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Automated Detection of Arrhythmia in ECG Signals using CNN

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Abstract: In this world, around 31% of the deaths are commonly caused because of cardiovascular diseases. Around 80% of sudden deaths occur due to cardiac arrhythmias and heart diseases. The mortality rate has increased for cardiac disease and therefore early heart disease detection is significant to preclude patients from dying. At the initial phase, the heart disease is detected by analyzing abnormal heartbeats. The existing models failed to select the features before performing the extraction of features. The developed model examined various databases to surpass the overfitting issue. Therefore, in the present research work, the CNN based Continual Normalization (CN) classifier is used to speed up the training to a higher learning rate to enable simpler learning for the standard deviation of the neurons' output. The extracted features were used to classify ECG signals into 5 important classes named as N, S, V, F & Q which denote the kinds of arrhythmia. The findings revealed that the proposed CNN based Continual Normalization technique obtained an accuracy of 99.2 % which is better when compared with the existing research namely the Dual Fully Connected Neural Network that obtained 93.4 % of accuracy, and the Optimization-Enabled Deep Convolutional Neural Network that accomplished 93.19 % of accuracy.

Keywords: *Cardiovascular Disease, Electro Cardio Gram, MIT-BIH, Convolution Neural Network Based Continual Normalization Classifier.*

1. Introduction

Heart diseases are commonly occurring diseases in humans regardless of age during an individual's life cycle. Irregular heartbeats are called arrhythmia which are classified into normal and fatal [1]. The prediction of arrhythmia is potentially life saving as it prevents further escalation of heart diseases. Arrhythmia is reflected in the ECG [2]. Arrhythmia has been associated with increasing mortality rates of heart failure and stroke resulting in heart attacks [3]. Thus, the analysis of ECG signals is a vital task which requires a perfect solution to predict reliably [4]. This is considered an important motivation conducting further research [5]. An abnormal heartbeat rhythm detection is based on irregular frequencies identified in the ECG signals [6]. There are various medical imaging techniques used for heart diagnosis such as the non-invasive diagnosis techniques that are used for arrhythmia detection [7]. The ECG diagnosis cost is cheaper and simpler for conducting researches [8]. The ECG records the heart electrical activities that are used mainly for arrhythmia disease diagnosis concerning the clinical practice [9]. From the existing works, the quality of ECG recordings is contaminated with noise signals [10]. Therefore, the size of the dataset and the ECG features are considered to analyse their impact on classification results [11]. The algorithms and methods are used for analyzing their influence on results [12]. The prior researches mostly used Support Vector Machine (SVM) for the classification of normal ECG and arrhythmia ECG signals [13]. The SVM classifier used in the existing models failed to sort out a various set of patterns of ECG signals for arrhythmia detection when the features were extracted [14]. The existing works showed drawbacks that are overcome by the proposed research [15]. The proposed research work uses a smart filter which eliminates noise before the classification of signals into normal and arrhythmia classes. The mathematical model having wavelet and hidden Markov is designed for extraction of important features from the ECG signals to detect the cardiac arrhythmia patterns. The contributions of the research work are given as follows:

- To acquire ECG signals from MIT-BIH that consists of arrhythmia diseased patients reports.
- To develop a Convolution Neural Network (CNN) based Continual Normalization (CN) classifier to speed up training and use higher learning rates, to make the learning easier for the standard deviation of the neuron's output.

The organization of this study is given as follows: Section 2 delivers a literature analysis that includes reviews of existing methods. Section 3 explains the proposed method technique that explains about the steps involved in it. Section 4 describes the results and comparison. Section 5 discusses the conclusion and future work.

2. Literature Review

The reviews detailed below are the researches that involved

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arrhythmia disease detection using the MIT-BIH database.

Wang [16] developed a classification model using a dual fully connected neural network. The existing methods showed difficulty in diagnosing arrhythmia for distinct people based on the heartbeat rhythms that were evaluated for each of them. This research work performed an automated arrhythmia detection based on the Dual Fully connected CNN model which classified the heartbeats. The developed model used the MIT-BIH and MIT Supra Ventricular Arrhythmia for evaluation of the results. The model consisted of a tool that automatically detected arrhythmia from the ECG signal. The data requested was not adequate to train the complex network structure.

Sangaiah [17] developed an intelligent learning approach to improve the classification of ECG records and to perform arrhythmia analysis. The developed model had been tested and trained for arrhythmia classification with the ECG records taken from the MIT-BIH. The main noises that were eliminated from the ECG signals were the baseline wander, electromyography, and power line interferences. An Internet of Medical Things (IoMT) approach was used to deploy the arrhythmia identification but could not be applied to real-time applications.

Atal and Singh [18] developed an optimization Enabled Deep CNN model for arrhythmia classification of the ECG signals. The developed model was utilized for arrhythmia classification but implementation was a hectic challenge when the developed model performed the automated monitoring and classification process. Handling the dynamic features based on the experimental signal using raw input signals with more datasets was difficult.

Mathunjwa [19] developed a CNN for performing ECG arrhythmia classification which depends on recurrence plot. The main aim was to design the model using deep learning to classify arrhythmia based on the segments for 2D recurrence. Next, the normal, AR, and premature VF categories were separated. The developed model mainly faced the limitation of imbalanced data as the data was not distributed equally throughout the database.

