A MULTIDIMENSIONAL AND MULTI-VIEW FEATURE FUSED HYBRID DEEP LEARNING MODEL FOR ARRHYTHMIA DETECTION FROM ELECTROCARDIOGRAM SIGNALS

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KEYWORDS

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ABSTRACT

Arrhythmia is a highly prevalent chronic cardiac disorder in senior citizens and is related to the high severity including cardiovascular accidents, heart failure and myocardial ischemia. The ability to correctly detect and categorize arrhythmia rhythms from ECG readings is critical for lowering death rates.From this view-point, One Dimensional- Convolutional Neural Network (1DCNN) with priority model integrated voting mechanism is developed for arrhythmia classification. But, this model needs vast number of ECG signals and takes more time to train the model because of using cross-validation. Also, it lacks multidimensional and multi-view data abstraction which degrades the accuracy of recognizing arrhythmia from similar ECG signals. To resolve this, **Ar**rhythmia **D**iseases **D**etection **Net**work (ArddNet) model is proposed to recognize arrhythmia disorders efficiently from similar ECG signals. In this model, the ECG signal database is collected and pre-processed to remove the noisy signals. The noiseless ECG signals are classified into Regular (R), Supraventricular ectopic beat (S), Ventricular ectopic beat (V), Fusion beat (F) and Unknown beat (U) based on heart specialist labeling.Initially, the statistical and dynamic characteristics of the raw ECG signal are computed to obtain handcrafted features.Then,representation learning technique is utilized to identify time-invariant salient features using the pre-processed ECG signals. The sequence residual learning is used composed of 1DCNNand Variable Scale CNN (VSCNN) to capture the temporal features. The obtained handcrafted features and the deep features (time-invariant salient features and temporal features) are fed into the Bidirectional Long Sort Term Memory (BiLSTM) to get a new feature representation i.e., Multidimensional and Multi-view Feature Representation (MMFR) of the ECG signal. Moreover, this feature vector is fed to the softmax function for classifying arrhythmia and its types precisely. Finally, the experimental results illustrate that the ArddNet on MIT-BIH and Arrhythmia Data Set achieves an accuracy of 93.09% and 92.84%, respectively than the other classical deep learning models for arrhythmia identification.

1. INTRODUCTION

Arrhythmia is an essential set of cardiovascular disorders, which are categorized by deliberate, rapid, or abnormal heartbeats [1-2]. They might happen alone or combined with other cardiovascular disorders. Additionally, a few severe arrhythmias might happen abruptly and result in an unexpected fatality, stroke, cardiac arrest, or coronary artery disorders [3]. Arrhythmia leads to serious health problems and perhaps death if not treated promptly, since it is the top cause of death worldwide [4]. Though the exact etiology of heart disorder has yet to be resolved, many threat aspects contribute to its development. A variety of risk factors add to the possibility of acquiring cardiovascular disorder. Hypertension, drinking, dyslipidemia, mellitus, malnutrition, family history, age, and other factors are among the most important [5-

6]. The recognition and categorization of patients at risk of cardiovascular disease is a key challenge in the healthcare sector.

In the case of cardiovascular disease recognition and categorization, early detection is crucial in the early stages of treatment, which reduces the risks associated with it. Cardiovascular disorders can be predicted using a range of blood tests and imaging studies [7]. Statistical data is also utilized to coordinate findings and predict the presence of sickness based on outcomes and procedures. The most frequent and critical diagnostic diagnostics are echocardiography (echo), Magnetic Resonance Imaging (MRI) and Computed Tomography (CT) [8]. Although MRI and CT scans produce high-quality cardiac images, they are not used for prediction due to their lengthy collection time, limited availability and use of radiotherapy. The ECG is utilized to tackle this challenge since it is a graphical representation of the repolarization and depolarization of the ventricles and atria [9].

ECG is a quasi, low-cost and reliable diagnostic technique that reveals the particular variations in electric signal behavior over a period [10]. It is a key paradigm in arrhythmias recognition and prognosis. ECG signals have essential morphological features, which are typically captured by ECG assessment tools like echo, 24-hour Holter and smart sensor. Also, they are broadly utilized in the examination of heart activity [11]. Nowadays, arrhythmias are treated by the physical analysis of the ECG data. To recognize arrhythmias using ECG data without human intervention, forecasting tools should examine the structural features of ECG waves and the relationship among heartbeats. By using such relationships, the irregular heartbeats are identified and their categories are determined [12]. The Federation for the Development of Medical Instrumentation divides ECG data into five kinds(R, S, V, F and U) based on cardiologists' assertions which are then employed in a categorization system. All ECG data have a distinct inference and need various desired therapy under various cardiac activity states.Recently, visual examination depending on cardiologists is an essential diagnostic standard [14]. It takes a large number of skilled professionals to accurately detect the kind of signal, which not only tends to a difference between subjective assessment and the real condition but also takes a significant amount of time and power. So, it is critical for cardiologists to automatically recognize irregular cardiac rhythms before medical therapy. During the earlier centuries, ECG signal detection and categorization have become a well-established technology that may successfully aid physicians in clinical diagnosis. Classical template matching approaches are used in the appropriate automated classification systems. Such approaches have established significant advances; however, the sophisticated feature mining procedure requires a significant amount of computational power [15]. Deep Learning (DL) has been a popular object detection approach these days [16-17]. It is a complete training strategy, which did not need a time-consuming mining procedure. From this perspective, Wang et al. [18] developed a novel ECG detection approach for arrhythmia classification model that makes use of the priority model integrated voting mechanism and the dual channel 1DCNN model. However, this model fails to capture the time-invariant salient and temporal features and it lacks multidimensional and multi-view data abstraction which degrades the accuracy of recognizing arrhythmia from similar ECG signals.Also, it needs a vast number of ECG signals and takes more time to train the model because of using cross-validation.

