# Development of GUI in Python for Diagnosis and Analysis of ECG Signal Using Metaheuristic Algorithm

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# Development of GUI in Python for diagnosis and analysis of ECG signal using metaheuristic algorithm.

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***Abstract - The system efficiently studies and analyzes electrocardiographic signal processing using a machine learning language-based engine. Research on ECG signals includes things like ECG signal generation and simulation, real-time ECG data acquisition, ECG signal filtering and processing, feature extraction, comparison of algorithms and other techniques together to analyze ECG signal (such as wavelet transform), detect any abnormalities in the electrocardiogram, calculate beat frequency, etc. To increase the efficiency of evolution results, we can process and analyze real-time electrocardiogram data and simulation with high accuracy and ease by using functions with Linguistics Open CV Python 3.6.3 library (both built-in and user-defined).***

*Keywords*— ***ECG signal data from Kaggle website, preprocessing, feature extraction, Denoising signal, Simulation by using Python Language3.6.3.***

## I. INTRODUCTION

Introduction An electrocardiogram (ECG) is a recording of cardiac activity. Examples of ECG symptoms associated with the same heart cycle are shown in Fig. Monitoring heart rate, heart rate analysis, heart problem diagnosis, emotional recognition, and biometric detection of a few of the biological ECG applications are valuable to them. One of the most commonly used methods of ECG analysis is to diagnose heart disease. According to the World Health Organization, heart disease is the leading cause of death in the world. Since cardiac arrhythmias are the most common diseases of the heart and blood vessels, proper classification has attracted the interest of biomedical research [4].

One of the most effective ways to diagnose arrhythmia is to examine ECG symptoms [5]. Feature characteristics, morphological characteristics and visual acuity of each ECG stroke can be assessed to automatically detect ECG patterns to provide meaningful clinical information. Automatic isolation of ECG beats, on the other hand, is a difficult task because the morphological and temporal properties of ECG signals vary greatly from different people in different parts of the body. person, and different people may have different ECG morphologies in the same situation. In addition, there can be two different diseases. They have almost the same characteristics. Individually. Electrocardiogram Signal These problems compound the difficulty of determining the origin of heart disease. The electrical signal of each beat must be evaluated to find irregularities in the beat. Therefore, the evaluation of Holder recordings, especially for bedside monitoring or healthcare online portable monitoring, can be a difficult and time-consuming task for a person.

The use of ECG analysis in areas other than the diagnosis of heart disease has exploded in recent years. Many studies have used ECG signals to detect emotions, especially stress detection, in addition to various other symptoms such as electroencephalogram, skin temperature, blood pressure, electromyogram, heart rate, cortisol, and heat thinking. ECG symptoms are recorded in a variety of stressful situations, e.g. B. during anal exams, after a student vacation, in the office staff and when driving drivers. This study suggests that ECG signals can be used to differentiate between different psychological factors and stress levels. In addition, ECGs are used in the field of biometric detection.

To identify individuals, biometric recognition uses physical attributes such as faces, fingerprints, hand gestures, DNA, and irises, as well as behavioral features such as voice, step, signature, and keyboard power. Biometric systems provide limited security and access to restricted areas. The overall, variability, durability, and resistance to attack are the requirements of the features and attributes listed above. Scholars are increasingly using the ECG in this area because it has more personalized features.

### *I. Feature extraction:*

Discharge Since electrocardiography is a description of the electrical activity of the heart, a good representation of the ECG signal is essential in the diagnosis of heart disease. Various algorithms for extracting features have been reported in the literature to reveal different information from the ECG signals for various applications such as analysis and classification. These skills can be used alone or in combination with others. In this article, we categorize ECG components into five categories: QRS, mathematics, morphology, wavelet transform, and more.