Huang [20] implemented a Short-time Fourier transform-based Spectrogram and CNN to classify ECG arrhythmia. Conventional approaches required two stages for the identification of cardiac arrhythmia: feature extraction as well as pattern classification, which proved to be time consuming. To address the mentioned problem, an autonomous system based on artificial intelligence was used wherein the CNN was utilized to train a huge volume of data for feature extraction to enable it to recognize arrhythmia with greater expertise. A 2-Dimensional Deep Convolutional Neural Network (2D-DCNN) was used to classify ECG arrhythmia into five categories of heartbeats: N, S, V, F and Q. Even with the exclusion of other stages, the implemented model reached higher levels of accuracy. However, the number of phases was raised for every iteration, and the convergence process suffered substantial oscillations in every iteration.

Extreme Learning Machine (ELM) was combined with an efficient and reliable 12-layer deep one-dimensional (1-D) CNN by Kuila et al. [21] for classification. The presentation of proposed method was expressed using the well-known, publicly accessible MIT-BIH Arrhythmia as well as level of accuracy achieved by the model was associated with the prior similar types of work. The wavelet self-adaptive threshold denoising technique and numerous heart beat characteristics were found using the combined ELM and CNN. To improve categorization, hidden neurons were used to operate the ELM. To further increase the accuracy, a variety of features needed to be taken into account.

Fuzzy Clustering Network (Fuzz-ClustNet) and deep learning were created by Kumar et al. [22] for the purpose of identifying arrhythmia. The ECG signal was denoised using the IIR Notch Filter and FIR Filter to remove motion noise, power line interference, baseline drift, and other types of noise. Christov segmentation was then applied to make sure that the data augmentation and segmentation were carried out in order to minimize the effects of class imbalance. Additionally, CNN was employed to extract the features, and the resulting features were then subjected to fuzzy clustering in order to categorize ECG signals. The Deep Learning approach's hyperparameters were tuned using the Random Search heuristic. Due to the misclassifications, the number of positive classes were lower for the Fuzz-ClustNet.

3. Proposed Method

Here, the Fig. 1 shows the block diagram of proposed method's which uses the MIT-BIH dataset consisting of the ECG signals. After extraction of ECG signals, ECG arrhythmia signal classification is performed using a Continual normalized CNN model. Totally, 5 classes are classified from the ECG, they are, N (Normal beat), S (Supraventricular ectopic beat), V (Ventricular ectopic beat), F (Fusion beat) and Q (Unknown beat).

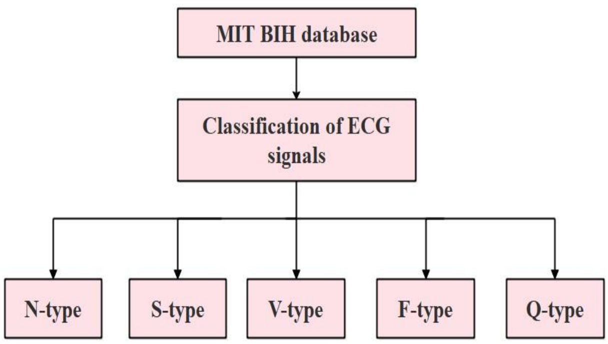


Fig. 1. Block diagram of the proposed research

3.1. Data preparation using MIT-BIH database

Here, 60% of the inpatient recordings were obtained from the database which has 23 records that are numbered from 100 to 124 inclusive of other missing statistics. The numbers were approximately chosen from the set that has a total of 200 to 234 inclusive data by some missing statistics. The numbers were chosen from similar sets to add a variety of rates. There are a total of 48 records of 30 minutes duration. The first group of records is intended to assist as the representative sample for the diversity of artifacts and waveforms that are utilized for arrhythmia detection in the clinical usage. The random numbers were used for the selection of tapes and the half-hour segments. The segments were selected and were excluded only if the 2 ECG signals were of adequate quality as per human experts' analysis.

The records from the second group include complex junctional, ventricular, and supraventricular arrhythmia abnormalities. There are several records in the rhythm which are chosen as features. The variation in the QRS morphology, or the quality, presented a difficulty for arrhythmia detection. Totally 25 male subjects from the age of 32 to 89 years and 22 female subjects from the age of 23 to 89 years' data are used. The record numbers 201 and 202 are from the same male subject. The collected sample data from the database is depicted in Fig. 2.

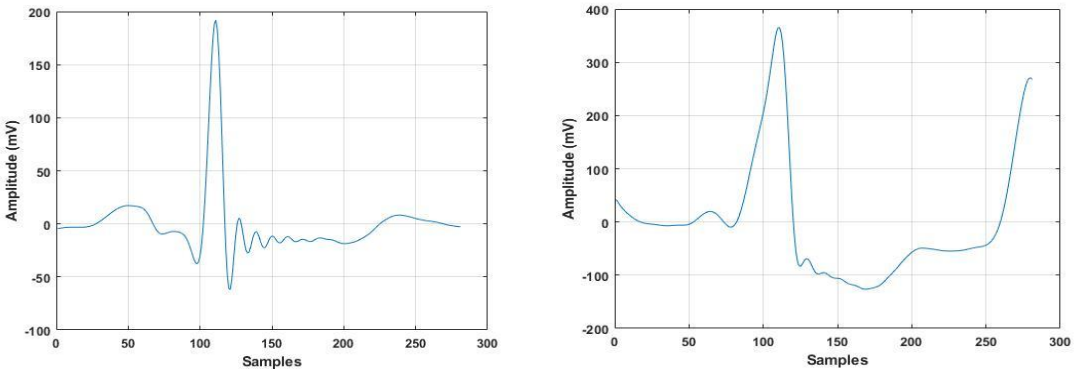


Fig. 2. Collected Sample data

3.2. Continual Normalization

Batch Normalization (BN) is a technique used in current methods of continuous learning to speed up training and enhance task generalization. The non-stationary settings of continuous learning data, particularly in an online environment, widens the gap among training and testing in BN makes it more difficult to solve the problems. In this paper, the cross-task normalisation effect of BN is examined in continuous learning. BN controls the testing data by moments that biased toward the current task and leading to more catastrophic forgetting. This constraint prompts the development of Continual Normalization (CN), a straightforward and practical technique that facilitates training similar to BN while minimizing its drawbacks. Numerous tests using various online settings and continual learning algorithms demonstrate that CN can significantly outperform BN and is a suitable replacement for it. Employing CNN and a continuous normalisation process, facilitates consistent and effective classification heartbeats in the ECG signals [23].

