Hybrid Deep Learning Approach For Ecg Signal Classification Using Sd-Rom

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Received: 15.07.2024 Revised: 20.08.2024 Accepted: 25.09.2024

ABSTRACT
Electrocardiogram (ECG) data show how the heart beats electrically and are used to diagnose and monitor heart problems. Advanced algorithms and deep learning methods can make ECG data analysis much more accurate, leading to better patient results. In this work, a new way to group ECG data is shown. In the proposed system, the Signal Dependent Rank Order Mean (SD-ROM) method, Recurrent Neural Networks (RNNs), and Convolutional Neural Networks (CNNs) all work together. The SD-ROM method cleans up and improves the ECG data by highlighting essential parts and lowering noise. After being worked on, the signs are sent to a CNN-RNN model. The CNN part looks for marks in space, and the RNN part looks for links between events over time. This method takes the best parts of both CNN and RNN systems and puts them together to get very good classification accuracy. Experiments show that the SD-ROM-enhanced CNN-RNN model is better at classifying things than other methods. It provides a solid way to look at ECG data in real-time and helps find early heart diseases.

Keywords: Electrocardiogram (ECG), Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Deep Learning

INTRODUCTION

In medicine, electrocardiograms (ECGs) are often used to check how the heart's electrical system works. It's simple to get and doesn't cost much. Probes on the skin that are connected to an electrocardiograph are used to record ECG readings without touching the heart [1]. Different parts of the heart send out depolarization and repolarization currents, which make up the ECG bio-signal [2]. The regular rhythms you see on an ECG are made up of these currents, set off by organized events in the heart cycle. The P-wave starts the atrium contracting (systole); the QRS complex begins the ventricles contracting (systole); the T-wave initiates the ventricles' relaxation (repolarization); Most of the time, the vertical, horizontal, and sagittal lines can help you understand this vector [3].

A normal 12-lead ECG, on the other hand, has six leg leads (I, II, III, avR, avL, and avF) and six chest leads (V1, V2, V3, V4, V5, V6). This is the best way to find heart problems. ECG waveform models are used to make global measurements. These models are made for each lead based on the recording's most important patterns. The most essential parts of an ECG are the gaps and amplitudes of the P-, QRS-, and T-waves, which are marked by several fiducial points such as signature wave peaks and start and offset borders. [4] Data from a single lead or mathematical combinations of data from multiple leads taken simultaneously can be used to measure them. This process is sometimes called ECG delineation or segmentation. Because measurement error significantly impacts how accurate ECG diagnostic statements are, guidelines say that ECG outlining systems should show their error tolerance levels based on test sets that have been carefully labelled. [5] Much research has gone into making accurate and reliable automatic ECG separation methods.

ML has also been used to figure out how to make an ECG. KNN and SVMs have been used to show that a simple band-pass filter design can improve the slope of an ECG and help find good P-waves, QRS complexes, and T-waves.

Others study the possible benefits of more complex preprocessing and delineation methods, such as an extended Kalman smoother framework followed by a differential evolution algorithm, a marginalized particle filter on a non-QRS signal and a sequential Bayesian detection estimation algorithm; [7] a model-based on Hermite and sigmoid functions combined with piecewise polynomial interpolation for the segmentation and low-dimensional representation of individual ECG beat segments; a bidirectional hidden

semi-Markov model based on the probability distributions of ECG waveform duration; a multiscale morphological derivative transform-based technique; and so on.
One way to separate an ECG is by using wavelet transform (W.T.) mother functions to assemble periodic P-QRS-T patterns. Different time scales are given to you here. These forms are made up of waves moving at different speeds. Li et al. showed the first ECG cutter based on W.T. in 1995. [8] An ECG is often taken apart and then put back together from different levels of separation to get sub-signals in frequency bands that only show QRS complexes or P- and T-waves. A lot of people do W.T. this way. [9] W.T. was sometimes used in more complicated ways to show an ECG. A hidden Markov modelling method splits the ECG signals after strong ECG pre-filtering with W.T.
Deep neural network (DNN) technologies have increased over the last few years. As a result, there have been many more projects to separate ECG signals. [10] They put the raw ECG results into four groups based on the network levels they used: Some networks use "bottleneck" designs, which lower the number of dimensions of the input by having fully linked layers with few output units and shared processes. When the data is hidden or sent out, some networks keep the original dimensions of the raw ECG data. [11] This method reduces the size of the input feature map and the hidden layer-trained parameters. It also gets more general copies of the raw ECG data that was sent in. [12] In the encoder path, the feature map is twice as big to see low-level and high-level network features. This is done so that only a little data is lost during the sharing process of the encoder path.
When tracing an ECG, different input leads are used to look at the input receptive field. A lot of them only use one lead or a mix of leads. The PhysioNet database, which has one of the most extensive and complete ECG records available to the public, is used to build most of it. [13] The standard 12-lead ECG or the three vectorcardiogram leads are usedin fewer studies.

