MIT International Journal of Computer Science and Information Technology, Vol. 8, No. 1, January 2019 ISSN 2230-7621

Myocardial Infarction Detection using Multi Biomedical Sensors

[1]Akash Patel, [2]Pratiksha Sahani, [3]Sakshi Saxena, [4]Samarth Goel, [5]Vikas Bhatnagar
Moradabad Institute of Technology, Moradabad

Abstract: Heart failure is one of the diseases that may require frequent physician visit and checkups. Automatic monitoring of specific biomedical signals and using signal analysis techniques, one can assess the patient health condition at his/her own residence and/or work in real time.

In this paper, classification of myocardial infraction condition was diagnosed using measurement from several biomedical sensors by rule based hierarchal decision fusion technique to provide a biomedical heart health assessment technique. The proposed approach combined the progress in signal analysis, sensor data fusion, and rule based simple adaptive threshold decision to process the data in real time and assesses the patient heart condition with low false alarm rate.

Data from ECG, blood pressure (BP) and pulse oximeter (SpO_2) have been used for analysis and diagnosis. Testing using biomedical data form 150 persons were carried out with sensitivity, specificity and accuracy were 94.92%, 92.31% and 93.33% respectively. The Physoinet ECG database was used for evaluation of the methods.

Keywords— Myocardial infarction, data fusion, simple adaptive threshold method, blood pressure, SpO_2.

1 INTRODUCTION

Given the high percentage of current elderly population prone to hypertension and risky heart conditions (such as heart attack), monitoring as well as analyzing real time biomedical signals are needed to avoid unnecessary visits to physician or emergency room. This would save time, money, and the hassle of traveling to a physician due to false alarm conditions.

During myocardial infarction, tissue death due to lack of oxygen can eventually contribute to severe consequences if supply of oxygen is not restored within 90 to 120 minutes [1]. Many researchers studied heart disease classification by improving Electrocardiogram signal analysis. In [2], a method of combining ECG signal from Lead-I and arterial blood pressure to detect premature supraventricular and ventricular contractions (PSC and PVC) which are pre-cursor of serious arrhythmia and other heart diseases. The use of information from one lead gives only heart rate which is not sufficient to detect complex heart diseases. A self-administered functional health infrastructure for data collection and storage using remote monitoring of vital signs such as ECG, blood pressure, respiration, movement, etc. has been proposed in [3]. This work was limited to collection as well as storage of biomedical data and didn't involve processing the data in real time and had to deal with the challenge of data security, storage, and retrieval. With same limitation, [4] used stand-alone medical wireless (or modified to become wireless) devices/sensors to a cell phone using blue tooth communication.

Wavelet transform was used to detect QRS complex (main three deflection in every ECG wave) [5]-[6]. Rothwell et al. showed that the blood pressure variability can be used as an independent variable for strong predictor of ischemic stroke ,even after exclusion of previous stroke patients it provided prediction of myocardial infarction, angina, and heart failure[7] .With the invent of machine learning algorithms, different feature types were used in order to recognize abnormalities in ECG automatically. A common shortcoming of all these approaches is that they are computationally extensive and didn't deal with myocardial infarction detection [8] - [14]. Some recent approaches were based on interval length, amplitude of QRS complex, etc. for pattern recognition but their ability to detect useful patterns decreased when the morphology of the ECG changed [15] - [16]. Currently, most of the methods used to detect potential heart attack scenarios were done by a physician using physical examination (heart rate and chest pain) with ECG or cardiac markers from specific blood tests [17]. Research has been done to perform automatic detection of heart arrhythmia or comparatively simpler heart rhythm related abnormality by analyzing the ECG signal but myocardial infarction detection needs complex algorithm and additional information from complimentary biomedical sensors to perform robust diagnosis decisions.

In this paper, the goal is to use heterogeneous complimentary biomedical sensors to automatically detect symptoms of myocardial infarction. This automated detection system should help the patient monitor his/her heart condition remotely without rushing to hospital when it is not necessary. In available research, arrhythmia or irregular beat detection were done using ECG signal, which were sufficient to provide heart rate. This work goes beyond relying on heart beat detection only. It rather attempts to detect/predict the symptom of heart attack. To accomplish this goal, blood pressure and pulse Oximeter measurements are proposed to complement the information provided by the ECG signals.

