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Fuzz-ClustNet: Coupled fuzzy clustering and deep neural networks for Arrhythmia detection from ECG signals

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ABSTRACT

Electrocardiogram (ECG) is a widely used technique to diagnose cardiovascular diseases. It is a non-invasive technique that represents the cyclic contraction and relaxation of heart muscles. ECG can be used to detect abnormal heart motions, heart attacks, heart diseases, or enlarged hearts by measuring the heart's electrical activity. Over the past few years, various works have been done in the field of studying and analyzing the ECG signals to detect heart diseases. In this work, we propose a deep learning and fuzzy clustering (Fuzz-ClustNet) based approach for Arrhythmia detection from ECG signals. We started by denoising the collected ECG signals to remove errors like baseline drift, power line interference, motion noise, etc. The denoised ECG signals are then segmented to have an increased focus on the ECG signals. We then perform data augmentation on the segmented images to counter the effects of the class imbalance. The augmented images are then passed through a CNN feature extractor. The extracted features are then passed to a fuzzy clustering algorithm to classify the ECG signals for their respective cardio diseases. We ran intensive simulations on two benchmarked datasets and evaluated various performance metrics. The performance of our proposed algorithm was compared with several recently proposed algorithms for heart disease detection from ECG signals. The obtained results demonstrate the efficacy of our proposed approach as compared to other contemporary algorithms.

1. Introduction

Cardiovascular diseases are amongst the most severe diseases causing millions of deaths annually. According to a recent survey in 2016, around 17.9 million people died from cardiovascular diseases globally. This shows a lack of a proper detection framework for cardiac diseases, which leads to such severity. The Majority of such deaths are due to heart strokes and heart attacks.[2] We, therefore, require advanced frameworks for early detection and diagnosis of cardiac irregularities to administer appropriate medical care. The recent advancements in wearable electronics and data transmission infrastructure has led to several devices capable of monitoring human health with the help of wireless sensors [1–3]. The human heart is a crucial organ responsible for blood circulation and the epicenter of cardiovascular diseases. Electrocardiograms can monitor the rhythmic motion of the heart (ECG) [4]. ECG is a non-invasive test that offers a quick diagnosis of the state of the heart. It is employed routinely to monitor the heart. It is a device that records the electrical signals produced by the heart while pumping blood throughout the body [5]. ECG is a popular medical device for monitoring heart rates due to the ease of testing it offers. However, it takes much expertise to analyze the ECG signals. It is also very cumbersome to interpret the ECG as it is often the case that every heartbeat has to be analyzed. Moreover, there is also the possibility of human error in the analysis. Hence, the need for an automated computational technique is crucial.

Among the various cardiovascular diseases, arrhythmia is one of the most severe. Arrhythmia refers to irregularities in the rate or rhythm with which the heart beats. A heart beating too fast, too slow, or

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irregular patterns can be characterized as an arrhythmic [6]. Arrhythmia can be divided into various categories depending on the patterns observed during the ECG recordings. Morphological and Rhythmic arrhythmia are the two broad classes of arrhythmia. Morphological arrhythmia is characterized by the rare occurrence of an irregular heartbeat, while rhythmic arrhythmia refers to the condition when irregular heartbeats follow a regular pattern. Arrhythmia can also be classified based on the location of occurrence in the heart. The four significant classifications of arrhythmia are Ventricular Arrhythmia (VA), Premature or extra heartbeat, Brady-Arrhythmia (BA), and Tachycardia or Supra-Ventricular Arrhythmia (SVA).

In this work, we present a deep learning and fuzzy clustering (Fuzz-ClustNet) based framework for detecting arrhythmia from ECG signals. We start by preprocessing and denoising the ECG signals. It helps us in removing irrelevant noise and errors like Gaussian noise, motion noise, contact loss, etc. After denoising the signals, we segment them to focus more on the relevant signal, thereby accentuating it. Thereafter, we augment the dataset to counter the effects of class imbalance and obtain a more balanced dataset for training and testing. The augmented dataset is then passed through a deep convolutional neural network architecture to extract the salient features from ECG signals. These extracted features capture the characteristic details of the ECG signals, which are relevant for detecting arrhythmia in the patient. The extracted features are then passed through a fuzzy clustering-based classifier to classify the ECG signals into their respective arrhythmia categories. An optimal hyperparameter tuning further fine-tunes the performance of our model. We performed an ablation study to understand the effectiveness of the various components of the proposed technique in the performance of our model. We conducted extensive simulations on several benchmarked arrhythmia-based ECG signal datasets and evaluated different standard performance metrics. The obtained results were compared with various contemporary algorithms. The obtained results demonstrate the efficiency and effectiveness of our proposed algorithm for arrhythmia detection to ECG signals. The major contributions of our work are as follows:

1. We present a deep learning and fuzzy clustering based framework, named Fuzz-ClustNet, for detecting arrhythmia from ECG signals.
2. We perform image denoising using IIR Notch Filter and FIR Filter. We also perform segmentation via R-peak values using Christov segmentation. Such signal processing techniques help in attenuating the irrelevant data and accentuating the useful information in the signal.
3. We propose a deep CNN based approach for feature extraction and exploit the fuzzy clustering algorithm for classifying the ECG signals into their respective arrhythmia categories. The deep CNN based approach paired with the image augmentation technique helps in improving the quality of the dataset and extract features optimally.
4. An ablation study is performed to analyze the effects of the various components of our signal processing techniques on the obtained results. This study gives us a profound understanding of the techniques that work.
5. We perform intensive experimentation using several benchmarked ECG signal based datasets for arrhythmia detection and calculate various performance metrics. The obtained results are also compared with several recently proposed algorithms for arrhythmia detection for ECG signals.

The rest of the paper is organized as follows. We present the literature review of the various works done in the field of arrhythmia detection from ECG signals in Section 2. Our proposed methodology is explained in detail in Section 4. A brief description of the datasets and the evaluation metrics used is given in Section 3. The experimental analysis performed by us is illustrated in Section 5. The concluding remarks and the scope for future improvement is given in Section 6.

