Turkish Journal of Computer and Mathematics Education Vol.12 No.10 (2021), 2721-2731

Research Article

Oppositional Butterfly Optimization Algorithm with Multilayer Perceptron for Medical Data Classification

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Article History: Received: 10 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 28 April 2021

Abstract: Medical data classification can be assumed to be a crucial process in the domain of medical informatics. Generally, medical data comprises a set of medical records and literature which are considered as the essential healthcare data sources. But the existence of medical data includes complicated medical vocabulary and medical metrics makes the classification process challenging. Though several models are available in the literature, there is still needed to improve the classification performance. In this view, this paper devises a novel oppositional based learning with butterfly optimization algorithm (OBLBOA)and multilayer perceptron (MLP) called OBLBOA-MLP for medical data classification. The presented OBLBOA-MLP model involves three stages of operation such as preprocessing, classification, and parameter tuning. Primarily, data preprocessing is carried out to remove the unwanted data and raise the data quality to a certain extension. Besides, MLP model is applied as a classifier to determine the existence of the diseases. In addition, OBLBOA is employed for the hyperparameter optimization of the MLP model. The application of OBL helps to increase the performance of the BOA. A detailed set of simulation analysis was performed to determine the appropriate detection results of the OBLBOA-MLP model. The obtained experimental values pointed out the improved classification performance by attaining a higher accuracy of 98.23% and 92.67% on the applied CKD and skin disease dataset respectively.

Keywords: Medical data classification, Healthcare, Multilayer perceptron, Hyperparameter optimization

1. Introduction

Presently, artificial intelligence (AI) techniques are commonly employed for disease diagnosis in healthcare sector. Machine learning (ML) aided decision systems are widely applied for assisting physicians in the disease diagnosis process. A doctor conventionally uses the knowledge according to the patient's medical symptoms and then identified the disease. Therefore, the diagnostic performance is mainly based on the experience of the physicians. As it is now comparatively easier to gather and save massive quantities of data in a digital way, the design of computer based decision support system becomes a possible way to assist doctors in the disease diagnosis process [1]. These systems are considered as the classification process to achieve predictive model on a new patient based on the existing medical records. These classification processes are treated as the crucial task in medical data analytics. With several statistical models that might be employed for medical data classification, the main limitation lies in the dependency of few assumptions for the successful applications.

At the same time, soft computing based techniques are not much dependent on this knowledge. Several soft computing based classification models are presented and examined in the literature for precise medical data classification. [2] presented a Pareto-differential evaluation algorithm with a local search technique called Memetic ParetoArtificial Neural Network (MPANN) for breast cancer diagnosis. [3] developed a statistic-based neural network oriented model for the diagnosis of breast cancer. [4] presented an expert model to detect breast cancer for reducing the data dimensionality problem using Association Rules (AR). [5] introduced a hybridization of feature selection technique for addressing the data dimensionality problem of healthcare data and simulated on the diagnosis of breast cancer data. [6] integrated a case based data clustering with fuzzy based decision tree model for classifying the medical data. It is used to diagnosis liver and breast cancer diseases.

[7] developed a set of three classifiers such as radial basis function (RBF), multilayer perceptron (MLP), and probabilistic neural network (PNN). In addition, the simulation process takes place on the breast cancer dataset and it is found that the PNN outperformed the MLP model. In the last decade, a set of different medical data classification models are available in the earlier works. [8] devised a medical data classification technique for the detection of breast cancer and Parkinson's disease by the integration of the Evolutionary Wavelet NNs. Besides, [9] has applied a set of weighted fuzzy rules for designing a clinical decision support system (CDSS) to

detect heart disease. Firstly, a set of fuzzy rules were generated depending upon the historical data to learn effectively. Besides, the weightage of fuzzy rules takes place depending upon the significance of the variables.

[10] introduced a modified SVM-RFE and performed simulation on many medical datasets by the incorporation of local searching operator into the technique. [11] applied a feature selection by the use of the idea of fuzzy entropy. [12] designed a feature selection model depending upon the Kernel F-Score. [13] presented a hybridization model by the use of K-Nearest Neighbor (KNN) and Genetic Algorithm (GA). A new CDSS using the evolutionary algorithm is developed in [14] by the use of NN, GA, SVM, KNN, MLP, RBF, PNN, self-organizing map (SOM), and Naive Bayes (NB) as classification models [19-28]. [15] presented a CDSS on 10 medical data and the experimental results ensured that the SVM model is found be better than the others. Finally, [16] introduced a new medical data classification model depending upon the Adaptive Genetic Fuzzy System (AGFS) where the rule generation process takes place and then optimal selection of rules is carried out by GA.

