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Arrhythmia Detection Using ECG Signal Processing

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Abstract: The implementation of machine learning in bioinformatics and medical analysis has brought about great improvement in the health care delivery sector of the economy. As the heart remains the pivotal organ of the human body pumping blood to all parts of the body the need for adequate care of this vital organ is required. This paper therefore reviews the different approach to electrical signal process of the heart through ECG analysis and proposed the development of an arrhythmia detection model using artificial neural network (ANN). The model developed in Python on Google Colab environment was trained and tested with dataset contains 3640 sample heart beats. The dataset was preprocessed and split in the ration of 70:30 for the training and the test dataset respectively and the model performance impressively well with a record 97.43 % accuracy showing the possibility of improvement after more training. The system indicates the average heartbeat of 72.0 and 12 peaks from the sample dataset showing no trace of arrhythmia.

Keywords: Arrhythmia, ANN, bpm, ECG, HRV

I. INTRODUCTION

The heart is an essential component of the human body, serving as a pump that circulates oxygenated and deoxygenated blood throughout the body and brain. It is a two-stage electrical pump that measures the electrical activity of the heart using electrodes put on the skin. The ECG may determine the pace and rhythm of the heartbeat and offer indirect evidence of blood flow to the cardiac muscle [1]. It, like all other organs, is prone to disease and aging, and when the heart fails and finally ceases beating and pumping blood, life ends abruptly. Heart rate variability (HRV) is a physiological phenomenon characterized by variations in the time interval between heartbeats. It is calculated using the variance in the beat-to-beat interval. Its variety might include signs of present illness or cautions regarding impending heart disease. The signs may be present at all times or appear at random during specific periods of the day. It is difficult and time-consuming to analyze and identify anomalies in large amounts of data gathered over several hours [2].

Arrhythmias, which are irregular or abnormal heartbeats, pose a major health danger to millions of individuals worldwide. Arrhythmias can be benign, meaning they have minimal impact on health, or severe, meaning they can be deadly as a result of causes such as cardiac arrest or stroke. As a result, timely diagnosis can help to provide efficient clinical treatment [3]. When the heart beats erratically, this disease can lead to cardiac arrhythmias. An arrhythmia heart may beat too slowly, too quickly, or irregularly. Arrhythmia symptoms, such as palpitations, vibration heart jump, dizziness, shortness of breath, and/or chest pain, might be mistaken for those of a normal heart, therefore a patient may be unaware of them. These symptoms can also occur in a normal heart, hence diagnosing arrhythmia based just on the symptoms is insufficient [4].

Regular testing and monitoring of the heart's electrical and muscular processes may be done with the use of an electrocardiogram (ECG), which displays the signal flow of these electrical activities as a waveform. The electrical conduction of the heart during contractions and relaxations is known as an electrocardiogram (ECG). An essential diagnostic tool for assessing heart function, it is a bioelectric signal that tracks the electrical activity of the heart throughout time. Myocardium all around is stimulated by the electrical current that travels throughout the heart from the Sinus Atria (SA) node, which becomes depolarized as the atrium contracts. The surface of the body receives a little quantity of the electrical current. The electrocardiogram (ECG) is a recording of the electrical potential generated by this current, which is achieved by putting electrodes on certain areas of the skin. One application of pattern recognition is the decipherment of electrocardiogram (ECG) signals. Automated system classification is the main objective of pattern recognition. It only takes a quick glance at the electrocardiogram (ECG) waveform output for a trained cardiologist to diagnose a number of heart conditions. Even while advanced ECG analyzers can sometimes beat human cardiologists, there are some ECG waveforms that computers just can't tell between.

Arrhythmias can be diagnosed using a variety of procedures, including a conventional electrocardiogram (ECG), blood and urine tests, Holter Monitoring, electro-physiology studies (EPS), event recorders, echocardiograms, chest X-rays, and the tilt-table test. ECG is a widespread and effective method for identifying arrhythmias and other cardiac abnormalities. Physicians and doctors utilize ECG to study the electrical activity of the heart in order to detect arrhythmias and other cardiac abnormalities. However, the use of computerized analysis has improved the process of obtaining ECG waveforms, minimizing the bother associated with prior approaches [5]. Although ECG diagnosis might be challenging due to the modest nature of the symptoms. In recent years, the application of machine learning and deep learning algorithms has provided a promising solution for automation and precise diagnosis in medical applications, as early detection allows for appropriate drug treatment and lifestyle changes, avoiding future consequences [6].

