DEEP LEARNING ECG DYSRYTHMIA CLASSIFIER

Naseem Alsadi
School of Engineering
Computer Engineering Undergraduate
Univeristy of Guelph
nalsadi@uoguelph.ca
0921859

ABSTRACT

The use of artificial intelligence in the medical field has exponentially increased in the last decade. More specifically deep learning has infected vast regions of the biomedical field and has directly advanced biomedical technology. Assistance from supervised learning algorithms has allowed processing and classification of nonlinear data to expand into erratic biomedical fields. The prevalent ECG, Electrocardiography, test yields nonlinear dynamic data that exposes abnormal cardiac behaviour. Processing ECG data with supervised learning algorithms will indeed transform the biomedical technology horizon, allowing for high precision cardiac abnormality predictions. An evaluation conducted at the Beth Israel Deaconess Medical Center showed that although pathologists were able to diagnose cancer at a rate of 4% higher than that of an intelligent system, the alliance of both the pathologist and the intelligent system provided a diagnostic accuracy of a whooping 99.5% [1]. Conclusively the use of intelligent systems, paired with the expertise of a medical professional will improve the diagnosis accuracy in modern medical facilities.

***K*eywords** Electrocardiography · Deep Learning

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1 Introduction

Cardiac dysrhythmia has proven to be an important cause of mortality as in the United States alone more than 300,000 causes of sudden death occur each year due to ventricular dysrhythmia [4]. Diagnosis of cardiac dysrhythmia is reflected by disturbances in impulse propagation or impulse initiations. Doctors perform Electrocardiograms (also known as EKG or ECG), in order to find these disturbances and test for heart disease and other abnormalities. An Electrocardiography (ECG) signal reproduces the electrical activity conducted by the cardiac organ, presumably, over a premeditated time frame. The signal produced is nonlinear and is described to be dynamic by nature. Analysis of the signal reveals indicative behaviour of normality or abnormality in the heart. Although, due to its very dynamic nature, simple algorithms, of which work to find abnormalities in ECG results without prior datasets are often frail, and inaccurate.

With the use of supervised learning algorithms abnormalities of the cardiac organ can be imperially classified and diagnosed accordingly. The use of an intelligent system coupled with the expertise of a cardiologist should allow for a more rigorous diagnosis of ECG signals. Upon analyzing previous work done on the matter, it was concluded that developed models that were largely successful, often did not dive deep into advanced neural architectures, and rather developed more simplistic models. An expansion on these models by applying a more advanced, intelligent network could result in a higher degree of accuracy. Given that more than 300 million ECGs are recorded annually, high-accuracy diagnosis from ECGs can save expert clinicians and cardiologists considerable time and decrease the number of misdiagnoses.

2 Overview of Previous Work

The integration of artificial intelligence, specifically deep learning, into the biomedical aspect has revolutionized modern medical technology. The sole use of ECG signal data in observing abnormalities of the cardiac organ has been conducted previously using supervised learning. The results of such models has been relatively high and has shown promising results. Although, many of these previously developed models were created using simple supervised learning and did not dive deep into advanced neural architectures. The recent developments and cornerstone achievements in the field of deep learning has paved way for new and efficient architectures to arise.

A model developed in 2013 by Sahar El-Khafif and Mohamed A. El-Brawany used a fully connected network structure and experimented with the successful classification rate whilst using variable manipulation of the number of hidden layers [7]. Using a simple fully connected structure they were able to achieve a success rate of 91.9%. This is a remarkable feat considering the simplicity of the designed architecture. The use of even more complex architectures which have been proven to show high success in similar classification problems can further expand on their success rate.