This paper devises a novel oppositional based learning with butterfly optimization algorithm (OBLBOA) and multilayer perceptron (MLP) called OBLBOA-MLP for medical data classification. Primarily, data preprocessing is carried out to remove the unwanted data and raise the data quality to a certain extension. Besides, MLP model is applied as a classifier to determine the existence of the diseases. In addition, OBLBOA is employed for the hyperparameter optimization of the MLP model. A detailed set of simulation analysis was performed to determine the appropriate detection results of the OBLBOA-MLP model.

2. The Proposed OBLBOA-MLP Model

The overall working principle involved in the OBLBOA-MLP model is depicted in Fig. 1. The presented OBLBOA-MLP model involves three stages of operation such as preprocessing, classification, and parameter tuning. Firstly, the data preprocessing takes place to improvise the data quality. Next, the MLP based classification process is performed to assign proper class labels to the medical data. At last, OBLBOA is employed for tuning the parameters such as weights and biases of the MLP model.

2.1. Data Preprocessing

At the beginning stage, the data preprocessing takes place in three stages such as format conversion, data normalization, and class labeling. Here, the medical data in any format (i.e. csv) is converted to a compatible. arff format. Then, data normalization procedure is followed by the minimum-maximum (min-max) approach [17]. At this point, the higher and lower values in the data are taken and the values are normalized effectively. The goal is to normalize the input values into the range of [0, 1] and disseminate other values to the intended range. The normalization process can be achieved by the use of Eq. (1):

$$Min - Max.Norm = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

At last, class labeling procedure will be carried out in which the data samples in the dataset are assigned to the appropriate class labels such as 0 and 1.

