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Swarm Spider Optimization with Machine Learning based Disease Detection on Blockchain Assisted Healthcare Environment

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Abstract: **-** Blockchain (BC) and artificial intelligence (AI) technologies are innovations in healthcare field. Over the last decade, BC technology was developing at a considerable rate of growth. It presented as the strength of cryptocurrencies like Bitcoin, it quickly establish its application in other domains due to its privacy and security features. BC was utilized in the medical field for various drives involving maintenance, secured data logging, and transactions utilizing smart contracts. An excellent work is conducted to make BC smart, with the combination of AI to synthesize the better features of two technologies. This study designs a new Swarm Spider Optimization with Machine Learning based Disease Detection on Blockchain Assisted Healthcare Environment (SSOML-DDBHE) technique. The presented SSOML-DDBHE technique exploits BC technology for accurate identification of diseases in the healthcare environment. In the SSOML-DDBHE technique, the SSO algorithm is used for selecting feature subsets. For disease detection, the SSOML-DDBHE technique employs extreme learning machine (ELM) model. The ELM Parameters are adjusted using the Bayesian optimization (BO) algorithm at last. To achieve security, blockchain technology is used. The SSOML-DDBHE method is being experimentally analyzed using a benchmark dataset for heart disease. The comprehensive outcome highlighted the superior performance of the SSOML-DDBHE algorithm over recent approaches.

Keywords: Artificial intelligence; Machine learning; Swarm spider optimization; Healthcare; Feature selection .

I. Introduction

The smart healthcare system received increased attention as the healthcare structure was further developed. Smart health care is a new idea that indicates a set of rules that incorporate management, diagnosis treatment, and prevention [1]. Dissimilar to conventional healthcare systems, smart healthcare systems can exchange and link data at any place and time. Smart health care includes the features of interconnection, preventability, and immediacy of data compared with conventional medical treatment using wireless networks, utilizing mobile gadgets [2], health care personnel can continually analyse, observe, and process clinical events. Clinicians can grab the case data of all patients at any time and rapidly advance a treatment and diagnosis plan [3]. BC followed privacy rules for detecting users relevant to transactions. It can be utilized for managing information systems to help achieve process automation, safe storage, transactions, and other applications [4]. In healthcare, ML was an important technology to perform complicated analysis, creative problem solving, and intelligent judgment [5].

To achieve patient-centricity and advance medical research [6], it uses technology for creating user- and customer-centric interface and data-driven decision for new data processing methods and superior outcomes [7]. For instance, artificial intelligence (AI) can help prioritize and detect patients for drug growth and monitoring, critical for managing drug production and short time frames. The success of dose measurement and medication formulations, and clinical trial data was monitored with the help of numerical drug design techniques and AI For repurposing marketed medication [8]. Due to these quickly evolving climates, governments should detect the potential means to use resources and drive reform while assuring essential constancy, data protection or compliance [9].

Safety measures in e-Health are presented by blockchain (BC) and AI. BC helps in the formation of a mechanism that manages and develops content block called ledger, with automated and safe data analysis. Every health-

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relevant data is securely analysed and recorded, permitting clinical experts, health care providers, to get updates on time [10].

This study designs a new Swarm Spider Optimization with Machine Learning based Disease Detection on Blockchain Assisted Healthcare Environment (SSOML-DDBHE) technique. The presented SSOML-DDBHE technique exploits BC technology for accurate identification of diseases in the healthcare environment. In the SSOML-DDBHE technique, the SSO algorithm is used for selecting feature subsets. For disease detection, the SSOML-DDBHE technique employs extreme learning machine (ELM) model. The ELM Parameters are adjusted using the Bayesian optimization (BO) algorithm at last. To achieve security, blockchain technology is used. The SSOML-DDBHE method is being experimentally analyzed using a benchmark dataset for heart disease.

II. RELATED WORKS

In [11], an ML-based Sine Cosine Weighted KNN (SCA_WKNN) technique was presented for the HD forecast which learns in the data has been saved in BC. While the data saved in BC are tamper resistant, it performs as a secured stored location for patient data and as authentic source for learning data. Abdel-Basset et al. [12] present a new structure dependent upon CAD and IoT for detecting and monitoring heart attack infected patients, whereas the data can be obtained from many other sources. The presented medical system purposes at attaining optimum precision of analysis with ambiguous data. The authors propose neutrosophic multi-criteria decision-making (NMCDM) system for supporting patients and doctors to identify when a patient was suffered in heart attack. In [13], a new effectual IoT-based tuned adaptive neuro-fuzzy inference system (TANFIS) technique was presented to correct HD prediction. At this point, the tuning parameter can be optimized with Laplace Gaussian mutation based grasshopper optimizer algorithm and moth flame optimizer.

Reddy et al. [14] purpose of adaptive GA with fuzzy logic (AGAFL) technique is for predicting HD which is support medical practitioners in analyzing HD at primary steps. This method comprises of rough set based HD feature selection component and fuzzy rule based classification component. Initially, an essential feature that effect HD can be chosen by rough set model. The secondary stage forecasts the HD utilizing the hybrid AGAFL classifier. In [15], the author's proposal is an IoT which utilizes a Modified Self-Adaptive Bayesian algorithm (MSABA) for providing more detailed calculations of HD. The blood pressure and ECG can be recorded by wearing the smartwatch and pulse sensor devices, and send the information to computer. For retrieving the features, kernel discriminant analysis (KDA) was utilized.

