DOI: https://doi.org/10.52756/ijerr.2024.v45spl.001 *Int. J. Exp. Res. Rev.*, Vol. 45: 01-14 (2024)

Original Article | Peer Reviewed | Open Access

International Journal of Experimental Research and Review (IJERR)

ISSN: 2455-4855 (Online)
www.iaph.in

Automatic ECG Arrhythmia Recognition using ANN and CNN

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Article History:

Received: 12th Jan., 2024
Accepted: 18th Oct., 2024
Published: 30th Nov., 2024

Keywords:
Atrial Fibrillation, Convolution Neural Network, Compression, Malignant Ventricular Ectopy, Normal Sinus Rhythm, Supraventricular Arrhythmia

How to cite this Article:
Ekta Soni, Arpita Nagpal and Sujata Bhutani (2024). Automatic ECG Arrhythmia Recognition using ANN and CNN. *International Journal of Experimental Research and Review, 45*, 01-14.
DOI: https://doi.org/10.52756/ijerr.2024.v45spl.001

Abstract: Present research highlights the need for more patient-oriented monitoring systems for cardiac health, especially in the aftermath of COVID-19. The study introduces a contactless and affordable ECG device capable of recording heart arrhythmias for remote monitoring, which is vital in managing the rising incidence of untimely heart attacks. Two deep learning algorithms have been developed to design the system: RCANN (Real-time Compressed Artificial Neural Network) and RCCNN (Real-time Compressed Convolutional Neural Network), respectively, based on ANN and CNN. These methods are designed to classify and analyze three different forms of ECG datasets: raw, filtere and filtered + compressed signals. These were developed in this study to identify the most suitable type of dataset that can be utilized for regular/remote monitoring. This data is prepared using online ECG signals from Physionet(ONLINE) and the developed real-time signals from Arduino ECG sensor device. Performance is analysed on the basis of accuracy, sensitivity, specificity and F1 score for all kinds of designed ECG databases using both RCCNN and RCANN. For raw data, accuracy is 99.2%, sensitivity is 99.7%, specificity is 99.2%, and F1-Score is 99.2%. For RCCNN, accuracy is 93.2%, sensitivity is 91.5%, specificity is 95.1%, and F1-Score is 93.5% for RCANN. For Filtered Data, accuracy is 97.7%, sensitivity is 95.9%, specificity is 99.4%, and F1-Score is 97.6%. For RCCNN, accuracy is 90.5%, sensitivity is 85.8%, specificity is 96.4%, and F1-Score is 90.9% for RCANN. For Filtered + compressed data, accuracy is 96.6%, sensitivity is 97.6%, specificity is 95.7%, and F1-Score is 96.5%. For RCCNN, accuracy is 85.2%, sensitivity is 79.2%, specificity is 94.5%, and F1-Score is 86.7% for RCANN. The performance evaluation shows that RCCNN with filtered and compressed datasets outperforms other approaches for telemonitoring and makes it a promising approach for individualized cardiac health management.

Introduction

The cardiology service has become even more crucial during the COVID-19 pandemic. The number of heart attack-related deaths has been increasing regularly (Fersia et al., 2020; Madhual et al., 2023; Deva and Dagur, 2024; Ranganathan et al., 2024) and patients with heart conditions are at a greater risk of contracting the virus (Nishiga et al., 2020). Some individuals require regular home heart monitoring. While several heart home monitoring systems are already available on the market, there is still some uncertainty around the credibility of such arrangements for several reasons. Firstly, due to the lack of technological support, the real-time ECG cannot be tracked efficiently (Güvenç, 2020). Secondly, they are expensive and not affordable for common people (Simanjuntak et al., 2020). Thirdly, without automatic classification, the devices are only considered to be ECG recorders (Shahidul Islam et al., 2019; S et al., 2024). Lastly, manual beat-by-beat classification is time-consuming and often susceptible to the observer's perception (Shaker et al., 2020). The above issues intensify whenever at-risk patients always pay a condition like a pandemic arises and the consequences.

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To address the above-mentioned issues, researchers like (Emokpae et al., 2021) have suggested low-cost techniques based on heart-sensor technology for real-time monitoring of heart signals (Swarnalatha et al., 2024; Yoo et al., 2020). The heart contracts while it processes blood, and eventually, a potential difference between two places on the body surface is generated, as measured by electrocardiogram electrodes (Zhou and Tan, 2020). The noninvasive technique of Electrocardiogram or ECG reveals the graphical representation of the heart's pathological condition periodically (Tutuko et al., 2021).

Based on the literature, a real-time ECG device has been designed using an AD-8232 ECG sensor (S et al., 2024). The heartbeat readings are typically taken for a defined time interval to eliminate sudden fluctuations, and a 1-minute-long signal is subsequently considered (Mahmud et al., 2020). The AD8232 is a differential amplifier instrument that is responsible for amplifying the heart signal amplitude from millivolts (mV) to 3.3 volts (Rincon et al., 2020).

Despite of being amplified through the AD8232, the ECG signals are not strong enough to sustain interference from various types of noise that can ultimately alter the signal's morphology. These noises include baseline wander, power frequency noise, electrode impedance interference, muscle noise, myoelectric noise, and respiratory interference (Zhou and Tan, 2020). Such altered morphology reduces the accuracy of predicting the rhythm class. To suppress both high and low-frequency noises, researchers have employed techniques such as adaptive filtering, Gaussian filtering, and bandpass filtering by selecting appropriate high and low cut-off frequencies (HCF and LCF) (Limaye and Deshmukh, 2016). In this work, a bandpass filter with 30 Hz HCF and 1 Hz LCF was chosen to achieve a good signal-to-noise ratio (SNR) value.

Due to regular monitoring and real-time solutions, healthcare data is increasing and the available storage space is becoming limited. Worldwide, more than 300 million ECG recordings are done each year (Tutuko et al., 2021). This raw data is structured or unstructured and requires a lot of computation time, processing power, storage, response speed, and bandwidth, making the system complex (Shaker et al., 2020). Therefore, an efficient data reduction technique must be designed. Various solutions have been proposed in the literature, and compression in the frequency domain gives better results while removing redundancy and retaining information (Li et al., 2021). The frequency domain techniques used in the literature include Discrete Wavelet Transform (DWT), Fast Frequency Transform (FFT), Discrete Cosine Transform (DCT), and more (Acharya et al., 2017). DCT is a simple technique with low complexity, giving a high compression ratio and less distortion on 1-D ECG signals.

