QRS COMPLEX AND ST SEGMENT DETECTION OF ECG SIGNAL FOR THE ANALYSIS OF MYOCARDIAL ISCHEMIA

A Project Report

Submitted in partial fulfilment of the requirements for the award of the degree

of

Bachelor of Technology

In

Computer Sc. and Engineering

By

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June 2020

INTRODUCTION

Myocardial Ischemia is a condition where ample amount of oxygen is not supplied to the heart. This reduction causes partial or complete blockage in coronary arteries causing damage to heart muscle. This problem may lead to Ischemic heart disease(IHD). In present world, according of world health organization 2019 around 32.4million people dies every year due to Myocardial Infarction(MI) caused by myocardial ischemia, also referred as heart attack. Symptoms of this disease are shortness of breath, tightness, heaviness,chest discomfort may gradually develop in many cases ,patient with ischemic episode remains unaware of IHD in early stages .Detection and treatment of this disease in time may prevent rupturing of the heart muscle and can save many lives. Our main aim is to design an algorithm to detect ischemic episode in ECG signal with less time complexity and cost effective and easy to implement in homecare ECG devices . Elevation (or depression) in the ST segment indicates presence of ischemia. The proposed method measures slope of ST segment which must vary in case of ST changes. People living in remote areas without proper medicinal facilities may get benefited. This can be further used for regular monitoring of the suspected ischemic patient and can help in early detection of myocardial ischemia.

LITERATURE SURVEY

The most prominent feature in ECG graph that helps us to detect Myocardial Ischemia is the elevation of depression of ST segment i.e. the slope of ST segment. Generally, ST segment stays at almost same level of isoelectric level, but in Ischemic cases, it forms a clear elevation. Many scientists have done so many researches on automated detection of Ischemia with the help of different algorithms. For example, we can mention the Karhunen-Loeve Transformation, popularly known as KLT. Besides, there had already been beat-to-beat quantification, back propagation algorithm, Continuous Wavelet Transform (CWT). Application of different neutral network, machine learning techniques, deep learning methods, real time analysis etc. have been visible in this field in recent times. Recently, there has been an approach to make this detection technique suitable for cell phone like devices. Predictive values for ST slope has been measured for some patients, who underwent coronary angiography, using per functional radionuclide images with 99mTc-2-methoxy-isobutil-isonitrile. These values showed 96% sensitivity whereas the conventional method can show only 73%.

Analysis of receiver-operating curves confirmed the superior performance of the heart rate-adjusted indexes throughout a wide range of test specificities. These findings suggest that heart rate adjustment of ST segment depression can markedly improve the clinical usefulness of the treadmill exercise electrocardiogram.

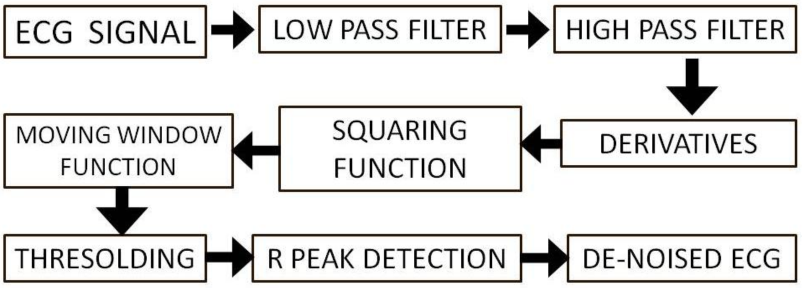
SYSTEM ANALYSIS & DESIGN

This section describes the database from where ECG signals were used for analysis. Also a detailed methodology of the proposed algorithm is discussed. Fig. 1 provides an overview of the system. The QRS complex (or R peak) is detected from the ECG signal. Based on that, ST segmentation is completed and slope of the ST segment is measured. A threshold is set and ischemic episode is detected according to that threshold.

- **Database:** ECG signals are used from the Physiobank database (Goldberger et al., 2000). The European ST-T database in Physiobank contains ECG signals with ST segment and T wave changes (Taddei, et al., 1992). The database contains ECG signals from ischemic patients where normal ECG sections and sudden ischemic episodes are annotated.

- **QRS Complex (R peak) Detection:** The Pan-Tompkins algorithm is one of the most efficient QRS detection algorithms. The algorithm consists of various stages.

Fig. 1: Pan-Tompkins Algorithm



The BPM can be calculated from this algorithm from the QRS complex of an ECG signal. It can detect if the heart is suffering from Tachycardia (BPM>100) or Bradycardia (BPM<60).