In [16], an IoT framework was presented for evaluating HD more correctly utilizing a Modified Deep CNN (MDCNN). The heart monitors device and smartwatch which are involved in patient monitoring the ECG and blood pressure. The method's performance was assessed by comparing it to the existing DLNN and LR using the presented MDCNN. Liu et al. [17] present a new BC-allowed contextual online learning method in local differential privacy for CHD analysis from mobile edge computing. The edge node is collaborated with every other for achieving data sharing that assurances which CHD analysis was reliable and appropriate. For supporting the dynamically maximal database, it is implemented a top-down tree design for containing medical data that is partitioned adaptively.

III. THE PROPOSED MODEL

In this study, we have designed a new SSOML-DDBHE method for disease detection in the healthcare sector. The presented SSOML-DDBHE algorithm exploits BC technology for accurate identification of diseases in the healthcare environment. It comprises three major processes namely SSO based feature subset selection, ELM based classification, and BO based parameter tuning. Fig. 1 demonstrates the working process of SSOML-DDBHE method.

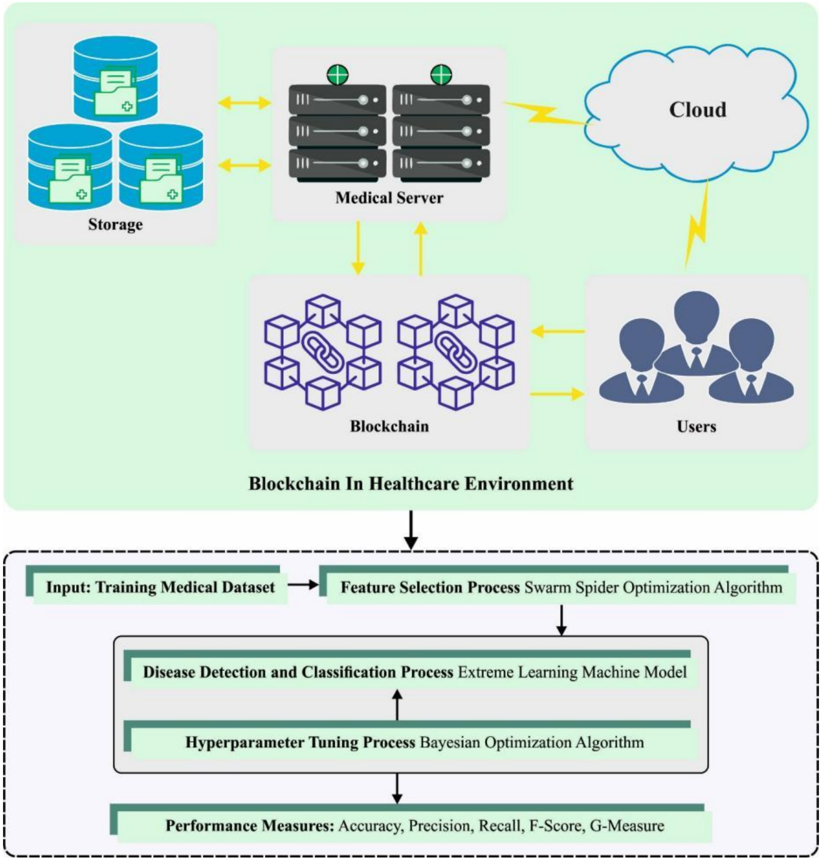

Figure 1. Working process of SSOML-DDBHE approach

3.1. Feature Selection using SSO Algorithm

To select the features properly, the SSO algorithm is employed. SSO method seeks to identify the optimum target based on the swarming spider's social behavior [18]. In the presented method, individual spider lives in high-dimension spider web. The movement, mating and other strategies of spiders continuously change the spider's position. The weight and position the spider denote the value of dependent and also denotes the value of independent variables of the objective function. The steps of SSO algorithm have been discussed in the following.
(1) Assume the spider population in a n-dimensional search space. Where N denotes the overall count, N_m and N_f denotes the count of males and females,respectively.

$$N_f = \mathrm{Floor}[0.9 - \mathrm{rand} \ \times 0.25] \times N \tag{1}$$

A male spider subpopulation$M = \{m_1, m_2, \cdots, m_{N_m}\}$, the spider population has female spider subpopulation $F = \{f_1, f_2, \cdots, f_{N_f}\}$.
(2) The weight of all spiders needs to be calculated

$$w_i = \frac{J(s_i) - worst_s}{best_s - worst_s} \tag{2}$$

Here $J(S)$ denoted the value of objective function fitness respective to the i-th spider position:

$$best_s = \max_{k\in\{1,2,\cdots,N\}}(J(s_k)) \tag{3}$$

$$worst_s = \min_{k\in\{1,2,\cdots,N\}}(J(s_k)) \tag{4}$$

(3) The vibration sent between spiders can be described as:

$$Vib_{i,j} = w_j \cdot e^{-d_{i,j}^2} \tag{5}$$

Here $d_{i,j}$ is computed as:

$$d_{i,j} = \|s_i - s_j\| \tag{6}$$

(4) Population initialization is described below:

$$f_{i,j}^0 = p_j^{low} + rand(0,1) \cdot \left(p_j^{high} - p_j^{low}\right) \tag{7}$$

In Eq. (7), p_j^{low} and p_j^{high} shows the lower and upper limitations of the components of the parameters set that should be optimized.$f_{i,j}$ denotes the j-th variable at the position of i-th female spiders. $f_{i,j}^0$ indicates the initial parameter set for the female spider.

$$m_{k,j}^0 = p_j^{low} + \mathrm{rand}(0,1) \cdot \left(p_j^{high} - p_j^{low}\right) \tag{8}$$

Denotes $m_{k,j}$ as the jt$h$ variable at the position of the kt$h$ male spider.