### ***II.P-QRS-T Complex features***:

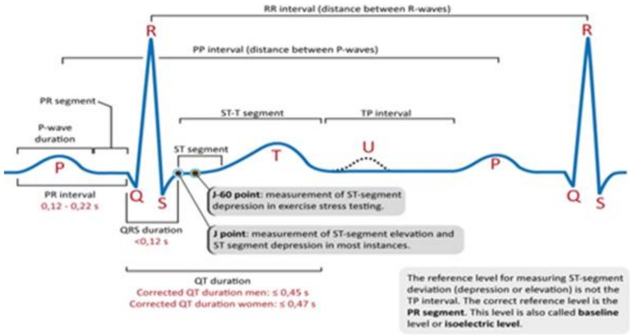


**Fig 1.1. Complex PQRST complex features**

Structures The complex structure of the PQRST ECG signal is basically related to the location, duration, amplitude and specific wavelengths or travel within the signal [106,107]. The ECG signal usually has five major frequencies, including P, Q, R, S, and T waves, as well as a small wave called U wave, as seen in. As the frontal depolarizing wave spreads to the tricuspid valve, the P-wave is a small, low-velocity deviation from the base caused by atrial fibrillation, atrial permeability. The Q wave is a vertical deviation following the P-wave. The R

The Q, R, and S waves all point to the same event. Therefore, they are more commonly known as the QRS complex. The complex functions of the QRS are among the most powerful in ECG analysis. When the ventricles shrink before they are shortened, the currents produced lead to the QRS complex. Although atrial repolarization occurs before ventricular depolarization, the latest waveform (QRS complex) is much larger in amplitude, so atrial repolarization is not visible on the ECG. The T-wave following the S-wave represents the ventricular repetition that prepares the heart muscle in turn. ECG cycle. Finally, the U wave is a small deviation that occurs immediately after the T wave. Most of the time, the U wave goes in the same direction as the T.er wave.

## II. LITERATURE REVIEW

This article describes how to convert one ECG time series into spectral images with two properties: rapid frequency and spectral entropy. Using the Fourier temporary transition, the ECG signal is converted into a series of visual images to produce a feature. Images are then converted into two signals, fast frequency and spectral entropy, using Fourier transform. [1]. The proposed model is a three-layer ECG signal analysis model that can be used for real-time wearable and wearable monitors. Using Matlab we design, build and replicate the proposed CNN network. We also provide the use of computer hardware for the proposed route to ensure its flexibility in wearable devices in real time. [both]. Using neural networks and similar artificial intelligence methods to deal with non-polynomial complex problems alone is a creative and intelligent problem that is not subject to process and is fully explained on the basis of theory [3]

The heartbeat and ECG signal are digitized and processed in a simple filtered way. At the same time, Lab VIEW uses waveform data, storage, and gaming functions. Finally, this study performed the separation of heart rate and placement using a Lab VIEW system. and ECG signal. The operation of the collection and analysis system is reliable, and the module is simple and easy to use. The measurement collection provides simplicity and reference for the analysis and detection of subsequent cardiac sounds, ECG data formation and pathology signals. [4]

The detection of important physical phenomena using traditional techniques and novel methods based on physics and indirect calculations, co-identification and signal separation, construct new knowledge, simulation of life and other signals, quantitative testing and comparisons analyzing methods, and analysis of interim processes. Physio Net is an online platform for the distribution and exchange of proprietary biological signals and open source software for its analysis.

Enables integrated data analysis and testing of new proposed algorithms. Physio Net provides online courses and training services and free electronic access to Physio Bank data and Physio Toolkit software via the World Wide Web (http://www.physionet.org). grimmer to measure spectral density of energy. As a result, all emerging signals are arrhythmic compared to the normal range of the standard scale. Then, to assess the variability of the heart rate in the arrhythmia database, the mean time pattern (statistical analysis) and the spectral analysis of the frequency domain method were used. The HRV analysis process is performed using MATLAB programs and data entries from the MIT site and BIH arrhythmia. [6]

Instead of quitting, researchers consider other solutions (ratings) to find an adequate response in a timely manner; these strategies are classified as heuristics and metaheuristics. The main difference between the two is that heuristics is used to solve problems. Heuristics is more dependent on problems than metaheuristics, which is an important difference. In other words, heuristics can be effective in solving a problem but may not be able to solve others. On the other hand, metaheuristic seems to be a standard algorithm framework or black box optimizer that can solve almost any problem of efficiency. [7].