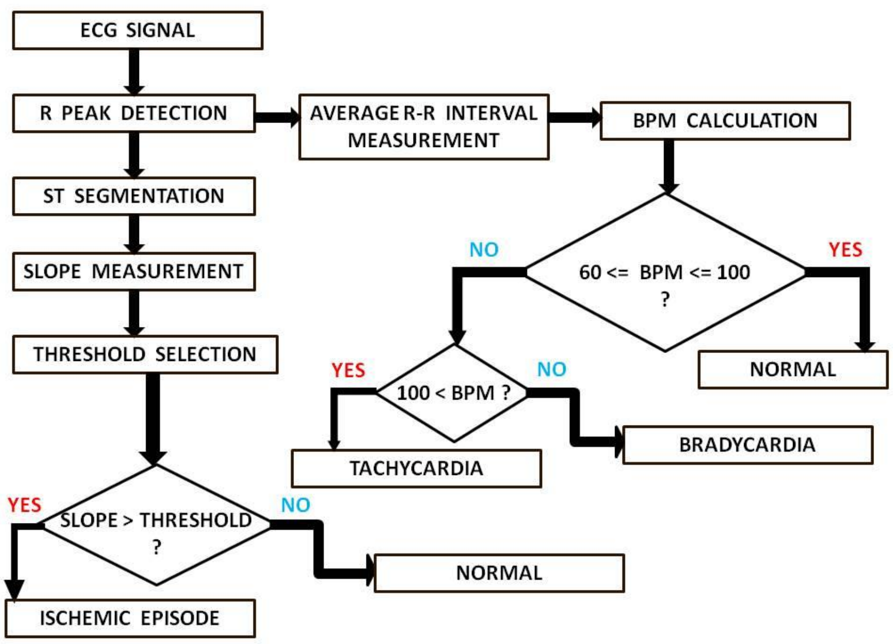
To Calculate the BPM , Machine Takes the Average R-R interval and Convert It into BPM.

Step 1: Average R-R interval in ms = ((RR_interval / fs) * 1000.0) where fs is Sampling Frequency

Step 2: BPM (Beats per Min) = 60,000 / average R-R interval of signal.

Once R peak is detected and machine is done with the QRS Complex ,moving towards ST segmentation is possible.

Fig. 2: Proposed Algorithm Process Flow



- **ST Segmentation:** After the detection of R peak in ECG Signal, ST segmentation is detected and slope of the ST segment is measured. A threshold is set and ischemic episode is detected according to that threshold. The ST segment depression (or elevation) indicates presence of ischemia. In case of ischemia or ST changes the measured slope will vary.

  The duration of ST segment is usually 120ms where BPM is 60. Here the ECG signal used have a sampling frequency of 250Hz. Now the ST segment can be found in number of samples by doing this (250*120)/1000 = 30. Now, it is known that QRS segment's duration is 110ms. So, it can be said that the ST segment will start after (110/2) i.e. 55ms of the R peak. So, for the sampling frequency 250Hz, the ST segment will start (55*250)/1000 i.e. 14 number of samples after the R peak.

  So, For 60 BPM range The steps are :

  Step 1: Start

  Step 2: Locate R Peak by Pan-Tompkins Algorithm.

  Step 3: Take the 14th sample after the R peak.

  Step 4: Take approximately 30 sample after the 14th sample

  Step 5: Save these 30 sample as ST SEGMENT

  Step 6: End

ST Segmentation Algorithm for various ranges of BPM :

After the detection ST segment of a signal where the BPM is 60, where the duration of every segment of ecg signal is experimentally proven, the approximate duration for every BPM value is to be calculated considering BPM 60 as base value.

Here, for 60 BPM, the duration of a complete cycle of ECG signal is 60/60 sec = 1sec = 1000 ms.

For every BPM value, the duration of one complete cycle will be (60/BPM)*1000 ms . Now considering the base 60 BPM, the time duration of each segment is calculated.

So, The steps are :

Step 1: Start

Step 2: Locate R Peak by Pan-Tompkins Algorithm.

Step 3: Calculate the BPM.

Step 4: Calculate the duration of one complete cycle.

Step 5: Calculate the time duration of QRS and ST segment.

Step 6: Convert the time into sample values.

Step 7: Take the A (Where A = duration of QRS / 2) samples after the R peak.

Step 8: Take approximately B (Where B = duration of ST Segment) samples after the Ath sample.

Step 9: Save these B samples as ST SEGMENT.

Step 10: End

Table 1 : Calculated Durations of each Segments of ECG signals where the BPM is in normal range (60 < BPM < 100)

BPM	DURATION OF A COMPLETE CYCLE	DURATION OF PR SEGMENT	DURATION OF QRS SEGMENT	DURATION OF ST SEGMENT
60 to 65	1000 ms	110 ms	110 ms	120 ms
66 to 70	910 ms	100 ms	100 ms	109 ms
71 to 75	850 ms	94 ms	94 ms	102 ms
76 to 80	790 ms	87 ms	87 ms	95 ms
81 to 85	740 ms	81 ms	81 ms	89 ms
86 to 90	700 ms	77 ms	77 ms	84 ms
91 to 95	660 ms	73 ms	73 ms	80 ms
96 to 100	630 ms	70 ms	70 ms	76 ms
101 to 105	600 ms	66 ms	66 ms	72 ms