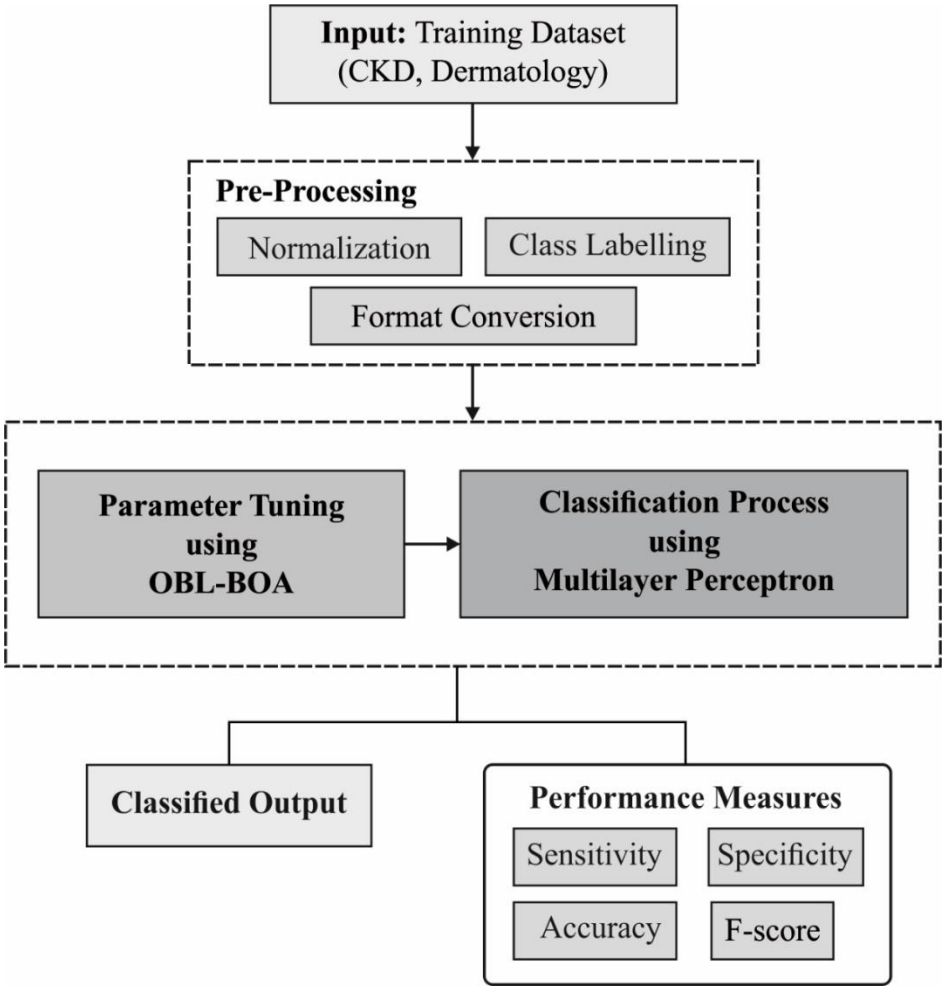

Fig. 1. Working principle of the OBLBOA-MLP model

2.2. MLP based Classification

To classify the medical data, an artificial neural network based classification model is applied. The ANN is used to categorize the patient data into the existence of diseases based on a process which is similar to human actions like understanding, learning, solving problems, and take decisions. Generally, NN is a model which can be represented in such a way that the human brain carries out a specific process. The ANN model comprises a set of 3 elements. The initial one is the input layer and the node count is computed using the input variables. Next, the final one is the output layer and the node count is represented by the specific outcome.

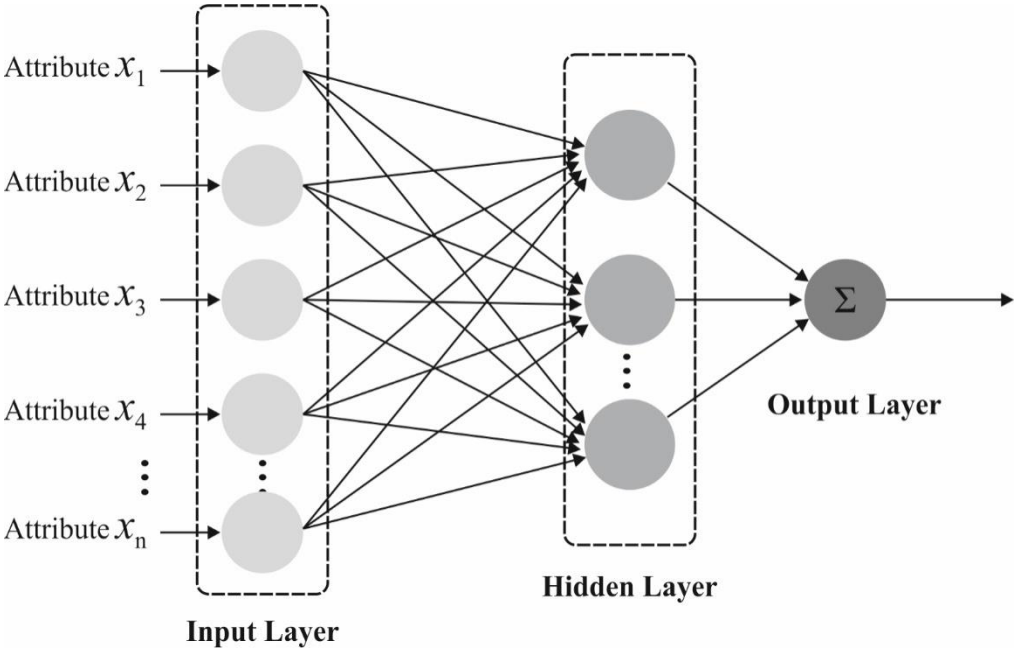

Fig. 2. Structure of MLP

The layers which existed amongst the input and output layers are termed hidden layers. In most of the ANN models, the hidden layer uses the non-linear activation function for data processing. Fig. 2 displays the structure of the MLP. The neuron is considered as the fundamental unit to the design of the ANN. The bias valueb_{k} has the consequence of raising or decreasing the net input of the activation function. A neuron $k$is defined using the following Eqs. (2-3):

$$u_k = \sum_{i=1} w_{ki}\, x_i \qquad (2)$$

$$y_k = \phi(u_k + b_k) \qquad (3)$$

Where $x_1, \ldots, x_n$denotes the input signals, $w_{k1}, \ldots, w_{kn}$ are the synaptic weights of neuron k, u_k is the linear combiner outcome because of the input signals, b_k is the bias, $\varphi(.)$ is the activation function, and y_k is the output signal of the neuron.

2.3. OBLBOA based Parameter Optimization

For optimally tuning the weights andbiases of the MLP, OBLBOA algorithm is incorporated. In addition, the OBLBOA incorporates the concept of OBL to improve the convergence rate.