The prevalence of cardiac illness and defects has recently increased, as has the mortality rate, necessitating the development of an improved ECG model that use machine learning to monitor and track the electrical signal flow in the heart. Consequently, this paper suggests building a machine learning model to process and monitor electrocardiogram (ECG) signals by simulating the ECG process in Python within the context of Colab Jupyter Notebook, and then analyzing the heartbeat signals to determine the likelihood of arrhythmia in the signals using an artificial neural network (ANN) model for ECG analysis and classification

II. LITERATURE REVIEW

A. Overview of ECG Framework

The heart's role is clearly that of a pump. According to Tate (2009), the heart has three main roles: first, in maintaining blood flow and generating blood pressure through myocardial contractions; second, in directing venous blood to the lungs through pulmonary circulation and arterial blood throughout the body through systemic circulation; and third, in regulating blood supply according to the body's metabolic demands by adjusting the rate and force of contraction. Important electrical currents cause cardiac muscle cells to contract, which in turn causes tissues to become depolarized and initiates action potentials [7] [8]. Electrocardiography is a method that uses electrodes placed on the body to detect and measure electrical currents generated and transmitted by the heart, which are represented by depolarization and repolarization fluxes. As seen in Figure 1, the electrocardiogram (ECG) is the resulting signal that, in normal circumstances, displays a cyclic repetition of five separate deflections: the P, Q, R, S, and T waves. According to [9], each of these sets of deflections represents a separate pulse that can be traced back to the beginning phase. Consistent deflections, characterized by substantial variability, are seen in the electrocardiogram (ECG) signal in both healthy and unhealthy heart conditions. A person's electrocardiogram (ECG) variability can be either intra-subject, meaning it varies within the same subject, or inter-subject, meaning it varies between subjects [10].

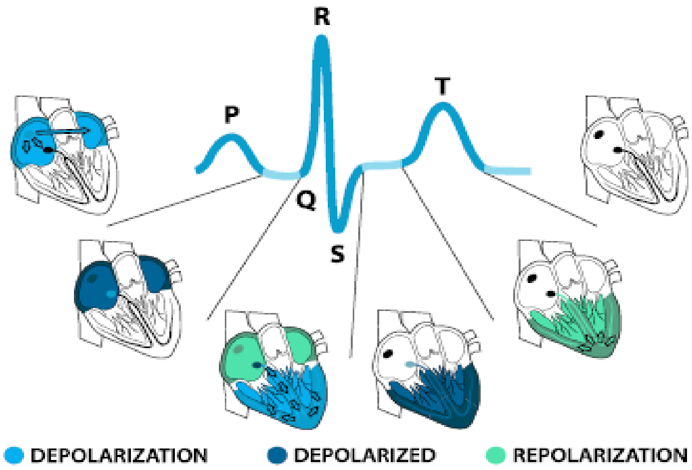


Figure 1: ECG Signal showing P.Q.R.S.T (Source: [10])

B. Significant features ECG wave for: PQRST Waves

- P wave: The P wave signifies the depolarization of both the left and right atria and is associated with atrial contraction. The atria constrict immediately following the onset of the P wave. Atrial repolarization is typically not discernible on an ECG due to its diminutive size. Typically, the P wave is characterized by a smooth, rounded appearance, with a height not exceeding 2.5 mm and a length not surpassing 0.11 seconds. It will exhibit positive in leads I, II, aVF, and V1 through V6, [11].

