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ARTICLE

AN OPTIMAL METAHEURISTIC BASED FEATURE SELECTION WITH DEEP LEARNING MODEL FOR AUTISM SPECTRUM DISORDER DIAGNOSIS AND CLASSIFICATION

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ABSTRACT

Autism spectrum disorder (ASD) is a neurological disorder defined by a particular set of issues linked to communication, social skill, and repetitive behavior. Recently, machine learning (ML) and healthcare sectors are integrated to determine the presence of several diseases. Therefore, this paper presents a new ASD diagnosis model using quasi oppositional based dragonfly algorithm (DOA) for feature selection (QODF) with deep SAE network (DSAN). The proposed QODF-DSAN model incorporates quasi oppositional based learning (QOBL) concept to increase the convergence rate of DOA. The QODF algorithm is employed for selecting an optimal subset of features. In addition, the DSAN model is applied for classification purposes. In order to ensure the effective performance of the QODF-DSAN model, a set of simulations takes place on three benchmark dataset. The resultant simulation outcome verified the effective classification results with the higher accuracy of 97.60%, 97.87%, and 97.12% on ASD-Children, ASD-Adolescent, and ASD-Adult dataset respectively.

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KEY WORDS
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INTRODUCTION

In general, Autism Spectrum Disorder (ASD) is a neuro developmental infection classified by pervasive defects in social communication, and repeated behaviors, diverse interests, and function. The traditional concepts are relevant to different ailments like autistic infection, Asperger's ailments, and genetic disintegrative disorder [1]. ASD is recently divided as a single disorder with severity level that fails to continue in final edition of Diagnostic and Statistical Manual of Mental Disorders (DSM-5) [1]. The shifting towards a categorical to dimensional method results in well-equipped physicians by applying standardized diagnostic tools which differentiate the signs of DSM-IV disorders [2]. Moreover, DSM-5 is composed of reports with co-occurring situations and age of onset. It modified to ASD diagnostic criteria which facilitates to categorize the subtypes of ASD [3]. As shown by recent diagnostic applications, ASD is one of the heterogeneous infections. The signs of ASD are language disability and skills in alternate developmental applications (adaptive skills and executive performance) [4] which differ in higher value over the examined individuals.

Followed by, onset of symptoms varies from one another that shows delays or plateaus in deployment, and regression of classically obtained achievements. Most of the patients affected with ASD have alternate disorders which are prevalent. ASD is caused for various reasons like genetics and environment functions. It can be examined with genetic variants of ASD cases, and massive number of cases is linked with genes. Moreover, the common rates of population of ASD are compared with alternate connections of individuals affected with ASD and patients with diverse genetic infections. The ecological factors are also considered as the root cause for ASD development. Prenatal exposures, aged parenting, longer gap between births, and birth complexities were embedded with ASD formation. While identifying the environmental and genetic infections to ASD, it is not replicated well and no single factor was examined in ASD. Additionally, the presentation and etiology, patients with ASD show different reactions for various treatments. A well-known treatment for ASD is Applied Behavior Analysis (ABA).

The principle behind ABA module is learning and motivation to change the timid behavior (enforces skill acquisition, limit the complicated behaviors) [5]. ABA is initialized at an earlier age and expressed on higher intensity like 25 to 40 h per week for massive days. Even though ABA shows an efficient result for ASD, the treatment response differs from each individual. Numerous factors are utilized in predicting the favorable response. The treatment aspects like treatment intensity consider a concerned number of variance monitored in treatment response, child based factors were found. Younger age, low severity of ASD signs, good IQ, robust adaptive skills, better language skills, and social skills were also related with supreme results. In spite of the reliable findings, the capability in predicting individual treatment response has been mitigated limited.