BOA is a familiar metaheuristic algorithm that is inspired by the foraging and mating nature of the butterflies. A major feature of BOA from the other metaheuristic algorithm is that every butterfly possesses its own scene. Then, the butterfly's fragrance can be defined in Eq. (4):

$$f_i = cI^a \qquad (4)$$

where f_i is the supposedorder of fragrance, $c$signifies the sensory modality, and I is the stimulus intensity, and $a$denotes the power exponent depending upon the degree of fragrance absorption. Hypothetically, any values of the sensory morphology coefficient c in the range $[0, \infty]$ can be considered. But the value can be computed using the specificity of the optimization issue in the iterated procedure of the BOA.

The sensory modality c in the optimum searching level of the technique can be defined in Eq. (5):

$$c_{t+1} = c_t + [0.025/(c_t \cdot T_{\max})] \qquad (5)$$

where $T_{\max}$denotes the maximum iteration count and the initial value of parameter c is equal to 0.01. Besides, two levels exist in the technique namely global and local searching phases and are represented in Eqs. (6) and (7).

$$x_i^{t+1} = x_i^t + (r^2 \times g_{best} - x_i^t) \times f_i \qquad (6)$$

where x_i^tmeans the solution vector x_i of the ith butterfly in $t$round and $r$denotes an arbitrary number in the range of 0 to 1. At this moment, the g_{best} indicates the existing optimal solution obtained between the solutions exist at the present level. Specifically, the $f_i$characterizes the fragrance of the ith butterfly. The local searching level undergo formulation as given in Eq. (7):

$$x_i^{t+1} = x_i^t + \left(r^2 \times x_i^k - x_j^t\right) \times f_i \qquad (7)$$

where x_j^t and x_i^k are jth and kth butterflies chosen randomly from the solution space. If x_j^t and x_i^k belong to the same iteration, it means that the butterfly becomes a local random walk. If not, this kind of random movement will diversify the solution. The global and local searching processes for food and a mating patient occurs naturally. So, a switching probability p is set to convert the normal global and exhaustive local searching processes. At every round, the BOA arbitrarily creates a number in the range of [0,1], which is compared with switch probability p to choose whether to perform global or local searching processes. In order to improve the performance of the BOA, the OBL concept is incorporated. Fig. 3 demonstrates the flowchart of BOA algorithm.