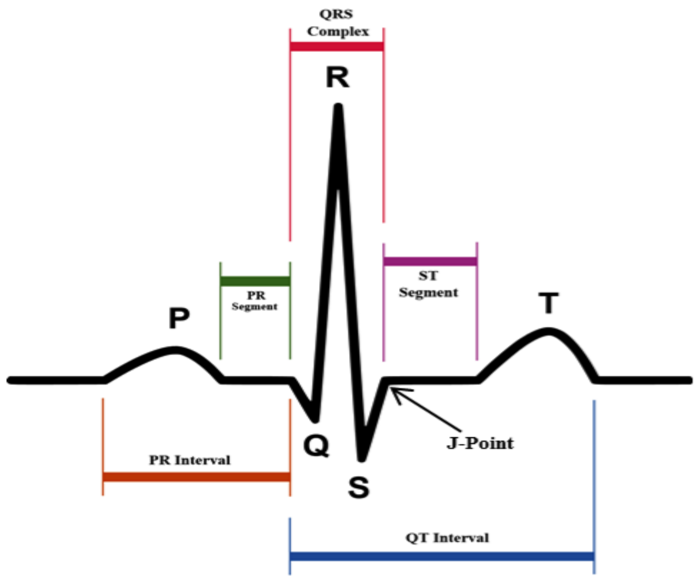


Figure 2: PQRST Structure (Source: ACLS, 2019)

- **QRS Complex:** There are three waves that make up what is known as the QRS complex. These waves are the Q, the R, and the S. These three waves occur in a sequential order from beginning to end. The QRS complex, which is an indication of the propagation of electrical impulses through the ventricles, demonstrates that the ventricles are depolarized. Immediately prior to the contraction of the ventricles, the QRS complex begins, which is reminiscent of the P wave itself. There will never be a QRS complex that does not contain all three waves—Q, R, and S. The majority of people believe that the Q wave is always negative and that the R wave is the first positive wave that the complex produces. A R wave is a QRS complex that only has an upward (positive) deflection rather than any other deflection. The initial negative deflection that comes shortly after the R wave is referred to as the S wave. When it comes to adults, a QRS complex that lasts between 0.06 and 0.10 seconds meets the criteria for normal. Positive values of the QRS complex are frequently observed in leads I, aVL, V5, V6, II, III, and aVF. This is a regular occurrence. It is common for leads aVR, V1, and V2 to have a QRS complex that is negative. The J-point is the point where the QRS complex and the ST segment converge. In addition, it is possible to consider it the initial stage of the ST process. The Junction, also known as the J-point, is an important diagnostic tool that is utilized in the case of ST-segment elevation myocardial infarction. Based on the assumption that the J-point is increased by two millimeters above the baseline elevation.

- **T Wave:** As demonstrated by the condition, the existence of the T wave that comes after the QRS complex is evidence that the ventricles have repolarized. A normal T wave has a peak that is located substantially closer to the end of the wave than it is to the beginning of the wave. This is in contrast to a P wave, which has its peak located at the beginning of the wave. It is clear from this that there is a little imbalance between the two situations. When it comes to leads I–II and V2–V6, T waves are normally positive, however when it comes to aVR, they are negative. That is the case with both of the leads. The direction that a T wave follows is often the same as the direction that the T wave follows, regardless of whether the preceding QRS complex was positive or negative. One of the most common indicators of cardiac illness is the existence of a T wave that diverges in the opposite direction of the QRS complex. This is because of the nature of the disorder. There is a chance that the little wave that is located in the middle of the T and P waves is actually a U wave. There is a possibility that this will take place. As of this moment, the specific biological underpinnings that are responsible for the construction of a U wave have not been determined.

III. HEART RATE

The electrocardiogram (ECG) may be used in a variety of different ways to provide information on the heart rate of a patient. A method that is quick to use is the sequence technique. In order to apply the sequence approach to an electrocardiogram (ECG), you will need to search for a R wave that coincides with one of the black vertical lines. It is possible to determine that the second R wave correlates with the following black vertical line, which indicates that the heart rate is 300 beats per minute. The 200, 150, 100, 75, 60, and 50 beats per minute are represented by the dark vertical lines. If there are three large boxes in between the R waves, then the patient's heart rate corresponds to one hundred beats per minute. This approach can still be useful for producing rapid estimates in emergency circumstances, despite the fact that there are more exact ways to measure heart rate from electrocardiograms.

IV. COMPUTERIZED APPROACH TO ECG ANALYSIS AND CLASSIFICATION

The implementation of an automated paradigm for processing data be it in business, scientific research, bioinformatics or the academia has proven to be more accurate than any other method deployed in history with ground breaking results that deliberately enforces a paradigm shift from the status quo. In bioinformatics and medical research, computers has enhanced the rate and results of medical research outcomes as it regards to access large volume of medical/ health related data in use on daily bases. The use of computers for ECG signal analysis and interpretation has brought about big advancement in noise reduction, heartbeat detection (QRS detectors), heart rate variability (HRV) and ECG shape classification with more enhanced and precise algorithms [12].The dataflow process of a computerized ECG process as propose by [13], indicates the input of ECG dataset into the system and the removal of noise that is the denoising and heartbeat segmentation stages and subsequently the rhythm information processing, time and amplitude normalization, information fusion via one-hot encoding to the binary image generation as shown in Figure 3.