LITERATURE REVIEW

An ECG can record changes in the heart's heartbeat as long as the person is not hurt. Putting lines on a patient's body lets an ECG machine keep track of their heartbeat. Heartbeats change, the signal's strength is minimal, and it's hard to figure out its parts. This makes ECG research challenging. The hard part is accurately naming and grouping the different rhythms [14]. To carefully look over ECG readings, you need a skilled doctor. If you do it by hand, you might make mistakes. [15] You can avoid making these mistakes using the newest and most famous technologies, like machine learning and deep learning, to create an intelligent automatic system.
There are several ways to find arrhythmia in the papers, but most studies have focused on removing noise from ECG data. [16] SVMs, signal segmentation, and hand feature extraction have all been used to create different machine-learning models. Higher-order statistics, Hermite functions, and several machine-learning-based methods have also been used to get more features. Some problems with the above techniques are that they are costly, take a long time, and the signals have to be preprocessed by hand. [17] Researchers have looked at ECG data using deep learning models such as CNNs and RNNs to get around these issues. However, they still have to handle the signals first, which can cause information to be lost [18].
Recently, deep learning has made huge strides in medical research. Making hearts appear independently has been used in some of this field's most important new studies. If you want to explain the type of ECG data better, DL-based ECG classification is better than SVMs and groups, which are both machine-learning-based classification methods. The feature extraction power hides multiple levels, which makes this happen. DL or DNNs are used instead. There was an idea for a DNN that used raw ECG data as its signal. This didn't have to be done by hand before feature extraction. [20] One study found that DNNs work better when given raw data and time. A lot of studies use different kinds of information. Some of them use simple datasets, like the MIT-BIH Arrhythmia Database and the PhysioNet Challenge datasets. Some studies get their information and call it what they want. [21] It was made using a Holter device to record long-term ECG readings, which the people who wrote used. This database keeps track of the events in the heart that don't happen very often but can lead to arrhythmia sickness. [22] It is clear from these studies that deep learning methods can find beats quickly and correctly. The next step might be to make arrhythmia diagnosis and treatment decision support tools for professionals who are more reliable and suitable at what they do.
Different deep-learning methods for finding rhythms can be found by comparing the techniques used in the books. [23] When extracting features from raw ECG data, CNNs have shown excellent results. However, RNNs prefer to avoid noise and might need a lot of data for each processing step. They are very good at guessing how different times are connected. [24,25] Deep learning systems that mix CNNs and RNNs are the best of both worlds.

METHODOLOGY

This part is shown below. Section 3.1 briefly summarises the collection and what it has in it. It talks about how to get the info ready in Section 3.2. We talk about the different filters that can be used on ECG data in Section 3.3. To learn more about models 1, 2, and 3, read Sections 3.4.1, 3.4.2, and 3.4.3. These sections go into more depth about how the models are made. In the last part (3.5), we discuss the success measures used to check and keep track of how well the model works.

Data Description

The MIT-BIH Arrhythmia Database showed 48 half-hour labelled two-channel mobile ECG records. From 1975 to 1979, the BIH arrhythmia laboratory looked into 47 people in the above dataset, released in 2005. Twenty-three songs were picked. There are beats in the last 25 tracks that are rare but very helpful for therapy. They were all picked from the same set. This was done to ensure the collection was vast and had a lot of different beats. The database's ECG recording was turned into a digital file, and two cardiologists fixed any differences in the data. Figure 1 shows how the heartbeats were labelled.

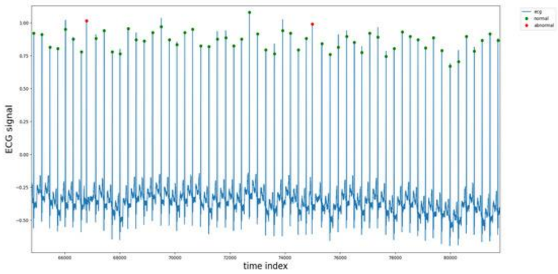

Fig 1: Heartbeat annotations in the dataset.

