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A Comparative Analysis of Multi Medical Data Classification using different Feature Selection Techniques

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Abstract

By using data mining tools for early analysis and better patient survival rates, healthcare informatics is crucial in disease prediction and classification. Problems with missing value processing and choosing the best features from medical datasets, however, continue. Here, we present a full-stack approach to feature selection and classification on multi-datasets using cutting-edge optimization algorithms (Liver, Lung, Heart, and Thyroid). Modified Monarch Butterfly Optimization (MMBO), the initial algorithm to be suggested, finds the best features and fixes missing values that occur during preprocessing. A Deep Neural Network (DNN) classifier uses these properties to sort data into healthy and unhealthy norms. In multi-dataset performance tests, the MMBO-DNN algorithm achieves better results than state-of-the-art methods with regard to both accuracy and execution time. This paper presents HBSOODNN, a second model that addresses the significance of feature selection in medical data classification. This model combines an Optimal Deep Neural Network (ODNN) for classification with Hybrid Brain Storm Optimisation (HBSO) for feature selection. We optimize computation time by tuning the Brain Storm Optimization (BSO) approach with Genetic approach (GA). Next, we use a DNN that has been fine-tuned using Particle Swarm Optimization (PSO), referred to as PSO-DNN, to classify the subset with reduced features. Superb classification results are achieved by the HBSO-ODNN model on four different medical datasets. The last method is an innovative one that uses an IWD-DNN based DNN for medical data categorization and Quantum Dragonfly Optimization (QDFO) for feature selection. While IWD fine-tunes the weight and bias settings of the DNN, the QDFO algorithm chooses the best subset of features. Extensive testing on the Indian liver patient (ILP), lung cancer (LC), heart disease (HD), and thyroid datasets has demonstrated that the IWD-DNN model achieves better accuracy.

Keywords: *Deep Neural Network, feature selection, Healthcare informatics, Hybrid Brain Storm Optimization, Optimal Deep Neural Network.*

1. INTRODUCTION

Data classification has recently emerged as a promising strategy for data mining, with potential uses across the board in education [1]. Medical researchers have been investigating various data classification methods in an effort to enhance the accuracy of medical diagnosis [2]. There is a wealth of information about different diseases stored in

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medical databases, with each parameter defining a specific type of ailment [3, 4]. Because robotization strategies have advanced so dramatically, medical data classification is more important than ever before [5]. Improving illness diagnosis, especially in the early stages, may be possible with the use of data classification algorithms applied to medical data [6]. The prognosis for the patient's recovery is much improved when it is identified early on.

A medical data classification model uses previously collected data to determine if a patient's symptoms are real or not, based on the patient's data. For the purpose of making predictions, the "course and result of disease procedure" [7-8] is predicted by selectively collecting and analyzing patient data. An crucial tool of medical organization is prediction. As the classifier problems, medical analysis and prediction are modeled. Patients' medical records serve as the feature for making predictions. It may include demographic, pathological, and clinical information. The illness procedure's trajectory and outcome constitute the class in the event of a forecast. As an example of a comprehensible classifier approach, production regulations and DM is are very appealing in the medical arena [9-10]. By utilizing these forms, classifier approaches are improving the problem at hand and have been proven by medical specialists [11]. An expert in the history of breast cancer, for example, has assessed the resulting requirements for basic breast cancer analysis and divided them into three types [12].

A new trend for large healthcare data sectors is the use of computational or machine intelligence in clinical diagnosis [13]. Smart data classifier models systematise the diagnostic procedures used in clinical applications. The use of information technology (IT) models to aid doctors in making decisions and improve disease prediction is known as computer-aided decision-making (CAD) [14–15]. One of the most common and prominent CAD system processors, categorization assigns a tag to each query instance based on the number of attributes chosen [16–17]. Therefore, problems with clinical database categorization are considered a kind of challenging optimisation crises whose primary goal is to guarantee the diagnostic procedure. The following diagnostic makes use of clinical dataset classification problems in addition to classical classification issues. Symptoms reveal the true illness, which is extremely important for clinical dataset classification problems, but details about patients or doctors are often lacking. The basic tenet of this approach to classification problems is learning the decision surface that accurately maps the input feature to the output space [18-19]. Classification approaches achieved maximum results, numerous computer planners were able to employ multiple modalities to improve data classification accuracy, and as a result, we can now locate the most capable patients and make the most accurate diagnoses possible. Clinical data has been effectively categorised in recent studies using metaheuristic methods like Genetic Algorithm (GA), Simulated Annealing (SA), etc. [20].

