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A NOVEL AND HYBRID WHALE OPTIMIZATION WITH RESTRICTED CROSSOVER AND MUTATION BASED FEATURE SELECTION METHOD FOR ANXIETY AND DEPRESSION

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Summary

Introduction: *Anxiety and depression are two leading human psychological disorders. In this work, several swarm intelligence-based metaheuristic techniques have been employed to find an optimal feature set for the diagnosis of these two human psychological disorders.*

Subjects and Methods: *To diagnose depression and anxiety among people, a random dataset comprising 1128 instances and 46 attributes has been considered and examined. The dataset was collected and compiled manually by visiting the number of clinics situated in different cities of Haryana (one of the states of India). Afterwards, nine emerging meta-heuristic techniques (Genetic algorithm, binary Grey Wolf Optimizer, Ant Colony Optimization, Particle Swarm Optimization, Artificial Bee Colony, Firefly Algorithm, Dragonfly Algorithm, Bat Algorithm and Whale Optimization Algorithm) have been employed to find the optimal feature set used to diagnose depression and anxiety among humans. To avoid local optima and to maintain the balance between exploration and exploitation, a new hybrid feature selection technique called Restricted Crossover Mutation based Whale Optimization Algorithm (RCM-WOA) has been designed.*

Results: *The swarm intelligence-based meta-heuristic algorithms have been applied to the datasets. The performance of these algorithms has been evaluated using different performance metrics such as accuracy, sensitivity, specificity, precision, recall, f-measure, error rate, execution time and convergence curve. The rate of accuracy reached utilizing the proposed method RCM-WOA is 91.4%.*

Conclusion: *Depression and Anxiety are two critical psychological disorders that may lead to other chronic and life-threatening human disorders. The proposed algorithm (RCM-WOA) was found to be more suitable compared to the other state of art methods.*

Keywords: *Depression, Anxiety, Diagnosis, Swarm Intelligence, Psychological Disorder, RCM-WOA.*

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INTRODUCTION

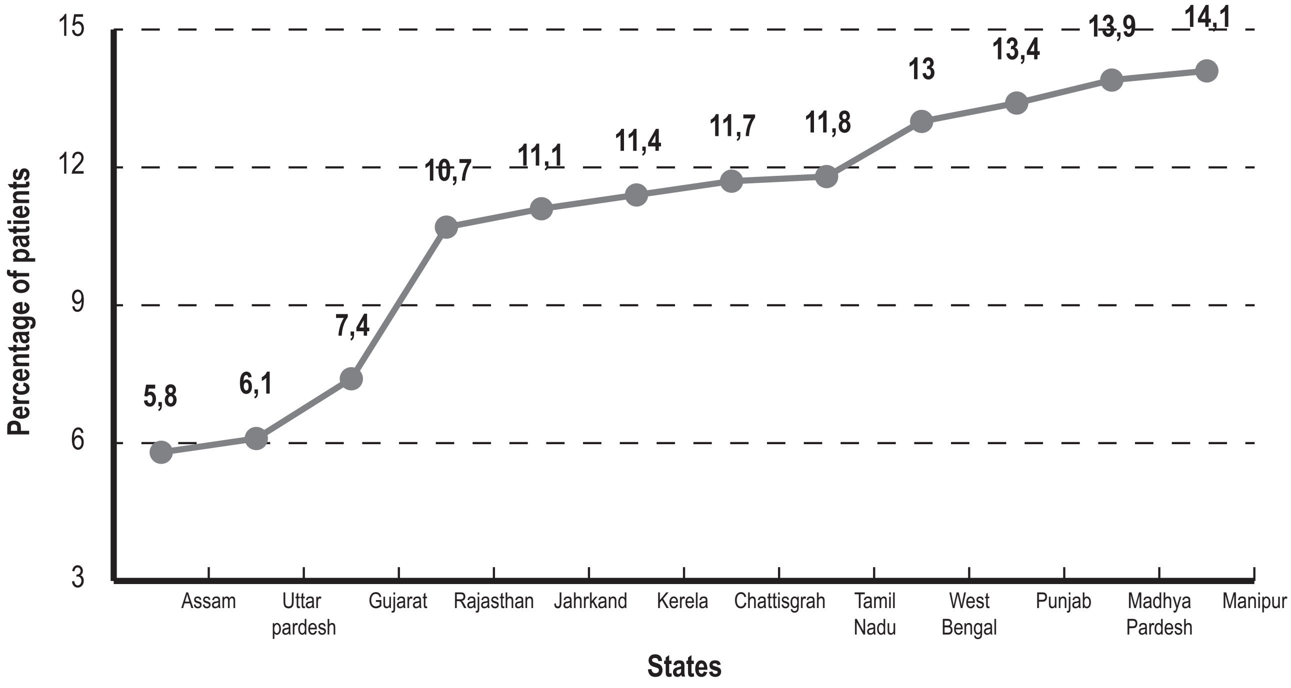
The study of the human mind and behaviour is scientifically known as psychology. It is related to mental health, development, behaviour, cognition etc. Something wrong with any of these gives rise to different disorders called psychological disorders in humans. These disorders are the conditions that affect the feelings, thoughts, emotions, cognition and behaviour of an individual. In other words, it is a psychological dysfunction in humans that is related to the impairment of unexpected reactions (Kaur, 2019). The term is interchangeably used as mental illness, psychiatric disorders or mental disorders. Like other disorders, psychological disorders also have genial as well as adverse states. An individual of any age can be a victim of this human disorder. Patients with poor physical health are more prone to suffer from any psychological disorder. Along with psychological and physical factors, other factors such as biological, environmental, social etc. increases the risk of different psychological disorders in human (Brewin, 2010).

