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Using Feature Optimization and Fuzzy Logic to Detect Hypertensive Heart Diseases

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Abstract **-** There is a recent increase of identification of coronary disease using computer aided methodologies. The information required for the diagnosis is gathered from different biomedical signals. In this paper we have proposed a fuzzy logic based diagnosis system of hypertensive heart disease (HHD) after optimizing the number of feature using firefly algorithm. Initially the bio signals such as: electrocardiography (ECG) and photoplethysmography (PPG) are collected and using the method from our previous research the blood pressure (BP) can be calculated. The feature extracted from ECG, PPG and the calculated BP was used through firefly algorithm and subsequently fuzzy logic approach to diagnose HHD. The proposed method was evaluated against physionet database and it shows improved performance while diagnosing HHD. The performance measures used for diagnosis of HHD showed sensitivity of 91.49%, specificity of 82.86% and accuracy 87.8%.

Keywords**:** Blood pressure, ECG, PPG, Firefly algorithm, Fuzzy logic, Hypertensive heart disease.

1. Introduction

The Hypertensive Heart Disease (HHD) mainly involves thickening of the heart muscles, heart failure, and condition of coronary artery disease. The root cause is Hypertension, also known as high or raised blood pressure, is a condition in which the blood vessels have persistently raised pressure account for 9.4 million deaths worldwide every year [1]. Uncontrolled high blood pressure can lead to heart failure. It may also develop bulges in weak spots of vessels and burst or clog. High pressure in the blood vessels can also cause blood to leak out in the brain causing stroke [1]. Kidney failure, blindness, rapture of blood vessels, cognitive impairment, hemorrhage and end stage renal disease are some of the other significant complications from hypertension [1]-[3] . In the countries with poor healthcare system, HHD mostly goes undiagnosed in early stages. Since BP is one of the vital signs effectively indicating the status of HHD, the need of non-invasive and long term ambulatory BP monitoring for home healthcare is greatly rising [4].

In attempt to remove the inconvenience of cuff based BP measurements, the concept of cuff-less BP measurement has been introduced. Among the popular cuff less BP measurement methods, pulse transit time (PTT) based method is the prominent one among researchers. PTT was discovered to be related to BP, vessel volume and vessel wall elasticity etc.[5]. Previous studies have proposed and developed various calibration models mainly based on Moens-Korteweg formula, heuristic modeling with regression technique or predictive modeling using machine learning [5]-[16]. All these studies focus on using only PTT to measure BP, but these are not highly accurate due in part to the unaccounted for physiological factors in the blood regulation mechanism [5], [13], [17]-[19].

Left Ventricular Hypertrophy (LVH) is frequently seen in patients with hypertension, Cuspidi [20] performed a review of the echocardiographic data of 37700 individuals, reported that the prevalence rate of LVH was 19%-48% in untreated hypertensive cohorts and 58%-77% in high-risk hypertensive patients. Also apparent is the link between HHD and atrial fibrillation, whose likelihood increases by 40% to 50% in the presence of hypertension [21]. Increased susceptibility to ischemic heart disease rounds out the cardiovascular squeal of HHD, with a 6-fold higher risk of myocardial infarction in hypertensive patients than in normotensive individuals [22]. Yin proposed a method of detecting coronary heart disease based on ST segment of ECG wave, heart rate and motion activity with accuracy around 80% [23]. Rafhanah brought forth a cardiac monitoring machine which can alert based on patient's heart rate [24], whereas Forkan [25] proposed context aware cardiac monitoring for early detection of heart disease based on classification of the heart condition of the patient not only based on ECG analysis. Ravish [26] developed an efficient method to acquire the clinical and ECG data, so as to train the Artificial Neural Network to accurately diagnose the heart's arrhythmia and predict abnormalities, the method requires data such as blood sugar, cholesterol level diabetes information as input along with ECG information. Several other studies [27]-[31] mainly dealt with either one particular heart disease (either LVH or MI) or didn't take the effect of blood pressure into account. Since getting the right diagnosis is a key aspect of healthcare, computer aided methods helps physician to make most accurate decisions by describing the medical process in Boolean or binary format. Although it's very difficult to define all medical aspect in terms of binary, as a result fuzzy logic has been introduced as a robust method to model uncertainty in medicine [32]-[36]. Also, during designing any computer aided diagnosis system, optimization of feature before using them as input can greatly reduce the computation time and power of the system. During last decade several popular meta-heuristic feature optimization approach imitating swarm movement have been used [37]-[40].