2. BACKGROUND STUDY

Ashraf, R. et al. [1] To classify medical photos, a deep learning architecture is proposed; the images themselves are used for training. The capacity to precisely detect and investigate certain illnesses is one of the most critical requirements of the present day. Physicists and doctors can save time and effort by using reliable image analysis and computer-aided technologies. Nowadays, there is a critical need for the development of image processing methods that can assist doctors in several fields of medicine. It is clear that diseases can be predicted before they impact the human body, and such procedures are important to preserve human lives. Researchers in computer vision have been working on automated systems to scan medical images and make decisions using machines in an effort to close this gap over the past few decades.

Ghaddar, B., &Naoum-Sawaya, J. [5] Using iteratively adjusted bounds on the l1-norm of the classifier function to enforce the required sparsity level, this paper developed a new hybrid support vector machine classification and feature selection method. For applications with high dimensional features, where applying typical feature selection models directly is computationally intractable, the suggested approach stands out due to its computational tractability and intuitive implementation. Two major classification difficulties serve as examples of the proposed approach in action. One of the most important ways for businesses to swiftly assess and react to customer feedback is through sentiment classification of online reviews. The second use case is gene expression-based cancer categorization, which tries to integrate the abundant medical data available to help doctors make more precise diagnoses.

Jain, D., & Singh, V. [10] Chronic diseases are becoming more common and have a devastating impact on global health. Patients can also die due to improper therapy or a delay in receiving it. Therefore, a crucial job in the medical area is the prognosis of chronic diseases. An overview of numerous feature selection and classification methods, useful for severity analysis in the context of rapid disease diagnosis, is provided in this article. Based on various principles, the literature presents a number of feature identification algorithms that are both trustworthy and efficient. Researchers are concentrating on developing new ways to increase the learning machines' efficiency, even if feature selection is an established area.

Lakshmanaprabu S. et al. [13] In this study, we introduced an Internet of Things (IoT) system that uses a cloud-based CDSS architecture to forecast the severity of chronic kidney disease (CKD). Using the UCI Repository dataset, this research presents a methodical approach to CKD and generates pertinent healthcare data. Also, medical sensors are utilised to gather data from CKD patients and keep it as medical records. To learn how to divide data into categories like "Normal" and "Abnormal," we used a DNN-based ML system. With a classification accuracy of 98.25 after using PSO based feature selection, the classifier output is a considerable improvement over the 99.25 output before feature selection.

Mohamed Elhoseny et al. [15] In order to categorize the CKD dataset, this study presents a healthcare intelligence prediction and classification system called the D-ACO approach. This method integrates DFS with ACO. The proposed D-ACO system, in contrast, eliminates unnecessary features while concurrently performing FS and ACO based learning. Using a benchmark CKD dataset, we assess the D-ACO algorithm's performance in comparison to other techniques. Comparative testing revealed that the suggested D-ACO algorithm performed better than its rivals in every respect. In conclusion, the suggested D-ACO approach is a suitable classifier for CKD detection.

Murad Al-Rajab, et al. [17] Making it easier to use hierarchical classification for early BC prediction was the driving force for creating a multiclass BMIC Net classification model. The primary classifier determines if the BC is benign or malignant; the secondary classifier refines the subtypes of benign or malignant BC based on the predictions of the top-level classifier. The proposed BMIC Net was trained and evaluated using the publically available Break His dataset. Following the acquisition of the MFVs and the tweaking of the pre-trained Alex Net architecture, the features were extracted using TL. There were enormous features in these vectors. To get the most discriminating features, IG and PCA were employed. Finally, the features that had been extracted were subjected to six traditional ML methods in order to evaluate the classification's correctness. When comparing IG and PCA, multiple studies found that IG successfully extracted more discriminative features than PCA.

3. MATERIALS AND METHODS

Specifically, the experimental setup, instruments, and processes used in the study are described in depth in the materials and methods section. To grasp the research's scientific rigour and ensure its replicability, this component is vital. The following is a detailed description of the study's methodology, including all of the materials and methods utilized to conduct the experiments.

