Multi-objective Chaotic Butterfly Optimization with Deep Neural Network based Sustainable Healthcare Management Systems

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Abstract

Sustainable healthcare systems are developed to priorities healthcare services involving difficult decision-making processes. Besides, wearables, internet of things (IoT), and cloud computing (CC) concepts are involved in the design of sustainable healthcare systems. In this study, a new Multi-objective Chaotic Butterfly Optimization with Deep Neural Network (MOCBOA-DNN) is presented for sustainable healthcare management systems. The goal of the MOCBOA-DNN technique aims to cluster the healthcare IoT devices and diagnose the disease using the collected healthcare data. The MOCBOA technique is derived to perform clustering process and also to tune the hyperparameters of the DNN model. Primarily, the clustering of IoT healthcare devices takes place using a fitness function to select an optimal set of cluster heads (CHs) and organize clusters. Followed by, the collected healthcare data are sent to the cloud server for further processing. Furthermore, the DNN model is used to investigate the healthcare data and thereby determine the presence of disease or not. In order to ensure the betterment of the MOCBOA-DNN technique, an extensive simulation analysis take place. The experimental results portrayed the supremacy of the MOCBOA-DNN technique over the other existing techniques interms of diverse evaluation parameters.

Keywords: Sustainability, Healthcare system, Clustering, Deep learning, Disease diagnosis, CH Selection.

1. Introduction

Recently, the medical fields have presented a dramatic increase and largest contributors to employment and revenue [1, 2]. Some years earlier, the diagnoses of disease and anomaly in the human body have been promising afterward possessing physical analyses in the clinic. Most patients have to stay in the medical institution through their process time. This resulting in improved medical costs as well as strain on the medical capability at remote and rural places. The technical development was attained by this year has currently permitted the diagnoses of several diseases and healthcare observing by means of reduced devices such as smartwatch. Fig. 1 shows the cycle of sustainable healthcare system. Furthermore, technologies have changed a hospital centric medical scheme to a patient's centric scheme [3, 4]. E.g., numerous medical analyses (like calculating blood glucose level, blood pressure, level, pO2, etc) are executed at home with no other help of medical experts. Furthermore, the medical information could have interacted with medical centers from remote regions by an innovative telecommunication service. The usage of these transmission facilities in combination with exponentially developing techniques [5-7] (like big data analysis, machine learning, wireless sensing, Internet of things (IoT), cloud computing, and mobile computing) have enhanced the availability of the medical facility. IoTs have improved

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independence as well as expanded the capability of humans to communicate through the exterior environments. IoT, using futuristic algorithms and protocol, developed the largest contributors to worldwide communications. It connects a huge amount of wireless sensors, devices, electronic devices, and home appliances to the Internet [8, 9].