A more recent paper published in 2017 by Stanford ML group called Cardiologist- level Arrhythmia Detection with Convoluted Neural Networks, shows a more complex developed model. In this model, they trained a 34-layer convolutional neural network in order to detect Arrhythmia's in arbitrary length ECG time series. The model outputs a new prediction once every second from a 30-second-long sampled ECG signal. They collected and annotated a dataset of over 64,000 ECG records from nearly 30,000 patients [4]. The ECG arrhythmia detection task is a sequence-to-sequence task which takes an ECG signal as an input, $X = [x_1, \dots x_k]$, and outputs a sequence of labels, $r = [r_1, \dots r_n]$, such that each r_i takes on one of m different rhythm classes, which corresponds to a segment of the input. Together the output labels cover the full sequence. The equation for a single example optimizes the cross-entropy function:

$$\mathcal{L}(X, r) = \frac{1}{n} \sum_{i=0}^{n} \log p \{R = r_i | X\}$$

Where $p()$ is the probability the network assigns to the i-th output taking on the value r_i. A sequence-to-sequence learning task is applied to the convolutional neural network shown below.

This architecture contains 33 layers of convolution followed by a fully connected layer, and a Softmax output to present the output being generated. To optimize the traceability of such a network, Stanford ML group employed techniques of the Residual Network Architecture to employ shortcut connections to allow for information to propagate well in very deep neural networks.

Residual Networks (ResNets) have been revolutionary for machine learning. The basic premise of a ResNet helps in eliminating problems such as vanishing and/or exploding gradients, while significantly reducing error.

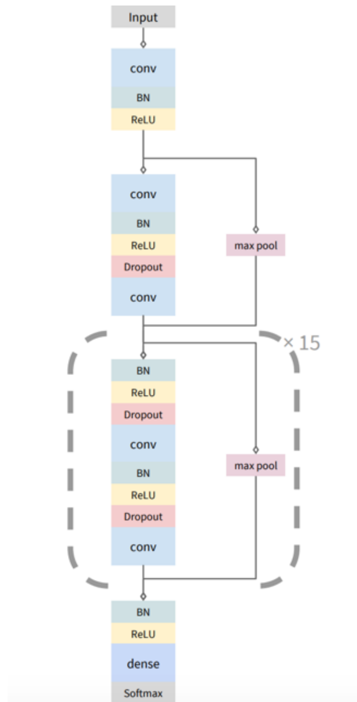

Figure 1: Stanford ML CNN Architecture

This is accomplished by a skip function, which sort of acts like a feed forward network. The skip functions eliminate the need of going through processes twice by essentially reducing the number of times a linear function is used to achieve an output. These skip functions create what is known as a residual block. In 2018, a comparison was made among all CNN architectures present. It was ascertained that the ResNet's ability for computer classification and vision out ranked its predecessors, including humans, by holding the lowest top 5% error rate [5]. Stanford ML Groups network consisted of 16 residual blocks with 2 convolutional layers per block [4].

To measure the model accurately, two metrics were used, Sequence Level Accuracy and Set Level Accuracy, while the cardiologist committee annotations were the ground truth. The Sequence Level Accuracy measures the average overlap between the prediction and the ground truth sequence labels, while the Set Level Accuracy does the same except it does not penalise for time misalignment within a record. The results are shown in the figure below.

