Risk assessment and Health monitoring in WBSN using an optimization-based Deep Learning Model

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Abstract: In monitoring patient's health conditions, the Wireless Body Sensor Networks (WBSNs) play an important role which is a minimum-cost solution to deal with various healthcare applications. Nevertheless, in order to process a huge number of data and creating reasonable decisions in urgent situation scenarios are the most important confronts obsessed by the WBSN. Hence, this research works concentrates on the aforesaid confronts by modeling a deep learning technique for health risk appraisal. Initially, to obtain certain parameters, the WBSN nodes are used to sense data from patient health records to make the assessment. Here, the Hybrid Particle Swarm Optimization (PSO) and Bat Algorithm (BA)are exploited to determine the optimal Cluster Head (CH). Subsequently, the outcomes attained using the proposed model are subjected to the target node for the health risk evaluation, in that the Deep Belief Network (DBN), is exploited to classify the health records. Here, exploiting the Hybrid Sine Cosine Algorithm (SCA) and Cuckoo Search algorithm (CS) (SCA-CS)are exploited to train the DBN to initiate the classification. The developed Hybrid SCA-CS exhibits superior performance by exploiting measures such as energy, accuracy as well as throughput correspondingly.

Keywords: Classification, DBN, Health Record, Optimization Algorithm, WBNS.

Nomenclature

Abbreviations	Descriptions
WSN	Wireless Sensor Networks
SWBs	Secondary Wearable Biosensors
TDMA	Time Division Multiple Access
KNN	K-nearest neighbor
MDE	Model-Driven Engineering
DTs	Decision Trees
WBSNs	Wireless Body Sensor Networks
RBMs	Restricted Boltzmann Machines
IACC	Interference-Aware Congestion Control

1. Introduction

In numerous countries, monitoring the health of aged people is considered one of the main concerns. The preceding year, the aged person was sent to hospitals or nursing homes to offer the treatment and fundamental health care solutions as well as for treatment of health. Nevertheless, it frequently confronts to present the health care due to a large number of expenses because of the effect on life quality [1].

In some circumstances, minimum concentration on the health situation of old aged people is given. In some emergency circumstances, critical treatment can frequently not be presented [2]. These issues can be overwhelmed with the help of current technology in health monitoring that permits the health incessant monitoring in private houses by exploiting the wearable devices. By means of the current technology, the old aged people residues in their house rather than repositioning to expensive old age home. Using event-based monitoring the status of the health is analyzed by means of the health monitoring procedure, and it compares with the health data attained from the wearable sensors in every transmission of data cycle with the data from the preceding cycle. In real-time, the health professional monitors the data at a remote facility. Therefore, the aged person can remains in their house in a safe environment with their family concerns [3].

To present important body function examination, the WSN plays an important role to monitor the health care systems [11]. To monitor the health, the WBSN constant monitor the health circumstances of peoples [10]. They can consist of several kinds within the body as well as ambient which are embedded in the patient. Generally, using the WBSN, the circumstances of the patients are monitored, which comprises cardiac arrhythmia, diabetes, asthma heart activity, and brain activity). By doctors, these parameters can be monitored remotely without affecting the patients' activities. In reality, these systems have considerably reduced the errors of humans, permitting superior considerate of the origins of the disease [4].

From a human body, a WBSN device incessantly monitors the ECG signal. This incessantly monitoring makes extreme data volumes which in order to need a large amount of storage space as well as it acquires larger transmission amount as well as power utilization. In addition, this higher number of data needs additional processing time, which needs to be executed using the processing subsystem of the WBSN device ensuing in a larger amount of power utilization. Hence, the frequency data compression method is used to sparse the encoding of this data. Therefore, sparse encoding of the processing needs to minimize that outcome into minimum power reduction in the processing subsystem.

In some works, the Baysein algorithm was developed to determine the abnormalities, and this was exploited to set down the medicine to the patient. To classify the features, by exploiting the KNN, DTs, naive Bayes, and Bayesian networks to fuse the information.