Therefore in this article, the ArddNet model is proposed to recognize arrhythmia disorders efficiently from similar ECG signals.In this model, the ECG signal database is collected and preprocessed to remove the noisy signals. Then, the noiseless ECG waves are partitioned into R, S, V, Fand U based on the labeling from heart specialists.Initially,handmade features are produced by computing statistical properties (min, max, mean, normal deviation, kurtosis, and skewness) ofthe raw ECG signals and dynamic characteristics (heart rate variation attributes from RR intervals).Then, the representation training is applied to generate the dynamic characteristic miner, frequency characteristic miner and pattern miner to jointly capture time-invariant salient characteristics from the ECG signals.Also, the sequence residual training comprises of 1DCNN and VSCNN utilized to capture the temporal features. Both the as time-invariant salient features and temporal features are considered as the deep features. The obtained handcrafted features and the deep features are fed into the Bi-LSTM to achieve MMFR of the ECG signal. In addition, this feature vector is fed to the softmax function for recognizing arrhythmia and its types accurately. This model effectively resolves the cross-validation complexity and improves the multidimensional and multi-view data abstraction for the early prediction of arrhythmia.

The rest of the article is organized as follows: Section II discusses the many studies linked with arrhythmia detection and classification models. Section III describes the ArddNet model, whereas Section IV demonstrates its validity. Section V summarizes the whole research and addresses forthcoming enhancements.

2. LITERATURE SURVEY

Darmawahyuni et al. [19] constructed a generalization DLtechnique for ECG signal categorization in intra and inter-patients' scenarios. Also, a 1DCNN structure was adopted to categorize ECG signals according to the rhythm and beat characteristics. On the other hand, the preprocessing was not effective in the scenario of ECG signals that contain several leads, noises and sampling frequencies. Also, the partition of the different wave categories from the ECG signals was not conducted before the categorization.

Mathunjwa et al. [20] designed an efficient ECG recurrence plot-based arrhythmia categorization scheme. The ECG time series was partitioned and transformed using a recurrence plot. A 2-level categorization was adopted, using ResNet18 for noise and ventricular fibrillation, and ResNet50 for normal, atrial flutter, early atrial dilation and preterm ventricular movements.However, the efficiency of classification was influenced by imbalanced data. Also, the memory requirement and network complexity were high because of color ECG scans.

Madan et al. [21] developed a hybrid deep learning-based model to automatically recognize and categorize arrhythmia from ECG signals. Initially, 1D-ECG signals were converted into 2D Scalogram images using Continuous Wavelet Transformation (CWT) to remove the noise and capture the characteristics. After that, 2D-CNN and the LSTM network were combined to categorize arrhythmias. But, the computation difficulty was high because of using CWT.

Irfan et al. [22] designed a new multi-modal deep learning method, which combines different networks such as CNN and LSTM by stacking similar layers in each network for detecting arrhythmia from the ECG signals. But, its computational cost was high because of the integration of more networks.

Islam et al. [23] created a distinctive composite approach for detecting arrhythmia that uses the Bidirectional GRU-BiGRU-BiLSTM and a multi-layered inflated CNN.The ECG signal data was preprocessed using Chebyshev type-II filtering and Daubechies wavelet to remove noise and discontinuities. A Generative Adversarial Network (GAN) was used to solve imbalanced signal classes. BiGRU-BiLSTM network was used to create united features and recognize arrhythmia.However, it needs larger and highly varied databases to improve the model's generalizability.

Rafi &Ko [24] adopted HeartNet to categorize the ECG signals into various classes and recognize arrhythmia. The method uses a multi-head attention mechanism on a CNN architecture enabling adversarial data synthesis to create new training examples when there are insufficient labels and unbalanced class distribution. But, it failed to converge its prediction when there were several negative instances.

Kumar & Chakrapani [25] presented the ECG arrhythmia categorization technique depending on the Fast Fourier Transform (FFT) and improved AlexNet (iAlexNet) classifier. In this technique, the FFT was used to extract features, whereas those extracted features were classified using the iAlexNet to recognize arrhythmia disorder. But, it was not deep compared to the advanced deep learning models.

Mohonta et al. [26] created a DL model that uses the CWT scalogram based on the sign of the arrhythmia. The CWT of the ECG data was obtained to train a 2D CNN for automatically detecting arrhythmias. In contrast, it requires a large-scale database with more arrhythmia types.