Recently, the developers have concentrated in different heuristics and statistical methodologies to comprehend and examine the models for diagnosing and recover from ASD. In this model, Machine Learning (ML) is one of the effective approaches used for examining the tedious concepts [6]. Thus, ML method is applied for implementing binomial classification tasks to find the features for predicting the infection. Only few works have concentrated on autism detection research. In particular, diagnosing ASD [7] is performed with the help of ML models where it enhances the diagnosing efficiency, for instance, [8] reduced the actual Autism Diagnostic Observation Schedule (ADOS) for massive number of behavioral parameters which has exhibited better sensitivity and specificity by mapping the performance level of developed ADOS models. In this method, Support Vector Machines (SVM) classifier has been used for ASD prediction by examining the subset of behavioral attributes in ADOS. To relate the analysis of these methods were examined using areas under ROC curves (AUCs) from the accomplished predictions on limited subset and previous subsets are projected by ADOS framework. On dividing the data as subgroups, an effective accuracy has been gained from the above-mentioned approaches.

[9] deployed a ML-centric estimation of autism with 3 complementary approaches for providing a diagnostic and better result: The 4-minute long, parent-report study has been accomplished by mobile apps, collection of basic behavioral parameters obtained from arbitrary clips of children, and a 2-minute study acquired from the physician in medical estimation. As a result, better medical analysis has been accomplished in US, over the age of 18–72 months. [10] projected a novel mobile application which has been applied for resolving the complexity in customers and health research community a friendly, time-effective, and applicable mobile-oriented ASD screening named as ASD Tests. [11] introduced an effective prediction approach according to ML model for developing a mobile application for ASD forecasting. It is manufactured under the combination of Random Forest CART and RF-ID3. The methods were computed with AQ-10 dataset, and real-time datasets have been gathered from users affected with autistic defects. Therefore, performance estimation has showcased that the presented approach has gained better accuracy for children, maximum in adolescents and greater in adults with AQ-10 datasets with optimal accuracy than real datasets.

This paper presents a new ASD diagnosis model using quasi oppositional-based dragonfly algorithm (DOA) for feature selection (QODF) with deep SAE network (DSAN). The proposed QODF-DSAN model incorporates quasi oppositional based learning (QOBL) concept to increase the convergence rate of DOA. The QODF algorithm is employed for selecting an optimal subset of features. In addition, the DSAN model is applied for classification purposes. To ensure the effective performance of the QODF-DSAN model, a set of simulations occur on three benchmark dataset.

METHODS

In overall working process of the QODF-DSAN method is shown in [Fig. 1]. As depicted, a patient's medical data is primarily preprocessed to improve data quality. After that, QODF algorithm is applied to select an optimal set of features. At last, the feature reduced subset is fed into the DSAN based classifier to determine the appropriate class labels.

Preprocessing

Initially, patient data is preprocessed in 3 stages namely format conversion, missing value replacement, and class labeling. At first, the input data in .arff format is changed into the companionable .csv format. Also, the missing values take place in the dataset are occupied by the median method. Finally, the class labeling process is carried out to map the class labels of the data into ASD.

Feature Selection Process using QODF algorithm

Once the patient data is preprocessed, QODF algorithm is executed to choose an optimal set of features. The QOBL is included to the DF algorithm to increase the convergence rate.

In dragonfly Algorithm (DA) is a recently developed bio-inspired optimization method deployed by [12]. It is mainly evolved from dynamic and static performances of dragonflies swarming behavior. Dragonflies are generally the class of fancy insects. Around 3000 varieties of these insects were found globally. Specifically, Nymph and adult are 2 major phases of dragonfly's lifecycle. Thus, nymph stage is passed for many years and then enters into metamorphism stage. Dragonflies are tiny predators. Additionally, nymph dragonflies consume tiny fishes and alternate types of marine insects. The DA approach is composed of 2 objectives namely, Hunting (static swarm) and Migration (dynamic swarm). In case of static swarm, dragonflies make tiny groups and move backward within a designated region for hunting the flying victims. A flying way feature of static swarm is immediate changes and local movements. Therefore, the feature differs from dynamic swarm, as larger dragonflies, count of migrating over longer distances create the swarm to move in single direction. It is evolved from developing sub-swarms and flies over numerous areas in a dynamic swarm that aims in exploration phase whereas static swarm tries to move in bigger swarms as decided in exploitation phase [13].

