How to Cite:
Thakkar, P. B., & Talwekar, R. H. (2022). Analysis and risk estimation system for heart attack using EDENN algorithm. *International Journal of Health Sciences*, *6*(S1), 5321–5330. https://doi.org/10.53730/ijhs.v6nS1.6093

Analysis and risk estimation system for heart attack using EDENN algorithm

Priyanka Bibay Thakkar
Research Scholar, Department of Electronics and Telecommunication Engineering, Rungta, College of Engineering and Technology, Bhilai, Chhattisgarh Swami Vivekanand Technical, University Bhilai
Email: bibay.priyanka@gmail.com

Dr R. H. Talwekar
Professor, Department of Electronics and Telecommunication Engineering, Government, Engineering College Raipur, Chhattisgarh Swami Vivekanand Technical University Bhilai
Email: ursk.talwekar@gmail.com

***Abstract*---**Heart related diseases are very common in the present scenario. In the past two decades the number of heart patients have increased to a large extent. Due to this abrupt rise in the number of patients, the death count has also increased. Thus, an efficient and accurate system must be developed for the diagnosis of heart related diseases, as the present methods available are not accurate enough and are insufficient for the Heart Attack (HA) and its Risk Analysis (RA). This paper propounds a system for HA risk estimation by the use of an Enhanced Deep Elman Neural Network (EDENN). In this system a Photoplethysmography (PPG) signal is inputted and pre-processed for noise removal. Further, Signal Decomposition (SD) is done, and the vital signs are estimated like Blood Pressure (BP), Respiratory Rate (RR) and Cardiac Autonomic Nervous System (CANS). For the BP estimation, Modified Maximum Amplitude Algorithm (MMAA) method is used and for the decomposed signal processing the Improved Incremental Merge Segmentation (IIMS) is used. As for features, Variation of amplitude, frequency and intensity are calculated and merged. With the aid of Pulse Rate Variability (PRV) extraction along with Pulse Rate (PR) calculation and estimation of CANS function is done and inputted to the system for RA. For RA part, AJM-FCM is used to get clustered output from which features were extracted and given to the EDENN which categorize the major or minor HA. Experiments shows that the EDENN attains greater performance and accuracy compared to the existing systems.

International Journal of Health Sciences ISSN 2550-6978 E-ISSN 2550-696X © 2022.
***Corresponding author**: Thakkar, P.B.; Email: bibay.priyanka@gmail.com*
Manuscript submitted: 27 Feb 2022, Manuscript revised: 18 March 2022, Accepted for publication: 09 April 2022

***Keywords*---**Photoplethysmography (PPG), Improved Incremental Merge Segmentation, Coronary Heart Disease(CHD), Systolic BP (SBP), Diastolic BP (DBP), Signal decomposition, Risk analysis, Pulse Rate Variability (PRV).

Introduction

In present days, the rise in the Heart Attack (HA) and heart related diseases have increased the concern of many peoples towards their health. Medical statistics shows that HA and Heart Diseases (HD) are the main cause of death worldwide [1]. Another silent killer disease is Coronary Heart Disease (CHD) [2] which is also the major cause of death across the globe. Early detection of HD can help the clinicians to provide and plan the proper treatment for patients. This can cure or control the disease and can prevent the death up to some extent [3] [4]. Hence, developing such type of system for the heart patient will be very beneficial for analyzing the risk of heart attacks. But statistics also shows that in medical field it is difficult to diagnose a patient promptly [5]. Therefore, monitoring the heath of peoples is a huge area for research and development nowadays.