(5) Movement is shown below:

f_i^{k+1} and m_i^{k+1} signify the spider's position in the search space. Reposition female spider depends on the cooperative mechanism, which is computed below:

$$f_i^{k+1} = \begin{cases} f_i^k + \alpha \cdot \mathrm{Vibc}_i \cdot (s_c - f_i^k) + \beta \cdot \mathrm{Vibb}_i \cdot (s_b - f_i^k) + \delta.(\mathrm{rand}\text{-} 0.5) \\ \text{wit}h \text{ probability PF} \\ f_i^k - \alpha \cdot \mathrm{Vibc}_i \cdot (s_c - f_i^k) - \beta \cdot \mathrm{Vibb}_i \cdot (s_b - f_i^k) + \delta.(\mathrm{rand}\text{-} 0.5) \\ \text{wit}h \text{ probability } 1 - \mathrm{PF} \end{cases} \tag{9}$$

In Eq. (9) k denoted the amount of iterations. α, β, δ and rand denoted random constants between one and zero. S_c specifies the individual closer with high quality i. S_b indicated the optimal individuals within population S.

Depending on the cooperative system, the modification in male spider location was computed below:

$$m_i^{k+1} = \begin{cases} m_i^k + \alpha \cdot \mathrm{Vibf}_i \cdot (s_f - m_i^k) + \delta.(\mathrm{rand} \ - 0.5), \text{if } w_{N_f+i} > w_{N_f+m} \\ m_i^k + \alpha \cdot \left(\dfrac{\sum_{h--1}^{N_m} m_h^k \cdot w_{N_f+h}}{\sum_{h=1}^{N_m} w_{N_f+h}} - m_i^k\right)', \text{if } w_{N_f+i} \le w_{N_f+m} \end{cases} \tag{10}$$

(6) Mating behavior was defined.

The radius of mating range was computed utilizing the following equation:

$$r = \frac{\sum_{j=1}^{n} = 1(p_j^{high} - p_j^{low})}{2 \cdot n} \tag{11}$$

At the time of mating, all spiders determined the probability of impact using roulette wheel:

$$Ps_i = \frac{w_i}{\Sigma_{j \in T^k} w_j} \tag{12}$$

The fitness function takes into account not only the number of selected features but also the performance of the classification.. It reduces the set of features selected and increases the classification performance. Therefore, the following fitness function is used to analyze individual solutions.

$$\mathrm{Fitness} = \alpha * \ \mathrm{ErrorRate} + (1 - \alpha) * \frac{\#SF}{\#All\_F} \tag{13}$$

In Eq. (13), The parameter α is used for controlling the importance of classification quality and subset length. In this experiment, α is set to 0.9.
represents the number of selected features, while it indicates the total number of features in the original dataset. ErrorRate implies the classification error rate. ErrorRate can be evaluated as a percentage of incorrectly classified to the amount of classifications made, expressed as a value ranging from zero to one.

3.2 Disease Detection Using ELM Model

For accurate detection of diseases, the ELM model is applied. A neural network (NN) is improved by the gradient technique, an ELM [19]. While another gradient learning method requires recurrent iteration to retain optimum network parameter, ELM just needs the bias parameter in the hidden layer before data training and a random initialization of weight connected amongst the output and input layers. Fig. 2 illustrates the structure of ELM. A single optimum key is attained when the neuron count of the hidden layer is defined. This kind of learning model could accelerate the learning algorithm and reduce the amount of time expended analyzing data.

In this work, there exist N random instances (X_i, t_j) , where $X_i = \ [x_{1i}, x_{2i}, \ldots, x_{ni}]^T \in R^n$, $t_i = [t_{1i}, t_{2i}, \ldots, t_{qi}, \ldots, t_{mi}]^T \in R^m$.

$$\sum_{j=1}^{N} \beta_j \, g\left(W_i . X_j + b_i\right) = 0_j, j = 1, \ldots, N \tag{14}$$

In Eq. (14), $g(x)$ denotes the initial hidden neuron, $W_i = [w_{i,1}, w_{i,2}, \dots, w_{i,n}]^T$ shows the input weight, β_i represent the output weight layer formulated by Eq. (15),

$$\sum_{j=1}^{N} \| 0_j - t_j \| = 0 \tag{15}$$

Particularly, there are appropriate β_i, W_i, b_i which can be content. The following equation can be expressed in the following manner:

$$H\beta = T \tag{16}$$

In Eq. (16) T represent the predicted output and H denotes the output matrix of hidden layer. Finding the optimum value for $W_i, \hat{b}, \hat{\beta}$ is corresponding to resolving the minimal cost function.

$$E = \sum_{j=1}^{N} \left[\sum_{i=1}^{L} \beta_i \, G(w_i . X_j + b_i) - T_j \right]^2 \tag{17}$$