According to world data in 2017 (Walker, 2015), New Zealand, Australasia and Australia were the top-ranked countries, where 18.7%, 18.4% and 18.3% of the population were suffering from different psychological disorders respectively. Surprisingly, only 9.7% population in Vietnam was suffering from mental illness. Figure 1 shows that 231 countries were affected by the risk of different psychological disorders all over the world.11% and 12 %population of 62 and 57 countries respectively were suffering from these disorders.

There are only three countries (Azerbaijan, Colombia and Vietnam) in the world where the rate of patients suffering from psychological disorders was 10% of the population. India is in the 47th position where 14.5% of the population was a victim of different psychological disorders. Figure 2 shows the prevalence of psychological disorders in twelve states (Assam, Uttar Pradesh, Gujarat, Rajasthan, Jharkhand, Kerala, Chhattisgarh, Tamil Nadu,

Figure 1. Percentage of the population suffering from psychological disorders all over the world(Walker, 2015)

Figure 2. Percentage of the population suffering from psychological disorders in India



West Bengal, Punjab, Madhya Pradesh and Manipur) of India. The percentage of psychologically disordered patients was highest (14.1%) and lowest (5.8%) in Manipur and Assam respectively.

There were three states (Assam, Uttar Pradesh and Gujarat) where the psychologically disordered victims were less than 10% and in nine states (Rajasthan, Jharkhand, Kerala, Chhattisgarh, Tamil Nadu, West Bengal, Punjab, Madhya Pradesh and Manipur) victims were more than 10% of the population.

Depression is a serious disorder with an unknown cause. Researchers suspect that the cause may be a combination of current events and some personal or long-term factors instead of immediate events. There are nine different types of depression namely major depressive disorder, persistent depressive disorder, bipolar disorder (major depressive disorder and mania), postpartum depression, premenstrual dysphonic disorder, seasonal affective disorder, atypical depression, situational depression and depressive psychosis from a medical standpoint. Symptoms of depression vary from minor to severe types of depression (Thapar, 2017).