2. Related work

In this section, we discuss the research work done by various researchers toward the enhancement of arrhythmia detection from electrocardiograms. The ECG signals contain inherent noise, which makes their analysis very difficult. Moreover, it also requires substantial expertise to interpret the ECG signals. This has motivated researchers over the years to propose more accurate and automated techniques to improve the effectiveness and efficiency of ECG signal analysis [7]. Most existing work in the enhancement of arrhythmia detection from electrocardiograms is classified as parametric feature-based and signal-processing based. The works done in these sub-domains are discussed below.

Parametric feature based methods:

Bhagyalakshmi et al. [8] proposed a supervised classification approach by using a support vector neural network (SVNN) to make the classification. In performing feature extraction, they used a wavelet and Gabor filter on the ECG signals. A genetic Bat Optimization algorithm was used by them to train the SVNN. Through their approach, they achieved a classification accuracy of 96.96%. Khazaee et al. [9] used the nonparametric power spectral density (PSD) technique for feature extraction and used the Support Vector Machine (SVM) for making the classifications. Particle Swarm Optimization (PSO) was used by them to select the parameters of the SVM. Their approach achieved a classification accuracy of 96.06%. Yıldırım et al. [10] classified the ECG signals into 13, 15, and 17 classes using a deep neural network. They achieved a classification accuracy of 95.2%, 92.5%, and 91.33% for 13, 15, and 17 classes, respectively. They clocked an average computation time of 0.015 s. Their work revealed a deteriorating performance with the increasing number of classes. Chen et al. [11] extracted the segmented features using Principal Component Analysis (PCA) along with Dynamic Time Warping (DTW). The extracted segmented features were then fed to a Radial Base Function (RBF) based SVM to make the final classification. They achieved an overall accuracy of 97.80%. Refahi et al. [12], proposed a least squared twin support vector machine based on a non-parallel margin instead of the classical SVM. This helps in considering the minor variations or deflections in the ECG signals, which are often not caught by human eyes. They did not employ any feature extraction technique and achieved a classification accuracy of 97.1%. Refahi et al. [12] proposed a deep learning-based approach for arrhythmia detection from ECG signals on the MIT-BIT arrhythmia database and achieved a classification accuracy of 94.2%. They performed feature extraction using a deep convolutional neural network and used a simple neural network with backpropagation for performing classification. Çınar et al. [13] proposed a hybrid transfer learning based Alexnet and Support Vector Machine based approach for arrhythmia detection. They achieved an overall accuracy of 68.75%, 65.63%, 90.67%, and 96.77% with SVM, K-nearest neighbors (KNN), long short-term memory (LSTM), and the proposed hybrid approach, respectively. Liu et al. [14] performed a study to classify the arrhythmia signal into one of the ten diseases like sinus arrhythmia. They used the radial basis probabilistic process neural network (RBPPNN) for performing the classification and achieved a classification accuracy of 75.52% while the highest disease specific accuracy of 86.75%. Wang et al. [15] worked on the MIT arrhythmia and MIT supraventricular arrhythmia databases. They proposed a two-layered, fully connected neural network architecture that classified the ECG signals into five arrhythmia classes. Both the layers of the architecture were independent and fully connected neural networks. They performed the simulations on the AAMI standards and achieved an accuracy of 93.4%.

Signal-processing based methods

Sodmann et al. [16] studied rhythmic cardiovascular movements to detect arrhythmia using a convolutional neural network architecture. They used dynamic wavelet transform, and Fourier transforms for resampling and denoising at the filtering stage. They achieved

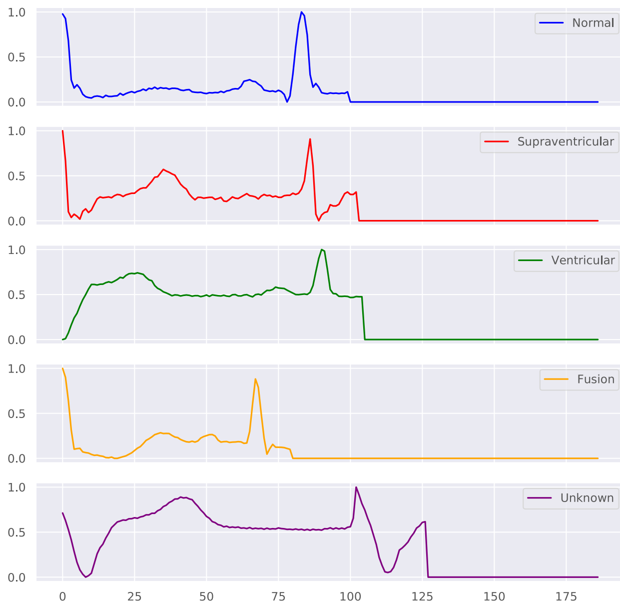

Fig. 1. Major types of heartbeats present in the MIT-BIH Arrhythmia Dataset.

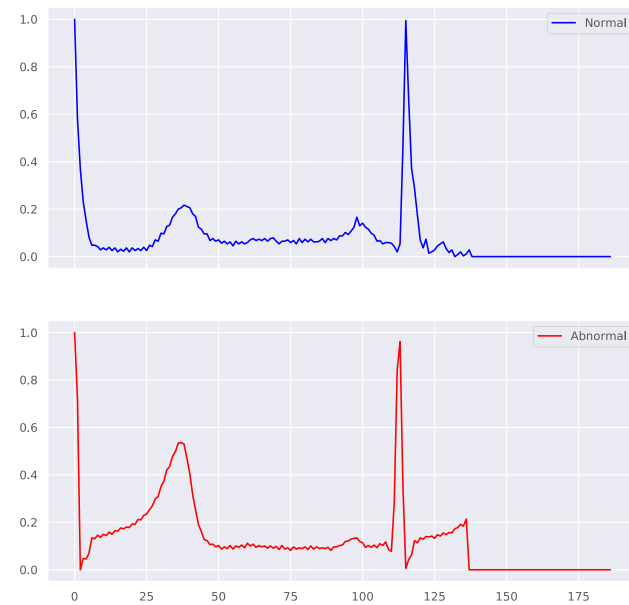

Fig. 2. Major types of heartbeats present in the PTB Diagnostic ECG Dataset.

