Ensemble RNNs for ECG signal classification

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Abstract

An electrocardiogram (ECG) is a medical assessment tool used to observe heart functionality based on its continuous electrical activity. Each heart beat is stimulated by an electrical impulse that causes the muscle to contract and pump blood through the body. When this impulse is recorded over time, it produces an ECG pattern, which can be used to detect normal or irregular heart activity. This project aims to evaluate the effectiveness of wavelets for extracting multi-scale features in sequence based classification. Recurrent Neural Networks (RNNs) are trained to classify ECG heart beats within a time series ECG signal. Experiments using (one or more) benchmark datasets will be used to test the effectiveness of combining models drawn from various time resolutions. This work could eventually be used in Computer Aided Diagnosis, where the interpretation of ECG signals is done electronically and potentially more objective than manual interpretation.

I. Introduction

ECG analysis is where healthcare professionals analyse or interpret electric signals sent to the heart. Obtaining the detailed physiological state of various parts of the heart by collecting signals is an indispensable means of objective clinical diagnosis[8]

Cardiovascular diseases (CVDs) are the leading cause of death worldwide[22]. ECG analysis helps flatten the curve of death by CVDs by early detecting the diseases and treatment is given at an early stage which increases chances of survival

What needs to be improved in this sector is the efficiency of data collected by wearables such as smartwatches. It s can make it easier to detect an irregular heartbeat as patients will no longer need to visit a healthcare facility to be tested and receive results effortlessly by uploading the heartbeat data to a cloud service and get results back. This study proposes and investigates the efficiency of using an ensemble from 3 models in which all different input ECG data are pre-processed using wavelets.

The remainder of this proposal is structured as follows. Section 2 describes some background concepts and terminology that are drawn from the field of ECGs and are essential for a complete understanding of this project. Section 3 discusses some of the previous work done under the same domain in this paper, where the section address how authors dealt with unbalanced data and its effects, how they integrated an ensemble framework using expect features and also using RNNs to classify heartbeat. Section 4 covers the methodology that this paper will cover with experiments to be conducted, and further explanation of the used dataset. Section 5 coveres the resuslts obtained in this paper and finally section 6 describes the conclusion and discusses the results obtained.

II. Background

The heart is a muscle tissue that pumps blood. Like all muscles, the heart needs an energy source and oxygen to function fully. The sinus node, which is a small tissue located in the heart's upper right chamber, generates an electrical stimulus that is used to send messages. The central nervous system (CNS) controls most functions of the body and mind. It controls the functions of the body by sending electrical messages from the brain to different muscles in the body. For eyes to blink, a signal is repeatedly sent to the eyelid muscles to tell them to relax then contract - this causes them to close then reopen. Likewise, if the heart is to pump blood to every part of the body reliably, its muscles need to be controlled to tell them when to contract and when to relax periodically. This is the purpose of the QRS electrical signals. When there is something wrong with these signals, the heart may not pump blood properly, leading to serious medical consequences.

An Electrocardiogram (ECG) records signals to one's heart. ECG is important for checking whether the heart is receiving the correct/typical signals. The heart has four chambers named ventricles and atriums (see *figure* 1) [21]. The two upper chambers (left and right atrium) contracts to pump the blood and produce the first wave called P wave. The line goes flat when the impulse goes to the bottom two chambers (left and right ventricles) to create the QRS complex wave[2][13]. Finally, the T wave is produced when it all returns to a resting state for the ventricles (see *figure* 3)[13]. The ECG is done mainly to diagnose many