In DA model, 3 primitive strategies of swarming behavior are defined in the following:

- Separation: It means the elimination of individuals' static collision from each other.
- Alignment: It means the individual velocity corresponding to alternate neighbourhood separates.
- Cohesion: it refers individuals' capacity to neighborhood' mass center.

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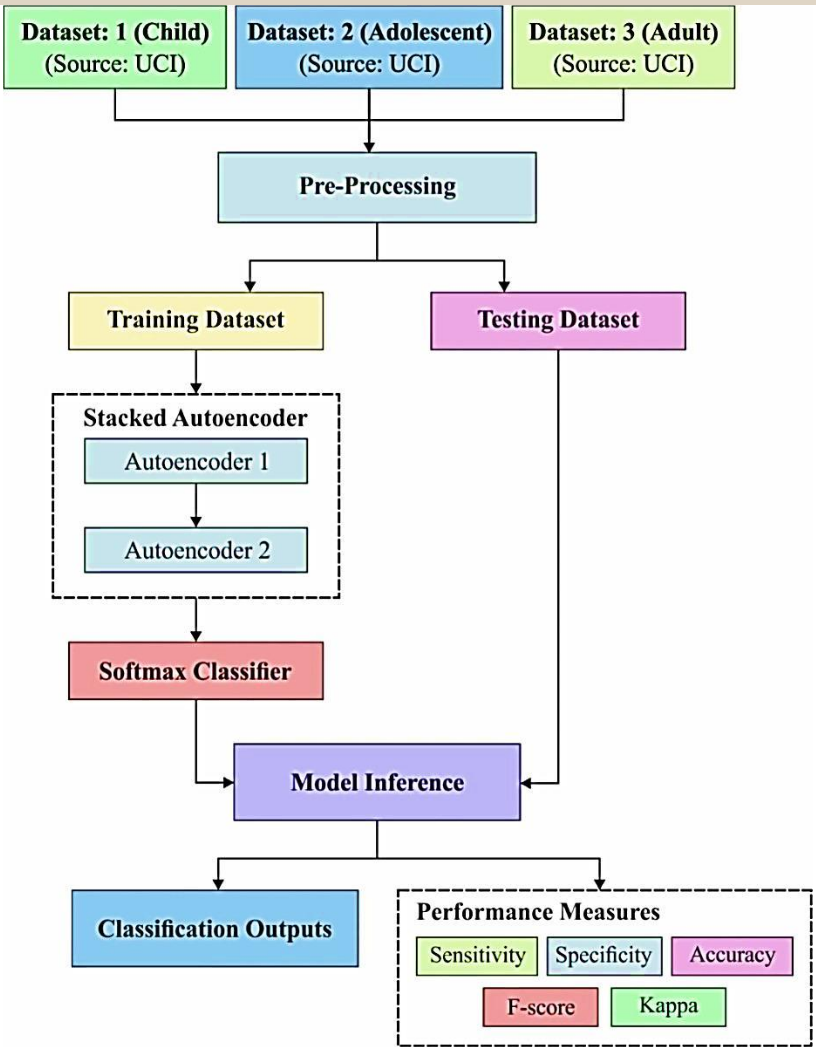

Fig. 1: Overall process of QODF-DSAN model.

Survival rate is one of the major goals of any swarm where each individual is disturbed externally and attracted to the food direction. Because of this behavior, 5 important attributes affect the individuals' upgrading location are Separation, Alignment, Cohesion, Attraction towards food source, and Distraction of enemy. Such attributes are explained numerically as given below.

Separation: This parameter is measured by given formula:

$$S_i = -\sum_{k=1}^{M} Y - Y_k, \tag{1}$$

where Y means the individual's recent place, Y_k denotes the location of *k-th* neighboring individual and M defines the overall count of neighboring separations.

Alignment: It shows the mean of velocities which is determined by given expression:

$$A_i = \frac{\sum_{k=1}^{M} V_k}{M}, \tag{2}$$

where V_k implies the velocity of *k-th* neighboring individuals.