82% in terms of F-Score. Zairi [17] used a multilayer perceptron (MLP) for detecting arrhythmia from ECG signals. They used a field-programmable gates array for feature extraction and then employed DWT for feature reduction. Their proposed approach achieved a classification accuracy of 98.3%. To identify the various cardiovascular diseases based on the ECG waves, deep deterministic learning (DDL) approach was proposed by Iqbal et al. [18]. They performed pattern recognition and classification using an artificial neural network architecture. The simulations were performed on various publicly available datasets along with ECG samples collected manually by them. Their proposed approach achieved an overall classification accuracy of 98%. Cai et al. [19] performed a study to improve the detection of atrial fibrillation of ECG signals. Atrial fibrillation (AF) is the most common form of arrhythmia. They proposed deep learning based one dimensional densely connected neural networks. The experimental results reveal that the proposed approach achieved a classification accuracy of 99.35%. Maglaversa et al. [20] presented a technique to capture the rhythmic changes in the heartbeats indicative of various conditions like atrial fibrillation. They performed enhanced QRS complex recognition for capturing relevant details from the ECG signals. They used a combination of neural network and principal component analysis by performing feature extraction using nonlinear principal component analysis and a radial basis function network (RBFN) for classification. Plawiak [21] proposed a technique to detect abnormal heart beats using evolutionary neural systems based on the SVM framework. They classified the ECG signals into 17 cardiac diseases and achieved accuracy and specificity of 98.85% and 99.39%, respectively.

3. Datasets and evaluation metrics

This section presents the various datasets used by us for running simulations of our proposed work. It also illustrates the several evaluation metrics used by us to evaluate the performance of our proposed work. The dataset description is as follows.

3.1. Datasets

For performing the simulations, we use two benchmarked datasets which have been extensively used in the recent literature. The datasets used by us are the MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Dataset. A brief description of the datasets is given below.

Table 1
Major types of heartbeats present in the MIT-BIH Arrhythmia Dataset.

Group	Description
Normal beat	Normal beat, Right bundle branch block beat, Left bundle branch block beat, Nodal (junctional) escape beat, Atrial escape beat
Supraventricular premature beat	Nodal (junctional) premature beat, Atrial premature beat, Supraventricular premature beat, Aberrated atrial premature beat
Premature ventricular contraction	Premature ventricular contraction, Ventricular escape beat
Fusion beat	Fusion of ventricular and normal beat
Unclassifiable beat	Fusion of paced and normal beat, Unclassifiable beat

1. MIT-BIH Arrhythmia Dataset [22,23]:
   The MIT-BIH Arrhythmia Dataset contains ECG recordings for 47 patients collected over the course of four years from 1975 to 1979. The data samples in the dataset are 48 half-hour excerpts of two-channel ambulatory ECG recordings. The data was recorded at Boston's Beth Israel Hospital (BIH). The data is publicly available at physionet.org. It contains five categories, namely, Normal Beat, Supraventricular premature beat, Premature ventricular contraction, Fusion of ventricular and normal beat, and Unclassifiable beat. Table 1 shows the major types of heartbeats, and Fig. 1 shows the sample signals belonging to each class of the MIT-BIH Arrhythmia Dataset.
2. PTB Diagnostic ECG Dataset [23,24]:
   The PTB Diagnostic ECG Dataset contains the collection of samples that were obtained using a non-commercial PTB prototype recorder to detect cardiovascular abnormalities. There are two classes, namely, normal and abnormal. The data is publicly available at physionet.org. Table 2 presents the major types of heartbeats, and Fig. 2 shows the sample signals belonging to each class of the PTB Diagnostic ECG Dataset.

Table 3 presents the number of samples belonging to each class for both datasets. Here, we observe a class imbalance in the datasets. There are 72471 normal heartbeat samples for the MIT-BIH Arrhythmia Dataset, while the samples belonging to all other classes are 15083. The

Table 2
Major types of heartbeats present in the PTB Diagnostic ECG Dataset.

Group	Description
Normal beat	Normal beat, Healthy controls
Abnormal beat	Myocardial infarction, Cardiomyopathy/Heart failure Bundle branch block, Dysrhythmia, Myocardial hypertrophy, Valvular heart disease Myocarditis, Miscellaneous

Table 3
The number of samples belonging to various classes in the different datasets.

MIT-BIH Arrhythmia Dataset		
Class	Samples (no aug.)	Samples (aug.)
Normal beat	72471	72471
Supraventricular premature beat	2223	72471
Premature ventricular contraction	5788	72471
Fusion beat	641	72471
Unclassifiable beat	6431	72471
PTB Diagnostic ECG Dataset		
Class	Samples (no aug.)	Samples (aug.)
Normal beat	7185	10047
Abnormal beat	10047	10047

PTB Diagnostic ECG dataset has 7185 normal heartbeats and 10047 abnormal samples. To counter the effects of dataset imbalance and class bias, we have employed augmentation techniques. Table 3 also presents the number of samples before and after data augmentation.

3.2. Evaluation metrics

In this section, we present the various evaluation metrics used by us to ascertain the performance of our proposed work. For our study, we have used several standard evaluation metrics. A brief description of the various evaluation metrics is as follows.

