IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received April 6, 2022, accepted May 20, 2022, date of publication May 30, 2022, date of current version June 6, 2022.

Digital Object Identifier 10.1109/ACCESS.2022.3178710

New Hybrid Deep Learning Approach Using BiGRU-BiLSTM and Multilayered Dilated CNN to Detect Arrhythmia

MD SHOFIQUL ISLAM[1,2], MD NAHIDUL ISLAM[3], NORAMIZA HASHIM[4], (Member, IEEE), MAMUNUR RASHID[3], (Member, IEEE), BIFTA SAMA BARI[3], (Member, IEEE), AND FAHMID AL FARID[4], (Member, IEEE)

[1]Faculty of Computing, Universiti Malaysia Pahang, Kuantan, Pahang 26300, Malaysia
[2]IBM Centre of Excellence (Universiti Malaysia Pahang), Cybercentre, Pahang Technology Park, Kuantan, Pahang 26300, Malaysia
[3]Faculty of Electrical and Electronics Engineering Technology, Universiti Malaysia Pahang, Pekan, Pahang 26600, Malaysia
[4]Faculty of Computing and Informatics, Multimedia University, Cyberjaya 63100, Malaysia

Corresponding author: Noramiza Hashim (noramiza.hashim@mmu.edu.my)

ABSTRACT Deep learning methods have shown early progress in analyzing complicated ECG signals, especially in heartbeat classification and arrhythmia detection. However, there is still a long way to go in terms of health-related data analysis. This research provides a duel structured and bidirectional Recurrent Neural Network(RNN) method for arrhythmia classification that addresses the issues with multilayered dilated convolution neural network (CNN) models. Initially, the data is preprocessed by Chebyshev Type II filtering that is faster and do not use statistical characteristics. Noise from the preprocesed filter is aslo removed by using Daubechies wavelet that can able to solve fractal problems and signal discontinuities. An then Z-normalization is done using Pan-Tompkins normalization technique for handling of different normally distributed samples. Finally, a generative adversarial network (GAN)-based synthetic signal is generated for recreation of signal to handle imbalanced signal class. The proposed Bidirectional RNN with Dilated CNN (BRDC) appears to take advantage of the potentiality of multilayered dilated CNN and bidirectional RNN unit (bidirectional gated recurrent Units, BiGRU - bidirectional long short-term memory, BiLSTM) architecture to generate fusion features. Finally, the signals are classified by fully connected layer and Rectified Linear Unit (ReLU) activation function. The PhysioNet 2017 challenge dataset is used to train and validate the proposed model. By combining fusion features with dilated CNN, the learned model significantly improves the classification performance and interpretability. The experimental findings show that, for MIT-BIH provided ECG (electrocardiogram) data to identify arrhythmia, the proposed BRDC model outperforms existing models with 99.90 % accuracy, 98.41 % F1, 97.96 % precision, and 99.90 % recall during training. One of the significant findings of this study is that the proposed approach can significantly reduce time length when employing RNN networks with multilayered dilated CNN. Overall, our hybrid model using BiGRU-BiLSTM and multi-layered dilated CNN provides a cost-effective ECG signal reduction and high-performance automated recognition technique to identify arrhythmia. Our future improvement will focus on the classification of numerous arrhythmia signal-based data, automatic and cloud based ECG classification.

INDEX TERMS Atrial fibrillation, filtering, Bi-GRU, BiLSTM, ECG, dilated CNN, RNN, arrhythmia.

I. INTRODUCTION

Despite recent technological advancements in health condition detection, cardiovascular diseases (CVD) continue to be the leading cause of mortality in developed countries [1]. Therefore, regular screening of cardiac abnormalities is critical to prevent serious physical harm. Among such different CVDs, arrhythmia is a prevalent condition that refers to irregular and abnormal heartbeats [2]. Cardiac arrhythmias are irregular heartbeats that develop when the electrical impulses

The associate editor coordinating the review of this manuscript and approving it for publication was Ali Shariq Imran.

which coordinate the heartbeats do not function properly, causing the heart to beat excessively rapidly, too slowly, or irregularly [3]. Arrhythmias are classified into several categories, including ventricular fibrillation, premature atrial contraction, and supraventricular arrhythmia [4], [5].

Nowadays, electrocardiograms (ECGs) are the most widely used method for detecting arrhythmias, which help to record the heart's electrical potential, but manual evaluation of ECG signals are frequently sophisticated, time-consuming, prone to human error, and challenging owing to a shortage of expertise [6], [7].

To address the considerable people's concern, researchers have developed numerous ways for early detection of arrhythmia, ranging from the classic feature-based machine learning process to the end-to-end deep learning process in recent years. Detecting the arrhythmia consists of four main phases: data collection, pre-processing, feature extraction, and classification. In the preprocessing phase, different noise removal techniques are now widely utilized to extract qualitative signals. The low pass filtering and the alternating directing method of multipliers (ADMM) optimization have been utilized in the signal denoising as well as the reconstruction process [8]. In another approach, an empirical mode decomposition (EMD) has been performed to remove noise from the electrocardiogram [9]. The wavelet function decomposes the signal into intrinsic mode functions (IMFs) and the outcomes [9] showed that their approach provides outperformed performance to the wavelet's empirical mode decomposition, including the total variation-based noise removal technique. Evolutionary techniques use a new adaptive noise cancellation system (ANC) [10] to eliminate the background with adaptive filter in variable step-size LMS. To extract the informative feature from the signals, numerous feature extraction methods are utilized, such as wavelet transform [11], [12], principal component analysis [13], independent component analysis [14], Jaya optimization algorithms [15], and Hermite function [16]. For performing classification with the extracted features, support vector machine [17], K-nearest neighbor [18], feed-forward neural network [14], [16], [19], [20], random forest [11] and transfer learning [21] have been widely used. For ECG signal classification, the support vector machine (SVM) algorithm provides poorer performance in complex and noisy data [22]. Bhattacharyya *et al.* [23] is proposed an arrhythmic heartbeat classification technique showing that the random forest (RF) algorithm is complex and expensive to handle overfitting. The decision tree (DT) technique can easily handle multiple data types [24], but it requires more impactful features, and generalization is not possible by this method [25]. The Naive Bayes (NB) [26] algorithm works well for large datasets but incorrectly predicts equally important and independent features. k-nearest neighbors (KNN) [27] algorithm is expensive in computation when it works on large data, takes higher memory, and works slower than other algorithms. To overcome these issues, deep learning (DL) architecture could be the best alternative as the DL architecture is widely used in image classification [28], video analysis [29], [30], and text recognition [31] and outperforms the other methods. Recently, several DL techniques have also been adopted to classify arrhythmias [32], [33] [34], [35] [30], [36]. In [32], [33] [34], [36], 1D-CNN and in [37], [38] [39], RNN and LSTM algorithms are utilized while in [33], [40], 2D-CNN is utilized by transforming one-dimensional ECG beats to two-dimensional images. The majority of DL methods face some similar challenges: (1) the direct feeding of raw ECG data from patients to the deep neural network complicates the classification process due to the existence of numerous low and high-frequency noises, (2) when dealing with a single-dimensional ECG signal, data augmentation is not always used, and even when it is used, the natural variational pattern of the ECG is not properly captured or preserved, as well as the majority of approaches use extremely deep CNNs with a large number of parameters, which does not only increase computational complexity but also results in the model overfitting to the training data. To overcome the limitations, some recent studies showed that effectively combining two or more classifiers provides an effective solution for task classification. In [41], [42] [43], [44], the researchers have developed hybrid models that perform comparatively much higher than a single classifier and, in some cases, effectively overcome the constraints of a single classifier. For example, even though the kNN method has some significant advantages, including a small number of parameters and a faster training procedure, it also has several drawbacks [41]. To begin, the KNN approach does not balance well with large datasets since it becomes difficult for the algorithm to calculate distances in each dimension. Calculating the distance between new and existing locations is prohibitively expensive, reducing the algorithm's speed. Additionally, prior to applying the KNN method to any dataset, feature scaling (or normalization) is required; otherwise, KNN may provide incorrect predictions. Srinivas and Sasibhushana Rao [45] develop a hybrid method (CNN-KNN) for the classification of brain tumors. This hybrid architecture achieved a maximum of 96.25 % classification accuracy which is better than the accuracy of the single KNN. Another recent article [41] proposes a novel hybrid scheme based on the convolutional layer of CNN and KNN classifier to classify the EEG-based AEP signals. They use the convolutional layer to extract the more informative information from the data, whereas the KNN method is utilized to classify the extracted feature. Their proposed architecture increases the KNN accuracy from 83.23 % to 92.26 % while using a 3-second decision window. In ECG signal analysis, CNN, as well as RNN, which predominantly incorporate LSTM and bidirectional LSTM (BiLSTM) networks, have demonstrated better performance as several effective deep learning networks [12]. BiLSTMs are an extension of typical LSTMs that can significantly increase model performance when used to solve sequence classification issues. BiLSTMs train the signals in two phases (one takes the input in a forward direction and the other in a backward direction) rather than one LSTM on the input sequence in instances where all time steps of the input sequence are provided. The difference between the bidirectional [44], [46] method and unidirectional method [47], [48] is that in the LSTM or BiGRU that runs backward, information from the future is preserved, and by combining of the two hidden states, it can be executed at any point in bi-direction [46]. Furthermore, when BiGRU and BiLSTM are combined, more independent and long-range characteristics are handled [49]. Dilated CNNs instead of normal convolution layer [50] perform better because of its larger receptive field (no loss of coverage), more computationally efficiency, robustness (provides wide coverage on the same computation cost) [51] and less memory consumption since it skips the pooling step [10] as well as does not degrade the output image's resolution (used dilated rather than using pooling) [51]. This paper proposes a novel hybrid system (BRDC) based on BiGRU-BiLSTM and multi-layered dilated CNN for arrhythmia detection to address the current issues. This hybridization's objective is that several hidden layers of the blocks can select discriminatory representations from the higher dimensional data. Besides, the dilated CNN helps to reduce the computational cost during the training of the proposed architecture. The key contributions of the paper are summarized as follows:

- A novel hybrid approach (BRDC) has been proposed for effectively detecting arrhythmia, which helps in improving the overall performance with low computational complexity.
- A dynamically dilated CNN is combined with multilayered BIGRU-BilSTM to incorporate even more complex and long-ranged features of the ECG signal during each convolution operation without raising network parameters which help in improving the classification performance with less complication.
- A sequential pre-processing technique has been designed including segmentation, filtering, and Z-normalization to generate the synthetic signal for improving lengthy ECG signal classification outcomes.

The remainder of the paper is structured as follows: Section II conducts cutting-edge surveys and provides the related research's findings and limitations. Section III presents data, its pre-processing, and its main methodology. This section discusses the experimental setup, methods, and development. Section IV presents the results, led by a perceptive result discussion before Section V presents the conclusion.