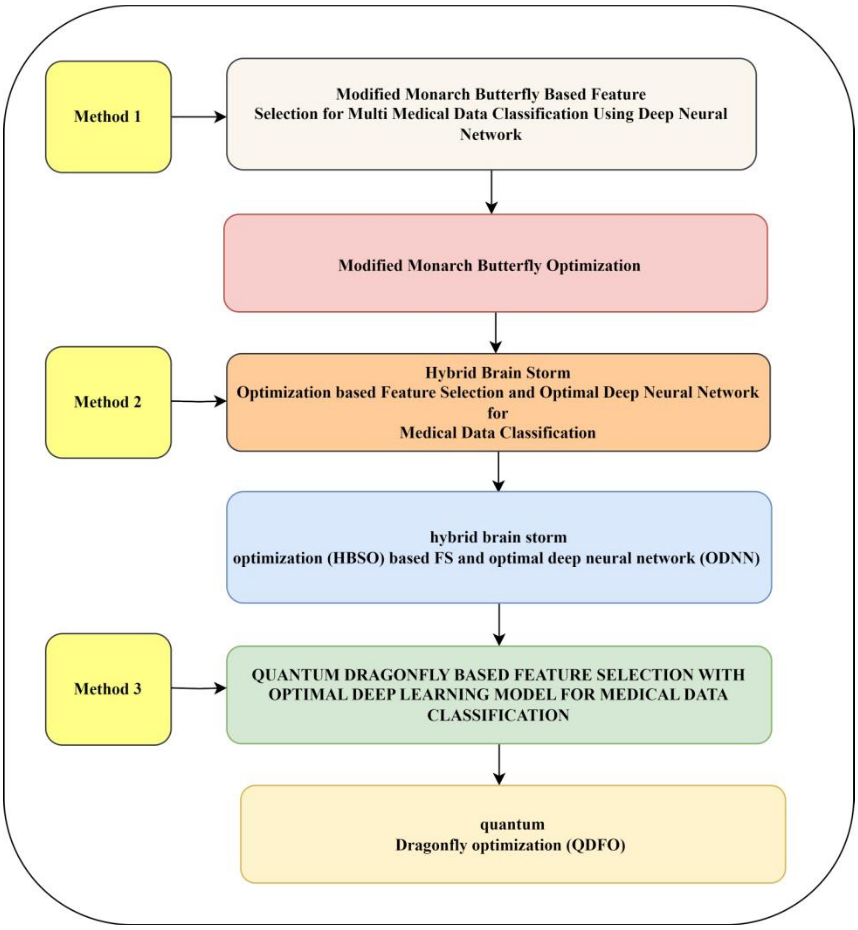

Figure 1: Proposed workflow architecture

3.1 MMBO-DNN Algorithm

An extremely difficult implementation technique assignment is processing a large number of features in databases. One of the primary goals of feature selection in data mining is to decrease the dimensionality and noise of datasets by identifying and removing relevant attributes. The purpose of feature selection is to extract useful information from datasets while excluding extraneous characteristics. If the risk of over-fitting grows in proportion to the amount of features, feature selection improves learning and classification performance. In this paper, we offer an MMBO algorithm for feature selection.

Monarch Butterfly Optimization: The metaheuristic algorithm known as Monarch Butterfly Optimization (MBO) takes its cues from the way monarch butterflies migrate [26].The migration behavior of MBO is explained as follows:

Rule 1: Only in Lands 1 and 2 can you find monarch butterflies.

Rule 2: The caterpillars of the monarch butterfly are produced by migratory operators in either Land 1 or Land 2.

Rule 3: If a newly-created MBO achieves better fitness function performance than its parent, the MBO algorithm will revert to its initial state. This indicates that there has been no change to the population range.

Rule 4: The next generation of butterflies is selected by comparing them to their parents; operators are unable to change the ones with the highest fitness levels. This will be valuable for years to come.

Modified Monarch Butterfly: Equation (3) explains the process of randomly selecting a value, with the value selected based on the Particle Swarm Optimization (PSO) method's velocity update, to alter the general monarch butterfly. What follows is a rundown of the steps to take.

Initialization: Both Land 1 and Land 2 begin with n populations of monarch butterflies in the Monarch Butterfly Optimizer. To assess fitness using a variety of criteria, we track the whereabouts of monarch butterflies.

Updating the positions of MMBO

The MBO location can only be changed through two operations: the migration operator and the butterfly adjustment operator.

Migration operator: In particular, monarch butterflies located in Land 2 are referred to as Subpopulation 2, whereas those found in Land 1 are referred to as Subpopulation 1. Subpopulations 1 and 2 serve as the starting points for the study, with their respective characteristics analyzed. This migration process can be explained as follows

$$f_{i,t}^{G+1} = f_{r1,t}^{G} \text{ ------------ (1)}$$

Two criteria in the migration process: (i) in cases when the freshly formed monarch butterfly's element t is produced by (2). Here, r can be computed as

$$r = rand * period \qquad \text{----------- (2)}$$

In equation (2), the random value is chosen based on the velocity update of Particle Swarm Optimization (PSO) algorithm (modified MBO). Its updation process is explained as in equation (3).