1. Accuracy:
Accuracy represents the correctness of the classifier to categorize the data points into their respective classes. More formally, it can be represented as the ratio of the total number of correctly classified samples to the total number of samples. Mathematically, it can be represented by Eq. (1).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

2. Precision:
It represents the correctly classified positive samples. More formally, it can be represented as the ratio of the actual positives that were classified as positives to the total number positively classified samples. Mathematically, it can be represented by Eq. (2).

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

3. Recall:
It represents the proportions of positive samples that were classified as positive. More formally, it can be represented as the ratio of the actual positives that were classified as positives to the total number of positive samples. Mathematically, it can be represented by Eq. (3).

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

4. F1 Score:
It represents the balance between precision and recall. More formally, it can be represented as the harmonic mean of precision and recall. Mathematically, it can be represented by Eq. (4)

$$F1\ Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{4}$$

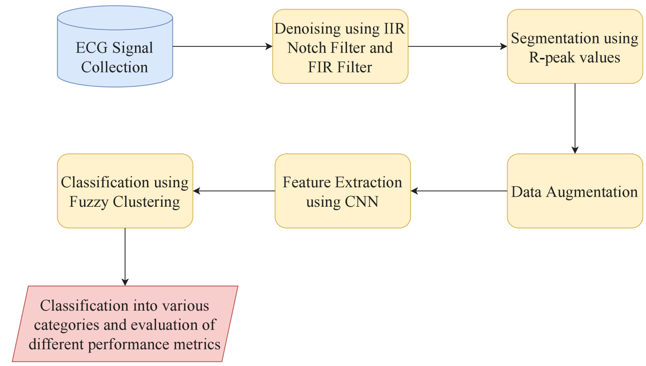

Fig. 3. Flow diagram of our proposed deep learning and fuzzy clustering (Fuzz-ClustNet) based framework for Arrhythmia detection from ECG signals.

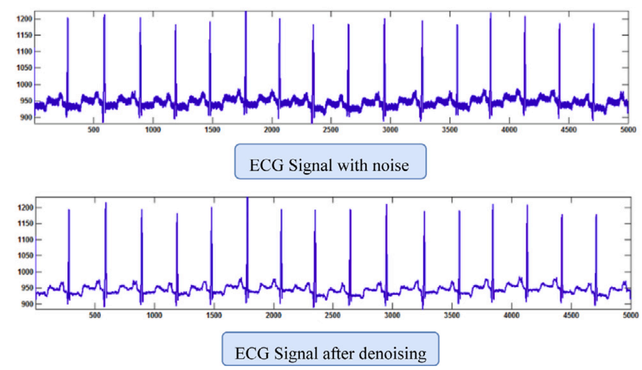

Fig. 4. Denoising of the ECG signals.

In the above illustrations of the evaluation metrics in the context of arrhythmia detection, True Positive (TP) represents the arrhythmic samples classified as arrhythmic, False Positive (FP) represents the non-arrhythmic samples classified as arrhythmic, True Negative (TN) represents the non-arrhythmic samples classified as non-arrhythmic, while False Negative (FN) represents the arrhythmic samples which were classified as non-arrhythmic samples.

4. Proposed work

In this section, we illustrate our proposed methodology for detecting Arrhythmia from ECG signals using deep learning and fuzzy clustering, named Fuzz-ClustNet. The proposed algorithm comprises of the following five phases: (i) Denoising the ECG signals, (ii) Segmentation of the ECG signals, (iii) Data Augmentation, (iv) Feature extraction using CNN, and (v) Classification using Fuzzy Clustering. We start by denoising the ECG signals to obtain clearer waves that are free from unnecessary interference. Then we go on to isolate the images of the waveforms using segmentation. The segmented images are further augmented to account for the sample imbalance. The augmented dataset is then passed to a deep Convolutional Neural Network (CNN) architecture for feature extraction. The extracted features are then passed to the Fuzzy clustering algorithm for final classification. source codes for the in a GitHub repository. The source code of the proposed Fuzz-ClustNet approach can be found at the GitHub repository: https://github.com/Abhishekmallik/Fuzz-ClustNet. Fig. 3 depicts the flow diagram of our proposed deep learning and fuzzy clustering (Fuzz-ClustNet) based framework for Arrhythmia detection of ECG signals. The various phases are described below.

4.1. Motivation

Most of the existing work done in the field of Arrhythmia detection from ECG signals relies on wavelet processing [8,17]. However, the recent popularity and utility of convolutional neural networks have proved their mantle in various fields including medical image diagnosis. Moreover, the signal processing based approaches are over-explored for the current problem statement. This motivates us to use image processing techniques to extract the features and detect Arrhythmia from them. This aims to enhance the existing signal processing techniques by exploring their visual aspects. Hence, the primary hypotheses of our approach can be summarized as: exploring the visual representations of the arrhythmia signals and utilizing image processing techniques and convolutional neural networks to extract the essential features of the signals and classify them as arrhythmic or non-arrhythmic. This approach also contributes to the existing works by utilizing various feature extraction and classification techniques. In this study, we convert the ECG signals to ECG images. The ECG images are then processed using denoising and segmentation techniques to achieve more accentuated and focused signals. We use a Convolutional Neural Network architecture to extract the features from the images. A CNN is used for feature extraction as, in recent years, it has proven effective in generating the features from images in an unsupervised scenario and without user intervention. The extracted features are then passed through a fuzzy clustering algorithm to categorize the ECG signal images into various Arrhythmia classes. We have used Fuzzy clustering as it can optimally explore the feature vectors of the samples and classify them into their respective categories in an unsupervised scenario. We also perform intensive experimentations using both supervised and unsupervised algorithms to understand their effects on detecting Arrhythmia from ECG signals.