II. RELATED STUDY

An unusual cardiac rhythm has been linked to an increased risk of stroke, heart disease, and cardiovascular disease. Furthermore, there is a link between atrial fibrillation (AF) and obesity, hypertension, atrial and sleep apnea, all of which can reduce life quality and increase the mortality risk. Consequently, AF is the most common arrhythmia illness, and it is critical to detect AF automatically in accurately diagnosing, managing, and avoiding relevant consequences [51]. Here we presented the most recent method to detect arrhythmia from MIT BIH data. Usually, CNN is the most commonly used deep learning-based method since it outperforms other conventional machine learning methods in terms of performance. We have listed some basic deep learning techniques for classifying ECG signals based on the MIT-BIH database. The hybrid deep learning-based method [46], [52] combines two or more fundamental deep learning methods (CNN, LSTM, GRU, attention, or others). In 2022, an automated method to classsify ECG to detect arrythmia using Hybrid CNN-LSTM Network [53]. This method got 99% accuracy with denoised signal of MIT-BIH data. Time complexity of this method is slightly more than conventional method. In 2022, another CNN [54] based method that classify Cardiac Arrhythmias using Individual ECG Signals. This method got 98.74% accuracy with denoised signal of MIT-BIH data. Faster method its performance is varries on type of data. In 2022, A method [55] to detect arrhythmia using Binarized Convolutional Neural Network got 95.67% accuracy. While boosting computing speed and lowering resource overhead, it retains high accuracy. This method classify raw signal to detect arrhythmia with duration of 10s ECG signal of MIT BIH data. Its adaptability should be improved. Another hybrid method was developed in [56] using deep CNN to detect arrhythmia from ECG signal of MIT BIH data. This method used PR,RR and QRS features and obtained an accuracy that is slightly lower than other methods compared in their study. In 2018, Yildirim *et al.* [40] proposes a method for classifying ECG signals using deep CNN and rescaling MIT BIH raw data. With 91.33 % accuracy, this method classifies ECG signals of short duration (0.015s). Therefore, the time complexity of this method need to be reduced. In 2019, another method with attention-based LSTM is proposed by Yildirim *et al.* for dealing with coded signals [47]. This method has a 99.11 % accuracy, however it is only applicable to short-duration ECG signals of MIT BIH data to detect arrhythmia. In 2020, a new and long-ranged (1.5s) ECG signal classification method is developed based on CNN and bidirectional LSTM with four RR intervals [46]. This method has achieved 96.77 % accuracy, 77.8 % precision, and 81.2 % recall, however its performance resilience should be improved. In 2021, Ma *et al.* [57] develops a dilated CNN-based technique with data denoising and normalization to classify five types of ECG signals. This method correctly classifies a 0.8s long ECG signal with 98.65 % accuracy. This method shortens training time, however it necessitates more normalization and dropout tasks, resulting in misclassification. In 2019, Dang *et al.* [51] proposes a deep CNN-BiLSTM approach to categorize ECG signals with RR, PR, and QRS complex features. This method divides 100 ECG signal samples into five categories. It classified five types of ECG signals with a success rate of 96.59 %. The main disadvantage is that it takes longer time to execute and has no generation capability in real-world applications. In 2020, Jin *et al.* [52] develops a CNN-LSTM hybrid deep learning method with attention and multi-domain features. This method classifies five types of ECG signals with 98.51 % accuracy, however, its adaptability to different data should be improved. In 2021 [44], a new and hybrid deep learning method is developed using CNN-BiLSTM that focuses on raw data features from 360 samples. This technique is 99.11 % accurate whereas it is necessary to improve pre-processing as well as generation capabilities.

The above discussion states that although traditional machine learning methods for ECG classification are faster, they are not as adequate as hybrid deep learning methods. However, as we discussed earlier in this section, each method has some limitations for arrhythmia detection in the early stage. Furthermore, some other issues that need to be addressed including more feature engineering, longer training time, greater space complexity, less adaptability/generalisation, greater computational complexity, lower accuracy, and a higher loss function for effectively arrhythmia detection. Therefore, the proposed method in this study has been developed that addresses the shortcoming of the existing conventional methods.

III. METHODOLOGY

In the proposed approach, we have designed a novel hybrid approach (BRDC) for detecting the arrhythmia classification, which helps in improving the overall performance with low computational complexity. We have combined a dynamically dilated CNN in multilayered form with BiGRU-BiLSTM to incorporate more complex and long-range ECG signal features during each convolution operation without raising network parameters to improve classification results in less complication. Our sequential pre-processing techniques including segmentation, filtering, and z-normalization help to extract the informative feature from the raw signals. Synthetic signal generation is completed after the pre-processing. The overall diagram of the BRDC model to classify ECG signals is shown in Fig. 1.

The followings are the technical strengths of our proposed study:

Our method has following steps:

1) At first, taking raw ECG signal, and then it has been pre-processed with our sequential pre-processing techniques. Initially, the data is preprocessed by Chebyshev Type II filtering that is faster and do not use statistical characteristics. Noise from the preprocesed filter is aslo removed by using Daubechies wavelet that can able to solve fractal problems and signal discontinuities. An then Z-normalization is done using Pan-Tompkins normalization technique for handling of different normally distributed samples. Finally, a generative adversarial network (GAN)-based synthetic signal is generated for recreation of signal to handle imbalanced signal class.
2) After the successful pre-processing, the pre-processed synthetic signal is sent to our proposed BRDC model. In the BRDC model Dilated CNN with duel structured BiLSTM-BiGRU for feature extraction and classify with fully connected layer and ReLu activation function.
3) After that, the BRDC method has been trained with train and validation set of ECG signals. In this stage BRDC extract features from ECG signal and classify it based on the extracted features.
4) Finally, the validation of the proposed model has done with different evaluation metrics result and comparison on ECG signals.

A. THE DATA INFORMATION AND VISUALIZATION

The experiment has been conducted with the MIT-BIH database [58] to validate the proposed architecture, in which the ECG signals were collected from 48 records of 47 patients. Multiple cardiologists annotated the beat labels separately, and the definitive diagnosis was reached through consensus. The dataset includes 48 half-hours of two-channel (MLII and V1) ECG recordings from 47 individuals, digitized at 360 samples per second per channel with 11-bit resolution. This dataset contains about 110,000 ECG beats divided into five major categories by the Association for the Advancement of Medical Instrumentation (AAMI) [5]. The five categories of heartbeat are labelled in this dataset are 'Normal', 'Atrial premature', 'Premature ventricular contraction', 'Fusion of ventricular and normal' and 'Fusion of paced and normal. In this work, the beat annotation offered by the AAMI is used. It should be mentioned that, as compared to other research studies, only the MLII channel is evaluated since it gives more significant data on the heart's health [59]. In the training phase, multiple forms of augmentations are used due to the significant degree of imbalance across the five categories in the dataset [60]. The MIT-BIH arrhythmia data set is the most used system dataset for detecting and classifying arrhythmia. Fig. 2 shows the total and each class sample of MIT-BIH data.

Fig. 3 shows the sample of each class of ECG signal with 175 milliseconds. Each signal's amplitudes are selected in the range of 0 to 1.

A correlation matrix is essentially a table that demonstrates the relationship between two variables. The measure works best with variables that have a linear connection with one another. A scatterplot may be used to visualize how well the data fits together. In this experiment, we have also visualized the correlation among target classes of ECG from MIT BIH data as shown in Fig. 4. We mentioned normal class, artial premature, premature ventricular contraction, fusion of ventricular and normal as well as fusion of paced and normal which are indicated by N, AP, FVC, FVN, and FPN respectively.

B. ECG DATA PRE-PROCESSING

ECG signals can be affected by a variety of noise and artifacts including loose lead artifact (the distortion of ECG wave signal component due to shaking with rhythmic movement), motion artifact as well as power line electrical disruptions. Consequently, increasing the signal-to-noise ratio (SNR) to train any deep learning method that relies on them is critical. In this study, three stages including filtering, denoising and Z-score normalization are used to remove noise from

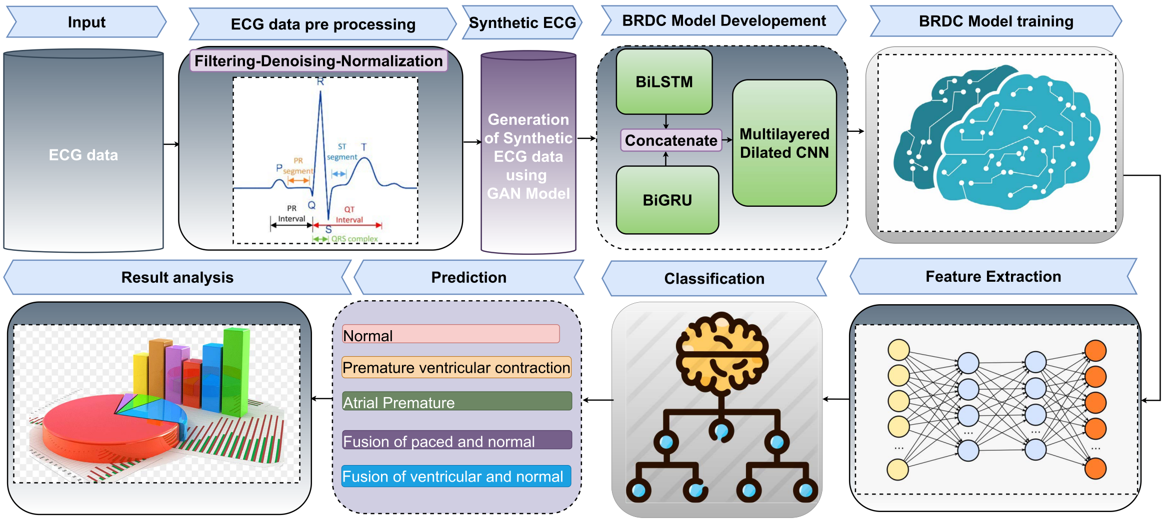

FIGURE 1. The overall process of the BRDC model.

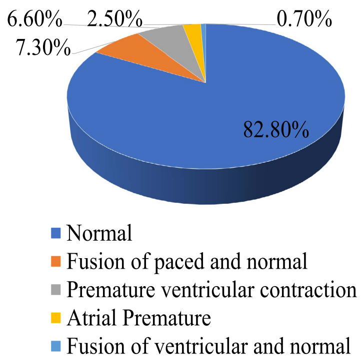

FIGURE 2. Amount of each class in MIT BIH dataset.

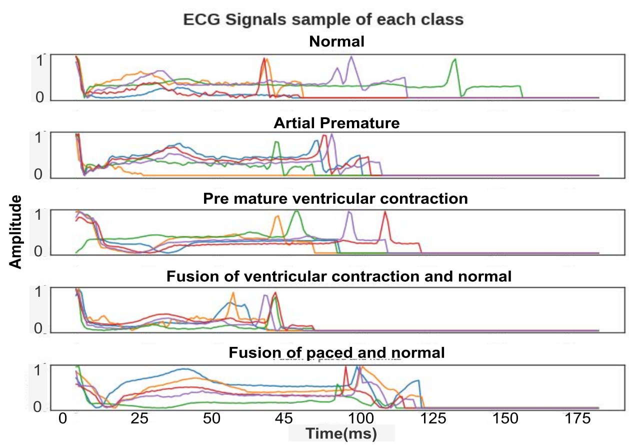

FIGURE 3. Samples of each class in the MIT-BIH dataset.

signals. ECG beats are synthesised using the GAN (Generative Adversarial Network) model after pre-processing of each signal.

C. FILTERING

This study has used filters to remove unwanted noise from the ECG signals. Because of containing low signal levels in the ECG task, it is critical to use filtering to remove a wide range of noise. ECG signals are known to have a frequency band of 0.5 Hz to approximately 48 Hz [61]. Consequently, we use a Chebyshev Type II passband to preserve the frequency range between 0.5 and 48 Hz. Due to its sharp cut-off frequency as well as lack of ripple, the Chebyshev Type II filter has been selected. The following equation (1) depicts the basic operational equation of a Chebyshev Type II filter.

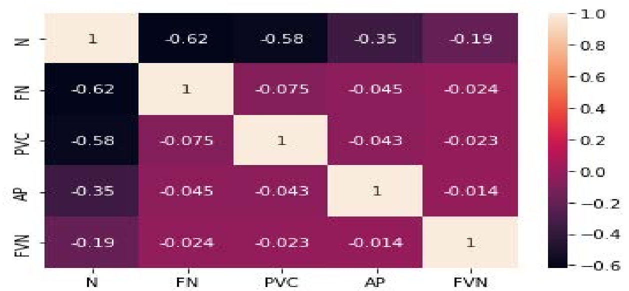

FIGURE 4. Correlation matrix of each target class MIT BIH dataset.

$$G_n(\omega) = |H_n(j\omega)| = \frac{1}{\sqrt{1 + \epsilon^2 T_n^2 \left(\frac{\omega}{\omega_0}\right)}} \tag{1}$$

Here, ϵ indicates ripple factor, ω_0 is used for cut-off frequency and T_n is used for the Chebyshev polynomial of the *n-th* order.