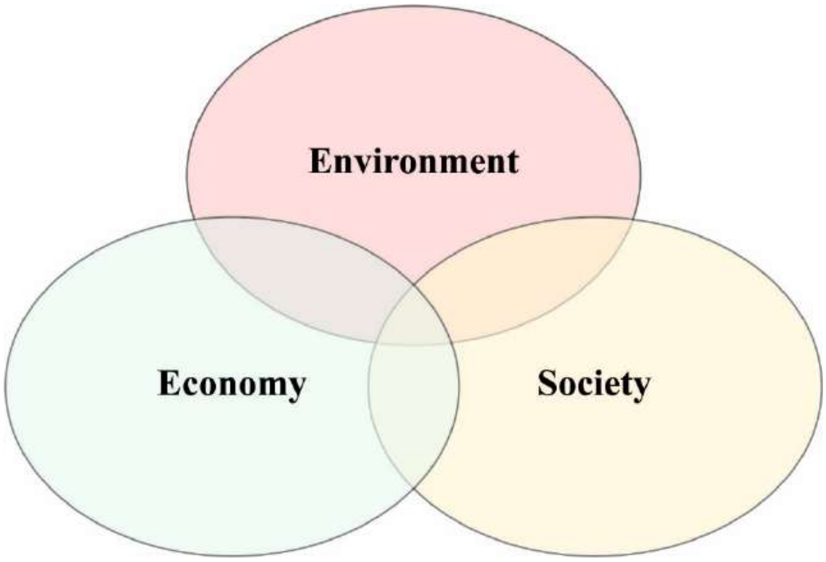

Fig. 1. Cycle of Sustainability

Currently, the cloud based IoT platform is used extensively in intelligent remote medical and health observing systems [10]. The integration of IoT and cloud have various advantages from resources managing aspects like robust handling, resources sharing, support users mobility in monitoring system and avoid from information destruction on many datasets [11]. A recent remote healthcare observing scheme in cloud based IoT environments includes contexts where the patient's information is stored as well as transmitted in cloud, also distributed to the purposes of attaining analysis from everywhere [12]. Because of the transmitting of the patients' healthcare information via the IoT network and store them in the cloud, the security and confidentiality problems have turn into critical concerns in this system [13]. Hence, apply information security methods like light weighted block encryption approaches for limited healthcare IoT resources appears to be a vital requirement for secure and safe health and medical information managing as significant problems in limited IoT platforms in crucial systems. In order to attain diagnosis data to predict the patients' healthcare anomalous variations, mining information method is extensively employed in healthcare observing system includes clustering and classification approaches, NN, and another method according to distinct ML methods [14].

In [15], a diagnosis predictions method for CKD and its seriousness are presented which employs IoT multi-media information. As the impacting characteristics on CKD are huge as well as the amount of the IoTs multi-media information are generally larger, electing distinct characteristics depends on physicians medical experiences and observations along with prior researches for CKD in distinct sets of multi-media datasets are performed for assessing the efficiency measure of CKD predictions and phase determinations through distinct classifier methods.

Bharathi et al. [16] introduce an EEPSOC method for the efficient election of CHs amongst different IoTs devices. The selected CHs would transmit the information to the cloud servers. Next, the CHs are accountable to transmit information of the IoT device to the cloud server via fog device. Then, ANN based classifier models are employed for diagnosing the medical information in the cloud servers for identifying the seriousness of the disease. In [17], a remote healthcare observing system employs a light weighted block encryption technique to provide safety for medical and health information in cloud based IoT environments are proposed. In these methods, the patient healthcare status is defined by forecasting serious situations via mining information method to analyze their Janakiraman

In this study, a new Multi-objective Chaotic Butterfly Optimization with Deep Neural Network (MOCBOA-DNN) is designed for sustainable healthcare management systems. The goal of the MOCBOA-DNN technique aims to cluster the healthcare IoT devices and diagnose the disease using the collected healthcare data. The MOCBOA technique is derived to perform clustering process and also to tune the hyperparameters of the DNN model. In addition, the DNN model is used to investigate the healthcare data and thereby determine the presence of disease or not. In order to ensure the betterment of the MOCBOA-DNN technique, an extensive simulation analysis take place.

2. The Proposed Model

The proposed MOCBOA-DNN technique intends to perform clustering of the healthcare IoT devices and diagnose diseases. Firstly, the clustering of IoT healthcare devices takes place using a fitness function to select an optimal set of cluster heads (CHs) and organize clusters. Secondly, the collected healthcare data are sent to the cloud server for further processing. Finally, the DNN model is used to investigate the healthcare data and thereby determine the presence of disease or not.

2.1 Optimal Clustering Process

BOA has been new speed optimized techniques with minimal processing difficulty and optimum solving convergence. This technique has been progressed by butterflies' food exploring performance. The butterflies are kinds of insects with different abilities namely hearing, smelling, and taste with use of defining appropriate nectar, partner mating, and egg laying from adoptable places and escape an attacker [18]. The process contained in the BOA is given in Algorithm 1. The fragrance in BOA has been categorized as to three parts as provided under Power exponent (a), Sensory modality (c), and Stimulus intensity (I). The power is an exponent utilized to select essential density that leads to linear response, regular, and response compression. Otherwise, sensory was determined as the procedure of energy but modality determines the implemented input by sensor. The elements of butterflies were established by 2 important issues: the variance of fragrance (f) and stimulus intensity (I). It can be written as provided in the subsequent:

$$f = cI^{\beta} \tag{1}$$

where, and β c are in range 0 and 1. The effort of butterfly has been collected to three important stages provided as Initialization, Searching, and Finalizing. Once the parameter is set the optimized method was introduced. An initial place of butterfly is created from arbitrary approach in solution space. Once the iteration was modified, artificial butterflies existing in explore space migrate to novel places and attained the cost value. Afterward, the butterfly generates a fragrance from the similar places as provided:

$$x_i^{t+1} = x_i^t + (r^2 \times g^* - x_i^t) \times f_i \tag{2}$$

where g* illustrates the optimum solutions to iteration t, x_i^t determines the solution vectors x_i to i^{th} butterflies, fragrance of i^{th} butterflies are denoted as and f_i and r illustrate the arbitrary constant in 0 and 1. The BOA parameters, together with partner mating and food explore of butterflies are applied from global as well as local scales. The local search from this technique is obtained as given under:

$$x_i^{t+1} = x_i^t + \left(r^2 \times x_j^t - x_k^t\right) \times f_i \tag{3}$$

The BOA technique is attained optimum results from exploring optimal measures that are the limit from the convergence. During the method, a novel manner was proposed for changing the needed metrics of BOA with respect to convergence speed. For resolving these problems, the vector of main parameters to BOA is provided as $V = [a, c, r]$ which is based on chaos theory. The chaos science has been mentioned that the learning tasks are arbitrary and unpredictable. It can be extremely utilized from maximal sensation which obtains affected by minimal modifications. The feature produces point with superior distribution and resolve difficulty for enhancing the point distribution. The general design to chaos theory has been demonstrated as:

$$V_{i+1}^j = f\left(V_i^j\right), j = 1,2, \dots, l \tag{4}$$

Where, l implies the map dimensional, and $f\left(V_i^j\right)$ represents the chaotic system generator. At this point, the logistic mapping is implemented as:

$$a_{k+1} = \rho a_k(1 - a_k) \tag{5}$$

$$c_{k+1} = \rho c_k(1 - c_k) \tag{6}$$

$$r_{k+1} = \rho r_k(1 - r_k) \tag{7}$$

Where, k signifies the iteration values, $a_0, c_0, r_0 \in [0,1]$ is the primary arbitrarily measures, and ρ indicates the controlling parameter from the interval of $\rho \in [0,1] - [0.25, 0.5, 0.75]$. It can be noted that $\rho = 4$, the function should be considered that N nodes from the network label K cluster with $\mathrm{M}(\mathrm{K} << M)$ candidate CH. Next, the $\mathrm{C}_\mathrm{n}^\mathrm{k}$ possible cluster approaches as well as chooses an optimum clustering method is called as optimized problem. During the executing CBOA FF for resolving an optimum cluster technique, this technique of FF is to consider the local density of CH, the maximal distance inside the cluster, and power dissipation of nodes from the clusters. Therefore, the managing of uneven network clusters was affected because of CH dispersion. Primarily, the cloud server evaluates the maximal power of all nodes on the fundamental energy data in the network. The node that Residual Energy (RE) is superior if related to maximal energy considered as candidate CH of existing round. The BS applies the CBOA technique for computing an optimum cluster for identifying superior FF measures as shown in Eq. (8).

$$\mathrm{f(x)} = \varepsilon_1 \mathrm{f}_1(\mathrm{p_j}) + \varepsilon_2 \mathrm{f}_2(\mathrm{p_j}) + \varepsilon_3 \mathrm{f}_3(\mathrm{p_j}) + \varepsilon_4 \mathrm{f}_4(\mathrm{p_j}) \,. \tag{8}$$

