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Wearable IoT enabled smart heart disease monitoring on WSN

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Abstract: The age profiles of many countries are increasing day by day with increasing population of individuals affected by the chronic diseases such as diabetes, cardiovascular disease, obesity and so on. In order to maintain the individual living, remote health monitoring with daily activity by recognising people is a promising solution. Cardiovascular disease (CVD) is the major cause of mortality globally. Most of the deaths due to CVD are sudden and without any chance of medical help. In order to avoid this accidental death, precautions are required with continuous monitoring of body parameters such as heart rate, pulse rate and electrocardiogram (ECG) to show the current status of the health. Internet of Things (IoT) is rapidly growing industry in many disciplines including healthcare. In current research, heart disease is monitored with processing of electrocardiogram signals. The existing monitoring system lacks in prediction accuracy and remote monitoring. In this proposed work, the gathered data from the wearable devices are preprocessed to remove the noise. The relevant features for better recognition are selected using the proposed LBPNet with particle swarm optimisation (PSO). Then sequential minimal optimisation based SVM classifier recognises the abnormalities of heart disease from normal patients for diagnosis. These data are available in remote servers for doctors and care takers with IoT application. The care takers are notified about the patient health using smart phones. This proposed system is useful for cardiac patient monitoring and updation with high accuracy.

Keywords: cardiac disease; health monitoring; IoT; Internet of Things; WSN; wireless sensor network; deep learning; PSO; particle swarm optimisation; LBPNet; ECG; electrocardiogram; SMO-SVM.

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1 Introduction

Due to the disorder of the heart and blood vessels, 32% of adult death is caused because of cardiovascular diseases [1]. This consists of various heart diseases such as coronary heart disease, raised blood pressure called hypertension, rheumatic heart disease, cerebro vascular disease called stroke, heart failure, peripheral artery disease and congenital heart disease. These kind of cardiovascular diseases need to be monitored continuously. The patients in the hospital are monitored using bedside monitors by hospital staff. Due to the immobility, wired connection and weight of these instruments, the patients are stuck in bed and feel uncomfortable. It is difficult to monitor the patients suffered from cardiovascular disease continuously due to the hospital cost and shortage of hospital qualified healthcare professionals.

This paper introduces a wearable IoT based smart heart disease monitoring system with wireless communications. The wearable devices such as heart rate sensor, temperature sensor attached to the patient's body will send the status about the patients as bio signals to the server. The data are processed and the stored about the patients data. Doctors and care takers are notified about the patient health if there is any abnormality detected. These data also available in hospital server and cloud for further treatment. The contribution of this paper is as follows:

- Gathered data from wearable IoT devices of the patients are preprocessed to remove the noise and missing values.
- The relevant body parameters such as heart rate, blood pressure and ECG are extracted using the proposed deep LBPnet algorithm.
- The relevant features related to heart diseases will improve the diagnosis process. Hence, the feature selection process is further optimised with the optimisation algorithm called PSO to get optimal feature set.
- The HD is predicted using SMO-SVM with optimal features for better diagnosis.
- The results are evaluated with corpus dataset using the evaluation metrics and error calculation.
- The proposed system results are compared with previous algorithms to prove the efficiency and effectiveness of the smart monitoring system.
- The doctors, caretakers are notified about the patient's health status through smart phones for early diagnosis.

The remaining sections of this paper are as follows: Section 2 discusses about the related work, Section 3 introduced the smart monitoring HD system with proposed deep learning approaches, Section 4 discusses the results and evaluations, and Section 5 concludes the proposed work with future work.

2 Related work

The existing literature discussed about the difficulties of the elderly people who independently living with chronic diseases such as heart disease, Alzheimer's and diabetes. Varatharajan et al. [2] proposed a dynamic time warping method for early diagnosis of Alzheimer disease using wireless sensors. Romero et al. [3] proposed a diagnosis system for Parkinson's disease. Pigadas et al. [4] proposed a smart phone based method for smart monitoring with the data gathered from GPS, accelerometer and wearable sensors. These devices can transmit the data to the remote servers and send notification on hazardous situations.

Pirani et al. [5] proposed smart phone based application to manage wandering behaviour and context information. The user behaviour pattern is learned through decision theoretic model. The navigate users are provided with verbal prompts for monitoring. Sensor networks are the key techniques to collect number of health related signals including ECG and heart beat [6]. The remote health monitoring utilise the smart phone as the gateway that can collect the sensor signals and transmit the relevant medical centre with or without processing.