Fig. 3.1: R Peak & ST Segment Detection (Sample 1)

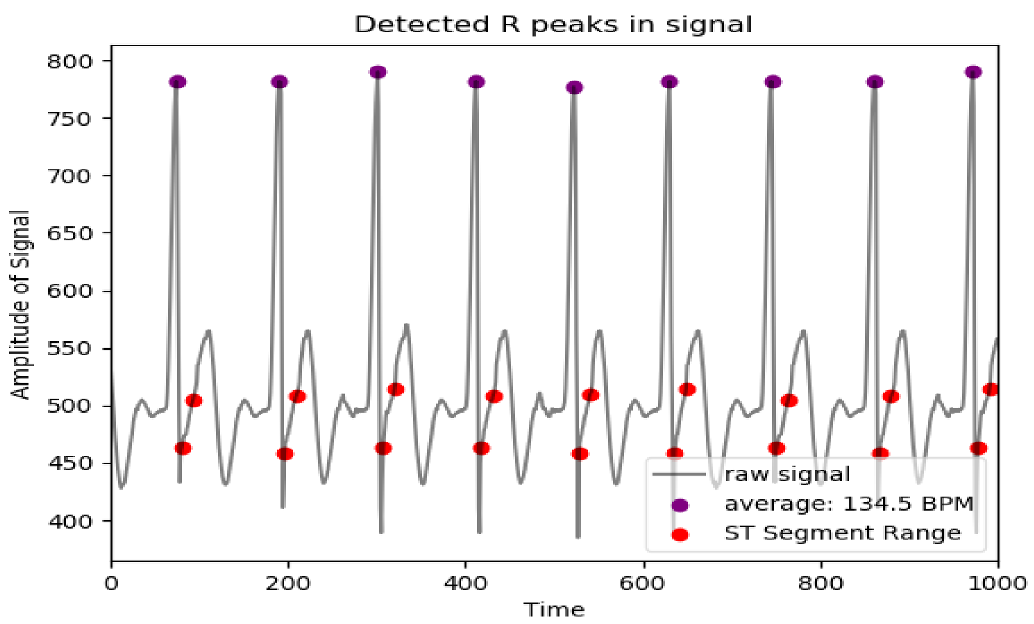


Fig. 3.2: R Peak & ST Segment Detection (Sample 2)

