A Study On Binary Particle Swarm Optimization Grey Wolf Optimization with A Modified Augmented Lagrangian Grey Wolf Optimization (BPSOMGWO) For Psychological Disorder

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Abstract

This study proposes a hybrid of two different versions of Grey wolf optimization. It proposes a novel Hybrid Binary Particle Swarm Optimization Grey Wolf Optimization with a Modified Augmented Lagrangian Grey Wolf Optimization (BPSOMGWO) for classification of Anxiety Disorder. The velocity and position of Particle Swarm is substituted by Grey Wolf optimization. The tuning parameter is modified in lagrangian Grey wolf optimization. This novel algorithm is hybrid of modified Particle Swarm Optimization with improved Grey Wolf Optimization algorithm. To check the dependency on the tuning parameter μ, various values are considered in the range of [0,3].

Keywords: *Psychological Disorder, Behavioral Disorder, Anxiety, Swarm Intelligence, Particle Swarm Optimization, Grey Wolf Optimization*

1. INTRODUCTION

Behavioral Disorders encompass a diverse spectrum of conditions that impact an individual's thoughts, emotions, and actions, often resulting in disruptions to their daily life and interactions [1]. These disorders can appear as alterations in behavioral patterns, emotional control, and social interaction, impacting an individual's overall state of well-being. A precise diagnosis is essential for developing an appropriate treatment plan tailored to the individual's needs. Additionally, early diagnosis and intervention can significantly improve outcomes for individuals with behavioral disorders. While medications or psychotherapy may offer potential benefits to certain individuals, however the integration of artificial intelligence has the potential to enhance the role of psychologists and the diagnostic process [2]. The use of machine learning and swarm intelligence models in the domains of cognitive clinical psychology and psychiatry has significant potential to influence assessment, forecasting, prediction of treatment outcomes, and tracking of biomarkers[3].

This study proposes a novel hybrid swarm intelligence algorithm called Hybrid Particle Swarm Optimization (PSO)[4] with a Modified Augmented Lagrangian Grey Wolf Optimization for Anxiety Disorder(MLGWO)[5] technique used to classify anxiety disorder. Swarm intelligence techniques play an important role in the classification of disease diagnosis by harnessing the collective behavior of simple agents to solve complex problems. They contribute to feature selection, data clustering, model optimization, ensemble learning, handling imbalanced data, real-time monitoring, and the creation of interpretable models, ultimately enhancing the accuracy and effectiveness of disease diagnosis and classification. The main principle of swarm intelligence is the emulation of collective behavior observed in natural systems, particularly social organisms like ants, bees, birds, and fish, to solve complex problems. This principle is based on the idea that simple agents, when interacting with each other and their environment according to a set of local rules, can collectively exhibit intelligent, coordinated, and adaptive behavior that is often superior to what any individual agent could achieve on its own[6].

1.1 Literature review

The application of swarm intelligence in disease diagnosis offers the potential to enhance the accuracy, speed, and adaptability of diagnostic processes, ultimately leading to improved patient outcomes and healthcare efficiency. Various kinds of swarm optimization technique include and throw light upon various optimization problems, due to fast convergence, high levels of performance, and simplicity. Tate et al. (2020) [7] created a model using machine learning to screen the general population for the risk of developing mental health problems and investigated the performance of the proposed model over standard logistic regression techniques. Kaur et al. (2019) [8] implemented supervised learning along with nature-inspired computing for the diagnosis of psychological disorders. De Silva et al. (2019) [9] discuss studies of ADHD recognition using eye movement data and functional magnetic resonance imaging. Srividya et al. (2018) [10] developed a framework using machine learning to determine the mental health of an individual. Beriha (2018) [11] proposed a computer-aided diagnosis (CAD) technique to distinguish ADHD children from other children having behavioral disorders like anxiety, depression, and conduct order. Duda et al. (2016) [12] used forward feature selection, under-sampling, and 10-fold cross-validation to train six machine learning techniques to distinguish Autistic and ADHD patients. Sonuga-Barke et al. (2016) [13] found that Ineffective decision-making is a significant cause of persistent cognitive disability and decreased quality of life for mentally impaired young people. Kim et al. (2015) [14] found that there are no objective biological tests that can robustly model methylphenidate administration in attention deficit hyperactivity disorder (ADHD). Seixas et al. (2012) [15] emphasized the main symptoms of ADHD and the current disease diagnosis criteria. Delavarian et al. (2012) [16] designed a decision support system to differentiate children with ADHD from similar behavioral disorders like anxiety, depression, and conduct disorders based on symptoms. Frick et al. (2012) [17] evaluated the diagnostic criteria for three of the most common psychological disorders referred to in children and adolescents which are attention deficit hyperactivity disorder (ADHD), oppositional defiant disorder (ODD), and conduct disorder (CD).