2 PROPOSED HEART ATTACK PREDICTION TECHNIQUE

For a potential MI patient the elevation of ST segment (flat isoelectric section of the ECG between the end of the S wave and start of T wave) is one of the first symptom which comes with chest pain [18]. Another sign for MI can be pathological Q wave which once starts to be visible and doesn't go away. The ECG findings of a pathological Q wave include a Q wave with magnitude of > 25 percent of QRS magnitude. High blood pressure (BP) has consistently been associated with an increased risk of MI.Also the control of hypertension with appropriate medication has been shown to reduce the risk of MI significantly [19].To develop a technique that has low probability of false alarms for MI detection, Figure 1 shows a conceptual block diagram of the whole process which includes data acquisition, processing and decision making. Hemodynamic parameters regulating the cardiovascular system are strongly correlated [20].

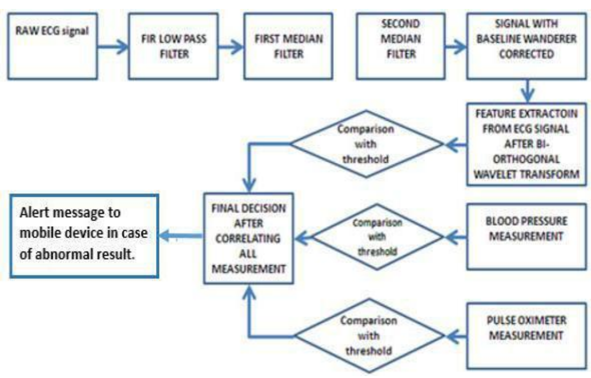

Figure 1: Conceptual Block diagram of the ECG processing and decision recommendation

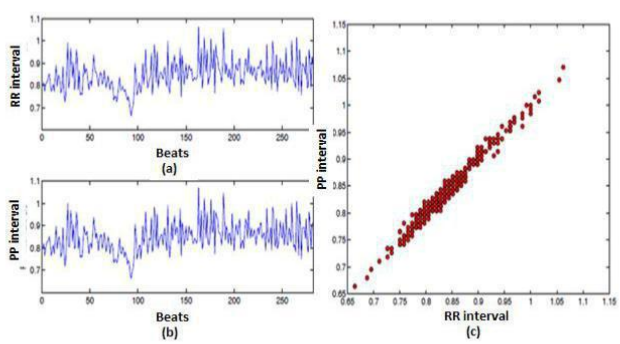

Figure 2: a). RR interval from ECG. b) PP interval from pulse pressure c) correlation between RR interval and PP interval.

Figure2 shows an example of such correlation, where RR interval (the time between two consecutive R waves in ECG measurement) from ECG and pulse pressure interval are present on the left and correlation between those are on the right.

2.1 ECG Sensor and Processing

MIMIC database [21] was used for testing; this database contains multi-parameter recordings obtained from bedside recording of patient. The database includes arterial blood pressure, ECG signal and finger PPG signal with each recording duration is 10 second with average 10 cycle. The systole and diastole are covered 60mmHg to 150 mmHg whereas the ECG was recorded with 500 samples/second with 12-bit resolution [21]. A study using MRI to diagnose myocardial infarction has shown that more emphasis on ST segment depression could greatly improve the yield of the ECG information in the diagnosis of myocardial infarction (sensitivity increase from 50% to 84%) [23]. Pathological Q wave indicates prior or current myocardial infarction, after QT prolongation (measure of the time between the start of the Q wave and the end of the T wave), hyper acute T waves are the earliest-described electrocardiographic sign of acute ischemia, preceding ST-segment elevation [23]. A Matlab GUI was developed for convenience, to determine the symptoms for myocardial infarction which runs through the ECG signal beat by beat and extracts all necessary features.