To experiment with ECG data, we used an online open-source physionet. However, the data available from each class is often imbalanced and unequal in quantity. To bring balance to the databases, we have reduced the number of signals in each class until they are equalized. Unfortunately, this process has also reduced the total number of signals available from each class, potentially affecting the classification accuracy of deep learning methods. To overcome this issue, we have applied data augmentation techniques to increase the size of the dataset, which will also improve the chances of detecting any arrhythmia (Pan et al., 2020). By at least tripling the size of the dataset, we divided it into training, testing, and validation datasets for automatic arrhythmia classification.

The heart mostly suffers from three kinds of irregularities i.e., Cardiovascular diseases (CVD), myocardial infarction and arrhythmias (Alqahtani et al., 2022). Arrhythmias are irregularities in the heart signals' normal rhythm that can be further classified into morphological and rhythmic arrhythmias (Yoo et al., 2020). When the morphology of each irregular heartbeat is considered, it is called morphological arrhythmia. Rhythmic arrhythmia is a set of irregular heartbeats (Yoo et al., 2020). In the proposed work, rhythmic arrhythmias have been encountered as these are the most common. These arrhythmias can further be put into the routine, i.e., non-life threatening and serious, i.e., life-threatening arrhythmias. The serious arrhythmias eventually lead to heart attacks and other CVDs but the routine arrhythmias occur many times a day and are not fatal. Basically, the category of arrhythmia is decided through the classes of consecutive heartbeats (Shaker et al., 2020). It depicts that a person can suffer from one or more kinds of arrhythmia at a particular interval of monitoring (Alqahtani et al., 2022). The origin of these arrhythmias is from any of the two heart chambers, i.e., Atrial and ventricular chambers. Arrhythmias like Atrial Fibrillation (AFIB), Atrial Flutter (AF), etc., are related to the Atrial chamber and arrhythmias like Ventricular Flutter (VF), Ventricular Ectopy Beat (VEB), Ventricular Fibrillation (VFIB) etc. are originates in Ventricularchamber. Among these arrhythmias, some are considered life-threatening like AFIB, AF and VFIB. If Classification is done for these major groups of arrhythmias it escorts to detect of irregularity in the overall heart. The Supra-vetricular is related to the upper ventricular or the Atrial region and the database covers all arrhythmias related to this region. For classification, there are mostly two techniques suggested by the researchers i.e. Machine learning (ML) and Deep learning (DL). The ML and DL collectively come under artificial intelligence (AI).

Artificial intelligence (AI) has revolutionized the way we manage big data and solve complex problems. Machine learning (ML) relies on handcrafted feature selection and extraction, which can be time-consuming and computationally intensive. Furthermore, it struggles to classify imbalanced datasets found online (Nurmaini et al., 2020). However, deep learning (DL) models, which are based on neural networks, are a powerful tool that can extract and select intrinsic features from neurons independently (Liu et al., 2021). They can also project output using a high number of feature sets. Therefore, in our proposed work, which aims to incorporate big data solutions for in-home setups, we have included compression and automatic classification using DL methods.

Many algorithms can be used in deep learning. By adding more layers between the input and output, the performance of the model can be improved. However, this comes at the cost of increased processing time and complex computations. It is important to find a balance between the number of layers in the network and the processing time and complexity. The goal is to include as many layers as needed to achieve good performance without sacrificing efficiency. In the literature algorithms like Long Short-Term Memory (LSTM), Artificial Neural Network (ANN) (Aslam et al., 2021), Convolution Neural Networks (CNN)(Acharya et al., 2017; Kumar et al., 2024; Niu et al., 2019; Simanjuntak et al., 2020; Yıldırım et al., 2018; Zhou & Tan, 2020) Deep Belief Network (DBN), RNN (Recurrent Neural Network)(Elamir, 2022), and Multilayer Perceptron (MLP) (Ebrahimi et al., 2020) etc. are used for DL implementation. The accuracy of Artificial Neural Networks (ANN) can be limited by the number of layers used for processing. To address this, deep learning methods increase the number of layers employed in the ANN model. The back-propagation algorithm, which is based on gradient descent, adjusts the weights to achieve the required classification. While ANN supports fault tolerance and parallel processing, it has limitations in terms of network interpretability and hardware dependency (Aslam et al., 2021). On the other hand, Recurrent Neural Networks (RNN) are typically used for sequential data, but they cannot learn from unprocessed data. Therefore, they must be trained using encoded features from inputs, rather than raw features (Xiong et al., 2018). The CNN algorithm can perform well on real-time devices with low memory capacity (Nurmaini et al., 2020). It can effectively analyze short rhythms and examine their morphological attributes. The algorithm uses a convolution window to identify morphological patterns and creates local features of the signal. A matrix of tunable parameters is applied for the transformation, which scans the signal from left to right and top to bottom. This transformation is applied uniformly to every part of the signal encountered, allowing for non-varying translation and pattern learning (Nurmaini et al., 2020). Reducing the number of layers in the algorithm can increase its training efficiency while also decreasing its computational complexity (Nurmaini et al., 2020).

CNN, which stands for Convolutional Neural Network, combines convolution and pooling layers to classify inputs. Before the output layer, a flattened layer is included to change the matrix dimension of the last layer into a 1-column matrix. With CNN, the inputs are convolved with a stride, which calculates the stride matrix's dot multiplication. The pooling layer can be of two types: Maxpooling and Average pooling. Max pooling selects the maximum number from each feature map's convolved output. The final output is the number of classes in which the input data is to be classified.

The large amount of input data often requires a significant number of comparisons, which can increase the likelihood of type I errors. Therefore, the best-performing model can be identified using significance tests such as analysis of variance (ANOVA), Friedman test, etc. In this work, the K-fold Friedman significance test is utilized on 30 outputs of classifiers chosen at random (Elamir, 2022). The proposed work involves the design of two models - Real-time Compressed Artificial Neural Network (RCANN) and Real-time Compressed Convolution Neural Network (RCCNN). The methodology involves

The development of a real-time ECG data capturing device and the acquisition of ECG data from 18 volunteers.

An algorithm is designed to de-noise and compress the database created by combining real-time data and online data to achieve a good signal-to-noise ratio and Compression Ratio.

To achieve novelty, three different datasets were created - one with raw signals, the second with filtered signals and the third with filtered plus compressed signals.

Finally, the Classification of raw, de-noised, and compressed datasets was implemented through ANN and CNN. The goal is to obtain the finest classification

scheme for arrhythmias and determine the dataset type that can work suitably for telemedicine applications.

Table 1. ECG Dataset was obtained from different sources (Goldberger et al., 2000).