Velocity updation of PSO: Particle velocities are modified in accordance with Gbest and Best values based on swarm behaviour, i.e. the PSO algorithm. The formulation for updating the velocity of the particles in the PSO is given as:

$$v_i(t+1) = v_i(t) + b_1 rand(Pbest(t) - r_i(t)) + b_2 rand(Gbest - r_i(t)) \text{ ------------ (3)}$$

Where, V_i is the particle velocity, r_i is the current particle, rand is a random number between (0, 1), b_1, b_2 are the learning factor, usually $b_1 = b_2 = 2$.

(ii) If $r > p$ then the element t in the newly generated monarch butterfly is generated by

$$f_{i,t}^{G+1} = f_{r2,t}^{G} \text{ -------------- (4)}$$

Parameter Description: From equation (1), $f_{i,t}^{G+1}$ symbolizes the t^{th} element of f_i at generation $G+1$ that introduces the position of the monarch butterfly i. $f_{r1,t}^{G}$ Indicates the t^{th} element of f_{r1} that is the newly generated position of the monarch butterfly $r1$. G is the current generation process. The term $r1$ is randomly chosen monarch butterfly from subpopulation 1. A integer selected at random from a uniform distribution, rand, denotes the migration period in equation (2). The MMBO algorithm can rebalance the migration operator's direction by changing the value of p. The migration period determines the value of p, which is 5/12.

Butterfly Adjusting Operator: The position of MMBO is also updated by another operator i.e. butterfly adjusting operator. Considering all the MMBO elements (medical data attributes) are in j. If ($rand \leq p$), the position can be updated as

$$= \begin{cases} f_{j,t}^{G+1} = f_{best,t}^{G}, & , \quad if\ rand \le p \\ f_{j,t}^{G+1} = f_{r3,t}^{G} & , \quad if\ rand > p \end{cases} \text{ -------------- (5)}$$

Under this condition, if rand> BAR (Butterfly Adjusting Rate), it can be further updated as follows:

$$f_{j,t}^{G+1} = f_{j,t}^{G+1} + \alpha \times (dx_t - 0.5) \text{ ------------ (6)}$$

Where BAR indicates butterfly aligning rate. The term α indicates the weighting factor that is afforded as $\alpha = WS_{\max} / G^2$ where $WS_{\max}$ max walk step that a monarch butterfly individual can move in one step at the current generation G.The parameter dx is the walk step of the monarch butterfly j that can be computed by performing Levy flight.

$$dx = Levy(f_j^g) \text{ ------------ (7)}$$

By selecting the most relevant features from the medical dataset, this MMBO algorithm simplifies the classification procedure.

3.2 HBSO-DNN based Feature selection

When faced with an issue that no one person can possibly solve, brainstorming sessions have become standard practice. We assemble people from all walks of life to brainstorm solutions to these concerns. By generating as many different kinds of solutions as possible, BSO hopes to find the one that works best for a given problem.BSO is an innovative human-generated ST technology that uses a population-based approach. Based on a fitness function, BSO generates a set of hypothetical outcomes and assigns an estimate to each. Idea generation, person clustering, and disordered cluster centres are the three steps that make up BSO.

In order to classify users, BSO employs the k-means clustering method. There are a lot of similar ideas in all kinds of art. In the process of generating novel ideas, a P-possibility disrupts the regular operation of the cluster centre, leading to the emergence of an arbitrary cluster centre. At last, BSO can use one or two clusters to generate a new individual. When creating a new individual, BSO uses the likelihood of Pone to randomly select one or two clusters. Next, BSO arbitrarily choose 1individual based on 1 or 2 cluster(s) center(s), as pursue:

$$\mathrm{X_{selected}} = \{\mathrm{X_i}\ \mathrm{rand} \times \mathrm{X_{1i}} + (1 - \mathrm{rand}) \times \mathrm{X_{2i}} \text{ -------------- (8)}$$

where X1i and X2i are the ith dimension of the selected clusters, and rand is a random value between 0 and 1. BSO updates the selected individual as follows:

$$\mathrm{X_{new}} = \mathrm{X_{selected}} + \varepsilon * \mathrm{random}(0,1) \text{ ------------ (9)}$$

where random is a Gaussian random value with 0 mean and unit variance, respectively; ξ is the adjusting factor, i.e.,

$$\varepsilon = \mathrm{logsin}\left(\frac{0.5 * \mathrm{m_i} - \mathrm{c_i}}{\mathrm{k}}\right) \times \mathrm{rand} \text{ ---------------- (10)}$$

where iteration is currently occurring and where the maximum number of iterations has been; For the logarithmic sigmoid function, we have losin (); for every integer between 0 and 1, we have rand(), and for the rate at which the slope of the logsin () function changes, we have.