There is another serious mental condition i.e. anxiety disorder. It is a group of mental disorders characterized by significant feelings of anxiety and fear. Occasional anxiety is an expected part of life. Normally there exist many events where we feel anxious. We might feel anxious when faced with a problem at work, before taking a test, or before making an important decision. Anxiety disorders, on the other hand, are more than just a fear. Anxiety does not go away in those who have anxiety disorders, and it can get worse with time. Symptoms might disrupt daily activities such as work, school, and relationships. Generalized anxiety disorders, particular phobias, social anxiety disorders (SAD), agoraphobia, separation anxiety disorders, panic disorder, and selective mutism are all examples of anxiety disorders. (Kaltenboeck, 2017).

Depression and anxiety are recurrent mood disorders that cause low mood, persistent sadness, loss of interest in things, numbness in the body or emotions of anger. Feeling sad or low from time to time is an unexceptional routine in life (Peyrot, 1997). But when the hopelessness and self-disappointments will not go away or lasts for a minimum of two weeks, then it will take a shape of a complex issue called depression (Kessler, 2013). The process goes in a cycle, initially, any stressor situation arises due to any personal, financial, environmental or social factor (Arora, 2020) (Sharma 2020). This stress or bad time is classified into a mild, minor serve or major serve. Stress triggers the changes in thoughts and feelings of an individual such as feelings of afraid, guilt, hopelessness, discouragement, embarrassment, and lonely. This change leads to wrong and incongruous beliefs in the patient that are further reflected in his/her behaviour. Behavioural changes get worse as time passes and actuate some physical changes such as sleeping issues, poor appetite, memory issues, concentration problems etc(Craske, 1990).

The remaining part of this manuscript has highlighted related works. The description of the proposed method has been presented in subjects and methods section. Afterward, results have been presented and discussed. Finally, the conclusion and future scope has been mentioned.

RELATED WORK

Yoon et al. have stated that the mentally ill, sexually abused, and lethargic individuals are the primary victims of depression in the US population. The authors classified data of these individuals and discovered that the accuracy rate attained with J48 is between 80% and 820% (Yoon, 2014). Mohammadi et al. used decision trees and genetic algorithms to mine data from depressed individuals. Electroencephalogram signals (EEG) of 100 patients were evaluated and they were classed as healthy or depressed and disordered. The key features were identified using GA, and the predictive model was developed using a decision tree. MATLAB was used to analyze the data (Mohammadi, 2015). Mwangi B.et al. developed a hybrid technique for depression prediction using feature selection and machine learning methods. The authors analyzed a dataset of sixty-five records with seventy-two attributes. The Relevance Vector Machine (RCM) and support vector machine were used to accurately diagnose depression in patients (90 %) (Mwangi, 2012). Daimi K. et al. have presented a strategy for early depression prediction in patients. Algorithm J48 was deployed by classifying the dataset using the WEKA tool. The approach demonstrated an accuracy rate of 83.3 % in predicting (Daimi, 2014). Dipnall et al. identified important biomarkers related to depression using a hybrid strategy that included boosted regression and logistic regression. The author used data from National Health and Nutrition Examination Study (2009–2010), which included 5230 samples. The study examines three biomarkers for depression (glucose, serum, total bilirubin, red cells distribution width) out of twenty (Dipnall, 2016). Kundra D. et al. classified many psychiatric and associated illnesses using the J48 method. The algorithm's specificity and sensitivity are between 94 and 100 % and 70 and 100 %, respectively (Kundra, 2014). Huang QR et al. confirmed the prevalence of sleep apnea using data mining techniques. The study establishes obesity as a significant risk factor for this disease (Huang, 2008).