In this work, to analyze the patient health records, a model for health risk evaluation is presented by exploiting the adopted hybrid SCA-CS-based DBN classifier. Initially, the patient health record is sensed by the WBSN nodes to acquire information such as the patient's id no, sex, age, and chest pain position, etc. Subsequent to sensing the needed parameters, the sensed data to the destination node is transmitted using the WBSN nodes. In the WBSN, to select the optimal CH the hybrid PSO-BA method is exploited. The outcomes produced using the Hybrid PSO-BA are fed to the target node in that the DBN is exploited to classify the patient's health records to analyze the patient's health situations. Moreover, exploiting the novel optimization method called Hybrid SCA-CS is exploits to train the DBN model.

2. Literature Review

In 2020, Long Zhang et al [1], worked on a distributed optimization model of dynamic power optimization through the differential game theory, by in cooperation taking into consideration of use increases as well as a sampling of physiological data quality for every SWBs, to satisfy evolution principle of energy utilization in SWB's battery. Moreover, the differential game model was transformed into two sub-issues, such as effectiveness maximization issue as well as total effectiveness maximization issue.

In 2020, Avrajit Ghosh et al [2], worked on an IoT-based microcontroller stage which was embedded to operate as an end-to-end WBSN system in real-time. In the Time-frequency domain by exploiting the wavelet coefficients, the WBSN possesses the ability to compress the ECG signals through sparse encoding. Moreover, the signal compression models have modeled a two stage method such as the GBM model and WTIT model. Moreover, a method was developed to carry out optimum trade-off amid the signal quality, energy consumption, and bandwidth usage.

In 2019, Qian Yu Xu et al [3], proposed an exponential arbitrary early recognition method was exploited in interactive node to manage congestion by dropping the packet. At the same time, on the basis of the WBSN characteristics, the packet dropping probability was subdivided using the diverse priority traffic. Finally, packet dropping probability of traffic in diverse network environments, priorities as well as queue lengths was attained.

In 2019, K. Dhakal et al [4], worked on the EREEAL approach to minimize the end-to-end delay as well as data losses to enhance the transmission reliability in WBSN. Here, during diverse time slots, the sensor data was transmitted by exploiting the analysis of TDMA and by reducing redundant sensitive data.

In 2017, Ahmed Harbouche et al [5], developed an MDE technique in the WBSN to identify each node's derivation behavior from WBSN global behavior. This technique permits developers to attain the system model from the global requirement of its requirement. The model analysis was represented as the effectual formal techniques to verify the logical correctness of such concurrent systems. Here, a model checking technique was exploited which was on the basis of a model transformation. It was exploited to examine the automatically derived WBSN behavior to monitor health.

3. System Model

Fig 1 demonstrates the architecture diagram of WBSN to monitor the healthcare applications.

The WBSN comprises sensors; the sensor possesses a power unit, memory, processor as well as transceivers, which are embedded in the human body. To sense the information from the human body, the WBSN plays an important role, and also it works to process the attained information and transmits it to CH to aggregate information within the human body. The data gathered using the CH is transferred to the target node, whereas the information is used in the evaluation of the health risk. For furthermore processing as well as transmission, the BS, as well as the control nodes, possesses charge. The WBAN can be controlled by laptops, PDA, or cell phones and the present graphical interface between the users and transmit the healthcare information to the medical server via the internet.

In order to interfere with the medical server, the personal server exploits the mobile networks. The aged peoples who are staying at home can be easily monitored by this. To maintain each registered user's records, the medical server plays an important role and presents numerous services to the health providers as well as users.