D. DENOISING

The signals are pre-processed and then generated synthetic ECG. At first, using Daubechies wavelet filters [62], all ECG signals have been initially denoised and the baseline eliminated. Then, the signals are divided into beats and sorted based on cardiologists' annotation. The following equation (2) is a basic and commonly used operation of Daubechies wavelet that acts as a filter.

$$a_i = h_0 S_{2i} + h_1 S_{2i+1} + h_2 S_{2i+2} + \cdots + h_n S_{2i+n} \tag{2}$$

Here, the data element is denoted by n, matrix element is denoted by S, h is used to represent wavelet function coefficient for individual signal and I is used to represent the incremental value.

E. Z-SCORE NORMALIZATION

The Pan-Tompkins [63] method is used to detect R-peaks for normalisation. At first, the ECG information is split into 360-sample segments centred on the identified R-peaks. Then, before feeding into the teaching approach, each segment is normalized using z-score normalization to address amplitude scaling and reduce the offset effect. The following equation (3) is the key operational formula for Pan-Tompkins Z normalization.

$$H(z) = \frac{\left(1 - z^{-6}\right)^2}{\left(1 - z^{-1}\right)^2} \tag{3}$$

Here, *H(z)* is used for Z normalization in the high pass filter.

F. GENERATION OF SYNTHETIC DATA USING GAN

To optimize the imbalance in the amount of ECG heartbeats in the five classes, synthetic data generation by GAN has been used. The synthetic data samples are prepared after the pre-processing. The standard deviation, mean of the Z score, and other processing tasks are computed from the original normalised ECG signals as a part of the pre-processing. The segments in the N class are left unchanged since they are the most numerous. To match the number of segments in the N class, the number of remaining types of segments is raised. Following augmentation, the entire number of segments including five classes has grown. The GAN model completes the procedure when all signals have been pre-processed, and a synthetic signal is generated.

We evaluated the data that is generated by GAN model. We used Maximum Mean Discrepancy(MMD) that determines how the dissimilarity between two signal probability distributions PB_r and PB_g that are independent. MMD^2 is calculated using the value generated by $\frac{1}{n(n-1)} \sum_i \sum_{j \neq i}^{n} S(a_i, a_j) - \frac{2}{nm} \sum_i \sum_j S(a_i, b_j) + \frac{1}{m(m-1)} \sum_i \sum_{j \neq i}^{n} S(b_i, b_j)$. Here a,b indicated two different signal to be compared, S is function of dissimilarity measurement and m,n used for the features range.

Then, the pre-processed signals are used for classification, and the following phases are shown in Fig. 5.

G. PROPOSED BRDC MODEL BUILDING AND FINE-TUNING

In this study, we have proposed a BRDC system to detect arrhythmia in the early stage. A two-way RNN and a multilayered dilated convolution have been developed to extract the informative feature from the raw ECG signals in the proposed system. The fully connected layer is used to classify the extracted features.

At the initial stage of the BRDC model, the input features are as follows *(Feature1, Feature2,...,FeatureN)* from the synthetic signal. Extraction of pre-processed features into N numbers as *(p1, p2,...,pN)*. Process ECG features inputted and operated as $P = \left[p_1, p_{2,\ldots.}, p_N\right] \in R^{N^*d}$, here d is dimension.

Then, BiGRU-BiLSTM and dilated CNN have been used to extract the essential information from the filtered ECG signals. The operation of bidirectional RNN (BiGRU-LSTM) is shown in Fig. 6. Here, h indicates the hidden layer's processing output, its direction indicates its bidirectional operations, and x indicates the input of the bidirectional models from the pre-processed stage.

The BiGRU-BiLSTM has been computed using the following equations (4) and (5);

$$Vector_G = BGRU = \left[bigru_1, \ldots, bigru_N\right] \in R^{N*d'} \tag{4}$$

$$Vector_L = BLSTM = \left[l_{stm_1}, \ldots., l_{stm_N}\right] \in R^{N*d'} \tag{5}$$

After that, the parallel output features from the BiGRU and BiLSTM layers concatenated as $vector_{ij}$ and then are sent to the multilayered dilated convolutional layer. The operation of dilated convolutional layer has been computed and processed with the following equation. In the equations, W is a weight vector, M is vector dimension, and L indicates the number of layers, computed with the equations (6), (7) and (8). The operation of dilated CNN is illustrated in Fig. 7. The green dot indicates the operation selection by dilated convolution. Blue coloured dot is not active during the operation of dilated CNN. This saves operation time and uses fewer parameters in feature extraction.

$$\widetilde{vector}_{ij} = \left[vector_1^{lg}, \ldots\ldots, vector_N^{lg}\right] \epsilon R^{N^*k} (lg \epsilon [1, L]) \tag{6}$$

$$convolutionvector_{ij} = \sum_{i=1}^{M} convolutionvector_{ij} * \widetilde{vectoror}_{ij|\iota} \tag{7}$$

$$vector_{J|\iota} = convolutionvector_{j|i} * W_j \tag{8}$$

After flattening the features, those features have been used as the input of the SoftMax layer for the classification. Finally, the operation has been computed with the equation (11).

Multilayered dilated CNN outputs are then sent to the next aggregation layer. The aggregation layer is processed and computed using the following equations (9) and (10);

$$aggregation_{ij} = vector_{j|\iota} * convolutionvector_j \tag{9}$$

$$output = aggregation_{ij} * convolutionvector_{ij} \tag{10}$$

Since the output is produced, this aggregated output is sent to the prediction layer to classify the target class of ECG data as follows,

$$p(y \mid S) = p(y \mid output) = SoftMax(MLP(output)) \tag{11}$$

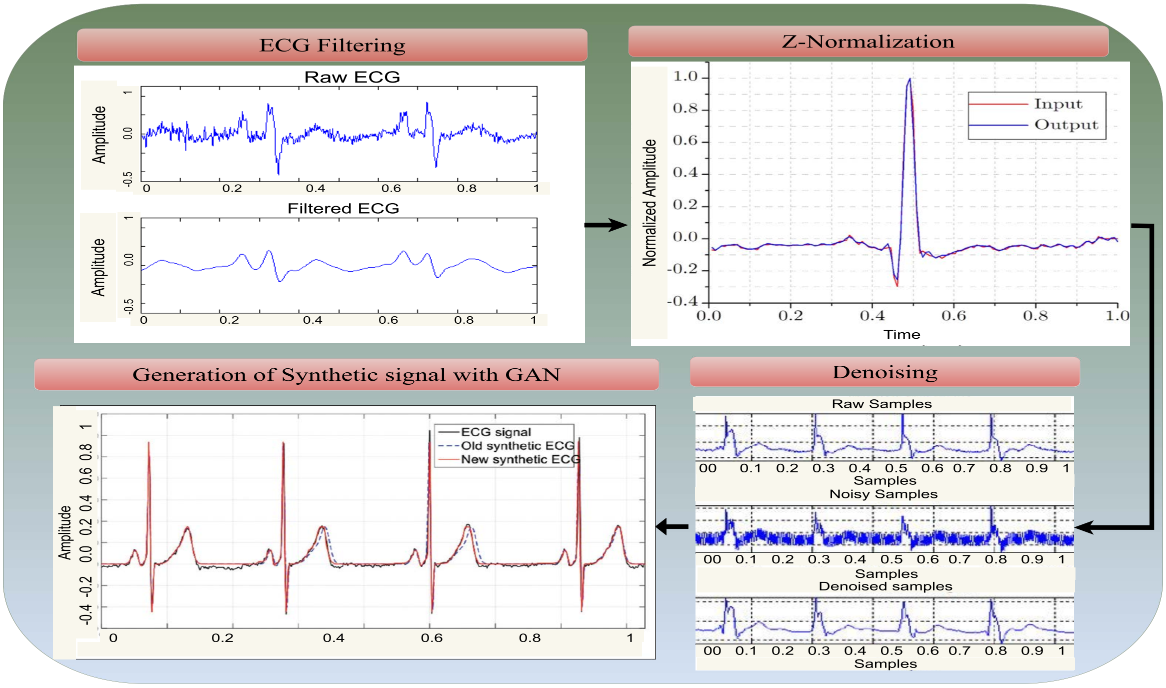

FIGURE 5. The Pre-processing steps of ECG signals.

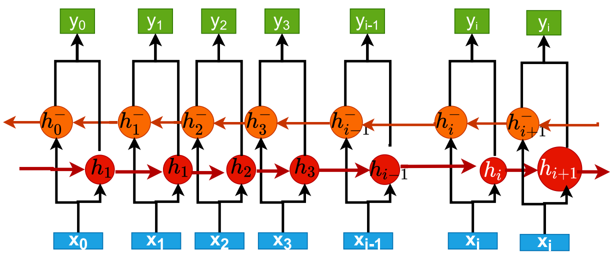

FIGURE 6. Basic architecture of Bidirectional RNN.

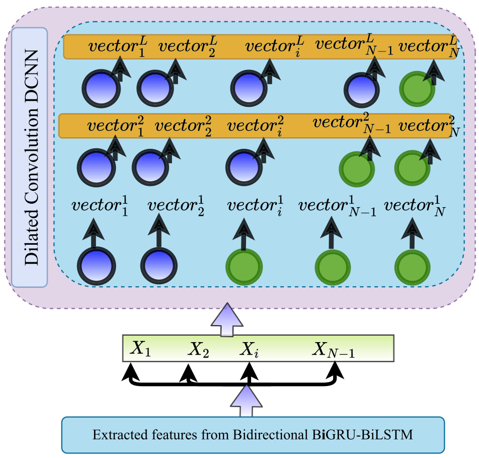

FIGURE 7. Dilated CNN mechanism.

We have used binary cross-entropy to calculate the loss in training and validation of the model. The Adam optimizer and the ROC evaluate the training in our proposed system. These layers are combined in a multilabel ECG identification module.

Fig. 8 illustrates the operational phase of the proposed architecture. This diagram depicts the fundamentals of each layer, from the source term to the accurate prediction layer, in detail. In one way, the generated synthesis output is passed through the data pre-processing layer as input. In real time analysis, we will use ECG data to evaluate the performance of our model. The fresh raw signal is first preprocessed for synthetic signal generation. Filtering, segmentation, and Z-Normalization has done for synthetic signal generation. Then forward it into the learning algorithm, which is then performed sequentially. The ECG goal category is predicted at the end.

This section outlines the procedure of the core method on ECG signal, where the algorithm has used the pre-processed signals for classification. At first, the synthetic ECG signal is generated from pre-processing with our sequential pre-processing tools. Then, the pre-processed signal is received by the BiGRU- BiLSTM layer, which extracts informative features. After that, the outcome of the multilayered dilated CNN is sent to the hierarchical prediction layer. Finally, the output layer uses the SoftMax function to predict the ECG signals. Here, Algorithm1() is for our BRDC model which is shown in Algorithm. 1.