Maintaining all required criteria, bi-orthogonal wavelet is the most common choice for ECG signal analysis [22] .Using temporal feature conservation ability of bi-orthogonal wavelet transform, the features such as PQRST peak and ST segments can be calculated. Wavelet transform with features such as scale, transition, mother wavelet, orthogonality can preserve both time and frequency domain information at the same time with certain accuracy .The shape of mother wavelet is very significant because there should be maximum correlation between our signal of interest (ECG) and mother wavelet. Using bi-orthogonal wavelet transform, the signal can be decomposed into 4 scales ranging from 2^1 to 2^4. The larger scale relates to lower frequency and smaller scale relates to higher frequency components. Most of the energy of QRS complex is found using 2^3 and 2^4 on the other hand the noises such as electrical interference, muscle activity etc remain in 2^1 and 2^2 level.

2.2 Blood Pressure and Pulse Oximeter System

BP indicates the force of blood through the heart, systolic pressure is when the when the blood ejects from atrium or ventricle and diastole pressure is when atrium or ventricle fills up with blood. On the other hand, the features available in ECG also signify the contraction and expansion of atrium & ventricle. Pressure generated by heart, duration of systole, mean arterial pressure, pulse wave velocity, pulse wave reflection and stiffness of the arterial vessels influence the blood pressure. So, not only the systole-diastole pressure point but also continuously recorded blood pressure waveform should be analyzed for appropriate representation of cardiac shock. In treated hypertensive participants, the heart rate for systolic blood pressure with potential myocardial infarction and stroke are less pronounced than in participants without treated hypertension [24].Hypertensive heart disease is the leading cause of death from high blood pressure. Hypertension has been shown to be related to risk factors for kidney failure, heart failure, and myocardial infarction and stroke [25].

Pulse Oximeter is a simple and low cost sensor which provides measurement of oxygen level in blood. A percentage over 95 indicates healthy body Oxygen saturation. It can be lower than 93% due to respiratory disease or congenital heart disease. Therefore, monitoring blood saturation can be used as an indication of one of those severe cardiovascular conditions. From pulse Oximeter sensor, the irregular heart bit as well as reduction of oxygen saturation in blood can be observed. Though oxygen saturation is commonly used for monitoring critical patient,

in a study [26] baseline SpO2 provided reliable information establishing the diagnosis and severity of acute heart failure as a complication of acute myocardial infarction with a warning cut-off value of <93 percent. The use of pulse oximetry for diagnosis purposes may be recommended when managing patient with risk of acute myocardial infarction [26].

2.3 Decision Fusion from Sensor

A data fusion system must perform whether the data presents different aspect of same event, its redundancy and mismatch. Two mainstream data fusion techniques are, rule-based decision making and fuzzy logic decision making. Here we adopted the rule based approach by taking into account measurements of ECG, blood pressure and SpO_2, these are fused to get more accurate estimation of actual patient parameters and status. Fusion of multimodal event can be modeled as multidimensional process as below:

$$O(m) = [A(m)\ B(m)\ S(m)] \quad (1)$$

Where m denotes the discrete time and A(m) , B(m) and S(m) point to ECG measurement, Blood pressure measurement and SpO_2 level respectively in equation (1).

$$A(m) = (a(m), a(m+1), a(m+2), a(m+3)\ldots\ldots\ldots) \quad (2)$$

$$B(m) = (b(m), b(m+1), b(m+2), b(m+3)\ldots\ldots\ldots) \quad (3)$$

$$C(m) = (c(m), c(m+1), c(m+2), c(m+3)\ldots\ldots\ldots) \quad (4)$$

In equation (2) a(m) presents ECG measurement at $(m)^{th}$ instant of time, b(m) refers blood pressure and c(m) the SpO_2 at m^{th} instant respectively by equation (3) and (4).

$$A(m) = [a_1(m), a_1(m+1), a_1(m+2), \ldots\ldots), a_2(m), a_2(m+1), a_2(m+2), \ldots\ldots)] \quad (5)$$

Here, $a_1(m)$ and $a_2(m)$ are two parameters of ECG features extracted from processed ECG measurements at m^{th} instant in equation (5).

$$B(m) = [b_1(m), b_1(m+1), b_1(m+2), \ldots\ldots), b_2(m), b_2(m+1), b_2(m+2), \ldots\ldots), b_3(m), b_3(m+1), b_3(m+2), \ldots\ldots)] \quad (6)$$

Here, $b_1(m)$, $b_2(m)$ and $b_3(m)$ are systolic , diastolic and mean pressure extracted from patients' blood pressure measurement as in equation (6).

$$C(m) = [c_1(m), c_1(m+1), c_1(m+2), \ldots\ldots)] \quad (7)$$

Here, $c_1(m)$ presents the SpO_2 measurement at m^{th} as in equation (7). Multiple measurements of same data can be fused to yield single estimation which get rid of the erratic measurement which is wayward than the average of other data. Each feature from ECG measurement is analyzed from several windows to use the competitiveness of collected data. Another aspect of fusing is multimodal or integration of overlapping data. In this case, each data presents status of part of the total block. The different sensors also provide complementary measurement. For example, heart rate can be achieved from ECG as well as SpO_2.