2. PROPOSED APPROACH

This section introduces the hybrid version of Binary Particle Swarm Optimization and a modified Grey Wolf Optimization (HPSOGWO) [30] with modified Grey Wolf optimizer [31]. The fundamental concept behind PSOGWO is to enhance the algorithm's capacity by combining the strengths of PSO for exploitation and GWO for exploration. In the context of HPSOGWO, the update of positions for the initial three agents within the search space differs from conventional mathematical equations. Instead, it governs the exploitation and exploration aspects of the grey wolf using inertia constant. In [30] the velocity,v and position, x is depicted in equation (i) and (ii).

$$v_i^{t+1} = w * (v_i^t + c_1 r_1 (x_1 - x_i^t) + c_2 r_2 (x_2 - x_i^t) + c_3 r_3 (x_3 - x_i^t) \quad \text{(i)}$$

Where $x_i^{t+1} = x_i^t + v_i^{t+1}$ (ii)

This is a modified PSO equation which consists of velocity (v) and position (x) information. Here *x1, x2, x3* are grey wolf positions given from GWO algorithm. The tuning parameter in GWO used in [30] is

$$\vec{a} = 2 - \frac{2t}{\max\_iter} \quad \text{(iii)}$$

The parameter a is defined to be declined linearly from a maximum value of 2 to zero.

In [31] an improved version of GWO is proposed by modifying the tuning parameter.

$$\vec{a} = \frac{1-(^{iter}/_{iter_{max}}}{1-\mu.(^{iter}/_{iter_{max}}} \quad \text{(iv)}$$

μ is nonlinear modulation index from the interval (0,3) to achieve better balancing between exploration and exploitation. In the hybrid method proposed [30] is modified by [31]. That is, it is hybrid of PSO and an improved version of GWO. To check the dependency on the tuning parameter μ, various values are considered in the range of [0,3].

3. Experimental Results

In this work, anxiety related datataset (Anxiety and Depression) has been taken into consideration to evaluate the proposed hybrid algorithm **(**BPSOMGWO) for identifying optimal feature selection for the diagnosis of anxiety disorder. Anxiety and Depression dataset comprises 757 instances sourced from the Depression and Anxiety data dataset available on Kaggle[32]. These data points are derived from the Beck Depression and Beck Anxiety inventories and are utilized for the classification of depression and anxiety. It has total 16 features. The dataset employs age and gender as physical attributes for distinguishing between individuals with normal and pathologically high levels of anxiety. The feature set of the dataset is depicted in Table 1 below. The output label was gad_score which was a binary value. 0 indicating absence and 1 indicating presence.

Features
BMI
who_bmi
phq_score
depression_severity
depressiveness
suicidal
depression_diagnosis
depression_treatment
gad_score
anxiety_severity
anxiousness

anxiety_diagnosis
anxiety_treatment
epworth_score
sleepiness

To assess the effectiveness of the proposed algorithm, its performance was evaluated by computing classification accuracy, sensitivity, specificity, precision, recall and F1-Score. True Positives (TP) and True Negatives (TN) represent the portions of correctly identified positive and negative cases, respectively. False Positives (FP) and False Negatives (FN) indicate the portions of negative cases misclassified as positive and positive cases misclassified as negative, respectively. The proposed hybrid algorithm is run in matlab 2020a, 10 times with 10 iterations in each round. The average of 10 rounds is taken to present the average values of accuracy, sensitivity, specificity, precision, recall and F1-score.