In this paper, we propose a method which uses a swarm intelligence approach named firefly algorithm to optimize the feature from ECG, BP and PPG from human and diagnose the hypertensive heart disease using fuzzy logic approach. This paper is organized as follow. Section 2.1 focuses on our previous research [41] use of PTT and HR for cuff-less BP measurement. Section 2.2-2.4 discusses on the detection of hypertensive heart disease, section 3 discusses the performance of the proposed technique, while section 4 contains conclusion and future work.

2. Materials and Methods

This section is comprised of BP measurement, ECG feature to detect CHD and LVH, feature optimization using firefly algorithm and using fuzzy logic to diagnose HHD.

2.1. Use of PTT and HR for cuff less BP measurement

The PTT-based approach of cuff-less measurement of blood pressure used in this paper [41] involves three steps: Measurement of ECG and PPG wave, Calculation of PTT and HR from ECG and PPG wave, as shown in, and relating PTT-HR to BP and calibration for accurate result. Among the challenges facing the PTT based approach are calibration which depends on distance between measurements, blood density, and atrial wall thickness which are evident from experimental data. So a calibration curve has to be discovered for optimal solution. Curve fitting is a set of techniques used to fit a curve with available data points; on the other hand regression is a method for statistical inference. Though curve fitting encompasses regression as one of the method but regression doesn't necessarily mean curve fitting. In this section, polynomial curve fitting method has been used to get a polynomial multiple variable relationships among PTT, HR and BP [41].

To use a polynomial curve fitting model, generalizing from straight line to a kth degree polynomial

$$y = a_0 + a_1 x + a_2 x^2 + \cdots + a_k x^k \tag{1}$$

The residual is given by [41],

$$R^2 = \sum_{i=1}^{n} [\, y_i - (\, a_0 + a_1 x + a_2 x^2 + \cdots + a_k x^k]^2 \tag{2}$$

The partial derivatives of equation (2) are,

$$\frac{\partial (R^2)}{\partial a_k} = -2 \sum_{i=1}^{n} [y_i - (\, a_0 + a_1 x + a_2 x^2 + \cdots + a_k x^k] x^k = 0 \tag{3}$$

These leads to the equation as follow,

$$\begin{gathered} a_0 n + \; a_1 \sum_{i=1}^{n} x_i \; + \cdots + a_k \sum_{i=1}^{n} x_i^k = \; \sum_{i=1}^{n} y_i \\ a_0 \sum_{i=1}^{n} x_i^k + \; a_1 \sum_{i=1}^{n} x^{k+1}{}_i \; + \cdots + a_k \sum_{i=1}^{n} x_i^{2k} = \; \sum_{i=1}^{n} x_i^k y_i \end{gathered} \tag{4}$$

Equation (4) can be expressed as Vandermonde matrix, **V** (matrix with the terms of a geometric progression in each row) and the value for a0-ak can be measured solving the equation **V.a** = **y.**
In this experiment second order polynomial is used and the model is as below [41]:

$$SBP = a_0 + a_{10}PTT + a_{01}HR + a_{20}PTT^2 + a_{11}PTT * HR + a_{02}HR^2 \quad (5)$$
$$DBP = a'_0 + a'_{10}PTT + a'_{01}HR + a'_{20}PTT^2 + a'_{11}PTT * HR + a'_{02}HR^2 \quad (6)$$

(5) And (6) were used to calculate the value of all necessary coefficients using the clinical blood pressure data (SBP and DBP) from MIMIC database along with calculated PTT and HR value and solving Vandermonde matrix [41].