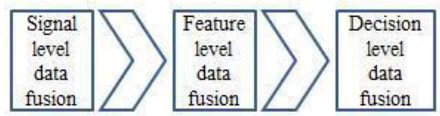

Figure 3: Hierarchical level for data fusion

Three hierarchical levels were used for data fusion as mention in above figure. They are signal level data fusion, feature level data fusion and decision level fusion. Signal level considers the individual signal which provides similar property of an event to deduce parameter. With data which doesn't provide similar property can be used in feature level fusion to come up with a feature vector. Decision level fusion is performed at the top level with either raw data or feature vector to make higher level decision. A rule based decision making implements series of yes/no to check whether a particular condition is existing or not. Our approach is more towards rule based approach and also makes use of the prioritizing aspect of fuzzy logic too. Our objective is to produce an early warning heart attack score (EWHAS) to predict heart attack conditions before a patient is admitted in a hospital. A new index is produced that uses information from only the sensors needed for heart attack prediction such as ECG, BP and oxygen saturation are included.

During MI while the cell death occurs, the ST segment of the ECG gets elevated which is a sufficient diagnosis to start treatment [23]. Pathological Q wave indicates an absence of electrical activity in an area of heart that can be a result of minor myocardial infarction. After QT prolongation, hyper acute T waves are the earliest-described electrocardiographic sign of acute ischemia [26]-[27]. Hypertension, according to Framingham heart study database, is the most common cause of heart failure [28]. Hypertension increases the risk of heart failure four to eight fold [29]. A study suggests baseline SpO_2 lower than 93% can be considered a sign for acute heart failure (AHF) due to myocardial infarction and the lower the SpO2 value, the higher the probability and severity of AHF [30]. Patients with low (<90%) SaO2 had higher rates of worsening heart failure at 1 to 6 months and also higher rates of mortality, SBP <120 mm Hg was associated with a statistically significant increase in mortality at 1 to 6 months, so combined low SaO2 and systolic blood pressure (SBP) had a particularly strong prognostic implication [31].

Table 1: Feature weight distribution

Features/Measures	Feature weight	Feature weight
abnormal Q wave /Inverted or hyper acute T Wave	1	
abnormal QT interval	2	
ST_Depressions/ST elevation	4	
Hypertension (systolic)	1 (140 -159)	2 (>160)
Hypotension (systolic)	1 (105-90)	2 (< 90)
oxygen saturation	1 (93 to 88)	2 (< 88)

A sensitivity of 50% and specificity of 97% for AMI were achieved with only the currently applied ST-segment elevation criteria while adding the ST-segment depression with elevation increased sensitivity for detection of AMI from 50% to 84% [23]. So the highest weight was given to ST-segment elevation and depression. In a number of epidemiological studies, QT interval prolongation has been associated with an increased risk of being markers of ventricular hypertrophy or myocardial ischemia [32]. This resulted in lower weightage of QT interval. After minor myocardial infarction, people with consistent abnormal Q wave with symptoms such as ST segment change are at 2.7 fold excess risk of coronary death compared to those who have normalized ECG [33]. When an electrocardiogram shows persistent T wave inversion along with ST elevation, further ischemia may make the T wave inversion more pronounced. The lower weight given by the decision system to abnormal Q and T waves reflects their secondary importance when compared to changes in the ST segment [34].