Algorithm 1: Pseudo Code of BOA

```
Objective function f(x), x= (x1, x2…, xd)
Create the population of n butterflies xi= (i=1, 2…, n)
Representing sensor modality c, power exponents a, and switch probabilities p
while end criteria were unsatisfied do
for all butterflies bf in population do
    Estimate the fragrance
end for
Define optimal bf
  for all butterflies bf from population do
        Create an arbitrary number of rand in 0 and 1
        if rand < p then
              Moves nearby the optimum butterfly
        else
              Move arbitrarily
        end if
        Evaluate a novel butterfly
        When the novel one is optimum, then upgrade the population
  end for
  Upgrade the value of c
  Explore the current global optimum butterfly
end while
Show the reached better solutions
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2.2 Optimal Disease Diagnosis Process

The optimal DNN model with MOCBOA based hyperparameter tuning process is applied to classify the medical data. The presented DNN depends on analysis and forecast method was utilized in find disease and calculates the severity level. The benefits of this technique were selecting an important parameter and categorizing medicinal information dependent upon time limitations for utilizing an effectual decision. The ANN has been supposed a computational intelligence technique which appeared in the scheme of biological neurons for solving the forecast challenges, NLP, and drug recognition. The DNN is a particular level of difficulty, NN that is enormous layers. A DNN executes the complex arithmetical approach in calculating the data. Therefore, the NN has gained a performance from tedious application for finding the pattern from end decades. The DNN has been collected of input layers to actual descriptor X_l, L hidden layer, and outcome layer to data forecast. The output layer was dependent upon softmax functions, and the cost function is called cross-entropy [19]. The rectifier is supposed that activation function as provided in Eq. (9):