The African Vulture Optimization Algorithm (AVOA) moderates the search for food and browsing of African vultures. To test the effectiveness of AVOA, it is first tested in 36 standard benchmark operations. The advantage of the proposed algorithm over many existing algorithms is then shown by the comparative analysis. AVOA is used to identify appropriate solutions to eleven engineering design challenges to demonstrate their functionality and black box environment. Based on test results, AVOA is the best algorithm for 30 of the 36 comparative tasks and surpasses most technical issues research. Wilcoxon level measurement was performed for statistical analysis and showed that the AVOA algorithm was significantly higher at 95% confidence intervals. [8]

The proposed method is compared to the most advanced algorithms in the field of efficiency. In addition, Barrier Engineering Design Problems are used as design examples, which include other Design Development Challenges from previous Evolutionary Computing (CEC 2020) competitions. The results of the AOS algorithm in dealing with barrier problems are comparable to those of a few common, advanced, and hybrid metaheuristic algorithms published in the literature.

The results show that the proposed AOS algorithm yields the best results when it comes to mathematical and technical design challenges. [9]

In this article (GEO), the Golden Eagle Optimizer, an ecosystem-based metaheuristic, is proposed to address globalization problems. The golden eagle's maneuverability to adjust the speed at various stages of its circular hunting pattern is a source of GEO inspiration. In the early stages of hunting it is possible to walk and look for prey, and in later stages they are more likely to attack. The golden eagle balances these two features in a very short period of time. [10]

## III. SYSTEM ARCHITECTURE

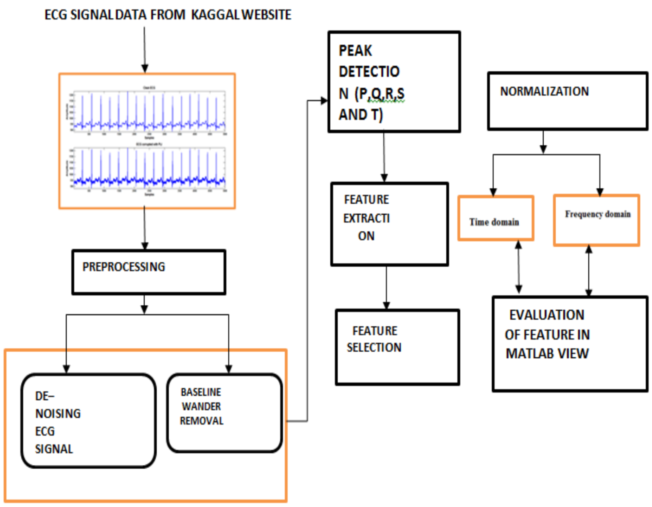


**Fig 3.1 Anatomy of the system.**

Denoising is used because the first degree of pre-processing reduces noise and away from the effects of the feature at the end of the signal segments. Data should be filtered to eliminate power lines at 50 or 60 Hz, base rotation or base flow of about 0.five Hz, electromyogram sounds above 50 Hz, and intermittent and high frequency audio interference of symptoms. The number 3 supplements for the ECG indicators are P wave, QRS complex, and T wave, and waves that range from 5 to 40 Hz. We learn different filtering algorithms in the same types of situations. Conditions, as described in Section 3.1 The initial filtering method includes low-pass and high-pass filtering.

### *1. PREPROCESSING*:

ECG indicators include several types of sound. As a result, the preliminary processing phase, among other things, seeks to reduce pollution (noise) caused by muscle noise, electrical disturbances, movement skills, and foundation erosion. Predictability is important because the ECG signal condition affects the performance of the stages. Figure 3.1 shows the key functions within the processing stage.