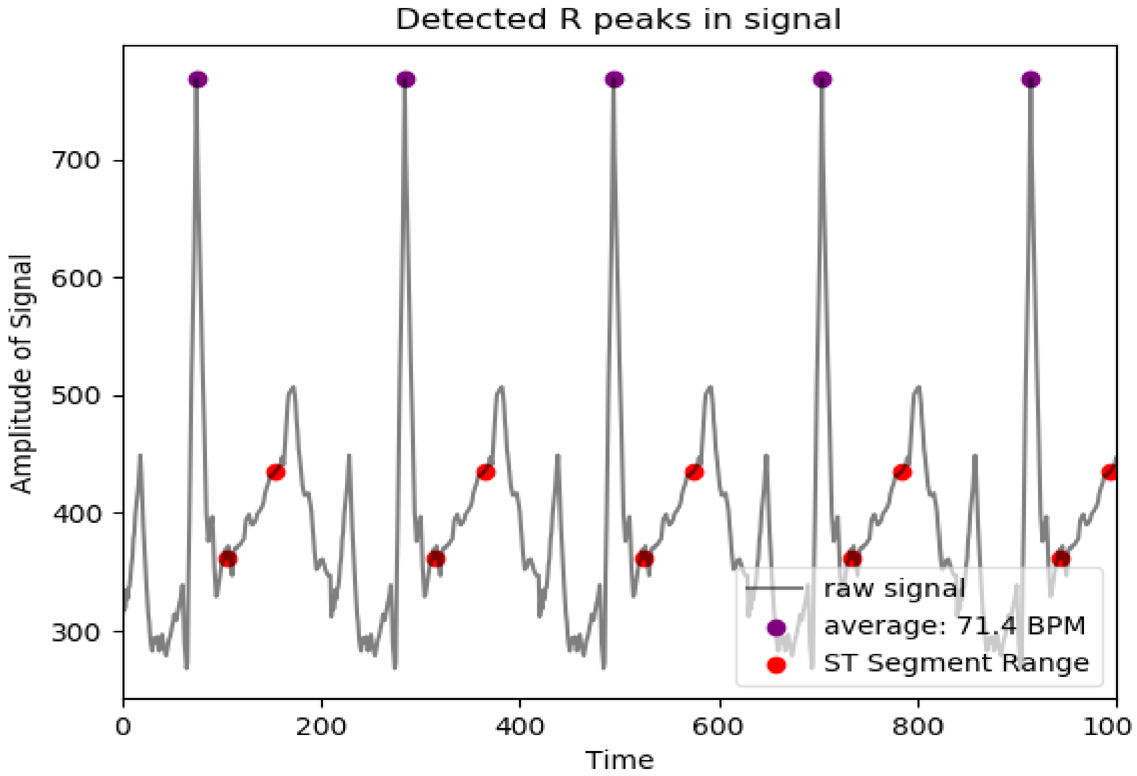
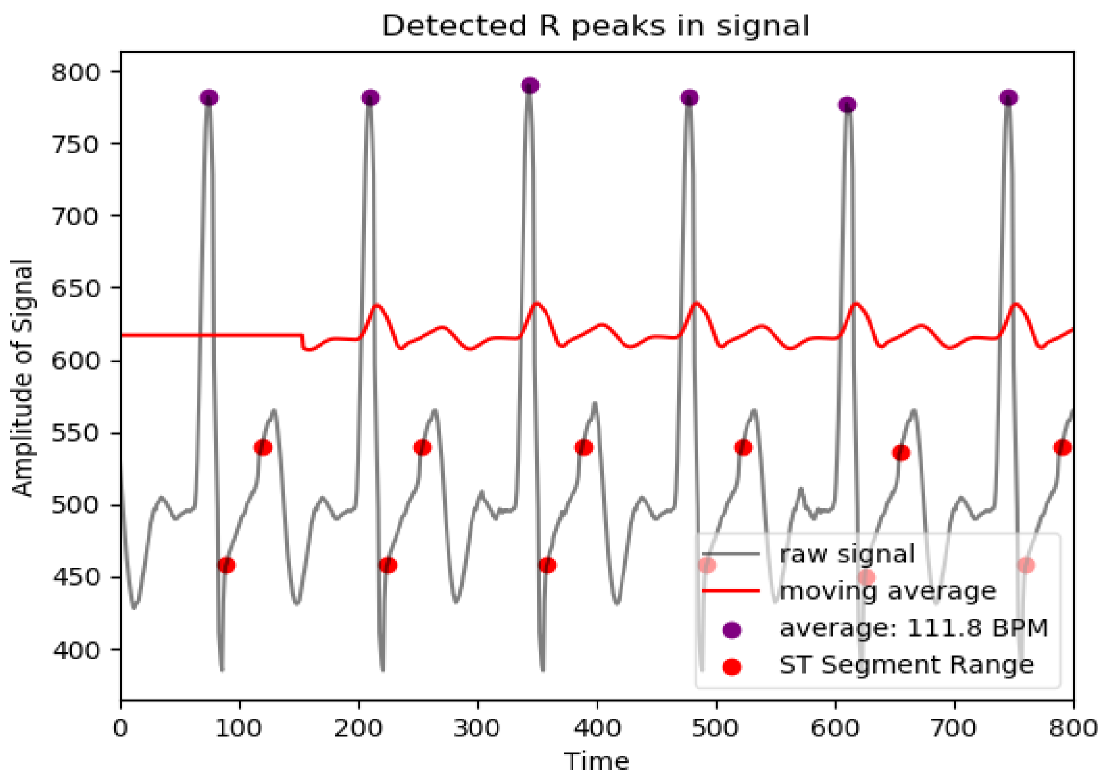
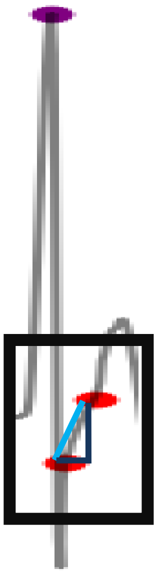


Fig. 3.3: R Peak & ST Segment Detection (Sample 3)



- **Slope Measurement :** The Slope can be defined by tanX = (A – B)/C , where A and B are the first and last sample values respectively. C is the total number of Sample. Slope of each ST segment of a portion of ECG signal is calculated and averaged to get an overall trend.

Fig. 4: Selection of threshold from slope values



- **Thresholding:** The thresholding of slope value to classify a portion of ECG as ischemic episode or normal ECG episode is done experimentally.

  If Slope < Threshold then *NORMAL*

  if Slope > Threshold then *ISCHEMIA*.

  The target of the proposed work is to examine whether slopes of ST segments of ischemic episode and normal ECG episode cluster in different groups. Following Table 1 contains detailed information of the ECG signals used. From each of the five patient records episodes of normal ECG and ischemia is taken. Also can be seen the average slope of all the ST segments in that particular episode of ECG.