A. Preprocessing

The Arrhythmia Database at MIT and BIH At 360 Hz, ECG data was handled. Even though the data used in the study was carefully chosen, ECG readings are noisy in real life. A lot of noise was added to the dataset to help the model learn how to work in those conditions. The moving average filter, the low-pass Butterworth filter, the 1-D Gaussian filter, and the median filter were all used to improve the data. You can see the data and how well each filter worked in this section. Since it worked the best, we used it to eliminate the noise in the ECG message. Since the information has notes, ECG values are broken into heartbeats. A Z-score method is used to adjust each ECG slice so that there is more data and less noise.

This method fixes the amplitude scaling issue and eliminates the shift effect. After the dataset is cleaned up, the data is split randomly into two sets, one with 80% of the data and the other with 20%.

B. Filters

Some signals are annoying and need to be taken out of signals gathering data before they can be used in critical cases. The authors used six filters to eliminate the noise in the ECG readings. Here's what the filters are:

a) The median filter

The median denoising filter takes out the noise that sounds like salt and pepper. It's not a straight-line filter. A window is slid over it in this filter, and the middle of the window is found for each case. After that, the middle number is used to replace the other pixels.

b) The Gaussian filter

Gaussian blur is another name for a Gaussian denoising filter. It produces kernels with a normal distribution and denoises the signal. The complete input data or signals have been denoised by creating a Gaussian impulse.

c) Moving Average Filter

The Moving Average filter helps make the data smoother, which is one of its main jobs. This filter gets the mean of all the data points that come in. This evens out the sound. You can see long-term trends in the stream after getting rid of noise and short-term changes.

d) In the filter of Savitzky and Golay:

It has parts where you can fit a polynomial and change the input for the result. When done over the signal input, this makes the signal smoother.

C. Architecture

Three (1D) unique CCNNs are talked about in this piece. There are two unique CCNN structures with only one dimension (1D): Model 1 and Model 2. Each one has five (5) max-pooling layers, five (5) convolution layers, and one (1) fully linked layer. Three max-pooling layers, four fully linked layers, four convolution layers, and seven dropout and max-pooling layers make up the third and only CCNN that is truly unique. It is called Model-3. The dropout, max-pooling, and convolution layers move around in the models.

Model 1:Figure 2 shows model 1, which is this thing. The form to enter is (2160, 1), and the triggering function is RELU. The filters for each convolution layer are 400, 256, 178, 88, and 44. They come in sizes of 20, 15, 7, 5, and 3 mm. To protect it, padding is used, and the largest pool size is set to 2. Also, the steps are set to 2. A sigmoid is used to turn on the last layer, the output layer.

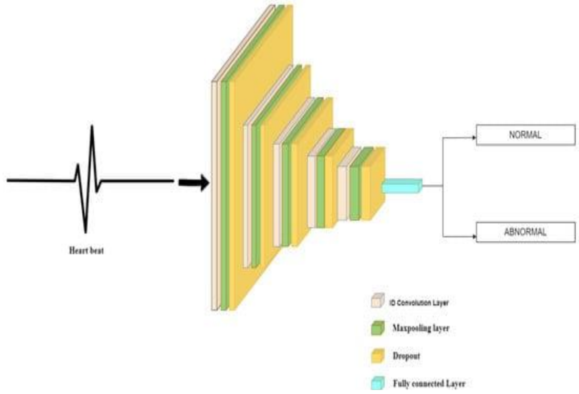

Fig 2: Diagram of Model-1 architecture.

Model 2:This is how Model 2, seen in Figure 3, is put together: There is a failure between the convolution and max-pooling layers. It can hold info that is 2160 bytes long and 1 byte wide. A method called RELU is used to turn on the input layer and all of the convolution layers. Each alternate layer's seed size is set to 20, 15, 10, 7, and 20. In that order, the filters are set to 600, 400, 266, 178, and 88. The most considerable pool size for each max pool layer is two (2), and two (2) steps are set for each layer. The model is smoothed before the dense layer, and the sigmoid activation is set for the thick layer.

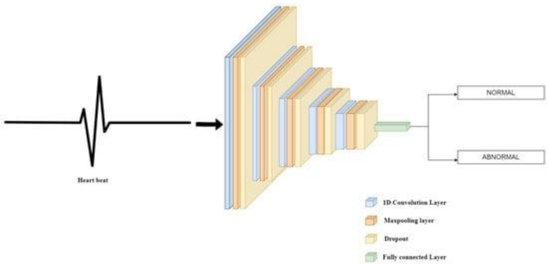

Fig 3: Diagram of Model-2 architecture.