The benefit of CN is that it uses the same input as that of the traditional normalisation layers and does not include any more learnable factors that can be disastrously forgettable. Additionally, the selection of Instance Normalization (IN) and Layer Normalization (LN) is not beneficial for issues related to picture identification. The values from BN and IN are combined by Task Norm in a manner similar to SN using a blending factor that is unique to each task. Due to the poor normalisation of its outputs, Task Norm also suffers as a result. Furthermore, Task Norm neglects the third requirement of having more information than BN but the CN tackles the Meta issue by demanding knowledge of the task identification at test time.

Prior to choosing a group normalisation, CN does a spatial normalisation on the feature map [24]. A batch normalisation layer is then used to further normalize the group-normalized features. Formally, given the input feature map a, which represents the batch normalisation and group normalisation layers even without factorization parameters. $BN_{1,0}$ and $GN_{1,0}$ gain the normalisation features as a_{CN} which is mentioned in (1),

$$a_{GN} \leftarrow GN_{1,0}(a); a_{CN} \leftarrow \gamma BN_{1,0}(a_{GN})+ \beta \quad (1)$$

In order to verify that the feature map $BN_{1,0}(a_{GN})$ is normalized across the mini-batch and spatial dimensions, the GN element does not perform the transfer function in the initial step. Additionally, performing GN first enables the spatially-normalized features to contribute to the BN's running average, thus minimizing the influence of cross-task normalisation. Fig. 1 shows how CN is represented. CN is created with the specifications of a continuous learning normalisation layer. A balance between encouraging training and lessening the impact of normalizing across tasks is reached by CN by normalizing the input feature across mini-batch as well as individually. As a consequence, CN strikes a reasonable balance between BN and other instance-based normalizers, is adaptive during validation, and provides well-normalized features in the mini-batch and spatial dimensions.

3.3. Classification of ECG signals

The CNN [25] model utilizes the structural features for performing classification that convolve the kernel inputs to learn the input features in an image. The activation of the non-linear activation function is expressed as shown in (2).

$$a_{i,j} = f\left(\sum_{m=1}^{M}\sum_{n=1}^{N} w_{m,n} \cdot x_{i+m,j+n} + b\right) \quad (2)$$

From (2), $x_{i+m,j+n}$ are the upper neurons that are connected to neuron (i,j), $a_{i,j}$ is known as the corresponding activation, $w_{m,n}$ is known as the convolution weight matrix, f is known as the non-linear function, and b is the bias value.

Convolution layers of Rectified Linear Unit (ReLU) are applied to measure feature maps. The non-linear function is given in (3).

$$\sigma(x) = max\ (0, x)$$
(3)

More convolution kernels are needed in the model for mining the hidden features from the samples of input. Two convolution layers are used in the LSTM-CNN model. The 64 convolutional kernels are applied to extract the features and a 1×5 convolution kernel is set in the first convolutional layer. The 128 convolution kernels are needed for deeper feature extraction and 2 sliding steps are set in the convolution window. Each convolution kernel with the size of 1×3 is set and 1 step size of the convolution window is applied in the layer. The Max-pooling layer is applied between two convolutional layers to perform down-sampling. Executing these two processes filter noise interference in images and dominant feature is maintained to reduce the features.

3.4. Pooling Layer

Many features in the activation map provide overfitting problems and computational burden. In the pooling layer, sub-sampling of non-linear is performed to reduce the features [26]. Pooling is performed for translation invariance. The commonly applied two pooling methods are average pooling and max-pooling. In each pooling region, the element of average value is selected for average pooling and max value is selected for max pooling.

The pooling region is denoted as E, the activation set is denoted as P, and the activation is expressed in (4).

$$P = \{p_k | k \in E\} \quad (4)$$

Equation (5) denotes the average pooling.

$$AP = \frac{\sum P_E}{|P_E|} \quad (5)$$

Equation (6) denotes the max-pooling. The cardinal number of set x is denoted as $|x|$.

$$MP = \max\ (P_E) \quad (6)$$

3.5. Output Layer

A softmax classifier and a fully connected layer are applied in the output layer. The fully connected layer is added as the last layer. Every node is fully connected to the nodes of the upper layer to merge extracted features. This is applied to overcome the Global Average Pooling layer (GAP).

After fully connected layer, softmax classifier is applied to convert output of the upper layer into a probability vector to represent label of classes probability. The softmax layer formula is given in (7).

$$S_j = \frac{e^{a_j}}{\sum_{k=1}^{N} e^{a_k}} \quad (7)$$

Where N denotes the number of classes, in the fully connected layer a_j is the output vector in j^{th} value. The proposed CNN model diagram is shown in Fig. 3.