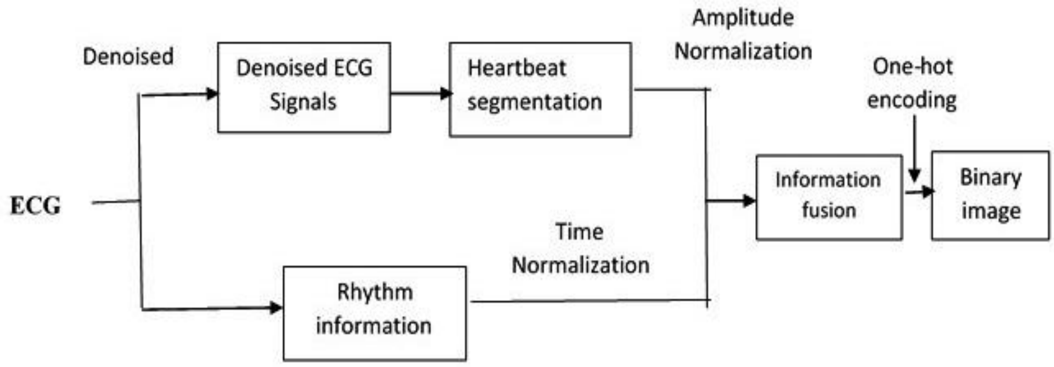


Figure 3: ECG Signal Processing Flowchart (Source: [13])

The application of machine learning in ECG has also brought in more accurate real-time analysis and predictive approach to the diagnosis of heart disease with precision, with accuracy level that ranges from 80 to 90 percent depending on the machine learning algorithm deployed.

V. Machine Learning for ECG Analysis

ECG (Electrocardiogram) classification approach using machine learning based on several ECG features. In order to determine the patient's state, ECG abnormalities must be handled, which is the main problem in ECG classification. In order to categorize ECG data accurately from heartbeat, a machine learning technique is necessary, and it must be efficient. Heartbeats can be difficult to categorize due to the fact that the action impulse waveforms generated by the many specialized cardiac heart tissues vary from person to person. The results generally from different machine learning models developed for these analysis shows that the approach has achieved an overall accuracy of 96.75% and more [14].

VI. Related work

Over the past two decades, significant advancements have been made in the identification and classification of cardiac disorders, including arrhythmias. While these methods continue to require refinement, they hold considerable potential for early disease detection and the reduction of casualties through the application of machine learning, deep learning algorithms, and statistical learning techniques.

[15] proposed a novel deep learning approach for ECG classification based on adversarial domain adaptation to address challenges such as poorly labelled training samples, data distribution discrepancies caused by individual variances, and the need to improve classification accuracy for cross-domain electrocardiogram (ECG) signals. This technique is made up of three basic components: classification (C), domain discrimination (D), and multi-scale feature extraction (F). Module F uses three independent concurrent convolutional blocks to broaden the scope of feature extraction. Module D combines three convolutional blocks and a fully connected layer to solve concerns such as missing model layers and poor feature abstraction. Module C improves feature variety by mixing deep learning-based features with time-domain properties in the fully connected layer. Experimental findings proved the model's efficacy, with a classification accuracy of 92.3%.

In their paper "Heart Beat Classification Using Wavelet Feature Based on Neural Network," [4] described an automated approach for classifying arrhythmia types. This approach reduces noise by segmenting ECG data into individual beats, using the R peak as a reference, then extracting features with a wavelet algorithm. Backpropagation and fuzzy-neuro learning vector quantization (FLVQ) were used to pre-process the data, categorizing beats into four classes: premature ventricular contraction (PVC), left bundle branch block (LBBB), normal (NOR), and right bundle branch block (RBBB), as well as a "unknown" category. The FLVQ model had an accuracy of 95.5% when evaluated without the "unknown" category; however, when this category was included, the accuracy dropped to 87.6%.