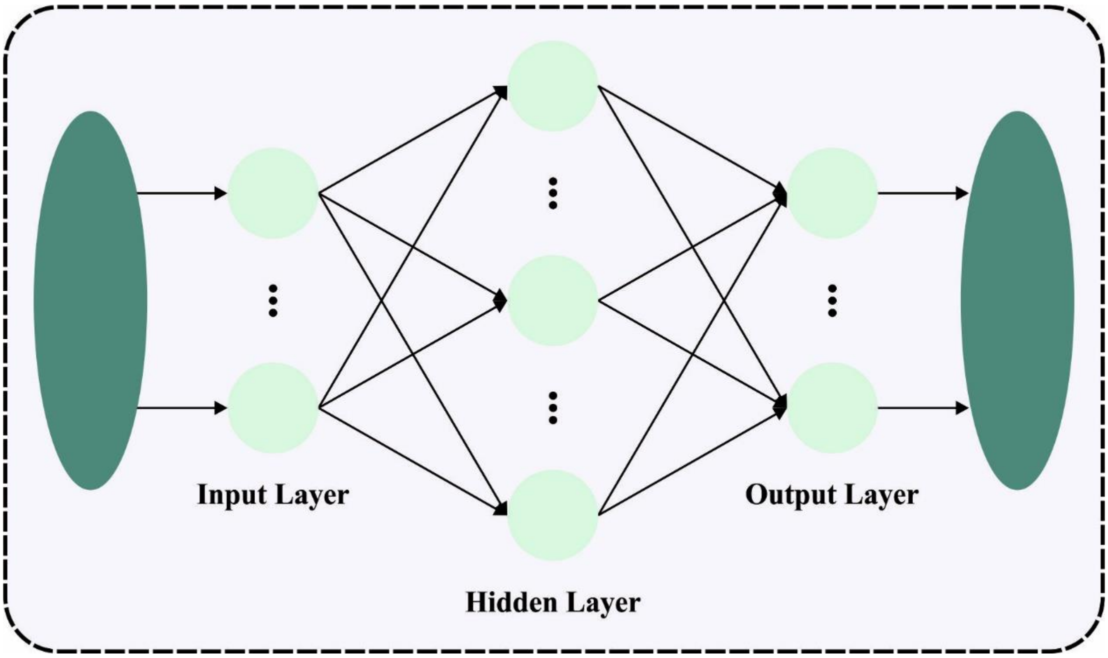

Figure 2. Structure of ELM

A widespread classifier that can achieve, the above mentioned ELM is accurately what is required. The learning pace is dramatically improved without the requirement for iteration learning. Even though ELM has universal approximation, it needs significant hidden layers to make sure better performance of generalization that is prone to over-fitting. This prevents overfitting problems. As a regularization technique for FC networks, DropConnect and Dropout could efficiently prevent over-fitting. Below are the steps of the ELM algorithm:

Step 1: Assume training set $= (x_i, t_i) | x_i \in R^n, t_i \in R^m, i = 1, \dots, N$, the amount of hidden neuron L, and activation function $G(x)$.
Step 2: Randomly allocate the values of input weight w_i and b_i bias. The optimum solution for weight can be recognized using BO algorithm.
Step 3: Evaluate H hidden layer production matrix**.**
Step 4: Evaluate the output weight: $\beta = H \dagger T$, where $H \dagger$ denotes the MoorePenrose widespread inverse matrices H. The ELM classifiers can provide the sample labelling output for the input image. The binary output “0” and “1” can be attained using ELM, which can be labelled using the input image.

3.3 Parameter Tuning using BO Algorithm

Lastly, the BO algorithm is utilized for the parameter tuning of the ELM model. The BO algorithm is used to actively choose the assessment point with global optima through the acquisition function [20] and to update and establish the probabilistic surrogate model by using prior evaluation of objective function. BO could efficiently apply the previous data to attain the optimum solution within some evaluation and judge the uncertainty of unknown regions.

The Gaussian process primarily includes covariance function k and the mean function m:

$$f(x) \sim GP\big(m(x), k(x, x')\big) \tag{18}$$

$$m(x) = E[f(x)] \tag{19}$$

$$k(x, x') = E\big[\big(f(x) - m(x)\big)\big(f(x') - m(x')\big)\big] \tag{20}$$

Here, x denotes the thermal conductivity. Once there is observation noise, then observed value is $y = f(x) + e$, and assume that the noise ε fulfils $p(\varepsilon) = N(0, \sigma^2)$. In this context, the joint distribution of Gaussian variable is attained by Eq. (21):

$$\begin{bmatrix} Y \\ f(x^*) \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} m(x_1) \\ \vdots \\ m(x_t) \\ m(x^*) \end{bmatrix}\right); \begin{bmatrix} K + \sigma^2 I & k(x^*, X) \\ Xk(x^*, X)^T & k(x^*, x^*) \end{bmatrix} \tag{21}$$

The test point x^* and training dataset D is set to attain the posterior predictive distribution of (x^*), where I represent the unit matrix, X denotes the training input set $x_{1:t}$, Y indicates the training output set $y_{1:t}$, and K shows the matrix of covariance function $k(x, x)$ as follows:

$$p(f(x^*)|x^*, D) = \frac{p(f(x^*), Y|X, x^*)}{p(Y|X)} \tag{22}$$

The conditional posterior Gaussian distribution is described by the mean and variance in the following manner.

$$\mu(f(x^*)|x^*, D) = m(x^*) + k(x^*, X)^T(K + \sigma^2 I)^{-1}\left(Y - \left[m\big(X_{:,1}\big)\right], \dots, m\big(X_{:,nD}\big)\right) \tag{23}$$

$$var(f(x^*)|x^*, D) = k(x^*, x^*) - k(x^*, X)^T(K + \sigma^2 I)^{-1}k(x^*, X) \tag{24}$$

$k(x, x')$ can be determined by the kernel function. The squared exponential kernel function selected is always continuous, infinitely differentiable and infinitely derived and, and hasθ_1 and θ_2 two hyperparameters:

$$k(x - x') = \theta_1^2 \exp\left(-\frac{\|x - x'\|^2}{2\theta_{2^2}}\right) \tag{25}$$

$$EI(x) = \begin{cases} (f(x^*) - \mu_f(x) - \zeta)\Phi(Z) + \sigma_f(x)\psi(Z), \sigma_f(x) > 0 \\ 0, \sigma_t(x) = 0 \end{cases} \tag{26}$$

$$Z = \frac{f(x^*) - \mu_t(x) - \zeta}{\sigma_f(x)} \tag{27}$$

Where $f(x^*)$ denotes the objective function value of existing evaluation point, ζ shows the equilibrium parameter (balancing the relationships between the global and local search). $\sigma_f(x)$ and $\mu_f(x)$ denotes the variance and expectation of Gaussian distribution at x, correspondingly. $\Phi(\cdot)$ and ψ shows the cumulative density and standard Gaussian probability functions, correspondingly.