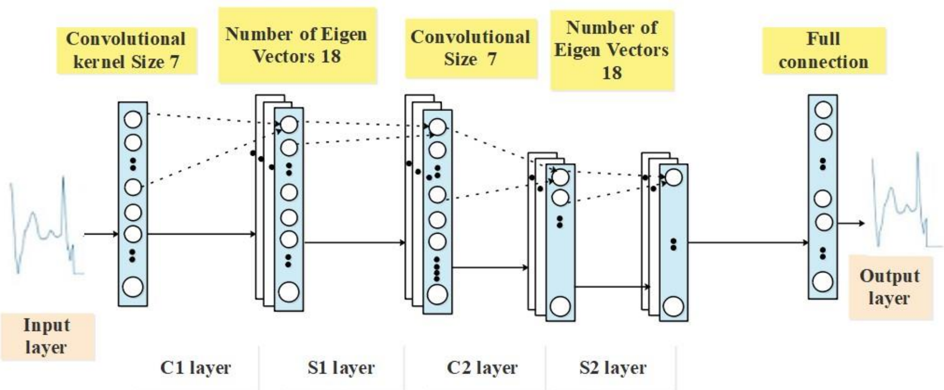


Fig. 3. Convolutional Neural Network (CNN) structure

Here, CNN model has the convolution with subsampling layers, accompanied by a fully linked output layer. The model is trained for the propagation mechanism, and the CNN seeks to mimic the architecture. The propagation algorithm is used for the training. The extraction of features is similar to that of the input space unless the standard techniques are used for the manual feature extraction. These features are given to the classifier to conduct the classification process. To determine the huge number of parameters, a higher dimensional data is needed. The training data was formerly quite huge in number giving rise to overfitting of the data. The CNN handles the problems related to pooling or subsampling, and local connectivity.

3.6. Local connectivity

The signal is separated into patches or blocks of similar size. The receptive fields are the blocks acquired from the signal. The blocks are overlapped and non-overlapped in nature. The overlapping block shares the signal's common part but the signals are not shared by the non-overlapping blocks. The smooth features are removed, and the overlapping blocks are taken into account. The hidden unit is connected to only one input signal block that extracts features from every image block. The local features are extracted from the exact feature location that becomes less significant. Therefore, extracting the local features is essential till the remaining features are preserved in the relative location.

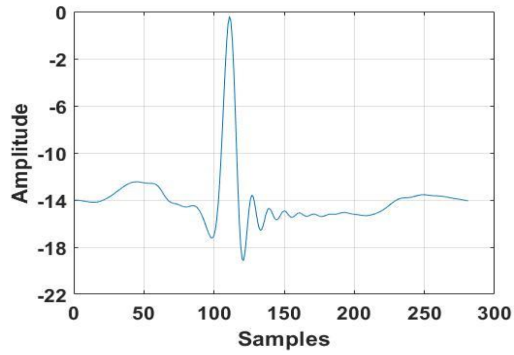
3.7. Parameter Sharing

Each computational layer in the network comprises certain feature maps, and the fundamental concept is to enable multiple neurons to transfer the parameters. Thus, the hidden neurons are structured in a way that it enables mapping and transmission of parameters. The hidden units present in the feature map have covered distinct blocks of a signal that share and extract similar features from the distinct blocks of the signal. Every block of the signal is located with a greater number of feature maps & neurons in which features from the same block have different feature maps. The activation values from the hidden unit result in weights from the input channel that maps the features. The generated features are multiplied by the input vector and the primary focus is on the procedure of discrete convolution.

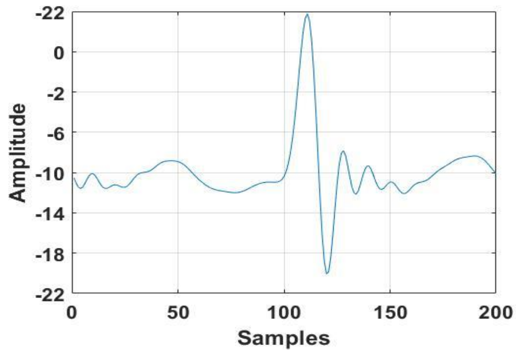
3.8. Pooling and subsampling

The neural network comprises the pooling layer with convolutional layer from which the features are obtained. The convolution layer transforms data through the convolution technique. The set of digital filters is employed in two different ways: average & max pooling. The window consists of the predefined size that selects the data by using these methods. The highest activation value incorporates the window in max pooling, and activation values from average pooling window are included. To conduct dimension reduction, the current work employs fully linked layers. This fully linked layer is commonly referred to as a convolutional neural network. CNNs are utilized to analyse image data, and computations on such layers are conducted in the 2D plane [27].

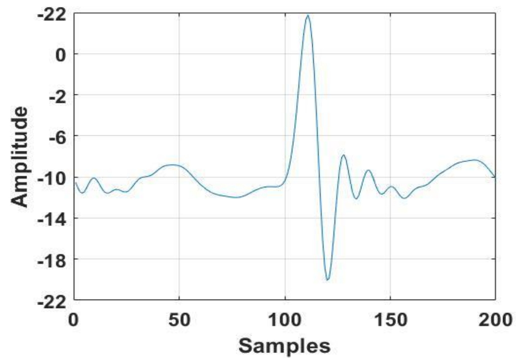
Processes such as regression or classification are carried out on the basis of extracted features from which the output is produced. To conduct dimensionality reduction, the threshold is determined from the pooling layer. Hence, the convolution layers are used to conduct the processes of the convolution as well as pooling layers on the 2D planes into 5 classes which is shown in Fig. 4, that has (a) N beat (b) S-beat (c) V-beat (d) F-beat (e) Q-beat.