DATA SET	DURATION	SOURCE	SPECIFICATION					
			Records	Digitization Resolution	Duration	Fs: Sampling frequency (Hz)	Subjects	Channels
MIT-BIH Atrial Fibrillation (Goldberger et al., 2000)	1080 seconds recording	Open SourceMIT-BH (Physionet)	23	12(bit/sample)	10-hour	Digitized at 250 Hz	23	2
MIT-BIH Malignant Ventricular Ectopy	1080 seconds recording	Open SourceMIT-BH (Physionet)	22	12(bit/sample)	30mins	Digitized at 250 Hz	22	2
Arduino AD8232 real subjects recording	300 seconds recording	Volunteer Data	All the 18 volunteers were in the age group 24-47 years and showed normal heart-beat pattern					
MIT-BIH Normal Sinus Rhythm	780 seconds recording	Open Source MIT-BH (Physionet)	18	12 (bit/sample)	1 hour	128 Hz	18	2
MIT-BIH Supraventricular Arrhythmia	1080 seconds recording	Open SourceMIT-BH (Physionet)	78	12(bit/sample)	30 mins	128 Hz	78	2

The proposed algorithm shows that the raw signals provide almost the same classification performance as the compressed signals. However, in clinical applications, pre-processed data is required. Therefore, it is recommended to use filtered or filtered plus compressed data. Although these types of data show slightly lower accuracy than the raw dataset, they still perform better than many classification algorithms in the literature that only classify raw signals.

The paper is organized into four sections. The first section is the introduction, followed by the methodology section that describes the tools and techniques used. The third section is the result section, which explains the major findings. Finally, the fourth section concludes the work and elaborates on the proposed future work.

Methodology

The system comprises a wearable heart sensor accompanied by an appropriate group of algorithms to classify the heart rhythms in the correct cluster finally. These algorithms include the most suitable denoising, compression, and classification techniques according to the dataset. Consequently, the methodology of the proposed RCCNN model comprises various strides, which are well explained in Figure 1. A brief description of each block is given in the next subsections.

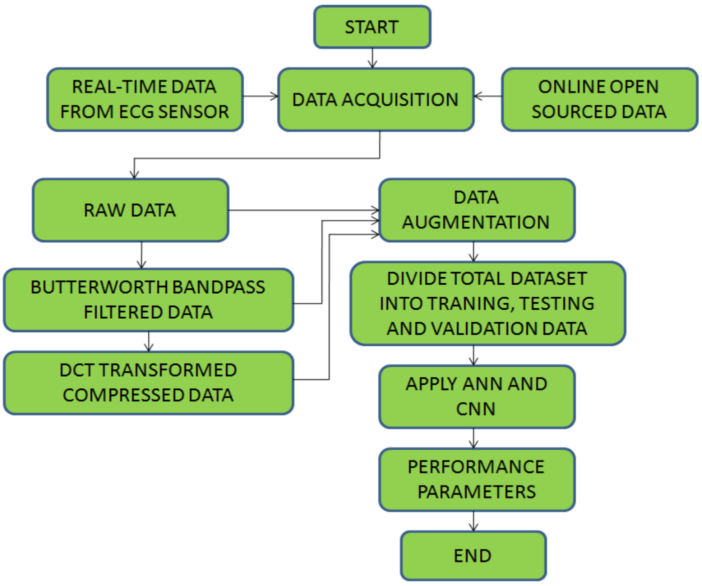

Figure 1. Structure of Real-time Classification Methodology.

DOI: https://doi.org/10.52756/ijerr.2024.v45spl.001

Data Acquisition

The proposed work introduces a combination of two datatypes i.e., Real-time data taken from Arduino and stored for analysis and online data taken from open source. Both of them were mixed to check the designed algorithm performance. Table 1. depicts the specifications of the various datasets used.

Real-Time Ecg Acquisition Setup

The Arduino UNO microcontroller and the ECG sensor chip AD8232 are small portable units that formulate home-based health monitoring systems when accompanied by three sensor patches and connecting wires (Jain et al., 2024). Later, wires capture the biopotential signals from the surface of the skin. The setup of the proposed work is shown in figure 2.

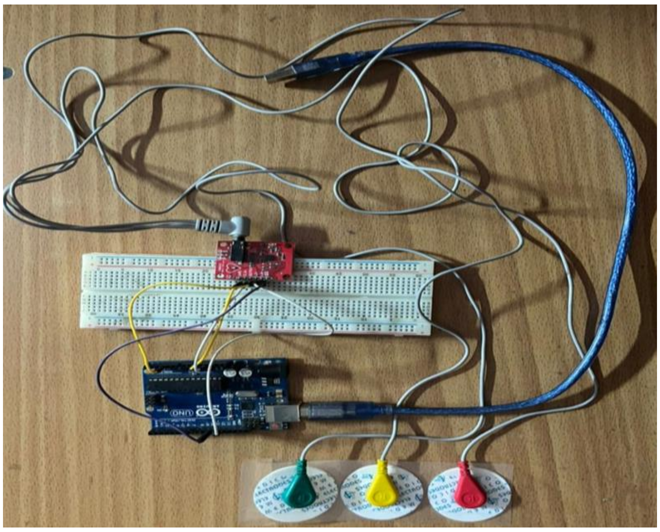

Figure 2. Design of Real-Time data acquisition model setup.

The microcontroller unit used in Arduino UNO (R3) is based upon ATmega328. It has a speed of 16 MHz with a memory of 32 Kb. An operating frequency of170 µA(micro ampere) (ultra low frequency), common-mode rejection ratio is 80 dB with 100 times amplification factor and filters available to the signals extracted.

In this experiment, a total of 18 random volunteers participated within the age group of 24-47 years. All the volunteers at the monitoring time showed normal characteristics of ECG signal and the heartbeat was in the range of 50-100 bps. Hence, all the volunteer data was placed into a normal sinus rhythm class. A total of 780 seconds of the signal was retained and later combined with 300 seconds of normal sinus signal database from Physionet. A sample real-time signal collected is shown in figure 3.

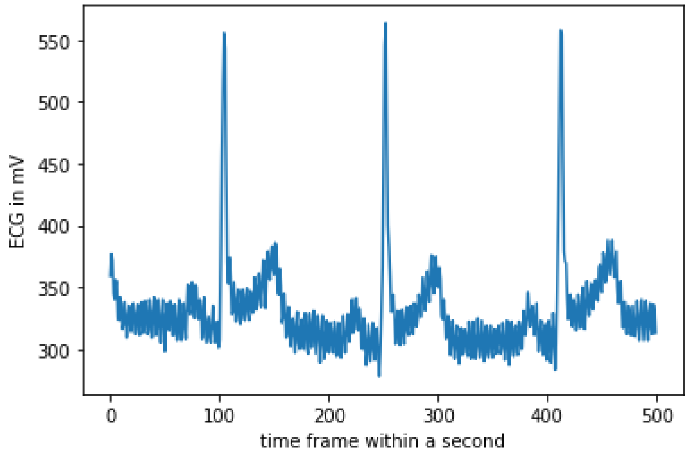

Figure 3. Sample of Real-Time Signal acquired.