Table 2: Local threshold for ECG features

ECG features	ST elevation	ST depression	hyperacute T wave	pathologic al Q wave	Prolong Q wave
single feature	counter3/counter1>=0.95	mean_ST_dvalue >1	abs(H_T_peak) >.5	mean_path_c<=-0.25	mean_path_QT >.4
Combination	(counter3/counter1>=0.95 ||mean_ST_dvalue >1) then e=4		(mean_path_c<=-0.25 ||H_T_peak >.5) then f=1		(mean_path_QT >.4) then g=2

High blood pressure increases the likelihood of MI, while excessive drop of blood pressure will hamper coronary perfusion severely introducing new acute coronary events [34].Local decisions of individual sensors are fused by first, for each feature of ECG, care is taken to ensure that an abnormality in a feature appears at least in two consecutive windows of ECG data to avoid false alarm. The final ECG local decision consists of adding the weighted features as shown in table 2. Second, the local decisions made by all the sensors are fused to provide a global and final decision.

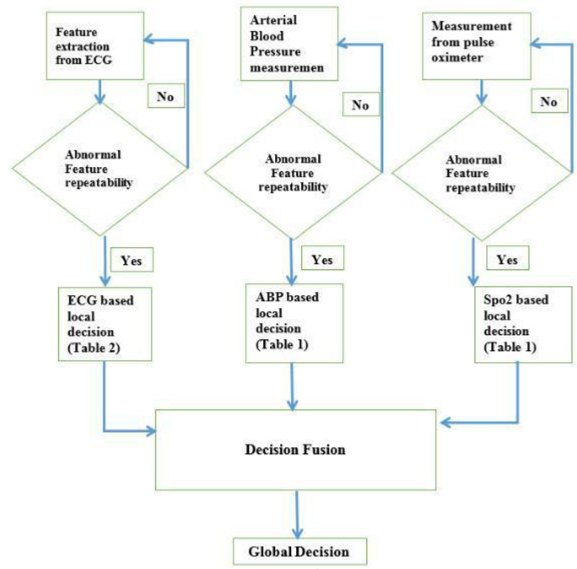

Figure 4: Flowchart for algorithm steps.

The rationale of the global decision uses the fact that prior research reveals ST level is highly correlated with potential heart attacks. However, relying on ST alone will not prevent false alarm from occurring [23]. Table 1 contains the weight assigned to different features used by the decision system. While features from ECG are checked, the weight from extracted features are saved into memory until one finds any relevant reading beyond threshold from blood pressure or oxygen saturation to confirm the potential alert from ECG. Figure 4 provide a flow chart for automatic monitoring and detection of heart health assessment.

3 Biomedical data analysis

Testing of the proposed index system was done using biomedical data from 150 patients from MIMIC database, by extracting necessary features for myocardial infarction. The measurements are classified later using simple adaptive threshold method. A Matlab GUI was developed to process and display relevant features/information forms the different sensors. In the raw ECG wave, the presence of baseline wander and high frequency noise was evident. Two median filters have been used to remove of the baseline wander. The first median filters cancel the prominent QRS complex and second median filter cancel P peak. 2^1 to 2^4 level bi-orthogonal wavelet transform helps to reduce high frequency noise. Understandably 2^4 levels have been picked to extract R peak of ECG signal. To get an idea about iso-scale line (ISO) and ST segment several other points on ECG have to be extracted. P-point with K-point constituted ISO line and J-point with T-point constructed

ST segments. Using the K and P point, the isoelectric line (ISO) can be determined and using J and T point the ST segment can be determined. If 95% of the beat shows ST elevation, a conclusion can be drawn about accurate ST elevation detection. ST depression and pathological Q wave of an ECG signal can be determined.

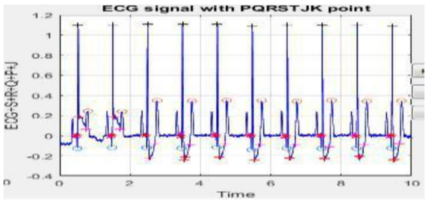

Figure 5: Temporary ST Elevation in first two beats creating a false alarm.

Sometimes, ST elevation or depression or pathological Q wave emerge from ECG signal but it does not stay for long. It is necessary to calculate information from each beat and compare whether the incident is consistent throughout the ECG signal of just a onetime deflection. In figure 5, an example is shown where the ST elevation happened temporarily but it can be concluded as a false symptom of MI.

