and techniques, the MIT-BIH dataset can fine-tune and improve upon its data [7, 17, 21, 4, 12].

Further, it takes cues from pre-existing solutions to improve upon itself. There are 36 recordings used here; all of them from the MIT-BIH regular sinus rhythm database [14], which has 18 long-term ECG measurements from individuals diagnosed at Boston's BIH arrhythmia facility. There were no serious arrhythmias among the patients in this collection, including five males aged 26–45 and thirteen females aged 20–50.

The BIDMC heart failure collection [7] provided the source for these 30 recordings. Collection of 15

Figure 1
The overall structure of the proposed methodology



long-term ECGs from individuals with NYHA class 3-4 cardiovascular failure. Each recording lasts for over 20 hours and features 250 samples per second sampling rate, 12-bit resolution over a 10-millivolt spectrum, and two ECG signals. Table 1 shows the datasets used in our proposed model and Figure 3 shows the number of each beat type from the dataset.

Nonectopic beats (N), ventricular ectopic beats (V), supraventricular ectopic beats (S), unknown beats (Q), and fusion beats are the five larger heartbeat categories that were created after the original 18 types of heartbeats were reorganised as shown in the Figure 2. Nonectopic beats (N) are the most common type of heartbeat (F).

Table 1
Datasets used in our proposed model

Database	MIT-BIH cardiac arrhythmias database	MIT-BIH normal sinus rhythm database	BIDMC congestive heart failure database
Recording	96	36	30
Age group	34 to 79	20 to 50	22 to 79
Samples per second	128	128	250
Sampling rate	360Hz	128Hz	0.1 Hz to 40 Hz

Figure 2
Sample beats from each class in the dataset

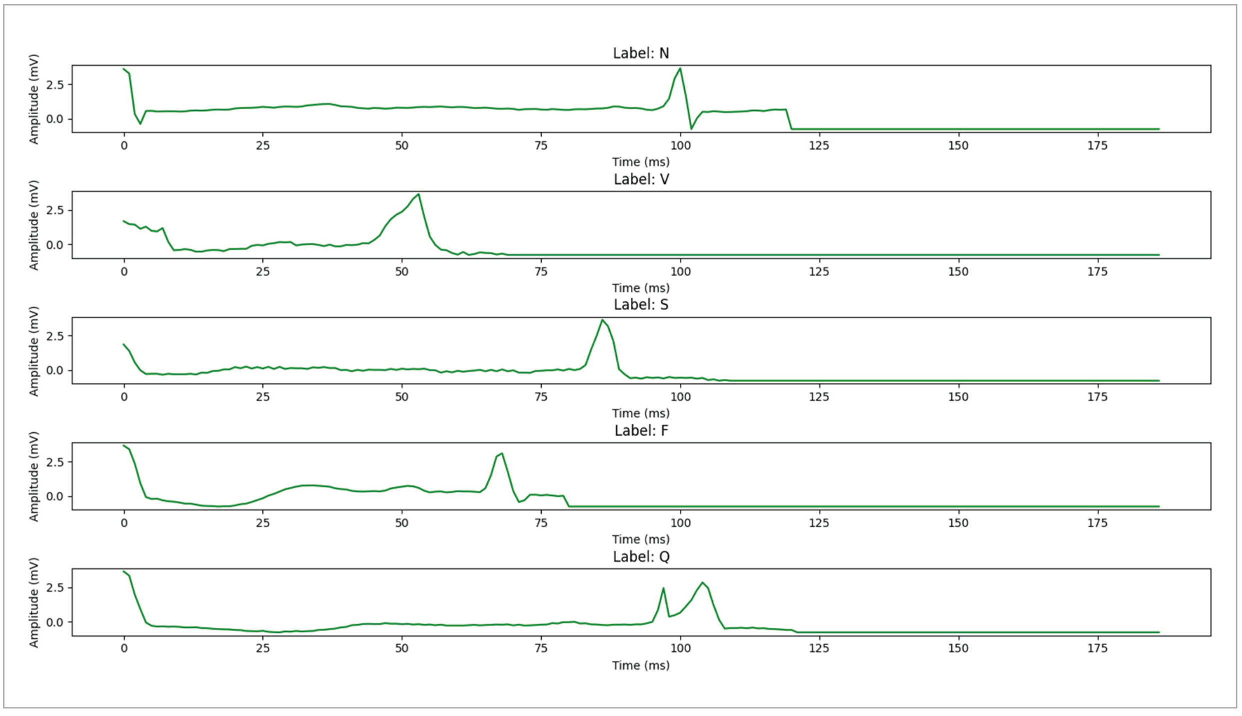
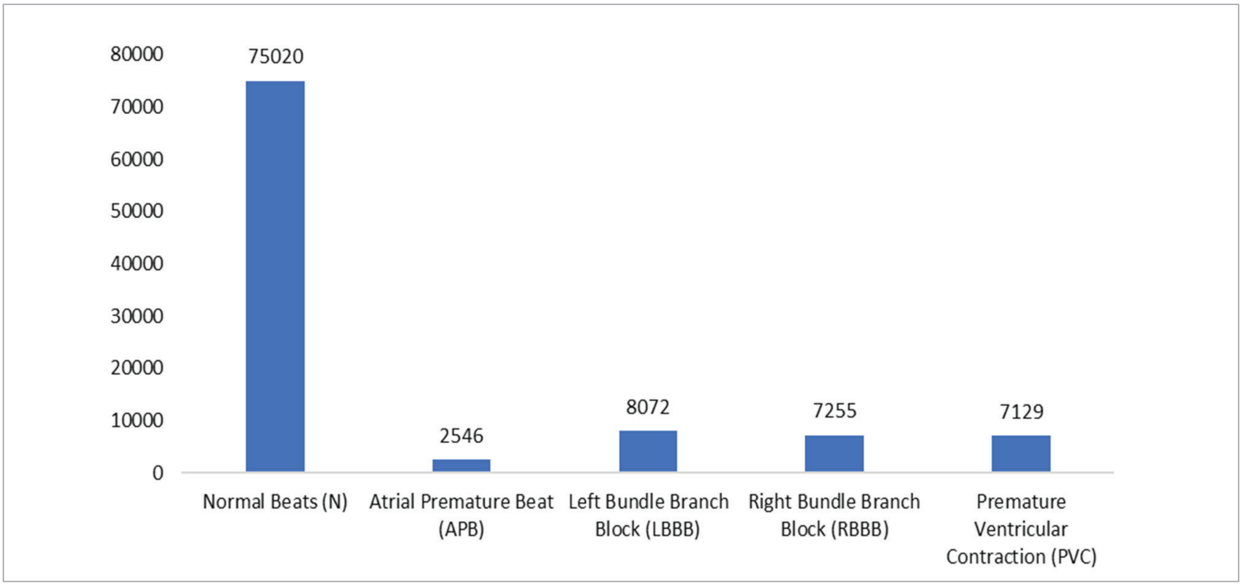