(a)



(b)



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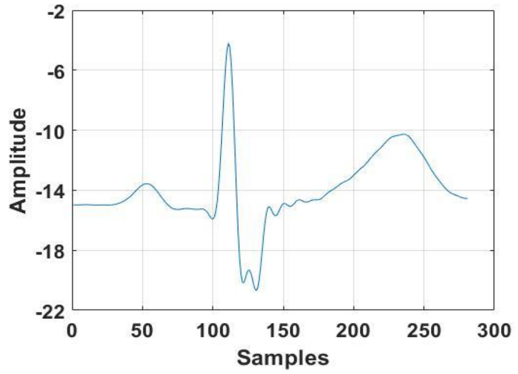

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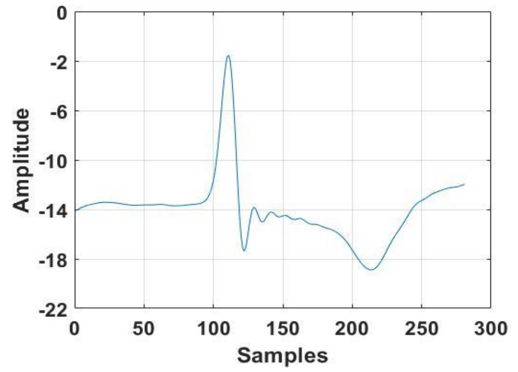

(e)

Fig. 4. (a) N beat (b) S-beat (c) V-beat (d) F-beat (e) Q-beat

4. Results and Discussions

This section briefly describes the performance evaluation of the arrhythmia detection displayed by the proposed research. The proposed spatial and temporal feature extraction method is applied to the MIT-BIH dataset. For the implementation, having a system of 16 GB RAM with an i7 CPU is a necessity. During the classification process, 90% of the dataset was utilised for training and 10% for testing. Following are the performance metrics utilized to analyze the classified signals: Accuracy, Precision, recall, F-measure and Error Rate are expressed from equation (8) – (12).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (8)$$

$$Precision = \frac{TP}{TP+FP} \times 100 \quad (9)$$

$$Recall = \frac{TP}{TP+FN} \times 100 \quad (10)$$

$$F-measure = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (11)$$

$$Error\ Rate = 100 - Accuracy \quad (12)$$

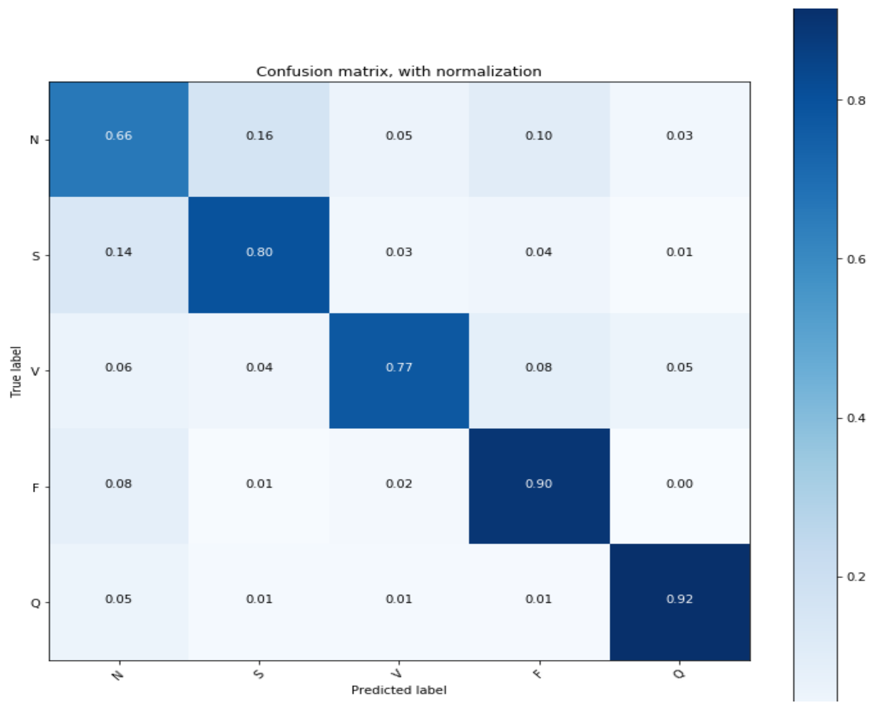

Fig. 5. Confusion matrix

4.1. Quantitative Analysis

Table 1 displays the better results attained by the proposed method based on various performances. Fig. 5 shows the Confusion matrix and a total of 5 classes ranging from 0 to 4 are evaluated. The data of various instances are considered in the present research work with distinct numbers. The dataset that has a lower number of 162 values obtains a lower number of precisions, f-score, and recall values.

Similarly, if the data used are higher in number, then the values obtained are also having higher values of F-score, Precision, and Recall. Table 1 includes two types of signal properties, signals with divisions (intervals) and signals without divisions. The main reason of evaluating results for sub-divided signals is because, in each of the ECG signal segments, a change in the duration of time may happen because of one or more waves. Therefore, it is important to evaluate results for the generated signals and thus sub-divisions are made for getting better values. The results obtained in the proposed method showed that the support with 18118 samples without division of signals gave 98% of precision whereas the sub-division in the signal had 82 % of precision. Whereas, the lowest number of supports considered is 162 which obtained 7% of precision for without division in the signals and 99% of precision for the signal with the sub-division. This is because higher number of sub-samples proportionally gives higher results with respect to the size, and greater the sample size, the more statistically significant the results will be.