[16] used a deep neural network to automate the categorization of ECG data using the PTB-XL database in their study "ECG Signal Classification Using Deep Learning Techniques Based on the PTB-XL Dataset". Three architectures were used: (1) a convolutional neural network (CNN); (2) a SincNet model; and (3) a CNN with entropy-based features. The dataset was separated into three subsets: training

(70%), validation (15%), and testing (15%), with experiments performed on datasets with two, five, and twenty distinct disorders. Among these models, the CNN with entropy-based features had the greatest classification accuracy. Although the CNN without entropy-based features had somewhat poorer accuracy, it was more computationally efficient due to reduced neural complexity.

[3] created a compact convolutional neural network (CNN) model and compared its performance to pre-trained architectures like GoogLeNet. Using three PhysioNet databases—the MIT-BIH Arrhythmia Database, the MIT-BIH Normal Sinus Rhythm Database, and the BIDMC Congestive Heart Failure Database—the model categorized ECG signals into three categories: arrhythmia (ARR), normal sinus rhythm (NSR), and congestive heart failure. The suggested compact CNN, created in Matlab, obtained a validation accuracy of 92.31% and an overall accuracy of 91.20%, beating GoogLeNet. These findings highlight the usefulness of deep learning algorithms in detecting arrhythmias using ECG data.

[5], in their study "A Neural Network Approach for ECG Classification," stressed the importance of electrocardiograms (ECGs) in identifying heart diseases. They presented a pattern recognition framework that included signal preprocessing, QRS detection, and feature extraction, with artificial neural networks (ANNs) functioning as the best classification technique. Their investigation compared multiple ECG feature inputs to see which ones were most successful for categorization. The best-performing model used a three-layer network design with 25 input nodes, five hidden layer neurons, and five output layer neurons to accurately diagnose five distinct heart diseases.

[17] developed a rapid and effective arrhythmia detection approach based on the YOLO algorithm. Their method identifies arrhythmias and detects heartbeats in long ECG records without needing R-peak detection. The model processes raw ECG data using one-dimensional convolutional neural networks (1D-CNNs) rather than standard two-dimensional CNNs, and it does so using a bounding window rather than a box. This approach performed well, with a recall of 0.95, F1 score of 0.96, and average accuracy of 0.97. These findings indicate that the algorithm is extremely successful in identifying arrhythmias, with both high accuracy and processing speed.

[18] used a deep learning strategy to divide cardiac arrhythmia patients into 16 groups using attributes taken from an electrocardiography dataset. The dataset, supplied from the University of California, Irvine (UCI) repository, has 279 properties, making it a high-dimensional dataset. The researchers created an intelligent classification system employing a long short-term memory (LSTM) deep learning algorithm and noise reduction techniques like principal component analysis (PCA). Their methods revealed higher classification accuracy, with a precision of 93.5%, outperforming prior arrhythmia classification techniques.

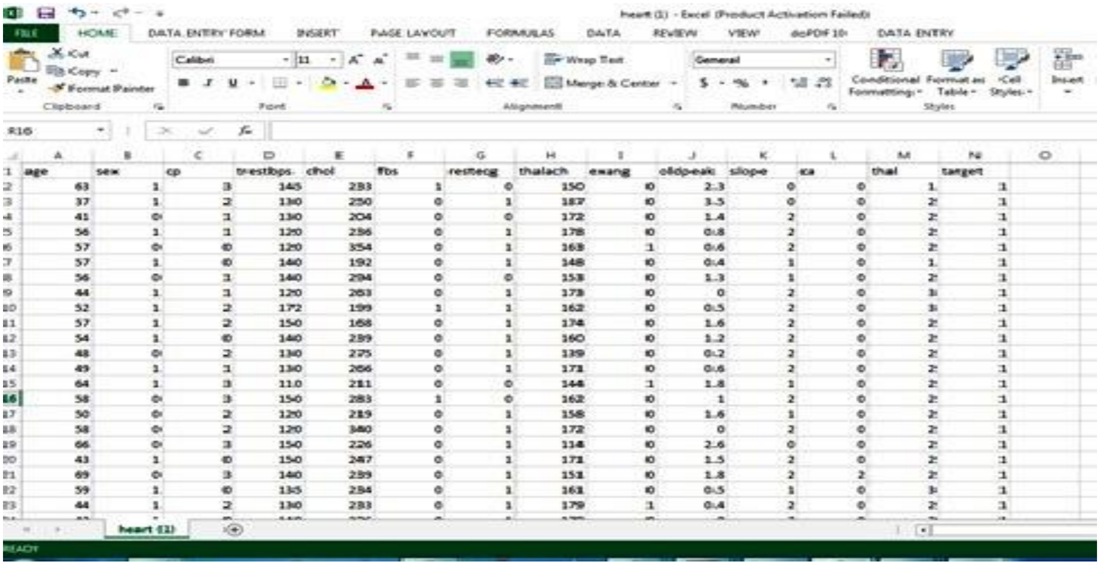
[13] used deep learning approaches for ECG classification in their paper "Deep Convolutional Neural Network-Based ECG Classification System Using Information Fusion and One-Hot Encoding Techniques," which was based on a CNN. While CNNs are often employed for multidimensional pattern detection, this work used them to one-dimensional ECG data processing. The model automatically extracted characteristics from heartbeat shape and rhythm and converted them into a two-dimensional information vector. The model exhibited good classification performance using an adjustable learning rate and biased dropout approaches, with average accuracy of 99.1% and 97.1% across test sets, respectively.