Cohesion: In this attribute is evaluated as follows:

$$C_i = \frac{\sum_{k=1}^{M} Y_k}{M} - Y \tag{3}$$

Attraction towards a food source: It signifies a distance among location of present individual and location of food source (Y^+) and it can be determined by the provided notion:

$$F_i = Y^+ - Y \tag{4}$$

Distraction outwards an enemy: It means a distance among position of recent individual and location of an enemy (Y^-) which is measured by:

$$E_i = Y^- - Y \tag{5}$$

In dragonfly, nature is a unification of 5 variables. Then, 2 vectors are employed for upgrading dragonflies' place in a search space, such as step vector ($\triangle Y$) and position vector (*Y*). Step vector is illustrated by the given function:

$$\triangle Y_{t+1} = (aA_i + sS_i + cC_i + eE_i + fF_i) + w \triangle Y_t\,, \tag{6}$$

where a means the alignment weight, $A_i$refers to the alignment of *i-th* individual, $s$denotes the separation weight, $S_i$implies the differentiation of *i-th* individual, $c$defines the cohesion weight, $C_i$represents the cohesion of *i-th* individual, e depicts enemy weight, $E_i$defines the location of enemy in *i-th* individual, $f$signifies the food weight, $F_i$showcases a food source of *i-th* individual, w shows the inertia weight, and t exhibits the described as iteration number.

The individual's position vector is depicted as given in the following:

$$Y_{t+1} = Y_t + \triangle Y_{t+1} \tag{7}$$

In case of optimization mechanism, diverse exploitative and explorative behaviors have been accomplished by using 3 variables ($a, s, c, e,$ and f). Besides, these parameters are also employed in managing exploration and exploitation phases.

In dragonflies' convergence is ensured by the iterations of parameters weight that is modified accordingly. Hence, flying direction of dragonflies was changed as an optimization model is processed.

This approach utilizes a random walk (Lèvy flight) for improvising stochastic, randomness as well as DA searching. An upgrading location of dragonflies is described as given in the following:

$$Y_{t+1} = Y_t + \text{Lè}vy(d) \times Y_t, \tag{8}$$

$$L\text{è}vy\,(y) = 0.01 \times \frac{n1 \times \sigma}{|n_2|^{\frac{1}{\beta}}},$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}} \right)^{1/\beta}$$

where d shows the dimension of position vector, $n1$, $n2$ means 2 random valued in [0, 1],β implies a constant, and $\Gamma(x) = (x-1)$!. To enhance the convergence rate of DF technique, QOBL concept is introduced.

Initially, OBL is coined by Tizhoosh [14] which ensures the efficient model for particle swarm optimization (PSO), differential evolution (DE), and ant colony optimization (ACO). Similar to Evolutionary Algorithms (EA), biogeography-based optimization (BBO) is invoked as population string that has been produced randomly if there is no primary knowledge regarding the known solution space. Hence, process of evolution is terminated once reaching the stopping criteria. The processing time is directly proportional to distance of guess from best result. The possibilities of accomplishing best results are enhanced by initializing closer (fittest) solutions by validating the inverse solution at the same time.

QODF algorithm for FS

Feature Selection (FS) is referred as a binary optimization issue, in which solutions are limited to binary {0, 1} values. Thus, binary extension of DA model is applicable for resolving the above-mentioned problem. Here, vector of 0s and 1s have been executed to exhibit the accurate solution for a given problem, where the 0 refers the equivalent feature is not decided while 1 represents the required feature is decided. During this approach, a wrapper FS model which depends upon DA method has been presented. Followed by, DSAN classification approach has been employed to estimate the decided feature subsets. FS is assumed as multi-objective issues in which 2 contradictory objectives should be accomplished to enhance the classification accuracy and try to mitigate the count of decided features. Thus, cardinality of reduct is applied in the objective function and classification error rate. Eq. (9) implies the objective function.

$$Fitness = \alpha\gamma_R(D) + \beta\frac{|R|}{|c|} \quad (9)$$

where $\gamma_R(D)$ denotes the classification error rate of DSAN classifier. Moreover, $|R|$ refers the cardinality of chosen subset and $|C|$ means the overall count of features in a dataset, α, and β are 2 attributes that shows the significance of classifier quality as well as subset length, $\alpha \in [0, 1]$ and $\beta = (1\text{-}\alpha)$ applied s from [15].