Sumathi et al. have applied eight ML techniques for the diagnosis of anxiety and other mental issues. A dataset of sixty disordered cases was collected. Twenty-five characteristics that have been found as crucial in diagnosing the issue were considered. Feature Selection techniques were applied to the entire attributes dataset to decrease the attributes. The author compared the accuracy of multiple ML algorithms on both the entire attribute set and a subset of the attributes. The results indicate that the three classifiers tested, the Multilayer Perceptron, the Multiclass Classifier, and the LAD Tree produced more accurate results (Sumathi, 2016). Deziel M. et al. conducted a survey of engineering students at a Canadian institution. The authors analyzed the mental health of pupils using five components ability to live happily, balance, resilience, flexibility and self-actualization. The authors noted that second-year students scored higher on mental health than first- and final-year students. Second, pupils enrolled in academic programs with a flexible curriculum score highly in terms of mental health. Finally, female students' mental health is poorer th an male students (Deziel, 2013). Kimberly et al. have used machine learning algorithms to analyze PAPA data from two large community studies to find subsets of PAPA items that could be converted into an efficient and relevant screening tool for determining a young child's anxiety disorder risk. Moreover, the authors were able to reduce the number of elements required to determine a child who is at risk for an anxiety disorder by an order of magnitude using ML, with an accuracy of over 96 % for both GAD and SAD. A continuous risk score has been given to represent the child's risk of satisfying GAD or SAD criteria, rather than seeing GAD or SAD as discrete entities (Kimberly, 2016). AnuPriya et al. used five machine learning algorithms to predict anxiety, depression, and stress in the study. This disorder Scale questionnaire was used to collect data from employed and unemployed people from various cultures and group them to implement these algorithms (DASS 21). As a result, the F1 score metric was added, which assisted in identifying the best accuracy model as the Random Forest among the five used algorithms. The specificity parameter also demonstrated that the algorithms were particularly sensitive to unfavourable outcomes (Anu, 2020).

Table 1 summarizes the research conducted by several prominent writers on diagnosing various psychiatric diseases, including the details of the various soft computing methodologies used to diagnose the disease. Additionally, the prediction rate of accuracy obtained by multiple authors in their study utilizing various soft computing techniques for diagnosing various psychiatric diseases is shown.

Table 1. Review of different research using soft computing techniques

(Author, Year)	Disorder	Best Technique	Accuracy
(Xiao, 2012)	Parkinson	GA, SVM	91.8%
(Xiao, 2012)	Parkinson	GA, SVM	91.8%
(Yang, 2013)	Alzheimer	PSO-SVM	94.12%
(Hiesh, 2013)	Schizophrenia	GA, SVM	88.24%
(Sivapriya, 2013)	Dementia	PSO-LSSVM	96%
(Shahbakhi, 2014)	Parkinson	GA (4 features)	96.06%
(Abed, 2015)	Sleep Apnea	GA, SVM	90.09%
(Naskar, 2016)	Parkinson	GA-NN	96.55%
(Ranjith, 2017)	Stress detection	PSO, FFNN	93.25%
(Sayed, 2017)	Alzheimer	MFO	78.33%
(Shon, 2018)	Stress detection	GA	71.76%
(Vaishali, 2018)	Autism	FA, SVM, MLP	96.66%

SUBJECTS AND METHODS

Clinical diagnosis is subject to a variety of errors. It's challenging to notice and work with indirect and unknown correlations between symptoms and the end product. When the symptoms of one disease overlap with those of another, experts and doctors sometimes identify the condition incorrectly. Aside from that, the temporal nature of symptoms may go overlooked by traditional diagnostic techniques, which are based on discrete data. A disease's stage evolves with time, necessitating the use of up-to-date treatment. Various inconsistencies in the forecast may go overlooked in the absence of doctors in the time of telemedicine and widespread self-diagnosis tools. The treatment's dynamism is also a source of concern. Treatment must be modified as a condition progresses to provide better results for patients. When a diagnosis comprises a vast dataset and a lot of unknowns, maintaining accuracy becomes tough (Raymer, 2015).

Data Description

The dataset has been collected under the guidance of the subject experts. It has been collected through personal meetings with the patients under the guidance of healthcare professionals and subject experts. A questionnaire designed under the guidance of subject experts was designed and used for the same. The criteria (attributes) along with their Likert scales have been finalized with the help of subject experts and as per the DSM benchmark. A copy of the approval of the institution's ethics committee has also been attached (Annexure).