Kim et al. [27] classified Arrhythmia using Residual Network Combined with LSTM. In order to achieve distinguishable intersubject qualities, this method utilizes ResNet in conjunction with squeeze-and-excitation (SE) block and BiLSTM to extract features from raw ECG data. Previous augmentation strategies were outperformed when the new method was used with SMOTE to overcome imbalance issues in the arrhythmia categorization. However, the model needs longer to train and more computing power than is often available in a clinical context.

Daydulo et al. [28] proposed detecting cardiac arrhythmias using a deep learning model and temporal frequency representations of ECG data. The model employs an analytic Morse wavelet to convert time series data into 2D images of time-frequency depiction, showing both latent and obvious aspects of fluctuating signals. Fine-tuned pre-trained AlexNet and ResNet 50 was used for the classification performance.However, the computation time of this model was high.

3. PROPOSED METHODOLOGY

In this part, the ArddNet method for ECG signal classification and arrhythmia recognition is briefly described. An overall pipeline of this work is depicted in Figure 1. First, the input ECG recordings are pre-processed using various methods. Then, manual attributes are derived using the raw ECG signals using statistical measures. Also, time-invariant salient and temporal features are retrieved from the pre-processed signals by employing the 1DCNN and VSCNN model. After extracting various features, those are merged and fed into BiLSTM to get a final MMFR vector which is learned by the softmax function to identify arrhythmia events. Moreover, the recognition efficiency of this model is validated by the test ECG recordings, i.e. unlabeled data.

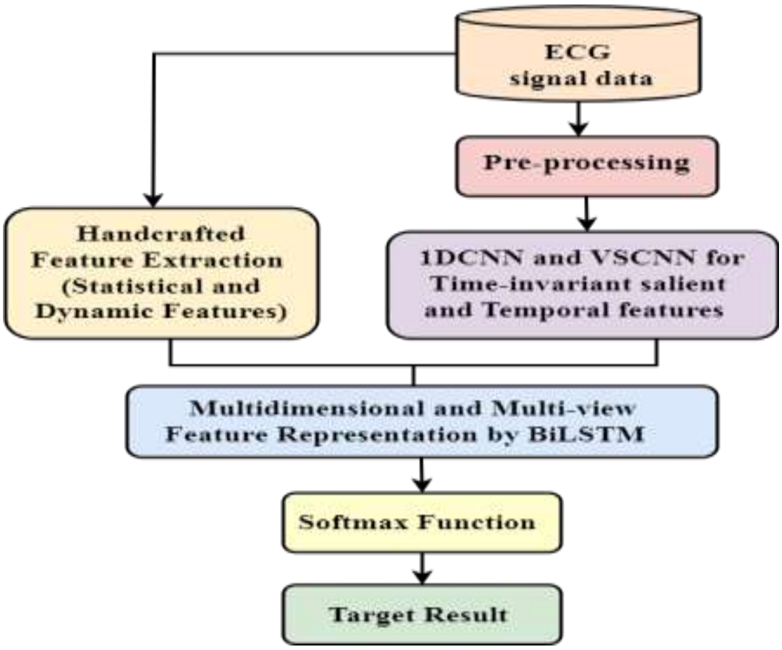

Figure 1. Overall Pipeline of ArddNet Model for Arrhythmia Recognition

3.1 Database Description

In this study, two benchmark databases are considered, including:

1. **MIT-BIH arrhythmia database:** It is a public PhysioBank corpus [29-31], which is broadly considered to investigate the identification and categorization of ECG signals.

The research includes 48 half-hour ECG recordings from 47 subjects, each with two leads (leads II and V) obtained by different sensors. Such participants involve 19 female aged from 23 to 89 and 26 male from 32 to 89. ECG recordings have 17 categories: regular sinus pulse, pacemaker pulse and 15 categories of heart disorders (for all classes, a minimum of 10 signal fragments are acquired). The recordings were digitized at 360 pulses/sec and 11-bit resolution/channel over a 10mV. All recordings were independently labeled by 2 or many specialists; discrepancies have been solved to get the machine-understandable benchmark labels for all heartbeats (approximately 110,000 labels) contained in the corpus. For the evaluation, 1000, 10-second (3600 pulses) pieces of the ECG data (non-overlapping) have been arbitrarily chosen. The waves obtained from a single lead, i.e. the MLII are only utilized.

2. **Arrhythmia Data Set:** It is also a public corpus [32-33] used to categorize the existence and non-existence of arrhythmia in one of the 16 classes. It has 279 elements, 206 of which are linear ranged and the remaining is nominal. Class 1 is the normal ECG class, Classes 2 to 15 are the various categories of arrhythmia and Class 16 is the remaining uncategorized ones.

After acquiring these corpora, filtering-based denoising is applied to eradicate noise from all ECG recordings. The preprocessed samples are divided into R, S, V, Fand U depending on the benchmark annotation. Additionally, time-shift and noise augmentation schemes [34] are applied to 2 distinct sets of ECG samples, namely Collection A including 251 samples, and Collection B including 361 samples to solve the class imbalance problem.

3.2 Handcrafted Feature Extraction

The handcrafted features are extracted by determining the statistical and dynamic features of the raw ECG recordings which is briefly illustrated below.