It is a noisy signal affected by both high and low-frequency noise (as shown in figure 3). The noise couldn't be suppressed wholly by on-device ECG filters. For in-home monitoring set up, the automatic classification may need signals to be clean enough to get classified without imprecision. Therefore, supplementary de-noising will be done by applying filtering algorithms during processing.

Filtering

The signal may be affected by baseline wander, power frequency noise, power line impedance, electrode impedance interference, muscle noise, myoelectric noise, and respiratory interference. These noises constitute of both high and low-frequency noise and get reduced through low and high pass filters, respectively. So, the proposed work envisioned a Butterworth Bandpass filter with Low and High cut-off frequencies 1 Hz and 30 Hz correspondingly instead of using two different filters. A second-order Butterworth Bandpass filter was used. It can be more clearly depicted mathematically by the following Eq.1.

$$G2(W) = H(jw) = \frac{G_0^2}{1+\left(\frac{jw}{jw_c}\right)^{2n}}, n = 2 \quad (1)$$

Where, G_0 is defined as DC gain, n is the filter order, w is the angular gain and w_c is the cut-off frequency. The output filtered signals and their respective raw signals are shown in the result section.

The home monitoring system has fabricated the problem of big data management due to the need to store huge amounts of medical data. If the dimensions of the data are reduced without compromising the signal's fidelity, it may reduce vast storage size and transmission bandwidth. It is introduced here to compress the online and real-time signals through a common method.

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Table 2. Data Augmentation.

Data Set	Duration of data before Augmentation applied				Duration of Augmented data			
	TRAIN	TEST	VALID ATION	TOTAL	TRAIN	TEST	VALID ATION	TOTAL
Atrial Fibrillation	863sec	108sec	94sec	1065sec	2849 sec	359 sec	320 sec	3528sec
Malignant Ventricu lar Ectopy	883sec	108sec	93sec	1084sec	2879 sec	315 sec	334 sec	3528sec
Normal Sinus Rhyt hm	877sec	108sec	94sec	1079sec	2873 sec	356sec	309 sec	3538sec
Supraventricular Arrhythmia	876sec	108sec	108sec	1092sec	2837 sec	383sec	308 sec	3528sec
TOTAL	3499sec	432 sec	389sec	**4320 sec**	11438 sec	1413 sec	1271 sec	**14122 sec**

Compression

The designed algorithm compresses the signals after disposing of redundant disturbances through compression. A frequency domain-based predesigned compression algorithm is suitable for ECG signals as it utilizes the signal's spectral and energy distributions (Jha and Kolekar, 2021). The predesigned compression algorithms are already performing remarkably. In lieu of designing a new algorithm, we have trialed on these techniques. The discrete cosine transform (DCT) compression scheme is encountered out of these. The DCT is a lossy and orthogonal Fourier transform-based technique that uses only positive components. Its transform coefficients contain most of the signal information with reduced redundancy. It possesses high energy compaction and decorrelation of the transform coefficients. It divides the original signal into subparts and calculates DCT on them. Thresholding and quantization of these ‘N’ transform coefficients is done later. Mathematically DCT can be explained through the under given Eq.2 as

$$X(n) = \sqrt{\left(\frac{1}{N}\right)} \sum_{i=0}^{N-1} x(i)\, cos\left[\frac{\Pi n}{2N}(2j+1)\right] \qquad (2)$$

In the decompression phase, the inverse of DCT i.e., IDCT, will be applied and it is given by Eq.3

$$x(i) = \sqrt{\left(\frac{1}{N}\right)} \sum_{i=0}^{N-1} X(n) \cos\left[\frac{\Pi n}{2N}(2j+1)\right] \qquad (3)$$

The compressed signals are either stored for automatic classification or can be sent to the practitioner. The databases were balanced by lowering the number of signals in each database and making them equal to the database with the lowest number of signals. However, it reduces the size of the total available combined database. Thus, before classification, we have introduced data augmentation to enhance the size of the final database.

Data Augmentation

Data augmentation is the technique that can be implemented on shorter strides to obtain more data by overlapping regions common between two consecutive strides or samples. It helps by making the data up to six times the original (Kim and Jeong, 2021). It reduces overfitting during classification(Niu et al., 2019) and increases data artificially by generating new data points. The proposed work uses a sliding windows technique and the data is implemented starting from one-third of the previous recording. It converts the data in the form given in the Table 2.

Table 3 shows the data duration change before augmentation, i.e., raw data, and after suitably augmenting it. It shows that before augmentation, the total duration of data was 4320sec, including all the databases and real-time data. After applying augmentation, the data's total duration is 14122 sec, which is more than thrice of the original duration of the data. It increases the classification accuracy as no rhythm has been missed to detect. Finally, the whole database is parted into trained, test and validation signals for classification

Classification

The database was classified using two techniques, i.e., ANN and CNN. CNN is a feedforward network with a hierarchal structure. Normally, it is made up of an input layer, convolution layers, pooling layers, learning filters instead of fully connected layers as in ANN, and an output layer. It applies operation on each sub-reason (Liu et al., 2021). The proposed sequential model of CNN consists of two-layer CNN. It has to have two-layers of each i.e., Batch normalization, max-pooling, dropout, Dense or fully connected layers and a single flattened layer to change the output into a single-column matrix. The convolution layer does feature categorization through convolution and the dimensions are reduced through pooling by down sampling. The convolution operation extracts the higher features and reduces noise

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(Simanjuntak et al., 2020). In the convolution layer, each sub-reason of input does convolution with the applied filter kernel and extracts features from the input layer (X. Liu et al., 2021). For the ith feature map in the kth layer, Eq. 4 is given.

$$c_i^k = \theta\left(\sum_{h\in M_i} x_h^{k-1} * w_{hi}^k + b_i^k \right) \quad (4)$$

Where θ is the activation function and M_i and feature maps from the previous layer. w_{hi}^l is the weight for the i^{th} feature map and h^{th} filter index and b_i^k is the corresponding bias.