Therefore, to authenticate the users, the medical server plays an important role, to update the medical record, and to analyze the data and to verify the health issues, and presents the instructions. Moreover, the doctor, as well as the patients, has the right to use the data from the hospital via the internet as well as to analyze the data and to assure the patient with superior health. The WBAN interfacing is on the basis of the network configuration as well as its management and its steps are stated as follows:

The initial step is the sensor node registration in that the sensor nodes type, and also analyze the number of sensors, subsequent to the customization that includes the operation mode type, sampling frequency specification as well as subsequently starts the secure communication. Subsequent to the WBAN configuration, the health status is attained to the person server and presents the feedback to the users.
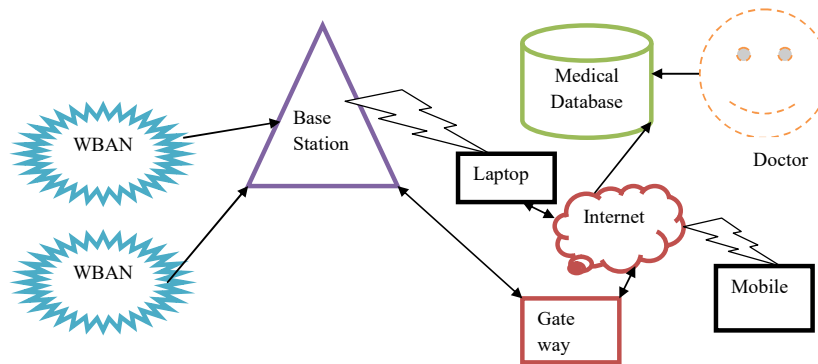
Fig. 1 *Architecture digaram of the WBAN*

4. Developed SCA-CS Based DBN Model

Here, the adopted Hybrid SCA-CS-based DBN is explained in order to analyze the health risks. To train the DBN classifier, the developed technique is a model and also it examines the health risks by exploiting particular parameters to sense the data from patient health records. The novel optimization technique is the hybridization of the SCA and CS [8] algorithm. Initially, to sense the data, the WBSN nodes are exploited by exploiting the patient preceding health records as well as subsequently definite attribute information [7]. To transmit the sensed data to the target node, the WBSN nodes are responsible. Moreover, the hybridization approach called H PSO-BA [6] is exploited to reduce the loss of transmission as well as delay. Subsequently, the H PSO-BA is employed to determine the optimal CH in the WBSN. In addition, using the Hybrid PSO-BA technique the selection of Optimal CH is performed that is fed to the DBN to perform the classification. Moreover, by exploiting the novel Hybrid SCA-CS is used to train the DBN. Hence, the developed technique is liable to analyze the healthcare for the classification in order to estimate the health risks.

4.1 Hybrid PSO-BA method for CHS

In order to convene the energy crisis in the network, the clustering is considered as an effectual process because of the battery-operated sensor nodes. By exploiting the CHS the energy crisis can be identified for that the hybrid optimization algorithm is developed, which aims at clustering the sensors nodes in the environment. The hybrid optimization called H PSO-BA is exploited for the clustering of the nodes so that Cluster Heads are selected via the elucidation of the optimal cluster head attained till now in the preceding iterations. The PSO is exploited to improve the prediction of global optimum by exploiting the

exploitation as well as exploration phases and the BA is used to generate novel solutions. Integrating both PSO and BA enhances the analysis by attaining the global optimal solutions by choosing the optimal CH. In addition, the clustering accuracy is improved as well as the optimal chosen

In addition, the clustering accuracy is improved and best chosen gives a superior CH, in order to extend the network lifetime. The technique functioning is partitioned into rounds. From the nodes, the CHs collect the data and transfer the attained data to the BS in each round.

Initialize the particle location as $[Y_{min}, Y_{max}]$ and fitness function as h, velocity as $[U_{min}, U_{max}]$, and hybrid vector as H and virtual bat as D_m^o. The swarm size and virtual bat are initialized. The proposed model comprises a set of an arbitrary solution comprising m CHs, whereas each row indicates a random solution.

$$\begin{bmatrix} D_1^1 & D_2^1 & \cdots & D_m^1 \\ D_1^2 & D_2^2 & \cdots & D_m^2 \\ \vdots & \vdots & \ddots & \vdots \\ D_1^o & D_2^o & \cdots & D_m^o \end{bmatrix} \begin{bmatrix} h_1 \\ h_2 \\ \vdots \\ h_p \end{bmatrix} = \begin{bmatrix} H^1 \\ H^2 \\ \vdots \\ H^o \end{bmatrix}$$
(1)