$$F(x) = x^+ = \max(0, x) \tag{9}$$

where x implies the input. It can be termed as ramp function which is similar to half-wave rectification calculation. The unit that executes the rectifier is termed ReLU.

$$f(x) = \ln [1 + \exp(x) \tag{10}$$

It is called a softplus function. But investigating with forecast model, a new representation of actual descriptor was removed in hidden layer as provided in the subsequent:

$$X_{t+1} = H(W_l X_l + B_l) \qquad l = 1, \dots, L \tag{11}$$

where W_l and B_l refers the weight matrix as well as biasing l^{th} hidden layers and H represents the related activation functions.

3. Performance Evaluation

The MOCBOA-DNN technique is implemented using MATLAB tool. The results are investigated under varying number of instances with different evaluation parameters.

A detailed sensitivity analysis of the MOCBOA-DNN technique takes place in Table 1 and Fig. 2. From the attained results, it is exhibited that the MOCBOA-DNN technique has resulted in proficient results with higher sensitivity values over the other methods. With 2000 instances, the MOCBOA-DNN technique has depicted an increased sensitivity of 0.951 whereas the KNN-CA, NB-CA, SVM-CA, DT-CA, and OANN-CA techniques have obtained a reduced sensitivity of 0.926, 0.879, 0.832, 0.933, and 0.948. Moreover, with 6000 instances, the MOCBOA-DNN manner has demonstrated an enhanced sensitivity of 0.957 whereas the KNN-CA, NB-CA, SVM-CA, DT-CA, and OANN-CA methods have reached a lower sensitivity of 0.932, 0.864, 0.839, 0.936, and 0.956. Eventually, with 10000 instances, the MOCBOA-DNN manner has showcased a superior sensitivity of 0.981 whereas the KNN-CA, NB-CA, SVM-CA, DT-CA, and OANN-CA methodologies have attained lower sensitivity of 0.936, 0.891, 0.842, 0.960, and 0.979.

Table 1 Comparative analysis of MOCBOA-DNN technique interms of sensitivity

No. of Instances	KNN-CA	NB-CA	SVM-CA	DT-CA	OANN-CA	MOCBOA-DNN