Figure 3
Number of beats from the dataset



3.2. Data Pre-processing

Z-score normalization was utilized for data dispensation to lessen the effects of extreme data value disparities and speed up model execution generally.To define the normalization function, we use the formula

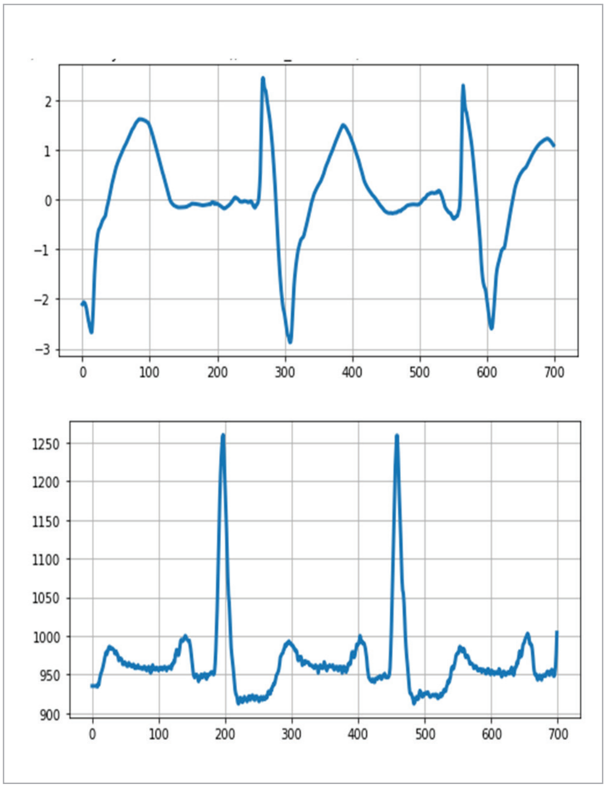
$$A^{*} = \frac{A - C}{X}, \tag{1}$$

where A^* is the ECG recording's values and C and X are the average and standard deviation of those values. Figure 4 shows the beats from the MIT-BIH cardiac arrhythmias database after the Z-score normalization.

In this step, information is readied for use in subsequent stages of the learning and assessment process. To begin, we use a converted storage service and the expand information helper procedure to divide up the information into manageable chunks. To create the scalograms, 1-D ECG signals were transformed using Continuous Wavelet Transformation (CWT), which was then used to create the final 2-D color images [5, 40, 16, 41, 18, 37].

$$\psi_{x,y}(t) = \frac{1}{\sqrt{x}}\psi\left(\frac{t-y}{x}\right) x, y \epsilon R, \tag{2}$$

Figure 4
Sample Beats from MIT-BIH cardiac arrhythmias database after Z-score normalization



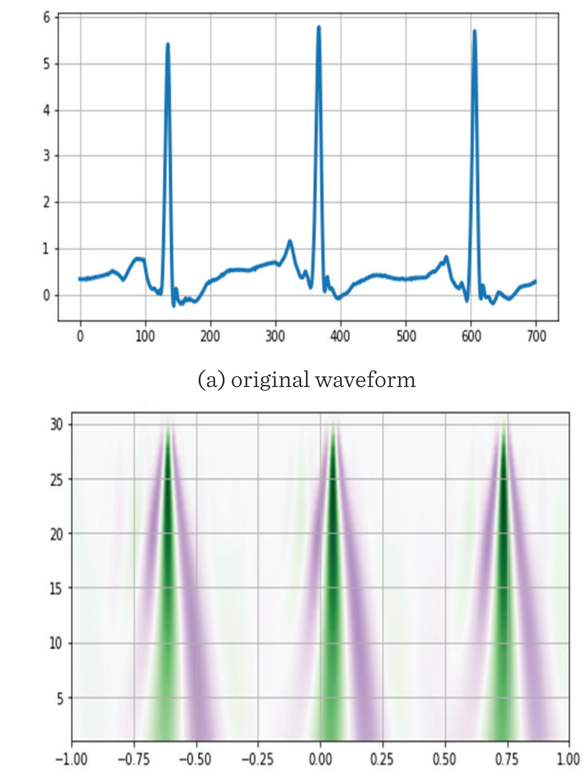
where R denotes the real waveform. x, y represents the dilation and translation of the waveforms.