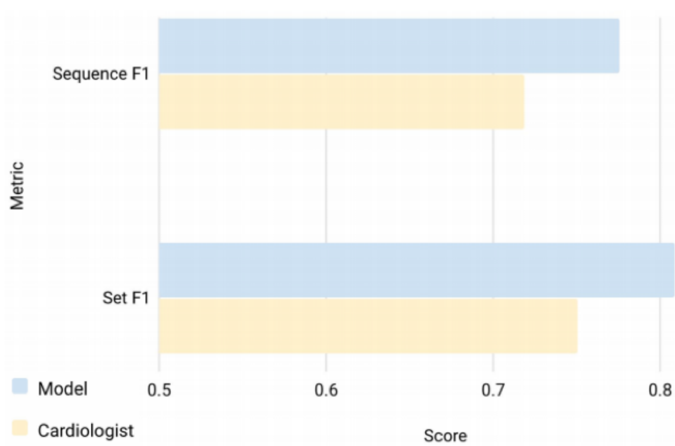

Figure 2: Model vs Cardiologist Comparative Results

As can be seen by the results in Figure 2, the Model outperformed the average Cardiologist score on both the sequence and set F1 metrics. The mistakes made by the model however were largely due to many arrhythmia being confused with sinus rhythms. Stanford ML hypothesized that this can be attributed to the sometimes-ambiguous locations of the arrhythmia in the ECG record. Nevertheless, the model architecture developed by Stanford ML proves that a more complex, and deeper network will result in a more accurate system. They created a CNN by employing ResNet to their 33-layer convolution. The question then arises as to whether or not this model can be improved upon. Squeeze and Excitation Networks could pose the solution to this question.

Squeeze and Excitation Networks (SENets) introduce the building blocks for CNNs that improve channel interdependencies at almost no computational cost. After being used at this year's ImageNet competition, they helped improve the result from last year by 25% [6]. The most remarkable thing about these networks is how simple it is to add these to existing networks. The premise behind SENets is essentially to add parameters to each channel of a convolutional block so that the network can adaptively adjust the weighting of each feature map. This can be done with only a few lines of code. Figure 3 below illustrates the addition of SENets to a ResNet Module.

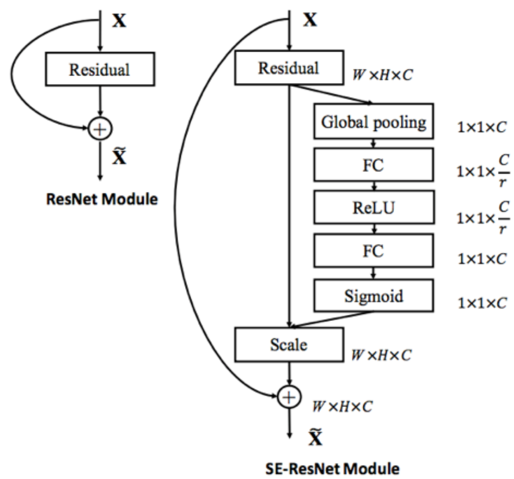

Figure 3: ResNet Module vs Proposed SE-ResNet Module

The authors showed that by adding the SE-blocks to ResNet, you can expect greater accuracy for almost no computational cost. The study further investigates and concludes that the modified version concludes a top-5% error of 3.79% [6].

3 Proposed Approach to the Problem

3.1 Neural Network Architecture

Introducing a supervised learning model into the biomedical field calls for unwavering attention to output accuracy. Especially when classifying myocardial infraction, which is leading cause of death worldwide. Being able to classify heart beat abnormality with absolute certainty is the aim of this approach. This calls for a thoroughly well developed and accurate model, and convolutional neural networks provide us with such. Our approach involves the assistance of a relatively new convolutional neural network, namely, SENets (Squeeze and Excitation Networks). This network gained exposure in 2017 after winning the ILSVRC 2017 classification challenge. This network surpassed all other networks in 2017 and even had a top-5 error 25% less than the previous year's winner.

Squeeze and Excitation Networks are convolutional neural networks at the foundation. Although they make a small but impactful change to the typical architecture of a convolutional neural network. SENets make it possible for the network to make adaptive adjustments to the weighting of each feature map. This change is enough to create a dramatic impact in the accuracy of the model. The extraordinary feat of this network architecture is that it has no additional computing cost, and be virtually extended on to any existing model.