Table 3: Threshold for decision fusion

MI state	Decision Fusion
Severe case of MI	(e+f+g)>3 && (c_bp>160 || c_bp<90)&& c_ox<88
Mild case of MI	((e+f+g)>0 & (e+f+g)<3)) && (((c_bp >= 140 & c_bp < 160)||(c_bp>=90 & c_bp<105)) || (c_ox>=88 & c_ox<93))
	((e+f+g)>0 & (e+f+g)<3)) && ((c_bp >= 140 & c_bp < 160)||(c_bp>=90 & c_bp<105)) && (c_ox>=88 & c_ox<93)
No MI but arrhythmia symptoms	(H_R>100 || H_R<60)&& (e+f+g)==0
Normal condition	(60<H_R<100) && (e+f+g)==0

The system also takes in to account Blood pressure measurements and Oximeter readings to check whether the readings are normal or abnormal. Such additional information can provide significant insight about the conformity of myocardial infarction.In table 3, the thresholds for decision fusion have been provided. Oxygen saturation decreases with the increase in severity of MI condition and to compensate the ischemic region of heart, heart rate increases as well [28]-[34], on the other hand increase in systolic blood pressure directly relates to risk of MI, stroke and even mortality [24] with the risk getting higher with pressure getting in to different stage of hypertension or hypotension. Thus the threshold values are set similar way to the chronological importance of the event occurs at onset of MI or potential MI. Here, measurement of blood pressure, oximeter are denoted as c_bp and c_ox, respectively. Also features from ECG such as ST elevation/depression, hyper acute T wave and prolonged Q wave are denoted by e, f and g, respectively.

4 Performance evaluation

Four common performance measures have been used to assess the performance of the proposed automatic MI monitoring system: specificity (true negative rate), sensitivity (true positive rate), accuracy, and predictive accuracy.

Table 4: Count of performance measures

Type	TP (True positive)	FN (False negative)	TN (True negative)	FP (False positive)
ECG single feature	46	12	62	30
Fusion of all sensor	56	3	84	7

Table 5: Assessment based on performance measures

Measures	Use multi sensors	Using only ECG	Performance improvement
Sensitivity	94.92%	79.31%	15.60%
Specificity	92.31%	67.39%	24.92%
Accuracy	93.33%	72.00%	21.33%
Predictive value (positive)	88.89%	60.53%	28.36%
Predictive value (negative)	96.55%	83.78%	12.77%

Accuracy measures the probability of correctly diagnosed both diseased and non-diseased persons in the entire population used for testing. Positive predictive value is probability of having positive detection of a diseased person among all the positive result (including false positive result) and negative predictive value is probability of having correct negative detection of a healthy person among all the negative result (including false negative result).A population of 150 persons at rest has been analyzed. The relevant data was obtained from physionet database [21]. The performance of the proposed technique is summarized in table 4 and 5. As shown in Table 5, with only the ECG information, the decision algorithm is prone to false negative and false positive which keeps the sensitivity and specificity lower than acceptable range. However, with the support of blood pressure and oximeter sensor, the false negative and false positive count reduces and sensitivity and specificity improve.

5 CONCLUSIONS AND FUTURE WORK

In this paper, the concept of using multiple complementary biomedical sensors was proposed and applied to MI disease detection. The performance evaluation using 150 patients has shown significant improvement in detecting MI with lower false alarm rate when the proposed technique is used. Similar concept will be used in the future to tackle diseases such as brain stroke.

A pre-requisite for proper use of heterogeneous multi biomedical sensors is the ability to collect all the sensors data at the same time. Toward this goal, a stand-alone device that collects such data, perform real time diagnosis, and communicate diagnosis results to the appropriate personnel/facility as need is being developed.

References

[1] P.d. Chazal, M. O'Dwyer and R.B. Reilly, "'Automatic classification of heartbeats using ECG morphology and heartbeat interval features," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 7, pp. 1196-1206.

[2] R. Palaniappan and S.M. Krishnan, "'Detection of ectopic heart beats using ECG and blood pressure signals," *2004 International Conference on Signal Processing and Communications, 2004. SPCOM '04*, pp. 573-576.

[3] N.H. Lovell, F. Magrabi, B.G. Celler, K. Huynh and H. Garsden, "'Web-based acquisition, storage, and retrieval of biomedical signals," *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 38-44.