$$CWT_{(x,y)} = \left(f, \psi_{x,y}\right) = \frac{1}{\sqrt{x}} \int_{-\infty}^{+\infty} f(t) . \psi^{*}\left(\frac{t-y}{x}\right) dt . \quad (3)$$

Spectral analysis of signals is where CWT really shines. It can be used to analyze vibration patterns, frequency jumps, temporal jumps, bursts of signals, and the dampening of signals. Scalograms of CWT coefficients can be used to feed images into a deep neural network for the purpose of signal categorization. Figure 5 shows the scalogram of the original signal.

Figure 5

Scalogram of the original signal



(a) original waveform

(b) scalograms

where s denotes movement and e represents magnitude. Decentralization for DWT is expressed as Equation (4).

$$w(s,e) = 2^{\frac{e}{2}\sum_{m} a(m)\varphi\left(2^{e} m-1\right)} . \quad (4)$$

A total of n samples is indicated. The basic function of DWT is to use high-pass and low-pass filters to divide a signal into several resolutions. Employing a low- and high-class filter to a signal is how DWT breaks it down into its constituent parts. The coefficient approximation is denoted by CA and the detailed coefficient is denoted by CD. The signal breakup may be expressed analytically as follows:

$$CA = \sum_{m} A(m) h(2x-m) \quad (5)$$

$$CD = \sum_{m} A(m) l(2x-m) . \quad (6)$$

Algorithm 1: ECG signal Pre-processing

1. input: $S = \{s_1, s_2, s_3 .... s_m\}$

2. level $= m$

3.output: Wavelet Coefficient

4. Identify the length of the input signal

5. calculate $N_x = len(S)$

6. repeat the step 7 to 10 until the end of the signals

7. Initialize high pass and low pass filter

8. LPF = $\sum_{m} A(m) l(2x-m)$

9. HPF = $\sum_{m} A(m) h(2x-m)$

10. End loop

11 return coefficients

The aforementioned technique partitioned the whole number of samples into a set of discrete frequency ranges. The time domain signal is filtered using a combination of high-pass and low-pass filters sequentially to produce it. At last, a coefficient has been determined for the ECG signal that aids in suppressing background noise.The term “augmentation” is used to describe the act of adding new, relevant information to an existing set of data. As a result, it can occasionally enhance data quality and decrease the time spent manually entering new information. This procedure might be useful if CNN models are fed 2D pictures as input. For certain models, augmenting data may be more useful than for others. The outcomes of certain earlier efforts improved, while the results of others suffered, after being enhanced.

3.3. Model Architecture

The RACLC model is constructures with CNN+LSTM+CNN with residual and attention layers as shown in Figure 6. CNNs depend on the slides of the convolutional window being applied to the input to extract meaningful local insights from the data. CNN's also depend on the pooling layer in order to further improve the features and extract essential information from the input data. In general, the number of convolutional layers determines the level of sophistication that can be achieved with the characteristics that are extracted. However, once a certain threshold is reached in terms of the number of convolutional layers, the model begins to experience an issue known as gradient explosion. As a result of this, a residual block structure was incorporated into the system to ease the gradient problem. The skip connection is implemented on the residual network to link important information to a deeper network for the purposes of transmission. This result is preferable to the classic CNN's straightforward layered structure, which it replaces.

Conventional feed-forward networks are impractical for 2D image classification as the number of free components in the raw picture continues to grow. By associating pixels in close proximity, however, it is now feasible to extract a wide variety of local information from 2D pictures using a CNN model. This study presents the introduction of the translation of a 1D ECG signal into 2D ECG pictures since it is possible to extract and filter the spatial neighborhood of 2D images using convolution and down-sampling layers. This method improves the ECG classification performance to at least the level attained by human examination. Consequently, the 2D CNN model can replace the current form of ECG arrhythmia diagnosis, which relies on the visual inspection of specialists. To acquire the convolution layer's output, we first offset the convolution kernel and then pass it on to the activation function.

If the input to the convolution layer is $I(k, l)$ and then the output $z(k, l)$ is generated by the following formula:

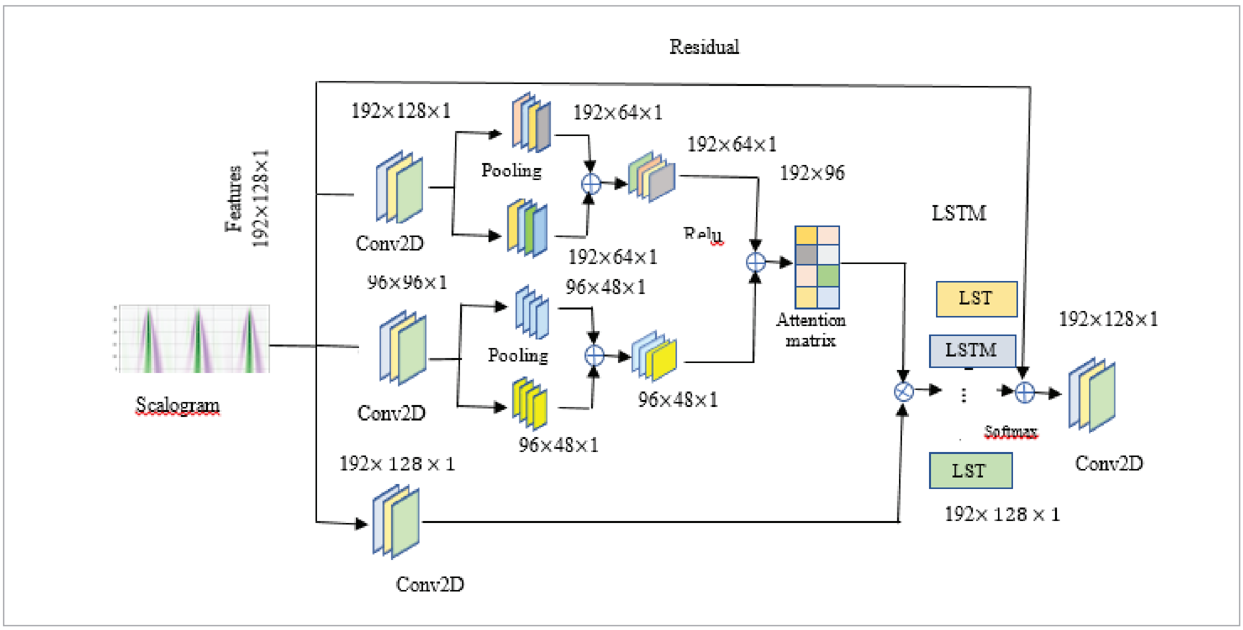
$$z(k,l) = I(k,l) * w(k,l) = \sum^{m=-xx} \sum^{n=-yy} I(m,n).w(k-m,l-n) \quad (7)$$

Using Batch normalization, the characteristics discovered by the convolution layer may be normalised. The network's Relu activation function, denoted by the function $\sigma(.)$, has the form,

$$\sigma(x_i) = \frac{e^{x_i}}{\sum_{i=1}^{n} e^{x_i}}. \quad (8)$$

Figure 6

Proposed model architecture



The next layer, the max-pooling layer, receives the features. Non-linear down-sampling is carried out by the pooling layer to lower the feature quality. In order to represent the characteristics generated by the max-pooling layer, we may use the following formula:

$$z_k^l = \underbrace{max}_{\forall r \epsilon k} z_r^l. \quad (9)$$

Furthermore, when the input travels further into the network, dimensionality reduction occurs. The output is then sent to the Long Short-Term Memory (LSTM) section of the network, which is responsible for learning and remembering the data's long-term dependencies. One LSTM layer, one flatten layer (to produce one-dimensional result from multi-dimensional input), one fully connected layer, one dropout layer, and one output layer (to predict a class for each input ECG beat) make up the LSTM portion. Non-linearity of the function In both the convolutional and fully-connected layers, ReLu is employed as the activation function. The softmax activation function is used for the output layer. Multi - classification networks often utilise an extension of the logistic function called softmax at the output layer, whereas a sigmoid function is used for binary classification issues. We can write down the formulae for the ReLU and softmax kernel function:

$$f(k) = \begin{cases} 0, k < 0 \\ k, k >= 0 \end{cases}, \quad (10)$$

where K is convolutional kernal input. Due to the variable activation mapping on the relevant properties of arrhythmias, the identification degree varies, and other signals may create interference during arrhythmia detection. hence, it is possible that there is no connection between generational traits and arrhythmia disorders. Thus, the researchers here employed the attention block to amplify data related to arrhythmias while dampening data that was not. The recognition performance of the model was improved by continually enhancing the necessary information using four attention blocks in this study. To increase the size of the reception area, the input data first go via a convolution layer and then into a down-up sampling phase. The down-sampling and up-sampling procedures were Maxpooling and nearest interpolation, respectively. To compute the attention weight, the outcome of the ultimate features formed by the residual structure and the 1x1 convolution layer is fed into a softmax function. This allows the attention weight to be computed. The receiving domain may rapidly expand to acquire global data using symmetric down-sampling and up-sampling systems. A batch normalization layer is placed before the softmax function to avoid the gradient issue and overfitting during training.

Target-to-estimated-label discrepancy is modeled as a cost function. To close the chasm, an optimizer procedure is used. Although the neural network uses many other cost functions, the cross-entropy function is by far the most common.

$$cost(C) = \frac{-1}{m} \sum^{k=1M} \left(\left[z_k \times l_k(a_k) + (1 - z_k) l_k (1 - a_k) \right] \right), \quad (11)$$

where C is the cost function that must be reduced to the smallest possible value. The goal value is indicated by z_k, while the class index is indicated by c. M is the total number of classes, and a_k is the value considered accurate. The optimization process uses a gradient descent algorithm with a learning rate of 0.00001 percent. RACLC model, and after fewer iterations, it arrived at the best possible solution. The models that achieve the highest levels of accuracy with the training data will be identified through the validation of the data. If we did not apply the validation data approach, then the model would suffer from the issue of overfitting because of the lack of data. Generally, the validation standard is the loss value that the RACLC model generates. In addition, based on our notice, the maximum sensitivity will not be received in the various arrhythmia ECG signal classifications if we have halted the RACLC model according to lost value. As a result, we use the mean of the sensitivity values found in the validation data as the criterion for validation. When the weighted sensitivity means stops rising, we will no longer use the learning approach and will instead begin the process of evaluating the test data