Table 2 : Average Slopes of ST Segment

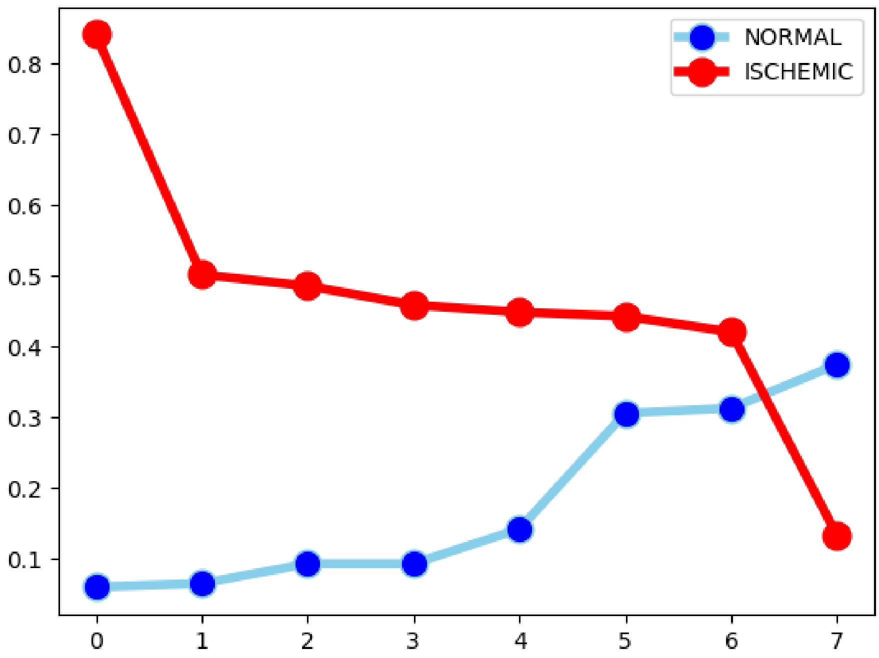
Patient Record	Normal ECG episode			Ischemic episode		
	Duration	No. of ST segments	Avg. slope	Duration	No. of ST segments	Avg. slope
e0610 (V3)	00.05-02.45	159	0.3060	38.25-41.26	186	0.4493
	03.45-04.55	72	0.3139	48.39-51.00	161	0.5027
e0605 (V5)	00.05-02.55	270	0.0932	62.30-64.35	138	0.4431
e0302 (V3)	00.05-02.15	240	0.3579	19.46-39.12	2490	0.8427
	03.10-04.45	213	0.4922	20.23-21.26	90	0.4864
e0609 (V5)	00.05-02.15	167	0.0932	23.05-24.56	161	0.4596
	03.10-04.45	123	0.1425	26.35-27.30	80	0.4214
e0607(V4)	00.05-02.15	189	0.0609	17.34-22.1	448	0.1331
	03.10-04.45	101	0.0652	12.49-26.12	1131	0.0652

For finding a threshold to separate into two classes, the slope values of normal ECG episodes are sorted in ascending order and ischemic episodes in descending order. Table 2 shows the sorted values. Fig. 4 illustrates the sorted values and it can be observed that the two series intersects at around 0.35. So if a threshold is selected based on it then any value over 0.35 would be a detected as an ischemic episode.

Table 3 : Sorted Slope Values

Normal ECG episode slope values in ascending order	Ischemic episode slope values descending order
0.0609	0.8427
0.0652	0.5027
0.0932	0.4864
0.0932	0.4596
0.1425	0.4493
0.3060	0.4431
0.3139	0.4214
0.3579	0.1331

Fig. 5: Selection of threshold from slope values



RESULTS :

The next step is to test the algorithms accuracy against threshold values at or around 0.35, which is listed in Table 3. The accuracy is calculated as Accuracy = $(TP + TN) / TP + FN + TN + FP \times 100$