Bao and Intille [7] proposed a smart monitoring system used to detect the motions and activities with the help of user mounted acceleration data from accelerometers attached to the body. The activities such as walking, sitting, standing, relaxing, watching TV, scrubbing, laundry, folding, carrying items, eating, reading, cycling, vacuuming, climbing stairs and lying down are detected. Roy et al. [8] proposed a smart phone based infrastructure assisted recognition system for multi in habitant environment. This method used to recognise the daily living activities through smart phone enabled sensors. ActiServ [9] is a android phone based accelerometer sensors with fuzzy classification used to recognise simple gestures.

Sarmah [10] proposed a heart disease diagnosis and medication using deep learning modified neural network (DLMNN). It consists of three steps for authentication, encryption and classification. Heart patients of the hospital are authenticated using substitution cipher (SC) with SHA-512. The sensor data are transferred to cloud using wearable IoT devices using PDH-AES method. Then the DLMNN classifier classifies the data as normal and abnormal. The abnormal condition alert is sent to the physician for further treatment. Mohan et al. [11] proposed a ML techniques to enhance the detection of cardiovascular disease with improved accuracy. They used hybrid method with random forest and linear model. This method obtained 88.7% of accuracy on prediction of HD.

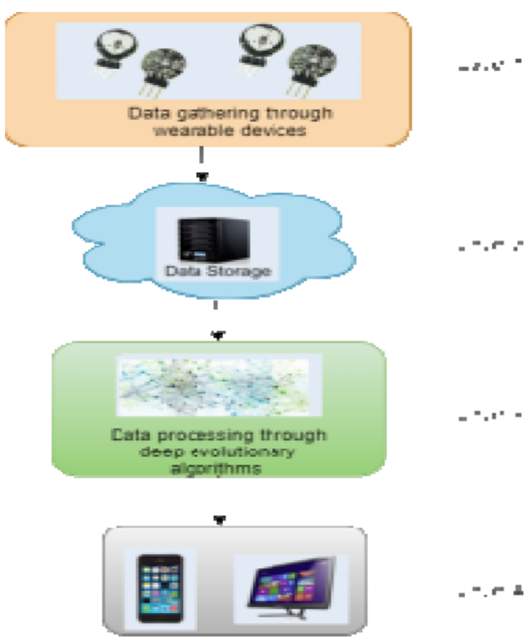
ElSaadany et al. [12] proposed a IoT enabled multi sensory system that gather heart rates with body temperature. The sensor system with Bluetooth communication gathers the ECG data utilising the smart phone. This signal processing mechanism was incorporated with ML approaches to prevent the sudden heart attack. Khan [13] proposed a model for IoT enabled heart disease prediction using modified deep convolutional neural network. The patient data such as ECG and heart rate are gathered using smart watch and heart monitor device. This model obtained 98.2% accuracy on prediction.

Vijayashree and Sultana [14] proposed a optimum weight based fitness function for PSO and SVM for HD prediction. The PSO-SVM used to select six relevant features such as sex, maximum heart rate, resting ECG, fasting blood sugar, multiple major vessels and exercise induced angina. Mutlag et al. [15] reviewed the issues, difficulties and challenges included in healthcare IoT systsm and provide the suggestions to resolve the issues with load balancing, computation offloading and interoperability. Internet of things in vehicle (IoV) tracking is discussed in Napoléon and Alfalou [16]. The sensors track data and uses big data platform to store the data. Under water sensor network with IoT is implemented in Eberhart and Kennedy [17] and machine learning performance in diseases prediction is Sharkawy et al. [18] highly encouraged by recent researchers. Agricultural decision making [19] process is designed with machine learning and sensors for optimal results.

3 Proposed LBPNet-PSO methodology

The proposed smart heart disease monitoring system on WSN is based on deep learning and meta heuristic algorithms. The overview of the system is show in Figure 1. It consists of four layers. Layer 1 is responsible for gathering the patient health data such as heart rate, ECG, glucose level and blood pressure using wearable IoT devices. These raw data are pre-processed to remove the missing values and noise. Layer 2 is responsible for networking process to store the processed data and monitoring. Layer 3 is responsible for knowledge driven processing on predicting the heart disease patients condition and Layer 4 is responsible for self management and updating the condition of the patients to doctors and care takers through smart devices for early diagnosis.