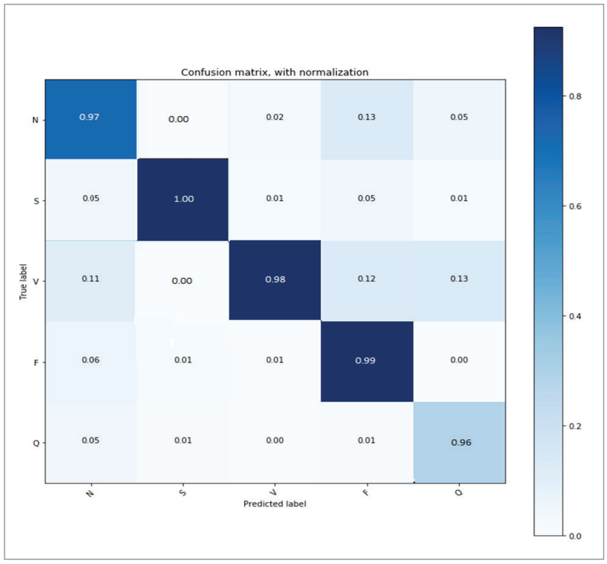
4. Experimental Setup

We have utilized the Keras Deep Learning Toolkit with the TensorFlow backend to apply deep learning methods. Initially, raw ECG signals were scaled in the range of 0-1 before being normalized. For this step, we relied on the sci-kit-learn library. The duration of the learning process was calculated using an early stopping strategy. Training can be halted before the model becomes overfit by keeping an eye on the loss values. Consequently, learning was halted to prevent overfitting issues in the various networks. We find a few frequent hyper-parameter tweaks for models for a learning rate of 0.00001 and a batch size of 64. The analyzed networks dictate the optimization strategies and other parameters used. Every single experimental investigation has its unique presentation of the relevant modifications.

The same databases were utilized in all model parameters, and the data was split into 80% training, 10% validation, and 10% testing to stay consistent throughout all trials. During the training phase, the sci-kit-learn package gave a class score to each class to account for the asymmetry in the data patterns across types. Results acquired for the test data were evaluated using the accuracy, sensitivity, specificity, precision, and F-score performance criteria.

Figure 7

Confusion matrix of proposed method RACLC



5. Results and Discussion

The results of the proposed work are discussed in this section of the report. Using a variety of test cases, the performance is evaluated based on several distinct metrics, including the overall precision, recall, f-score, accuracy, and execution time. In addition, to assess the work that is being submitted, a comparison study with previously published studies is also given.

5.1. Performance Evaluation

Figure 7 is an example of the confusion matrix, and it compares the subclasses that were predicted by using the planned work to the categories that were acknowledged and used as actual fact. You can see an example of the confusion matrix in this figure. According to the data in the table, there are five distinct classes of heartbeat, with 75020, 2546, 8072, 7255, and 7129 beat samples, respectively, assigned to classes numbered 1 to 5. Class 2 through Class 5 are considered to be examples of arrhythmia, whereas Class 1 is an example of normal heart beat samples.

However, the confusion matrix is not able to provide a quantitative measurement of the effectiveness of the model; Nevertheless, the point of a deep learning model is dependent not only on its ability to accurately forecast the class to which the data belong (sensitivity), but also on its ability to exclude incorrect classifications (specificity). This literally implies that certain models are capable of reliably predicting the correct class for the bulk of the data (Tr_{pos}, Fa_{pos}), but they fail to reject the erroneous classes for part of the data (Tr_{neg}, Ta_{neg}). For this reason, the model's sensitivity and specificity should both be sufficiently high enough so that it can perform well even when presented with data that has not yet been observed. Hence, it is necessary to compute several commonly used metrics, which are as follows.

$$Precison\left(P_r\right)=\frac{Tr_{pos}}{Tr_{pos}+Fa_{pos}} \tag{12}$$

$$\begin{aligned}&Accuracy\left(A_c\right)=Recall\left(R_c\right)\\&=sensitivity\left(S_e\right)=\frac{Tr_{pos}}{Tr_{pos}+Fa_{neg}}\end{aligned} \tag{13}$$

$$Specificity\left(S_p\right)=\frac{Tr_{neg}}{Tr_{neg}+Fa_{pos}} \tag{14}$$

$$F1-score\left(F1_s\right)=2\times\frac{R_c\times P_r}{R_c+P_r} \tag{15}$$

The assessment metrics for each of the five modules may be determined using the equations presented before, and the results can be found in Table 2.