3.3 QDFO-DNN algorithm based FS Model

For population-related meta-heuristics, Mirjalili's Dragonfly Algorithm (DA) has recently been introduced. It turns out that DA emerged from optimal dragonfly migratory technologies and a hunting principle called static swarm. For the most part, dragonflies forage for food in small groups. It is named a hunting mechanism.

The dragonflies swarming nature is simplified by 5 operators:

Separation is defined as models which make sure that maintaining search agent distant from neighbourhood. The numerical modeling of isolation nature is depicted in Eq. (11).

$S_i = -\sum_{j=1}^{N} \quad X - X_i$ --------- (11)

Not long ago, Mirjalili introduced the Dragonfly Algorithm (DA) for meta-heuristics pertaining to populations. As it turns out, DA evolved from static swarm hunting principles and optimum dragonfly migratory technology. Dragonflies typically come in small groups while they start foraging. Hence, numerical form of alignment behavior is illustrated in Eq. (12):

$A_i = \frac{\sum_{j=1}^{N} \quad V_j}{N}$ ------------- (12)

where $V_j$implies the efficiency of j-th neighbor.

Cohesion is the process of flying an operation from a nearby area to the mass centre. It denotes everyone's capacity to gravitate towards a nearby centre of mass. Thus, arithmetical function of Cohesion behavior is demonstrated in Eq. (13).

$C_i = \frac{\sum_{j=1}^{N} \quad x_j}{N} - X$ ------------------ (13)

Attraction denotes how food source attains the individual which flies towards them. Thus, mathematical format of this nature is implied in Eq. (14).

$F_i = F_{loc} - X$ ------------ (14)

where F_{loc}implies a place of food source.

Distraction means the ability of individuals to move away from an opponent individual. Hence, distraction among i^{th} solution and enemy is arithmetically designed in Eq. (15).

$E_i = E_{loc} + X$ ------------- (15)

Where E_{loc}refers the location of enemy.

Using a candidate with optimal fitness has improved the DA search, food source fitness, and position processes. Furthermore, an opponent's fitness and position can be enhanced by a poor candidate.

The generic approach of PSO method is applied by DA as it applies 2 vectors for upgrading place of a dragonfly namely, step vector (ΔX) which is same as PSO velocity vector as well as position vector. The step vector (Eq. (16)) is facilitated to change the dragonflies' action.

$\triangle X_{t+1} = (sS_i + aA_1 + cC_i + fF_i + eE_i) + w \triangle X_t$ ------------ (16)

where s, a, c, f, and emeant to be weights of separation S_i, alignment A_i, cohesion C_i, movement efficiency with food source F_i, and an enemy interruption level E_i of i^{th} individual correspondingly. Eq. (17) implies the parameters tuning at the optimization task to manage exploration and exploitation. It is pointed that w is an inertia weight which is estimated according to Eq. (18). The details regarding the measures of such parameters and the impact on DA nature is identified.

$c = 2 \times r \times pct$ --------------- (17)

$w = 0.9 - Iter * \frac{(0.9-0.4)}{Max\_iter}$ ------------------ (18)

where pct is determined as Eq. (19)

$$pct = \{0.1 — \frac{0.2 \times iter}{max - iter}, \text{if } (2 \times Iter) \leq Max\_Iter \ 0, \text{otherwise} \quad \text{----------} \ (19)$$

where rimplies a random value from [0,1]. The position of an individual is upgraded as shown in Eq. (20):

$$X_{t+1} = X_t + \triangle X_{t+1} \quad \text{--------------} \ (20)$$

where tmeans a recent step. Algorithm 1 implies pseudo-code of DA.

4. RESULTS AND DISCUSSION

A comprehensive analysis and explanation of the data acquired are provided in the results and discussion section, which also gives the study's findings. This section is essential for elucidating the significance and relevance of the results in relation to the study's aims. In this brief overview, we focus on the results and discussion, drawing attention to important conclusions that can be drawn from the experimental findings.