Finally, [19] used LSTM-based recurrent neural networks (RNNs) to patient-specific ECG beat categorization. Their suggested architecture included two simultaneous LSTM models, each processing a single ECG channel, allowing for a unique patient-specific analysis. By training on the first five minutes of heartbeats from each patient's ECG record and testing on subsequent segments, the model enhanced classification accuracy by adapting its predictions to unique patient features.

[20] introduced a rapid and entirely automated ECG arrhythmia classifier utilizing the fundamental machine learning method termed Echo State Networks, which is modeled after the human brain. Our classifier employs a one ECG lead for its minimalistic feature processing. The validation and training occur via an inter-patient procedure. The MIT-BIH Arrhythmia and the AHA ECG datasets are utilized to evaluate the heartbeat classifier. Employing the single lead II, the MIT-BIH AR database produced a sensitivity of 92.7% and a positive predictive value of 86.1% for ventricular ectopic beats, whereas using lead V1 resulted in a sensitivity of 95.7% and a positive predictive value of 75.1%.

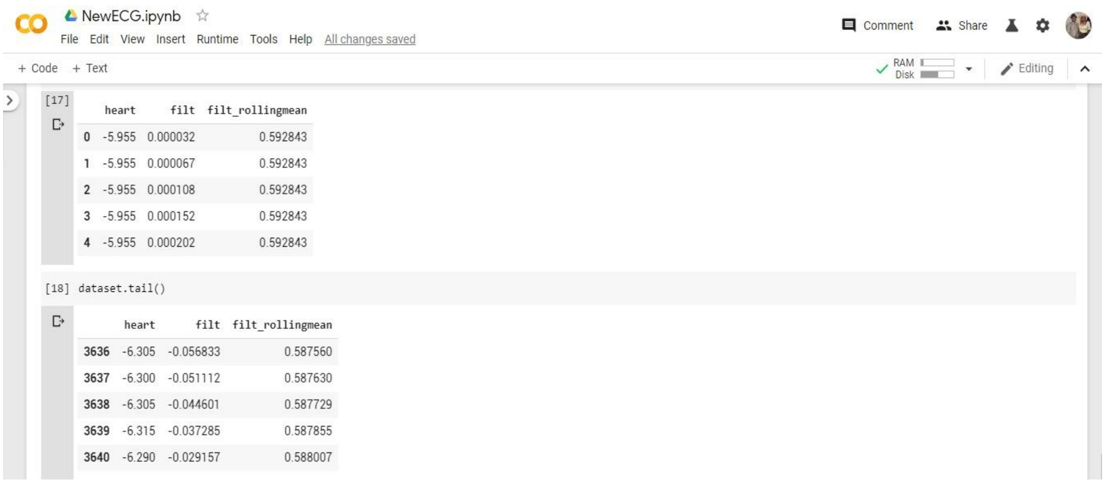
VII. METHODOLOGY

This paper deploys artificial neural network methodology for the analysis of the heartbeat to ascertain the presence of arrhythmia condition, the peak and average heartbeat. Using ANN, machine learning paradigm is suitable because the system learns from the dataset during the training phase and uses the information to make classification for the test data. The heartbeat dataset used for this work was sourced from UCI Machine Learning Repository (Heart Disease UCI: https://archive.ics.uci.edu/ml/datasets/Heart+Disease) as showed in figure 4. The ANN model for this analysis was developed using python programming language and Google Colaboratory Jupyter notebook.