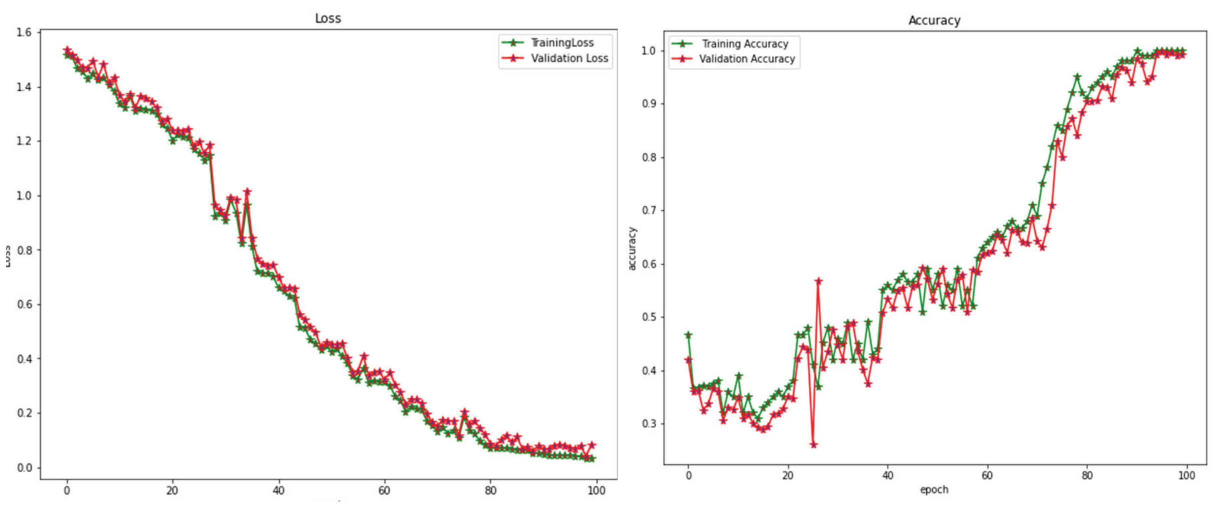
Figure 8 displays the lines of the total loss and efficiency during the model's training by using all of the data. These curves can be seen in the previous figure. After 100 epochs, it is easy to see that the network has reached a point where both values have converged.

After having conducted an extensive and comprehensive research to assess the accuracy of the findings made for all of the categories, it was deduced that the accuracy rate for the five major heart rhythm classes, as well as the regular class, was greater than 99.8%. This was the conclusion reached following the completion of the study. When it came to the assessment of the model, a method known as laminated 10-fold cross validation was utilised. This indicates that the dataset was divided into 10 groups, with the goal of making sure that each group has the same proportion of observations corresponding to a certain category value. The model was trained on each of the ten folds by utilising the nine folds as training data, and the trained model was then verified on the data that remained after the training process was complete (the 10th fold). After a total of one hundred epochs of training, the procedure was finished, and the optimal weights were re-established for each training phase.

Table 2
Precision, recall, f1-score of proposed model RACLC

Class	precision	recall	f1-score
Nonectopic beats (N)	0.99	0.99	0.99
Supraventricular ectopic beat (S)	1.00	1.00	1.00
Ventricular ectopic beat (V)	0.99	0.99	1.00
Fusion beat (F)	1.00	1.00	0.98
Unknown beat (Q)	0.98	0.98	0.99

Figure 8
Accuracy and Loss of the proposed model RACLC



(a) Loss (b) Accuracy

5.2. Performance Comparison

A random deviation test is conducted in order to investigate the differences in organization performance between the proposed RACLC algorithm and other methods for the datasets. The comparative findings of the suggested RACLC algorithm's performance assessment with those of existing CNN algorithms are presented in Table 3,4,5. The suggested RACLC model that we developed had an average accuracy of 99.8%. In recent times, 2D CNN models have been used for the purpose of classifying the input ECG signals into their appropriate groups. Before beginning the process of feature extraction, the 1D ECGs that are provided as input are converted into 2D.

Table 3
Performance analysis of CNN model

CNN Model								
Class	N	S	V	F	Q	S_e(%)	S_p(%)	P_r(%)
N	95	10	0.5	12	12	95	94	95
S	0.5	96	0.5	15	15	93	94	95
V	0.11	12	95	20	20	94	93	94
F	0.2	0.7	0.0	93	12	95	96	94
Q	0.01	0.2	0.2	0.5	94	93	94	95

Table 4
Performance analysis of LSTM model

LSTM Model								
Class	N	S	V	F	Q	S_e(%)	S_p(%)	P_r(%)
N	97	14	12	8	4	97	96	96
S	4	96	1	10	2	96	97	96
V	0.10	10	96	16	10	95	95	96
F	0.8	0.8	0.5	95	8	96	96	95
Q	0.6	0.5	0.9	0.8	95	94	96	93

Table 5
Performance analysis of CNN-LSTM model

CNN - LSTM Model								
Class	N	S	V	F	Q	S_e(%)	S_p(%)	P_r(%)
N	98	7	0.5	0.8	0.5	98	97	98
S	0.2	97	0.2	0.0	10	97	97	97
V	0.12	5	98	0.1	3	98	98	97
F	0.5	0.4	0.2	98	0.8	97	98	98
Q	0.2	0.0	0.0	0.5	97	97	97	98

The 2D CNN models provide greater uniqueness and are more resilient when dealing with noise in the input signals. Before mining vigorous features, the model that has been suggested makes use of the CWT to transform the input 1D ECG into a 2D signal.