To attain the novel bat vector indicates as $[D_1', D_2', \cdots, D_x', \cdots, D_m']$. Moreover, every module of novel harmony vector D_x' is attained by exploiting the formulation as stated as follows,

$$D_x' \leftarrow \begin{cases} D_x' \in P \text{ with prob } z \\ D_x' \in D_x \text{ with prob } (1-z) \end{cases}$$
(2)

whereas, $\text{prob}(z)$ signifies the probability, and $\text{prob}(1-z)$ signifies the probability of selecting a module arbitrarily.

$$D_x' \leftarrow \begin{cases} D_x^n \in P \text{ with prob } K \\ D_x' \text{ with prob } (1-K) \end{cases}$$
(3)

The fitness function formulation is stated as follows,

$$h = \alpha \times h_1 + (1-\alpha) \times h_2$$
(4)

whereas, α signifies scaling factor which ranges in [0, 1], as well as h_1 and h_2 contribute to attaining the fitness function h.

Moreover, h_1 represents the ratio of distance measured amid normal node and CH node to the total nodes and it is devised as,

$$h_1 = \max_m \left\{ \sum_{\forall N_i \in C_m} \frac{D(N_i^N, N_m^C)}{\| T_m \|} \right\}$$
(5)

whereas, N_i^N signifies i^{th} normal node, T_m signifies the number of nodes which be owned by cluster C_m, and N_m^C signifies m^{th} CH.

The function h_2 is stated as the energies measured ratio at i^{th} normal node to the energies measured at x^{th} CH and is devised as,

$$h_2 = \frac{\sum_{i=1}^{Q} E(N_i)}{\sum_{x=1}^{m} E(N_x^C)}$$
(6)

whereas, $E(N_x^C)$ signifies the energy at x^{th} CH as well as $E(N_i)$ signifies the initial energy of ith node. The receiving node as well as transmitting node needed energy for the transmission and they are calculated as,

$$E_T(\mu, D) = \begin{cases} \mu E_e + \mu E_f D^2, D \leq D_o \\ \mu E_e + \mu E_a D^4, D > D_o \end{cases}$$
(7)

whereas, D signifies the distance between the node and CH, E_e signifies electronic energy, μ signifies the data packets (bits) being sent, E_a signifies amplifier energy, and E_f signifies radio amplifier energy for the free space model.

The energy needed to receive the transferred data packets is stated as,

$$E_R = \mu E_e \tag{8}$$

Hence, the optimal solution is signified as J^* is attained by exploiting the devised fitness function. Hence, the optimal location is identified by updating the particle velocity as well as a position by exploiting the best location of CH with minimum fitness.

$$Z_{i,x}(s+1) = y(s)Z_{i,x}(s) + b_1 a_1 (J^*_{i,x} - T_{i,x}(s)) + b_2 a_2 (G^*_{i,x} - T_{i,x}(s)) \tag{9}$$

$$T_{i,x}(s+1) = T_{i,x}(s) + Z_{i,x}(s+1) \tag{10}$$

whereas, $y(s)$ signifies inertia weight factor, $T_{i,x}(s)$ as well as $Z_{i,x}(s)$ signifies the position of the particle in i^{th} position and x^{th} dimension at s , a_1 and a_2 signifies uniform arbitrary values, b_1 and b_2 signifies acceleration constants, $J^*_{i,x}$ and $G^*_{i,x}$ signifies global and local optimal location. The inertia weight factor is minimized to enhance the performance and its value is set as,

$$y(w) = y_j - (y_j - y_d)(\frac{w}{w_{max}}) \tag{11}$$

whereas, w_{max} signifies total iterations as well as w signifies current iteration. Hence, the particle swarm with minimum fitness is represented as J^* as well as an optimal solution from J^* is taken from G^*. Hence, the nodes adjacent to G^* are chosen as CHs. Moreover, for each round, the positions, as well as velocity, are updated by exploiting eq. (9) and (10).