2.2. ECG feature to detect CHD and LVH

Heart conditions caused by high blood pressure are termed by hypertensive heart disease. Among different resultant heart disorders heart failure, coronary artery disease, thickening of heart muscle are most significant ones. Main two types of HHD include a. Narrowing of the arteries b. enlargement of the heart. Result of narrowing of the arteries is coronary heart disease (CHD) or coronary artery disease where it gets difficult for the heart to supply proper amount of blood to other organs due to narrowing of arteries with clot or plaque. Left ventricular hypertrophy (LVH) is the result of thickening and enlargement of the heart due to overload of heart pumping. Though the main risk factor or triggering point is high blood pressure but being overweight, smoking habit and unhealthy food habit increases the probability as well.

When myocardial blood supply gets reduced to any region of heart the first effect is trans-mural ischemia followed by start of cell death or necrosis, when blood supply doesn't get restored within certain amount of time fibrosis or scarring of the tissue happens. From physical point of view, the patient starts to feel pain when the arteries gets blocked and heart muscle doesn't get enough blood, the pain turns eventually to heart attack if the problem kept untreated for long time. It's very hard to diagnose CHD or even LVH just form pain sensation and to make accurate prediction of disease precise information about hearts activity is necessary such as ECG. Being convenient for patient as well as inexpensive both of these qualities make ECG prime component of a noninvasive diagnose tool for CHD and LVH. In table 1 the approach to interpret ECG for CHD is described [42].

Table 1: Approach to ECG interpretation for CHD.

Approach	Description
Rate	Need to check if Bradycardia or tachycardia is present
Rhythm	The absence of P wave in ECG can indicate atrial fibrillation, the number of P wave and QRS should match
Axis	Need to determine axis deviation by checking direction of QRS complex deflection in lead I and II
Intervals	Long PR or QRS interval indicate either AV block or bundle branch block
P wave	P wave amplitude more than .25 and duration more than 120 milliseconds indicate atrial enlargement
QRS complex	Prominent Q wave indicates myocardial infarction whereas wide QRS complex indicates bundle branch block.
ST segment- T wave	Elevated or depressed ST wave, inverted T wave indicate myocardial ischemia.

The four major types of acute coronary syndromes available in ECG patterns which lead to CHD are as follows: firstly, classic angina where transient ST segment depression happens without any change in QRS complex, secondly, transient ST elevation to indicate transmural ischemia , thirdly, ST depression or T wave inversion without Q waves indicating non-ST elevation MI , fourthly hyper-acute T wave or ST elevations followed by T wave inversion indicating ST elevation MI [43]. In this paper a point system is used which represent a graduation of myocardial ischemia shat is documented in ET [44] . The following table 2 classifies different pattern of ST wave part of ECG into 3 fundamental aspects resulting into a scale that ranges from 0 to 4.

Table 2: Graduation of MI that is documented in ET [44].

Magnitude of ST	Morphology of ST	Moment of ST	Score
Absent of ST deviation	Upsloping depression	Transitory peak	0
Shift inferior to 1mm	Convex depression	Exercise peak	1
Shift from 1 to 1.5mm	Horizontal depression	Rapid reversion	2
Shift from 1.6 to 2.0 mm	Downsloping depression	Slow reversion	3
Shift greater than 2mm	Elevation	Very early reversion	4

2.3. Feature optimization using Firefly algorithm

It is unlikely that the entire extracted feature will play equal part in diagnosis of hypertensive heart disease. So, feature with poorer performance can be ignored by employing feature optimization algorithm. Here, firefly algorithm which is a popular optimization algorithm has been used. Firefly algorithm is a multimodal optimization algorithm based on flashing characteristics of fireflies in nature. The main assumption is each solution (firefly) moves towards more attractive solutions (fireflies). Since the real firefly behavior is much more complex and sophisticated it requires some simplified rules to use them in other practical diagnoses [45].