4.2. Denoising the ECG signals

To detect Arrhythmia in a patient, we utilize ECG signals. But the ECG recordings are prone to errors or interference due to Power Line Interference, White Gaussian Noise, Electromyogram/Motion Noise, Baseline Drift, and Electrode Contact Loss. These errors can be broadly classified into high-frequency and low-frequency noises. The errors reduce the accuracy and reliability of the analysis. Hence, it is paramount to remove such errors. Therefore, we use the IIR Notch Filters [25], and FIR Filters [26] to eliminate the unnecessary noise. These filters eliminate both high and low-frequency noises. The IIR Notch filters are amongst the simplest denoising techniques and work well with fixed-frequency noise sources. The IIR Notch filters are usually used to remove high-frequency noise like motion or power line interference. The Finite impulse response (FIR) filters use high and low cut-off frequencies, hence are also called Windowing or Band-pass filters. Only the part of the wave in the specified band is kept, while the rest is attenuated. These filters work in the range of 1 Hz to 100 Hz and are very stable. This makes them suitable to be used with ECG signals. The Butterworth filter is the most common form of FIR filter. Considering the normal heart rate for healthy adults to be 60 to 80 beats per minute while that for athletes to be 30 to 120 beats per minute, we choose the frequency band for the filters to be 0.5 Hz to 2 Hz. Fig. 4, shows the denoised ECG signals using the IIR Notch filter and FIR filter.

4.3. Segmentation of the ECG signals

After denoising the ECG signals in the previous step, we cleaned ECG waves without irrelevant interference. Then we plot the ECG images from the ECG signals. We further segment these ECG images to increase focus on the ECG signals. For segmentation, firstly, we extract the R-peaks in the ECG signals. The R-peak of an ECG refers to the interval from the earliest onset of the QRS complex to the peak of the R wave. After the R-peaks are determined, the wave is segmented by taking the present R-peak value and the last R-peak value and splitting the distance between them to include the wavelets in the current wave. The process is repeated for consecutive wavelets. This is done in accordance with the Christov segmentation [27]. This gives us clearer and more focused ECG images, which can be more efficiently used by our algorithm. This also helps in feature extraction as it only considers the relevant information. Fig. 5 shows the segmented signal extracted from the original ECG signal.

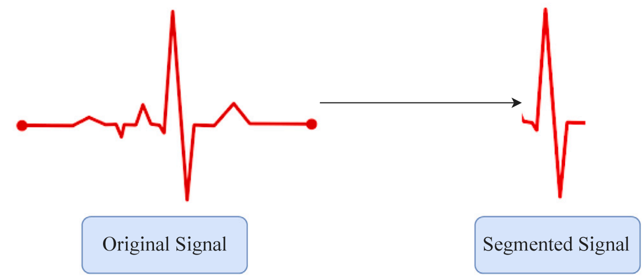

Fig. 5. The segmented signal extracted from the original ECG signal.

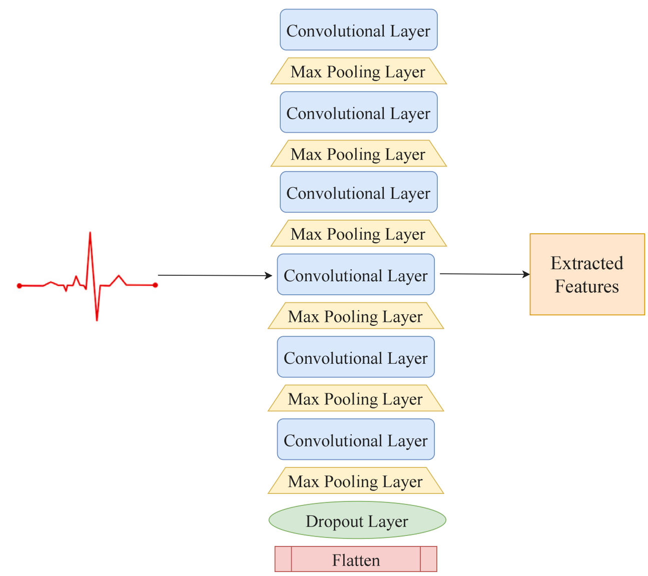

Fig. 6. The CNN architecture used to extract features from the ECG signals.

4.4. Data augmentation

The number of ECG signals belonging to the different classes varies greatly. This makes the dataset highly imbalanced. We use data augmentation for training purposes on the ECG images as a regularization technique to counter the effects of class bias and obtain a more generalized framework. Data augmentation increases the samples of the class which earlier had a lesser number of samples by generating newer samples for that class. We use several standard data augmentation techniques like cropping and resizing, shifting the image through a particular value, and horizontally flipping the ECG image. The data augmentation techniques help our algorithm avoid class bias and over-fitting over a specific class and generate a more generalized framework.

4.5. Feature extraction using CNN

The denoised, segmented, and augmented ECG image dataset obtained in the previous steps is passed through a deep Convolutional

Table 4
The various hyperparameters for our CNN architecture.

Layer name	Filters	Kernel size	Input shape	Output shape
Convolutional	32	3 × 3	128 × 128 × 1	128 × 128 × 32
Max Pooling		2 × 2	128 × 128 × 32	64 × 64 × 32
Convolutional	32	3 × 3	64 × 64 × 32	64 × 64 × 32
Max Pooling		2 × 2	64 × 64 × 32	32 × 32 × 32
Convolutional	32	3 × 3	32 × 32 × 32	32 × 32 × 32
Max Pooling		2 × 2	32 × 32 × 32	16 × 16 × 32
Convolutional	32	3 × 3	16 × 16 × 32	16 × 16 × 32
Max Pooling		2 × 2	16 × 16 × 32	8 × 8 × 32
Convolutional	32	3 × 3	8 × 8 × 32	8 × 8 × 32
Max Pooling		2 × 2	8 × 8 × 32	4 × 4 × 32
Convolutional	32	3 × 3	4 × 4 × 32	14 × 4 × 32
Max Pooling		2 × 2	4 × 4 × 32	2 × 2 × 32
Dropout			2 × 2 × 32	2 × 2 × 32
Flatten			2 × 2 × 32	1 × 128

Neural Network (CNN) architecture to extract the salient features from the images instead of manually extracting the required features. The CNN architecture employed in this study consists of six Convolutional layers, each followed by a Max Pooling layer. A dropout layer further follows these layers. The dropout layer is followed by the flatten layer, which generates the final feature vector to be used by our algorithm. The initial image size is 128 × 128, while the length of the final feature vector is 128. Fig. 6 shows the CNN architecture used to extract features from the ECG signals. Table 4 presents the various hyperparameters of the CNN architecture as depicted in Fig. 6. The deep CNN architecture helps in extracting all the essential features from the ECG images. Moreover, a suitably deep CNN architecture also ensures the reliability of the extracted features while maintaining a feasible computational complexity. The Fuzzy clustering algorithm uses these extracted features in the next step.