Figure 1 LBPNet-PSO system overview (see online version for colours)



3.1 Data processing using eigen PCA

To make the gathered input data from the wearable devices as an elegant one for processing, dimensionality reduction is an important step to reduce the dimension of the input data into low dimensional space. In this proposed work, Eigen-PCA has been used to reduce the dimension of feature space. Principal Component Analysis (PCA) has been used to reduce the high dimensional of data space into low dimension of feature space. PCA used here to calculate the eigenvector of covariance matrix. The high dimensional data space transformed into low dimensional space with the eigenvectors with larger eigen values. The vector dimension of image is represented as $M \times N$. the set of images are represented as, $[P_1, P_{2,} \dots P_N]$. the image set is represented in equation (1),

$$P = \frac{1}{N}\sum_{i=1}^{N} P_i \tag{1}$$

The covariance matrix C is declared as in equation (2),

$$C = \frac{1}{N}\sum_{i=1}^{N} (P - P_i)(P - P_i)^T \tag{2}$$

The eigen values and vectors are calculated as in equation (3),

$$EV = \lambda V \tag{3}$$

where V-eigen vectors associated with C with the eigenvalue λ. All the input image set is projected into the eigen-subspace as in equation (4),

$$y_j^i = w^T (p_i)\, i = 1, 2, 3..N \tag{4}$$

y_j^i-projection of p which is called as the principal components. The input face image is the combination of principal components.

3.2 Feature extraction using deep LBPnet with PSO

Once the preprocessing and dimensionality reduction process are over, the features related to the heart disease such as blood pressure, heart rate, ECG are extracted from the data using proposed optimised deep learning approach called deep local binary pattern (DLBP) network with PSO. Irrelevant features leads to reduce the performance of the diagnosis system. The relevant and important features are need to be extracted to improve the recognition system with high accuracy. LBP is a texture based feature extraction technique used in many applications including face recognition to extract the features [16]. These feature extraction network structure consist of two layers such as DLBP layer and Eigen-PCA layer.

Deep LBP layer: this LBP divides the input feature image into arrays. The 3×3 matrix is mapped into the pixel matrix. It consists of central pixel with the threshold (P_0). If the neighbour pixel value is lower than central pixel is then that pixel value is replaced with zero or else it is filled with one. These binary values represent the local texture of the image. Histogram of this pixel square is calculated and that are concatenated to form the vector of features. The LBP is declared as in equation (5)

$$LBP = \sum_{p=1}^{8} 2^{p} s\left(in_{n} - in_{cp}\right) \tag{5}$$

where

$s(x) = \begin{cases} 1 & x \geq 0 \\ 0 & x < 0 \end{cases}$ and in_n, in_{cp} – intensity values for neighbour and central pixel. Figure 2 shows the Deep LBP Net architecture with two layers and Figure 3 represents the process of DLBP.

Figure 2 Architecture of deep LBPNet (see online version for colours)

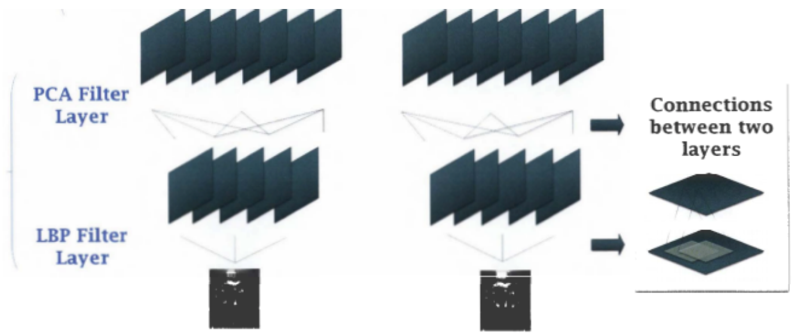
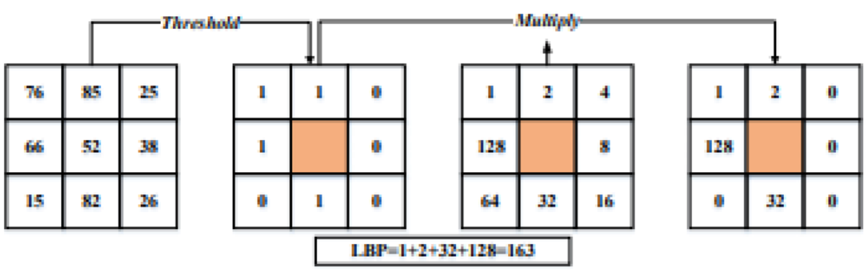
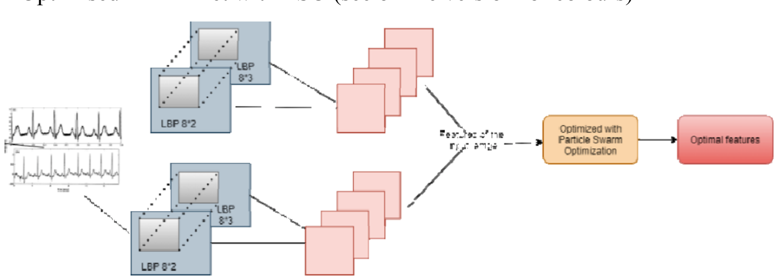