To diagnose depression and anxiety among people, a random dataset comprises 1128 instances and 42 attributes(16 attributes for personal details such as name, state, city, area, occupation, weight, diet, height, marital status, family size, addiction, income, family history, physical injury, suffering from any disorder etc. and 26 attributes are symptoms of depression and anxiety such as depressed mood, crying episodes, loss of interest, memory loss, fatigue, concentration problem, pounding heart, sweating, shortness of breath, abdominal distress, fainting feeling, decision making, confidence, sleeping problem, headache, poor appetite, level of thinking, a feeling of guilt, loss of libido, the thought of death etc.) The responses for symptoms were recorded in the form of categorical variables (five-point psychometric scale) such as 0-Never, 1-Rarely, 2- Sometimes, 3-Often, 4-Very often.

The data collected is grouped into variables related to personal details and physical features (variables from 1–16); and psychological features (variables from 17–42). Table 2 shows these variables.

Table 2. Feature sets

Category	Feature Set	Values	Level
Personal and Physical Features	State	Text	N/A
	City	Text	N/A
	Area	Rural/ Urban	2
	Occupation	Student: UG/ PG/ PhD Employee: Private/ Govt./ Business	4
	Gender	Male/ Female	2
	Age	0-12/13-18/19-40/41-60/ Above 60	5
	Weight (Kgs)	Number	N/A
	Height (Fts)	Number	N/A
	Deit	Veg/Non Veg	2
	Marital Status	Married/ Unmarried/ Other	3
	Addiction	Smoking/ Alcohol/ Drug/ None	4
	Family Size	Nuclear/ Joint	2
	Financial status (Lakhs)	Less than 1/ 1-2/ 2-5/ above 5	4
	Any family history	Yes/no	2
	Patient suffering from any physical injury	Yes/no	2
	Patient suffering from any mental stress	Yes/no	2
	Suffering from diabetes or thyroid	Yes/no	2
	Abnormal mensturation cycle	Yes/no	2
Psychological Features	Level of depressed mood	0-4	5
	Level of Crying Episodes	0-4	5
	Feeling loss of interest in doing things once pleasurable	0-4	5
	Memory loss	0-4	5
	Level of fatigability	0-4	5
	Facing concentrating problem	0-4	5
	Pounding Heart	0-4	5
	Sweating	0-4	5
	Shortness of Breath	0-4	5
	Abdominal Distress	0-4	5
	Fainting Feeling	0-4	5
	Facing problem in making decisions	0-4	5
	Level of Confidence	0-4	5
	Trouble falling asleep/ Sleeping too much	0-4	5
	Feeling tired upon waking	0-4	5
	Headache	0-4	5
	Poor appetite	0-4	5
	Level of Irritability	0-4	5
	Level of thinking	0-4	5
	Moving or speaking so slowly that other people could have noticed	0-4	5
	Anxious or worried for no good reason	0-4	5
	Feeling of guilty	0-4	5
	Being so fidgety or restless that you have been moving around a lot more than usual	0-4	5
	Loss of Libido	0-4	5
	Satisfaction in Sexual life	0-4	5
	Thoughts that you would be better off dead, or of hurting yourself in some way.	0-4	5

Design of Restricted Crossover and Mutation-based Whale Optimization Algorithm (RCM-WOA)

Several nature-inspired and swarm intelligence based algorithms have proven to be convenient and effective for addressing different real-life optimization in the domain of machine learning (feature selection (Kaur, 2022), query optimization (Sharma, 2013), finance (Gao, 2022), robotics (Zhang, 2022), image processing (Shang, 2022), agriculture (Maravea, 2022) and medical diagnosis (Monga, 2022) (psychological (Sharma, 2018), neurological & neuropsychiatric (Gautam, 2020), diabetes, cardiology (Kaur, 2018)).These algorithms can also be easily parallelized, which makes them ideal for large-scale problems (Sharma, 2012).