***Statistical features*:** Average (μ) is calculated by the mean of each data points in the ECG recordings. The signal variances quantifies the sample points which is deviated from their median which is calculated by

$$variance,\ \sigma^2 = \frac{1}{N}\sum_{i=1}^{N}|X_i-\mu|^2 \tag{1}$$

In Eq. (1), X_i denotes the input ECG indication, N defines its length, and μ denotes the signal mean. Similarly, the standard variance σ is calculated as:

$$standard\ variance, \sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}|X_i-\mu|^2} \tag{2}$$

Skewness generates the imbalance of the ECG signal relative to its mean. Positive and negative skewness indicates that the signal is inclined towards the left and right respectively which is determined in Eq. (3),

$$skewness = \frac{\mu^3}{\sigma^3} \tag{3}$$

In Eq. (3), μ and σdenotes the signal mean average and standard variance.

Kurtosis: It is a measure of a signal's peak which is critical to normal distribution adjusted to 0. Positive excess kurtosis suggests a high peak while negative kurtosis shows a flat-topped curve. Eq. (4) defines the kurtosis computation.

$$kurtosis = \frac{\mu^4}{\sigma^4} \tag{4}$$

***Dynamic features*:** The heart rate variability characteristics generally assesses the variation of continuous heart rate cycle, which is a significant index for recognizing arrhythmia. In this study, 9 distinct heart rate variability indexes are obtained from the lead II ECG recordings.

- **SDNN:**The typical deviation of the Inter-Beat Interval (IBI) of typical sinus rhythms is measured in milliseconds (ms).
- **SDANN:**It is the average range of median Normal-to-Normal (NN) durations for all 5 minute intervals throughout a 24-hour period, measured in ms.

- **RMSSD:** The RMSSD is obtained by determining all successive interval variance between pulses in ms.The result is summed and multiplied before calculating the square root of the sum which represents the beat-to-beat change in the heart's rhythm.
- **NN50:**The amount of neighboring NN intervals that differ from each other by more than 50 ms requires a 2-minute epoch.
- **pNN50:**For a frequency larger than 50 ms, a 2-minute period is necessary to calculate the NN50, pNN50, and RMSSD from the discrepancies across subsequent NN intervals.
- **Average Heart Rate:**It is the mean variation between the maximum and minimum heart rates during all respiratory cycles.

3.3 Deep Feature Extraction and Fusion

On the other hand, the pre-processed ECG recordings are given to the representation learning and 1DCNN and VSCNN network. The representation learning is applied to capture the time-invariant salient features and the sequence residual learning which composed of1DCNN and VSCNN is used to capture the temporal features from the ECG signals. The key concept of the ArddNet is to create a robust feature mining for capturing characteristics from ECG recordings. This network can simply adapt to various databases by transfer learning strategy. The structure of the ArddNet is depicted in figure 2 which is majorly relies on the ID-CNN and VSCNN with BiLSTM model.

As shown in figure 2, the 1DCNN network includes three convolutional (Conv) units, two fully connected (FC) with non-linearlayers (pooling, batch normalization (BN), Rectified Linear Unit (ReLU) and softmax).The proposed VSCNN model consist of 3 parallel Convblocks for representation training, whereas 7 Conv layers, 2 residual learning modules, 2 max-pooling layers, single global mean pooling. The extracted features from both the modules are passed to the 2-BiLSTM model, 2 FC layers and one softmax layer for sequence residual training.

The 1DCNN generates two convolutional units from representation learning input which is subsequent to max-pooling, BN and ReLU, with only the latter convolutional units preceded by global average pooling. The dropout, BN and ReLU layers will be accompanied prior to FC layer. The proposed VSCNNhas 3 parallel CNN such as dynamic characteristic miner, frequency characteristic miner and pattern miner. The frequency characteristic miner has 4 1D Conv units and 2 max-pooling including the major kernel dimension of sampling rate $s_r \times 4$ and stride dimension $s_t/2$ for the 1D Convunit to obtain the occurrence elements. The successive kernel and stride dimensions are selected by hyperparameter adjustment.

Likewise, the pattern miner involves 4 1D Conv units and 2 max-PUs. But, the fine-grained CNV including kernel and stride dimensions assigned as $s_t/2$and $s_r/16$, correspondingly are utilized to find the emergence of different ECG waves. The successive kernel and stride dimensions are selected using hyperparameter adjustment. The incoming signals are redesigned into a 2D tensor and passed to the dynamic characteristic miner. It has 2D Conv units, batch regularization, max-pooling and squeeze-expansion units. So, the results from these 3 CNN layers are aggregated and passed to the sequence residual training module.

The sequence residual training is performed to capture the sequential characteristics from the series of characteristics mined in the preceding module. In this training,both the handcraft and deep features are fed into the 2 BiLSTM to determine a MMFR. The 2 BiLSTM model is applied to train sequential data that facilitates the encoding of history and upcoming data using 2 separate Bi-LSTM. A skip link is used to execute the residual operation and facilitate the fusion of temporal characteristics and earlier captured characteristics from the CNNs.