The fitness selection is a main factor in the BO method. Solution encoding is utilized to evaluate the goodness (aptitude) of solution candidate. The accuracy value is the crucial condition exploited to design a fitness function.

$$Fitness = \max(P) \tag{28}$$

$$P = \frac{TP}{TP + FP} \tag{29}$$

Where FP represent the false positive value and TP denotes the true positive.

3.4 BC based Secure Healthcare

BC technology in healthcare service maintain EHRs, and data distribution between patients, physicians, health insurance companies and laboratories has become smooth [21]. Data integrity is most prominent in permissionless (public) and permissioned (private) BC. Ethereum technology makes use of proof of stake (PoS) consensus protocols that are valuable for cooperation, integrity and accuracy between the stakeholders to share the decentralized security and data. PoS authorizes the size of chains and blocks, it implements the function automatically called a "smart contract" (SC) which add accuracy to the data and adaptableness to the Ethereum chain, BC has retained EHRs by using SC which can be performed using Ethereum, it is a decentralized platform that runs SC. The BC framework and paradigm were performed by Ethereum virtual machine (EVM). It also provides decentralized computer resources. The transaction of EHR using cryptographic secure transaction through peer-to-peer protocols.

IV. Results And Discussion

The experimental result of the SSOML-DDBHE technique is tested on the heart disease dataset from UCI repository [22]. The dataset involves 303 samples with two classes as depicted in Table 1. Out of available 14 features, the SSOML-DDBHE technique has chosen a set of 6 features such as (cp), (trestbps), (chol), (fbs), (restecg), and (slope).

Table 1 Details on dataset

Classes	No. of Instances
Presence	139
Absence	164
Total Number of Instances	303

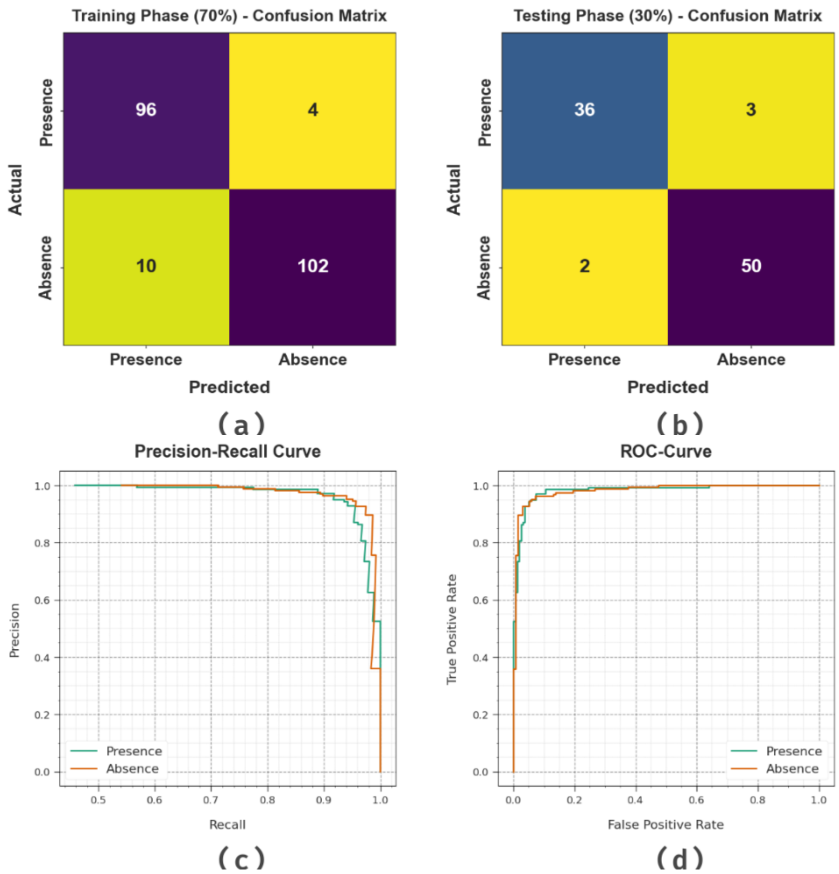

Figure 3. Classifier result of (a-b) Confusion matrices, (c) PR curve, and (d) ROC curve

Fig. 3 depicts the classifier results of the SSOML-DDBHE method under test dataset. Fig. 3a demonstrates the confusion matrix provided by the SSOML-DDBHE method on 70% of TRP. The figure indicates that the SSOML-DDBHE method has detected 96 instances under presence and 102 instances under absence. In addition, Fig. 3b demonstrates the confusion matrix provided by the SSOML-DDBHE method on 30% of TSP. The figure indicates that the SSOML-DDBHE technique has detected 36 instances under presence and 50 instances under absence.

Similarly, Fig. 3c illustrates the PR investigation of the SSOML-DDBHE method. The figures indicated that the SSOML-DDBHE approach has attained highest PR performance under 2 classes. Lastly, Fig. 3d demonstrates the ROC investigation of the SSOML-DDBHE method. The figure portrayed that the SSOML-DDBHE method has resulted in proficient outcomes with maximum ROC values under 2 class labels.