Performance Evaluation Matrices

A combination of performance parameters has been used to evaluate the designed algorithm's performance. These performance parameters are used at each stage, i.e., after filtration, after compression and finally after classification. The filtering parameter is SNR(Signal to Noise Ratio) = Signal/Noise. The compression performance parameters (Jha and Kolekar, 2021) used in this paper are as given in eq. 5,6 and 7. The classification performance parameters are given in eq, 8, 9,10, 11 and 12.

$$\text{Compression ratio } (CR) = \frac{\text{Size of Original ECG Signal}}{\text{Size of Compressed ECG Signal}} \quad (5)$$

Percent root-mean-square difference

$$(PRD) = 100 \times \sqrt{\frac{\sum_{n=0}^{N-1}(x(n)-r(n))^2}{\sum_{n=0}^{N-1}\sum_{n=0}^{N-1}(x(n))^2}} \quad (6)$$

Where x(n) is the original ECG signal and r(n) is the reconstructed ECG signal.

$$\text{Quality score (QS)} = \frac{CR}{PRD} \quad (7)$$

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

Accuracy is defined as the ratio of the number of correctly classified cases. TP is True Positive, and TN is True Negative (Swarnalatha et al., 2024).

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (9)$$

In eq. 9, FN is a false Negative. Sensitivity is a True Positive Rate, sometimes also termed as Recall value. The fraction defines the capability of the model to predict true positive rates within the class correctly.

$$\text{Specificity} = \frac{TN}{FP+TN} \quad (10)$$

In eq. 10, TN is true Negative, FP is False positive and TN is True negative. Specificity is defined as the capability of the model to calculate true negative samples out of the true positive and false negative samples within the class.

$$F - \text{measure} = \frac{2\times P \times R}{P+R} \quad (11),$$

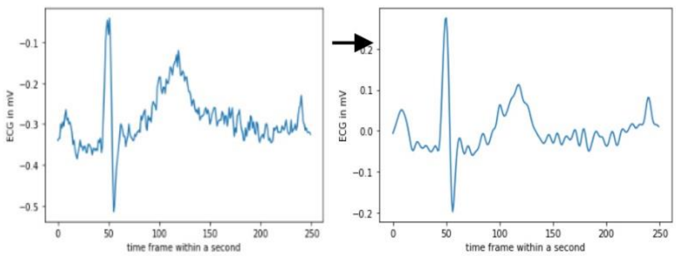
In eq. 11, P and R are the Precision and Recall, respectively. It calculates the poise between recall and precision and gives better results for imbalanced classes (Haloi & Chanda, 2024).

$$\text{Precision} = \frac{TP}{TP+FP} \quad (12)$$

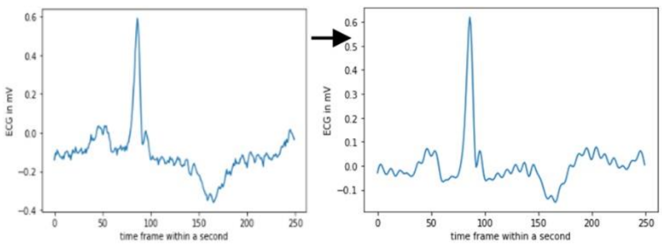
Precision gives positive predictivity by calculating the fraction of true positive observations and the total predicted positive samples.

Results and Discussion

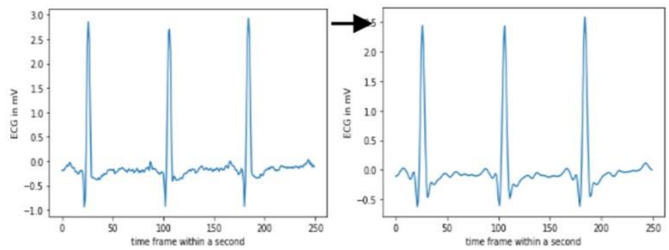
The proposed work aims to get a suitable dataset for remote ECG monitoring through ANN or CNN. The first dataset considered was raw, the second was filtered and the third was compressed. To get the second type of the dataset, we have applied the Butterworth Bandpass filter on each database. The signals from each category are shown in figure 4.



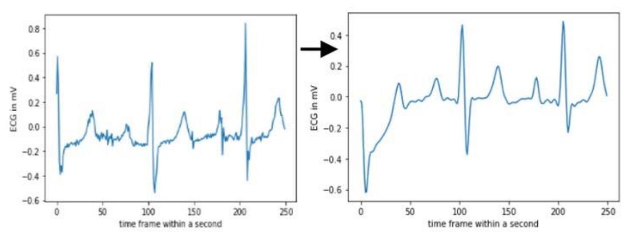
[A]Atrial Fibrillation



[B] Malignant Ventricular Ectopy



[C] Normal Sinus Rhythm



[D] Supraventricular Arrhythmia

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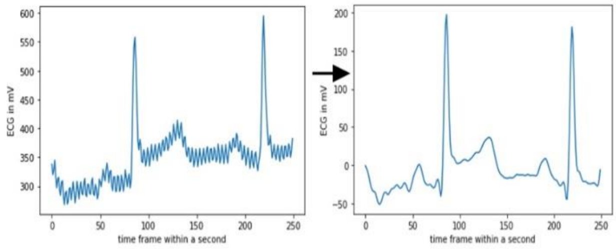
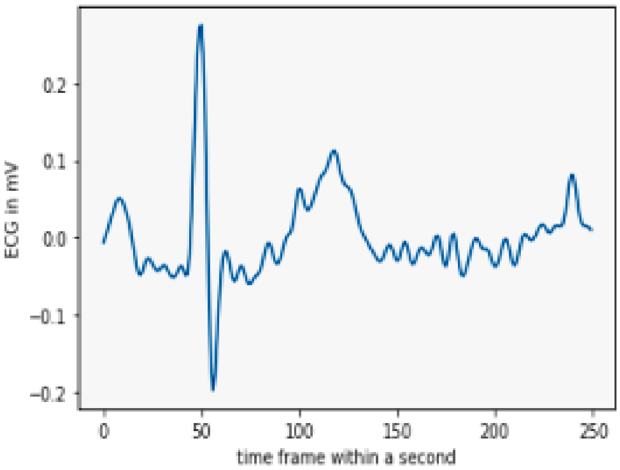


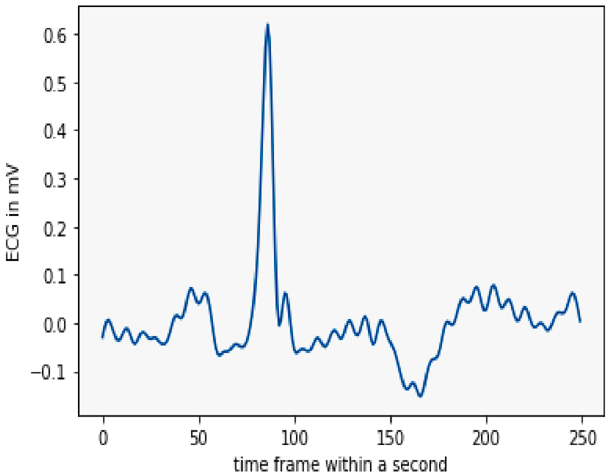
[E] Real-Time Signal

Figure 4. Illustrating raw and filtered signal samples from AFIB, MVE, NSR, SA and Real-Time databases.