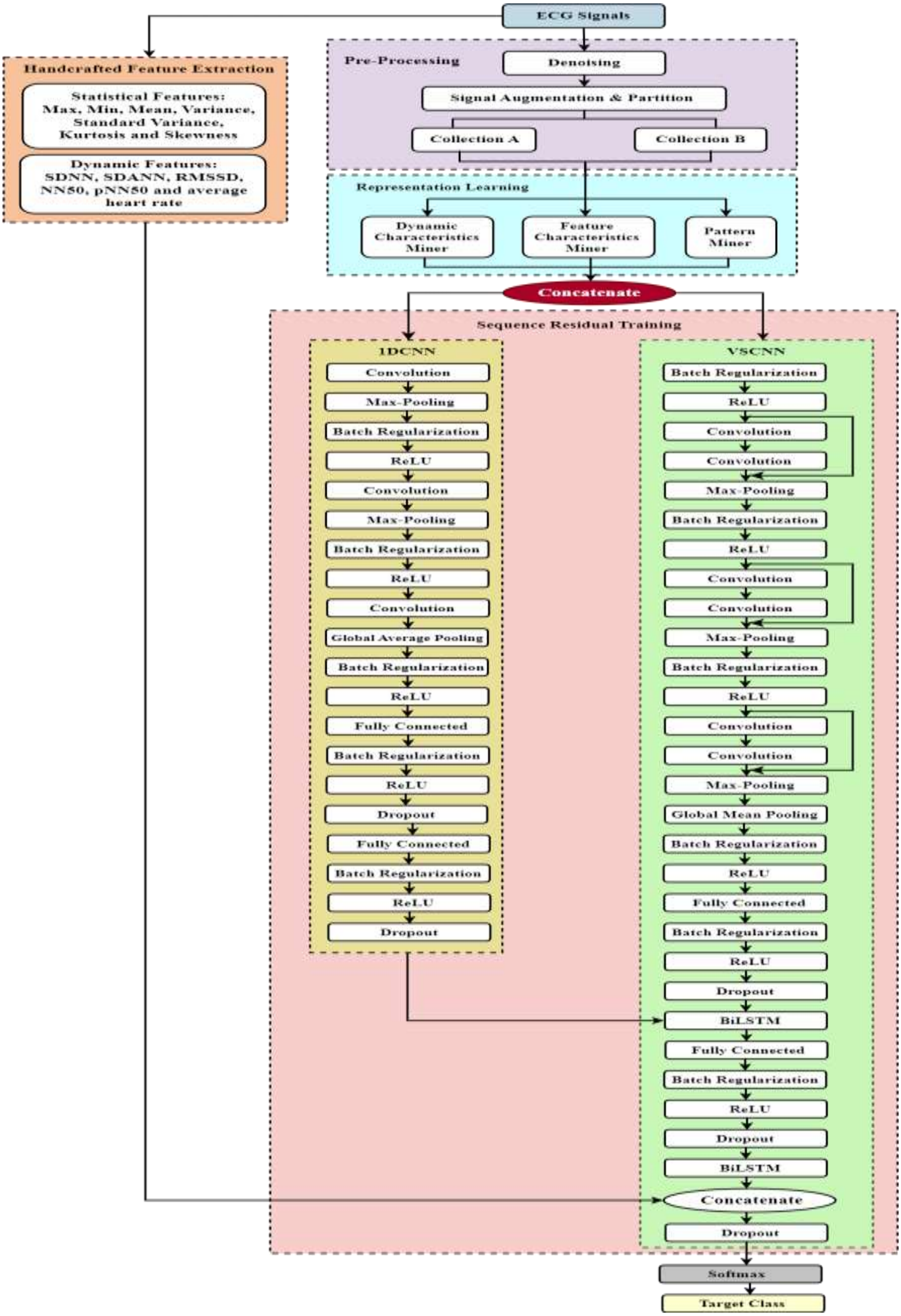

Figure 2. Overall Architecture of ArddNet Model

The aggregated characteristics vector is then passed to the softmax unit, which determines the probability of five different ECG signal waves and identifies the arrhythmia disorder categories.The obtainedMMFR results are incorporated into the softmax, ensuring that the model is trained completely in a sequential order. Finally, the trained model is applied to categorize the ECG recordings to identify different arrhythmia types.The ArddNet model improves the recognition of various arrhythmia pulses from ECG data effectively in accordance with the MMFR values.Table 1 provides a comprehensive overview of the proposed network configuration of 1DCNN+VSCNN. Table 2 depicts thenetwork configuration of BiLSTM. Since, theVSCNNmodel is upgraded version of 1DCNN so both the models shares the same parameter configuration.