In Table 2 and Fig. 4, the outcomes of the SSOML-DDBHE method is provided. The findings pertain to the successful detection of illnesses. On 70% of TRP, the SSOML-DDBHE technique gains average $accu_y$ of 93.54%, $prec_n$ of 93.40%, $reca_l$ of 93.54%, F_{score} of 93.39%, and $G_{measure}$ of 93.43%. Simultaneously, on 30% of TSP, the SSOML-DDBHE method gains average $accu_y$ of 94.23%, $prec_n$ of 94.54%, $reca_l$ of 94.23%, F_{score} of 94.37%, and $G_{measure}$ of 94.38%.

Table 2 Classifier outcome of SSOML-DDBHE approach on 70:30 of TRP/TSP

Class	$Accu_y$	$Prec_n$	$Reca_l$	F_{score}	$G_{measure}$
Training Phase (70%)					
Presence	96.00	90.57	96.00	93.20	93.24
Absence	91.07	96.23	91.07	93.58	93.61
Average	93.54	93.40	93.54	93.39	93.43
Testing Phase (30%)					
Presence	92.31	94.74	92.31	93.51	93.51
Absence	96.15	94.34	96.15	95.24	95.24
Average	94.23	94.54	94.23	94.37	94.38

Figure 4. Accuracy curve of the SSOML-DDBHE approach

Fig. 4 examines the accuracy of the SSOML-DDBHE technique during the training and validation process on test dataset. The figure notifies that the SSOML-DDBHE method reaches increasing accuracy values over increasing epochs. In addition, the increasing validation accuracy over training accuracy exhibits that the SSOML-DDBHE technique learns efficiently on the test dataset.

The loss analysis of the SSOML-DDBHE method at the time of training and validation is demonstrated on the test dataset in Fig. 5. The outcomes indicate that the SSOML-DDBHE technique reaches closer values of training and validation loss. The SSOML-DDBHE method learns efficiently on the test dataset.

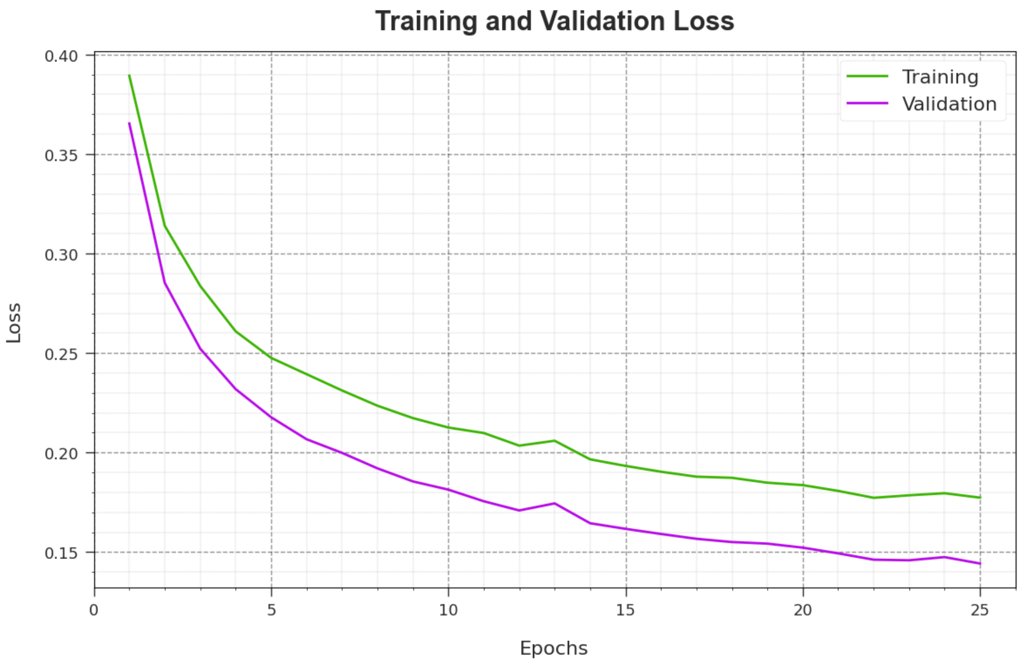

Figure 5. Loss curve of the SSOML-DDBHE approach

In Table 3, an overall comparison study of the SSOML-DDBHE system with recent approaches are given [11]. In Fig. 6, a comprehensive $accu_y$ inspection of the SSOML-DDBHE method with existing models are given. The outcomes stated that the KNN and SVM methods obtain reduced $accu_y$ values of 81.49% and 82.70% respectively. Meanwhile, the RF and MLP models accomplish considerably closer $accu_y$ of 89.14% and 90.14% respectively. Although the SCA-WKNN model reached near optimal $accu_y$ of 92.13%, the SSOML-DDBHE technique outperformed the existing ones with maximum $accu_y$ of 94.23%.