Model 3:Figure 4 shows how it's put together: There is a loss between the convolution layer and the max-pooling layer. It has 2160 bytes of space and 1 byte of width. An activation function called relu works on the input layer and all the other convolution layers. There are two different convolution layers. The kernel size for each is 5, and the filters are set to 256, 128, 72, and 36. There is a failure point with a rate of 0.50 in the model between each set of convolution and max-pooling layers. The most considerable pool size for each max pool layer is two (2), and two (2) steps are set for each layer. It's made flat before the thick layers are added. There are neurons in three dense layers, which are called 50, 32, and 1.

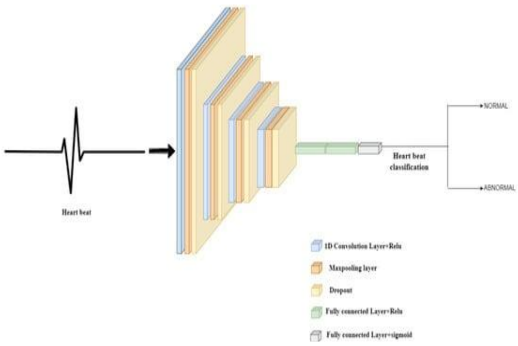

Fig 4: Model 3 architecture.

The steps in the process are shown in Figure 5. The data is at the beginning, and the data is at the end.

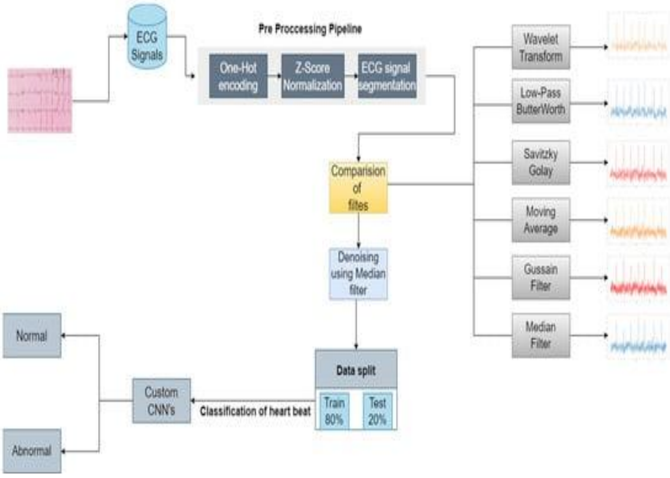

Fig 5: Proposed custom CCNN heartbeat classification algorithm.

The information that one-hot encoding is done on is used to get the ECG signal. Z-score is used to standardize these data, and then heartbeat segmentation is done. Several types of filters are used to remove noise from the data. Some of these are the Gaussian filter, the moving average filter, the median filter, the low-pass Butterworth filter, and the wavelet transform. Once the data is clean and ready to be used, it is split into training and testing sets. Then, these sets are sent to CCNNs so that they can sort the heartbeats into groups.

RESULTS

This part discusses the outcomes of following the suggested steps to clean up noisy ECG data, including natural and fake data. We will also look at what happens to HRV data when Gaussian and ectopic noise amounts change.

A. Validation of the pre-processing tool

When 2 dB of Gaussian noise is added, Figure 6 shows how well the suggested way lowers noise in ECGgau. The result of time-frequency domain denoising shows that the partly reconstructed denoised ECG (ECGden) is correct and easy to see. Also, there is less noise. With the CEEMDAN-WD method, the noise is taken out, but the energy profile of the rebuilt ECG signal stays the same. This is especially true for the QRS complex, as shown in Fig. 6.

The effectiveness of each approach is shown by the root mean square error (RMSE) and mean association coefficient values. The RMSE and correlation score for each of the four methods are shown in Figure 6.

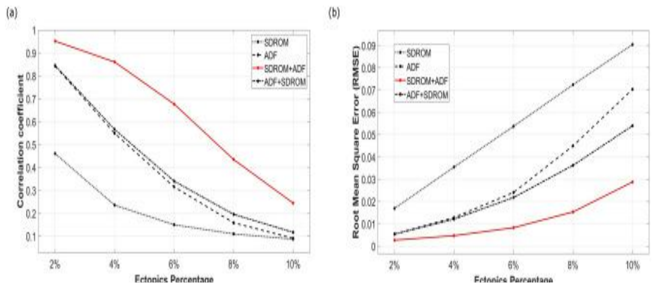

Fig 6: Look at the RMSE and mean correlation coefficient for the SDROM, ADF, SDROM-ADF, and ADF-SDROM

Denoising methods in (a) and (b) to see how well the ectopic filter works. This kind of noise is present in different amounts for each technique.