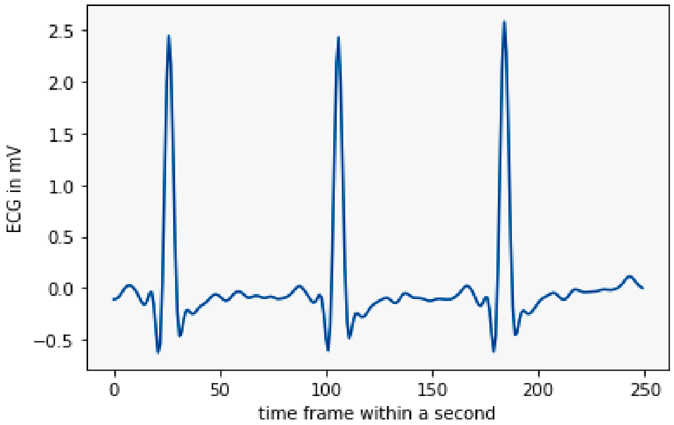
Figure 4 depicts the performance of the applied filter on the raw data-set from all arrhythmia categories. After this process, the second set of datasets, i.e., the filtered dataset, is obtained. Further, to get the third type of the dataset, which is the compressed form of the filtered database acquired in the last step, DCT of each database signal has been computed. The performance of the DCT compression scheme was calculated by average mean squared error (MSE), average percentage root means square difference (PRD) and average compression ratio (CR) i.e., 0.165, 0.261 and 2.6, respectively. The compressed form of the filtered output from the previous stage is shown in Figure 5.



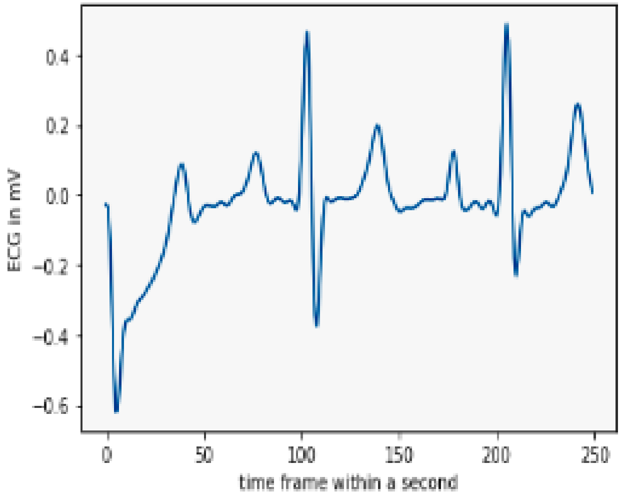
[A]AF



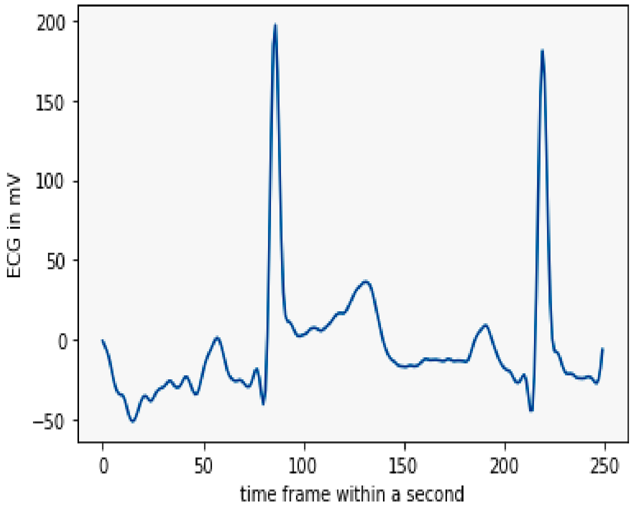
[B] MVE



[C]NSR



[D] SVA

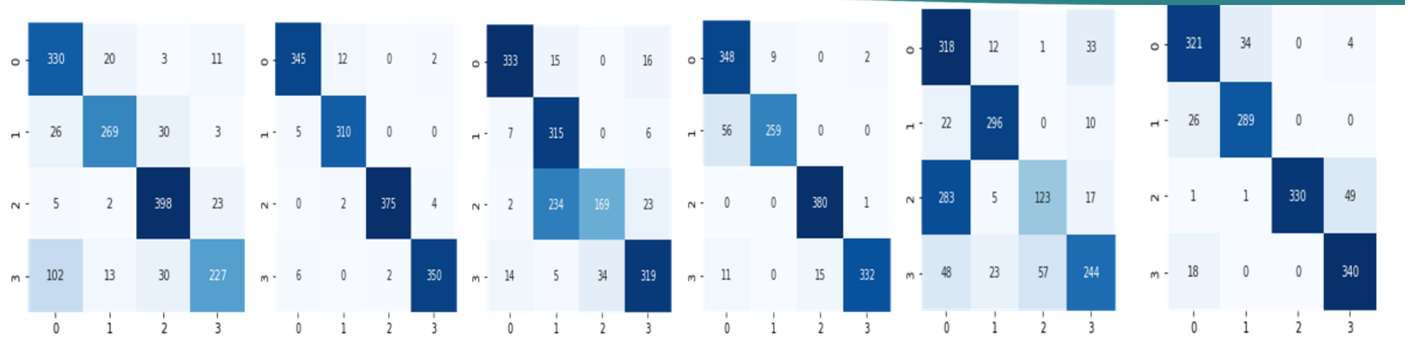


[E] Real-Time Signal

Figure 5. Compressed output from all the databases.

ANN and CNN are applied to check the accuracy of all three datasets. The confusion matrixes in figure 6 are calculated after analyzing true positive, true negative, false positive and false negative results through both methods.