Table 3 Comparative outcome of SSOML-DDBHE approach with recent algorithms

Methods	Accuracy	Precision	Recall
SSOML-DDBHE	94.23	94.54	94.23
SCA-WKNN	92.13	88.21	93.27
K-NN Algorithm	81.49	69.70	62.00
SVM Algorithm	82.70	79.00	71.03
RF Algorithm	89.14	81.00	81.04
MLP Algorithm	90.14	87.13	85.13

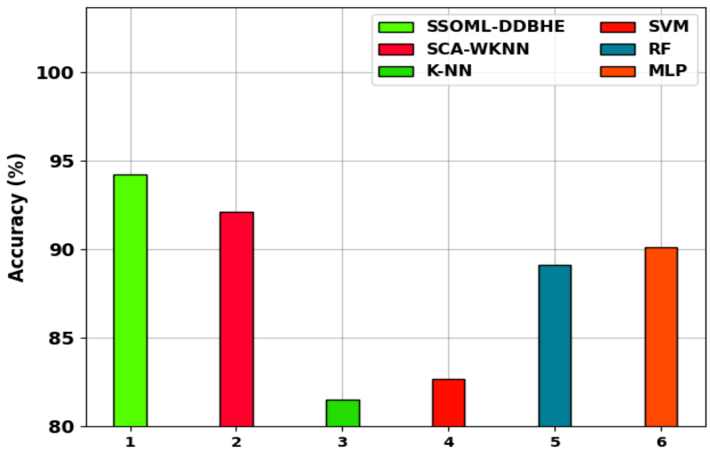

Figure 6. $Accu_y$ outcome of SSOML-DDBHE method with recent algorithms

In Fig. 7, a comprehensive $prec_n$ examination of the SSOML-DDBHE system with present approaches are given. The outcomes stated that the KNN and SVM methods obtain reduced $prec_n$ values of 69.70% and 79% correspondingly. Meanwhile, the RF and MLP models accomplish considerably closer $prec_n$ of 81% and 87.13% correspondingly. Although the SCA-WKNN model reached near optimal $prec_n$ of 88.21%, the SSOML-DDBHE technique outperformed the existing ones with maximum $prec_n$of 94.54%.

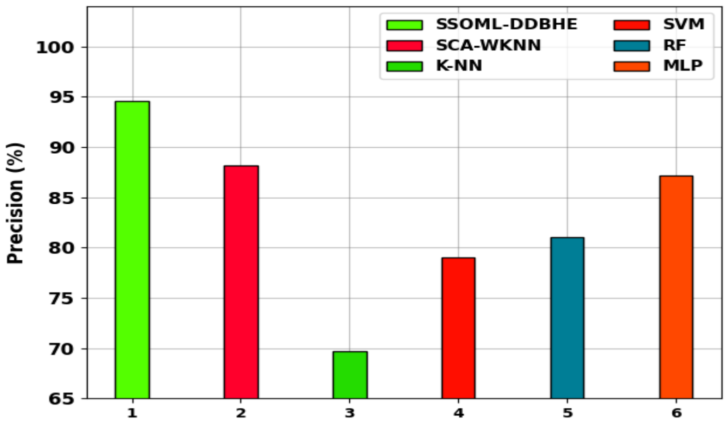

Figure 7. $Prec_n$ outcome of SSOML-DDBHE method with recent algorithms

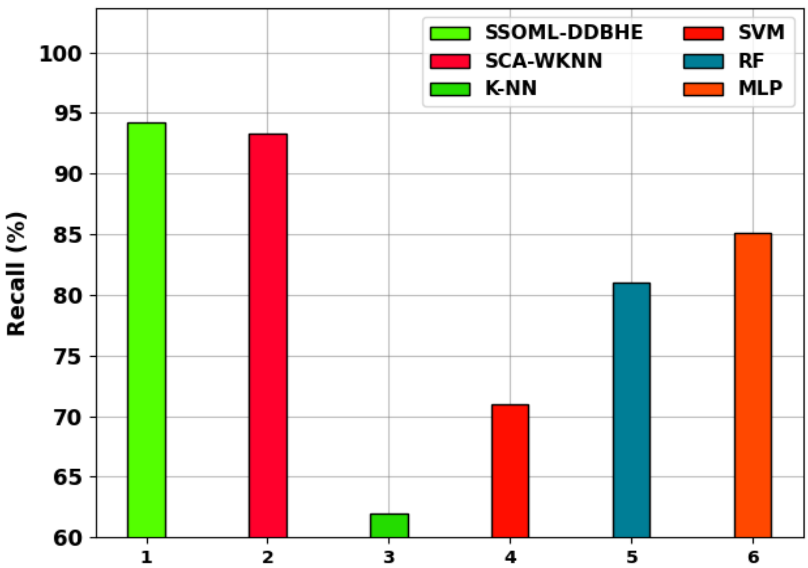

Figure 8. $Reca_l$ outcome of SSOML-DDBHE approach with recent algorithms

In Fig. 8, a comprehensive $reca_l$ inspection of the SSOML-DDBHE technique with present methods are given. The outcomes stated that the KNN and SVM methods obtain reduced $reca_l$ values of 62% and 71.03% correspondingly. Meanwhile, the RF and MLP models accomplish considerably closer $reca_l$ of 81.04% and 85.13% correspondingly. Although the SCA-WKNN model reached near optimal $reca_l$ of 93.27%, the SSOML-DDBHE method outperformed the existing ones with maximum $reca_l$ of 94.23%. These outcomes confirmed the enhanced performance of the SSOML-DDBHE technique over other models.

V. CONCLUSION

In this study, we have designed a new SSOML-DDBHE technique for disease detection in the healthcare field. The presented SSOML-DDBHE technique exploits BC technology for accurate identification of diseases in the healthcare environment. It comprises three major processes namely SSO based feature subset selection, BO based parameter tuning, and ELM based classification. In the SSOML-DDBHE technique, the SSO algorithm is used for selecting feature subsets. For disease detection, the SSOML-DDBHE technique employs the ELM model. Lastly, the BO algorithm is used to adjust the parameter of ELM. To achieve security, blockchain technology is used. TThe SSOML-DDBHE method is being experimentally analyzed using a benchmark heart disease dataset. The comprehensive outcomes highlighted the superior performance of the SSOML-DDBHE method over recent approaches.