Fig. 6 shows the graphical representation and average values attained by all 5 classes with an accuracy of 69 %, precision of 49 %, recall of 81 %, and F-score of 52 %. The performances are evaluated in terms of various metrics, where the values of F-score was better when compared to the existing models. Fig. 7 is a graphical representation of the model's accuracy. Table 2 and Fig. 8 shows the average performances for the proposed model. Fig. 9 shows the average performances obtained for Model loss.

Table 1. Performance Metrics Evaluation for the Proposed Method

Classes	Support	Signal properties	Precision (%)	Recall (%)	F1-score (%)
0	18118	Without division in the signals	98	66	79
		Sub-division in the signal	82	100	90
1	556	Without division in the signals	13	80	22
		Sub-division in the signal	99	93	90
2	1448	Without division in the signals	53	77	63
		Sub-division in the signal	95	93	96
3	162	Without division in the signals	7	90	13
		Sub-division in the signal	99	97	96
4	1608	Without division in the signals	73	92	81
		Sub-division in the signal	99	99	99

Table 2. Average Performances for the Proposed Method

Metrics	Signal properties	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Proposed Method	Without division in the signals	69	49	81	52
	Sub-division in the signal	99.2	95	94	94

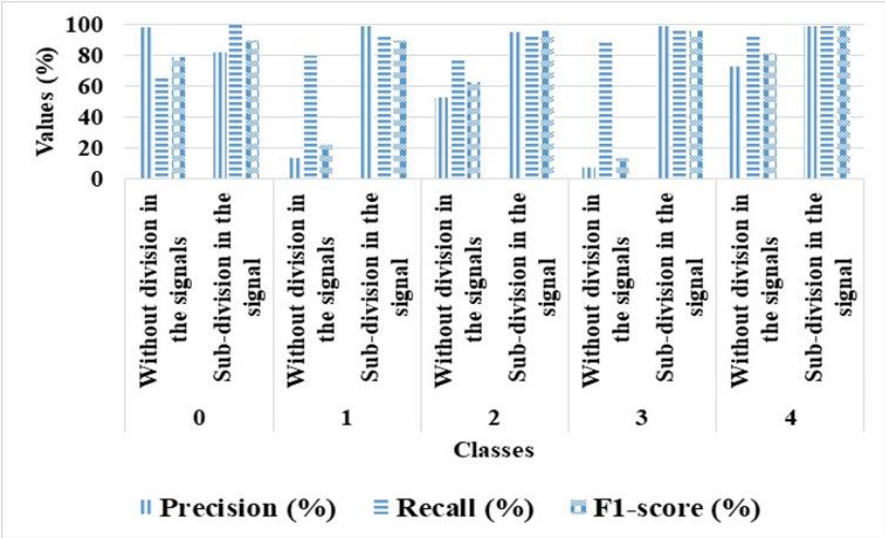

Fig. 6. Graphical representation of the proposed method

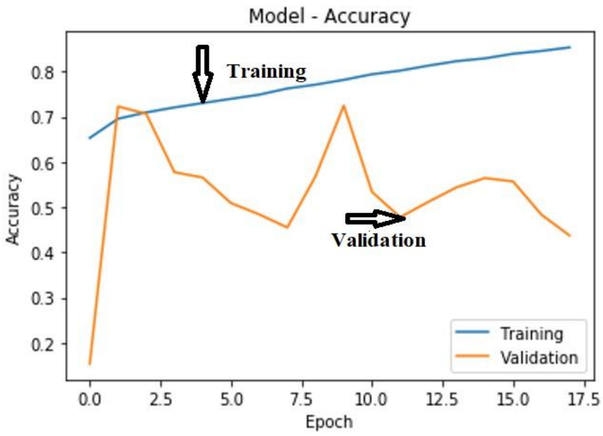

Fig. 7. Graphical representations for the model accuracy

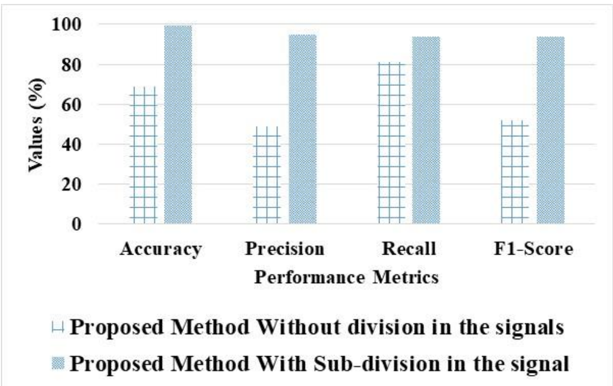

Fig. 8. Average performances of proposed method along with the signal properties

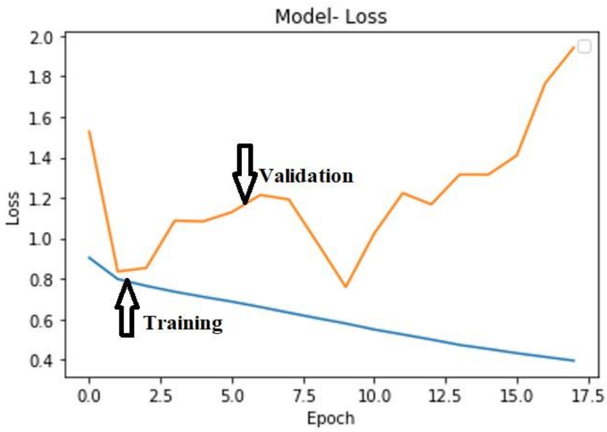

Fig. 9. Average performances obtained for Model loss

The convolution layers are used, in order to conduct the convolution procedures and group the layers on the 2D planes into 5 distinct classes. N, S, V, F and Q are the types of arrhythmia present in the dataset. The different classifiers considered for evaluation are Support Vector Machine (SVM), Random Forest (RF), Decision Tree (DT), K Nearest Neighbor (KNN) and Recurrent Neural Network (RNN).