The accuracy of the 2D CNN model that was suggested is superior to that of the existing model. In the work that has been proposed, DWT is used to extract characteristics of the ECG signal waveform. The success of the developed RACLC-based arrhythmia classification is further examined in comparison to the works that have already been done employing various neural network-based approaches found in the published research. The exactness that the earlier study has developed is shown in Figures 9-10, along with the work that will be undertaken in the future.

The following is a list of the drawbacks of our approach: complicated structure requiring lengthier systems integration (more extended training and optimization). Following many trials and tribulations about the variety of layers and their respective numbers, the hybrid RACLC model has emerged victorious and has

Figure 9
Accuracy Loss of the LSTM model

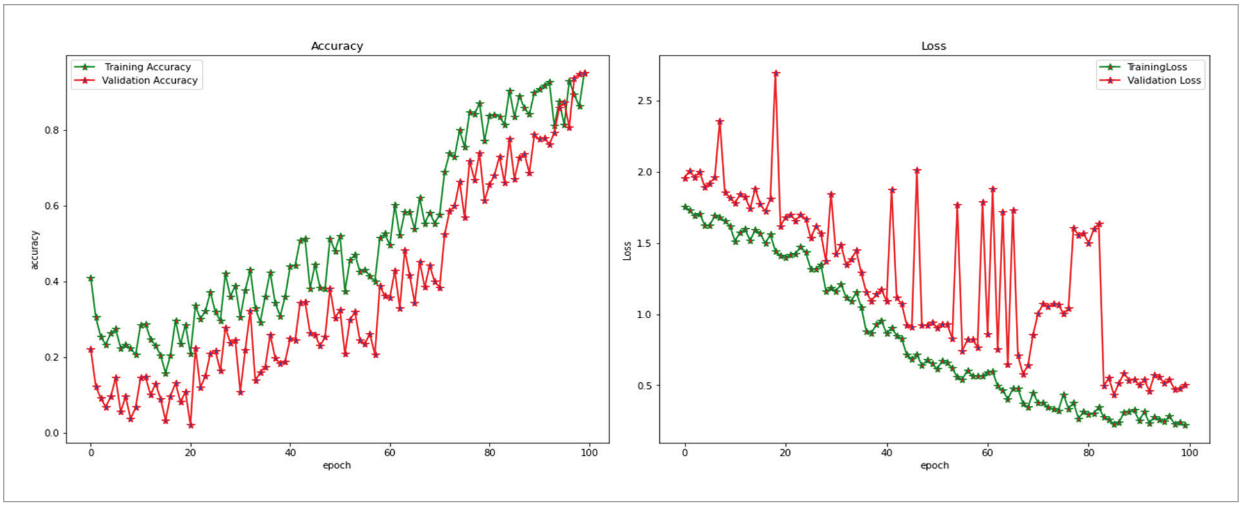


Figure 10
Accuracy Loss of the CNN model

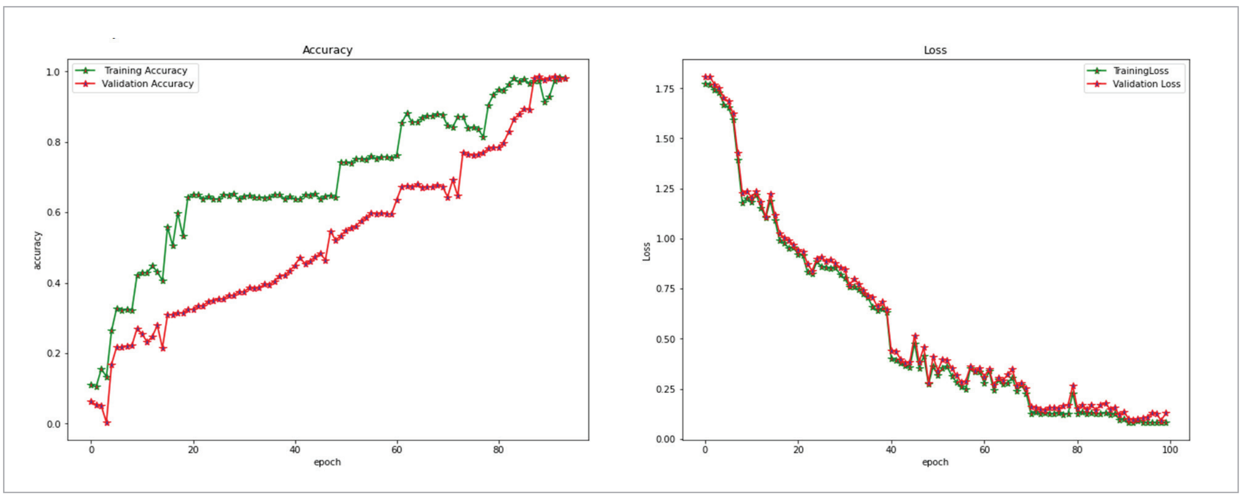
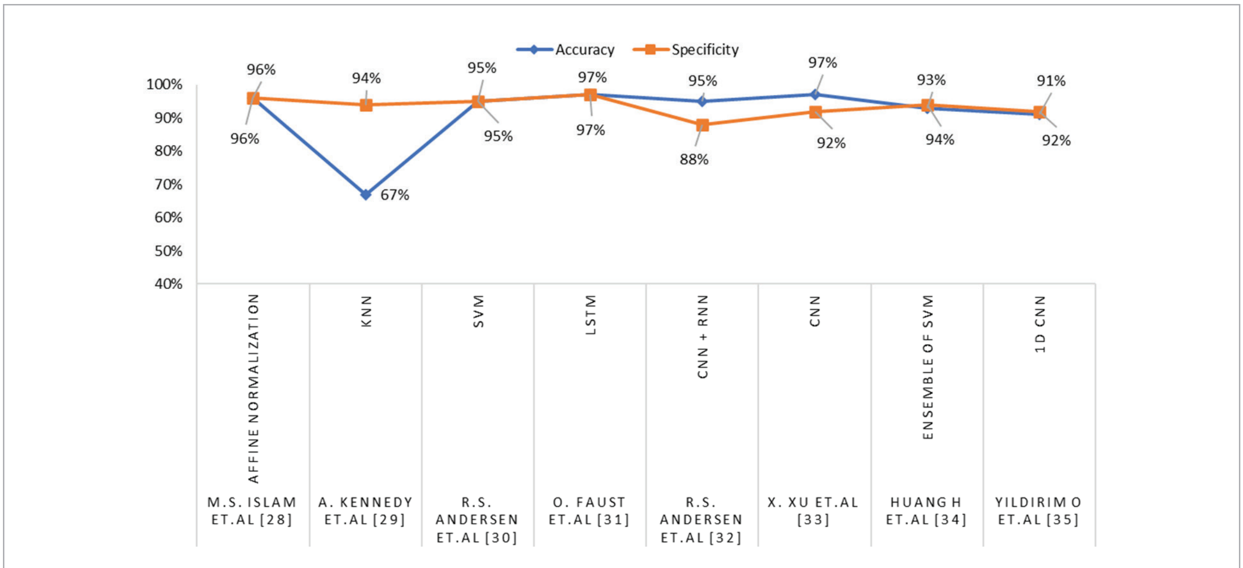