The proposed hybrid is evaluated on various quality measures. The following descriptions are based on the predictive classier outputs as depicted in Table 2.

Table 2. Quality Measures

True positive (TP)	number of samples with presence of disorder predicted a disorder
False positive (FP)	number of samples with absence of disorder predicted a disorder
True negative (TN	number of samples with absence of disorder predicted as absence of disorder
False negative (FN)	number of samples actually have presence of disorder predicted as absence of disorder.
Accuracy	It's the average of 10 accuracy values. Accuracy=(TP+TN) / (TP+TN+FP+FN)
Precision:	To evaluate the model's capability of classifying positive samples based on feature selection. Out of all the samples that predicted as positive, how many are really positive. Precision = (TP) / (TP+FP)
Recall	To determine the proportion of positive samples based on feature selection accurately identified by the model. Which of the positive cases is projected to be a success Recall = (TP) / (TP+FN)
Sensitivity	Indicates the proportion of positive observations that are accurately anticipated.
Specificity	The accuracy with which the model accurately predicts real negatives. It's the fraction of True negatives for which the model makes accurate predictions.

In different studies metrics have been used to examine the performance of the model or algorithm. Likewise, several metrics have been examined to understand the significance of the BPSOMGWO[31][32][33][34]. Table 3displays average accuracy , sensitivity, specificity, precision, recall and F1 Score rates for the proposed hybrid (BPSOMGWO) algorithm for the dataset.

Table 3. Average Accuracy, Sensitivity, Specificity, Precision, Recall and F1-Score

	a=0	**a=0.5**	**a=1**	**a=1.5**	**a=2**	**a=2.5**	**a=3**
Accuracy	87.24%	<u>87.30%</u>	87.27%	87.28%	87.13%	87.23%	87.21%

Sensitivity	<u>96.83%</u>	96.81%	96.83%	96.83%	96.79%	96.79%	96.81%
Specificity	98.54%	98.51%	98.53%	98.53%	98.54%	<u>98.57%</u>	98.52%
Precision	99.21%	99.20%	99.21%	99.21%	99.21%	<u>99.23%</u>	99.20%
Recall	<u>96.83%</u>	96.81%	<u>96.83%</u>	<u>96.83%</u>	96.79%	96.79%	96.81%
F1-Score	<u>98.00%</u>	97.99%	<u>98.00%</u>	<u>98.00%</u>	97.99%	<u>98.00%</u>	97.99%

The maximum values obtained are underlined in Table 2. It has been found that different performance metrics are highest for different tuning parameters on the same datasets. Highest Accuracy of 87.30% is achieved by tuning parameter a=0.5, highest Sensitivity of 96.83% is achieved by a=0, highest Specificity of 98.57% is achieved by a=2.5, highest Precision of 99.23% is achieved by a=2.5, highest Recall of 96.83% is achieved by a=0, 1, 1.5 and F1-Score of 98% is achieved by a=0, 1, 1.5, 2.5.

4. Conclusion

In this study, a novel approach that combines Binary Particle Swarm Grey Wolf Optimization with a Modified Augmented Lagrangian Grey Wolf Optimization (BPSOMGWO) algorithm to effectively address constrained optimization problems. The proposed hybrid is tested on online benchmark “Depression and Anxiety data”dataset available on Kaggle. The experiments are performed in matlab 2020a with 10 iterations of the algorithm . The average values of all the performance metrices are calculated and found out that the highest value are found for different tunning paramters. Future works aims to conduct comparative analyses against alternative evolutionary computation-based algorithms, address additional benchmark problems, and fine-tune the algorithm's parameters. There is scope to comprehensively assess the proposed evolutionary computation-based algorithm. This involves comparing it with existing alternatives, expanding its applicability to a broader set of benchmark problems, and optimizing its performance through parameter tuning. These efforts aim to enhance the algorithm's effectiveness and utility in solving real-world optimization and search problems.

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