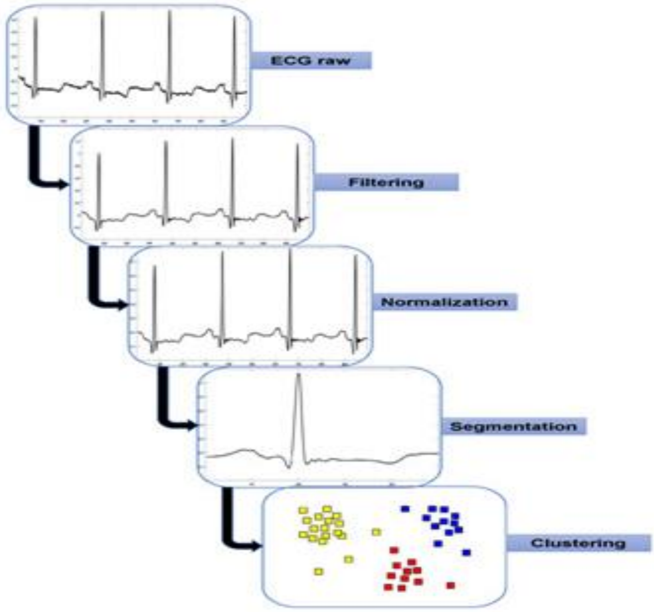


**Fig 3.2 Diagram of prepossessing**.

Denoising is used because the first degree of pre-processing reduces noise and avoids local effects at the end of signal segments. Data needs to be filtered to remove power line interference of 50 or 60 Hz, basic rotation or basic floating of about 0.five Hz, electromyogram sounds above 50 Hz, and occasional high frequency frequencies that interfere with signal interpretation. . Appendix 3 number ECG notifications for P wave, QRS complex, and T wave, and waves from 5 to 40 Hz. We look at different filtering algorithms for specific situations. Circumstances, as described in Section Three.1 The first method of filtering involves filtering out low and high pass.

In the second one method, wavelets are used. The reason for the comparison is to research that special filtering techniques and metaheuristics techniques affect the overall performance of the classification model. Low-pass and high-pass filtering techniques have been selected because they have been proven to be effective in reducing noise from ECG data, including muscle noise, basic floating, power line distortion, electromyography sound, and electrosurgical noise. We used the Fast Fourier redesign method because it proved to be a useful tool for reading non-desktop alerts including ECG; as a result, we have used a denoising system primarily based on a metharustic algorithm, as did the previous authors.
Figure 3.3 depicts the equal sign earlier than and after the filtering system. Panel A's uncooked sign incorporates styles of noise: strength line interference and baseline float. Panel B depicts the sign after low-pass and high-pass filtering; the noise from the uncooked sign has been removed, however there are minor amplitude differences: with inside the uncooked sign, the Q wave is deeper than the S wave, while the opposite is authentic with inside the filtered sign. Panel C

illustrates the sign following It has been wavelet filtered, which removes strength line interference and baseline float, and the sign is smoother than the alerts in Panels A and B.

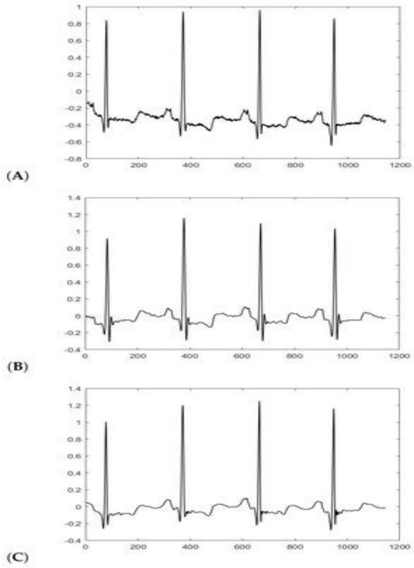


***Fig 3.3 (A) The signal before it was filtered. (B) Signal after applying a high-pass and low-pass filtering combination. (C) After FFT, the signal.***