Tables 3 shows the analysis of SVM, RF, DT, KNN, RNN and proposed CNN based CN for MIT-BIH database. Figures 10 shows the classification performances of different classifiers for MIT-BIH database.

Table 3. Analysis of different classifiers for MIT-BIH database

Classifiers	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)	Error rate (%)
SVM	92.89	87.83	89.75	90.32	6.18
RF	92.76	89.06	87.36	89.03	5.77
DT	94.96	90.45	85.53	90.47	4.03
KNN	98.12	92.14	91.88	92.69	2.01
RNN	98.14	92.29	92.01	93.53	0.99
CNN based CN	99.2	95.00	94.00	94.00	0.12

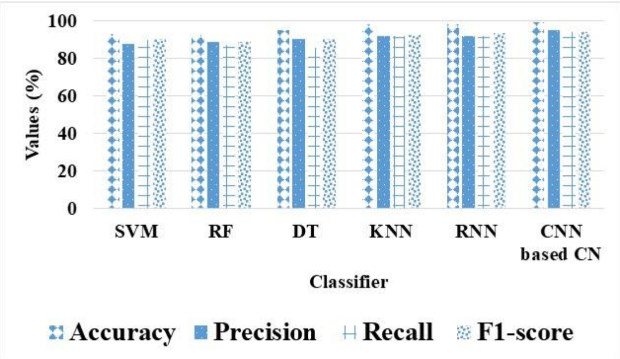

Fig. 10. Graphical illustration of different classifiers on MIT-BIH database

This analysis reveals that the proposed CNN based CN provides better performances when compared to the other classifiers. In the arrhythmia classification, the proposed CNN based CN achieves the accuracy of 99.2% which is definitely higher when compared to MSVM, KNN, sparse auto encoder, stacked auto encoder and LSTM. Figure 11 shows the graphical performance results of different classifiers in terms of Error Rate.

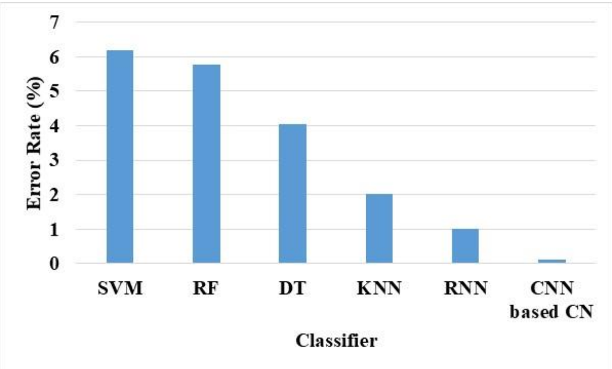

Fig. 11. Graphical illustration of different classifiers on Error Rate Performance

Additionally, the developed CNN based CN is analyzed for different configurations of k-fold validation. The different k-fold values considered for the analysis are 3, 5, 8 and 10 which is shown in Table 4.

Table 4. Analysis of CNN based CN for different configurations on k-fold validation

Performances	k-fold validation			
	3	5	8	10
Accuracy (%)	97.90	98.16	97.28	93.11
Precision (%)	94.31	97.54	94.74	93.02
Recall (%)	93.13	97.17	93.18	92.06
F1- score (%)	93.76	97.06	93.71	92.94
Error rate (%)	2.05	0.12	2.34	5.98

This analysis of table 4 shows that the CNN based CN processed under the cross-fold validation size of 5 provides better performances than the other configurations. Figure 12 shows the graphical evaluation of k-fold validations on CNN based CN with various performance metrics. The figure 13 shows the k-fold validation process in terms of error rate.

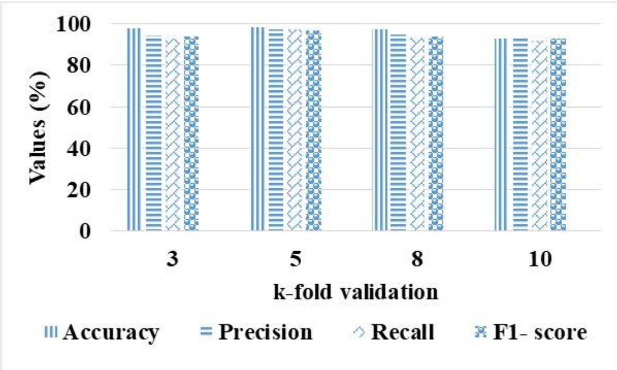

Fig. 12. Graphical representation of k-fold validation on CNN based CN

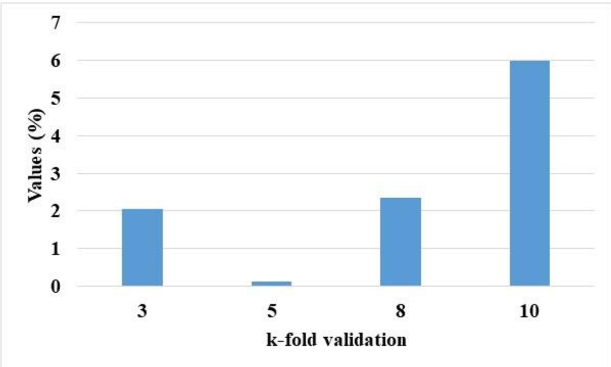

Fig. 13. Graphical representation of k-fold validation on CNN based CN

Here, Table 5 shows the analysis of different classes on MIT-BIH dataset. There are totally, 5 classes considered in this analysis, they are class 0 (N), class 1 (S), class 2 (V), class 3 (F) and class 4 (Q) respectively. The following are the performances taken for the investigation, they are False Positive Rate (FPR), False Discovery Rate (FDR), True Positive Rate (TPR), False Negative Rate (FNR) False Acceptance Rate (FAR) respectively.