Table 1. Configuration details of 1DCNN+VSCNN

Model Parameters	**Ranges**
No. of Convolutional Kernels	64
Feature Map	64
Batch Size	128
Epochs	35
Optimizer	Adam
Decay rate	0.0001
Momentum	0.9
Learning Rate	0.001
Activation Function	ReLU
Dropout	0.3
Loss factor	Cross Entropy (CE)

Table 2 BiLSTM Parameter Configuration

Hyperparameters	**Range**
Batch size	512
Learning rate	0.001
Number of epochs	15
Number of hidden layers	4
Hidden neurons	256
Dropout ratio	0.5
Activation function	$tanh$
Output neuron	1
Optimizer	Adam
Loss factor	Mean squared error (MSE)

Algorithm: ArddNet model
Input: Collected ECG signals
Output: Arrhythmia Prediction
Start
{{
\\ Training Set
Pre-process the collected signals to remove the noises
Augment and divide the pre-processed signals as A and B
Integrate the signals A and B for representation learning (Dynamic, Feature and pattern miners)
Combine the representation learning to evaluate theheart rate variability indexes
Input the features independently into 1D-CNN and VSCNN-BiLSTM for sequence learning

Extract the hand-crafted features from the ECG signals
Integrate the deep and hand-crafted features into the softmax classifier for desired output label
Train the model by Rectified Linear Unit (ReLU)to get the trained model
}
{
\\ Testing Set
Obtain the trained model and validate it
Test the data by using the trained model to estimate the desired arrhythmialabels
Evaluate the efficiency of prediction;
End
}
}

The proposed ArddNet effectively alleviates the difficulty of the cross-validation process and enhances the multidimensional and multi-view data abstraction to increase the efficiency of identifying arrhythmia and its types rapidly.

IV. PERFORMANCE EVALUATION

This section evaluates the effectiveness of ArddNet techniqueby implementing it in MATLAB 2019a using the MIT-BIH and Arrhythmia Data Set (discussed in Section 3.1). The collected dataset is splitted into 70% for training and 30% testing. As well, a comparative analysis is carried out to understand the improvement of the ArddNet model contrasted to the existing models, including 1DCNN [18], BiGRU-BiLSTM [23], HeartNet [24], FFT-iAlexNet [25] and ResNet50 [28]. The efficacy of the suggested and existing models is evaluated by the following assessment metrics:

- **Accuracy:**It is the proportion of the number of exact identifications of normal and arrhythmia cases to the overall cases analyzed.

$$Accuracy = \frac{True\ Positive\ (TP) + True\ Negative\ (TN)}{TP + TN + False\ Positive\ (FP) + False\ Negative\ (FN)} \quad (5)$$

In Eq. (11), TP represents the number of well categorized normal beats, while TN represents the number of properly classified arrhythmia beats. In addition, FP indicates the number of arrhythmia beats that were incorrectly categorized as normal, whereas FN represents the number of normal beats that were incorrectly classified as arrhythmia.

- **Precision:**It is computed as follows

$$Precision = \frac{TP}{TP + FP} \quad (6)$$

- **Recall:** It is calculated using the Eq. (7)

$$Recall = \frac{TP}{TP + FN} \quad (7)$$

- **F-score $(\boldsymbol{F})$:** It is evaluated by Eq. (8)

$$F = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (8)$$

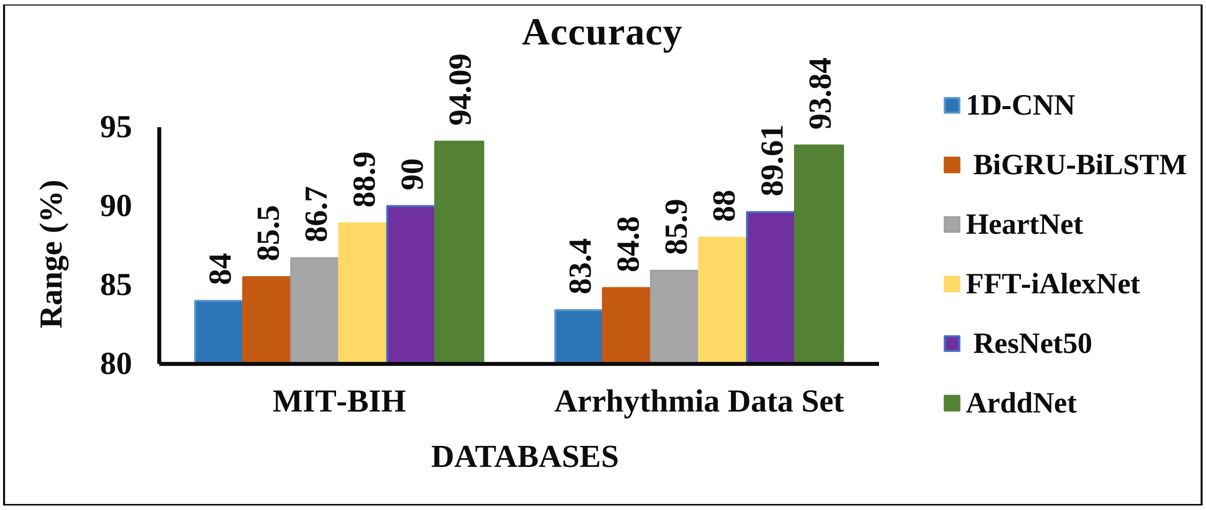

Figure 3. Comparison of Accuracy

Figure 3 displays the accuracy (in %) realized by the different arrhythmia identification and classification models applied to 2 different databases. It addresses that the accuracy of the ArddNet model on the MIT-BIH database is 10.82% greater than 1DCNN, 8.88% greater than BiGRU-BiLSTM, 7.37% greater than HeartNet, 4.71% greater than FFT-iAlexNet and 3.43% greater than ResNet50models. Similarly, the accuracy of the ArddNet model on the Arrhythmia Data Set is 11.32% greater than 1DCNN, 9.48% greater than BiGRU-BiLSTM, 8.08% greater than HeartNet, 5.5% greater than FFT-iAlexNet and 3.62% greater than ResNet50 models. This is because of capturing both time-invariant and temporal characteristics along with the deep features from the ECG recordings to classify arrhythmia classes.