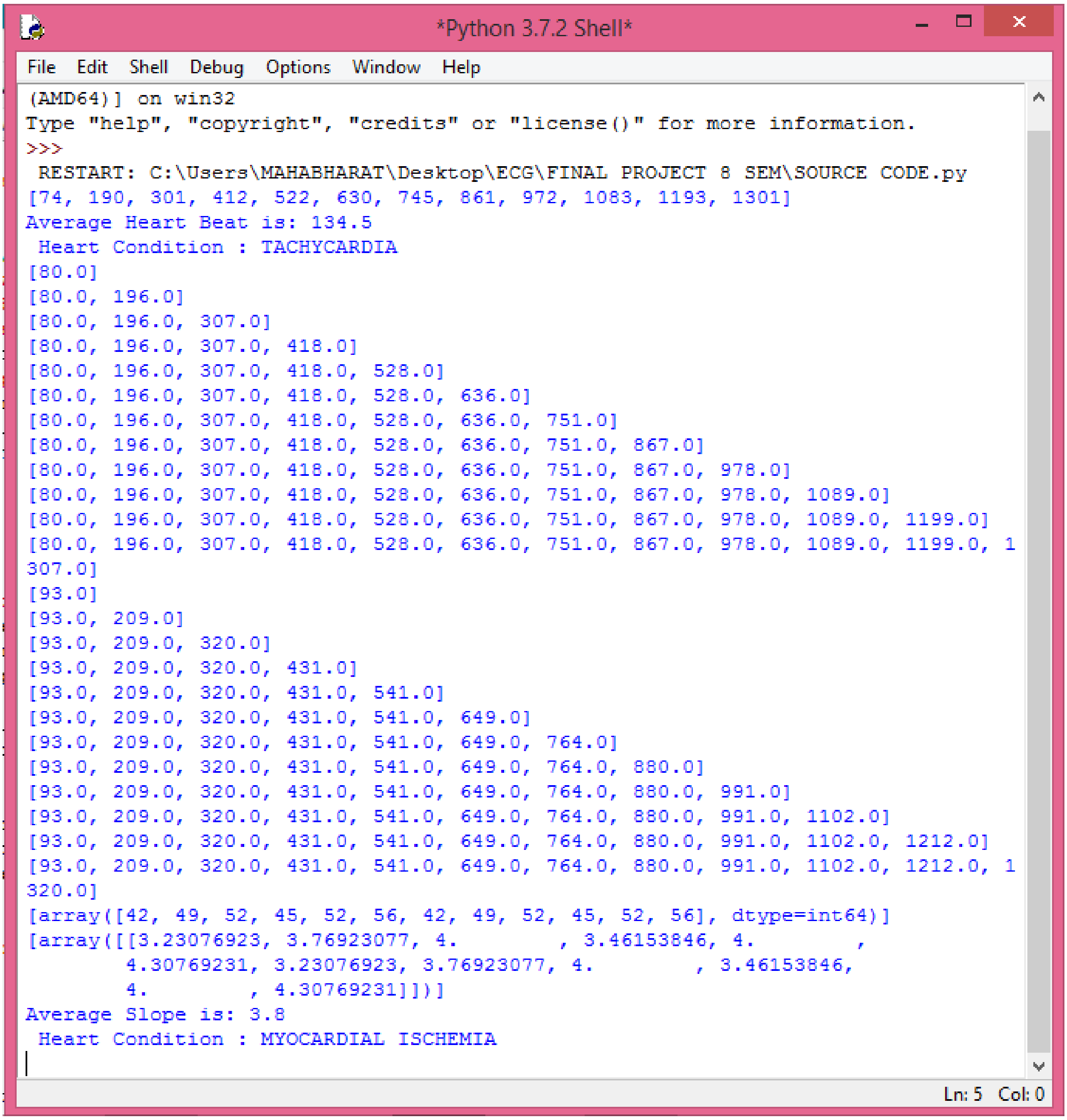
A correctly identified normal ECG episode is termed as True Negative (TN) and correctly identified ischemic episode is True Positive (TP). Incorrect identification of a normal ECG episode as an ischemic episode is False Positive (FP). Similarly, incorrect identification of an ischemic episode as a normal ECG episode is False Negative (FN). From the data there are total 18 episodes; 9 normal and 9 ischemic. The accuracy at 0.35 is 83.33%.

For Threshold Value 0.35 :

TP is 8 , FN is 1 , TN is 7 , FP is 2

So, Accuracy is 83.33% .

Fig. 6.1: Sample Output Of Source Code (Sample 1)