Mirjalili and Lewis of Australia introduced the WOA as a revolutionary swarm intelligence optimization algorithm in 2016 (Mirjalili, 2016). The diminishing surrounding, spiral updating position, and random hunting methods of humpback whale pods are all simulated by this algorithm, which was inspired by the natural hunting mechanism of humpback whales. Humpback whales are the world's largest mammals. They are one of seven distinct whale species. It also features a one-of-a-kind hunting technique called bubble-net feeding. Because their brains have spindle cells, they are undeniably intelligent. The production of unique bubbles in the shape of a spiral or route allows for this foraging behaviour. When the leader whale sees the prey, he dives down 12 metres and forms a spiral-shaped bubble around it before swimming up to the surface and following the bubbles. The expert whale assists the leader by giving a synchronization call. Behind the leader, the rest form a formation and occupy the same place for each lunge. Encircling prey, bubbling-net attacking, and searching for prey are the three stages of this model.

In terms of convergence speed and producing an optimal solution, meta-heuristic optimization algorithms have both advantages and limitations. The WOA has several advantages over other optimization algorithms, including its ease of use and a low number of adjustment parameters. The algorithm can establish a good balance between exploration and exploitation capabilities by adjusting, and enhancing the probability of having away from the local optimum. The exploitation phase of the WOA, on the other hand, is entirely reliant on randomness, resulting in less convergence accuracy and speed. But, the limitations of WOA have also been observed. Convergence and speed are also affected by controlled parameters. This parameter has a significant impact on WOA performance. As a result, in both the exploration and exploitation stages, WOA has a slow convergence rate. As a result, adequate augmentation is required for balancing formulation between exploitation and exploration. Furthermore, WOA employs the encircling process in search space, which is less capable of jumping out of local optima. As a result, it leads to poor performance. It is worth stating that WOA cannot be used for classification or dimensionality reduction because it was not designed for binary spaces. It requires extra functions to handle single and multidimensional problems.

In response to the drawbacks of WOA, a new hybrid feature selection technique called Restricted Crossover and Mutation-based Whale Optimization Algorithm (RCM-WOA) is proposed. This method has been designed by hybridizing WOA with GA (crossover and mutation). Each feature subset in a feature set with n features is regarded as the position of a whale, which is an n-dimensional vector with each element being 0 or 1. A value of "1" indicates that the related feature is selected, whereas a value of "0" indicates the feature is not selected. Crossover is performed to replace the features with low fitness values with the features with high fitness values to improve the results.

$$X_H = Fitness(X_i) > 0.5 \tag{1}$$

$$F(X) = \begin{matrix} rand \times X_H : rand < 0.5 \\ rand \quad : rand > 0.5 \end{matrix} \tag{2}$$

And, a suitable rate of mutation has been induced to get more optimal results.

$$X_{new\_leader} = Position(X) \tag{3}$$

$$X_{new\_leader}[1] = \sim X_{new\_leader}[1] \tag{4}$$

The main work in the proposed algorithm is to improve the updated location process. It boosts whales' ability to hunt prey while also improving the algorithm's overall performance. This method not only preserves the ability to balance but also improves the algorithm's convergence accuracy and speed.

Hybrid RCM-WOA Algorithm

Initialize the position of search agents (Whales): X_i (i=1, 2, 3….n)
Calculate the fitness of each search agent: Fitness(X_i), X_{Leader} is the best search agent
While (t < maximum iteration)
    For each search agent (Xi)
Update a, A, C, l, and p
    If (p<0.5)
        If (|A|< 1)
            Crossover the high fitness value agents (X_H) with the low fitness value agents (X_L)
            X_H = Fitness(X_i)>0.5

$$F(X) = \begin{cases} rand \times X_H & : random<0.5 \\ rand & : random>0.5 \end{cases}$$