Studies has shown that there are 2 level of HA risk (i) high risk and (ii) borderline level [6]. Both the levels of HA risk are centered on the Blood Pressure (BP) of a person. Similarly, Cardio-Vascular Diseases (CVD) are related to blood vessels or heart [7] and hypertension is the key factor for most of the CVDs [8]. Vitals like human's Heart Rate (HR) and breathing rate are very important in the detection of such diseases [9]. Therefore, these vital signs need to be monitored continuously to analyze patient's health and heart condition. These days, the availability of wearable devices, wireless sensors, body sensors, as well as mobile technology along with cloud resources availability makes it easy to develop a remote monitoring system [10]. All these devices use a most popular non-invasive approach to measure the necessary vitals i.e., the PPG technique.

PPG technique is well capable of measuring the HR and other vitals [11] as it uses a photodetector on the top of the skin and a light source to measure the blood circulation and the volumetric variations in the blood vessels [12]. This helps in the estimation of HR, BP etc. and the risk prediction for HA [13]. Although many researchers have incorporated PPG signal analysis with the help of digital sensors [14], wearable devices [15][16], signal processing and machine learning algorithm in their work. There is still need of a more advanced risk analysis system which can accurately predict the possibility of having a heart attack at an early stage so that one must beware towards his health and could take precaution accordingly. Thus, this research work propounds an estimation of human vital signs and risk analysis centered on EDENN. The diagnosis and risk analysis of HD is a challenging problem. To visualize the HDs at early stages, several methods of data mining and machine learning must be performed. To do so, there occurs some issues like errors and inaccurate results. This research work reduces the error in estimation of human vitals like BP, RR and CANS function for the HA risk analysis by using the EDENN. Organization of this paper is as follows: First section gives an introduction about the problem. Second section deals with the related works done in this area. Third section explains about our proposed methodology. Fourth section displays the results of experiment and the last section concludes the paper.

Literature survey

Yuwen Chen and Baolian Q [17] suggested a design on intra-operative vital signs focused on Heart Failure (HF) risk prediction. Initially the system is intended to monitor the data of surgical patients thru statistical analysis and extract the vital signs. Then this vital sign data is converted into text format. Latent Dirichlet allotment model is utilized to extract the text topic of patients for HF prediction. Later, the vital time-series data is converted into a grid image. Finally, the convolutional neural network is used for the HF prediction. Despite a good and efficient system this couldn't have the potential for developing a modern medical diagnosis as well as treatment.

Jae Kwon Kim and Sanggil Kang [18] proposed a neural network based CHD risk analyzer which was centered upon a Feature Correlation Analysis (FCA). In the FCA, the presence of correlations betwixt feature relations along with the output data of NN predictor is analyzed and HA risk is predicted. The NN using FCA was assumed to be superior to the Framingham Operating Characteristics (FOC). It also provides a big Receiver Operating Characteristics (ROC) curve and a more precise HA risk prediction in the Korean population similar to FRS. But in comparison to the other methods the precision was low.

Ludi Wang et al. [19] developed a NN centered on photoplethysmography (PPG) for BP estimation. The Multi-Taper Method was used in obtaining the spectral components and constituting the inputted parameters. The system was trained from the database and extracted the various parameters from the signal for the measurement of BP. This system performance was improved but the efficiency of the assessment algorithm was found lowered in case of individual.

Remo Lazazzera et al. [20] proposed a method for the measurement of BP based on photoplethysmogram. In this method, 2 pulse oximeters are used in which 1 is placed on the back and other is placed at the front. PPG data is collected by putting the oximeter on the index finger. Obtained signal was filtered and cross-correlated for getting a time delay called Pulse Transit Time (PTT). For the calculation of the Diastolic-BP and Systolic-BP (DBP and SBP) the HR and PTT was represented on linear design. Experiments shows better outcomes but there is a big drawback of PPG signal for the variation due to movement which lowers the system performance.

Senthilkumar Mohan et al. [21] proposed a system for Heart Diseases prediction based on the modified Machine Learning (ML) technique. For the CVDs prediction, the system uses the ML technique and disparate combination of aspects to generate a prediction design. Then targeted at HD with the hybridized Random Forest (RF) and a linear design improved the performance of system to 88.7% accuracy. The RF features along with the Linear Method (LM) were combined for a satisfactory outcome. But still the performance of the system was very low.