H. EXPERIMENTAL SETUP

In this study, the proposed BRDC model has been developed using BiGRU-BiLSTM and dilated CNN. To train the model and check the validation, we have divided the dataset into two parts: 80 % for training and 20 % for validation. Besides, we have randomly picked 20 % of unlabeled data from the entire dataset to test the model's effectiveness. In this

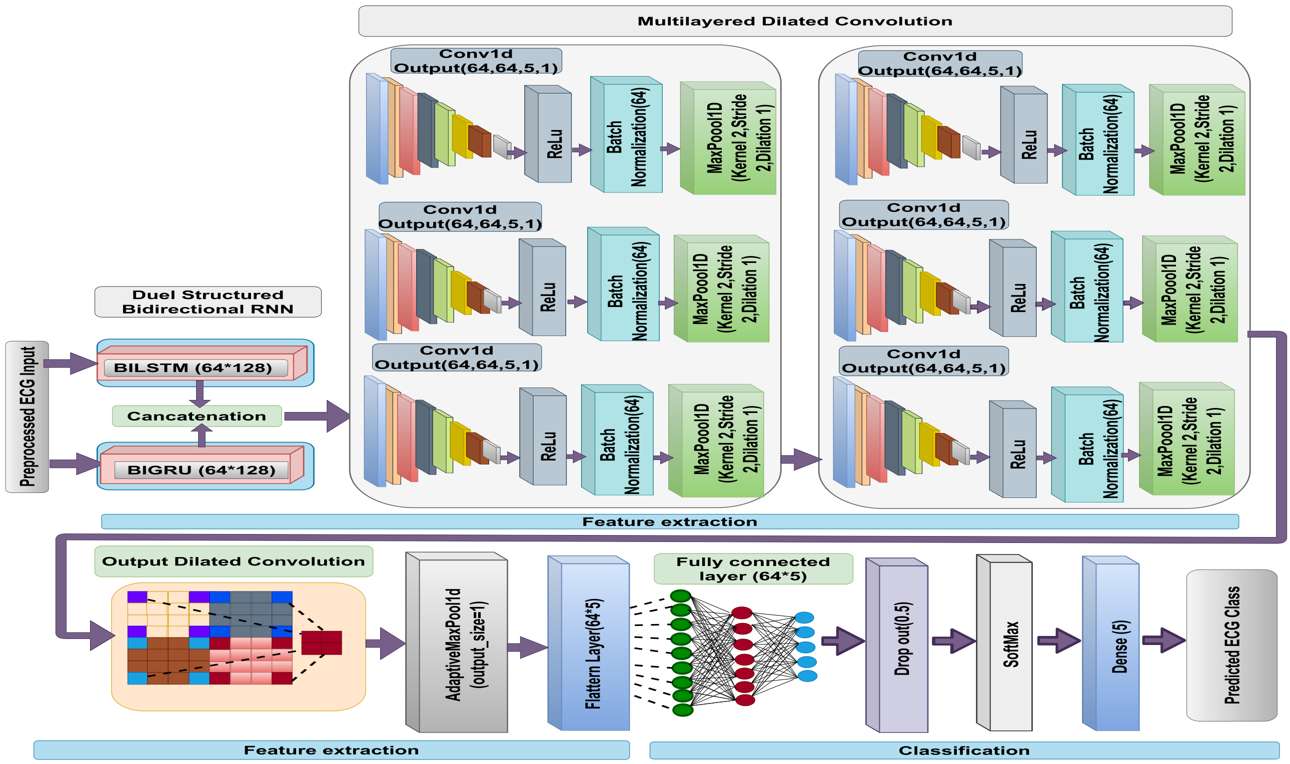

FIGURE 8. Overall operational process diagram of our BRDC model.

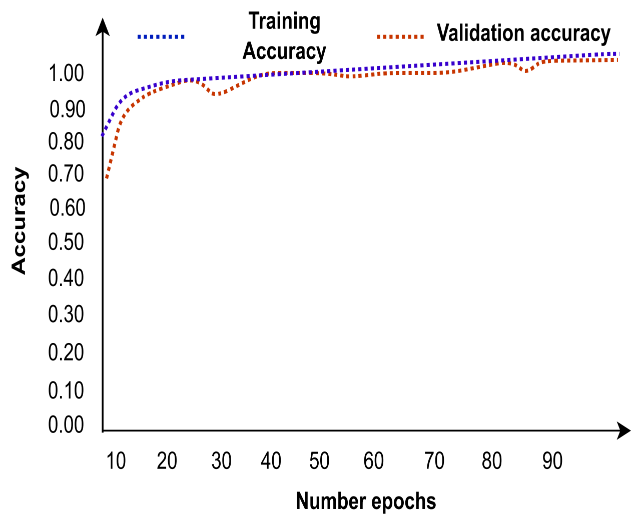

FIGURE 9. Training and validation accuracy of BRDC model.

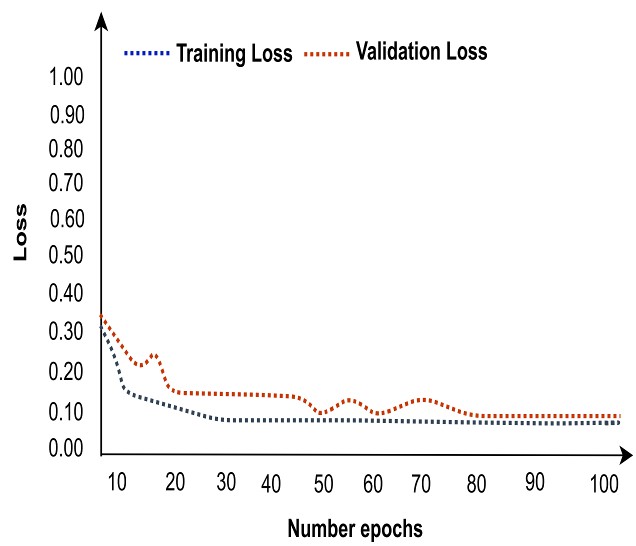

FIGURE 10. Training and validation loss of BRDC model.

experiment, the model has been trained with 100 epochs, in which we set the batch size of 256. The Adam optimizer with a learning rate of $1e^{-5}$ has been used to minimize the loss (L). In tuning the model, the kernel size is set to 5, the RNN source size is set to 46, the RNN nerve cell units are set to 128, the dilated CNN Convolution is set to 3*3, and the global dropout is set to 0.2.

I. PERFORMANCE EVALUATION METRICS

Our model classify five class of ECG. So we need to calculate the weighted average of each evaluation metrics. The evaluation metrics for weighted average (accuracy, precision, recall, F1 score and Loss) are used to check the performance of our model which are calculated with the equations (12), (13), (14), (15) and (16). In these equations i indicates the class and N indicates the number of class, Here maximum value of N is 5.

$$\begin{aligned} &\textit{Weighted Average Accuracy} \\ &= \sum_{i=1}^{N}\left[\frac{TP_i + TN_i}{TP_i + TN_i + FP_i + FN_i}\right] \end{aligned} \tag{12}$$

Algorithm 1 Main Algorithm for BRDC Model

Input: Dataset of ECG signal Ds, Number of features $Feature_i$
Result:Predicted class from ECG data
Initialization of features variables of ECG signal:
Take features ($Feature_1, Feature_2, \ldots., Feature_N$) from generated synthetic signal
Extract pre processed features into N numbers as
$P = p_1, p_2, \ldots., p_n$
Process ECG features:$X = p_1, p_2, \ldots., p_n \in R^{n*d}$,here d is dimension
Get and pass BiGRU and BiLSTM output to multilayered Dilated CNN:
for Each iteration n in range(0,N)
$vector^{bg} = BiGRU = bigru_1, bigru_2, \ldots, bigru_n \in R^{n*d^{\sim}}$
$vector^{bl} = BiLSTM = bilstm_1, bilstm_2, .., bilstm_n \in R^{n*d^{\sim}}$
end for
Process BiLSTM and BiGRU layers output to set it as input of Dilated CNN:
for Each iteration in range(0,N)
$Vector_G = [vector_1^{bg}, vector_2^{bg}, \ldots., vector_l^{bg}] \in R^{n*d^{\sim}}, l \in (1, L)$
$Vector_L = [vector_1^{bl}, vector_2^{bl}, \ldots., vector_l^{bl}] \in R^{n*d^{\sim}}, l \in (1, L)$
Here L is number of layers.
end for
for Each iteration n in range(0,N)
for Each iteration n in range(0,N)
$convolutionvector_{ij} = concatenate(Vector_G, Vector_L)$
end for
end for
Get Multilayered Deep CNN output:
Process dilated CNN
for each iteration i in range(0,N)
for each iteration j in range(0,N)
$\widetilde{Convolution}vector_{ij} = \sum_{i=1}^{M} convolutionvector_{ij} * \widetilde{vector}j|i$
$vectorj|i = convolutionvector_{ij} * W_j$, *Here W is a weight vector, M is vector dimension.*
end for
end for
Execute aggregation mechanism
for each iteration i in range(0,N)
for each iteration j in range(0,N)
$aggregation_{ij = \widetilde{vectorj}|i * Convolutionvector_{ij}}$
$output = \sum_{i=1} aggregation_{ij} * convolution_{ij}$
end for
end for
Execute prediction function
$p(y|S) = p(y|o) = SoftMax(MLP(output))$
Find evaluation metric result EM
End

$$Weighted\ Average\ Precision = \sum_{i=1}^{N} [\frac{TP_i}{TP_i + FP_i}] \tag{13}$$

$$Weighted\ Average\ Recall = \sum_{i=1}^{N} [\frac{TP_i}{TP_i + FN_i}] \tag{14}$$

$$Weighted\ Average\ F1 = \sum_{i=1}^{N} 2 * \frac{Precision_i * Recall_i}{Precision_i + Recall_i} \tag{15}$$

where, TP = True Positive, TN = True Negative, FP = False Positive and FN = False Negative.

The model un-predictivity is measured by the Categorical cross entropy (CCE) [64] loss. The entropy of a variable that is used to determine its unpredictability. It determines the most useful data for assessing the existing state of information exchange. The Cross entropy is rapidly being used to identify poorly distributed states as well as to substitute for log distributions that are erroneous. The categorical cross entropy loss improves when the expected probability differs. CCE loss is calculated with equation (16), where y is the prediction value and N indicates the number of class to be predicted.

$$Loss(y) = \sum_{i=1}^{N} [y_i log\left(y_i^{\wedge}\right) + (1 - y_i) * log\left(1 - y_i^{\wedge}\right)] \tag{16}$$

IV. RESULT ANALYSIS

A comprehensive experimental analysis for arrhythmia detection has been described in this section. In this study, we have designed a hybrid architecture (BRDC model) to classify the arrhythmia signals effectively. The experimental analysis has been conducted on a publicly available reputable five class ECG dataset (obtained from 47 patients). After data pre-processing, the entire dataset has been split into three parts: training-set to train the model, validation-set to check the validation and testing-set is used for testing the effectiveness of the model. Additionally, in this experimental analysis, we have also investigated five widely used DL models (LSTM, GRU, LSTM-BIGRU, BiLSTM, and BiGRU) along with the proposed BRDC model to show the comparison and robustness of the proposed model. During the training of each DL model, we have set the same hyperparameters for each model. The performance of each class is shown in Table 1. Table 1 clearly demonstrates that the proposed BRDC model performs slightly better results than other arrhythmia detection models. Our model has achieved 99.90 % training accuracy and 99.71 % validation accuracy. We have also calculated the other performance evaluation matrics to check the proposed model's robustness. The proposed BRDC model has been achieved a precision of 97.6 % for training and 96.00 % for validation as well as an F1 score of 98.41 % for training and 96.86 % for validation.

The overall training and validation accuracy of the proposed model has been demonstrated in Fig. 9. The proposed architecture has been achieved a total of 99.90 % training accuracy, and 99.71 % validation accuracy, respectively, in the 100 epochs.

Fig. 10 illustrate the training and validation loss of the proposed BRDC model. We have used the categorical cross-entropy loss function for training and achieved 0.0918 training loss and 0.1518 validation loss.