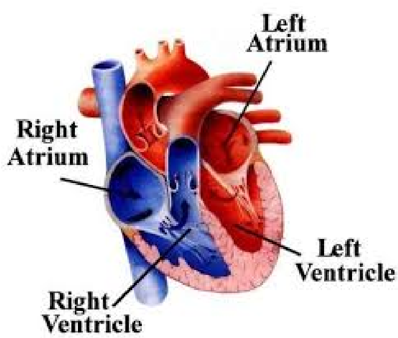

Figure 1: *The Structure of the heart [21]*

heart-related diseases. ECG can aid in finding if a heartbeat or heart rhythm is normal or abnormal. ECG can also help with the detection of arrhythmias, of which it is just an irregular heartbeat, coronary artery diseases which are a blocked or narrowed arteries that lead to heart attack, and also ECG can help detect if you have ever had a heart attack previously. ECG does not only help with tracking how well the prescribed medication is working. Things like caffeine, alcohol or stress are some of the causes of the irregular heartbeat[1]

In today's times, many machines are used to detect a heartbeat. We even have smart wearable watches that we can wear every day and can detect impulse and rate. In hospitals and other health institutions, they mostly use a Holter monitor. This is a portable machine that can detect and record ECG for 24 – 48 hours continuously. Using this machine is purely painless, the medical technologist has to attach 4 to 12 sensors in one's chest, and if you have hair, they might have to shave the part where the sensor will be assigned for better and accurate readings(see *figure* 2)[10]. These sensors called leads are placed explicitly in the mid-Axillary line and Anterior. Misplacement of the limp leads may lead to abnormality. There is no side effect of using this machine. This machine is mainly made to be portable so that it can be used in most places, and it is used in ambulances on the way to health institutions, also used in medical helicopters, hospitals. It also plays a huge role in training athletes and the sports department. Apart from a Holter monitor we also have an Event monitor which does not take readings continuously but take readings for specific minutes which are chosen by the user when usually when feeling some symptoms and it can function for up to 30 days We have many diseases; some are known,

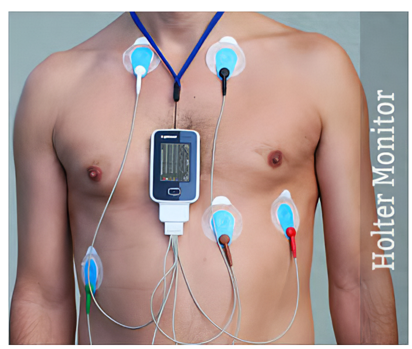

Figure 2: *The Holter monitor[10]*

and some remain unknown. ECG can help with the detection of both kinds of conditions (the known and unknown); it has the advantage that as a patient does not need to first feel pain or other symptoms before being diagnosed with a heart abnormality disease With all the good that comes with ECG, it also have shortfalls like sometimes abnormalities shown by the ECG analysis have no medical significance after an in-depth assessment has been made, and if arrhythmia occurs sporadically the ECG may not be able to detect it since it reveals the heart rhythms and rate only during the few seconds it takes to record tracking[18]

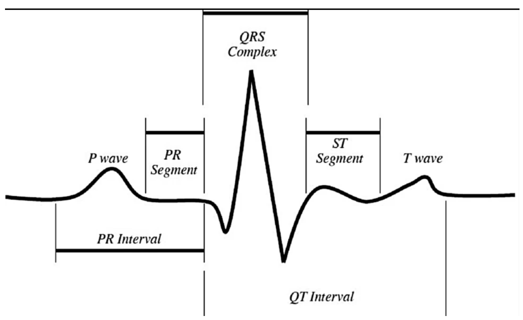

Figure 3: *The segments of a single ECG wave[13]*

III. Literature review

This section covers some of the work done under the same research domain.

[19] used the 1-lead ECG dataset that has a total of 12186 instances which 30% of the dataset is used as test data and made public by the organizers of the challenge [9]. The dataset consists of 4 classes, which are normal, other, atrial fibrillation, and noise. [19] proposed a two-level blender ensemble model, which got an F1 score of 0.79. the distribution of each class score is shown in table 1. [19] did not cater to the imbalance of the data variation among the dataset, and it decreased the final F1 score drastically.