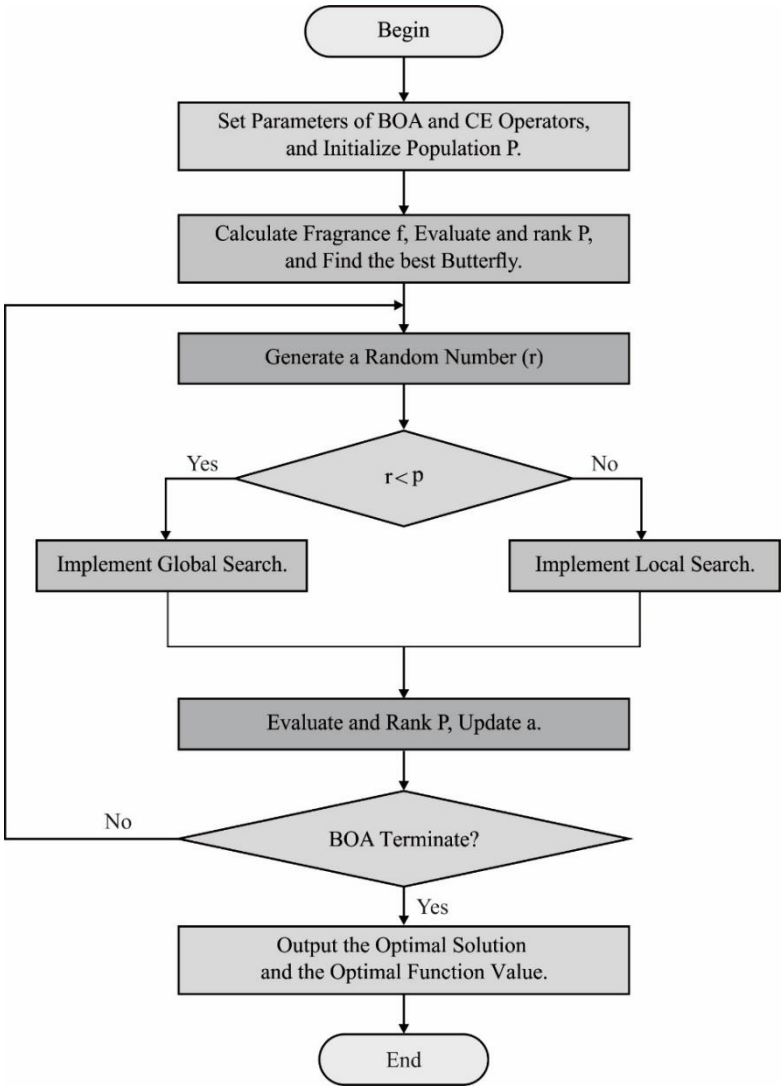

Fig. 3. Flowchart of BOA

OBL is a kind of optimization process that is commonly employed by several works for enhancing the quality of the initial solution by diversifying the solutions. The OBL mechanism takes place by searching every direction in the searching area. The two directions comprise the actual solution and another one indicates the opposite solution. At last, the OBL scheme takes to consider the fittest solution from the existing solutions.

Opposite number: $x$is defined using a real number over the interval $x \in [lb, ub]$. The opposite number of $x$could be represented by$\tilde{x}$and it determines the value by the use of Eq. (8):

$$\tilde{x} = lb + ub - x \quad (8)$$

Eq. (8) is employed for the searching area with multiple dimensions. For generalization, each search agent position and the opposite positions can be defined using the Eqs. (9)-(10):

$$x = [x_1, x_2, x_3, \dots x_D] \quad (9)$$

$$\tilde{x} = [\tilde{x}_1, \tilde{x}_2, \tilde{x}_3, \dots, \tilde{x}_D] \quad (10)$$

The values for everyelement in $\tilde{x}$can be defined using Eq. (11):

$$\tilde{x}_j = lb_j + ub_j - x_j \; where \; j = 1,2,3, \dots, D \quad (11)$$

Here, the fitness function is considered to be $f(.)$. So, when the fitness value $f(\tilde{x})$ of the opposite solution exceeds the $f(x)$ of the original solution, afterward $x = \tilde{x}$; else $x = x$.

The processes involved in the integration of OBL with the BOA are listed as follows.

- Initialization of butterfly populationX as $x_i where (i = 1,2, \dots, n)$.
- Compute the opposite position of butterfly population OX as $\tilde{x}_i where (i = 1,2, \dots, n)$.
- Choose the $n$optimal butterflies from $\{X \cup OX\}$ and it is employed for the new initial population of BOA.

Algorithm 1: Butterfly Optimization Algorithm

```
Begin
    Objective function f(x), x = (x_1, x_2, ..., x_d)^T, where d denotes the dimensionality.
    Produce initial population P comprising n butterflies pop_i (i = 1,2, ..., n).
    Induce I_i intensity at is pop_i computed using the fitness value f(pop_i).
    Represent the sensor modality c, power exponent a, and switch probability p.
    while termination criteria are not satisfied do
        for all butterflies in the population P do
            Determine fragrance f
        end for
        Assess and sort the population P, and determine the optimal butterfly.
        for all butterflies in the population,P do
            Produce an arbitrary number r ~ U[0, 1].
            if (r < p)
                Execute global searching process.
            else
                Execute local searching process.
            end if
        end for
        Update the value of the power exponent a.
    end while
    Generate the optimal solution and value.
End
```

3. Performance Validation

In order to validate the superior medical data classification performance of the OBLBOA-MLP model, an extensive experimental analysis was performed using Python 3.6.5 tool. In addition, the performance of the OBLBOA-MLP model is tested against two benchmark datasets namely CKD [18] and skin dataset.

3.1. Results analysis of OBLBOA-MLP model on CKD dataset

Table 1 provides a detailed comparative result analysis of the OBLBOA-MLP with existing methods interms of sensitivity, specificity, accuracy, and F-measure.

Fig. 4 examines the sens. and spec. analysis of the OBLBOA-MLP model with existing techniques on the applied CKD dataset. The figure illustrated that the SVM model has showcased ineffective classifier results with the sens. and spec. of 74.19% and 93.98%. Additionally, the OlexGA model has attained slightly improved outcomes by offering sens. and spec. of 80% and 66.66%. Besides, the LR model has obtained a somewhat increased outcome by offering a sens. and spec. of 83% and 82%. At the same time, the XGBoost model has accomplished a closer sens. and spec. of 83% and 83%.Eventually, the PSO algorithm has showcased somewhat reasonable results with a sens. and spec. of 88% and 80%.