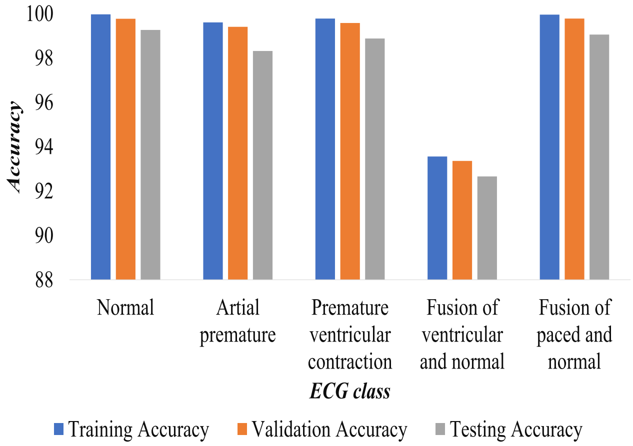

FIGURE 11. **The training Performance of the BRDC model.**

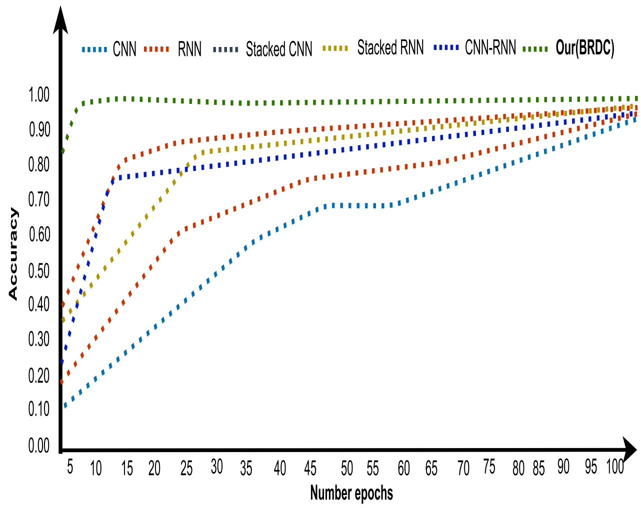

FIGURE 12. **Compared performance during training.**

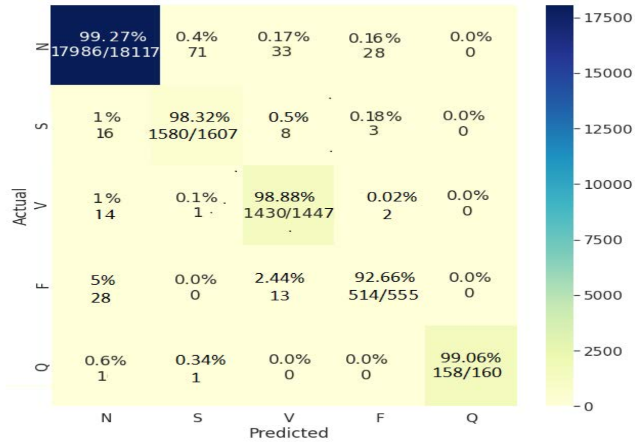

FIGURE 13. **The confusion matrix of the BRDC model.**

Fig. 11 show the overall training, validation and testing performance of each class for arrhythmia classification respectively. This experimental analysis has calculated in accuracy. Each evaluation metric has been labeled with a different color in these figures, and each bar on each figures represents the accuracy of each ECG category. Proposed BRDC during testing taken 20 % unlabelled data with four evaluation metrics score. The proposed BRDC model has achieved 99.99 %, 99.71 % and 99.00 % accuracy on train, validation and testing data respectively.

We have also implemented some widely used DL models on MIT-BIH data and compared the performance with the proposed model. This study has investigated CNN, RNN, Stacked CNN, Stacked RNN, CNN-RNN, and the proposed BRDC model to show the effectiveness of the proposed model. During the training, the same hyperparameters (batch size, learning rate, activation function, optimized, and the dropout rate) have been utilized in each model, as shown in Table 2. From Table 2, it is clear that the proposed model has achieved significant performance compared to the others five DL models. The proposed model has achieved 4.1 %, 2.71 %, 3.11 %, 1.81 % improvement than the CNN, RNN, stacked-CNN, CNN-RNN respectively.

Fig. 12 shows the accuracy of each model during the training of the models. Each model has been trained with 100 epochs, and it is clearly demonstrated that the proposed model's line bar is stated over than the other methods in each epoch.

In this experimental analysis, we have used a total of 20 % unlabeled data to test the effectiveness of the BRDC approach. The testing data sample used in testing performance analysis is 21886 rows by 187 columns. We have also calculated the confusion matrix with the BRDC model, which helps to visualize the difference between the actual class and the correctly predicted class. Fig. 13 shows the confusion matrix of the BRDC model on test data. In this figure, N indicates the Normal class, S indicates the Atrial Premature, V indicates the premature ventricular contraction, F indicates the fusion of ventricular and normal, Q indicates the fusion of paced and normal. The BRDC method has achieved 99.27 % accuracy on N class and 99.06% on Q class, 98.32 % on S class, 98.88 % on V class, and 92.66 % on F class. The proposed model has been predicted a total of 21668 samples out of 21886 samples which illustrates that only a total of 218 samples have been misclassified.

V. DISCUSSION

Classification is a hot topic in healthcare and bioinformatics, especially when detecting arrhythmias. Arrhythmias are anomalies in the pace or rhythm of the heartbeat that can occur periodically throughout a person's daily life. As a result, automatically detecting aberrant heartbeats from a vast amount of ECG data is a critical and significant undertaking. We have developed a hybrid technique (BRDC) based on a deep neural network (DNN) to automatically categorize aberrant ECG beats that differs from normal ones in this research. The proposed DL strategy is created utilizing the Tensor Flow framework and consists of numerous hidden layers to extract the most informative feature from ECG data. As compared to other existing approaches for arrhythmia identification, the suggested architecture gives more precise results in a quicker duration during model testing (with testing dataset). For example, within 26 seconds, the model

TABLE 1. Performance of the experimental analysis.

Class	LSTM Dilated CNN Training				LSTM Dilated CNN Validation				LSTM Dilated CNN Testing			
	Accuracy	precision	Recall	F1	Accuracy	precision	Recall	F1	Accuracy	precision	Recall	F1
N	99.72	97.74	99.65	98.25	99.45	97.53	99.54	98.06	99.03	96.85	98.81	97.34
AP	99.41	97.23	99.38	97.85	99.12	97.15	99.13	97.71	98.02	96.55	96.01	96.74
FVC	99.52	97.45	99.55	98.13	99.33	97.35	99.32	97.82	98.63	96.64	98.65	97.11
RVN	93.2	91.24	93.39	91.85	93.15	91.23	93.15	91.64	92.53	90.43	92.44	90.88
FPN	99.67	97.68	99.78	98.25	99.55	97.46	99.51	97.98	98.89	96.78	98.94	97.24
Class	GRU Dilated CNN Training				GRU Dilated CNN Validation				GRU Dilated CNN Testing			
	Accuracy	precision	Recall	F1	Accuracy	precision	Recall	F1	Accuracy	precision	Recall	F1
N	99.75	97.78	99.75	98.3	99.56	97.58	99.57	98.11	99.14	96.92	98.85	97.38
AP	99.51	97.38	99.42	97.93	99.15	97.18	99.19	97.79	98.11	96.63	96.07	96.76
FVC	99.61	97.58	99.58	98.14	99.37	97.43	99.39	97.88	98.64	96.67	98.71	97.21
RVN	93.32	91.36	93.44	91.89	93.23	91.27	93.18	91.71	92.54	90.45	92.45	90.96
FPN	99.81	97.79	99.81	98.33	99.62	97.56	99.56	98.01	98.91	96.85	98.95	97.35
Class	GRU-LSTM Dilated CNN Training				GRU-LSTM Dilated CNN Validation				GRU-LSTM Dilated CNN Testing			
	Accuracy	precision	Recall	F1	Accuracy	precision	Recall	F1	Accuracy	precision	Recall	F1
N	99.8	97.81	99.83	98.31	99.63	97.62	99.63	98.15	99.17	96.93	98.91	97.41
AP	99.55	97.41	99.47	97.97	99.18	97.24	99.23	97.81	98.16	96.65	96.12	96.81
FVC	99.66	97.62	99.63	98.18	99.43	97.48	99.44	97.91	98.73	96.71	98.75	97.26
RVN	93.41	91.42	93.47	91.91	93.24	91.21	93.23	91.75	92.55	90.53	92.51	91
FPN	99.84	97.82	99.85	98.32	99.65	97.63	99.63	98.06	98.93	96.93	98.96	97.42
Class	BiLSTM Dilated CNN Training				BiLSTM Dilated CNN Validation				BiLSTM Dilated CNN Testing			
	Accuracy	precision	Recall	F1	Accuracy	precision	Recall	F1	Accuracy	precision	Recall	F1
N	99.85	97.87	99.87	98.34	99.67	97.69	99.67	98.2	99.18	96.98	98.97	97.47
AP	99.51	97.45	99.51	98.01	99.21	97.3	99.26	97.83	98.23	96.61	96.18	96.86
FVC	99.68	97.68	99.67	98.21	99.52	97.48	99.47	97.96	98.78	96.78	98.78	97.31
RVN	93.48	91.48	93.48	91.97	93.28	91.28	93.26	91.78	92.57	90.58	92.57	91.06
FPN	99.85	97.86	99.87	98.38	99.68	97.67	99.68	98.11	98.97	96.98	98.99	97.47
Class	BiGRU Dilated CNN Training				BiGRU Dilated CNN Validation				BiGRU Dilated CNN Testing			
	Accuracy	precision	Recall	F1	Accuracy	precision	Recall	F1	Accuracy	precision	Recall	F1
N	99.91	97.91	99.91	98.42	99.71	97.71	99.71	98.24	99.22	97.01	99.01	97.52
AP	99.56	97.55	99.56	98.07	99.26	97.35	99.31	97.88	98.27	96.65	96.23	96.89
FVC	99.73	97.71	99.71	98.25	99.57	97.51	99.51	98.04	98.82	96.82	98.82	97.35
RVN	93.51	91.5	93.52	92.01	93.31	91.31	93.32	91.82	92.61	90.6	92.63	91.12
FPN	99.9	97.9	99.91	98.42	99.73	97.72	99.71	98.15	99.02	97.01	99	97.52
Class	BRDC Training				BRDC Validation				BRDC Testing			
	Accuracy	precision	Recall	F1	Accuracy	precision	Recall	F1	Accuracy	precision	Recall	F1
N	99.97	97.96	99.96	98.48	99.77	97.76	99.77	98.29	99.27	97.06	99.07	97.58
AP	99.61	97.6	99.61	98.12	99.41	97.4	99.4	97.92	98.32	96.7	96.32	**97.22**
FVC	99.78	97.77	99.77	98.29	99.58	97.56	99.58	98.09	98.88	96.87	98.87	97.39
RVN	93.56	91.55	93.57	92.07	93.36	91.36	93.36	91.88	92.66	90.65	92.66	91.17
FPN	99.96	97.95	99.95	98.47	99.78	97.76	99.75	98.18	99.06	97.05	99.06	97.57

TABLE 2. Performance comparison with the existing popular algorithms.