2000	0.926	0.879	0.832	0.933	0.948	0.951
4000	0.884	0.846	0.824	0.923	0.950	0.954
6000	0.932	0.864	0.839	0.936	0.956	0.957
8000	0.924	0.886	0.824	0.969	0.972	0.977
10000	0.936	0.891	0.842	0.960	0.979	0.981

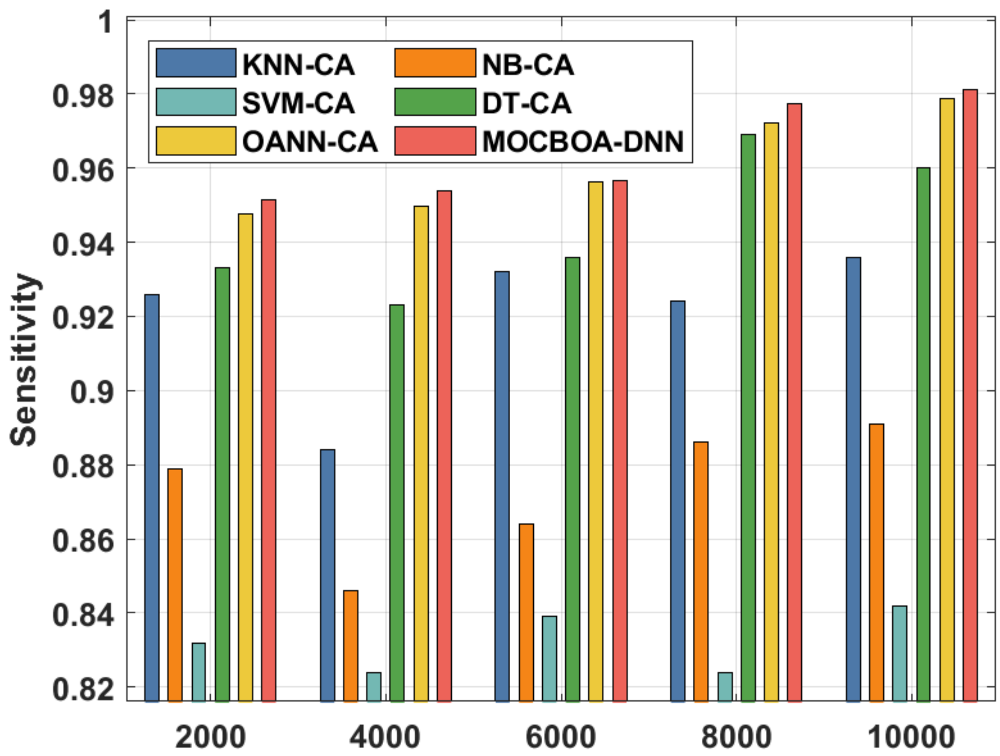

Fig. 2. Comparative sensitivity analysis of MOCBOA-DNN technique

Table 2 Comparison study of MOCBOA-DNN technique interms of specificity

No. of Instances	KNN-CA	NB-CA	SVM-CA	DT-CA	OANN-CA	MOCBOA-DNN
2000	0.842	0.834	0.802	0.926	0.943	0.945
4000	0.861	0.836	0.821	0.912	0.935	0.938
6000	0.873	0.869	0.834	0.924	0.949	0.949
8000	0.883	0.821	0.784	0.886	0.924	0.935
10000	0.893	0.864	0.843	0.904	0.924	0.938

Comprehensive specificity analysis of the MOCBOA-DNN manner takes place in Table 2 and Fig. 3. From the obtained outcomes, it can be demonstrated that the MOCBOA-DNN approach has resulted in proficient results with higher specificity values over the other techniques. With 2000 instances, the MOCBOA-DNN manner has exhibited a superior specificity of 0.945 whereas the KNN-CA, NB-CA, SVM-CA, DT-CA, and OANN-CA techniques have obtained a decreased specificity of 0.842, 0.834, 0.802, 0.926, and 0.943. In line with, with 6000 instances, the MOCBOA-DNN technique has portrayed an increased specificity of 0.949 whereas the KNN-CA, NB-CA, SVM-CA, DT-CA, and OANN-CA techniques have obtained a reduced specificity of 0.873, 0.869, 0.834, 0.924, and 0.949. Also, with 10000 instances, the MOCBOA-DNN technique has depicted an enhanced specificity of 0.938 whereas the KNN-CA, NB-CA, SVM-CA, DT-CA, and OANN-CA methods have gained a minimum specificity of 0.893, 0.864, 0.843, 0.904, and 0.924.

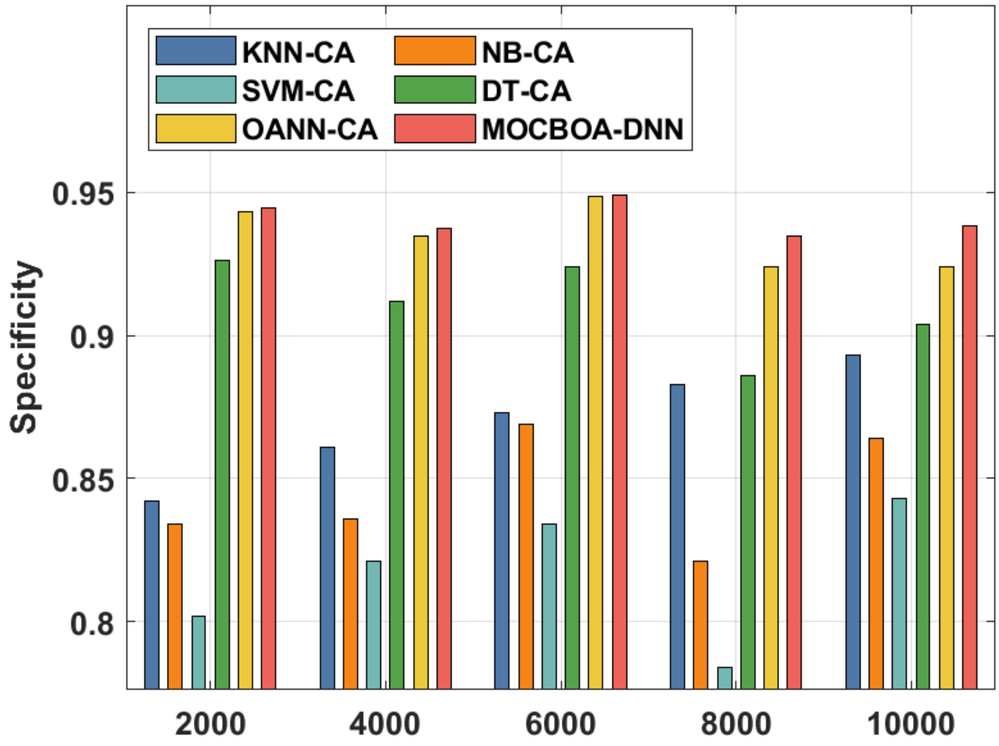

Fig. 3. Comparative specificity analysis of MOCBOA-DNN technique

Table 3 Comparative Accuracy Analysis of MOCBOA-DNN with existing techniques

No. of Instances	KNN-CA	NB-CA	SVM-CA	DT-CA	OANN-CA	MOCBOA-DNN
2000	0.894	0.768	0.734	0.916	0.935	0.940
4000	0.913	0.786	0.777	0.924	0.943	0.952
6000	0.876	0.778	0.756	0.904	0.935	0.950