The SDROM makes the least amount of noise regarding connection. The ADF filter and the ADF-SDROM combination filter work the same way when there isn't a lot of out-of-band noise. The ADF-SDROM filter works better than the ADF filter when there is more noise, as shown in Figure 10a. Most of the time, the SDROM-ADF method works best when there is noise. The number that goes with it is the best.

The denoising method was used on one ECG signal from each of the actual ECG signal files shown above. What was done to clean up the "16,539," "119," and "52" ECG files from theMIT-BIH normal sinus rhythm, arrhythmia, and sudden heart death files? These show that the denoising works well on real ECG clips. It only removes the Gaussian noise and doesn't change the ECG data. The SDROM-ADF method removes most of the noise from outside the HRV.

B. Effects of noise type on HRV measures

The RRIart, RRIgau, and RRIect files were used to get 24 HRV traits. How can I find out how different the breaks between the beats are regarding time? You can find the number of N-to-N intervals longer than 50 ms, the root mean square of the changes between each N-to-N interval, or the standard error of the mean N-to-N interval. Table 1 shows the outcomes of the linear regression study. This link showed the percentage change in HRV features (RHRV).

Table 1: Sort the HRV data in the absolute slope (B) of linear regression by time, frequency, non-linear, and fragmentation measures

POWER	0.611	< 0.0001	17,416.08	17,416.08	VLF POWER	0.030	0.014	−91.591	91.591
LF POWER	0.644	< 0.0001	51,760.12	51,760.12	LF POWER	0.057	0.001	−138.717	138.717
HF POWER	0.622	< 0.0001	102,963.27	102,963.27	HF POWER	0.071	1.42E−04	−245.000	245.000
TOTAL POWER	0.636	< 0.0001	172,579.35	172,579.35	TOTAL POWER	0.060	4.84E−04	−477.852	477.852
alpha1	4.969E−05	**0.921**	−0.026	0.026	SD1	0.136	< 0.0001	−0.033	0.033
SAMPLE ENTROPY	0.004	**0.346**	0.210	0.210	SD2	0.102	< 0.0001	−0.037	0.037
alpha2	0.014	**0.092**	0.297	0.297	alpha1	0.130	< 0.0001	0.603	0.603
SD1	0.948	< 0.0001	0.958	0.958	MEALS	0.309	< 0.0001	−0.903	0.903
MEALS	0.751	< 0.0001	1.307	1.307	SAMPLE ENTROPY	0.050	0.002	−1.681	1.681

DISCUSSION

Holter records and the newest computer programs have allowed HRV research to be used in medical situations. HRV research is becoming essential for determining the risk and outlook for many heart diseases, how long a chronic disease will last, and how it will grow. It has also been seen that people with dementia61, stroke60, mental illness62, kidney failure, diabetes, sleep apnea, stress, and pain5,63,64 have changes in their HRV. These diseases are not connected. It would help if you also considered how sensitive the HRV values are to Gaussian and ectopic noise to avoid coming to the wrong conclusions. A two-step mixed screening method is used in this study to suggest a solid automatic preprocessing tool for HRV research. This is meant to fix some issues with preprocessing ECGs and RRIs.

It has been found that all editing methods affect HRV measurement. How much effect there is depends on how the signal was edited, how long it was, and how much ectopic noise there was .25. Because of this, it is essential to pick the right changing methods to keep the results the same. This research used spontaneous adaptive filtering, which can change the unique properties of each signal while preserving the HRV analysis's diversity.

CONCLUSION

A new two-step preparation method was made to eliminate both technical and ectopic noise for a complete denoising method; both types of noise were taken out by the tool without changing the signal, as shown by a high link and a low RMSE number. Ectopic noise, not technical noise, was the main reason why HRV readings changed more. As this study shows, most of the HRV readings are changed by noise. However, one difference is how sensitive HRV readings are to various kinds and amounts of noise. This means that when picking HRV features to describe physiological signals, you should consider how each HRV measure needs to be preprocessed based on how well they deal with noise.

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