Pseudo code for firefly algorithm:

1. Generation of initial population randomly
2. Calculation of fitness of initial population based on light intensity.
3. While (t<objective criteria is fulfilled)
4. For a=1:m ; (m=number of firefly)
5. For b=1:n;
6. Calculate the light intensity using fitness function
7. Distance is calculated
8. If (I(m)<I(n))
9. Firefly a is moved towards b.
10. Come up with new solution
11. Else
12. Firefly a will move randomly towards b
13. End (all loop)
14. Rank the firefly according to light intensity value

In the above mentioned algorithm, information gain has been used to calculate the intensity of a feature to rank itself among all the features (in the pseudo code it has been mentioned as light intensity of a firefly).

2.3. Using Fuzzy logic approach

Computational intelligence techniques are widely used in diagnosis of diseases. Here after optimizing the number of feature using firefly algorithm, the fuzzy logic will be applied. Firstly, the input will be fuzzified by transforming the crisp input into fuzzy input using membership function. After that, if-then rules are applied and fuzzy outputs are achieved. Form the fuzzy output, using defuzzifier the crisp output can be released.

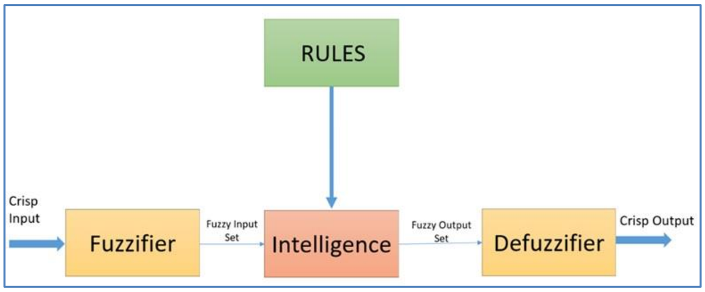


Fig. 1: Fuzzy logic blocks.

The complete process can be summarized using the following diagram in figure 2. The final block represents the optimization and fusion of all the features to diagnose HHD.

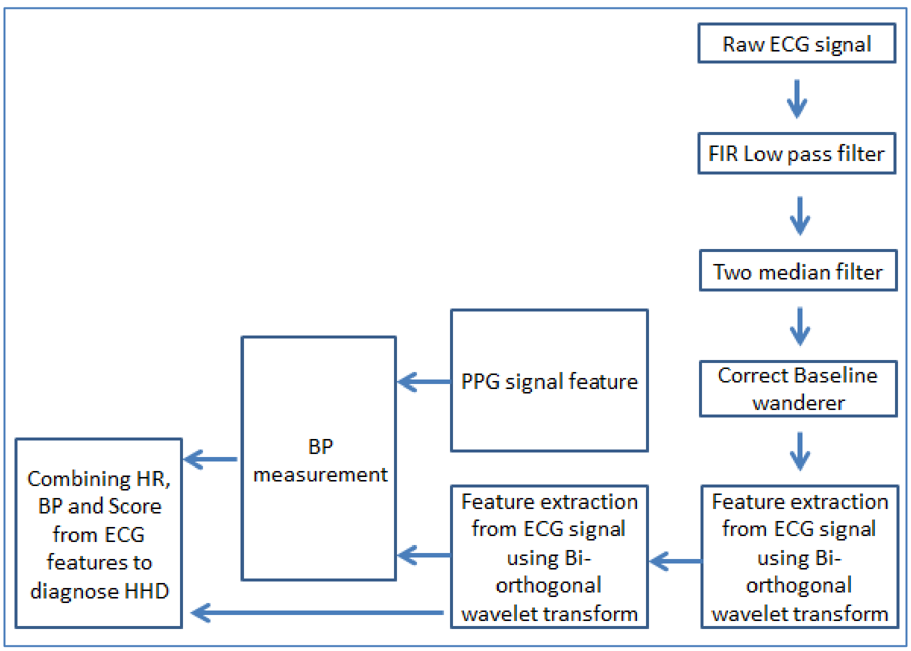
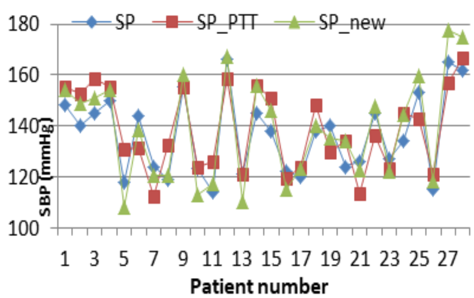


Fig. 2: Block diagram of BP measurement technique and HHD diagnosis.