Table 1: Classification metrics Comparison for Lung Cancer Dataset

Methods	Sensitivity	Specificity	Accuracy
FOA-SVM	93.20	90.00	93.52
PSO-DNN	78.52	86.22	71.25
GA-DNN	75.22	86.45	84.22
MBO-DNN	86.55	82.22	88.52
MMBO-DNN (Method 1)	95.58	94.80	97.59
HBSO-ODNN (Method 2)	96.94	95.79	98.65
QDFO-DNN (method 3)	97.63	98.90	98.87

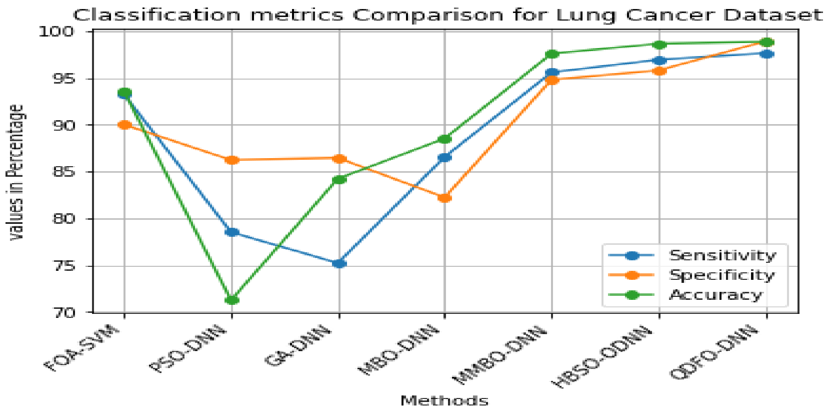

Figure 2: Classification metrics Comparison chart for Lung Cancer Dataset

The table 1 and figure 2 shows the performance metrics (sensitivity, specificity, and accuracy) of various methods in a classification task. Among the methods, "QDFO-DNN (Method 3)" stands out as the top performer, achieving the highest values in sensitivity (97.63%), specificity (98.90%), and accuracy (98.87%). "HBSO-ODNN (Method 2)" closely follows with impressive results, boasting high values in sensitivity (96.94%), specificity (95.79%), and accuracy (98.65%). "MMBO-DNN (Method 1)" also performs exceptionally well, particularly excelling in sensitivity (95.58%) and accuracy (97.59%). On the other hand, "PSO-DNN" demonstrates lower performance across all metrics, indicating a potential area for improvement. The results underscore the varying effectiveness of different optimization algorithms coupled with deep neural networks for classification tasks, with "QDFO-DNN" showing notable superiority in this context.

Table 2: Performance metrics Comparison for Indian Liver Patient

Methods	Sensitivity	Specificity	Accuracy
FOA-SVM	92.00	92.00	82.22
PSO-DNN	88.52	86.22	86.44
GA-DNN	92.22	88.20	83.56
MBO-DNN	82.20	90.00	94.52
MMBO-DNN (method 1)	90.00	96.45	97.48
HBSO-ODNN (method 2)	92.37	97.87	98.45
QDFO-DNN (method 3)	94.89	98.97	98.86