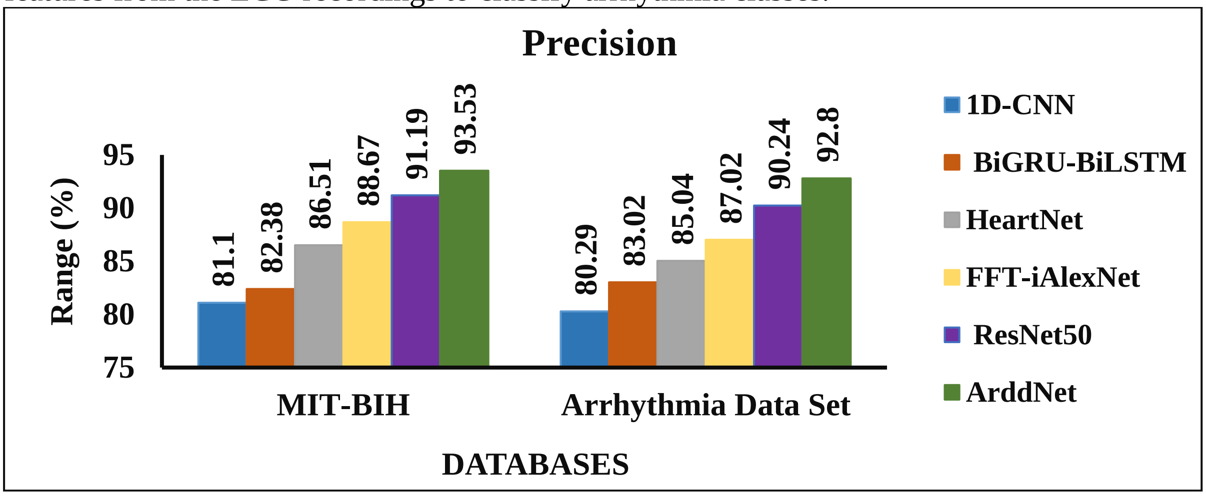

Figure 4. Comparison of Precision

In Figure 4, the precision (in %) of the ArddNet model is compared with various arrhythmia identification and classification models applied to 2 different databases. It observes that the precision of the ArddNet model on the MIT-BIH database is 15.33% greater than 1DCNN, 13.53% greater than BiGRU-BiLSTM, 8.11% greater than HeartNet, 5.48% greater than FFT-iAlexNet and 2.57% greater than ResNet50 models.Similarly, the precision of the ArddNet classifier on the Arrhythmia Data Set is 16.83% greater than 1DCNN, 12.98% greater than BiGRU-BiLSTM, 10.30% greater than HeartNet, 7.79% greater than FFT-iAlexNet and 3.95% greater than ResNet50 models due to the implementation of representation training and sequence residual training processes.