            Mutate leader (5% mutation)
X_{new_leader} = Position(X); $X_{new\_leader}[1] = \sim X_{new\_leader}[1]$
elseif (|A|< 1)
            Select random leader: $X_{rand\_leader} = abs(C*X_{Leader} - X)$
            Update the position of new leader: Position(X_{rand_leader}) = X_{Leader}–A.D
        End if
elseif (p>0.5)
        Change the search direction and position of search agents
        $D = X_{Leader} - X$
$X(t + 1) = D \cdot e^{bl} \cdot \cos(2\pi l) + X*(t)$
        end if
        end for
Calculate fitness of each search agent
Update X_{Leader}
t = t+1
end while

RESULTS AND DISCUSSION

The performance analysis of nine meta-heuristic swarm intelligence algorithms viz. ((Genetic algorithm (GA) (Mirjalili, 2019), binary Grey Wolf Optimizer (GWO) (Mirjalili, 2014), Ant Colony Optimization (ACO) (Dorigo, 2006), Particle Swarm Optimization (PSO) (Poli, 2007), Artificial Bee Colony (ABC) (Karaboga, 2007), Firefly Algorithm (FA) (Gandomi, 2013), Dragonfly Algorithm (DA) (Mirjalili, 2016), Bat Algorithm (BAT) (Yang, 2010) and Whale Optimization Algorithm (WOA)) and the proposed algorithm (RCM-WOA) in terms of performance metrics viz. accuracy, sensitivity, specificity, precision, error rate, execution time and convergence graphs are elaborated in this section. Table 3 shows the minimum, maximum and average accuracy rates of GA, bGWO, ACO, WOA, ABC, BAT, PSO, FA, DA and RCM-WOA in finding the optimal set of features for depression and anxiety datasets.

From all nine meta-heuristic swarm intelligent algorithms (GA, bGWO, ACO, WOA, ABC, BAT, PSO, FA and DA) the proposed algorithm RCM-WOA shows better results. The rate of accuracy has been improved by 1-2.6%. The best rate of accuracy, sensitivity, specificity, precision, f-measure, error rate and execution time achieved is 0.914, 0.855, 0.984, 0.857, 0.843, 0.057 and 1.85 respectively. However, the lowest average accuracy rate is shown by bGWO and FA.

The convergence speed is another important characteristic of the optimizer. For the validation of the results, the convergence graph of all ten techniques has been presented. Figure 3 represents thirty different convergence curves with minimum, maximum and average convergence speeds of these techniques when the number of