Figure 3 DLBP layer (see online version for colours)



Eigen-PCA filter layer: The objective of this layer is to transform the input features into low dimensional space using the Section 3.2 and performing the PCA on each square of window. The overall DLBPNet is shown in Figure 4. Now the filtered image features are optimised with particle swarm optimisation to find the optimal features for classification.

Figure 4 Optimised DLMP net with PSO (see online version for colours)



The particle swarm optimisation (PSO) was developed by Kennedy and Eberhart in 1995 which is widely used optimisation technique due to its efficiency [17,18]. In PSO, each individual of the population is called as particle which consist of its position, velocity vector and fitness value to control the particle movement. Based on the internal intelligence (pbest) and best experience (gbest). Each particle performance is evaluated using the predefined cost functions at the end of the iterations. Among the whole population, each particle takes neighbour particle value referred as optimal global value called Gbest. The PSO process is calculated using the equations (6) and (7)

$$v_i^{t+1} = wv_i^t + c_1.r_1\left(Pbest_i^t - X_i^t\right) + c_2.r_2\left(Gbest^t - X_i^t\right) \tag{6}$$

$$X_i^{t+1} = X_i^t + v_i^{t+1} \tag{7}$$

where, i = 1…N – no. of swarm population. v_i^t – velocity vector, t – iteration, X_i^t – current position of ith particle, $Pbest_i^t$ -previous best position of ith particle, $Gbest^t$ - previous best position of whole particle, c_1 and c_2 – coefficients called cognitive parameter an social parameter. The cognitive parameters in PSO are particle numbers, acceleration, weight of inertia and size of near by particle. r_1, $r_2 \in [0,1]$ -random numbers, w-internal coefficient to control the local and global search. The standard PSO can update the position of the particle using the equation (8)

$$X_i = \begin{cases} 1 & \text{if } rand < s\left(v_i^{t+1}\right) \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

where $s(v_i^{t+1})$ is the sigmoid function that will transform the velocity into the range (0, 1), rand()-random number selected from the distribution in the range [0,1]. The normal fitness function in the equation (9) is used to minimise the classification error during the training process.

$$\text{fitnessfunction } f = \text{Errorrate} = \frac{FP + FN}{TP + TN + FP + FN} \tag{9}$$

3.3 Smart heart disease prediction using SMO-SVM

The support vector machine is proven to be the best classification algorithm for all prediction problems. In this proposed work, sequential minimal optimisation [19] has been used to train the SVM to improve the accuracy of classification result. The linear classification of SVM is in the form represented in equation (10),

$$f(x) = w^T(x) + b \tag{10}$$

Our problem is a binary classification problem, the output is predicted as $y = 1$ if $f(x) >= 0$ and $y = -1$ if $f(x) < 0$. The linear function is also improved with the kernel which is represented as equation (11),

$$f(x) = \sum_{i=0}^{n} \alpha_i y^i \times k\left(x^i, x\right) + b \tag{11}$$

The kernel function

$$k\left(x^i, x\right) = \exp\left(-\frac{\left\|x_i - x\right\|^2}{2\sigma^2}\right) \tag{12}$$

where $\left\|x_i - x\right\|^2$ – squared Euclidean distance, σ – free parameter (not predefined by this model). With this standard SVM, SOM can improve the SVM for binary classification using the equation (13)

$$f'(x) = \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} y^i y^j \alpha_i \alpha_j k\left(x^i, x\right) \tag{13}$$

where $0 \le \alpha_i \le C$,$i = 1, 2 \ldots n$ and $\sum_{i=1}^{n}\alpha_i y^i = 0$

