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Advancing Heart Beat Classification in Alignment with AAMI EC57 Standards for Enhanced Medical Instrumentation

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Abstract
An electrocardiogram, commonly known as an EKG or ECG, captures a visual representation of the heart's electrical conduction. Physicians use this diagnostic tool to detect a wide range of cardiovascular activities by identifying deviations from the normal pattern. Tracking the performance of the cardiovascular system is one of the applications of an electrocardiogram (ECG). Recently, there has been increased attention to reliable heartbeat classification due to greater similarities among various ECGs. In this study, we propose a method for classifying heartbeats based on a generalized linear model, which, in accordance with the AAMI EC57 standard, accurately classifies five different arrhythmias. To facilitate portable representation, we utilize a dataset in our research. Additionally, we introduce a transfer method to apply the knowledge gained from classifying arrhythmias to the challenge of identifying myocardial infarctions (MIs). We evaluated our approach using the PTB Diagnostics and MIT-BIH datasets from Physion Net. The results show that, on average, our proposed method achieves an accuracy of 95.96% in predicting arrhythmias.

Keywords — ECG, Transferable, Linear model, arrhythmias, AAMI EC57.

1. INTRODUCTION

The ECG is used at the most by all cardiologists for observation of patient cardiac health. The problem of manual classification is an error because all signals appear similar and it results in more time consumption [1]. The proper diagnosis is much important because most of heart diseases cause death around the world [2]. Consequently, it is very desirable to diagnose arrhythmic heartbeats accurately and affordably [3].In order to solve the problems associated with the manual analysis of ECG data, a number of research in the literature looked into utilizing machine learning techniques to reliably detect the anomalies in the signal [4], [5]. Regarding the inference engine, traditional machine learning techniques for ECG analysis comprise decision trees, Support Vector Machines, etc.[6][7][8].The machine can learn the features most appropriate for the particular task it is assigned to perform with the help of an end-to-end deep learning framework [9] [10] [11].

With the help of this method, we can obtain a more precise representation of the ECG signal, we can make the machine more competitive when analyzing the data compared to a human cardiologist [12]. For example, in computer vision, knowledge has been transferred across different picture comprehension tasks using the ImageNet dataset and state-of-the-art deep learning models [13]. As an additional illustration, research has demonstrated that a significant portion of sentence understanding can be shared across various sentence categorization tasks [14] [19]. However, transfer learning hasn't been applied very often in the field of health informatics. Alaa et al. [15] have used the parameters of a Gaussian expert method trained on patients with stable conditions for patients whose conditions are deteriorating.
The electrocardiogram, or ECG, measures the strength and direction of the heart's contraction-related activity as well as that produced by the atria and relaxation ventricles. ECG signal and various intervals, including the P-R interval, ST interval, and the QRS complex interval, are shown in Figure 1. The letters P, Q, R, S, and T stand for the five peaks and valleys shown on an ECG. The QRS complex is the most remarkable aspect of them. The left and right atria of the cardiac cells get the signal. This signal causes the atria to tighten. By doing this, blood is forced into both ventricles through the atria's open valves.[16][20]

The AV node, which is close to the ventricles, receives the signal. It slows down for a brief period of time to allow blood to enter the heart's left and right ventricles. The ventricle walls of the heart's ventricles are where the signal is emitted and travels via a channel known as the bundle of His. The Purkinje fibers allow the signal fibers to split from the His bundle into the left and right bundle branches. The cells that comprise the walls of the heart's left and right ventricles are directly connected to these fibers. Both ventricles constrict as the signal passes across their cells on the ventricle walls.[17] However, this does not occur simultaneously. Prior to the right ventricle contracting, the left ventricle does. Blood must travel through the pulmonary valve in the case of the right ventricle and the aortic valve in the case of the left ventricle in order to reach the lungs and the rest of the body. The walls move as the signal fades.[18].

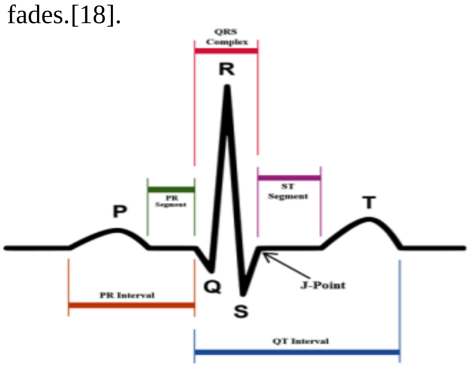

Fig.1: The basics of ECG

1.1 Motivation

The ECG's variability includes elements that show how a person's heart rate varies based on their physical and mental state. The heart rate may alter as a result of stress, energy, exercise, and other strenuous activities. The key factor affecting heart rate is fluctuation in the RR interval, PR interval, and QT interval. The effect of the variable heart rate should be eliminated, and these features should be properly adjusted. Each patient has a unique ECG waveform, and since each patient's ECG signal might differ from one patient to the next in terms of amplitude, time, and signal, changing ECG patterns, signal classification is necessary[21].