Figure 11

Performance comparison with other research work



been adopted. Figure 11 shows the recital assessment of the existing model proposed by other researchers. To provide even more specifics, it was discovered that the learning curve could be considerably lowered by deactivating constituents of the network layers. This would result in a substantially lower actual number of matrix multiplication for the system, which, in turn, would lead to the training being considerably lower. This was because deleting these layers would occur in a much reduced average quantity of simulations. When just the CNN component of the system was utilized, the values for particularity and sensitivity were found to be 97.48% and 98.16%, respectively. On the other hand, when only the LSTM component of the network was utilized, the optimal making was 96.30% and 97.77%, respectively. However, it was shown that reducing layers resulted in a reduction in both the average sensitivity and specificity of the test. This suggests that the hybrid network is superior to both past editions since it integrates the strengths of both previous models to utilize them fully.

This is the case even though the time required for training is somewhat decreased in both scenarios. On the other hand, increasing the number of CNN layers resulted in no change to the overall sensitivity or specificity, even though the training period rose to around one minute for each epoch. The hybrid RACLC approach gives the maximum aggregation of performance (sensitivity and specificity) when combined with all of the past empirical investigations. The provided model fulfills well for enormously unbalanced datasets. The center of focus loss function produces enhanced consequences than the conventional cross entropy function for predictions and classification. Additionally, the technique might be applied for accurate arrhythmia identification as the predictor. Below is a listing of the general achievements made possible because of this study: The hybrid RACLC method provides the maximum possible level of accuracy, measured in terms of sensitivity and specificity.

6. Conclusion and Future Work

Recent advances in medical technology have resulted in substantial shifts in the organization of medical care and its delivery. The electrocardiogram (ECG), a portable instrument, made it possible to record the heart's electrical activity, which was helpful in responding to medical problems. However, due to its intricacy and the noise acquired from previous generations, its accurate interpretation has yet to be questioned. In this study, three different approaches to the classification of electrocardiogram (ECG) signals are proposed. Each system can accurately and effectively categorize ECG data into one of five primary arrhythmia types. DWT is utilized in the first step to denoise the ECG samples, and RACLC is then used for classification. The proposed work outperformed most of the state-of-the-art structures consisting of neural networks to improve accuracy for ECG classification. This was determined through a similar evaluation with existing methods for classifying arrhythmias that take advantage of the architecture of neural networks. Our proposed model fitted to the ECG signal, discovering helpful characteristics from the provided data. In the final step, automated cataloging of the ECG signal is performed using the earlier recovered features. An accuracy of 99.8 percent may be achieved when classifying the ECG signal by utilizing a 2D CNN with an LSTM model. This level of accuracy is superior to that attained by the other algorithms utilised in earlier research. Similarly, it is possible to build efficient and practical algorithms for classifying arrhythmia ECG signals by first translating 1D ECG signal into 2D ECG pictures and then using this as an input to the 2D CNN algorithm. This process may be accomplished. Using 2D pictures, the method that we have recommended can classify arrhythmia with a 99.8 percent accuracy rate.

In the future, the effort that was presented can be expanded to cover more arrhythmia classes to provide an all-encompassing method for the categorization of arrhythmias via ECG data. Future work will involve the development of an integrated system for the classification of arrhythmia ECG signals. This system will be able to monitor and scan the patient's ECG using the internal camera of the robot. It will also be able to forecast and identify the arrhythmia ECG signal in order to provide advice to the medical professional. The current investigation makes use of a single ECG signal as its data source. In the future, it will be helpful to categorise ECG data by using data from many channels at the same time.

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