Proposed Methodology

Below figure 1 shows the block diagram of our proposed system. There are 3 stages in this proposed work i.e., (i) preprocessing, (ii) estimating the human vitals and (iii) risk analysis. Initially the PPG signal goes to the preprocessing where an Independent Component Analysis (ICA) and an Improved Kalman Filter (IKF) is used to remove the corrupted signal and noise. After this, signal decomposition is done using Differential Evaluation-based Ensemble Empirical Mode Decomposition (D3EMD). Then the threshold value is gauged and analogized to the fixed value for checking of any corrupted signal. Further, the PPG signal is inputted to the next stage where the human vitals are evaluated. The BP is estimated by the MMAA efficiently, then segmentation is performed using IIMS, variation calculation along with fusion for the estimation of RR. Next, CANS function is evaluated by extracting the PRV from PPG signal and the pulse rate is gauged. The evaluated values of BP, RR and CANS function are then inputted to the risk analysis phase. The risk analysis phase is based on AJM-FCM which clusters the input data into chances of HA and no chances of HA. If the patient's data have a possibility of HA then it is extracted as the evaluated value and is inputted to the next stage. In the next stage the EDENN classifies the data into attack possibilities as major and minor.

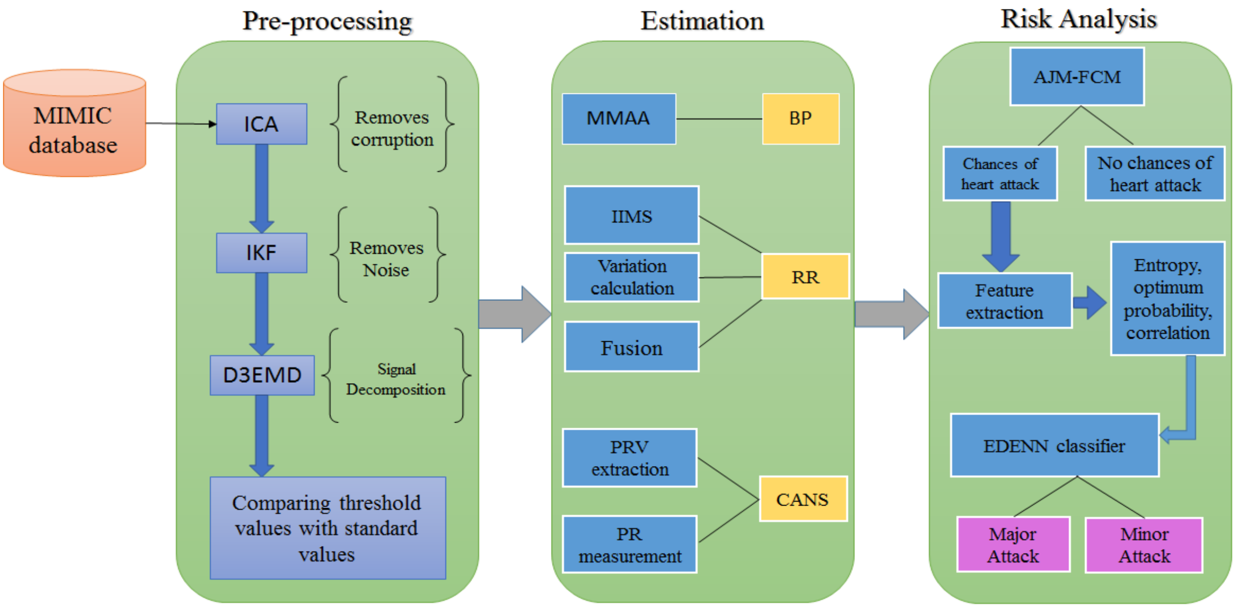

Figure 1: Block diagram of proposed system

Dataset and preprocessing

An online available dataset (MIMIC database) was used in this study. This dataset comprises of total 503 samples of PPG signal in which 150 were normal, 150 were major and 203 were of minor heart attack. For the training of the system 345 samples are taken out of which 100 are normal, 100 are cases of major and 145 are of minor HA. Similar to the training process, testing of the system is also performed by utilizing 50 samples of normal, 50 of major attack and 58 of minor attack. The preprocessing of the signal is done for the removal of unwanted distortion and improving the performance of the system. This phase consists of 3 stages i.e., (i) corruption identification using an ICA, (ii) noise removal using an IKF and (iii) signal decomposition using D3EMD. In the first step of corruption identification, the signal components are assumed to be autonomous as well as non-Gaussian by the ICA. Then the signal is weighted as the linear combination of autonomous components. It is denoted by the equation

$$\chi = \sum_{i=0}^{N} \eta_i \kappa_i \tag{1}$$

Where, χ = Set of observed corrupted signals, κ_i = Independent component,

η_i = Real coefficient.