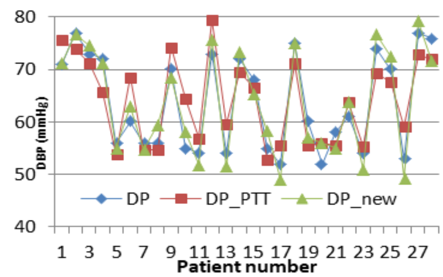
3. Performance Evaluation

In our previous study[41], two separate ways of measuring BP were evaluated. The first one is based on multiple linear regression models. The second one uses polynomial curve fitting method. To evaluate the performance of the proposed method, MIMIC Data base [46] was used. The first set of data (18 patients) was used for modeling and the second set of data (10 patients) was used for performance evaluation.

To evaluate the HHD diagnosis method using firefly algorithm to optimize the feature and fuzzy logic to classify, we have used physionet database since that contains all the necessary bio signals we have used in the method and diagnosis information as well. Four performance measures have been used to assess the performance of the proposed HHD diagnose system. The measures are sensitivity which is true positive rate, specificity which is true negative rate, accuracy of measurement and accuracy of prediction. A population of 82 person's data has been analyzed from PTB Diagnostic ECG Database physionet database [47] and the measurement results are 43 as true positive, 4 as false negative, 29 as true negative and 6 as false positive. So the measures are calculated according to formula mentioned in following table 3.



3a. Actual and measured SBP [41]



3b. Actual and measured DBP [41]

Fig. 3a, 3b: Comparison among actual BP, BP measured using PTT (BP_PTT) and BP measured using PTT & HR (BP_new)

Table 3: Assessment based on performance measures.

Measures	Equation	Percentage
Sensitivity	TP/(TP+FN)	91.49%
Specificity	TN/(TN+FP)	82.86%
Accuracy	(TP+TN)/(TP+TN+FP+FN)	87.80%
Predictive value (positive)	TP/(TP+FP)	87.76%
Predictive value (negative)	TN/(TN+FN)	87.88%

4. Conclusion and Future Work

A new hypertensive heart disease diagnosis method has been proposed using firefly algorithm and fuzzy logic with bio signal such as: blood pressure, ECG and PPG. Our previous research helped us to measure blood pressure from PTT and HR combination; we have used that information and extended to detect HHD in this paper. The firefly algorithm takes in all the features which indicates possible HHD and ranks into a series based on how significant each feature was. The fuzzy logic input the important features only and provided the classification of whether the patient has hypertensive heart disease or not. We have evaluated the method using popular database and showed improved performance in detection of HHD.

Future work will focus on making the proposed model more robust, with inclusion of additional biomedical signals.

References

[1] World Health Organization, *Global Status Report on Noncommunicable Diseases 2010.* Geneva: World Health Organization, 2011.

[2] M. J. Klag , Paul K. Whelton, Bryan L. Randall, James D. Neaton, Frederick L. Brancati, Charles E. Ford, Neil B. Shulman, and Jeremiah Stamler, "Blood pressure and end-stage renal disease in men," *N. Engl. J. Med.*, vol. 334, *(1)*, pp. 13-18, 1996.