The optimal CHs are derived iteratively till the utmost count of iterations is attained.

4.2 Hybrid SC-CS for CHS based DBN for Classification

To classify the health records the developed Hybrid SC-CS-based DBN classifier is exploited for health risk assessment. Moreover, the Hybrid SC-CS-based DBN is developed by integrating Hybrid SC-CS in the DBN technique, to select the optimal weights in the WBSN. In order to modify the DBN [9] performance, the proposed optimization is aided to choose the optimal weights.

(a) DBN classifier model

The DBN is an element of DNN and comprises diverse layers of MLPs as well as RBMs. RBMs comprise visible as well as hidden units that are connected on the basis of the weighted associations. The MLPs are indicated as the feed-forward networks which comprise input, output, hidden layers. The network with multiple layers can resolve any complex tasks and hence, create the health records classification highly efficient to evaluate the health risks.

By sensing the patient health records, the input is subjected to the visible layer, which is the attribute information obtained and the hidden layer of the first RBM is indicated as,

$$f^1 = \{f^1_1, f^1_2, ..., f^1_e, ..., f^1_m\}; 1 \le e \le m \tag{12}$$

$$L^1 = \{L^1_1, L^1_2, ..., L^1_k, ..., L^1_l\}; 1 \le k \le l \tag{13}$$

whereas, m signifies total features used and $m = 14$, as 14 features are represented for the evaluation, L^1_k signifies the kth hidden neuron as well as l signifies total hidden neurons f'_e signifies the eth visible neuron in the first RBM. The hidden, as well as visible layers comprise neurons, whereas every neuron creates a bias. Consider A signifies the biases in the visible layer and B signifies the biases in the hidden layer and these biases for the first RBM layer is devised as below,

$$A^1 = \{A^1_1, A^1_2, ..., A^1_e, ..., A^1_m\} \tag{14}$$

$$B^1 = \{B^1_1, B^1_2, ..., B^1_k, ..., B^1_l\} \tag{15}$$

whereas, B^1_k signifies the bias in proportion to k^{th} hidden neurons as well as A^1_e signifies the bias in proportion to e^{th} visible neurons. In the first RBM, the weights are used that areindicated as,

$$R^{\mathbf{1}} = \left\{ R_{e,k}^{\mathbf{1}} \right\}; \mathbf{1} \le e \le m; \mathbf{1} \le k \le l \tag{16}$$

whereas, $R_{e,k}^{\mathbf{1}}$ signifies weight amid e^{th} visible neuron and k^{th} hidden neuron. Moreover, the hidden layer output from the first RBM is computed by exploiting weights as well as the bias connected with each visible neuron. This is indicated as,

$$L_k^{\mathbf{1}} = \alpha \left[B_k^{\mathbf{1}} + \sum_e (N_e^c)^{\mathbf{1}} R_{e,k}^{\mathbf{1}} \right] \tag{17}$$

whereas, α signifies activation function. Hence, the output produced from the first RBM is stated as follows,

$$L^{\mathbf{1}} = \left\{ L_k^{\mathbf{1}} \right\}; \mathbf{1} \le k \le l \tag{18}$$

Moreover, the first RBM output is subjected as the input to the visible layer of the next RBM as input. Therefore, the second RBM layer input is indicated as $f^{\mathbf{2}}$. Likewise, the hidden layer of the second RBM is indicated as $L^{\mathbf{2}}$. The bias in the hidden layer and the visible layer is signified as $A^{\mathbf{2}}$ and $B^{\mathbf{2}}$. The $B_k^{\mathbf{2}}$ is the bias connected with the kth hidden neuron and the second RBM weight vector is signified as $R^{\mathbf{2}}$ the kth hidden neuron output is signified as $L_k^{\mathbf{2}}$. Thus, the output produced from the hidden layer is signified as L^2.