In the second step, the noise due to power line interference is removed from the signal to separate the H. Then better smoothening is provided by utilizing the Kalman filter with Covariance Matrix (CM). For uniform and smooth image, the CM and correlation matrix are interchanged. Due to this, smooth and uniform outcome are obtained and it is called IKF.

For the third step, signal decomposition is done using D3EMD for the signal $\overline{S}$ into signal bands. Due to the possibility of mode mixing and issue in selecting the initial parameter, the differential assessment algorithm is used. Then the inputted signal is converted into Intrinsic Modes Function (IMF).

$$\overline{S}(t) = \sum_{p,q=1}^{t} \Gamma_{pq}(t) \tag{2}$$

Where, $\Gamma_{pq}(t)$ = IMF component.

After the SD, the threshold values like standard deviation (σ), kurtosis (ψ) and skewness (θ) are calculated and equated to the fixed values.

$$S^*(t) = \begin{cases} S(t) & \tau_o = \tau_f \\ S & otherwise \end{cases} \tag{3}$$

Where, $S^*(t)$ = Enhanced PPG signal, τ_o = Obtained value, τ_f = Fixed value

If the obtained value is equal to the fixed value then no corruption is present and the signal is inputted to the Estimation stage.

Estimation of human vital signs

In this stage, the corruption free PPG signal is inputted to various algorithm for the estimation of BP, RR and CANS function. The BP is estimated using MMAA efficiently. The BP measurement is done by measuring the cuff pressure (CP) of the maximum amplitude of the oscillometric waveform envelop (OWE). Then DBP and SBP is measured using the linear relation between the Mean Arterial Pressure (MAP) with DBP and SBP, which is given below:

$$BP_{map} = (BP)_{low} + \frac{1}{3}[(BP)_{up} - (BP)_{low}] \tag{4}$$

Where, BP_{up} = SBP , BP_{low} = DBP.

The RR is the breath taken by a person in a minute. Estimation of RR is done using a 3 step process of Pulse segmentation, Variation calculation and Fusion. The Pulse segmentation is done utilizing IIMS method and variation calculation is done through the respiratory induced variation in the intensity, amplitude and frequencies. Later, these parameters are merged in the fusion process and can be represented by the equation below

$$\Delta_{RR} = \Delta_I + \Delta_F + \Delta_A \tag{5}$$

Where, Δ_{RR} = last outcome after fusion process, Δ_I = Intensity variation,
Δ_F = Frequency variation, Δ_A = Amplitude variation

The CANS function is calculated with the help of PRV and PR. For the PRV calculation the Peak to Peak (PP) time interval and equivalent timestamps are calculated.

$$PRV(t) = \{\tau^{pp_i}, \tau^{st_i}\} \tag{6}$$

Where, τ^{pp_i} = PP time interval, τ^{st_i} = timestamps

Then, PR is calculated using the mean of PP time interval and estimating the time window and performing FFT to the $PRV(t)$.

$$r_p = \frac{\rho_n}{\overline{t^{pp_i}}} \tag{7}$$

Where, ρ_n = number of pulses, $\overline{t^{pp_i}}$ = mean of the PP intervals.