DSAN based Classification

At the last stage, the feature reduced subset is given as input to the DSAN model, which executes the classification process to find out the proper class labels. Generally, Autoencoder (AE) is evolved from Deep Learning (DL) structure which is same as Artificial Neural Network (ANN) applied to perform encoding and decoding operations for input as relied on unsupervised learning. In easy AE system which is embedded with input, hidden, and resultant layer as same as ANN. Every layer in ANN contains certain number of neurons. Input and resultant layers are composed of identical count of neurons whereas hidden layer is composed of minimum neurons that make an effective process than feed-forward neural networks (FFNN).

Initially, an input is supplied to AE and considers it as x. Followed by, the input vector is encoding to accomplish hidden code by applying encoder portion that is provided as input to decoding portion. Hence, decoder portion is responsible for reforming original input from code, x'.

The central premises of AE are to filter essential featured by limiting the data size and for obtaining noise-free information. Eq. (10) is applied in encoding phase to accomplish code c while Eq. (11) is employed in decoder phase to recreate the input data x. Next, BackPropagation (BP) method is utilized for calculating the error as provided in Eq. (12) that is used for fine-tuning the system and to make their formed output as adjacent to input data. Hence, basic idea of developed approach is to mine significant designs in the applied data.

$$c = F(w^t x + b) \quad (10)$$

$$x' = F(wc + b') \quad (11)$$

$$e = \min \sum_{i=1}^{n} (x' - x)^2 \quad (12)$$

In Eq. (10) and (11), Frefers the activation functions applied, b implies the bias value and w signifies the weights of input and hidden layer. The value x' exhibits the reformed form of input $x$by applying c. The regularization is employed to mitigate the over-fitting in ANN as depicted in Eq. (13).

$$\min\left[\left\{\sum_{i=1}^{n}(x' - x)^2\right\} + \gamma L(w)\right] \quad (13)$$

In Eq. (13), $L(w)$ refers the weight alteration variable while γimplies the regularization term. These values are selected using hit and trial method. Several AEs are "stacked" in greedy layer-wise fashion for invoking the weights of Deep Neural Network (DNN) to accomplish a deep-stacked AE.

Next, these features are induced as a softmax classifier to classified issues. A softmax layer is employed behind DSAN to classify the input data. It applies the essential features and guides in enhancing the classification function.

$$F(x_i) = \frac{Exp(x_i)}{\sum_{j=0}^{k} E\,xp(x_j)}, where\ i = 0, 1, \cdots, k \quad (14)$$

The Eq. (14) signifies the softmax function. It determines the exponential of given input x_i and the summation of exponential values and fractions result in softmax function [16]. For multi-classification module, softmax function offers the possibilities of every class in which output class should have maximum probability when compared with all other classes.

RESULTS AND DISCUSSION

In productive classification results of the QODF-DSAN method has been sampled over 3 ASD dataset. The ASD children, Adolescent, and Adult dataset [17-19] are composed of 292, 104, and 704 sampled with same set of 21 features.

Table 1 signifies the FS outcomes of the QODF-FS scheme with traditional approaches by means of optimal cost and selected set of features. The table refers that the PCA-FS approach is considered a poor

FS approach, which has gained low best cost of 0.9208. Simultaneously, the GA-FS and PSO-FS methodologies have gained moderate best cost of 0.8167 and 0.7891 correspondingly. Similarly, the GWO-FS framework has attained closer optimal results with a maximum cost of 0.6523. Meantime, the QODF-FS scheme has depicted supreme results with a best cost of 0.3127.