Table 1: Classification Categories

Key	Description
0	Normal
1	Premature Atrial Contraction
2	Premature Ventricular Contraction
3	Mixture of Premature Ventricular and Normal Contraction
4	Paced or Unclassified

Table 2: Outcome of Model Training

Training Accuracy	Testing Accuracy	Precision
99.8%	**94.12%**	**97.3%**

3.2 ECG Signal Database

The dataset used to train and test the model was obtained from The National Metrology Institute of Germany's Diagnostic ECG Database. They have provided a public dataset with precisely 549 recording from 290 subjects, observed in the year 2004. The signal was recorded with a 14 lead ECG. Although, for simplicity reasons a modified sub-selected dataset was used of which contained 52 healthy controls and 148 subjects diagnosed with myocardial infraction. This sub-selected modified dataset was provided publicly by Kachuee et al.[6]. The dataset was categorized with the criteria seen in Table 1.

3.3 ECG SENet Dysrhythmia Classifier Model

The dynamic nonlinear ECG data is absolved as the input to the model. The model architecture is constructed using a convolutional neural network variant, namely SENet. The model then classifies the the input from the categories displayed in Table 1.

To autonomously classify abnormalities from the recorded ECG signal, assistance is needed from a neural network structure. A supervised learning model was used to provide a more accurate means of prediction due to its ability to learn from previous experiences. Although, a supervised learning model is only as accurate as the provided training data. Thus, it was necessary to a train the model on an accurate and well documented training data.

Using an SENet to classify abnormalities within the cardiac organ provides a fundamentally stable and accurate model. To accomplish the goal at hand the model firstly must be organized and data flow must be mapped. Firstly, the complete ECG dataset must be split into training and testing sets. To prevent negative effects such as over fitting, a split of 80%-20% will be used for training and testing sets respectively. All computational, data manipulation, and model development efforts will be conducted using the TensorFlow Library [2].

The practical use of the model can vary, and should be analyzed for achieving maximum efficiency and accuracy. An evaluation conducted at the Beth Israel Deaconess Medical Center showed that although pathologists were able to diagnose cancer at a rate of 4% higher than that of an intelligent system, the alliance of both the pathologist and the intelligent system provided a diagnostic accuracy of a whooping 99.5% [1]. Conclusively, the use of an intelligent system, such as the one proposed, is more accurate when in alliance with a medical expert.

With the inclusion of a deep learning network architecture such as SENet, ECG test data will be classified in a precise nature. The model proposed in theory out preform models constructed previously. As cornerstone network architectures are introduced, biomedical technology will continue to advance.

4 Results

Given the model above, the theoretical accuracy was estimated to surpass previous expectations, consequently providing a high accuracy model. Indeed, these were the findings that were discovered through analysis of outcome data.

The results of the model after being trained and tested can be seen in Table 2. The resulting training accuracy is very high, although this set of data is not as important to the characteristics of the model as the testing accuracy. The testing

Table 3: Comparative Study of Models

Author	Accuracy
This Model	**94.12%**
Acharya et al. [8]	93.5%
Kachuee et al. [6]	93.4%
Martis et al. [9]	93.8%

accuracy achieved is quite high and shows that this model was successful, for the most part, in classifying unseen data in the correct categories.

Furthermore, the model was assessed using using a confusion matrix, displayed in Figure 4. The confusion matrix indicates that out of 4000 samples, 3799 were classified correctly. Consequently, the manually calculated accuracy can be equated to 94.9%. This calculated accuracy is higher than any previous author's suggested accuracy, which indeed shows that this model is an improvement in comparison to previously suggested models.