Class	Normal	Atrial fibrillation	Other
F1 Class Score	0.90	0.79	0.68

Table 1: *summary of [19] results*

[11] used the same dataset as [19], which is supplied by [9] to extract Important expert features from each ECG instance and proposed a hybrid fusion model of Convolutional Neural Network(CNN) and RNN. [11] used different expert features to create an ensemble model. The test data for this dataset is kept private.[11] used cross-validation to test the model's robustness and got an overall F1 score of 0.8530; the results' layout is shown in Table 2. This proposed approach uses a fixed number of the sliding window, which is 0.6. Any data containing anything above that will not work for this approach will also affect the hyperparameters' performance as they are also dependent on the sliding window used.

Class	Normal	Atrial fibrillation	Other	Noise
F1 Class Score	0.9204	0.8692	0.8068	0.8156

Table 2: *summary of [11] results*

[8] used the MIT-Bih-arrhythmia-database-1.0.0 dataset, which has a total of 93371 ECG beats. The dataset is separated into eight different classes, N, LBBB, RBBB, APC, NESC, ABERR, NPC, and AESC, where N represents Normal, and others represent different variations of arrhythmia. [8] solves the data imbalance problem by introducing focal-loss to the proposed RNN and received a total F1 score of 99.27. The disadvantage of this paper is that the study is conducted only on eight beat types whereas some existing literature like [14] who used up to 16 beat-types, and the proposed Network takes too much time to train

IV. Methods

The method used in this study is as follows: preprocessing, noise removal, classification

i. Recurrent Neural Networks

Recurrent Neural Networks are a class of artificial Neural Networks. They are derived from the feedforward Neural Network. They have an internal memory(Hidden state); it is recurrent because it does the same computation for every input. It considers the previous output and the current input as inputs. Unlike feedforward Neural Networks, RNN uses their internal memory to process the inputs. This makes them dynamic enough to perform tasks such as speech recognition, handwriting recognition, or guess the next word to be used when constructing a sentence. Unlike other Neural Networks inputs, all RNN inputs are related to each other. Although RNN's are computationally slow, they can process the input of any while model size, not increasing with the size of the input[15].

Suppose that we have a Traditional Neural network with an input layer, two hidden layers, and an output layer. In the Traditional Neural Network, all the hidden layers will have their own independent bias and weights. We can say hidden Layer one has an input weight and bias of (w1,b1), respectively, and hidden layer two have (w2,b1) as weight and bias respectively, and they do not memorize the output. RNN will convert all the independent activations to dependent activations by providing the same weights and bias across all the hidden layers, thus reducing the complexity of increasing parameters. Hence the two layers can be joined together such that all the weights and bias of the hidden are the same into a single recurrent layer.A structure of RNN is shown in *figure*4 [15]. where First, it takes the X(0) as initial input, process it and then outputs h(0) which then also becomes input for second processing along with X(1). So, the h(0) and X(1) is the input for the next step. the model will keep taking previous output along with current input so to keep on remembering the content while still training.[15]

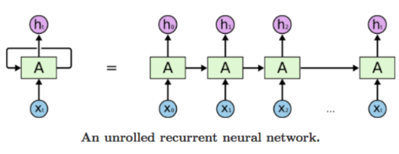

Figure 4: *The Structure of Traditional Neural Network and Recurrent Neural Network respectively[15]*

$$A_t = f(A_t - 1, x_t) \tag{1}$$

$$A_t = tanh(X_{AA}h_t - 1 + X_{xA}X_t) \tag{2}$$

$$h_t = X_{Ah}A_t \tag{3}$$

The formula for the current state is shown at 5, where A is the single hidden vector. Using the activation function will yield to equation 6, where X is the weight,X_{AA} is the weight at the previous hidden state, X_{xA} is the weight at the current input state, $tanh$ is the activation function. The formula for output is shown at 5, where h_t is the output state, X_{Ay} is the weight at the output state[15]. I acknowledge that there are many types of RNN like the Bidirectional LSTM, Gated Recurrent Network, etc. but in this research, since it is an honors research and I have limited time, I will be focusing on and using a variant of RNN called LSTM.

ii. Wavelets

The raw data have many details and also lots of noise. Wavelets are a way to minimize this data into different groups of samples that focus on various information. Wavelets have different levels, i.e., let's say we have and averaging wavelet that takes the average of every five consecutive numbers and makes them one point. If we have data that have 5000 points level, one will average to a wavelet with 1000 points, and level 2 will average to a wavelet with 200 points and so on.