4.6. Classification using Fuzzy clustering

The features extracted by the deep CNN in the previous phase are used in this step to classify the ECG images into their respective classes. Firstly, we split the entire dataset into an 80:20 ratio by keeping the 80% for training and the remaining 20% for testing, forming the training and testing dataset, respectively. The whole dataset is split into such proportions so that enough dataset can be reserved for both training and testing while avoiding problems like over-fitting and under-fitting. The training dataset is used to train the Fuzzy clustering algorithm and evaluate the centroids for the various data points in the form of feature vectors. The number of arrhythmia classes act as the number of clusters for the algorithm. Once the framework is trained, it is used for testing on the testing dataset. The various evaluation metrics are evaluated thereby.

4.7. Proposed algorithm

The various steps of our proposed technique are summarized in Algorithm 1. ECG signals dataset, labels for those ECG signals, and the number of arrhythmia classes act as the input for our algorithm. While our algorithm outputts the evaluated performance metrics. We start by denoising the ECG signals using the IIR Notch filters and the FIR filters, as explained in Section 4.2. This is followed by appropriate segmentation by utilizing the Christov segmentation. This has been illustrated in Section 4.3. The segmented signals are thereby augmented using the various augmentation techniques like cropping, resizing, shifting, and flipping, as presented in Section 4.4. The augmented signals are further passed through a deep convolutional neural network architecture having six layers. The details about the architecture are discussed in Section 4.5. The extracted features are then passed through

Table 5
The various hyperparameters for the used convolutional neural network architecture in the proposed model.

Hyperparameter	Description or value
Number of Convolutional Layers	6
Number of Max Pooling Layers	6
Kernel Size for Convolutional Layers	3 × 3
Pool Size for Max Pooling Layers	2 × 2
Strides	2
Activation Function	ReLU
Dropout Rate	0.5

the fuzzy clustering algorithm to classify the arrhythmia signals into their respective categories. This is further explained in Section 4.6. Finally, the various performance metrics are evaluated and returned.

Algorithm 1 Algorithm for our proposed Deep Learning and Fuzzy Clustering (Fuzz-ClustNet) based technique

Input: ECG signals dataset, *D*; Labels, *L*, Number of arrhythmia classes, *n*
Output: Evaluated performance metrics
1. DenoisedSignals ← Denoising(D, filters={IIR Notch Filters, FIR Filters})
2. SegmentedSignals ← Segmentation(DenoisedSignals, type={Christov})
3. AugmentedSignals ← Augmentation(SegmentedSignals, type={Cropping, Resizing, Shifting, Flipping})
4. ExtractedFeatures ← CNNFeatureExtractor(AugmentedSignals, parameters = {NoOfConvLayers=6, KernelSize=3×3, PoolSize=2×2, Strides=2, ActivationFunction=ReLU, DropoutFunction=0.5})
5. TrainingDataset, TrainingLabels, TestingDataset, TestingLabels ← SplitDataset(ExtractedFeatures, Labels, TrainingRatio=80)
6. TrainedClassifier ← FuzzyClustering(TrainingDataset, TrainingLabels, n)
7. ClassifiedLabels ← TrainedClassifier(TestingDataset)
8. PerformanceMetrics ← EvaluatePerformanceMetrics(ClassifiedLabels, TestingLabels)
return PerformanceMetrics

4.8. Hyperparameter tuning

The architectural design specifications of a model are known as hyperparameters. Selecting a suitable set of hyperparameters is essential as it is crucial to the performance of a machine learning or deep learning model. The task of choosing the most appropriate hyperparameters is known as hyperparameter tuning.

In this study, we use the Random Search heuristic for performing the hyperparameter tuning. It is a technique that iterates over a search space of hyperparameters, trying out random combinations from amongst them and finding the best solution [28]. The hyperparameters which generate the highest accuracy values are selected. We have used the random search technique for hyperparameter selection, enabling the model to train on optimal parameters while avoiding aliasing. We have performed the hyperparameter tuning of all the comparing methods used in this study for a fair performance comparison of the proposed framework. Table 5 lists various hyperparameters chosen in the proposed Fuzz-ClustNet framework.

5. Experimental analysis

In this section, we present the experimental analysis performed by us. We run simulations on all the datasets mentioned in Section 3.1 and evaluate all the evaluation metrics mentioned in Section 3.2. We perform a comparative study with various machine learning approaches, namely, Random Forest, Logistic Regression, K-means, Gaussian Naive

Table 6
The mean and standard deviation across the three channels for both the datasets.

MIT-BIH Arrhythmia Dataset		
Channel number	Mean	Standard deviation
Channel 1	0.441	0.233
Channel 2	0.511	0.235
Channel 3	0.317	0.224
PTB Diagnostic ECG Dataset		
Channel number	Mean	Standard deviation
Channel 1	0.507	0.267
Channel 2	0.486	0.256
Channel 3	0.440	0.276

Bayes, K Nearest Neighbors, Support Vector Machine, and Decision Trees. This helps us to understand the performance of our approach against other baseline alternatives. We also compare the performance of our proposed approach with several contemporary algorithms, namely, Sharma et al. [29], Wang et al. [15], Zairi et al. [17], Singh et al. [30], Bhagyalakshmi et al. [8], Iqbal et al. [18], Isin et al. [31], and Acharya et al. [32] for arrhythmia detection using ECG signals. We also perform an ablation study to study the effect of various techniques used by us, like denoising, segmentation, and augmentation, on the performance of our approach. The implementation of the code has been done entirely in the python programming language. We have used several python libraries like sklearn, TensorFlow, NumPy, pandas, etc., to aid the experimental study. We have also used some publicly available GitHub repositories. All the simulations were performed on a personal computer with an intel i7 11th generation processor, 16 GB RAM, and RTX 3070 graphics card.