The optimal solution is based on the condition as represented in equation (14),

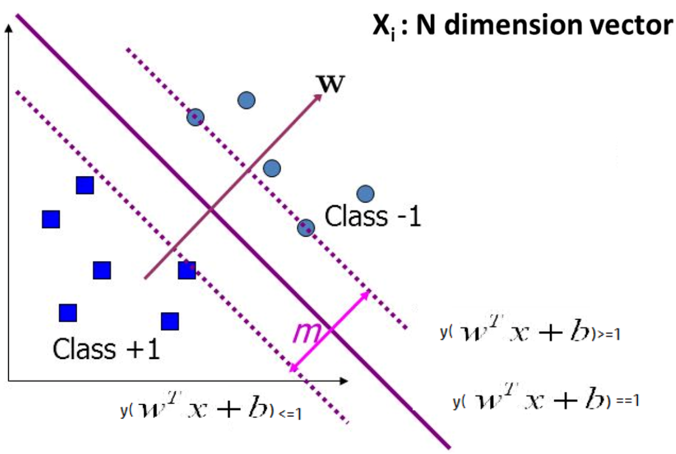
$$\alpha_i = 0 => y^i\left(w^T x^i + b\right) \ge 1$$

$$\alpha_i = C => y^i\left(w^T x^i + b\right) \le 1$$

$$0 \le \alpha_i \le C => y^i\left(w^T x^i + b\right) = 1 \tag{14}$$

The classification of SOM trained SVM is shown in Figure 5 based on the optimal solutions. The input data space is divided using the hyper plane and the decision is based on the SOM based optimal solution conditions.

Figure 5 SMO-SVM classification (see online version for colours)



Algorithm 1 LBPnet-PSO

Input: Input data from wearable IoT devices, preprocessed Diabetes dataset, swarm size *M*, maximum iteration $t_{\max}$, number of features/particle dimension *D*, r_1, r_2,c_1, c_2, *w* and $t = 1$

Output: Heart disease prediction

Step 1: gathered data are preprocessed using the dimensionality reduction technique called Eigen PCA

Step 2: extracting the relevant features using deep LBPnet procedure using the equation (5)

Step 3: Optimal features selection for better diagnosis using PSO

Step 4: while c < tmax do

Step 5: for particle $i = 1$ to M do

Step 6: random initialisation of position X_{id}^{p} with values and velocity vector V_{id}

Step 7: end for

Step 8: for each particle i do

Step 9: Evaluate fitness of each particle using equation (9)

Step 10: end for

Step 11: for $i = 1$ to M do

Step 12: update the pbest of particle i

Step 13: update the gbest of particle i

Step 14: End for

Step 15: for particle $i = 0$ to M do

Step 16: for dimension $D = 0$ to D do

Step 17: change the velocity of particle using equation (6)

Step 18: Update the position of each particle using equation (8)

Step 19: change the position using equation (7)

Step 20: End for

Step 21: End for

Step 22: $t = t + 1$

Step 23: End While

Step 24: return the position of gbest (selected feature subset)

Step 25: prediction of heart disease with patient status using SMO-SVM.

Hence, the proposed smart heart disease diagnosis with wearable IoT devices effort to increase the accuracy of the heart disease prediction system using the optimisation techniques for feature selection and classification will be useful for medical industry to better diagnose of the Heart disease. Compare to the normal data mining and machine learning algorithms, optimisation based improvement will used to select the best features which will leads to improve the classification accuracy.