Python 3.7.2 Shell

File Edit Shell Debug Options Window Help

```
(AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>>>
 RESTART: C:\Users\MAHABHARAT\Desktop\ECG\FINAL PROJECT 8 SEM\SOURCE CODE.py
[74, 190, 301, 412, 522, 630, 745, 861, 972, 1083, 1193, 1301]
Average Heart Beat is: 134.5
 Heart Condition : TACHYCARDIA
[80.0]
[80.0, 196.0]
[80.0, 196.0, 307.0]
[80.0, 196.0, 307.0, 418.0]
[80.0, 196.0, 307.0, 418.0, 528.0]
[80.0, 196.0, 307.0, 418.0, 528.0, 636.0]
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307.0]
[93.0]
[93.0, 209.0]
[93.0, 209.0, 320.0]
[93.0, 209.0, 320.0, 431.0]
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[93.0, 209.0, 320.0, 431.0, 541.0, 649.0, 764.0, 880.0, 991.0, 1102.0, 1212.0, 1
320.0]
[array([42, 49, 52, 45, 52, 56, 42, 49, 52, 45, 52, 56], dtype=int64)]
[array([[3.23076923, 3.76923077, 4.        , 3.46153846, 4.        ,
        4.30769231, 3.23076923, 3.76923077, 4.        , 3.46153846,
        4.        , 4.30769231]])]
Average Slope is: 3.8
 Heart Condition : MYOCARDIAL ISCHEMIA
```
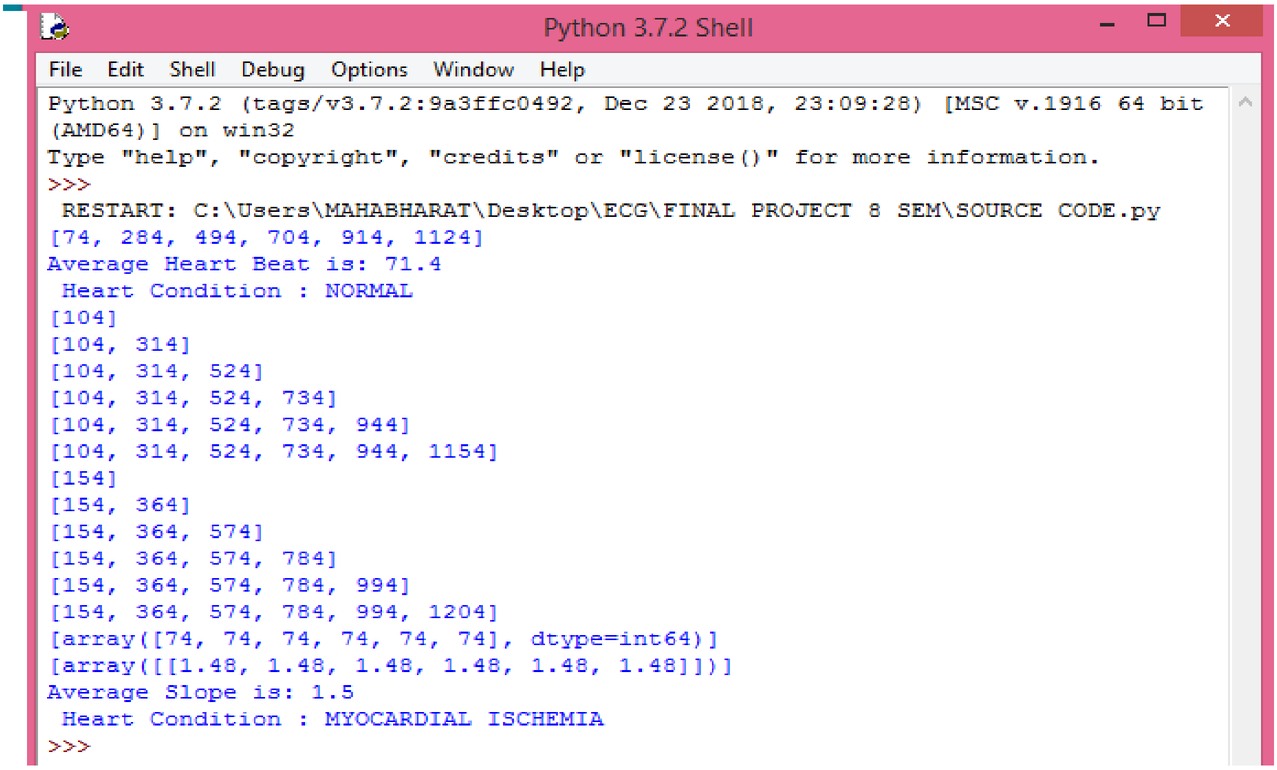
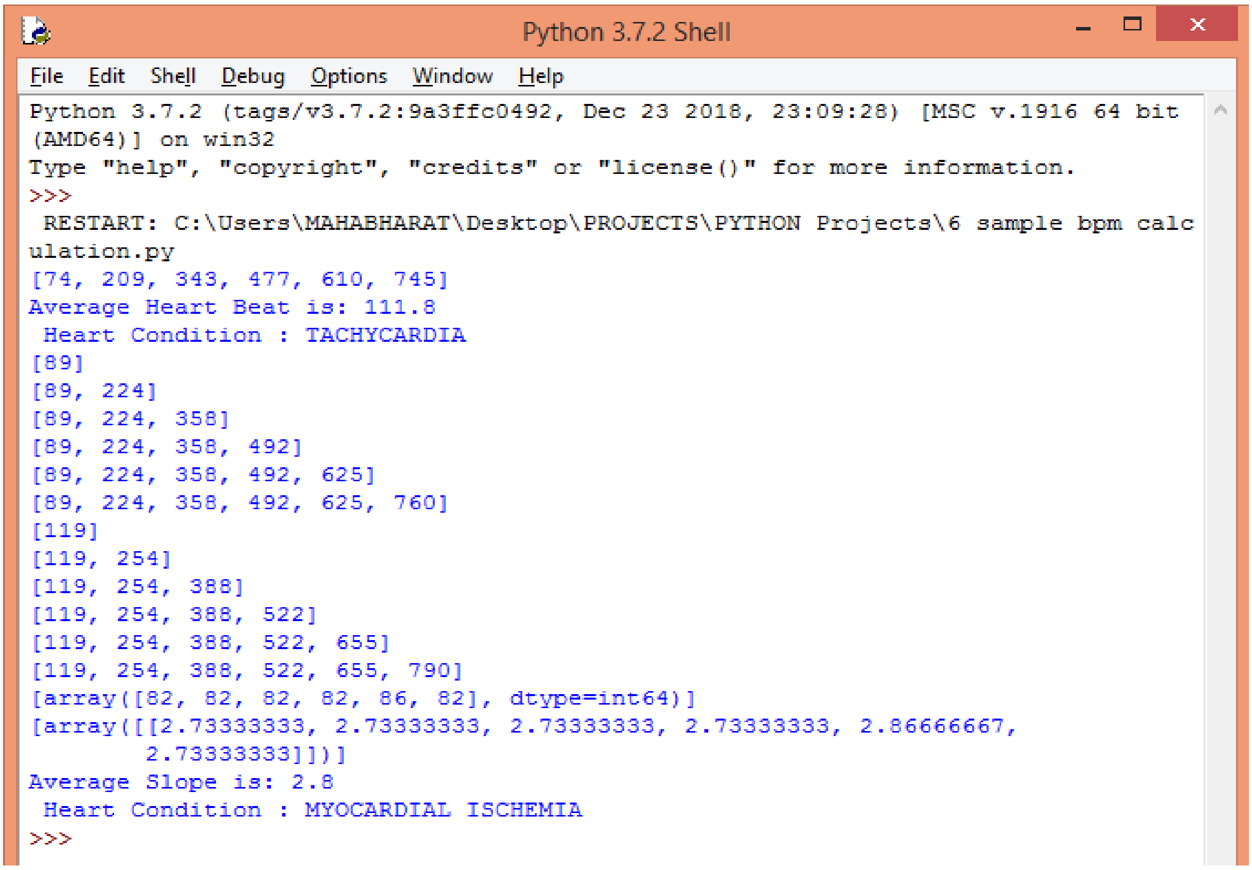