[3] D. P. Zipes , Peter Libby, Robert O. Bonow, Douglas L. Mann, and Gordon F. Tomaselli, *Braunwald's Heart Disease E-Book: A Textbook of Cardiovascular Medicine.* Elsevier Health Sciences, 2018.
[4] B. H. McGhee and E. J. Bridges, "Monitoring arterial blood pressure: what you may not know," *Crit. Care Nurse,* vol. 22, *(2),* pp. 60-4, 66-70, 73 passim, Apr, 2002.
[5] R. Wang , Wenyan Jia, Zhi-Hong Mao, Robert J. Sclabassi, and Mingui Sun, "Cuff-Free Blood Pressure Estimation Using Pulse Transit Time and Heart Rate," *Int. Conf. Signal. Process. Proc.,* vol. 2014, pp. 115-118, Oct, 2014.
[6] W. Chen , T. Kobayashi, S. Ichikawa, Y. Takeuchi, and T. Togawa, "Continuous estimation of systolic blood pressure using the pulse arrival time and intermittent calibration," *Medical and Biological Engineering and Computing,* vol. 38, *(5),* pp. 569-574, 2000.
[7] J. Muehlsteff, X. Aubert and M. Schuett, "Cuffless estimation of systolic blood pressure for short effort bicycle tests: The prominent role of the pre-ejection period," in *Engineering in Medicine and Biology Society, 2006. EMBS'06. 28th Annual International Conference of the IEEE,* 2006, pp. 5088-5092.
[8] C. Ahlstrom , Christer, Anders Johansson, Fredrik Uhlin, Toste Länne, and Per Ask, "Noninvasive investigation of blood pressure changes using the pulse wave transit time: a novel approach in the monitoring of hemodialysis patients," *Journal of Artificial Organs,* vol. 8, *(3),* pp. 192-197, 2005.
[9] J. Foo , C. S. Lim, S. J. Wilson, G. R. Williams, M. A. Harris, and D. M. Cooper, "Pulse transit time ratio as a potential marker for paediatric crural and brachial blood pressure index," *J. Hum. Hypertens.,* vol. 21, *(5),* pp. 415, 2007.
[10] J. S. Kim , Young Joon Chee, Ju Wan Park, Jin Wook Choi, and Kwang Suk Park, "A new approach for non-intrusive monitoring of blood pressure on a toilet seat," *Physiol. Meas.,* vol. 27, *(2),* pp. 203, 2006.
[11] M. Masè , Walter Mattei, Roberta Cucino, Luca Faes, and Giandomenico Nollo, "Feasibility of cuff-free measurement of systolic and diastolic arterial blood pressure," *J. Electrocardiol.,* vol. 44, *(2),* pp. 201-207, 2011.
[12] J. E. Naschitz , Jochanan E., Stanislas Bezobchuk, Renata Mussafia-Priselac, Scott Sundick, Daniel Dreyfuss, Igal Khorshidi, Argyro Karidis, "Pulse transit time by R-wave-gated infrared photoplethysmography: review of the literature
and personal experience," *J. Clin. Monit. Comput.,* vol. 18, *(5-6),* pp. 333-342, 2004.
[13] Y. Yoon, J. H. Cho and G. Yoon, "Non-constrained blood pressure monitoring using ECG and PPG for personal healthcare," *J. Med. Syst.,* vol. 33, *(4),* pp. 261-266, 2009.
[14] V. P. Rachim, T. H. Huynh and W. Chung, "Wrist photo-plethysmography and bio-impedance sensor for cuff-less blood pressure monitoring," in *2018 Ieee Sensors,* 2018, pp. 1-4.
[15] D. Griggs , Manuja Sharma, Arian Naghibi, Colton Wallin, Victor Ho, Karinne Barbosa, Tadesse Ghirmai, Hung Cao, and Sandeep K. Krishnan, "Design and development of continuous cuff-less blood pressure monitoring devices," in *Sensors, 2016 Ieee,* 2016, pp. 1-3.
[16] M. Y. Wong, C. C. Poon and Y. Zhang, "An evaluation of the cuffless blood pressure estimation based on pulse transit time technique: a half year study on normotensive subjects," *Cardiovascular Engineering,* vol. 9, *(1),* pp. 32-38, 2009.
[17] Mamun, Mohammad Mahbubur Rahman Khan and A. T. Alouani, "Myocardial Infarction Detection using Multi Biomedical Sensors," *The 10th International Conference on Bioinformatics and Computational Biology,* pp. 117-122, March 19 - 21, 2018.
[18] R. Mukkamala , Ramakrishna, Jin-Oh Hahn, Omer T. Inan, Lalit K. Mestha, Chang-Sei Kim, Hakan Töreyin, and Survi Kyal, "Toward ubiquitous blood pressure monitoring via pulse transit time: theory and practice." *IEEE Trans.Biomed.Engineering,* vol. 62, *(8),* pp. 1879-1901, 2015.
[19] W. Parandyk, D. Lewandowski and J. Awrejcewicz, "Human circulatory system in terms of a closed-loop hydraulic structure," in *Conference Book of the 12th Conference on Dynamical Systems–Theory and Applications, Lodz, Poland,* 2013, .
[20] C. Cuspidi , C., C. Sala, F. Negri, G. Mancia, and A. Morganti, "Prevalence of left-ventricular hypertrophy in hypertension: an updated review of echocardiographic studies," *J. Hum. Hypertens.,* vol. 26, *(6),* pp. 343, 2012.