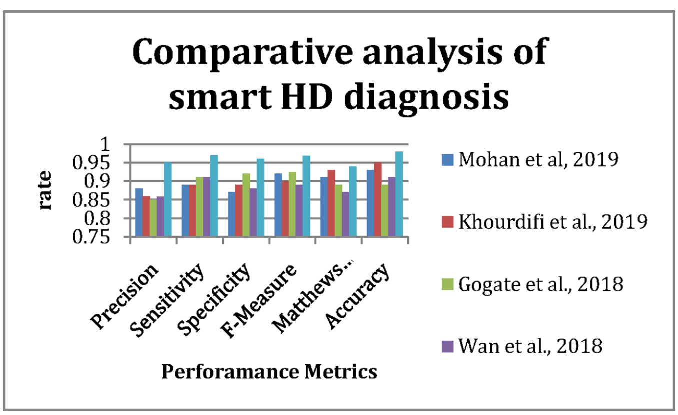
4 Results and discussions

This section discusses about the experimental results which is carried our using Python Sklearn and the proposed method is compared with the other four methods proposed by Mohan et al. [11], Khourdifi et al. [20], Gogate et al. [21] and Wan et al. [22]. For evaluation, the dataset Cleveland heart disease from California university was used in this study [(https://dataverse.harvard. edu/dataset.xhtml?persistentId=doi:10.7910/DVN/QWXVNT]. The database of heart disease is created by Long Beach medical center, Cleveland clinic foundation, and V.A in 1998 [23]. The dataset consists of 303 samples. Among them 300 samples without missing values which consist of 140 positive and 160 negative patients records. This dataset consist of 76 features and all the tests are implemented in 13 features. The positive and negative HD patients are classified separately. The performance analysis is done with the statistical assessment metrics to measure the accuracy of the proposed model and other existing models. The metrics are precision, true positive rate/sensitivity, true negative rate / specificity, classification accuracy, *F* measure and Matthew's correlation coefficient. The results obtained from these metrics for the proposed model with existing models are shown in Table 1.

Table 1 Comparative analysis of proposed model with existing models based on performance metrics

HD prediction models	*Precision*	*Sensitivity*	*Specificity*	*F-measure*	*Matthews correlation coefficient*	*Accuracy*
Mohan et al. [11]	0.88	0.89	0.87	0.92	0.91	0.93
Khourdifi and Bahaj [20]	0.86	0.89	0.89	0.9	0.93	0.95
Gogate and Bakal [21]	0.85	0.91	0.92	0.925	0.89	0.89
Wan et al. [22]	0.858	0.91	0.88	0.89	0.87	0.91
Proposed DLBPNET-PSO	0.95	0.97	0.96	0.968	0.94	0.98

Figure 6 Performance evaluation of HD prediction systems (see online version for colours)



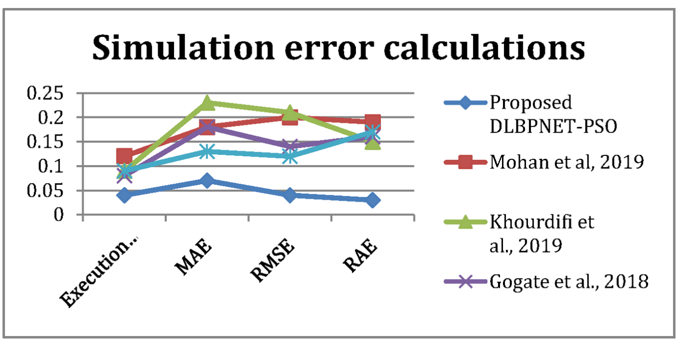
The observed results from the Table 1 shows the performance metrics results of the various HD prediction systems. From the statistics, it is proven that the proposed method outperforms better than other existing approaches. The proposed deep learning with evolutionary method obtains 98% of accuracy on predicting the heart disease patients from the non-heart disease patients. The next best method on predicting the HD is proposed by Khourdifi and Bahaj [20]. The pictorial illustration of these results is shown in Figure 6 for better understanding of the performance of the proposed optimisation based classification algorithm.

Performance evaluation in terms of execution time and error calculation such as Mean absolute error, Root mean square error, and Relative absolute error are calculated and compared with existing approaches which is shown Table 2 followed by illustrated in Figure 7.

Table 2 Simulation error calculations of various HD prediction systems

HD prediction models	*Execution time (s)*	*MAE*	*RMSE*	*RAE*
Proposed DLBPNET-PSO	0.04	0.07	0.04	0.03
Mohan et al. [11]	0.12	0.18	0.2	0.19
Khourdifi and Bahaj [20]	0.09	0.23	0.21	0.15
Gogate and Bakal [21]	0.08	0.18	0.14	0.16
Wan et al. [22]	0.09	0.13	0.12	0.17

Figure 7 Execution time and error calculation (see online version for colours)



From the observation from Figure 7, the proposed deep evolutionary based smart HD diagnosis minimises the error comparatively with existing approaches. The time to train the model and executing also reduced comparatively. The proposed system obtains the execution time of 0.04 s for prediction with the error rate such as MSE, RMSE and RAE are 0.07, 0.04 and 0.03 respectively which is optimally minimum than existing approaches.