Ln: 5 Col: 0

Fig. 6.2: Sample Output Of Source Code (Sample 2)



```
Python 3.7.2 Shell
File  Edit  Shell  Debug  Options  Window  Help
Python 3.7.2 (tags/v3.7.2:9a3ffc0492, Dec 23 2018, 23:09:28) [MSC v.1916 64 bit
(AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>>>
 RESTART: C:\Users\MAHABHARAT\Desktop\ECG\FINAL PROJECT 8 SEM\SOURCE CODE.py
[74, 284, 494, 704, 914, 1124]
Average Heart Beat is: 71.4
 Heart Condition : NORMAL
[104]
[104, 314]
[104, 314, 524]
[104, 314, 524, 734]
[104, 314, 524, 734, 944]
[104, 314, 524, 734, 944, 1154]
[154]
[154, 364]
[154, 364, 574]
[154, 364, 574, 784]
[154, 364, 574, 784, 994]
[154, 364, 574, 784, 994, 1204]
[array([74, 74, 74, 74, 74, 74], dtype=int64)]
[array([[1.48, 1.48, 1.48, 1.48, 1.48, 1.48]])]
Average Slope is: 1.5
 Heart Condition : MYOCARDIAL ISCHEMIA
>>>
```

Fig. 6.3: Sample Output Of Source Code (Sample 3)



```
Python 3.7.2 Shell
File  Edit  Shell  Debug  Options  Window  Help
Python 3.7.2 (tags/v3.7.2:9a3ffc0492, Dec 23 2018, 23:09:28) [MSC v.1916 64 bit
(AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>>>
 RESTART: C:\Users\MAHABHARAT\Desktop\PROJECTS\PYTHON Projects\6 sample bpm calc
ulation.py
[74, 209, 343, 477, 610, 745]
Average Heart Beat is: 111.8
 Heart Condition : TACHYCARDIA
[89]
[89, 224]
[89, 224, 358]
[89, 224, 358, 492]
[89, 224, 358, 492, 625]
[89, 224, 358, 492, 625, 760]
[119]
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[119, 254, 388, 522]
[119, 254, 388, 522, 655]
[119, 254, 388, 522, 655, 790]
[array([82, 82, 82, 82, 86, 82], dtype=int64)]
[array([[2.73333333, 2.73333333, 2.73333333, 2.73333333, 2.86666667,
        2.73333333]])]
Average Slope is: 2.8
 Heart Condition : MYOCARDIAL ISCHEMIA
>>>
```

CONCLUSION & SCOPE FOR FUTURE WORK

The proposed myocardial ischemia detection algorithm has an accuracy of 83.33%. The accuracy can be improved when the threshold is selected from a larger dataset. However one thing is observed that this method can provide a patient specific monitoring system for ischemia. A healthy person's ECG can be analyzed and a threshold for ST segment slope can be set. In a monitoring system whenever that threshold is crossed, it would indicate a possible ischemic episode. Though more work needs to be done in collaboration with cardiologists to establish such a relation; it is clearly evident that simple slope measurement of a ST segment can aid in detection of myocardial ischemia.

It is an statistical analysis based algorithm and can be modified further with implementation on various dataset . A person's ECG can be analyzed in a system and detect if the ischemic episode is present.

In future the computer vision and machine learning approach can be used to detect the ischemic episode. A large set of data can be used to train the machine and test the output. This concept will possibly be very effective in near future.

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