The output produced from the hidden layers of the second RBM is fed to MLP as an input, with q input layer. The MLP input layer is indicated as,

$$E = \{E_{\mathbf{1}}, E_{\mathbf{2}}, ..., E_k, ..., E_l\} = \left\{ L_k^{\mathbf{2}} \right\}; \mathbf{1} \le k \le l \tag{19}$$

whereas, l signified the total neurons available in the input layer that is fed by the output of the hidden layer of the second RBM $\left\{ L_k^{\mathbf{2}} \right\}$. The MLP hidden layer is signified as,

$$F = \{F_{\mathbf{1}}, F_{\mathbf{2}}, ..., F_\omega, ..., F_\beta\}; \mathbf{1} \le \omega \le \beta \tag{20}$$

whereas, β signified total hidden neurons. Let ℓ_ω signified the bias of ω hidden neuron, whereas $\omega = \mathbf{1}, \mathbf{2}, ..., \beta$. The MLP output layer is devised as,

$$S = \{S_{\mathbf{1}}, S_{\mathbf{2}}, ..., S_C, ..., S_I\}; \mathbf{1} \le C \le I \tag{21}$$

whereas, I signified the total neurons available in the output layer. MLP represents two weight vectors, one amid the hidden as well as the input layer, and the other amid the output as well as the hidden layer. Presume R^γ signified the weight vector amid hidden as well as input layer is signified as,

$$R^\gamma = \left\{ R_{k\omega}^\gamma \right\}; \mathbf{1} \le k \le l; \mathbf{1} \le \omega \le \beta \tag{22}$$

whereas, $R_{k\omega}^\gamma$ signified the weight amid k^{th} neuron and ω^{th} hidden neuron. The hidden layer output is calculated as,

$$F_\omega = \left[\sum_{k=\mathbf{1}}^{l} R_{k\omega}^\gamma * E_k \right] l_\omega \forall E_k = L_k^{\mathbf{2}} \tag{23}$$

whereas, E_k signifies the kth MLP input layer. The weights amid hidden and output layer are stated as R^L and are signified as,

$$R^L = \left\{ R_{\omega C}^L \right\}; \mathbf{1} \le \omega \le \beta; \mathbf{1} \le C \le I \tag{24}$$

Hence, by the weights R^L, the output vector is computed and hidden layer output and is signified as,

$$S_C = \sum_{\omega=\mathbf{1}}^{\beta} R_{\omega C}^L * F_\omega \tag{25}$$

where, $R_{\omega C}^L$ signified the weight amid c^{th} output neuron and ω^{th} hidden neuron, F_ω signified hidden layer output.

b) Proposed Hybrid SC-CS model
The training process of the developed Hybrid SC-CS-based DBN classifier and is done by presenting the training data. Here, the Hybrid SC-CS is used to calculate the optimal weights that are calculated by exploiting an error function. The hybrid SC and CS is the hybridization of SC and CS [8].

The proposed method uses the advantages of both the SCA and CS algorithm to overwhelm the disadvantages of the method and assure the global convergence properties.

$$\text{Fun} = \alpha * \text{ErrRate}(d) + \beta(L/T)$$

(26)

Where, L indicates the current weights, α are a real value fit in [0,1] range, $\text{ErrRate}(d)$ indicates the error rate, α, β represents the constant parameters which are exploited to control the performance, T indicates the weight at the current iteration.

5. Result and Discussions

In this section, the analysis outcomes of the developed and conventional techniques on the basis of the performance measures were demonstrated and the value of the technique is calculated via the performance analysis. For the analysis, the measures are used such as energy, accuracy as well throughput. From the UCI machine, the analysis was carried out. Here, the proposed method was compared with the conventional models such as PSO, CS and BA approaches.