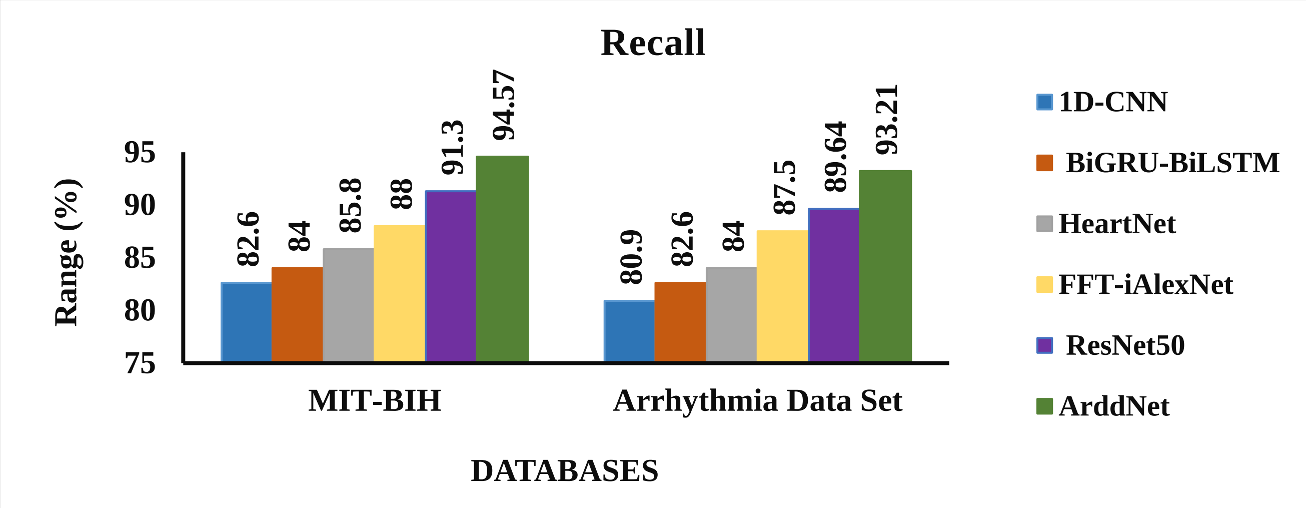

Figure 5. Analysis of Recall

Figure 5 demonstrates the recall (in %) obtained by the different arrhythmia identification and classification models applied to 2 different databases. It analyzes that the recall of the ArddNet model on the MIT-BIH database is 14.49% greater than 1DCNN, 12.58% greater than BiGRU-BiLSTM, 10.22% greater than HeartNet, 7.47% greater than FFT-iAlexNet and 3.58% greater than ResNet50 models. Similarly, the recall of the ArddNet model on the Arrhythmia Data Set is 15.22% greater than 1DCNN, 12.85% greater than BiGRU-BiLSTM, 10.96% greater than HeartNet, 6.53% greater than FFT-iAlexNet and 3.98% greater than ResNet50 models. This realizes that the ArddNet model increases the recall of identifying and categorizing arrhythmia classes compared to the other models because of improving the feature learning tasks.

Figure 6 portrays the F-score (in %) achieved by the different arrhythmia identification and classification models applied to 2 different databases. It indicates that the F-score of the ArddNet model on the MIT-BIH database is 15.35% greater than 1DCNN, 13.41% greater than BiGRU-BiLSTM, 11.43% greater than HeartNet, 9.89% greater than FFT-iAlexNet and 8.79% greater than ResNet50 models. Similarly, the F-score of the ArddNet model on the Arrhythmia Data Set is 14.58% greater than 1DCNN, 12.28% greater than BiGRU-BiLSTM, 10.16% greater than HeartNet, 7.75% greater than FFT-iAlexNet and 5.68% greater than ResNet50 models.

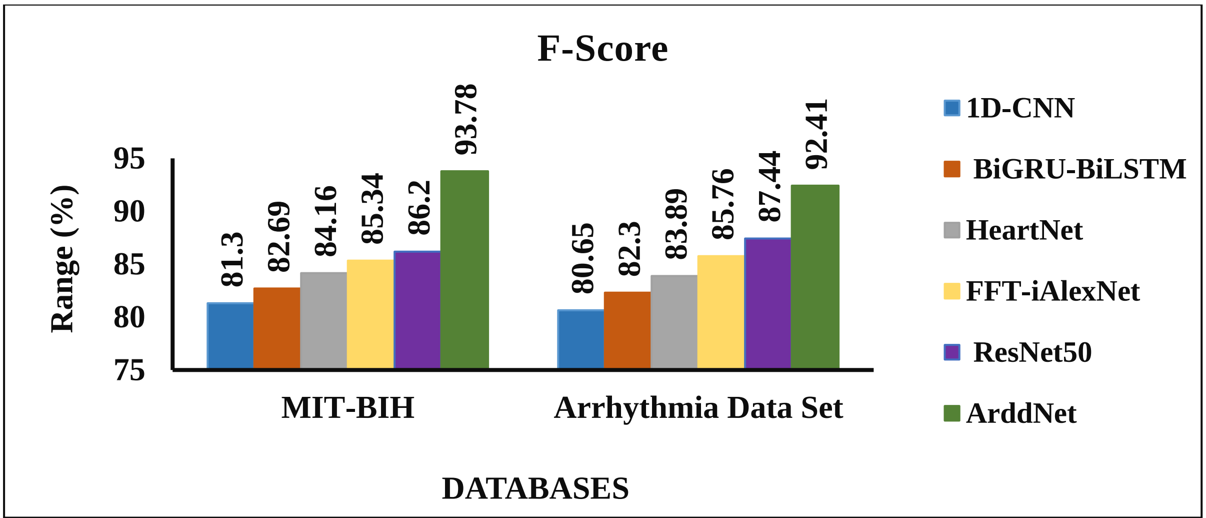

Figure 6. Comparison of F-score

Thus, it summarizes that the ArddNet model maximizes the efficiency of identifying and categorizing arrhythmia classes compared to all existing models due to the consideration of both representation and sequence residual training stages, which enhances the feature mining and classification.

5. CONCLUSION

In this article ArddNet technique is suggested for the prediction of arrhythmia disorders from ECG signals. This model collects and pre-processes the ECG signal database to remove noisy signals, partitioning them into different ECG segments. Handcrafted features are obtained from the raw ECG signal and representation learning is applied to capture time-invariant salient features. Sequence residual learning is used to capture temporal features. The handcrafted features and deep features are fed into the Bi-LSTM to create MMFR of the ECG signal. This feature vector is then used to classify arrhythmia and its types. Experimental results show ArddNet achieves an accuracy of 93.09% and 92.84% compared to other classical deep learning models for arrhythmia identification.

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