Hence, the proposed smart wearable IoT based HD prediction on WSN will diagnose the Heart disease with high accuracy and minimum error. The status about the patients is updated to the nearby hospital, doctor and care taker through smart phone through WSN. This timely update about the patient health monitoring will helps to real time monitoring and early diagnosis of heart attacks and prevent death.

5 Conclusion

We proposed smart wearable IoT based heart disease diagnosis on WSN using deep evolutionary algorithms. The gathered data from the wearable IoT devices of the patients such as temperature, heart rate and ECG are pre-processed. Processed data is further predicted using the proposed deep learning with meta heuristic algorithms, which tends to produce high accuracy and minimum error. This prediction report will be sent to the doctors and caregivers if there is any abnormality detected. The processed data are also stored in cloud and remote servers for hospital access. The proposed design obtained security, correctness, availability, efficiency and accuracy of 98%. This proposed system helps for continuous monitoring of cardiac patients. In future, the proposed system will be extended to monitor elderly people and baby care monitoring with two way communication IoT protocols. The patients can be given suggestion through online from doctors. Error in prediction can be reduced by intelligent algorithm with global optimum solutions.

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References

1 Lancet (2013) *Global, Regional, and National Age-Sex Specific all-Cause and Cause-Specific Mortality for 240 Causes of Death, 1990–2013: A Systematic Analysis for the Global Burden of Disease Study 2013*, Vol. 385, No. 9963, pp.117–171, doi:10.1016/S0140- 6736(14)61682-2.

2 Varatharajan, R., Manogaran, G., Priyan, M.K. and Sundarasekar, R. (2017) ‘Wearable sensor devices for early detection of alzheimer disease using dynamic time warping algorithm’, *Cluster Comput.*, Vol. 6, pp.1–10.

3 Romero, L.E., Chatterjee, P. and Armentano, R.L. (2016) ‘An IoT approach for integration of computational intelligence and wearable sensors for Parkinson’s disease diagnosis and monitoring’, *Health Technol.*, Vol. 6, No. 3, pp.167–172.

4 Pigadas, V., Doukas, C., Plagianakos, V.P. and Maglogiannis, I. (2011) ‘Enabling constant monitoring of chronic patient using android smart phones’, *4th International Conference on Pervasive Technologies Related to Assistive Environments*, ACM, New York, pp.63–64.

5 Piraniy, E.Z., Bulakiwala, F., Kagalwala, M., Kalolwala, M. and Raina, S. (2016) ‘Android based assistive toolkit for alzheimer’, *Procedia Comput. Sci.*, Vol. 79, pp.143–151.

6 Özgür, K., Bromuri, S., Sindlar, M., van der Weide, T., Pelaez, E.A., Schaechtle, U., Alves, B., Zufferey, D., Rodriguez-Villegas, E., Schumacher, M.I. and Stathis, K. (2013) ‘COMMODITY12: a smart e-health environment for diabetes management’, *J. Ambient. Intell. Smart Environ.*, Vol. 5, No. 5, pp.479–502.

7 Bao, L. and Intille, S. (2004) ‘Pervasive computing. Activity recognition from user-annotated acceleration data’, *Proc. Pervasive*, Vol. 3001, pp.1–17.

8 Roy, N., Misra, A. and Cook, D. (2013) ‘Infrastructure-assisted smartphone-based ADL recognition in multi-inhabitant smart environments’, *IEEE International Conference on Pervasive Computing and Communications*, IEEE, San Diego, pp.38–46.

9 Hui, S. and Zhongmin, W. (2017) 'Compressed sensing method for human activity recognition using tri-axis accelerometer on mobile phone', *J. Chin. Univ. Posts Telecommun.*, Vol. 24, No. 2, pp.31–71.

10 Sarmah, S.S. (2020) 'An efficient IoT-based patient monitoring and heart disease prediction system using deep learning modified neural network', *IEEE Access*, Vol. 8, pp.135784–135797, doi: 10.1109/ACCESS.2020.3007561.

11 Mohan, S., Thirumalai, C. and Srivastava, G. (2019) 'Effective heart disease prediction using hybrid machine learning techniques', *IEEE Access*, Vol. 7, pp.81542–81554.