Table 1 Comparative Analysis of various classifiers on CKD Dataset

Classifiers	**Performance Measures**			
	Sens.	Spec.	Acc.	F-measure
OBLBOA-MLP	98.82	96.91	98.23	98.45
Adam-LR	98.78	96.07	97.75	98.19
Fuzzy Neural Classifier	95.68	95.86	95.75	96.63
D-ACO	96.00	93.33	95.00	96.00
Multi-Layer Perceptron	92.30	92.86	92.50	94.11
Decision Tree	90.38	89.28	90.00	92.15
ACO	88.88	84.61	87.50	90.56
PSO	88.00	80.00	85.00	88.00
XGBoost	83.00	83.00	83.00	80.00
SVM	74.19	93.98	90.58	73.02
Logistic Regression	83.00	82.00	82.00	79.00
OlexGA	80.00	66.66	75.00	80.00

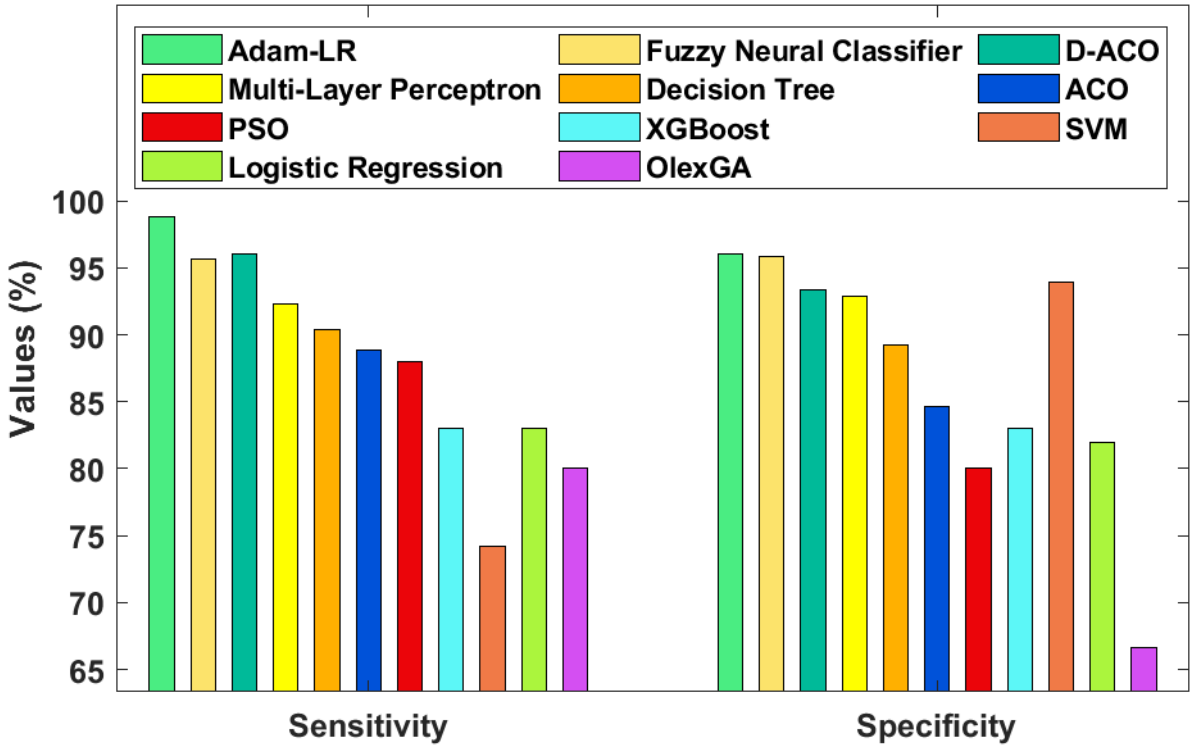

Fig. 4. Sensitivity and specificity analysis of OBLBOA-MLP model on CKD dataset

Likewise, the ACO algorithm has demonstrated even improved results with a sens. and spec. of 88.88% and 84.61%. Moreover, the DT model has depicted certainly considerable sens. and spec. of 90.38% and 89.28% respectively. Furthermore, the MLP model has resulted in a reasonable sens. and spec. of 92.3% and 92.86% whereas even higher classification performance is achieved by the FNC model with a sens. and spec. of 95.68% and 95.86% respectively. In the meantime, the D-ACO algorithm has led to a nearly acceptable outcome with a sens. and spec. of 96% and 93.33% respectively. Though the Adam-LR model has demonstrated near optimal outcome with a sens. and spec. of 98.78% and 96.07%, the presented OBLBOA-MLP model has accomplished a maximum sens. and spec. of 98.82% and 96.91%.