Table 1: Selected Features of Existing with Proposed QODF-FS Method

Methods	Best Cost	Selected Features
QODF-FS	0.3127	1,2,3,4,7,9,10,11,14,15,20
GWO-FS	0.6523	1,4,5,6,7,8,9,11,12,13,14,15,16,17,19
PSO-FS	0.7891	3,4,5,6,7,8,10,11,12,13,14,15,16,17,18
GA-FS	0.8167	1,5,6,7,9,10,12,13,15,16,17,18,19,20
PCA-FS	0.9208	2,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19

Table 2 depicts a brief comparative results analysis of the QODF-DSAN method with traditional approaches [20-22] by means of diverse metrics. On measuring the classifier outcome by means of accuracy, the worse classifier performance is illustrated by DT with the minimum accuracy of 54.7%.

Table 2: Result Analysis of Existing with Proposed QODF-DSAN Method on Applied Dataset

Methods	Sensitivity	Specificity	Accuracy	F-score	Kappa
QODF-DSAN(Children)	97.86	97.37	97.60	97.51	95.19
QODF-DSAN(Adolescent)	95.31	98.83	97.87	96.06	94.60
QODF-DSAN(Adult)	96.88	97.50	97.12	97.64	93.93
Decision tree	53.30	54.90	54.70	-	-
Logistic regression	55.50	62.60	59.10	-	-
Neural network	53.30	71.20	62.00	-	-
k-Nearest neighbor	46.60	72.10	61.80	-	-
SVM (linear)	57.10	66.70	61.40	-	-
RF-CART	82.06	77.02	80.71	-	-
Optimal-KNN	-	-	69.20	-	-
Optimal-LR	-	-	68.60	-	-
Optimal-RF	-	-	67.78	-	-

Then, the LR model has surpassed the DT with the moderate accuracy of 59.1%. Moreover, the SVM (linear), KNN, and NN methodologies have attained acceptable classification results with a closer accuracy of 61.4%, 61.8%, and 62%. Afterward, the Optimal-RF, Optimal-LR, and Optimal-KNN frameworks have illustrated considerable accuracy values of 67.78%, 68.6%, and 69.2%. Even though the RF-CART scheme has performed well than classical methods with an accuracy of 80.71%, it is ineffective to represent better outcomes over the projected QODF-DSAN model which has gained optimal accuracy of 97.6%, 97.87%, and 97.12% on ASD-Children, ASD-Adolescent, and ASD-Adult dataset correspondingly.

On determining the classifier outcomes interms of sensitivity, the inferior classifier function is depicted by kNN with minimum sensitivity of 46.6%. Then, the NN and DT models have outperformed the kNN with acceptable and closer sensitivity of 53.3%. Moreover, the LR approach has achieved considerable classification outcomes with sensitivity of 55.5%. Followed by, the SVM (linear) scheme has exhibited moderate sensitivity value of 57.10. Though the RF-CART model has surpassed the previous approaches with the sensitivity of 82.06%, it has failed to exhibit better results over the presented QODF-DSAN approach which has accomplished higher sensitivity of 97.86%, 95.31%, and 96.88% on ASD-Children, ASD-Adolescent, and ASD-Adult dataset respectively. From the detailed experimental analysis, the resultant simulation outcome verified the effective classification results with the higher accuracy of 97.60%, 97.87%, and 97.12% on ASD-Children, ASD-Adolescent, and ASD-Adult dataset respectively.

CONCLUSION

This paper has presented a new ASD diagnosis method utilizing QODF-DSAN model. The processes involved in the ASD diagnosis are preprocessing, FS, and classification. The patient's medical data is primarily preprocessed to improve the data quality. After that, QODF algorithm is applied to select an optimal set of features. At last, the feature reduced subset is fed into the DSAN based classifier to determine the appropriate class labels. To ensure the efficient performance of the QODF-DSAN method, a set of simulations takes place on three benchmark datasets. The resultant simulation outcome verified the effective classification results with a higher accuracy of 97.60%, 97.87%, and 97.12% on ASD-Children, ASD-Adolescent, and ASD-Adult dataset respectively. In future, the proposed model can be implemented in real time to assist physicians in ASD diagnosis.

CONFLICT OF INTEREST
There is no conflict of interest.

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None.

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