REFERENCES

[1] Nouman, A. and Muneer, S., 2022. A Systematic Literature Review On Heart Disease Prediction Using Blockchain And Machine Learning Techniques. International Journal of Computational and Innovative Sciences, 1(4), pp.1-6.

[2] Lobo, V.B., Analin, J., Laban, R.M. and More, S.S., 2020, March. Convergence of blockchain and artificial intelligence to decentralize healthcare systems. In 2020 Fourth International Conference on Computing Methodologies and Communication (ICCMC) (pp. 925-931). IEEE.

[3] Anand, R., Kareem, S.F., Mubeen, R.M.A., Ramesh, S. and Vignesh, B., 2021, October. Analysis of heart risk detection in machine learning using blockchain. In 2021 6th International Conference on Signal Processing, Computing and Control (ISPCC) (pp. 685-689). IEEE.

[4] Poongodi, T., Indrakumari, R., Janarthanan, S. and Suresh, P., 2021. A Systematic Framework for Heart Disease Prediction Using Big Data Analytics. Internet of Things, Artificial Intelligence and Blockchain Technology, pp.277-305.

[5] Rath, A., Mishra, D., Panda, G. and Satapathy, S.C., 2021. Heart disease detection using deep learning methods from imbalanced ECG samples. Biomedical Signal Processing and Control, 68, p.102820.

[6] Singh, S.P., Lavanya, P., Nirmala, M., Madhusudan, R. and Nikhil, B., 2022, October. Securing Healthcare Data with Blockchain for Diabetic and Cardio Disease Prediction. In 2022 International Conference on Distributed Computing, VLSI, Electrical Circuits and Robotics (DISCOVER) (pp. 299-304). IEEE.

[7] Islam, M.S., Umran, H.M., Umran, S.M. and Karim, M., 2019, May. Intelligent healthcare platform: cardiovascular disease risk factors prediction using attention module based LSTM. In 2019 2nd International Conference on Artificial Intelligence and Big Data (ICAIBD) (pp. 167-175). IEEE.

[8] Babu, B.M., Praveen, M., Kumar, T.S., Solanki, R.K. and Mayuri, A.V.R., 2023. Modified Cnn Based Heart Disease Detection Integrated With Iot. Journal of Pharmaceutical Negative Results, 14.

[9] Li, J.P., Haq, A.U., Din, S.U., Khan, J., Khan, A. and Saboor, A., 2020. Heart disease identification method using machine learning classification in e-healthcare. IEEE Access, 8, pp.107562-107582.

[10] Plati, D.K., Tripoliti, E.E., Bechlioulis, A., Rammos, A., Dimou, I., Lakkas, L., Watson, C., McDonald, K., Ledwidge, M., Pharithi, R. and Gallagher, J., 2021. A machine learning approach for chronic heart failure diagnosis. Diagnostics, 11(10), p.1863.

[11] Hasanova, H., Tufail, M., Baek, U.J., Park, J.T. and Kim, M.S., 2022. A novel blockchain-enabled heart disease prediction mechanism using machine learning. Computers and Electrical Engineering, 101, p.108086.

[12] Abdel-Basset, M., Gamal, A., Manogaran, G., Son, L.H. and Long, H.V., 2020. A novel group decision making model based on neutrosophic sets for heart disease diagnosis. Multimedia Tools and Applications, 79, pp.9977-10002.

[13] Sekar, J., Aruchamy, P., Sulaima Lebbe Abdul, H., Mohammed, A.S. and Khamuruddeen, S., 2022. An efficient clinical support system for heart disease prediction using TANFIS classifier. Computational Intelligence, 38(2), pp.610-640.

[14] Reddy, G.T., Reddy, M.P.K., Lakshmanna, K., Rajput, D.S., Kaluri, R. and Srivastava, G., 2020. Hybrid genetic algorithm and a fuzzy logic classifier for heart disease diagnosis. Evolutionary Intelligence, 13, pp.185-196.

[15] Subahi, A.F., Khalaf, O.I., Alotaibi, Y., Natarajan, R., Mahadev, N. and Ramesh, T., 2022. Modified Self-Adaptive Bayesian Algorithm for Smart Heart Disease Prediction in IoT System. Sustainability, 14(21), p.14208.

[16] Khan, M.A., 2020. An IoT framework for heart disease prediction based on MDCNN classifier. IEEE Access, 8, pp.34717-34727.

[17] Liu, X., Zhou, P., Qiu, T. and Wu, D.O., 2020. Blockchain-enabled contextual online learning under local differential privacy for coronary heart disease diagnosis in mobile edge computing. IEEE Journal of Biomedical and Health Informatics, 24(8), pp.2177-2188.

[18] Wei, Y., Zhang, H., Dai, J., Zhu, R., Qiu, L., Dong, Y. and Fang, S., 2023. Deep Belief Network with Swarm Spider Optimization Method for Renewable Energy Power Forecasting. Processes, 11(4), p.1001.

[19] Sridhar, K., Lai, W.C. and Kavin, B.P., 2023. Detection of Liver Tumour Using Deep Learning Based Segmentation with Coot Extreme Learning Model. Biomedicines, 11(3), p.800.

[20] Ji, H., Qi, L., Lyu, M., Lai, Y. and Dong, Z., 2023. Improved Bayesian Optimization Framework for Inverse Thermal Conductivity Based on Transient Plane Source Method. Entropy, 25(4), p.575.

[21] Mallikarjuna, B., Shrivastava, G. and Sharma, M., 2022. Blockchain technology: A DNN token-based approach in healthcare and COVID-19 to generate extracted data. Expert Systems, 39(3), p.e12778.

[22] https://archive.ics.uci.edu/ml/datasets/heart+disease.