[4] V. GAY and P. LEIJDEKKERS, "'A Health Monitoring System Using Smart Phones and Wearable Sensors," *International Journal of Assistive Robotics and Mechatronics*, vol. 8, no. 2, pp. 29-36.

[5] M. Vaessen, "'A QRS detection method using analog wavelet transform in ECG analysis," *Maastricht University, Department of Mathematics*, vol. 20.

[6] R. Schneider, A. Bauer, P. Barthel and G. Schmidt, "'Challenge 2006: QT interval measurement,", pp. 325-328.

[7] P.M. Rothwell, S.C. Howard, E. Dolan, E. O'Brien, J.E. Dobson, B. Dahlöf, P.S. Sever and N.R. Poulter, "'Prognostic significance of visit-to-visit variability, maximum systolic blood pressure, and episodic hypertension," The Lancet, vol. 375, no. 9718, pp. 895-905.

[8] Mackay, D. (1992). A practical Bayesian framework for backpropagation networks. *Neural Computation*, vol. 4, p. 448-472. 82

[9] HU, Y. H., Palreddy, S., & Tompkins, W. J. (1997). A patient-adaptable ECG beat classifier using amixture of experts approach. *IEEE Transactions on Biomedical Engineering*, vol. 44, p. 891-900.

[10] Coast, D., & Stern, R. (1990). An Approach to Cardiac Arrhythmia Analysis Using Hidden Markov Models, *IEEE Transactions on Biomedical Engineering*, vol. 37, p. 826-836.

[11] Lagerholm, M., Peterson, C., Braccini, G., Edenbrandt, L., & Sornmo, L. (2000). Clustering ECG complexes using hermite functions and self-organizing maps. *IEEE Transactions on Biomedical Engineering*, vol. 47, p. 838-848.

[12] Silipo, R., & Marchesi, C. (1998). Artificial Neural Networks for Automatic ECG Analysis. *IEEE Transactions on Signal Processing*, vol. 46, no. 5, p. 1417-1425.

[13] Thakor, N. V., & Zhu, Y. S. (1991). Applications of cardiac filtering to ECG analysis: Noise cancellation and arrhythmia detection. *IEEE Transactions on Biomedical Engineering*, vol. 39, no. 8, p. 785-794.

[14] Chang, W. H., Lin, K. P., & Tseng, S. Y. (1988). ECG analysis based on Hilbert transform in ECG diagnosis. In Proceedings of *IEEE Engineering and Medical and Biological Society 10th Annual International Conference*, p. 36-37.

[15] Zhou, S. H., Rautaharju, P. M., & Calhoun, H. P. (1993). Selection of a reduced set of parameters for classification of ventricular conduction defects by cluster analysis. In *Proceedings of Computers in Cardiology*, p. 879-882.

[16] Herrero, G. G., Gotchev, A., Christov, I., & Egiazarian, K. (2005). Feature extraction for heartbeat classification using independent component analysis and matching pursuits. In Proceedings IEEE International Conference on Acoustics, Speech, and Signal Processing, vol. 4, p. 725- 728.

[17] A.V. Chobanian, G.L. Bakris, H.R. Black, W.C. Cushman, L.A. Green, J.L. Izzo Jr, D.W. Jones, B.J. Materson, S. Oparil, J.T. Wright Jr, E.J. Roccella, Joint National Committee on Prevention, Detection, Evaluation, and Treatment of High Blood Pressure. National Heart, Lung, and Blood Institute and National High BloodPressure Education Program Coordinating Committee, "'Seventh report of the Joint National Committee on Prevention, Detection, Evaluation, and Treatment of High Blood Pressure," Hypertension, vol. 42, no. 6, Dec, pp. 1206-1252.

[18] "Coronary Artery Disease - Heart Valve Disease", Heart-valve-surgery.com, 2016. [Online]. Available: http://www.heart-valve-surgery.com/coronary-artery-disease.php. [Accessed: 28- Nov-2016]

[19] G. Antonakoudis, L. Poulimenos, K. Kifnidis, C. Zouras and H. Antonakoudis, "'Blood pressure control and cardiovascular risk reduction," *Hippokratia*, vol. 11, no. 3, Jul, pp. 114-119.