**2. NORMALIZATION*:***

The authors sought to employ amplitude normalization as one of the pre-processing procedures so as not to contribute to the amplitude change. In contrast, amplitude normalization is preferred but the resources within the apparent variation of facts from different patients, according to Thomas et al. use the standard method to reduce the amplitude variation from report to report. We use Equation (2) to make ECG indicators generally a choice between 1 and 1 to minimize discrepancies between patient readings. The Y reality matrix is matched. X (s) indicate the vector of the pattern. Figure 3.4 of the fourth shows the familiarity of the symbols before (Panel A) and after (Panel B), each of which may be similar in appearance.

$$Y(S) = 2.\left(\frac{\mathrm{x(S)} - \mathrm{x(S)min}}{\mathrm{X(S)max} - \mathrm{X(S)min}}\right) - 1 \ldots\ldots [1]$$

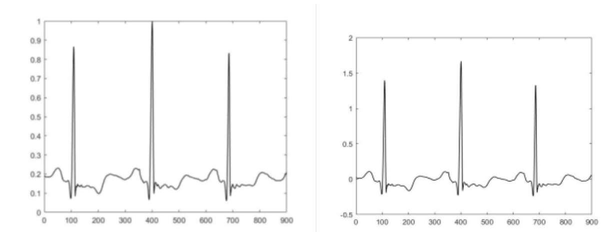

***Fig 3.4 (A) The signal before it has been normalized. (B) The signal after it has been normalized.***

**3. FEATURE EXTRACTION*:***

**A.** After the sound has been removed, a task release is performed. A major issue for ECG symptom testing is the detection of fiduciary points (i.e. R-peaks). In this function, the R peaks are identified by the use of WT first, after which all the different functions are returned. Acquisition strategies are accurate in this section of this section.

**B. R-peaks detection:**

The detection of R-peaks in these diagrams was done using DWT and thresholding. The following steps are used to hit the tops of R:

Step 1: EGG token acquisition: The Kaggle website is used as a token in this investigation.

Step 2: noise termination: noise is removed using MODWT and the universal limit is represented by Equation (13) in a variety of signal interfaces.

Step 3: Finding the peaks: Identifying the peaks is done using thresholding.

Step 4: R-height detection: R-peaks are detected the usage of an equation.

Ri = Pi ×2^j…. Equation (1)

Data sets from the kaggle website are highly screened and visualized. When R-peaks are detected, the R-R length and heart rate are recorded. ECG signal screening does not currently prevent the acquisition of coronary heart disease. The daily heart rate signal may indicate a series of abnormal rhythms or arrhythmias. The following arrhythmias are classified: supraventricular arrhythmias, atrial fibrillation, atrial flutter, paroxysmal supraventricular tachycardia, ventricular arrhythmias, ventricular tachycardia, ventricular fibrillation, and ventricular fibrillation, different arrhythmia. For those arrhythmias, all ECG signal supplements are checked (full view contains amplitude and time ECG wave attachments). In addition to coronary heart rate, different elements need to be restored in order to define ECG rhythm as daily or irregular.

B.Q and S-wave detection:

Step 1: Identify the ECG signal: To detect a Q-wave, a decaying third-degree ECG signal (used in the form of wave decay) is used.

Step 2: make a calculator: because the wavelength of R waves is expected to be equal to the width of the Q waves, set the calculator to the full width of R waves, above b = 1.

Step 3: Select system c time: Because the Q wave occurs without delay before R As a result, the detection name of the Q wave is 0.half s, or 9 samples of the third degree rotten sign before the full time.Step 4: Find the place with the least amplitude: Because the Q wave has the least amplitude.

**C. Detection of P and T peaks**

P / peaks are obtained by the use of the following steps:

Step 1: Take an ECG signal within the first Set the i1 calculation costs and threshold costs:

Step 2: Set the time limit: Because the P / P waves come in front of the Q / T waves, the time interval between them is 0.three.