age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	target
63	1	3	145	233	1	0	150	0	2.3	0	0	1	1
37	1	2	130	250	0	1	187	0	3.5	0	0	2	1
41	0	1	130	204	0	0	172	0	1.4	2	0	2	1
56	1	1	120	236	0	1	178	0	0.8	2	0	2	1
57	0	0	120	354	0	1	163	1	0.6	2	0	2	1
57	1	0	140	192	0	1	148	0	0.4	1	0	1	1
56	0	1	140	294	0	0	153	0	1.3	1	0	2	1
44	1	1	120	263	0	1	173	0	0	2	0	3	1
52	1	2	172	199	1	1	162	0	0.5	2	0	3	1
57	1	2	150	168	0	1	174	0	1.6	2	0	2	1
54	1	0	140	239	0	1	160	0	1.2	2	0	2	1
48	0	2	130	275	0	1	139	0	0.2	2	0	2	1
49	1	1	130	266	0	1	171	0	0.6	2	0	2	1
64	1	3	110	211	0	0	144	1	1.8	1	0	2	1
58	0	3	150	283	1	0	162	0	1	2	0	2	1
50	0	2	120	219	0	1	158	0	1.6	1	0	2	1
58	0	2	120	340	0	1	172	0	0	2	0	2	1
66	0	3	150	226	0	1	114	0	2.6	0	0	2	1
43	1	0	150	247	0	1	171	0	1.5	2	0	2	1
69	0	3	140	239	0	1	151	0	1.8	2	2	2	1
59	1	0	135	234	0	1	161	0	0.5	1	0	3	1
44	1	2	130	233	0	1	179	1	0.4	2	0	2	1

Figure 4: Heart Beat Dataset (Source: https://archive.ics.uci.edu/ml/datasets/Heart+Disease)



	heart	filt	filt_rollingmean
0	-5.955	0.000032	0.592843
1	-5.955	0.000067	0.592843
2	-5.955	0.000108	0.592843
3	-5.955	0.000152	0.592843
4	-5.955	0.000202	0.592843

	heart	filt	filt_rollingmean
3636	-6.305	-0.056833	0.587560
3637	-6.300	-0.051112	0.587630
3638	-6.305	-0.044601	0.587729
3639	-6.315	-0.037285	0.587855
3640	-6.290	-0.029157	0.588007

Figure 5: Dataset pre-processed showing the head and tail of table in Colab

VIII. RESULTS AND DISCUSSION

From the study average heartbeat rate was taken into consideration and the peaks. The dataset used for the analysis is 3640 different heartbeat sample dataset sourced from UCI machine learning repository this is aimed at the predicting the possible presence of arrythimia in the heart beat datasets.