2. DATASET AND PREPROCESSING

2.1 Data set

The data includes large collection of heartbeat signals taken from standard dataset of heartbeat classification named MIT-BIH Arrhythmia Dataset [16][17][18]. The count of signals count satisfies well for training. The dataset is used in heartbeat classification study.

Arrhythmia Dataset There are 109446 samples total. Physionet's the data source is the Arrhythmia Dataset from MIT-BIH.. There are five categories, five sampling frequencies, and five classes: ['N': 0, 'S': 1, 'V': 2, 'F': 3, 'Q': 4].

2.2 AAMI EC57 Categories

Five distinct categories that are connected to the Advancement of Medical Instrumentation (AAMI) EC57 standard are created by us using annotation [19]. The mapping is shown in below table 1.

Table 1: An overview of how beat annotations and AAMI EC57 categories are mapped.

Classification	Annotation
N	Standard bundle branch block for the left and right Atrial evasion Nodal detachment
S	premature atrial contraction Premature aberrant atrial contraction Nodal early premature supraventricular
V	early contraction of the ventricles Escape via ventricle
F	Combination of normal and ventricular
Q	A Blend of Normal and Paced Uncategorizable

2.3 Extracting the heart beat.

The steps taken to extract beats from an ECG signal are as follows:

1. Continuous heart beat signals classified using a 10-second window size figure 2 represents it.
2. Normalization between the range of 0 and 1, figure 3 and figure 4 represents it.
3. Identification of local maxima based on zero-crossing derivatives.
4. Determination of a threshold within the range 0-9 on local maxima.
5. Calculation of the median of R-R intervals.
6. Selection of signal segments around each R-peak with a length equal to 1:2T.
7. Zero-padding of all selected segments for clear analysis.

The method is good for extracting effective R-R intervals from signals. We have used Gaussian filtering for smoothening the signals and removal noise.

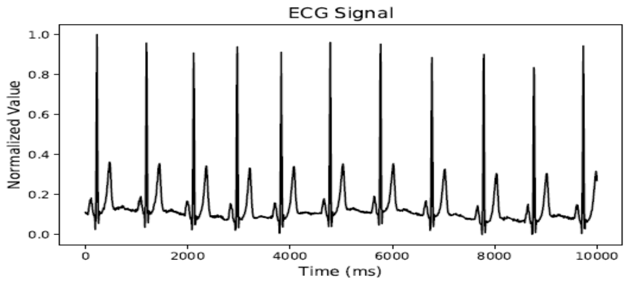

Fig2: Graph for 10 sec ECG window.

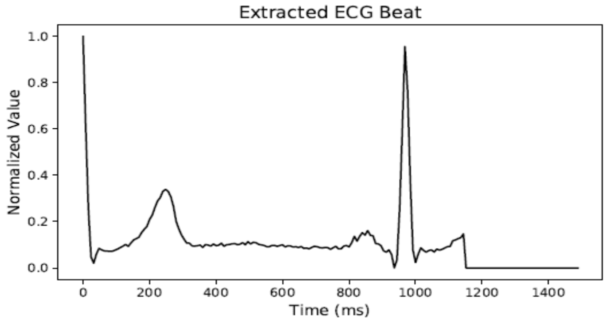

Fig3: Extracted ECG heart beat.

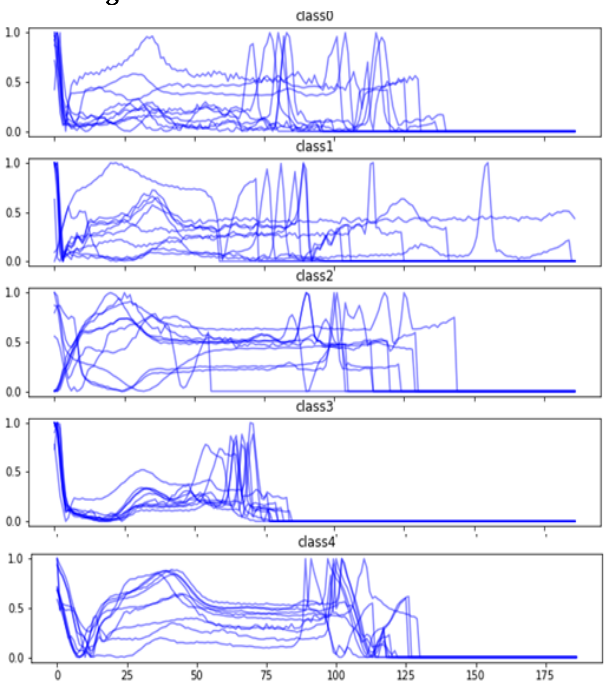

Fig 4: Graph for [0,1] interval normalized time Series.