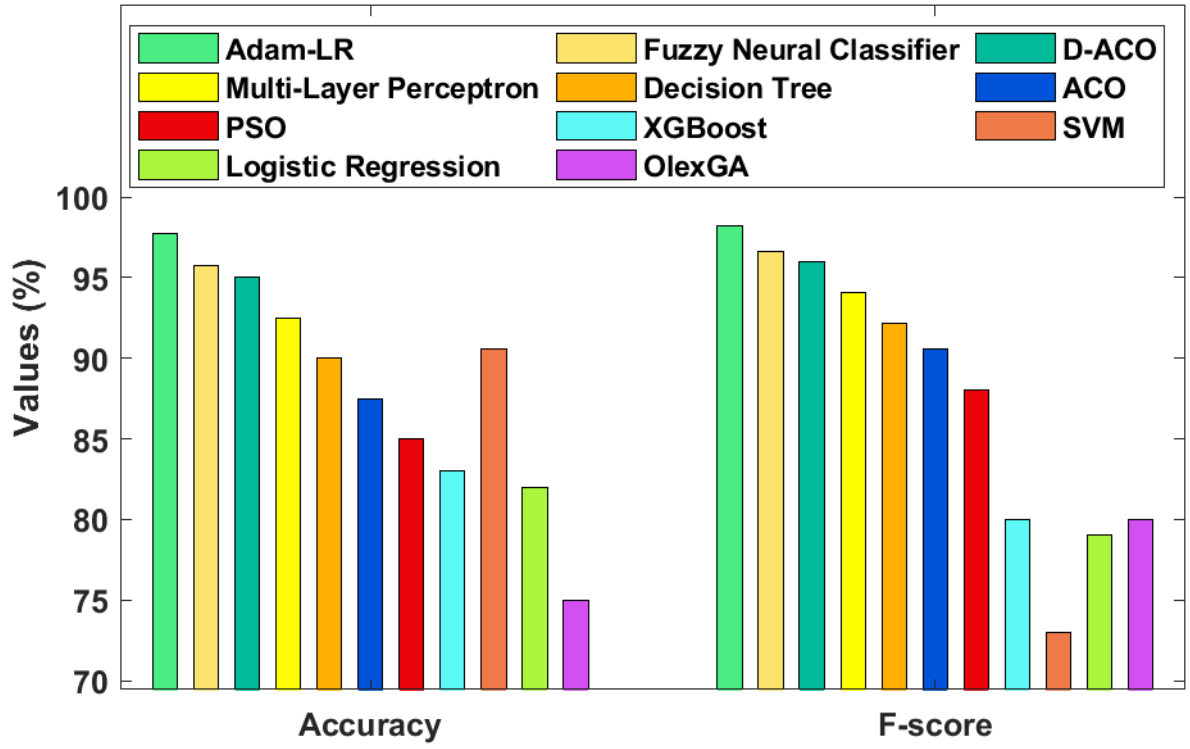

Fig. 5. Accuracy and F-score analysis of OBLBOA-MLP model on CKD dataset

Fig. 5determines the acc. and f-measure analysis of the OBLBOA-MLP techniquewith existing methods on the applied CKD dataset. The figure exhibited that the OlexGA model has portrayed ineffective classifier results with the acc. and f-measure of 75% and 80%. In line with, the LR model has obtained somewhat increased result by offering an acc. and f-measure of 82% and 79%. Besides, the XGBoost approach has reached a slightly higher outcome by offering an acc. and f-measure of 83% and 80%. Likewise, the PSO model has accomplished a closer acc. and f-measure of 85% and 88%. Followed by, the ACO algorithm has demonstrated somewhat reasonable results with acc. and f-measure of 87.5% and 90.56%. Along with that, the DT model has showcased even improved results with acc. and an f-measure of 90% and 92.15%. Also, the SVM model has depicted certainly considerable acc. and f-measure of 90.58% and 73.02% correspondingly. Furthermore, the MLP model has resulted in a reasonable acc. and f-measure of 92.5% and 94.11% whereas even higher classification performance is attained by the D-ACO model with acc. and f-measure of 95% and 96% respectively. In the meantime, the FNC method has led to a nearly acceptable outcome with acc. and f-measure of 95.75% and 96.63% respectively. But, the Adam-LR model has demonstrated near optimal results with acc. and f-measure of 97.75% and 98.19%, the proposed OBLBOA-MLP methodology has accomplished a higheracc. and f-measure of 98.23% and 98.45%.