[21] D. Levy , Martin G. Larson, Ramachandran S. Vasan, William B. Kannel, and Kalon KL Ho, "The progression from hypertension to congestive heart failure," *Jama*, vol. 275, *(20)*, pp. 1557-1562, 1996.
[22] D. Levy , F., F. Paneni, S. Sciarretta, G. Tocci, and M. Volpe, "The progression from hypertension to congestive heart failure," *Jama*, vol. 275, *(20)*, pp. 1557-1562, 1996.
[23] L. Yin, Y. Chen and W. Ji, "A novel method of diagnosing coronary heart disease by analysing ECG signals combined with motion activity," in *2011 IEEE International Workshop on Machine Learning for Signal Processing*, 2011, pp. 1-5.
[24] R. S. B. Rosli and R. F. Olanrewaju, "Mobile heart rate detection system (MoHeRDS) for early warning of potentially-fatal heart diseases," in *2016 International Conference on Computer and Communication Engineering (ICCCE)*, 2016, pp. 422-427.
[25] A. Forkan, I. Khalil and Z. Tari, "Context-aware cardiac monitoring for early detection of heart diseases," in *Computing in Cardiology 2013*, 2013, pp. 277-280.
[26] D. Ravish , D. K., K. J. Shanthi, Nayana R. Shenoy, and S. Nisargh, "Heart function monitoring, prediction and prevention of heart attacks: Using artificial neural networks," in *2014 International Conference on Contemporary Computing and Informatics (IC3I)*, 2014, pp. 1-6.
[27] U. R. Acharya, U. Rajendra, Hamido Fujita, Vidya K. Sudarshan, Shu Lih Oh, Muhammad Adam, Joel EW Koh, Jen Hong Tan, "Automated detection and localization of myocardial infarction using electrocardiogram: a comparative study of different leads," *Knowledge-Based Syst.*, vol. 99, pp. 146-156, 2016.
[28] M. Fathil , M. F. M., MK Md Arshad, Subash CB Gopinath, U. Hashim, R. Adzhri, R. M. Ayub, A. R. Ruslinda, "Diagnostics on acute myocardial infarction: Cardiac troponin biomarkers," *Biosensors and Bioelectronics*, vol. 70, pp. 209-220, 2015.
[29] A. S. Flett ,Andrew S., Viviana Maestrini, Don Milliken, Mariana Fontana, Thomas A. Treibel, Rami Harb, Daniel M. Sado, "Diagnosis of apical hypertrophic cardiomyopathy: T-wave inversion and relative but not absolute apical left ventricular hypertrophy," *Int. J. Cardiol.*, vol. 183, pp. 143-148, 2015.
[30] P. M. Okin , Peter M., Darcy A. Hille, Sverre E. Kjeldsen, and Richard B. Devereux, "Combining ECG criteria for left ventricular hypertrophy improves risk prediction in patients with hypertension," *Journal of the American Heart Association*, vol. 6, *(11)*, pp. e007564, 2017.
[31] M. Kumar, R. Pachori and U. Acharya, "Automated diagnosis of myocardial infarction ECG signals using sample entropy in flexible analytic wavelet transform framework," *Entropy*, vol. 19, *(9)*, pp. 488, 2017.
[32] Parewe, Andi Maulidinnawati Abdul Kadir , Andi Maulidinnawati Abdul Kadir, Wayan Firdaus Mahmudy, Fatwa Ramdhani, and Yusuf Priyo Anggodo, "Dental disease detection using hybrid fuzzy logic and evolution strategies," *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)*, vol. 10, *(1-8)*, pp. 27-33, 2018.
[33] M. Barman, J. P. Choudhury and S. Biswas, "A frame work for detection of the degree of skin disease using soft computing model," in *International Conference on Computational Intelligence, Communications, and Business Analytics*, 2018, pp. 57-66.
[34] H. Ahmadi , Hossein, Marsa Gholamzadeh, Leila Shahmoradi, Mehrbakhsh Nilashi, and Pooria Rashvand, "Diseases diagnosis using fuzzy logic methods: A systematic and meta-analysis review," *Comput. Methods Programs Biomed.*, vol. 161, pp. 145-172, 2018.
[35] A. Micheal and A. Olayinka, "Predictive model for likelihood of detecting chronic kidney failure and disease using fuzzy logic," *The International Journal of Computational Science, Information Technology and Control Engineering (IJCSITCE)*, 2018.
[36] S. Thukral and J. S. Bal, "Medical Applications on Fuzzy Logic Inference System: A Review," *International Journal of Advanced Networking and Applications*, vol. 10, *(4)*, pp. 3944-3950, 2019.
[37] P. Kavitha and S. Prabakaran, "A Novel Hybrid Segmentation Method with Particle Swarm Optimization and Fuzzy C-Mean Based On Partitioning the Image for Detecting Lung Cancer," 2019.
[38] X. Chen , Xiaohui Yao, Chen Tang, Yining Sun, Xun Wang, and Xi Wu, "Detecting parkinson’s disease using gait analysis with particle swarm optimization," in *International Conference on Human Aspects of IT for the Aged*