Table 6, tabulates the mean and standard deviation of both datasets across all the three channels. The mean and standard deviation helps us in channel-wise normalizing the images to obtain uniformity across the datasets.

5.1. Comparison with various baseline techniques

In this section, we compare the performance of our proposed method, Fuzz-ClustNet, with several baseline machine learning methods on both the MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Dataset. Table 7 lists the results obtained for the MIT-BIH Arrhythmia Dataset, while Table 8 tabulates the results obtained for the PTB Diagnostic ECG Dataset. The baseline methods used by us were also fine-tuned based on the problem statement and the dataset under consideration using the Random Search technique. This helps in generating a fair comparison among the algorithms. From Table 7, we see that our proposed Fuzz-ClustNet technique outperforms all the other baseline machine learning techniques by a considerable margin in terms of the values obtained for accuracy, precision, recall, and F1 score. Decision trees are the second-best performer, while the random forest is the worst performer for the MIT-BIH arrhythmia dataset. From Table 7, we see that the clustering algorithms like K-means and K nearest neighbors do not perform very well in clustering the ECG signals to their respective arrhythmia classes. The classical classification algorithms like Logistic Regression, Gaussian Naive Bayes, and Support Vector Machine perform slightly better than the clustering algorithms. However, they are still under-performer in our proposed Fuzz-ClustNet technique. For the PTB Diagnostic ECG Dataset, we see that the Fuzz-ClustNet approach is again the best performer in terms of accuracy. However, it is the second-best performer in terms of precision and recall, while for the F1 score, it is the fifth-best performer. For the PTB Diagnostic ECG Dataset, as evident in Table 8, we see a close competition among the various clustering and classical classification techniques like K-Means clustering, Gaussian Naive Bayes, K Nearest Neighbors, Support Vector Machine, Decision Trees, etc. The above discussion shows that our proposed Fuzz-ClustNet algorithm outperforms the various baseline machine learning algorithms.

5.2. Comparison with various contemporary techniques

Apart from the comparison with the baseline machine learning techniques, we also compare the performance of our proposed Fuzz-ClustNet technique with several existing contemporary techniques for arrhythmia detection from ECG signals. The results are obtained on both the datasets mentioned in Section 3.1 and the all the evaluation metrics mentioned in Section 3.2 are evaluated thereby. Tables 9 and 10 presents the computed results for the MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Dataset, respectively. From Table 9, we see that our proposed Fuzz-ClustNet technique is the best performer in terms of accuracy and the second-best performer in terms of precision, recall, and F1 score for the MIT-BIH arrhythmia dataset. In terms of precision and recall it is second to Sharma et al. [29] while Acharaya et al. [32] outperform it in terms of recall. Overall, Sharma et al. [29] is the second-best performer, while Singh et al. [30] is the worst performer for the MIT-BIH arrhythmia dataset. For the PTB Diagnostic ECG Dataset (Table 10), we see that our proposed technique outperforms all the other contemporary techniques in terms of accuracy and precision. However, for recall and F1 Score, our proposed Fuzz-ClustNet framework is the third and fifth-best performer, respectively. The above discussion demonstrates that our proposed methodology gives efficient and stable results throughout the performance metrics for both datasets.

5.3. Ablation study

In this section, we perform an ablation study to analyze the effects of using the various components of our proposed methodology on the results obtained. We study the effects of denoising, segmentation, and augmentation in our proposed framework. We evaluated eight different results for the following settings: Fuzz-ClustNet without Denoising, Segmentation, and Augmentation; Fuzz-ClustNet without Denoising and Augmentation; Fuzz-ClustNet without Denoising and Segmentation; Fuzz-ClustNet without Augmentation and Segmentation; Fuzz-ClustNet without Augmentation; Fuzz-ClustNet without Segmentation; Fuzz-ClustNet without Denoising; and Proposed Fuzz-ClustNet (with denoising, segmentation, and augmentation). The results are obtained on both the datasets and are presented in Tables 11 and 12 for the MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Dataset, respectively. From the results, we see that the proposed Fuzz-ClustNet, which uses the combination of denoising, segmentation, and augmentation, performs the best compared to the other technique variants. While removing just one component, the best results are obtained for Fuzz-ClustNet without denoising and Fuzz-ClustNet without segmentation for the MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Dataset, respectively. This shows the complementary effect of using the augmentation technique with denoising and segmentation. On the other hand, when two components are removed, Fuzz-ClustNet without Augmentation and Segmentation and Fuzz-ClustNet without Denoising and Segmentation outperform all the different variants for the MIT-BIH Arrhythmia Dataset and the PTB Diagnostic ECG Dataset, respectively. This shows the importance of using denoising and augmentation on the two datasets. When all three components are removed, we notice a sudden drop in the performance of our technique, thereby signifying the importance of these components. The above discussion demonstrates the relative importance of each component, their complementary nature to each other, and their usefulness in obtaining the most optimal results for arrhythmia detection from the ECG signals.