Table 2 Comparative Analysis of various classifiers on Dermatology Dataset

Classifiers	**Accuracy**
OBLBOA-MLP	92.67
Naive Bayes	89.18
Decision Tree	77.03
SVM	79.72
Random Forest	77.02
BNB	98.64

Table 2 and Fig. 6 give a detailed comparative outcome analysis of the OBLBOA-MLP with existing techniques with respect to accuracy on Dermatology Dataset. The figure represented that the RF model has exhibited ineffective classifier results with an accuracy of 77.02%. Likewise, the DT technique has obtained a slightly higher result by offering an accuracy of 77.03%. On continuing with, the SVM approach has portrayed somewhat reasonable results with an accuracy of 79.72%. At the same time, the NB manner has outperformed even improved outcomes with an accuracy of 89.18%. At last, the projected OBLBOA-MLP technique has accomplished a superior accuracy of 92.67%.

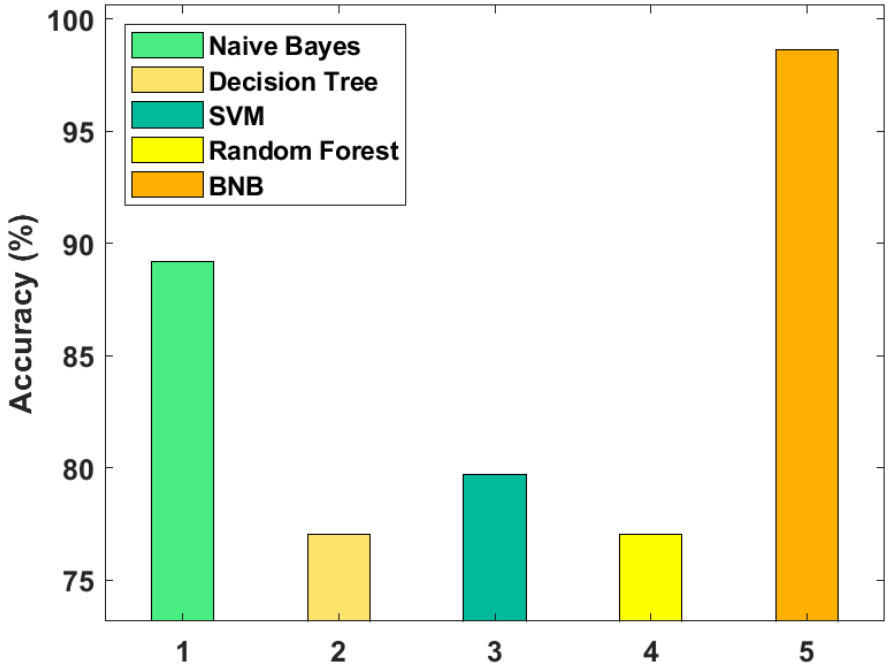

Fig.6. Accuracy analysis of OBLBOA-MLP model

4. Conclusion

This paper has presented a novel OBLBOA-MLP model for medical data classification. The presented OBLBOA-MLP model involves three stages of operation such as preprocessing, classification, and parameter tuning. At the initial stage, the data preprocessing takes place in three stages such as format conversion, data normalization, and class labeling. Next, the MLP based classification process is performed to assign proper class labels to the medical data. At last, OBLBOA is employed for tuning the parameters such as weights and biases of the MLP model. The application of OBL helps to increase the performance of the BOA. A detailed set of simulation analysis was performed to determine the appropriate detection results of the OBLBOA-MLP model. The obtained experimental values pointed out the improved classification performance by attaining a higher accuracy of 98.23% and 92.67% on the applied CKD and skin disease dataset respectively. As a part of future extension, deep learning architectures can be employed for enhancing the classification performance.

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