DOI: https://doi.org/10.52756/ijerr.2024.v45spl.001



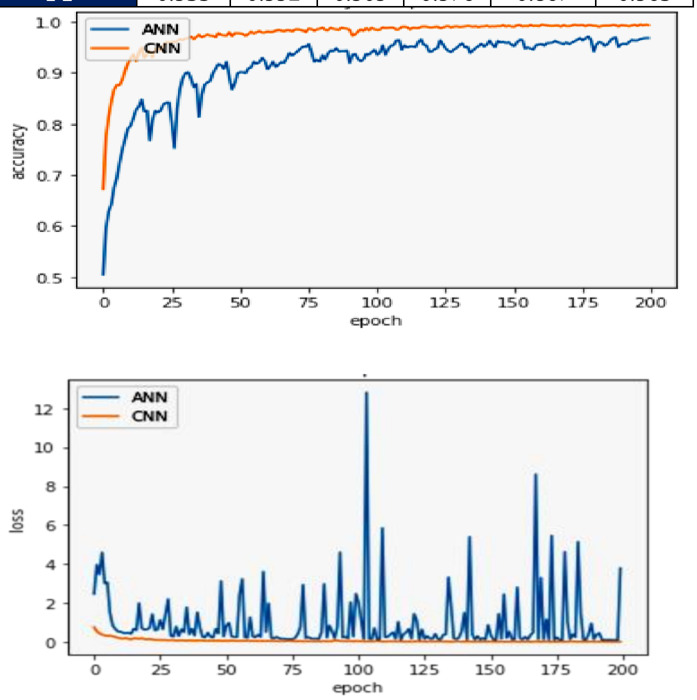
ANN (Raw Data) CNN(Raw Data) ANN (Filtered Data) CNN (Filtered Data) ANN (Compressed Data) CNN (Compressed Data)

Figure 6. Confusion matrixes of ANN and CNN on all the data sets.

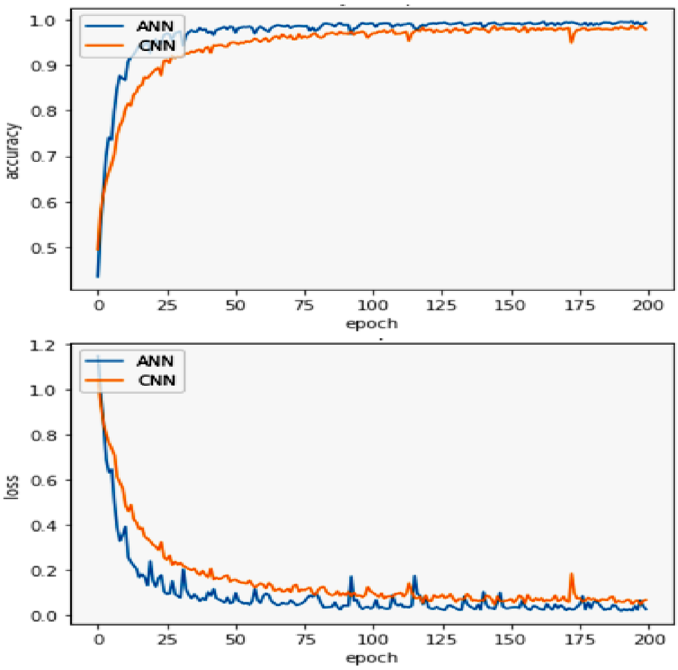
Table 3 depicts the comparative performance of each of the methods used on the unprocessed or raw, filtered and compressed form of the signal. As in the confusion matrix, the accuracy, sensitivity, and performance factors are calculated through TP, TN, FP, and FN values. It is evident from Table 3 that, from all three datasets, CNN's performance is better than that of ANN. Hence, the designed CNN can classify arrhythmia databases more accurately.

Table 3. Classification results of all the three datasets using ANN and CNN.

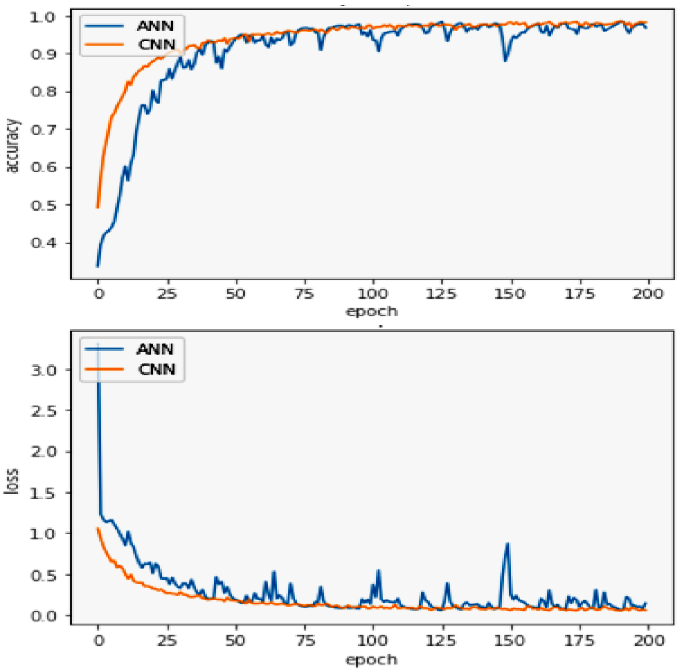
	RAW DATA		FILTERED DATA		COMPRESSED DATA	
	ANN	CNN	ANN	CNN	ANN	CNN
Accuracy	0.932	0.992	0.905	0.977	0.852	0.966
Sensitivity	0.915	0.997	0.858	0.959	0.792	0.976
Specificity	0.951	0.992	0.964	0.994	0.945	0.957
Precision(P)	0.955	0.991	0.967	0.994	0.958	0.955
Recall (R)	0.915	0.993	0.858	0.959	0.792	0.976
F1	0.935	0.992	0.909	0.976	0.867	0.965



1. Raw Data



2. Filtered Data



3. Compressed Data

Figure 7. All three datasets have comparative curves of ANN and CNN for Accuracy and Loss.

DOI: https://doi.org/10.52756/ijerr.2024.v45spl.001

Table 4. Description of the performance of different methods.