Risk analysis

After the calculation of BP, RR and CANS function, they are inputted to the risk analysis stage where they are clustered into chances of HA and no chances of HA. If the patient have a chance of HA then the feature extraction is done and inputted to the classifier. It then classifies the attack possibility as major or minor HA. Clustering is done using the AJM-FCM, here a centroid point is selected at random for bringing a convergence result then average is measured for every initial value. Then based on the average central value, the cluster centroid is selected and a Jacobian matrix is utilized in place of the membership matrix for achieving a better result.

After clustering, if the patient has a chance of HA the feature extraction is done. Features like entropy, correlation, optimum probability, inverse difference normalized, along with the energy are extracted from the estimated values.

$$\Phi_n = \{\Phi_1, \Phi_2, ..., \Phi_T\} \tag{8}$$

Where, Φ_n = Feature set, Φ_T = Total features.

The extracted feature set B_t is inputted to the EDENN classifier. Here the ENN is a recurrent network where Hidden Layers (HL) and context layer for memory gets added, thus for more number of layers the normal Activation Function (AF) is not suitable. So, it takes too much time to finish the task. To avoid this, the weight value is allotted based on the total neurons on the layers.

Result

Performance of various classifiers have been compared on the basis of parameters like Accuracy, Precision, Specificity, Sensitivity, Recall, F-measure, The performance comparison is given in the Table-1 below and the results of the best performing classifier has been highlighted with the bold font. It is clearly observed that, on comparing the EDENN with the currently existing algorithm like NN, Adaptive Neuro-Fuzzy Interference System (ANFIS), Moore-Penrose pseudo-inverse Weight centered Deep Learning Neural Network (MPPIW DLNN) and Optimized ANFIS (OANFIS) methods, the performance of EDENN is superior to the existing methods as it gives the best accuracy of 98.4% with the sensitivity and specificity of 96.2% and 99.0% respectively. Also, the lowest accuracy was given by ANFIS classifier which is 85.8% with very poor sensitivity of about 64.55% and specificity of 91.1%.

Table 1
Comparison of existing classifier and proposed classifier

Parameters	MPPIW DLNN	NN	ANFIS	OANFIS	Proposed EDENN
Sensitivity	89.87	78.48	64.55	81.01	96.20
Specificity	97.46	94.62	91.13	95.25	99.05
Accuracy	95.94	91.39	85.82	92.40	98.48

The comparative analysis shown in the table above depicts the proposed method is superior to the existing methods in terms of accuracy, precision and sensitivity of the system. The similar comparison is shown below in the pictorial representation:

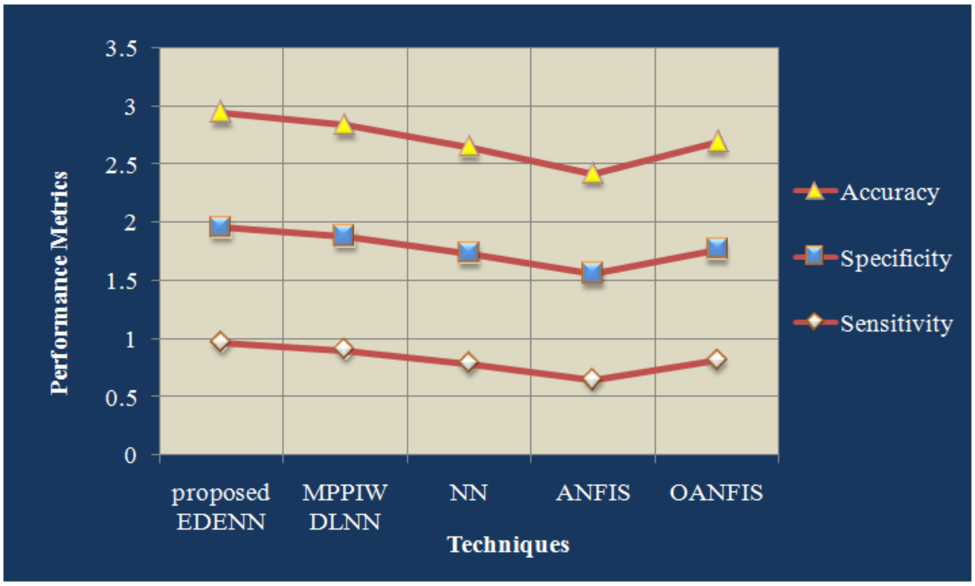

Figure 2: Performance analysis of proposed method with existing method

It is seen clearly from the performance matrices that the proposed EDENN system have an improved accuracy, sensitivity and specificity and can serve as a reliable system for prediction of heart attack and its risk analysis.

Conclusion

The main cause of death in present day is HD, making this a global concern. So as a preventive measure it is necessary to detect the individual at risk of heart related diseases. The proposed EDENN method for BP, RR and CANS function estimation provides a better HD detection and possible future HA. The comparative analysis show that the efficiency of the proposed system analogized to the existing system have attained 98.48% accuracy which is greater in comparison to the existing methods, making it more favorable for the detection of HD through risk analysis and focusing on the vital signs for the HA prediction in future.

References

1. MohamedAbdel-Basset, AbduallahGamal, GunasekaranManogaran, and Hoang Viet Long, “A novel group decision making model based on neutrosophic sets for heart disease diagnosis”, Multimedia Tools and Applications, vol. 79, pp. 9977-10002, 2020.
2. MehrbakhshNilashi, HosseinAhmadi, Azizah Abdul Manaf, Tarik A. Rashid, SarminahSamad, Leila Shahmoradi, NahlaAljojo, and ElnazAkbari, “Coronary heart disease diagnosis through self-organizing map and fuzzy support vector machine with incremental updates”, International Journal of Fuzzy Systems, vol.22, pp. 1376-1388, 2020.
3. Syed Muhammad Saqlain, Muhammad Sher, Faiz Ali Shah, Imran Khan, Muhammad Usman Ashraf, Muhammad Awais and Anwar Ghani, “Fisher

score and matthews correlation coefficient-based feature subset selection for heart disease diagnosis using support vector machines", Knowledge and Information Systems, vol. 58, no. 1, pp. 139-167, 2019.