Model	Batch size	Learning rate	Activation	Optimizer	Dropout	Input size	Accuracy (%)
CNN	256	$1e^{-5}$	ReLu	Adam	0.2	300*128*5	90.06
RNN	256	$1e^{-5}$	ReLu	Adam	0.2	300*128*5	97.20
Stacked CNN	256	$1e^{-5}$	ReLu	Adam	0.2	300*128*5	96.80
Stacked RNN	256	$1e^{-5}$	ReLu	Adam	0.2	300*128*5	97.22
CNN-RNN	256	$1e^{-5}$	ReLu	Adam	0.2	300*128*5	98.10
Proposed (BRDC)	256	$1e^{-5}$	ReLu	Adam	0.2	300*128*5	99.90

predicts a 20 % dataset. The proposed BRDC model has 99.90 % accuracy, 98.41 % F1 score, 97.96 % precision, and 99.90 % recall during training on the MIT-BIH data. Before deploying our BRDC technique, we have employed the GAN model to synthesize raw data. We have compared various well-known classifiers precisely to demonstrate the quality of the suggested architecture in terms of proper categorization. The numerical findings, particularly in terms of accuracy in Table 3, demonstrate the usefulness of the approach.

In our method, the GAN algorithm helps to generate synthetic data samples with our pre-processing tools of altering the standard deviation, mean of the Z-score and other pre-processing computed from the original normalized ECG signals. This helps to handle the problems of misclassifications to increase the performance. Furthermore, the filtering method helps to eliminate the interference of ECG signals in our method. Our technique uses Daubechies filtering, which uses overlapping windows to ensure that the high-frequency coefficient spectrum represents all high-frequency fluctuations. As a result, Daubechies wavelets are beneficial in ECG signal compression and noise removal. In our classification model, we have used BiGRU-BiLSTM in a dual structured manner, more independent and long-range characteristics are handled with it. As a result, dilated CNN has a larger receptive field (i.e., no loss of coverage), computationally efficient lesser memory consumption and no loss of output resolution.

Our proposed BRDC framework employs the dilated CNN with multilayered form with a dual structured BiGRU as well as BiLSTM. By continuously adjusting its hierarchy structure into such an engaged convolution, we suggest a new hybrid model to enhance the learning method, features extraction, and analysing ECG signal classification. The production process of the BiGRU-BiLSM layers and the dilated convolution-based hybrid subsystem can extract meaningful hierarchical interpretations of ECG features to fully exploit the features. Our suggested hybrid neural network convolution method successfully obtains implicit feature representations. The two-way structured bidirectional repetitive device (BiGRU-BiLSTM) differential and interdependence are utilized all through this method. This bidirectional objective is achieved by utilizing performance that allows the dilated convolution network to extract rich feature information in a short period of time. Multilayered dilated CNN with a bidirectional RNN reduces training time and gives a clear system framework to improve effectiveness. Furthermore, by adjusting the weight parameters for more reliable spatial information, the enhanced convolution network dynamic route optimization algorithm improves the effectiveness of adaptive routing optimization.

In most circumstances, the presence of major training beats in a particular class can lead to a bias toward predicting that category, resulting in a higher sensitivity score. Furthermore, the proposed technique almost solves this problem by providing very acceptable sensitivity values in all classes. However, due to the bias toward a bigger sized category, the number of false-positive predictions from those other smaller sized categories is more likely to be higher, leading to a lower positive predictive value in the bigger size class. It is indeed worth noting that the proposed framework consistently gives considerable predictive value across all classes. Furthermore, the F1 score integrates positive predictive value and sensitivity outcomes to create a reliable comparison method. It can be concluded that the suggested system produces superior improvement in the F1 metric for all five classes with excellent consistency.

Identifying arrhythmia is more important than detecting all detailed arrhythmia types in many circumstances. To illustrate the effectiveness of the proposed approach in such arrhythmia identification situations, all arrhythmia classes are treated as a single diseased class, and the provided methods are used to distinguish them from normal beats. Since the suggested technique has attained a classification accuracy of 99.90 % during training on five-class datasets, it will undoubtedly outperform this binary classification job (arrhythmia Vs normal).

The followings are the technical strengths of our proposed study:

1) With 1.5 seconds of the timespan of each ECG sample, the proposed model attained the highest training accuracy (almost 99.90%). By lowering the quantity of data in each trial, this short time window speeds up the system.
2) Our suggested BRDC algorithm could be effectively applied in identifying arrhythmias using EEG data due to its efficacy and robustness. Furthermore, the BRDC classification method can train autonomously while also performing tasks.
3) The proposed BRDC requires somewhat longer to learn than a classification model; nevertheless, when compared to many other algorithms, it is able to conduct as quickly as single classifiers during testing. Not only is the test short, but it is also unbiased in terms of the training set. Furthermore, the methodology given here is applicable to mobile devices.
4) The highly linked networks are detected using the proposed channel selection method based on correlation analysis. The suggested algorithm-based method has a 99.00 % accuracy on test data and improved performance, which might be helpful in an arrhythmia detection system that uses EEG.

All cutting-edge methods are presented and compared with our BRDC model here. To categories the incoming ECG signals across their appropriate groups, In 2022, An automated method to classsify ECG to detect arrythmia using Hybrid CNN-LSTM Network [53]. This method got 99% accuracy with denoised signal of MIT-BIH data.Time complexity of this method is slightly more than conventional method. In 2022, another CNN [54] based method that classify Cardiac Arrhythmias using Individual ECG Signals. This method got 98.74% accuracy with denoised signal of MIT-BIH data. Faster method its performance is varries on type of data. In 2022, A method [55] to detect arrhythmia using Binarized Convolutional Neural Network got 95.67% accuracy. 2D Convolutional networks have recently been used. Before the feature extraction stage, the input 1D ECGs are converted to 2D. The 2D CNN [48] models have a higher level of distinctness and robustness against noise in the input signals; they achieved 99.02 % accuracy. Before generating robust features, the system uses the CWT to convert the input 1D [48] ECG into a 2D signal. Compared to the suggested CNN [48] model with 92.70 % accuracy, SVM models achieved poorer classification accuracy [50] of 89.72 % and 86.40 %. 1D CNN [48] have gained an accuracy of classification of 97.38 % using 1D ECG signals as input to the 1D CNN model employed in the trials. CNN with SVM have got 96 % accuracy. A CNN method to classify ECG with synthetic and scaling-based pre-processing have got 94.03 % accuracy. A hybrid method combines CNN and RNN that uses patient-specific features from raw data to classify ECG signals with 98.10 % accuracy [48]. Yildirim *et al.* [40] have proposed a deep CNN-based method to classify short-duration ECG signals with 91.33 % accuracy. Another method by the same author used attention-based LSTM achieved 99.10 % accuracy [47]. ECG signal classification using CNN and bidirectional LSTM [46] yielded 96.77 % accuracy, 77.8 % precision,

TABLE 3. Compared performance of the selected method on MIT-BIH data set with the proposed approach.

Reference	Class	Method	Input Features	Accuracy (%)
[54]	5	Binarized CNN	Denoised features	98.74
[53]	5	CNN-LSTM	Denoised signal	99
[55]	5	CNN	Raw signal	95.67
[50]	5	SVM	Particle Swarm Optimization	89.72
[48]	5	2D CNN	Robust noised filtering	99.02
[40]	5	CNN-SVM	Filtering and normalization and L2 regularization	96.00
[47]	5	CNN	Raw ECG data	92.70
[46]	5	CNN	Synthetic and raw scaling	94.03
[10]	5	CNN-LSTM	Patient Specific features	98.10
[51]	17	DCNN	Pre-processing by Rescaling	91.33
[52]	5	CAE-LSTM	Coded signal	99.00
[44]	5	CNN-Bi LSTM	RR interval	96.77
[56]	5	Dilated CNN	Denoising with normalization	98.65
[17]	5	Deep CNN-BiLSTM	PR, RR intervals and QRS feature	96.59
[65]	5	CNN-LSTM Attention	Multi domain feature	98.51
[66]	5	CNN BiLSTM Attention	Raw data	99.10
Our Proposed	5	BiGRU-BiLSM Multilayered Dilated CNN	Synthetic and sequential pre-processed ECG signals	99.90

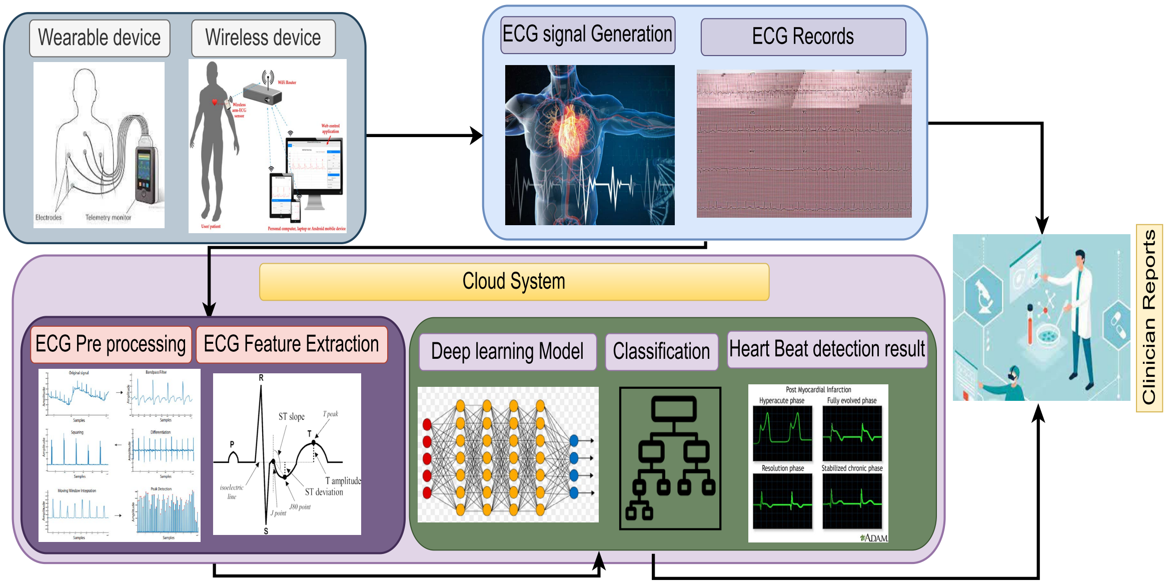

FIGURE 14. Cloud-based ECG classification to detect arrhythmia.

and 81.2 % recall. Ma *et al.* [10] have developed a dilated CNN-based method to classify ECG signals with 98.65 % accuracy. Dang *et al.* [51] have used a deep CNN-BILSTM to categorize ECG signals with 69.59 % accuracy. Jin et al [52] have used a hybrid deep learning approach with CNN-LSTM as well as multi-domain features to categorize five types of ECG signals with 98.51 % accuracy. Another novel and hybrid deep learning method, CNN-BiLSTM [44], is used and achieved 96.77 % accuracy. Table 3 compares the performance of the various methods on the MIT-BIH data set with the proposed method. Our proposed BRDC model is assessed and compared to a number of existing method benchmarks. On MIT-BIH published ECG data, the proposed BRDC model have achieved 99.90 % accuracy, 98.41 % F1, 97.96 % precision, and 99.90 % recall during training to classify arrhythmia. With 360 samples and 1.5 seconds, our method classifies five different types of ECG signals.

To illustrate the effectiveness of the proposed technique in aspects of runtime, we have formed a new hybrid deep neural BRDC model that used multilayered dilated CNN as well as bidirectional RNN. The model's actual recorded running speed on the testing dataset is greater than any learning algorithm. Due to longer learning of a general CNN, the suggested technique does not include one in the model. We have used a dilated convolution like a multi dilation method, which uses only the convolutions needed for extracting features, significantly reducing computation time. The training time of 80 % data takes two hours, and testing of 20 % of data has a run time of 26 seconds. Our framework has a low level of spatial complexity.