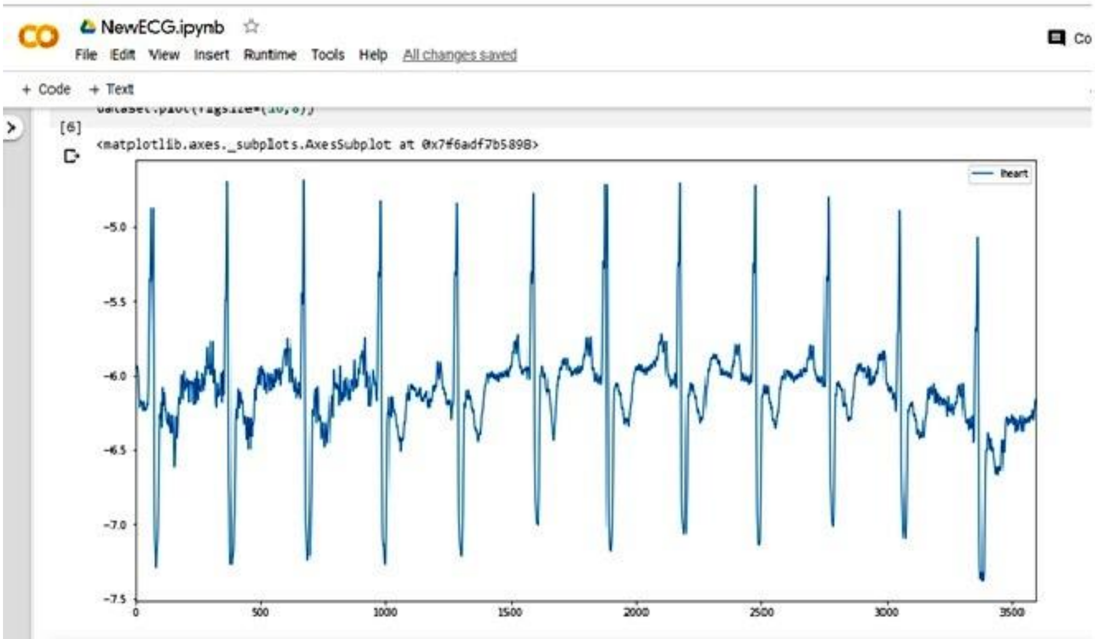


Figure 6: Heart beat Signal

From the analysis, figure 6 shows the ECG signal while figure 7 and 8 shows the 12 peaks from and average heart beat of 72 recorded from the sample heart beats taken. The average resting heartbeat for men between ages 18 to 65+ is between 70 to 73 bpm. Since the normal heartbeat rate is between 50 to 100 bpm and arrhythmia depicts irregularity in heart beat, which implies that heartbeats above 100bpm is prone to arrythmia and requires urgent medical attention. Therefore the results of the process shows normal heart beat with the recorded 72 heart beats.

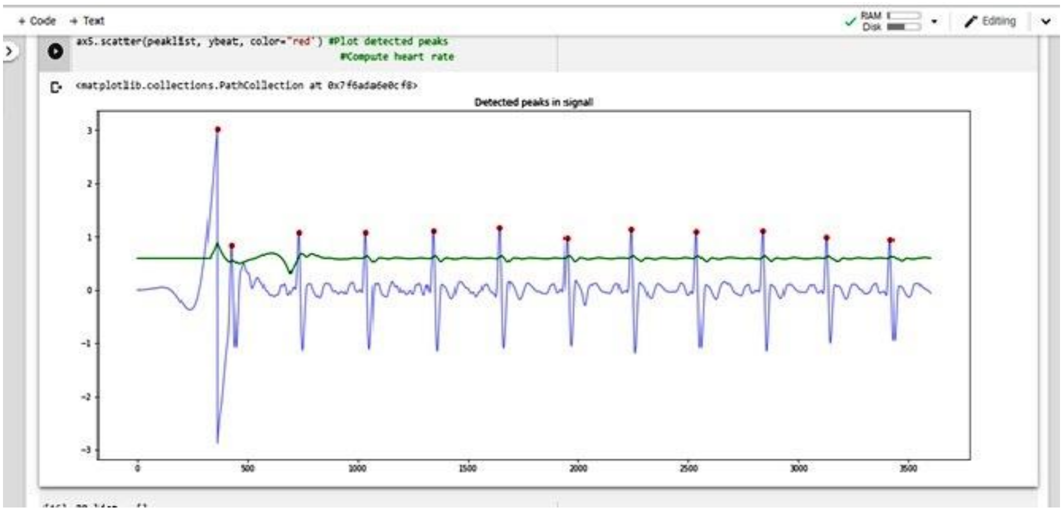


Figure 7: Heart Beat Signal flow showing Peaks

Figure 8: Output Showing average Heart Beat and number of Peaks

From the final result obtained from our artificial network model ECG analysis on the dataset, indicates that the heart is normal without any sign of arrhythmia or any other heart defect with predictive accuracy of 97.43 %.

IX. CONCLUSIONS

The use of machine learning algorithm for processing health information management and biostatistics has proven to be accurate with high level precision hence, its implementation for the analysis of heartbeat to ascertain the presence of arrhythmia and other heart conditions. It is also of importance carry out further research to ensure that more parameters are considered to make the model more robust and flexible to tackle more complex analysis. The model here developed was able to analyse the heartbeat dataset with 97.43 % accuracy level. To ensure this level of accuracy was achieved, the dataset was first pre-processed to reduce the rate of noise in the dataset. This model was specifically designed to analyse heartbeat for the detection of arrhythmia and it can also can be up-scaled and trained to analyse other heart conditions with high level precision.

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