8000	0.864	0.801	0.784	0.932	0.949	0.958
10000	0.893	0.824	0.816	0.928	0.942	0.954

Brief accuracy analysis of the MOCBOA-DNN method takes place in Table 3 and Fig. 4. From the reached results, it is portrayed that the MOCBOA-DNN method has resulted in proficient results with higher accuracy values over the other methods. With 2000 instances, the MOCBOA-DNN algorithm has showcased a maximum accuracy of 0.940 whereas the KNN-CA, NB-CA, SVM-CA, DT-CA, and OANN-CA techniques have reached a lesser accuracy of 0.894, 0.768, 0.734, 0.916, and 0.935. Followed by, with 6000 instances, the MOCBOA-DNN algorithm has demonstrated a higher accuracy of 0.950 whereas the KNN-CA, NB-CA, SVM-CA, DT-CA, and OANN-CA techniques have gained a lesser accuracy of 0.876, 0.778, 0.756, 0.904, and 0.935. Finally, with 10000 instances, the MOCBOA-DNN approach has depicted an enhanced accuracy of 0.954 whereas the KNN-CA, NB-CA, SVM-CA, DT-CA, and OANN-CA methodologies have achieved a minimal accuracy of 0.893, 0.824, 0.816, 0.928, and 0.942.

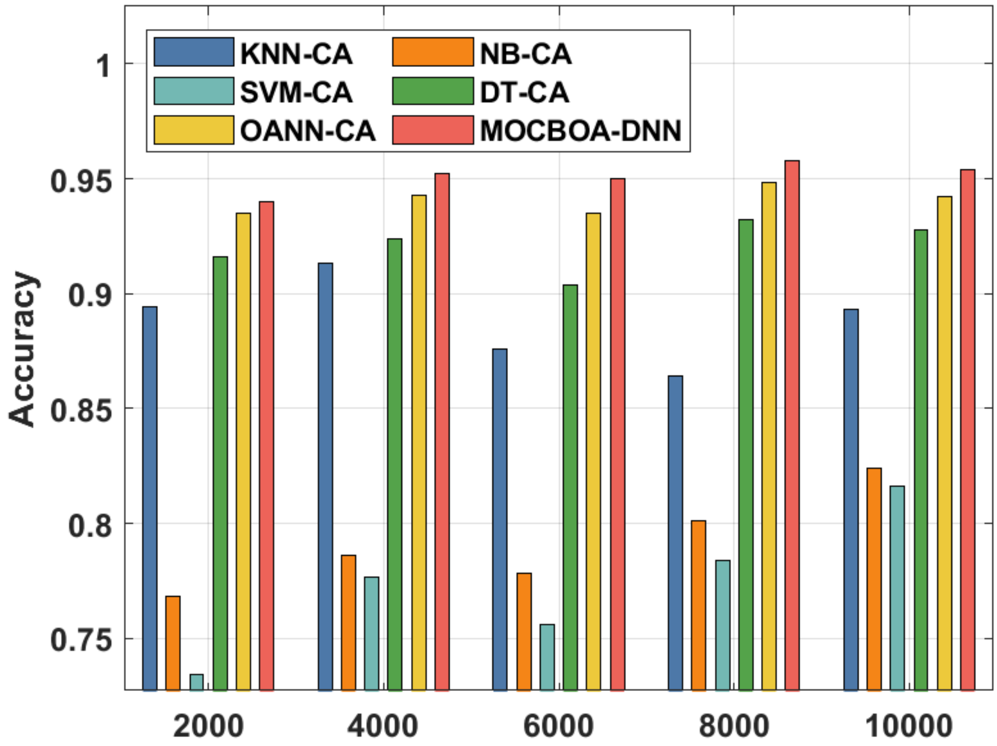

Fig. 4. Comparative accuracy analysis of MOCBOA-DNN technique

Table 4 and Fig. 5 investigates the TEC analysis of the MOCBOA technique under distinct node count. The results implied the energy efficient performance of the MOCBOA technique under all node count. For instance, with 100 nodes, the MOCBOA technique has accomplished a lower energy consumption of 43% whereas the EEPSOC, ABC, GWO, and ACO techniques have offered a higher energy consumption of 48%, 60%, 63%, and 69% respectively. Also, with 200 nodes, the MOCBOA approach has accomplished a minimal energy consumption of 46% whereas the EEPSOC, ABC, GWO, and ACO methods have accessible a superior energy consumption of 54%, 64%, 71%, and 76% correspondingly. Besides, with 300 nodes, the MOCBOA system has accomplished a decreased energy consumption of 55% whereas the EEPSOC, ABC, GWO, and ACO methodologies have offered a superior energy