Step 3: Increase i i in step 1

Seconds. Step 5: To determine the size of the P wave, see the size of the correct part of the sign.
Step 4: Increase i i in step 1.
Step 5: To determine the size of the P wave, see the size of the correct part of the sign.
Step 6: Repeat for all P waves: By repeating 3 to 5 steps, 1 counter, you can get all P / peaks. With the exception of step 2, the steps for detecting T waves are the same as for detecting P waves. Python system language time is used in this case.

## IV.METAHEURISTIC APPROACH

The layers of the metaheuristic approach to the type of heartbeat the use of nonlinear facts are shown in 4.1 Fig. The first, the discovery of facts, analyzes instructions on how to use facts from the Kaggle website of arrhythmia to produce a context of inequality. with 4 more commands and 4 smaller commands. The approximate rate for a new shiny set of eight commands is calculated in Section 3.2. Stage 2d, processing the ECG signal, consists of 4 components (see Section 4.1). To get started, we clean up the recordings to get rid of the noise in the indicators. Thereafter, each signal is subject to amplitude Normalization in order to reduce the transition between affected ECG or male and female ECG signals. The filtered references are then separated.

### 1. *METAHEURISTIC OPTIMIZATION:*

To solve the problem of unequal beauty, we provide a mixed development approach primarily based entirely on metaheuristic techniques that combine facts with algorithmic categories to maximize classification parameters. In comparative cases, we evaluate metaheuristics techniques, particle swarm optimization (PSO) and different evolution (DE), in order to determine the total number of parameters that will enhance the classification performance.

### *A. Particle Swarm Optimization:*

Particle swarm optimization (PSO) is a metaheuristic development based entirely on the movement styles of the chook and herds of fish. In the traditional PSO algorithm, the algorithm is produced in the form of a work-changing debris; every particle is a choice of volume in the problem, and that they rotate the work in accordance with 3 principles: (1) maintain inertia, (2) adjust the environment primarily based entirely on particle completeness.

### *B. Differential Evolution:*

Differential evolution (DE) is a method based on the stochastic community. In order to prepare tasks with real value, it repeats four stages: initiation, conversion, termination, and selection. The following is a breakdown of each step:
1. Implementation: In this phase, the number of parameter people is randomly generated between the lower and upper limits.
2. Transformation: In each generation or repetition, people from existing people become goals.
3. Symptoms. For each target vector, the method selects three more vectors anywhere for people; Next, a donor vector is generated from the weight difference of two to three vectors.
4. Crossover: After the donor vector creation, re-integration or crossover functionality is performed to increase the potential diversity of people.