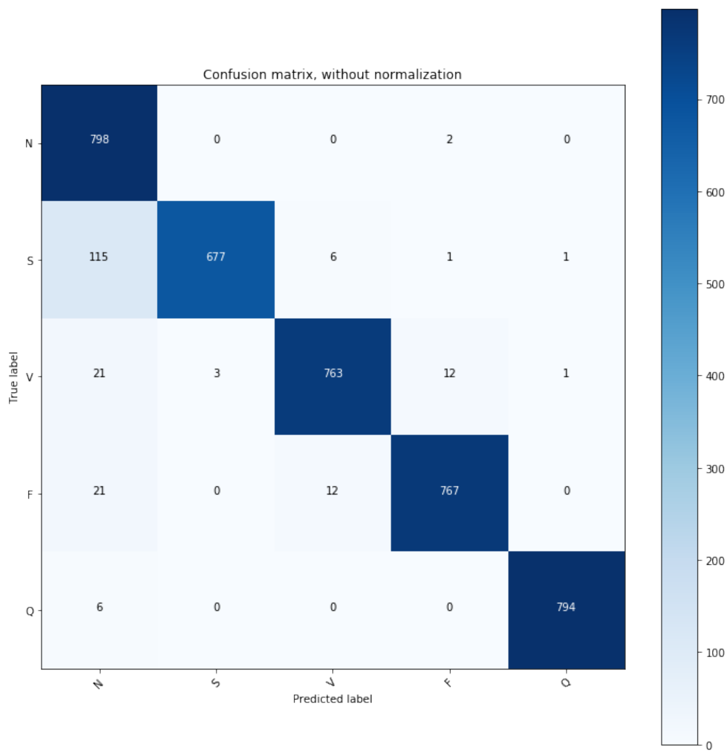

Figure 4: Confusion Matrix for Model

5 Discussion

The experimental outcome of the model has been allocated a row in Table 3 , along with the findings of other authors for comparative purposes.

The comparative study shows that this model surpassed all other author's set accuracy. The cause of the increase in accuracy can be attributed to a few different things. Mainly, although the increase in accuracy was an effect of the introduction of Squeeze & Excitation Networks. The debut of Squeeze and Excitation Networks directly improved channel inter dependencies without the addition of extracurricular or compulsory computational costs.

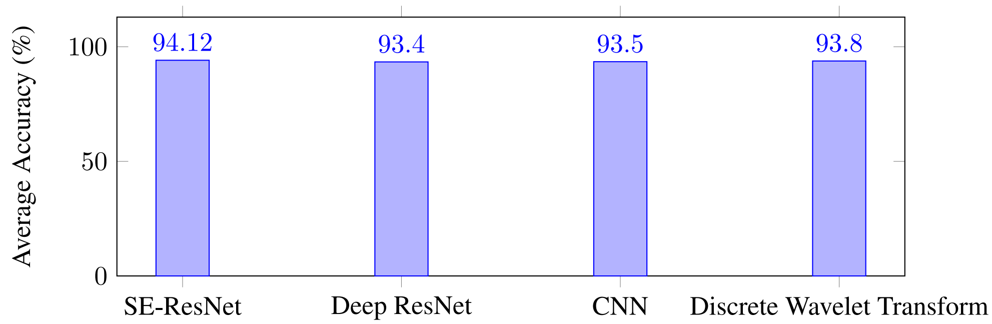

Figure 5: Comparative Study of Model Algorithm Accuracy

A comparative study of different model algorithm accuracies is displayed in Figure 5. The plot shows that Squeeze Excitation network proposed in this paper leads to the highest average accuracy. In turn, surpassing the accuracy of all the other model algorithms that were proposed beforehand.

Achieving accurate models in medical machine learning applications is of the upmost necessity, and requires time and effort. The model proposed has shown its worth, although the testing accuracy is not perfect, it is capable of handling real data and presenting accurate classifications. ECG testing can help save many peoples lives, therefore the testing procedure and results must be thorough, accurate and reliable. The results shown in this paper indicate that machine learning medical applications are slowly advancing and becoming a more reliable and accurate addition to the medical field.

6 Conclusion

Cardiac dysrhythmia is a major cause for mortality, the importance for accurate diagnosing is a pressing matter within cardiology. The goal to pair the expertise of medical professionals with an advanced intelligent system is definitely achievable. Upon evaluating previous work done on the subject, it is clear that applying Squeeze and Excitation Networks to present models that classify abnormalities within the cardiac organ should provide for a stable yet accurate model. Given the availability of a large database of ECG's, developing an advanced CNN should pose to be an achievable and excellent tool in learning about the applications of Neural Networks and Artificial Intelligence.

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