Reference	Method	Database	Performance					CR
			ACC. %	SEN. %	SPE. %	PREC. %	F1 - SCORE	
Simanjuntak et al., 2020	CNN and ELM	MIT-BIH arrhythmia dataset	97.50	NC	NC	NC	NC	NC
Emokpae et al., 2021	Deep CNN	MIT-BIH arrhythmia dataset	98	97.7	97.4	90	NC	NC
Zhou andTan, 2020	Deep NN, FFT	Real-time	83.67%	NC	NC	NC	83.83	1:32
Rincon et al., 2020	DNN	8.528 short single-lead ECG records	90	NC	NC	NC	NC	NC
Li et al., 2021	Automatic tuning 1-D CNN	MIT-BIH arrhythmia	NC	91.55%	98.65%	91.73%	92.14	0.2
Niu et al., 2019	multi-perspective CNN	MIT-BIH arrhythmia dataset	96.4	NC	NC	NC	76.6 89.7	NC
Niu et al., 2019	CNN + focal loss	MIT-BIH arrhythmia database+ MIT-BIH arrhythmia dataset	98.41% ± 0.06	98.41% ± 0.06	NC	98.37% ± 0.06	98.38% ± 0.05	NC
Yıldırım et al., 2018	1DCNN	MIT-BIH arrhythmia database	95.2	93.52	99.61	92.52	92.45	NC
Acharya et al., 2017	CNN	MIT-BIH arrhythmia database	92.50	98.09	93.13	NC	NC	NC
Hua et al., 2020	Sparse binary random measurement matrix, Deep Boltzman machine learning	MIT-BIH arrhythmia	90,81.8	NC	NC	NC	NC	40%
Chowdhury and Cheung, 2019	FFT	MIT-BIH arrhythmia, MIT-BIH NSR, European ST-T Database, MAC ECG Database, ANSI/AAMI EC13 Test Waveforms, ECG DMMLD Database	NC	NC	NC	NC	NC	90
Pandey & Janghel, 2019	ANN	number of subjects is 452	83.05	86.67	66.67	NC	NC	NC
Swetha and Ramakrishnan, 2021	K-means clustering optimized fuzzy logic control algorithm	SVT, NSR, MVE, VT, AF, Bradycardia and tachycardial arrhythmia	91.5%	NC	NC	NC	NC	NC
Proposed	RCANN	MIT-BIH AF, SVM, MVA, NSR, Real time	88.4	82.5	96.3	96.7	89	2.6
Proposed	RCCNN		99.0	99.2	98.8	98.8	99	

* AF-Atrial Fibrillation, ANN-Artificial Neural Network, CNN-Convolutional Neural Network, DCNN- Deep CNN, DNN-Deep Neural Network, ELM-Extreme Learning Machine, FFT-Fast Fourier Transform, MVE-Malignant Ventricular Ectopy beat, NC-Not Calculated, NSR- Normal Sinus Rhythm, SVT-SupravetricularTachycardiya, VT- VetricularTachycardiya.

DOI: https://doi.org/10.52756/ijerr.2024.v45spl.001

Though it is apparent from Table 4 and Figure 6 & Figure 7 that RCCNN performs better than RCANN, significant testing was also done on the random 30 outputs in each set-up to determine the significant difference between the two techniques used. When applied to raw, filtered and compressed output signals, K-fold significance always proves the CNN's significance over ANN. A relative study of the proposed RCCNN with the parallel state-of-the-art algorithms is shown in Table 4.

According to Table 4, we have compared different compression and classification algorithms from the literature. A few of them have implemented compression along with classification in a similar way to the one we have applied. However, both techniques are mostly used separately. For compression, FFT has achieved 1: 32% (Zhou and Tan, 2020) & 90% (Chowdhury and Cheung, 2019) compression. Meanwhile, the Sparse binary random measurement matrix achieved 40% compression (Hua et al., 2020).

For classification, CNN and ANN algorithms are compared with other state-of-the-art algorithms with similar algorithms but containing different structures. The deep CNN used in (Goldberger et al., 2000) achieved the highest accuracy i.e., 98.41% ± 0.06, than the other methods in literature. But, the proposed method performed even better than the best-performing method with 99% accuracy when applying CNN on compressed data. ANN (Thomas et al., 2015) gives very low accuracy i.e., 83 %, compared to the proposed ANN which gives 88.4% accuracy. K-means clustering optimized fuzzy logic control algorithm (Swetha and Ramakrishnan, 2021) with 91.5% accuracy is also performing lower than the proposed method.

The findings from the methodologies in the literature suggest that there is rarely any algorithm exists that compares three sets of data for two classification algorithms. The proposed algorithm is also solving big data problems. In addition, as far as we know, a few papers apply data augmentation to increase the data points.

Conclusion

The literature clearly depicts that an advanced ECG processing model for automatic classification of the complete database (that contains different types of rhythms) is essential to improve the workability of ECG monitoring devices. In view of that, current work focuses on discovering a type of data set that can be utilized in the future for Telemonitoring purposes. The proposed low-cost solution (ECG Device) is based on three generated signal datasets: first from the raw signals, second when the raw signals were filtered through a Butterworth Bandpass filter, i.e., filtered signal dataset and third when the filtered signals were DCT compressed, i.e., filtered plus compressed signal dataset. These datasets were derived with the help of online ECG dataset from Physionet and real-time data from Arduino UNO. All these datasets were supplied to deep learning ANN and CNN methods for the classification accuracy test. The proposed algorithm RCANN has used ANN and RCCNN has used CNN on the compressed plus filtered dataset and achieved the accuracies of 0.88 & 0.99, respectively. Accuracies with the other two datasets were 0.93 & 0.99 (with raw dataset) and 0.91 & 0.98 (with filtered dataset) through ANN and CNN, respectively. Based on the accuracy achieved in each case, the paper aimed to come across the finest performing classification methods amongst ANN and CNN and ensured the type of dataset suitable for the telemonitoring of ECG signals. The final results' evaluation suggests that when applied upon filtered plus compressed signals, CNN gives equivalent accuracy when applied to the raw signals. In addition to this, they also take lesser space as compared to others. Hence, the designed RCCNN is suggested for use in telemonitoring ECG arrhythmias.

In literature, the deep CNN (Goldberger et al., 2000) achieved the highest accuracy i.e., 98.41% ± 0.06, than the other methods. But, the proposed method outperforms all the existing methods with 99% accuracy by applying CNN on compressed data. ANN (Thomas et al., 2015) gives very low accuracy i.e., 83 %, compared to the proposed ANN, which gives 88.4% accuracy. K-means clustering optimized fuzzy logic control algorithm (Swetha & Ramakrishnan, 2021) with 91.5% accuracy is also performing lower than the proposed work. The only limitation of this work is that the designed work lacks the ability of automatic classification of ECG signals, as human intervention is still needed. The work shall be extended in the future by monitoring the real-time signals through the cloud gateway and then applying real-time classification.

Funding

This research received no external funding.

Ethics Approval

Written informed consent has been obtained from the patients to publish this paper.

Conflict of Interest

The authors declare no conflicts of interest.

Data Availability Statement

Data has been acquired by physionet and from Arduino uno ECG sensor (in real-time). https://www.kaggle.com/datasets/ektasoni/ecg-data-set (accessed on 6 January 2024).

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How to cite this Article:

Ekta Soni, Arpita Nagpal and Sujata Bhutani (2024). Automatic ECG Arrhythmia Recognition using ANN and CNN. *International Journal of Experimental Research and Review*, *44*, 01-14.

DOI : https://doi.org/10.52756/ijerr.2024.v45spl.001