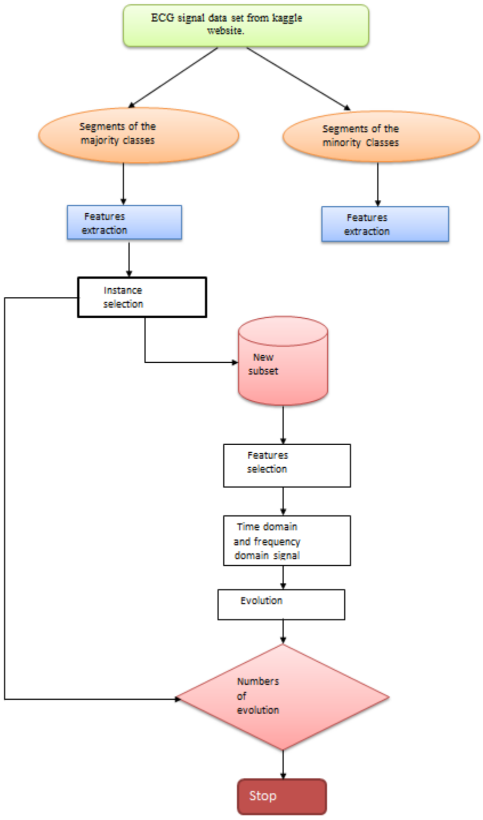


**Fig 4.1 Metahuristic approach diagram**.

Finally, most classes are divided into smaller groups using a combination method. The third stage is the elemental element, in which the mathematical elements are extracted from all the selected signals for each rhythm; see Section 4. In the final section, metaheuristic development is used to address the problem of inequality; Metaheuristic attempts to improve performance by selecting multiple parameters. Output by category In the data level, determines the SOM feature map size and the number of instances (percent) for each class group. At the algorithmic level, metaheuristic selects the number of neurons in the hidden layer of the artificial neural network as well as the training and evaluation functions of the separator. Each parameter is represented as a vector and its performance is assessed using a qualification function. In the following sections we will go for more details about each category. Four sections on how to differentiate metaheuristic bits using unequal data are presented.

Figure 4. The first step is data collection, which includes class analysis using data from the Kaggle Arrhythmia Database website to create a context of inequality consisting of four classrooms and four sub-classes. Section 3.2 calculates the unequal proportion of a new set of eight categories. The second phase, the ECG pre-processing signal, is divided into four phases (see section 4.1). First we filter the recorded signals to remove the sound. Then each signal is

usually measured to minimize variability between the patient's ECG data. After that, the filtered signals are separated into a heartbeat. each dial is drawn from all selected signals; se. In the final stage, metaheuristic improvement is used to address the problem of inequality. Metaheuristic attempts to improve performance by correcting a number of symptoms.

## V.RESULT AND DISCUSSION

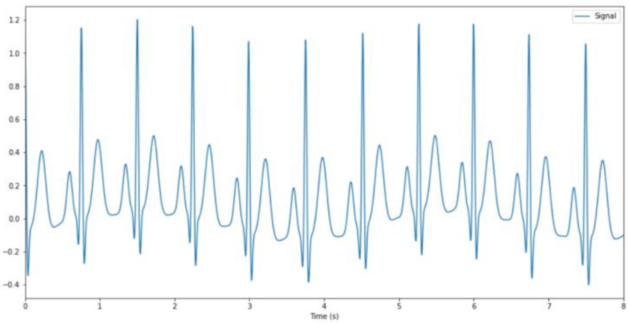


***Fig 5.1 Output Of signal after deniosing and feature extraction .***

The above signal is clearly detected using our design system test to detect signals that appear between the time zone and the frequency domain signals. We have clearly gained signals using a Python-based learning tool that works better. In order to increase performance, the basic FFT signal further enhances and integrates the output algorithms in the methauristic way used.

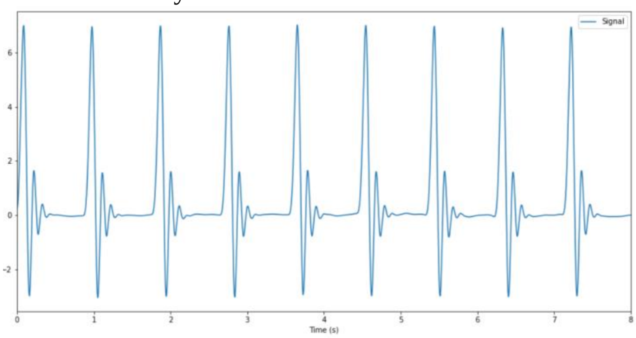


***Fig 5.2 Based on time–frequency analysis, an effective frequency-domain characteristic of arrhythmia.***

The signal fig 5.2 above is familiar to us between the time zone and frequency and we should get the parameters we have clearly detected unusual in the ECG signal. Without any LAB view .the process is done using a python-based learning tool that has done the whole process to Achieve the end of the goal. such as using an over-the-counter method and the overall result should be satisfied.

## VI.CONCLUSION

We have previously studied the processing of ECG signal has greatly observed by using MATLAB view, but how we design and implement our system, they are so useful and convenient that even without an ECG machine, one can monitor his or her cardiac condition by using machine learning based python to analyse abnormalities in ECG signal, which is one of the best methods to improve performance by using metharustic Approach to self-diagnosis algorithm. Even if we don't have any ECG data to replicate and analyse, the examples and approach presented here might be highly useful for experimental/lab reasons.

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