6. Conclusion

Cardiovascular diseases are amongst the most severe diseases causing several deaths every year. Arrhythmia is amongst the most prominent of such heart diseases. This forms the pretext for developing an automated and efficient technique for arrhythmia detection. In

Table 7
Performance comparison of our proposed Fuzz-ClustNet framework with various baseline techniques for the MIT-BIH Arrhythmia Dataset.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
Random Forest	70.62	66.76	84.85	74.72
Logistic Regression	75.73	69.21	91.08	78.65
K-Means	78.56	84.03	70.33	76.57
Gaussian Naive Bayes	74.09	70.95	79.44	74.95
K Nearest Neighbors	78.92	79.52	78.22	78.86
Support Vector Machine	84.76	83.0	86.28	84.61
Decision Trees	85.77	84.11	87.55	85.79
Proposed Fuzz-ClustNet	98.66	98.92	93.88	96.34

Table 8
Performance comparison of our proposed Fuzz-ClustNet framework with various baseline techniques for the PTB Diagnostic ECG Dataset.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1 score (%)
Random Forest	62.77	59.09	84.78	69.64
Logistic Regression	69.8	66.17	81.02	72.85
K-Means	71.71	69.95	71.71	73.64
Gaussian Naive Bayes	80.66	81.78	79.42	80.59
K Nearest Neighbors	85.58	90.26	80.18	84.92
Support Vector Machine	88.96	93.61	84.05	88.57
Decision Trees	91.51	96.91	85.79	91.01
Proposed Fuzz-ClustNet	95.79	96.29	85.38	80.37

Table 9
Performance comparison of our proposed Fuzz-ClustNet framework with various contemporary techniques for arrhythmia detection for the MIT-BIH Arrhythmia Dataset.

Methods	Acc	Prec	Rec	F1
Acharaya et al. [32]	82.04	77.94	93.81	85.14
Isin et al. [31]	82.04	76.64	82.04	85.02
Iqbal et al. [18]	82.52	80.51	87.96	84.07
Bhagyalakshmi et al. [8]	84.07	82.25	88.9	86.52
Singh et al. [30]	75.24	71.56	79.59	75.36
Zairi et al. [17]	82.04	72.73	98.97	83.84
Wang et al. [15]	86.89	84.35	91.51	87.78
Sharma et al. [29]	95.63	99.03	92.73	95.77
Proposed Fuzz-ClustNet	98.66	98.92	93.88	96.34

Table 10
Performance comparison of our proposed Fuzz-ClustNet framework with various contemporary techniques for arrhythmia detection for the PTB Diagnostic ECG Dataset.

Methods	Acc	Prec	Rec	F1
Acharaya et al. [32]	75.91	78.32	72.38	75.23
Isin et al. [31]	78.92	75.92	85.38	80.37
Iqbal et al. [18]	77.28	75.8	79.03	77.38
Bhagyalakshmi et al. [8]	80.47	78.58	83.49	80.96
Singh et al. [30]	85.22	83.3	86.77	85.0
Zairi et al. [17]	83.94	87.4	79.86	83.46
Wang et al. [15]	89.87	92.86	72.38	75.23
Sharma et al. [29]	88.59	87.34	90.07	88.69
Proposed Fuzz-ClustNet	95.79	96.29	85.38	80.37

Table 11
Ablation study for our proposed Fuzz-ClustNet framework to study the effect of denoising (Den.), segmentation (Seg.), and augmentation (Aug.) for the MIT-BIH Arrhythmia Dataset.

Methods	Acc	Prec	Rec	F1
Fuzz-ClustNet without Den., Seg. and Aug.	79.06	74.69	90.03	81.65
Fuzz-ClustNet without Den. and Aug.	81.34	77.44	86.88	81.88
Fuzz-ClustNet without Den. and Seg.	83.91	80.27	90.0	84.86
Fuzz-ClustNet without Aug. and Seg.	85.43	83.68	87.31	85.45
Fuzz-ClustNet without Aug.	87.1	86.71	87.5	87.1
Fuzz-ClustNet without Seg.	88.62	87.95	89.3	88.62
Fuzz-ClustNet without Den.	89.98	86.3	93.97	89.97
Proposed Fuzz-ClustNet	98.66	98.92	93.88	96.34

this work, we present a deep learning and fuzzy clustering (Fuzz-ClustNet) based technique for arrhythmia detection from ECG signals. We start by denoising the ECG signals using the IIR Notch filter and FIR filter. This helps attenuate the unnecessary noise associated with them for several reasons like recording error, instrument error, etc. The denoised signal is then segmented using the Christov segmentation to accentuate the ECG signal further and obtain a more precise and focused signal. We additionally employ various data augmentation techniques to get a more balanced dataset and generate a more generalized framework. The augmented dataset is then passed through a deep CNN architecture for feature extraction. The extracted features are then passed through the fuzzy clustering algorithm to classify the ECG signals into their respective arrhythmia classes finally. We also perform proper hyperparameter tuning to obtain optimal performance. We run intensive simulations on various benchmarked datasets and evaluate several standard performance metrics. We compare the performance of our approach with different baseline machine learning algorithms and several contemporary arrhythmia detection algorithms. We also perform an ablation study to analyze the effects of various components of our proposed technique on its performance. This work can further be extended by utilizing more sophisticated signal processing methods and detecting other heart diseases.

Table 12
Ablation study for our proposed Fuzz-ClustNet framework to study the effect of denoising (Den.), segmentation (Seg.), and augmentation (Aug.) for the PTB Diagnostic ECG Dataset.

Methods	Acc	Prec	Rec	F1
Fuzz-ClustNet without Den., Seg. and Aug.	72.38	66.43	87.89	75.67
Fuzz-ClustNet without Den. and Aug.	84.98	82.96	88.66	85.71
Fuzz-ClustNet without Den. and Seg.	85.73	84.68	87.72	86.18
Fuzz-ClustNet without Aug. and Seg.	84.37	84.01	85.76	84.88
Fuzz-ClustNet without Aug.	86.8	87.87	86.59	87.22
Fuzz-ClustNet without Seg.	87.71	83.42	94.26	88.51
Fuzz-ClustNet without Den.	87.41	86.94	89.68	88.29
Proposed Fuzz-ClustNet	95.79	96.29	85.38	80.37

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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