Fig 2,3 and 4 demonstrate the analysis outcomes of the conventional and developed techniques based on the measures considering a maximum number of rounds and training learning percentage. In Fig 2, the proposed model is 30% better than the PSO, 12% better than the CS and 10 % better than the BA for 40 learning percentage regarding accuracy. The proposed model is 40% better than the PSO, 29% better than the CS and 18 % better than the BA for 500 rounds regarding energy and it is exhibited in Fig 3. In Fig 4, the proposed model is 22% better than the PSO, 15% better than the CS and 13 % better than the BA for 40 learning percentage regarding throughput. Finally, the outcomes show the performance is computed for the developed model with the conventional models regarding the energy. The developed model attain maximum performance with energy, throughput, and accuracy respectively.
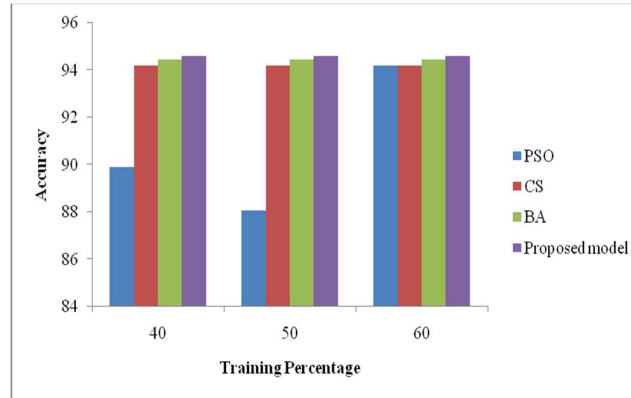
Fig. 2 *Performance analysis of the proposed model regarding the accuracy*
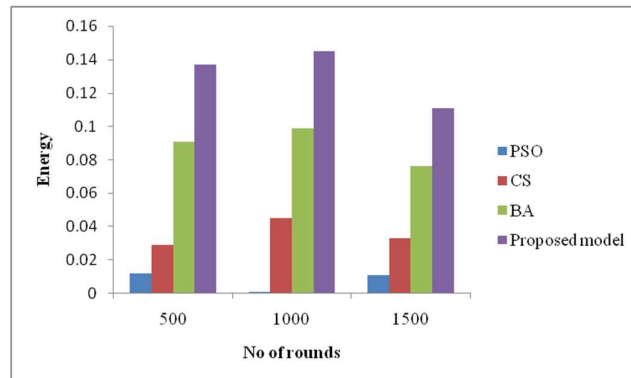
Fig. 3 *Performance analysis of the proposed model regarding energy*
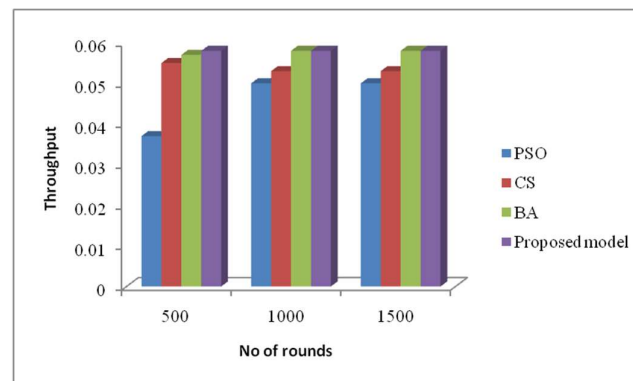
Fig. 4*Performance analysis of the proposed model regarding Throughput*

6. Conclusion

In this work, a Hybrid SCA-CS algorithm was developed for the DBN classifier training to analyze the health conditions of the patients. At first, to sense the data, the WBSN was used from the patient health records to obtain particular parameters to make the evaluation. On the basis of the attained parameters, to the target node, the WBSN nodes transmit the data. Moreover, the hybrid PSO-BA methods were exploited to determine the optimal CH. Subsequently, the outcomes attained using the PSO-BA was subjected to the target node, in that the Hybrid SCA-CS was used to classify the health records to analyze the health condition of the patients. The overall analysis exhibits the superiority of the proposed model with the conventional techniques.

Compliance with Ethical Standards

Conflicts of interest: Authors declared that they have no conflict of interest.

Human participants: The conducted research follows the ethical standards and the authors ensured that they have not conducted any studies with human participants or animals.

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