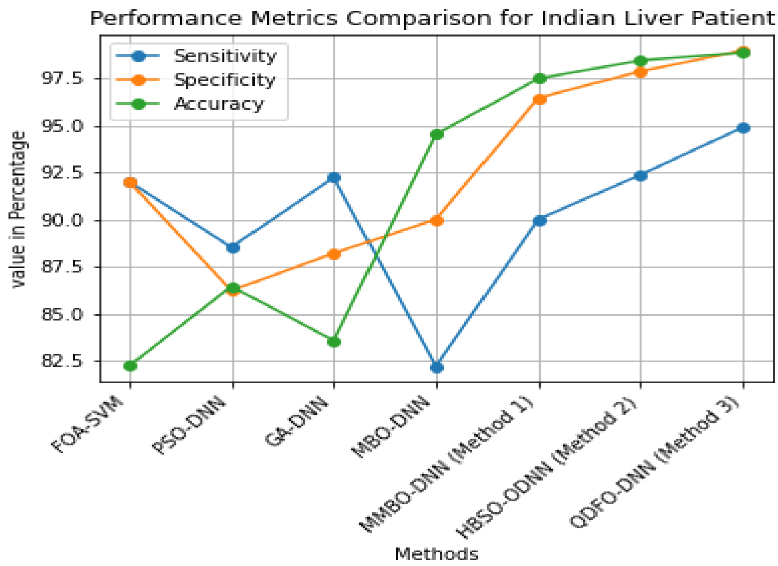

Figure 3: Performance metrics Comparison chart for Indian Liver Patient

The table 2 and figure 3 shows the performance metrics—sensitivity, specificity, and accuracy—for different methods applied to the classification of Indian Liver Patient data. Notably, "QDFO-DNN (Method 3)" emerges as the top-performing method, achieving the highest sensitivity (94.89%), specificity (98.97%), and accuracy (98.86%). "HBSO-ODNN (Method 2)" closely follows, demonstrating exceptional results with high sensitivity (92.37%), specificity (97.87%), and accuracy (98.45%). "MMBO-DNN

(Method 1)" also performs commendably, particularly excelling in specificity (96.45%) and accuracy (97.48%). Conversely, "MBO-DNN" stands out for its lower sensitivity (82.20%) despite achieving a high accuracy of 94.52%. The findings highlight the varying effectiveness of optimization methods coupled with deep neural networks in the context of liver patient classification, emphasizing the importance of selecting the most suitable approach based on specific performance criteria.

Table 3: Performance metrics Comparison for HD Dataset

Methods	Sensitivity	Specificity	Accuracy
FOA-SVM	93.20	91.22	92.10
PSO-DNN	89.45	79.22	86.22
GA-DNN	88.00	86.45	86.22
MBO-DNN	86.22	88.52	90.00
MMBO-DNN (method 1)	97.48	95.00	95.45
HBSO-ODNN (method 2)	98.23	95.96	96.89
QDFO-DNN (method 3)	98.78	96.92	98.24

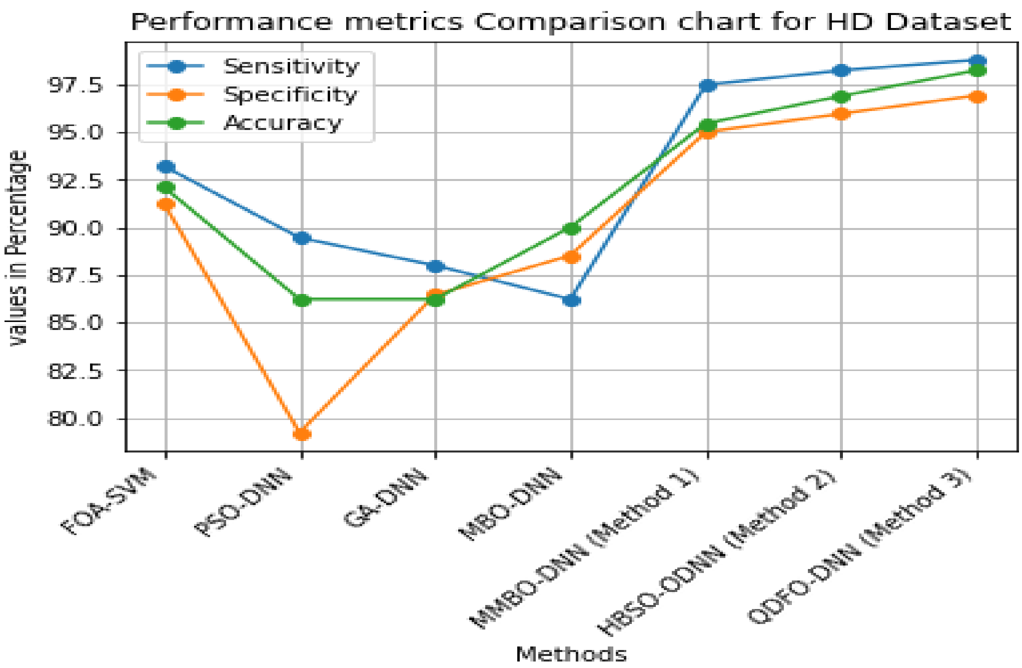

Figure 4: Performance metrics Comparison chart for HD Dataset

The table 3 and figure 4 shows the performance metrics—sensitivity, specificity, and accuracy—for different methods applied to a task, potentially related to health diagnostics or classification. Notably, "QDFO-DNN (Method 3)" emerges as the top-performing method, exhibiting the highest sensitivity (98.78%), specificity (96.92%), and accuracy (98.24%). "HBSO-ODNN (Method 2)" closely follows, demonstrating remarkable results with high sensitivity (98.23%), specificity (95.96%), and accuracy (96.89%). "MMBO-DNN (Method 1)" also performs commendably, particularly excelling in sensitivity (97.48%) and accuracy (95.45%). Conversely, "PSO-DNN" stands out for its lower specificity and accuracy despite a relatively high sensitivity, indicating potential trade-offs in performance. The findings underscore the varying efficacy of optimization methods coupled with deep neural networks in the context of classification tasks, emphasizing the importance of selecting an appropriate approach based on specific diagnostic requirements.