The disadvantage is the more you go up with levels; you keep on loosing details. Wavelets are rapidly decaying waves like the Oscillation that has zero mean. Wavelets exist for a finite duration, and they come in different sizes or shapes. Some of the more common wavelets include Morlet, Daubechies, Coiflets, Biorthogonal, Mexican hat, and Symlets. Wavelets have two significant concepts that it uses, namely Shifting and Scaling[12]. Scaling refers to the process of stretching or shrinking the signal in time which can be expressed using the equation $\varphi(\frac{t}{s})s > 0$. s is a scaling factor, which is a positive number and corresponds to how much a signal is scaled in time. There is a reciprocal relationship between the scale and frequency with a constant of proportionality. The constant proportionality is called the center frequency if the wavelet. The equivalent frequency is defined using $F_{e_q} = \frac{C_f}{s\delta t}$ where C_f is the center frequency, s is the wavelet scale, and δt is the sampling interval. A stretched wavelet helps in capturing the slowly varying changes in a signal while a compressed wavelet helps in capturing abrupt changes. Shifting a wavelet means delaying or advancing the onset of wavelet along the length of the signal with the notation $\phi(t-k)$ meaning it has shifted and centered at k. The two significant transforms in wavelets are Continuous wavelet Transform and Discrete Wavelet Transform. These transforms differ based on how the wavelet is scaled and shifted[17].

iii. preprocessing

The dataset has a total of 8528 instances; 10% of these instances are used for validation. Due to time restrictions, it was impossible to use crossz-validation to test the proposed model's robustness; instead, the last 10% is the testing set, and the rest is the training set. Each instance in the dataset has one feature. The number of timestamps varies per instance; the highest number of timestamps recorded is 18286. Every instance is Zero pre-padded, so to match the maximum timestamps. Pre-padding means this study gives more priority to the feature towards its end as opposed to its beginning. The study considers that there may be a lot of noise at the beginning resulting from the discomfort of the patient and other casualties. The dataset is then separated into three levels using wavelet Daubechies 6 (db6), with each level having half timestamps from the raw data.

iv. noise removal

Noise removal occurs after the data has been separated into different levels. Noise removal is done by using the Scikit library. The library uses a soft thresholding method, which takes the signal's average, removes any outlier, and adjusts the range. There are two significant thresholding methods, namely hard and soft thresholding. In hard thresholding, the coefficients below a threshold value are set to zero, and the value above the threshold is set to one. Soft thresholding is also called wavelet shrinkage as both negative and positive values are shrinking towards zero, while hard thresholding either keeps or removes coefficients' values.*figure* 5 shows the original level3 wavelet signal in the first 200 points and *figure* 6 shows the soft denoised level 3 wavelet. This study uses soft thresholding as it limits noise in the ECG very well.