12 ElSaadany, Y., Majumder, A.J.A. and Ucci, D.R. (2017) 'A wireless early prediction system of cardiac arrest through IoT', *Proc. IEEE 41st Annu. Comput. Softw. Appl. Conf. (COMPSAC)*, July, pp.690–695.

13 Khan, M.A. (2020) 'An IoT framework for heart disease prediction based on MDCNN classifier', *IEEE Access*, Vol. 8, pp.34717–34727, doi: 10.1109/ACCESS.2020.2974687.

14 Vijayashree, J. and Sultana, H.P. (2018) 'A machine learning framework for feature selection in heart disease classification using improved particle swarm optimization with support vector machine classifier', *Program. Comput. Soft*, Vol. 44, No. 6, November, pp.388–397.

15 Mutlag, A.A., Abd Ghani, M.K., Arunkumar, N., Mohammed, M.A. and Mohd, O. (2019) 'Enabling technologies for fog computing in healthcare IoT systems', *Future Gener. Comput. Syst.*, Vol. 90, January, pp.62–78, doi: 10.1016/j.future.2018.07.049.

16 Napoléon, T. and Alfalou, A. (2017) 'Pose invariant face recognition: 3D model from single photo', *Opt. Lasers Eng.*, Vol. 89, pp.150–161.

17 Eberhart, R. and Kennedy, J. (1995) 'Particle swarm optimization', *Proc. IEEE Int. Conf. Neural Netw.*, Vol. 4, November, pp.1942–1948.

18 Sharkawy, R., Ibrahim, K., Salama, M.M.A. and Bartnikas, R. (2011) 'Particle swarm optimization feature selection for the classification of conducting particles in transformer oil', *IEEE Trans. Dielectr. Electr. Insul.*, Vol. 18, No. 6, December, pp.1897–1907.

19 Allison, C., Auyeung, B. and Baron-Cohen, S. (2012) 'Toward brief âAIJred ˘ flagsâA˘ ˙I for autism screening: the short autism spectrum quotient and the short quantitative checklist in 1,000 cases and 3,000 controls', *J. Am. Acad. Child Adolesc. Psychiatry*, Vol. 51, No. 2, pp.202–212.

20 Khourdifi, Y. and Bahaj, M. (2019) 'Heart disease prediction and classification using machine learning algorithms optimized by particle swarm optimization and ant colony optimization', *International Journal of Intelligent Engineering and Systems*, Vol. 12, No. 1, pp.18–22.

21 Gogate, U. and Bakal, J. (2018) 'Healthcare monitoring system based on wireless sensor network for cardiac patients', *Biomed. Pharmacol. J.*, Vol. 11, No. 3, Available from: http://biomedpharmajournal.org/?p=22231

22 Wan, J., Al-awlaqi, A.A.H. and Li, M. (2018) 'Wearable IoT enabled real-time health monitoring system', *J. Wireless Commun. Network*, Vol. 298, https://doi.org/10.1186/s13638-018-1308-x

23 Blake, C.L. and Merz, C.J. (2014) *UCI Repository of Machine Learning Databases*, Available from: http://www.ics.uci.edu./~mlearn/ MLReporsitory.html

24 Kannimuthu, S., Somesh, C.K., Mahendhiran, P.D., Bhanu, D. and Bhuvaneshwari, K.S. (2016) 'Certain investigation on significance of internet of things (IoT) and big data in vehicle tracking system', *Indian J. Sci. Technol.*, Vol. 9, No. 39, pp.1–7.

25 Priyadharsini, C. and Kannimuthu, S. (2017) 'Polyhedron model for three dimensional node deployments in underwater sensor network', *J. Comput. Theor. Nanosci.*, Vol. 14, No. 12, pp.5858–5862.

26 Kannimuthu, S., Bhanu, D. and Bhuvaneshwari, K.S. (2020) 'Performance analysis of machine learning algorithms for dengue disease prediction', *J. Comput. Theor. Nanosci.*, Vol. 16, No. 12, pp.5105–5110.

27 Kannimuthu, S., Bhanu, D. and Bhuvaneshwari, K.S. (2020) 'A novel approach for agricultural decision making using graph coloring', *SN Appl. Sci.*, Springer, Vol. 2, No. 31, pp.21–25.