4. IbomoiyeDomorMienye,Yanxia Sun, and Zenghui Wang, "An improved ensemble learning approach for the prediction of heart disease risk", Informatics in Medicine Unlocked, vol. 20, pp. 1-5, 2020.
5. Kumar G. Dinesh, K. Arumugaraj, Kumar D. Santhosh, and V. Mareeswari, "Prediction of cardiovascular disease using machine learning algorithms", In 2018 International Conference on Current Trends towards Converging Technologies (ICCTCT),29 November 2018, IEEE,Coimbatore, India, 2018.
6. KritiGupt, PallaviKaul, and Arashdeep Kaur, "An Efficient Algorithm for Heart Attack Detection using Fuzzy C-means and Alert using IoT", In International Conference on Computational Intelligence & Communication Technology (CICT),04 October 2018, IEEE, Ghaziabad, India, 2018.
7. JalilNourmohammadi-Khiarak, Mohammad-Reza Feizi-Derakhshi, KhadijehBehrouzi, SamanehMazaheri, YasharZamani-Harghalani, and RohollahMoosaviTayebi, "New hybrid method for heart disease diagnosis utilizing optimization algorithm in feature selection", Health and Technology, vol. 10, no. 3, pp. 667-678, 2020.
8. Yongbo Liang, Zhencheng Chen, Rabab Ward, and Mohamed Elgendi, "Hypertension assessment via ECG and PPG signals: An evaluation using MIMIC database", Diagnostics, vol. 8, no. 3, pp. 1-10, 2018.
9. MostafaAlizadeh, George Shaker, João Carlos Martins De Almeida, PlinioPelegrini Morita, and SafeddinSafavi-Naeini, "Remote monitoring of human vital signs using mm-Wave FMCW radar", IEEE Access, vol. 7, pp. 54958-54968, 2019.
10. Abdur Rahim Mohammad Forkan, and Ibrahim Khalil, "PEACE-Home: Probabilistic estimation of abnormal clinical events using vital sign correlations for reliable home-based monitoring", Pervasive and Mobile Computing, vol. 38, pp. 296-311, 2017, 10.1016/j.pmcj.2016.12.009.
11. DivyaRamachandran, VanathiPonnusamyThangapandian, and HarikumarRajaguru, "Computerized approach for cardiovascular risk level detection using photoplethysmography signals", Measurement, vol. 150, pp. 1-11, 2020.
12. Karthik Subramanian,CelalSavur, and FeratSahin, "Using Photoplethysmography for Simple Hand Gesture Recognition", In IEEE 15th International Conference of System of Systems Engineering (SoSE), 01 July 2020,Budapest, Hungary IEEE, 2020.
13. Farhan Riaz, Muhammad Ajmal Azad, Junaid Arshad, Muhammad Imran, Ali Hassan and Saad Rehman, "Pervasive blood pressure monitoring using photoplethysmogram (PPG) sensor", Future Generation Computer Systems, vol. 98, pp. 120-130, 2019.
14. Mamady Kebe, Rida Gadhafi, Baker Mohammad, Mihai Sanduleanu, Hani Saleh, and Mahmoud Al-Qutayri, "Human vital signs detection methods and potential using radars: a review", Sensors, vol. 20, no. 5, pp. 1454, 2020.
15. Muhammad Chowdhury EH, Khawla Alzoubi, Amith Khandakar, Ridab Khallifa, Rayaan Abouhasera, Sirine Koubaa, Rashid Ahmed, and Anwarul Hasan, "Wearable real-time heart attack detection and warning system to reduce road accidents", Sensors, vol. 19, no. 12, pp. 2780, 2019.

16. Muhammad Chowdhury, EH, Amith Khandakar, Khawla Alzoubi, Samar Mansoor, Anas M Tahir, Mamun Bin Ibne Reaz, and Nasser Al-Emadi, “Real-Time Smart-Digital stethoscope system for heart diseases monitoring”, Sensors, vol. 19, no. 12, pp. 2781, 2019.
17. Yuwen Chen, and Baolian Qi, “Representation learning in intraoperative vital signs for heart failure risk prediction”, BMC Medical Informatics and Decision Making, vol. 19, no. 1, pp. 260, 2019.
18. Jae Kwon Kim, and Sanggil Kang, “Neural network-based coronary heart disease risk prediction using feature correlation analysis”, Journal of healthcare engineering, pp. 1-13, 2017, 10.1155/2017/2780501.
19. Ludi Wang, Wei Zhou, Ying Xing, and Xiaoguang Zhou, “A novel neural network model for blood pressure estimation using photoplethesmography without electrocardiogram”, Journal of healthcare engineering, 2018, 10.1155/2018/7804243.
20. Remo Lazazzera, Yassir Belhaj, and Guy Carrault, “A new wearable device for blood pressure estimation using photoplethysmogram”, Sensors, vol. 19, no. 11, pp. 2557, 2019.
21. Mohan, Senthilkumar, Chandrasegar Thirumalai, and Gautam Srivastava, “Effective heart disease prediction using hybrid machine learning techniques”, IEEE Access, vol. 7, pp. 81542-81554, 2019, 10.1109/ACCESS.2019.2923707.