Although the proposed strategy achieves significant results, the experimental study encounters several challenges. One of the key drawbacks of machine learning approaches, for example, is the dearth of gold standard labelling datasets. As a result, a widely publicly available benchmark dataset with clinical annotations has been used in this investigation. However, it should be emphasized that the dataset still contains a lot of noise. In addition, a large number of similar datasets are required to validate cross-validation and prove the practicality of our proposed network. However, we could not find a suitable dataset for further testing the proposed approach. There are also several constraints to the research as well. First of all, since the proposed model only concentrates on five types of ECG signal classification, we would then take into account using them for different types of ECG signal discriminatory practices. Secondly, we intend to create larger and more diverse datasets to test the proposed models and continuously increase the network system's generalization capability.

Despite the fact that the proposed technique achieves considerable results, future research can look into different possibilities. Other widely accessible databases, such as INCART and SVDB, will be used in future research to assess the precision of the technique and proposed scheme and maximize the neural network's learning capabilities. Furthermore, we intend to integrate our technique into a real-time ECG monitoring system and evaluate it in a real-world setting in collaboration with a specific hospital department. Another fascinating topic worth examining is the role of physicians inside the process, particularly in relation to the annotation. In fact, as stated in the database's descriptions, there are now too many ECG beats that must be tagged for this to be employed in the DNN's learning or testing phases. A potential cloud-based arrhythmias detection system that can be used on mobile phones is depicted in Fig. 14. The cloud receives the ECG signal from the patient and processes it. The cloud-based DL system interprets the processed information, and the results are conveyed to the physician with minimum human endeavor. After being verified by the practitioner, the verified results are provided to the patient's mobile phone. The practicality of such a system is determined by the DL model's processing expenses as well as the data dimension.

Furthermore, the cloud-based system allows users to complete online or offline processes, which should help to gain clinical acceptance. In addition, when compared to the seven popular current algorithms shown in Table 3, our suggested architecture have increased arrhythmia detection by more than 1 % using the ECG dataset. The results of the experiments clearly demonstrate the efficacy and applicability of our proposed hybrid architecture. As a result, our architecture has outperformed the results of other relevant research for arrhythmia diagnosis available in the literature.

VI. CONCLUSION

The most pressing issue in medicine and bioinformatics is fully automated categorization, especially arrhythmia identification. This article suggests a novel dilated CNN containing the multilayered form with bidirectional RNN for detecting arrhythmia signals in ECG records by extracting handle relevant as well as long-ranged self-reliant features. The multilayered dilated CNN layer is a simple convolutional layer that uses features extracted from ECG signals. Eventually, we have attained the status of precision. Our BRDC model does not necessitate expert biological knowledge or the time-consuming feature extraction method used in traditional machining learning. Otherwise, the network detects AF with little computational overhead, yielding true theoretical performance. Our future research will centre on the classification of numerous arrhythmia signal-based data. This study aims to enhance the model's generalization ability, the educational success of neural networks, and clinical advantages.

REFERENCES

[1] H. V. Huikuri, A. Castellanos, and R. J. Myerburg, "Sudden death due to cardiac arrhythmias," *New England J. Med.*, vol. 345, no. 20, pp. 1473–1482, 2001.

[2] S. C. Wang, D. Meng, H. Yang, X. Wang, S. Jia, Y.-F. Wang, and P. Wang, "Pathological basis of cardiac arrhythmias: Vicious cycle of immune-metabolic dysregulation," *Cardiovascular Disorders Med.*, vol. 3, no. 1, pp. 1–7, 2017.

[3] (May 2022). *Sudden Cardiac Death (SCD): Symptoms, Causes*. Accessed: May 21, 2022. [Online]. Available: https://my.clevelandclinic.org/health/diseases/17522-sudden-cardiac-death-sudden-cardiac-arrest

[4] H. Wellens, "Cardiac arrhythmias: The quest for a cure: A historical perspective," *J. Amer. College Cardiol.*, vol. 44, no. 6, pp. 1155–1163, Sep. 2004.

[5] *Testing and Reporting Performance Results of Cardiac Rhythm and ST Segment Measurement Algorithms | Engineering360*, Standard AAMI EC57, May 2022. Accessed: May 21, 2022. [Online]. Available: https://standards.globalspec.com/std/14370017/AAMI

[6] M. Falter, W. Budts, K. Goetschalckx, V. Cornelissen, and R. Buys, "Accuracy of apple watch measurements for heart rate and energy expenditure in patients with cardiovascular disease: Cross-sectional study," *JMIR mHealth uHealth*, vol. 7, no. 3, Mar. 2019, Art. no. e11889.

[7] R. S. Bhatia and P. Dorian, "Screening for cardiovascular disease risk with electrocardiography," *J. Amer. Med. Assoc. Internal Med.*, vol. 178, no. 9, pp. 1163–1164, 2018.

[8] R. Liu, M. Shu, and C. Chen, "ECG signal denoising and reconstruction based on basis pursuit," *Appl. Sci.*, vol. 11, no. 4, p. 1591, Feb. 2021.

[9] R. N. Vargas and A. C. P. Veiga, "Empirical mode decomposition, Viterbi and wavelets applied to electrocardiogram noise removal," *Circuits, Syst., Signal Process.*, vol. 40, no. 2, pp. 691–718, Feb. 2021.

[10] R. Shaddeli, N. Yazdanjue, S. Ebadollahi, M. M. Saberi, and B. Gill, "Noise removal from ECG signals by adaptive filter based on variable step size LMS using evolutionary algorithms," in *Proc. IEEE Can. Conf. Electr. Comput. Eng. (CCECE)*, Sep. 2021, pp. 1–7.

[11] T. Li and M. Zhou, "ECG classification using wavelet packet entropy and random forests," *Entropy*, vol. 18, no. 8, p. 285, Aug. 2016.

[12] R. J. Martis, U. R. Acharya, and L. C. Min, "ECG beat classification using PCA, LDA, ICA and discrete wavelet transform," *Biomed. Signal Process. Control*, vol. 8, no. 5, pp. 437–448, 2013.

[13] R. J. Martis, U. R. Acharya, C. M. Lim, and J. S. Suri, "Characterization of ECG beats from cardiac arrhythmia using discrete cosine transform in PCA framework," *Knowl.-Based Syst.*, vol. 45, pp. 76–82, Jun. 2013.

[14] S.-N. Yu and K.-T. Chou, "Integration of independent component analysis and neural networks for ECG beat classification," *Expert Syst. Appl.*, vol. 34, no. 4, pp. 2841–2846, 2008.

[15] M. Ahmed, A. B. Nasser, K. Z. Zamli, and S. Heripracoyo, "Comparison of performances of Jaya algorithm and cuckoo search algorithm using benchmark functions," in *Proc. Int. Conf. Emerg. Technol. Intell. Syst.* Cham, Switzerland: Springer, 2021, pp. 114–125.

[16] T. H. Linh, S. Osowski, and M. Stodolski, "On-line heart beat recognition using Hermite polynomials and neuro-fuzzy network," *IEEE Trans. Instrum. Meas.*, vol. 52, no. 4, pp. 1224–1231, Aug. 2003.

[17] F. Melgani and Y. Bazi, "Classification of electrocardiogram signals with support vector machines and particle swarm optimization," *IEEE Trans. Inf. Technol. Biomed.*, vol. 12, no. 5, pp. 667–677, Sep. 2008.

[18] J. Park, K. Lee, and K. Kang, "Arrhythmia detection from heartbeat using *k*-nearest neighbor classifier," in *Proc. IEEE Int. Conf. Bioinf. Biomed.*, Dec. 2013, pp. 15–22.

[19] S.-N. Yu and Y.-H. Chen, "Electrocardiogram beat classification based on wavelet transformation and probabilistic neural network," *Pattern Recognit. Lett.*, vol. 28, no. 10, pp. 1142–1150, 2007.

[20] N. Alfaz, T. B. Sarwar, A. Das, and N. M. Noor, "A densely interconnected convolutional neural network-based approach to identify COVID-19 from chest X-ray images," in *Proc. 11th Int. Conf. Robot., Vis., Signal Process. Power Appl.* Singapore: Springer, 2022, pp. 419–425.

[21] M. N. Islam, N. Sulaiman, F. A. Farid, J. Uddin, S. A. Alyami, M. Rashid, A. P. A. Majeed, and M. A. Moni, "Diagnosis of hearing deficiency using EEG based AEP signals: CWT and improved-VGG16 pipeline," *PeerJ Comput. Sci.*, vol. 7, Sep. 2021, Art. no. e638.

[22] S. Sahoo, B. Kanungo, S. Behera, and S. Sabut, "Multiresolution wavelet transform based feature extraction and ECG classification to detect cardiac abnormalities," *Measurement*, vol. 108, pp. 55–66, Oct. 2017.

[23] R. Cooley, B. Mobasher, and J. Srivastava, "Web mining: Information and pattern discovery on the world wide web," in *Proc. 9th IEEE Int. Conf. Tools Artif. Intell.*, 1997, pp. 558–567.

[24] L. Kumari, L. V. R. Kumari, and Y. P. Sai, "Classification of ecg beats using optimized decision tree and adaptive boosted optimized decision tree," *Signal, Image Video Process.*, vol. 16, pp. 695–703, Apr. 2022.

[25] P. Lu, Y. Zhang, B. Zhou, H. Zhang, L. Chen, Y. Lin, X. Mao, Y. Gao, and H. Xi, "Identification of arrhythmia by using a decision tree and gated network fusion model," *Comput. Math. Methods Med.*, vol. 2021, pp. 1–13, May 2021.

[26] D. K. R. Priyadarshini, "Cardiac arrythmia detection using Naïve Bayes and SVM models," *Turkish J. Comput. Math. Educ.*, vol. 12, no. 12, pp. 2697–2703, 2021.

[27] R. Swetha and S. Ramakrishnan, "*K*-means clustering optimized fuzzy logic control algorithm for arrhythmia classification," in *Proc. Int. Conf. Adv. Electr., Comput., Commun. Sustain. Technol. (ICAECT)*, Feb. 2021, pp. 1–7.

[28] I. Khandokar, M. Hasan, F. Ernawan, S. Islam, and M. Kabir, "Handwritten character recognition using convolutional neural network," *J. Phys., Conf. Ser.*, vol. 1918, no. 4, 2021, Art. no. 042152.

[29] N. Jaouedi, N. Boujnah, and M. S. Bouhlel, "A new hybrid deep learning model for human action recognition," *J. King Saud Univ., Comput. Inf. Sci.*, vol. 32, no. 4, pp. 447–453, May 2020.

[30] M. S. Islam, S. Sultana, U. K. Roy, and J. A. Mahmud, "A review on video classification with methods, findings, performance, challenges, limitations and future work," *Jurnal Ilmiah Teknik Elektro Komputer dan Informatika*, vol. 6, no. 2, pp. 47–57, 2020.

[31] A. Elad and R. Kimmel, "On bending invariant signatures for surfaces," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 25, no. 10, pp. 1285–1295, Oct. 2003.

[32] A. Hannun, P. Rajpurkar, M. Haghpanahi, G. H. Tison, C. Bourn, M. P. Turakhia, and A. Y. Ng, "Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network," *Nature Med.*, vol. 25, pp. 65–69, Jan. 2019.

[33] S. Kiranyaz, T. Ince, and M. Gabbouj, "Real-time patient-specific ECG classification by 1-D convolutional neural networks," *IEEE Trans. Biomed. Eng.*, vol. 63, no. 3, pp. 664–675, Mar. 2016.

[34] N. Strodthoff and C. Strodthoff, "Detecting and interpreting myocardial infarction using fully convolutional neural networks," *Physiol. Meas.*, vol. 40, no. 1, 2019, Art. no. 015001.

[35] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, M. Adam, A. Gertych, and R. S. Tan, "A deep convolutional neural network model to classify heartbeats," *Comput. Biol. Med.*, vol. 89, pp. 389–396, Oct. 2017.