Table 5. Analysis of different classes on MIT-BIH

	FPR	FAR	TPR	FNR	FDR
Class 0	0.063	0.263	0.667	0.333	0.267
Class 1	0.057	0.200	0.818	0.181	0.200
Class 2	0.050	0.216	0.725	0.275	0.216
Class 3	0.091	0.348	0.777	0.222	0.348
Class 4	0.05	0.216	0.763	0.236	0.216

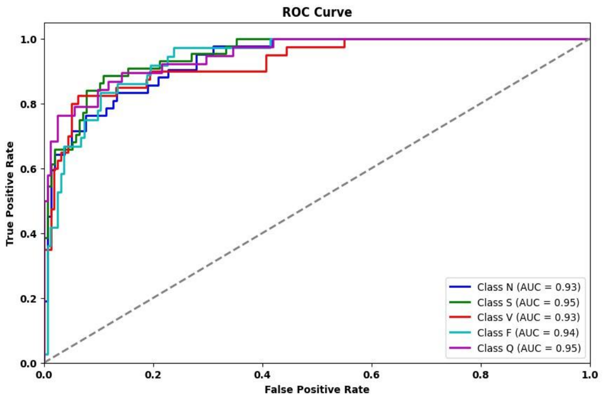

Fig. 14. Area Under the Curve of CNN based CN on MIT-BIH dataset

Figure 14 displays the Area Under the Curve (AUC) of CNN-based CN classification using the MIT-BIH dataset. The ROC curve's point corresponds to a location where there is an equal chance of misclassifying a positive or negative sample. From the figure 14, it clearly shows that the CNN based CN model shows 0 .95 AUC for the classification (classes S & Q) which designates that TPR considerably rises for the classification of arrhythmia. While the other classes such as N, V and F has 0.93, 0.93, 0.94 respectively.

4.2. Comparative Analysis

The comparison of proposed and existing models is represented in Table 6. The existing Dual Fully connected Neural Network does not utilize enough data for training the network structure. The Deep fully connected CNN [16] resulted with data complexity that obtained an accuracy of 93.4 %. Another model based on Optimization enabled Deep CNN is used to handle dynamic features that are based on the input raw signals. The dataset used by this model was difficult to handle, and the optimization enabled Deep CNN [18] accomplished an accuracy of 93.19%. The Short-Time Fourier Transform (STFT) Spectrogram with CNN model showed limitations in terms of imbalanced data that failed to distribute through the database equally. The existing CNN [19] has obtained an accuracy of 95.10%, while the existing STFT Spectrogram and Convolutional Neural Network [20] gained an accuracy of 90.93% and did not perform cross-validation instead it trained the data with respect to the MIT-BIH database; similarly, ELM-CNN [21] has achieved an accuracy of 98.82%. Whereas, the proposed CNN-based Continual Normalization techniques obtained accuracy of 99.2 %, precision of (99%), recall (99%) and f1-score (99%) which is way better when compared to the existing model Fuzz-ClustNet [22] which has obtained 98.66% of accuracy, 98.92% of precision, 93.88% of recall and 96.34% of f1-score for MIT-BIH dataset which is presented clearly in the below table 6.

Table 6. Comparative Analysis of accuracy

Authors	Method	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Haoren Wang [16]	Dual Fully Connected Neural Network	93.4	NA	NA	NA
Dinesh Kumar Atal, Mukhtiar Singh [18]	Optimization-Enabled Deep Convolutional Neural Network	93.19	NA	93.98	NA
B. M. Mathunjwa et al. [19]	Convolutional Neural Network	95.1	NA	NA	NA
Jingshan Huang [20]	Short-Time Fourier Transform (STFT)-Spectrogram and Convolutional Neural Network	90.93	NA	NA	NA

Kuila, S., Dhanda, N. and Joardar, S. [21]	Extreme Learning Machine (ELM)-Convolutional Neural Network (CNN)	98.82	NA	93.14	93.52
Kumar, S., Mallik, A., Kumar, A., Del Ser, J. and Yang, G [22]	Fuzzy Clustering Network	98.66	98.92	93.88	96.34
Proposed	CNN based Continual Normalization	99.2	99	99	99

5. Conclusion

Cardiac arrest is increasingly becoming a serious prognostic risk to life and it currently holds a higher mortality rate in this world. Conventional approaches have made significant contributions in identifying arrhythmia using ECG signals. However, the conventional approaches failed to select features prior to the extraction. The issues are overcome in the present research work as it obtains the ECG signals from MIT-BIH and eliminates unwanted artefacts by utilizing a Butterworth filter. The proposed CNN based Continual Normalization approach addresses the conventional system's over-fitting issues by achieving the highest accuracy, precision, recall and f1-score of 99.2%, 99%, 99% and 99% respectively. In the future, an effective optimization algorithm will be utilized to solve optimization issues.

Author contributions

Ghousia S. Begum: Visualization, Conceptualization, Methodology, Software, Field study, Writing-Original draft preparation. **Vipula Singh:** Validation, Data curation, Software, Field study Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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