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2.4 Preprocessing

As ECG beats are inputs here we need to suggest simple and an effective method of classification.Since we have padded data to all zeros, further we can add additional information using one of the mathematical form named discrete signal gradients into account. Another option is to manually apply convolution, perhaps using a discrete gaussian. Similarly, we may use the pd.DataFrame.rolling function to do manual max pooling. Additionally, we use scipy.signal.decimate to lower sample our signal.

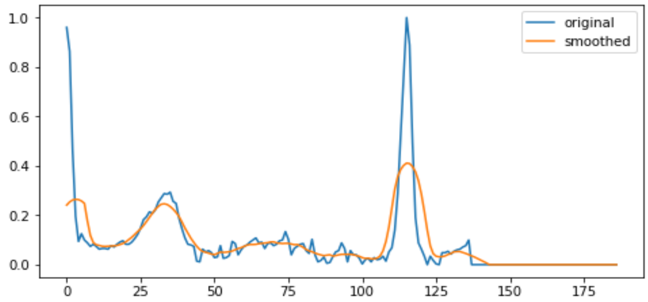

Fig 5: Graph of extracted heart beat after Preprocessing.

The above figure 5 represents the extracted heart beat after preprocessing with original and smooth signal indication graph.

The below figure 6 represents the normalized interval [0,1] after preprocessing.

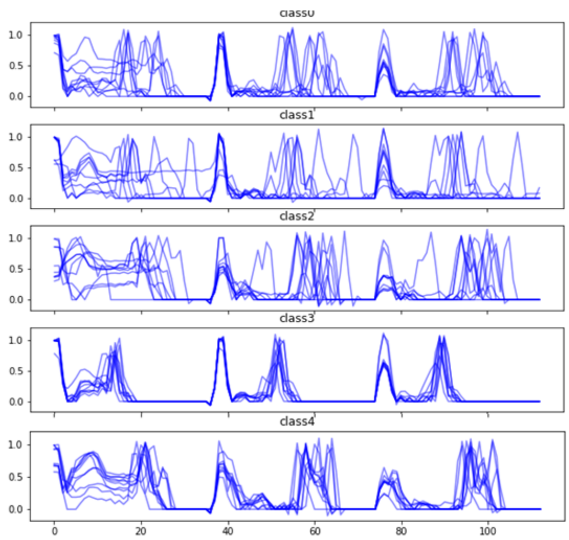

Fig 6: Graph for [0,1] interval normalized time series after preprocessing.

3. SYSTEM MODEL

The dataset is preprocessed to remove the noise and outliers. 10sec window size is taken to extract the heart beat. Make use of extracted heart beat to analyze the transferable representation. Train the data and classification report is given. Figure 7 depicts the process of classification.

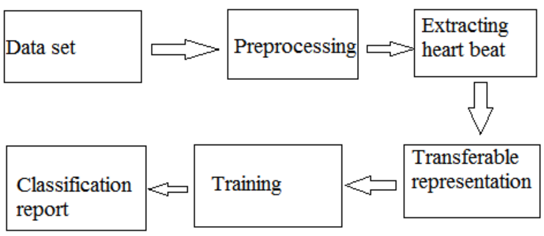

Fig 7: A model that illustrates the process of classification.

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3.1 Linear Model in Generalized Form

The generalized linear model is used to analyze the linear and nonlinear effects of predictor variables on discrete or continuous variables. A generalization of the general linear is the Generalized Linear Model (GLZ). In its most basic form, a linear model describes the (linear) relationship between a set of predictor variables (the X's) and a response variable (Y) such that

$$Y = b_0 + b_1x_1 + b_2x_2 + \cdots + b_kx_k \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

In this equation (1), the regression coefficient for the intercept is represented by b0, and the bi values stand for the regression coefficients (for variables 1 through k) that were computed using the data. Figure 8 shows linear function graph.