[36] E. Ihsanto, K. Ramli, D. Sudiana, and T. S. Gunawan, "An efficient algorithm for cardiac arrhythmia classification using ensemble of depthwise separable convolutional neural networks," *Appl. Sci.*, vol. 10, no. 2, p. 483, Jan. 2020.

[37] S. Mousavi and F. Afghah, "Inter- and intra-patient ECG heartbeat classification for arrhythmia detection: A sequence to sequence deep learning approach," in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, May 2019, pp. 1308–1312.

[38] E. D. Übeyli, "Combining recurrent neural networks with eigenvector methods for classification of ECG beats," *Digit. Signal Process.*, vol. 19, no. 2, pp. 320–329, 2009.

[39] Ö. Yildirim, "A novel wavelet sequence based on deep bidirectional LSTM network model for ECG signal classification," *Comput. Biol. Med.*, vol. 96, pp. 189–202, May 2018.

[40] Ö. Yıldırım, P. Pławiak, R.-S. Tan, and U. R. Acharya, "Arrhythmia detection using deep convolutional neural network with long duration ECG signals," *Comput. Biol. Med.*, vol. 102, no. 1, pp. 411–420, Nov. 2018.

[41] M. N. Islam, N. Sulaiman, B. S. Bari, M. Rashid, and M. Mustafa, "A hybrid scheme for AEP based hearing deficiency diagnosis: CWT and convoluted *k*-nearest neighbour (CKNN) pipeline," *Neurosci. Informat.*, vol. 2, no. 1, Mar. 2022, Art. no. 100037.

[42] S. Rasheed, D. W. Stashuk, and M. S. Kamel, "A hybrid classifier fusion approach for motor unit potential classification during EMG signal decomposition," *IEEE Trans. Biomed. Eng.*, vol. 54, no. 9, pp. 1715–1721, Sep. 2007.

[43] X. Li, L. Cui, S. Tao, J. Chen, X. Zhang, and G.-Q. Zhang, "HyCLASSS: A hybrid classifier for automatic sleep stage scoring," *IEEE J. Biomed. Health Informat.*, vol. 22, no. 2, pp. 375–385, Mar. 2018.

[44] J. Wang, "An intelligent computer-aided approach for atrial fibrillation and atrial flutter signals classification using modified bidirectional LSTM network," *Inf. Sci.*, vol. 574, pp. 320–332, Oct. 2021.

[45] B. Srinivas and G. S. Rao, "A hybrid CNN-KNN model for MRI brain tumor classification," *Int. J. Recent Technol. Eng.*, vol. 8, no. 2, pp. 2277–3878, 2019.

[46] A. Chen, F. Wang, W. Liu, S. Chang, H. Wang, J. He, and Q. Huang, "Multi-information fusion neural networks for arrhythmia automatic detection," *Comput. Methods Programs Biomed.*, vol. 193, Sep. 2020, Art. no. 105479.

[47] O. Yildirim, U. B. Baloglu, R.-S. Tan, E. J. Ciaccio, and U. R. Acharya, "A new approach for arrhythmia classification using deep coded features and LSTM networks," *Comput. Methods Programs Biomed.*, vol. 176, pp. 121–133, Jul. 2019.

[48] S. L. Oh, E. Y. K. Ng, R. S. Tan, and U. R. Acharya, "Automated diagnosis of arrhythmia using combination of CNN and LSTM techniques with variable length heart beats," *Comput. Biol. Med.*, vol. 102, no. 1, pp. 278–287, Nov. 2018.

[49] M. Islam and N. A. Ghani, "A novel BiGRUBiLSTM model for multilevel sentiment analysis using deep neural network with BiGRU-BiLSTM," in *Recent Trends in Mechatronics Towards Industry 4.0*. Singapore: Springer, 2022, pp. 403–414.

[50] O. Yildirim, T. R. San, and U. R. Acharya, "An efficient compression of ECG signals using deep convolutional autoencoders," *Cogn. Syst. Res.*, vol. 52, pp. 198–211, Dec. 2018.

[51] H. Dang, M. Sun, G. Zhang, X. Qi, X. Zhou, and Q. Chang, "A novel deep arrhythmia-diagnosis network for atrial fibrillation classification using electrocardiogram signals," *IEEE Access*, vol. 7, pp. 75577–75590, 2019.

[52] Y. Jin, C. Qin, Y. Huang, W. Zhao, and C. Liu, "Multi-domain modeling of atrial fibrillation detection with twin attentional convolutional long short-term memory neural networks," *Knowl.-Based Syst.*, vol. 193, Apr. 2020, Art. no. 105460.

[53] S. Rahman, S. Rahman, and A. B. Haque, "Automated detection of cardiac arrhythmia based on a hybrid CNN-LSTM network," in *Emergent Converging Technologies and Biomedical Systems*. Singapore: Springer, 2022, pp. 395–414.

[54] Y. Zhang, S. Liu, Z. He, Y. Zhang, and C. Wang, "A CNN model for cardiac arrhythmias classification based on individual ECG signals," *Cardiovascular Eng. Technol.*, vol. 13, pp. 1–10, Jan. 2022.

[55] A. Wang, W. Xu, H. Sun, N. Pu, Z. Liu, and H. Liu, "Arrhythmia classifier using binarized convolutional neural network for resource-constrained devices," 2022, *arXiv:2205.03661*.

[56] A. Ullah, S. U. Rehman, S. Tu, R. M. Mehmood, F. Khan, and M. Ehatisham-ul-Haq, "A hybrid deep CNN model for abnormal arrhythmia detection based on cardiac ECG signal," *Sensors*, vol. 21, no. 3, p. 951, Feb. 2021.

[57] H. Ma, C. Chen, Q. Zhu, H. Yuan, L. Chen, and M. Shu, "An ECG signal classification method based on dilated causal convolution," *Comput. Math. Methods Med.*, vol. 2021, pp. 1–10, Feb. 2021.

[58] G. B. Moody, R. G. Mark, and A. L. Goldberger, "PhysioNet: A web-based resource for the study of physiologic signals," *IEEE Eng. Med. Biol. Mag.*, vol. 20, no. 3, pp. 70–75, May/Jun. 2001.

[59] L. Sörnmo and P. Laguna, "Electrocardiogram (ECG) signal processing," in *Wiley Encyclopedia of Biomedical Engineering*. New York, NY, USA: Wiley, 2006.

[60] T. Mahmud, S. A. Fattah, and M. Saquib, "DeepArrNet: An efficient deep CNN architecture for automatic arrhythmia detection and classification from denoised ECG beats," *IEEE Access*, vol. 8, pp. 104788–104800, 2020.

[61] A. Zarei and B. M. Asl, "Performance evaluation of the spectral autocorrelation function and autoregressive models for automated sleep apnea detection using single-lead ECG signal," *Comput. Methods Programs Biomed.*, vol. 195, Oct. 2020, Art. no. 105626.

[62] B. N. Singh and A. K. Tiwari, "Optimal selection of wavelet basis function applied to ECG signal denoising," *Digit. Signal Process.*, vol. 16, no. 3, pp. 275–287, May 2006.

[63] J. Pan and W. Tompkins, "A real-time QRS detection algorithm," *IEEE Trans. Eng. Biomed. Eng.*, vol. BME-32, no. 3, pp. 230–236, Mar. 1985.

[64] A. Creswell, K. Arulkumaran, and A. A. Bharath, "On denoising autoencoders trained to minimise binary cross-entropy," 2017, *arXiv:1708.08487*.

[65] Z. Li, X. Feng, Z. Wu, C. Yang, B. Bai, and Q. Yang, "Classification of atrial fibrillation recurrence based on a convolution neural network with SVM architecture," *IEEE Access*, vol. 7, pp. 77849–77856, 2019.

[66] M. Zubair, J. Kim, and C. Yoon, "An automated ECG beat classification system using convolutional neural networks," in *Proc. 6th Int. Conf. IT Converg. Secur. (ICITCS)*, Sep. 2016, pp. 1–5.

MD SHOFIQUL ISLAM received the B.Sc. degree in computer science and engineering from Islamic University, Kushtia, Bangladesh, in 2015. He is currently pursuing the M.Sc. (research based) degree with the Faculty of Computing, University Malaysia Pahang, Malaysia. After the consummation of B.Sc. degree, he joined as a Lecturer at the Department of Computer Science, First Capital University of Bangladesh (FCUB), Chuadanga, Bangladesh, in 2015. In 2016, he joined as a Senior Lecturer of computer science and engineering at the Atish Dipankar University of Science and Technology (ADUST), Dhaka, Bangladesh. His research interests include sentiment analysis, deep learning, machine learning, bioinformatics, and human brain and human–computer interaction. He has published more than ten research articles in his research field. In addition to his professional activities, he is working on various research projects with excellent programing knowledge in machine learning and deep learning. He received the Graduate Research Scheme Scholarship from the University Malaysia Pahang for his M.Sc. degree.

MD NAHIDUL ISLAM received the B.Sc. degree in electrical and electronic engineering from the Jashore University of Science and Technology, Bangladesh, in 2019. He is currently pursuing the M.Sc. degree with the Faculty of Electrical and Electronics Engineering Technology, University Malaysia Pahang, Malaysia. He is working as a Graduate Research Assistant at the Faculty of Electrical and Electronics Engineering Technology, Universiti Malaysia Pahang. His research interests include brain–computer interface, artificial intelligence, biomedical signal processing, image processing, and machine learning.

NORAMIZA HASHIM (Member, IEEE) received the Diplôme d'Ingénieur and D.E.A. degrees in image processing from the Université Jean Monnet, France, in 2002, and the Ph.D. degree in information technology under a joint Ph.D. Program between Multimedia University, Malaysia, and the Université de La Rochelle, France, in 2008. She is currently lecturing at the Faculty of Computing and Informatics, Multimedia University. She is a Professional Technologist under the Malaysian Board of Technologist. Her research interests include digital image processing, object recognition, computer vision, and machine learning.

MAMUNUR RASHID (Member, IEEE) received the B.Sc. degree in electrical and electronic engineering from the Pabna University of Science and Technology, Bangladesh, in 2016, and the M.Sc. degree from the Faculty of Electrical and Electronics Engineering Technology, University Malaysia Pahang, Malaysia. He has more than 40 publications. His research interests include brain–computer interface, biomedical signal processing, machine learning, and deep learning. He received the Graduate Research Scheme Scholarship from the University Malaysia Pahang for his M.Sc. degree.

BIFTA SAMA BARI (Member, IEEE) received the B.Sc. degree in electrical and electronic engineering from the Pabna University of Science and Technology, Bangladesh, in 2016, and the M.Sc. degree from the Department of Electrical and Electronics Engineering Technology, University Malaysia Pahang, Malaysia, in 2020. Her research interests include brain–computer interface, biomedical signal processing, machine learning, microwave imaging, and wireless communications. She was a recipient of the Graduate Research Scheme Scholarship from the University Malaysia Pahang.

FAHMID AL FARID (Member, IEEE) received the B.S. degree in computer science and engineering from the University of Chittagong, Bangladesh, in 2010, and the M.S. degree from the Faculty of Computer Science and Electrical Engineering, University of Ulsan (UOU), South Korea, in 2015. He is currently pursuing the Doctor of Philosophy (Ph.D.) degree in information technology with Multimedia University, Cyberjaya, Malaysia. From 2013 to 2014, he was a Research Assistant with the Embedded System Laboratory, UOU. In 2015, he was a Research Assistant with the Ubiquitous Computing Technology Research Institute (UTRI), Sungkyunkwan University, South Korea. His current research interests include artificial intelligence, algorithm design, computer vision, human–computer interaction, image and video analysis, power generation, and green technology. He received the Korean BK21 PLUS Scholarship Supported by the Korean Government for his M.S. degree, from 2012 to 2014. He also received an ICT Fellowship from Bangladesh Government, in 2014.