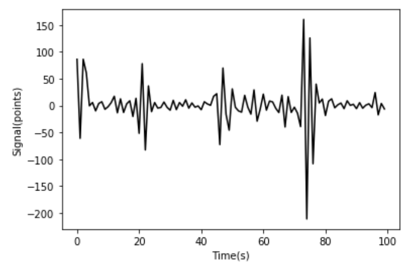

Figure 5: *original level3 wavelet ECG*

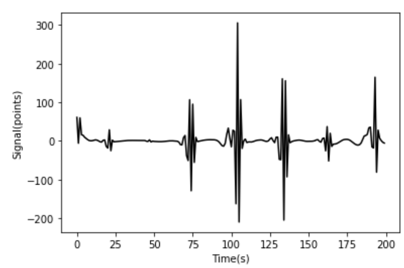

Figure 6: *soft denoised level3 wavelet ECG*

v. classification

This study aims to detect abnormal heart rate using the training dataset with four classes/labels, namely normal(5154 instances), atrial fibrillation(771 instances), alternative rhythm(2557 instances), and noise (46 instances) labeled by N, A, O, and P respectively from [9].Using the whole dataset saw the proposed model take four days and five hours to train fully, and that was the fastest variation model as it was running on level 3 data with the least timestamps; for level 2 and level 1, it took up to 16 days to train fully. This paper trimmed the dataset to only the first 1000 instances for training and 100 cases for testing. Trimming of data was due to time limitation as the project had to be submitted. Deduced From [8] and [11], this paper proposes a model that inputs ECG data. The model has 2 LSTM layers, a flatten layer, and two interconnected layers, with the last one being a softmax output layer with a formula:

$$g(z_i) = \frac{e^{z_i}}{\sum_j e_j^z} \tag{4}$$

which focuses on multiple classes, where z_i is the net for each output node. LSTM is a variant of a recurrent neural network that helps capture vanishing/exploding gradient. Recurrent neural networks have to backpropagate errors over several timestamps. They do this by the multiplicative chain rule, which leads to the gradient being too big or too less. Several measures have been made available to deal with the vanishing/exploding gradient. Using an activation function with a constant gradient such as RELU helps, also clipping maximum and minimum gradient allowable during backpropagation. There are types of RNN solutions to vanishing/exploding gradient; LSTM and GRU are one of them. This study uses focal-loss to calculate loss, so to deal with the imbalance of data. Focal loss helps by downweighing the class that contributes more while training to balance the dataset classes. Focal-loss is adapted from cross-entropy, which has the formula

$$\sum_{c=1}^{m} y_o, c \log(p_o, c) \tag{5}$$

Where $M > 2$ is the number of classes. y is an indicator function that outputs 0 or 1 depending on whether the class is the correct classification for observation o. P is the predicted probability of observation o being of class c. The focal-loss formula is

$$L(y\hat{p_y}) = (1 - \hat{p_y})^{\gamma} \log \hat{p_y} \tag{6}$$

where y represents the class labels and $\hat{p}$ is a vector representing the estimated probability over the classes. This loss function reduces the weights of easily classified ECG and makes the model focus more on the ECG that are hard to classify. The optimizer used is NAdam, which is a combination of the adam and NAG algorithm. From the raw dataset of 18286 timestamps, we obtained three levels of data with timestamps of 9241, 4221, and 2291 for level1, level2, and level3, respectively. The model has dropouts that were tested under 30 instances due to the limitation of time. The optimum gamma for the focal loss is 2. Each model receives different data and behaves differently. All three models have the same hyperparameters . This study implements a Bagging ensemble at the end of all training and testing of models. For each testing instance, the ensemble uses the majority voting to develop the final classification for that particular instance by taking the average of each output node in the softmax layer. The number of epochs is 350. each model has it own accuracy and F1 score which this paper uses to track the performance of each model and also the ensemble model. The formula to calculate F1 score used in this paper is shown at 7

$$F1 = \frac{2 * RECALL * PRECISION}{RECALL + PRECISION} \tag{7}$$

$$RECALL = \frac{TP}{TP + FN} \tag{8}$$

$$PRECISION = \frac{TP}{TP + FP} \tag{9}$$

where TP, FN, and FP represents the True Positive, False Negative, and False Positively classified number of instances. All modeles are trained using the accuracy matrics which is calculated by equation 10

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} \tag{10}$$

V. Results

This study proposed an LSTM that inputs three ECG data levels, then finally combines the results from the three models. Subsection 1, subsection 2, and subsection 3 elaborate on the results from level 3, level 2, and level 1 models, respectively then; finally, subsection 4 shows the ensemble model results. The study has a maximum of 350 epochs. Each model showed signs of obtaining better training accuracy, but due to time limitations, this paper did not train the models up to the final convergence. This project was run on an intel i5 8^{th} Gen HP Pavilion 360 with 8GB ram. The model took 8.5 days to complete training of all levels of the model.