Population, 2018, pp. 263-275.
[39] P. Kora, A. Abraham and K. Meenakshi, "Heart disease detection using hybrid of bacterial foraging and particle swarm optimization," *Evolving Systems*, pp. 1-14, 2019.
[40] Y. Zhang , Yudong, Shuihua Wang, Yuxiu Sui, Ming Yang, Bin Liu, Hong Cheng, Junding Sun, Wenjuan Jia, Preetha Phillips, and Juan Manuel Gorriz, "Multivariate approach for Alzheimer's disease detection using stationary wavelet entropy and predator-prey particle swarm optimization," *J. Alzheimer's Dis.*, vol. 65, *(3)*, pp. 855-869, 2018.
[41] Mamun, Mohammad Mahbubur Rahman Khan and A. Alouani, "Using photoplethysmography & ECG towards a non-invasive cuff less blood pressure measurement technique," in *2019 IEEE Canadian Conference of Electrical and Computer Engineering (CCECE)*, 2019, pp. 1-4.
[42] D. L. Mann , Robert O., Douglas L. Mann, Douglas P. Zipes, and Peter Libby, *Braunwald's Heart Disease E-Book: A Textbook of Cardiovascular Medicine.* Elsevier Health Sciences, 2014.
[43] K. Thygesen , Jeroen J., Helmut Baumgartner, Claudio Ceconi, Veronica Dean, Robert Fagard, Christian Funck-Brentano, David Hasdai, "Third universal definition of myocardial infarction," *Circulation*, vol. 126, *(16)*, pp. 2020-2035, 2012.
[44] A. H. Uchida, P. Moffa and A. R. Riera, "Exercise testing score for myocardial ischemia gradation," *Indian. Pacing Electrophysiol. J.*, vol. 7, *(1)*, pp. 61-72, Jan 1, 2007.
[45] X. Yang, "Firefly algorithms for multimodal optimization," in *International Symposium on Stochastic Algorithms*, 2009, pp. 169-178.
[46] A. L. Goldberger , "Physiobank, physiotoolkit, and physionet," *Circulation*, 2000.
[47] R. Bousseljot, D. Kreiseler and A. Schnabel, "Nutzung der EKG-Signaldatenbank CARDIODAT der PTB über das Internet," *Biomedizinische Technik/Biomedical Engineering*, vol. 40, *(s1)*, pp. 317-318, 1995.