consumption of 61%, 69%, 75%, and 79% correspondingly. Likewise, with 400 nodes, the MOCBOA approach has accomplished the least energy consumption of 55% whereas the EEPSOC, ABC, GWO, and ACO manners have obtainable an enhanced energy consumption of 66%, 74%, 78%, and 83% respectively. Similarly, with 500 nodes, the MOCBOA technique has accomplished a decreased energy consumption of 60% whereas the EEPSOC, ABC, GWO, and ACO techniques have existing maximal energy consumption of 71%, 80%, 85%, and 86% correspondingly.

Table 4 Comparative TEC Analysis of MOCBOA technique under diverse nodes

Number of Sensors	MOCBOA	EEPSOC	ABC	GWO	ACO
100	43	48	60	63	69
200	46	54	64	71	76
300	55	61	69	75	79
400	55	66	74	78	83
500	60	71	80	85	86

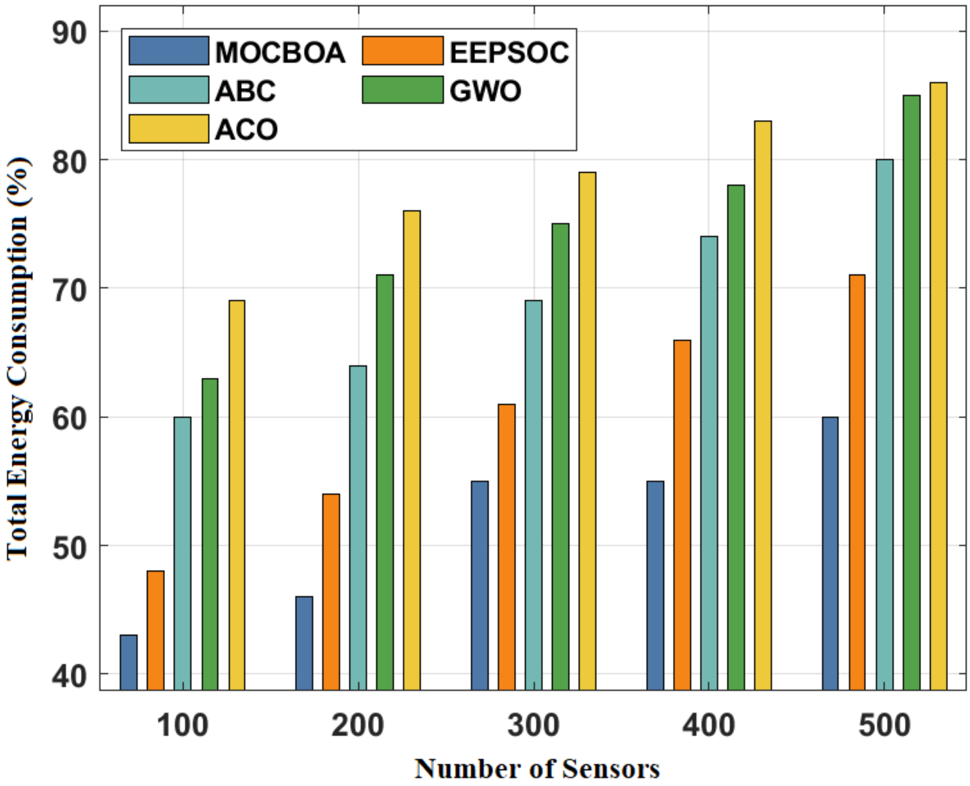

Fig. 5. Comparative ETC analysis of MOCBOA technique

4. Conclusion

In this study, a new MOCBOA-DNN technique is developed for sustainable healthcare management systems. The goal of the MOCBOA-DNN technique aims to cluster the healthcare IoT devices and diagnose the disease using the collected healthcare data. The MOCBOA technique is derived to perform clustering process and also to tune the hyperparameters of the DNN model. Primarily, the clustering of IoT healthcare devices takes place using a fitness function to select an optimal set of CHs and organize clusters. Followed by, the collected healthcare data are sent to the cloud server for further processing. Furthermore, the DNN model is used to investigate the healthcare data and thereby determine the presence of disease or not. In order to ensure the betterment of the MOCBOA-DNN technique, an extensive simulation analysis take place. The experimental results portrayed the supremacy of the MOCBOA-DNN technique over the other existing techniques interms of diverse evaluation parameters. In future, the DNN model can be replaced with other DL models to enhance the diagnostic performance.

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