i. Level 3 model

This model uses level 3 data which has 2291 timestamps. This model has the lowest timestamps among the three and trains faster. Each epoch in this model runs, on average, 63 seconds. Gamma is set to 2, and for better perfomance reasons, this study used both Nadam and Adam and evaluated that Nadam trains best and converges faster. Table 3 shows the training accurary and loss of both algorithms after a different number of epochs. from here

epochs		200	250	300	350
Nadam	Accuracy	0.9240	0.9460	0.9420	0.9520
	Loss	0.0769	0.0485	0.0525	0.0540
Adam	Accuracy	0.7958	0.8156	0.84	0.8409
	Loss	0.1607	0.1463	0.194	0.1942

Table 3: *model 1 performance*

onward the it was clear that NAdam is the most effective optimiser and every model used The NAdam Optimiser. After 350 epochs, this model had an testing accuracy of 0.69 and an F1 score of 0.5525. the F1 score class distribution is shown in table 4.

ii. Level 2 model

This is the middle dataset variation, which has 4221 timestamps per instances; this model was training on average of 206 seconds per epoch and ran for 350 epochs reaching the final training accuracy of 0.97, diagram 7 shows the ROC curve of training and validation for the last 10 epochs. this model obtained testing accuracy of 0.78 and a total F1 Score of 0.72, the rest of the results for the model are shown in table 4.

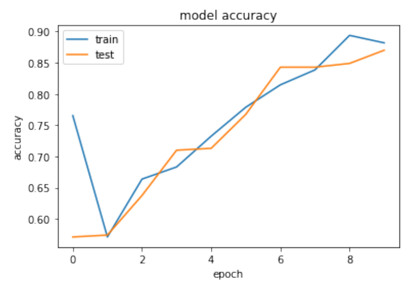

Figure 7: *soft denoised level3 wavelet ECG*

iii. Level 3 model

This is the last model and also had run the longest, with each instance consisting of 9148 timestamps. Each epoch runs, on average of 934 seconds. The model obtained the least training accuracy of 0.94 and took longer to reach 90+ training accuracy than the other two models. This model achieved a testing accuracy of 0.76 and a total F1 score of 0.7175.

iv. ensemble model

this is the model obtained by the average of each instance output of the 3 models with the accuracy of 0.82 and F1 score of 0.77, table 4 shows the rest of the results and also the F1 class distribution results.

Model	Accu	$F1_N$	$F1_A$	$F1_O$	$F1_P$	$F1$
Level 1	0.76	0.84	0.58	0.65	0.80	0.718
Level 2	0.78	0.84	0.78	0.69	0.57	0.72
Level 3	0.69	0.80	0.22	0.62	0.57	0.553
Ensemble	0.82	0.89	0.53	0.75	0.89	0.77

Table 4: *Summary of models results*

VI. Discussion and conclusions

Using wavelets helps in compressing the data into smaller fragments. The more you go with the levels of the wavelets, the smaller the data becomes. The trade-off is the more levels you go, the more you lose noise and essential data. In this paper, it was expected that the level 3 model would do the worst and the level 1 model be the best. The level 2 model did the best; it maintained an outstanding balance of reducing data and keeping essential data parts. Every model learned each class labels differently and have different F1 score for each class. The ensemble model aims to piece the models and prioritize the model, which did better in that segment. Level 2 model did the best in the classifying label 'A' In contrast, the others did worst. Model 1 did the best in classifying label 'P' so the Ensemble would piece all this information to become better. Using an Ensemble model in this regard increases the performance and classification rate. The ensemble did better and have a better overall F1 score; however, to create 2+ models is time and resource-consuming. This research project was completed under strict time constraints, which led to the proposed model not reaching the best clarification rate. This paper did not implement any robust testing techniques like cross-validation on the training set mainly due to limited time and the model taking up to 9 days to train.

i. Future work

Implement cross-validation and use the whole training dataset to test the robustness of the proposed ensemble model. Implement other kinds of Ensemble methods, i.e., stacking where there are different classifying models on the same training data, and evaluate which is the best performing ensemble under this domain

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