Table 4: Performance metrics Comparison for Thyroid Disease Dataset

Methods	Sensitivity	Specificity	Accuracy
FOA-SVM	92.20	90.00	93.33
PSO-DNN	75.52	83.21	69.45
GA-DNN	85.22	78.22	86.22
MBO-DNN	88.50	88.20	83.33
MMBO-DNN (method 1)	92.22	93.00	96.00
HBSO-ODNN (method 2)	93.21	93.80	96.85
QDFO-DNN (method 3)	96.83	98.27	98.09

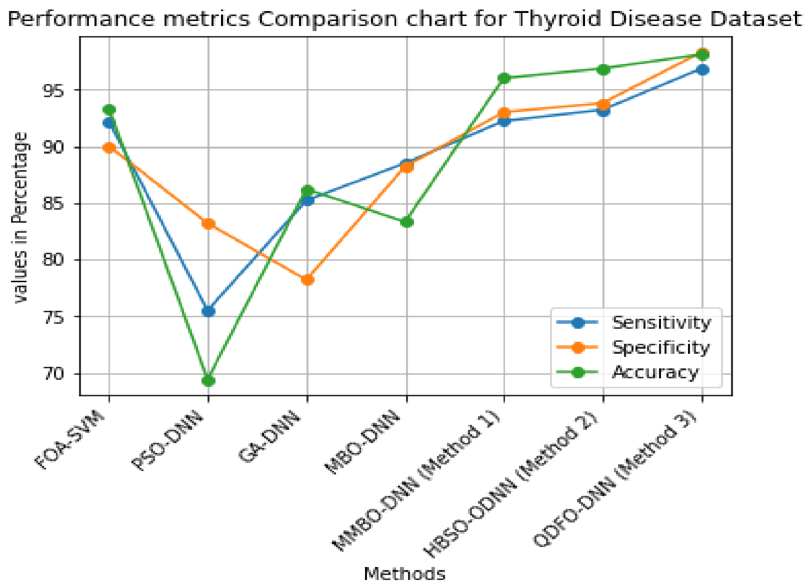

Figure 5: Performance metrics Comparison chart for Thyroid Disease Dataset

The table 4 and figure 5 shows the performance metrics—sensitivity, specificity, and accuracy—for various methods applied to a classification task. "QDFO-DNN (Method 3)" emerges as the most effective method, boasting the highest sensitivity (96.83%), specificity (98.27%), and accuracy (98.09%) among the methods considered. "HBSO-ODNN (Method 2)" closely follows, demonstrating strong results with high sensitivity (93.21%), specificity (93.80%), and accuracy (96.85%). "MMBO-DNN (Method 1)" also performs well, particularly excelling in sensitivity (92.22%) and accuracy (96.00%). On the other hand, "PSO-DNN" shows relatively lower performance, particularly in accuracy (69.45%), suggesting potential areas for improvement. These findings underscore the varying efficacy of optimization methods coupled with deep neural networks in the context of classification tasks, emphasizing the importance of selecting the most suitable approach based on specific performance criteria and application requirements.

5. CONCLUSION

Presenting and assessing three novel models for medical data classification, this paper concludes by tackling important issues in healthcare informatics. When it comes to selecting features and handling missing values in various datasets, the MMBO-DNN algorithm demonstrates outstanding efficiency and accuracy. A strong solution is the HBSOODNN model, which combines the Feature Selection (FS) and Optimal Deep Neural Network (ODNN) approaches. By fine-tuning the computational efficiency of the Brain Storm Optimization (BSO) technique with Genetic technique (GA), we are able to produce an amazing feature-reduced subset for classification. Following this, the PSO-DNN model's classification performs exceptionally well on four medical datasets. Moreover, a new method for medical data categorization is provided by the Intelligent Water Drops (IWD) Deep Neural Network (IWD-DNN) model and the Quantum Dragonfly Optimization (QDFO) based Feature Selection. Improved accuracy on several medical datasets is the consequence of the QDFO algorithm's effective feature selection and the IWD's fine-tuning of the DNN parameters.

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