3.1.1 Linear Regression

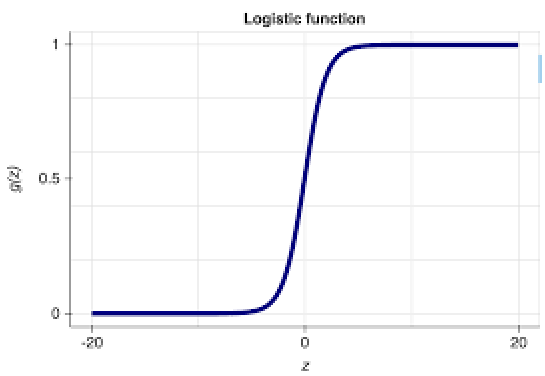

Fig 8: Linear Function graph.

Logistic regression is basically one of the classification algorithms. In this classification the output variable will take only discrete values from the input variables shows in equation 2.
Logistic regression is also used to predict probability of given entry belongs to the category named as “1”.

$$g(z) = 1/(1 + e^{-z}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

Logistic regression is useful only when we have the threshold the threshold value setting is very much important and also this depends on classification problem itself.

3.2 Random Fourier features

Random Fourier with the feature kernel ridge regression is a frequently utilized method for enhancing kernel methods. With random Fourier features, the statistical properties are still not well developed. This work closes this gap. Basically, our method of using spectral matrix approximation and random Fourier features delivers a close bound on the number of Fourier features desired to obtain a spectral approximation and demonstrates how it guarantees for kernel ridge regression which are represented by bounds on the spectral matrix approximation. Our findings indicate that, under reasonable assumptions, random Fourier feature approximation can likely boost kernel speed.

4. RESULT & DISCUSSIONS

Results observed by experimenting proposed method. Experiments are also designed to obtain the high accuracy. The performance measures are performed. In figure 9 interpretation of performance measures are shown.

		Predicted class	
Actual Class		Class = Yes	Class = No
	Class = Yes	True Positive	False Negative
	Class = No	False Positive	True Negative

Fig 9: Interpretation of Performance Measures

A basic sparse benchmark GLM requires 19.22157740 seconds of training time and achieves a total accuracy of 88%. Accuracy is determined by dividing the number of correctly predicted observations by the total number of observations (samples). The following table 2 is provided by the classification report.

Table 2: Classification report simple sparse benchmark GLM.

Class	Precision	Recall	F1-score
0	0.98	0.89	0.93
1	0.31	0.65	0.42
2	0.69	0.83	0.75
3	0.15	0.78	0.25
4	0.89	0.94	0.91
Average	**0.93**	**0.88**	**0.90**

In table 3 random Fourier feature GLM is shown, GLM achieves a total accuracy of >90% while performing a random Fourier feature. This adjusts to 84% accuracy when sampling bias is taken into consideration.

Table 3: Classification report random Fourier feature GLM.

Class	Precision	Recall	F1-score
0	0.99	0.92	0.95
1	0.40	0.71	0.51
2	0.74	0.88	0.81
3	0.23	0.87	0.37
4	0.93	0.94	0.94
Average	**0.95**	**0.92**	**0.93**

5. COMPARATIVE STUDY

The suggested method in Table 4 has an average accuracy that is much higher than other pertinent methods that have been published in the literature to yet. Through a meticulous examination of various methodologies, our approach not only exhibits robust performance but also establishes itself as a notable advancement in the field. This comparative analysis underscores the efficacy and superiority of the proposed method, highlighting its potential to outshine current state-of-the-art techniques.

Table 4: Comparative study table.

Title	Approach	Average accuracy (%)
Advancing Heart Beat Classification in Alignment with AAMI EC57 Standards for Enhanced Medical Instrumentation	Simple and Fourier feature GLM	**95.96**
ECG Heartbeat Classification.	CNN	**93.2**
Using ECG signals, a Deep Convolution Neural Network is applied to automatically detect myocardial infarction [2].	CNN	**95.2**

6. CONCLUSION

The study introduced an innovative method for ECG heartbeat classification, centered on a sophisticated approach to heartbeat classification. Also the GLM model is trained with arrhythmia classification task. As per the obtained results, the proposed method exhibits a notable capability to make accurate predictions for both tasks, demonstrating a degree of accuracy comparable to, or even higher than, the cutting-edge techniques described in the body of current literature. A basic sparse benchmark GLM requires 44.89 seconds of training time and achieves an accuracy of roughly 91%. This adjusts to 84% when sampling bias is taken into consideration. In contrast, An arbitrary Fourier characteristic GLM operates with an accuracy of about 88.21% with a training time of 19.22 seconds. As a result, we can state that using nonlinearity produces the best accuracy across extended training times. Future iterations of this work will involve comparing training accuracy and experimenting with PTB diagnostic data sets.

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