[20] G. Atanasova and M. Marinov, "'The pulse pressure amplitude as a marker of myocardial infarction risk," Journal of Clinical and Experimental Cardiology, vol. 4, pp. 251.

[21] "PhysioBank ATM", Physionet.org, 2017. [Online]. Available: http://www.physionet.org/cgi-bin/ATM. [Accessed: 29- Apr- 2017]

[22] P. Jouck, "'Application of the Wavelet Transform Modulus Maxima method to T-wave detection in cardiac signals," *Maastricht University Department of Mathematics and Maastricht Instruments,(22)*, pp. 1-32.

[23] T.N. Martin, B.A. Groenning, H.M. Murray, T. Steedman, J.E. Foster, A.T. Elliot, H.J. Dargie, R.H. Selvester, O. Pahlm and G.S. Wagner, "'ST-Segment Deviation Analysis of the Admission 12-Lead Electrocardiogram as an Aid to Early Diagnosis of Acute Myocardial Infarction With a Cardiac Magnetic Resonance Imaging Gold Standard," J.Am.Coll.Cardiol., vol. 50, no. 11, 9/11, pp. 1021-1028.

[24] B.M. Psaty, C.D. Furberg, L.H. Kuller, M. Cushman, P.J. Savage,
D. Levine, D.H. O'leary, R.N. Bryan, M. Anderson and T. Lumley, "'Association between blood pressure level and the risk of myocardial infarction, stroke, and total mortality: the cardiovascular health study," Arch.Intern.Med., vol. 161, no. 9, pp. 1183-1192.

[25] S.D. Pierdomenico, M. Di Nicola, A.L. Esposito, R. Di Mascio, E. Ballone, D. Lapenna and F. Cuccurullo, "'Prognostic value of different indices of blood pressure variability in hypertensive patients," Am.J.Hypertens., vol. 22, no. 8, Aug, pp. 842-847.

[26] J. Masip, M. Gayà, J. Páez, A. Betbesé, F. Vecilla, R. Manresa and
P. Ruíz, "'Pulse oximetry in the diagnosis of acute heart failure," Revista Española de Cardiología (English Edition), vol. 65, no. 10,
pp.879-884.

[27] "National Early Warning Score (NEWS) - MDCalc", Mdcalc.com, 2017. [Online]. Available: https://www.mdcalc.com/national-early-warning-score-news. [Accessed: 29- Apr- 2017]

[28] G. Lip, D. Felmeden, F. Li-Saw-Hee and D. Beevers, "'Hypertensive heart disease. A complex syndrome or a hypertensive 'cardiomyopathy'?" *Eur.Heart J.*, vol. 21, no. 20, pp. 1653-1665.

[29] W.B. Kannel, D. Levy and L.A. Cupples, "'Left ventricular hypertrophy and risk of cardiac failure: insights from the Framingham Study." *J.Cardiovasc.Pharmacol.*, vol. 10, pp. S135-S140.

[30] J. Masip, M. Gayà, J. Páez, A. Betbesé, F. Vecilla, R. Manresa and

P. Ruíz, "'Pulse oximetry in the diagnosis of acute heart failure," *Revista Española de Cardiología (English Edition)*, vol. 65, no. 10,
pp. 879-884.

[31] O. Milo-Cotter, G. Cotter, E. Kaluski, M.M. Rund, G.M. Felker, K.F. Adams, C.M. O'Connor and B.D. Weatherley, "'Rapid clinical assessment of patients with acute heart failure: first blood pressure and oxygen saturation--is that all we need?" *Cardiology*, vol. 114, no. 1, pp. 75-82.

[32] J.J. Candil and C.M. Luengo, "'QT interval and acute myocardial ischemia: past promises, new evidences," *Revista Española de Cardiología*, vol. 61, no. 06, pp. 561-563.

[33] N.D. Wong, D. Levy and W.B. Kannel, "'Prognostic significance of the electrocardiogram after Q wave myocardial infarction. The Framingham Study," *Circulation*, vol. 81, no. 3, Mar, pp. 780-789.

[34] K. Channer and F. Morris, "'ABC of clinical electrocardiography: Myocardial ischaemia," *BMJ*, vol. 324, no. 7344, Apr 27, pp. 1023-1026.