Table 3. Results

			GA	bGWO	ACO	WO	ABC	BAT	PSO	FA	DA	RCM-WOA
Accuracy	**m**	Min	0.854	0.852	0.853	0.854	0.845	0.852	0.854	0.809	0.818	0.871
		Max	0.865	0.864	0.864	0.863	0.861	0.863	0.864	0.865	0.862	0.887
		Avg	0.869	0.865	0.865	0.865	0.856	0.865	0.864	0.845	0.854	0.878
	M	Min	0.877	0.875	0.875	0.884	0.887	0.885	0.885	0.880	0.883	0.903
		Max	0.904	0.904	0.903	0.903	0.897	0.904	0.904	0.899	0.898	0.914
		Avg	0.900	0.900	0.898	0.900	0.892	0.897	0.895	0.893	0.894	0.911
	A	Min	0.871	0.873	0.875	0.871	0.874	0.871	0.873	0.865	0.873	0.889
		Max	0.878	0.875	0.888	0.889	0.882	0.885	0.890	0.884	0.885	0.899
		Avg	0.876	0.872	0.886	0.885	0.876	0.882	0.884	0.874	0.880	0.897
Sensitivity	**m**	Min	0.429	0.449	0.589	0.390	0.528	0.394	0.546	0.204	0.364	0.625
		Max	0.693	0.706	0.654	0.671	0.649	0.667	0.645	0.615	0.641	0.729
		Avg	0.604	0.632	0.618	0.592	0.579	0.592	0.607	0.451	0.548	0.658
	M	Min	0.728	0.748	0.749	0.739	0.732	0.723	0.739	0.714	0.731	0.766
		Max	0.823	0.818	0.823	0.836	0.805	0.836	0.818	0.818	0.797	0.855
		Avg	0.789	0.794	0.797	0.799	0.776	0.777	0.780	0.760	0.779	0.814
	A	Min	0.683	0.700	0.710	0.695	0.681	0.677	0.678	0.617	0.682	0.720
		Max	0.732	0.709	0.729	0.727	0.698	0.726	0.724	0.698	0.721	0.753
		Avg	0.721	0.704	0.727	0.721	0.688	0.708	0.716	0.646	0.695	0.737
Specificity	**M**	Min	0.909	0.910	0.902	0.902	0.903	0.897	0.897	0.906	0.906	0.920
		Max	0.922	0.921	0.916	0.920	0.918	0.921	0.921	0.913	0.923	0.935
		Avg	0.917	0.913	0.914	0.912	0.911	0.912	0.912	0.903	0.913	0.929
	M	Min	0.904	0.920	0.918	0.918	0.920	0.930	0.915	0.921	0.924	0.940
		Max	0.963	0.938	0.948	0.963	0.943	0.971	0.939	0.965	0.944	0.984
		Avg	0.939	0.932	0.937	0.938	0.936	0.940	0.933	0.947	0.936	0.958
	A	Min	0.924	0.924	0.924	0.926	0.922	0.921	0.921	0.911	0.927	0.936
		Max	0.932	0.930	0.930	0.934	0.930	0.932	0.932	0.935	0.931	0.949
		Avg	0.928	0.927	0.927	0.928	0.925	0.927	0.927	0.933	0.928	0.947
Precision	**M**	Min	0.682	0.693	0.662	0.664	0.643	0.629	0.629	0.603	0.592	0.701
		Max	0.701	0.708	0.705	0.696	0.689	0.702	0.702	0.690	0.705	0.717
		Avg	0.692	0.699	0.688	0.681	0.663	0.676	0.676	0.661	0.665	0.707
	M	Min	0.740	0.739	0.734	0.745	0.722	0.733	0.733	0.742	0.725	0.752
		Max	0.759	0.762	0.763	0.790	0.747	0.778	0.778	0.756	0.753	0.857
		Avg	0.749	0.750	0.748	0.756	0.730	0.748	0.748	0.750	0.738	0.781
	A	Min	0.717	0.710	0.706	0.715	0.695	0.702	0.702	0.694	0.702	0.726
		Max	0.726	0.719	0.728	0.723	0.719	0.725	0.725	0.724	0.719	0.738
		Avg	0.721	0.716	0.719	0.721	0.702	0.716	0.716	0.710	0.711	0.729
F-measure	**M**	Min	0.546	0.676	0.637	0.522	0.582	0.523	0.523	0.304	0.450	0.698
		Max	0.700	0.714	0.680	0.694	0.673	0.689	0.689	0.664	0.671	0.722
		Avg	0.650	0.694	0.660	0.640	0.623	0.644	0.644	0.535	0.603	0.709
	M	Min	0.756	0.759	0.738	0.757	0.738	0.742	0.742	0.727	0.745	0.778
		Max	0.770	0.770	0.775	0.775	0.759	0.781	0.781	0.761	0.761	0.843
		Avg	0.762	0.765	0.762	0.767	0.748	0.759	0.759	0.746	0.755	0.819
	A	Min	0.697	0.734	0.707	0.706	0.686	0.693	0.693	0.643	0.688	0.745
		Max	0.734	0.749	0.732	0.734	0.708	0.719	0.719	0.710	0.718	0.766
		Avg	0.719	0.742	0.722	0.719	0.694	0.710	0.710	0.672	0.702	0.752

			GA	bGWO	ACO	WO	ABC	BAT	PSO	FA	DA	RCM-WOA
Error Rate	M	Min	0.096	0.096	0.098	0.098	0.103	0.096	0.096	0.101	0.102	0.057
		Max	0.103	0.105	0.107	0.103	0.113	0.106	0.106	0.110	0.107	0.101
		Avg	0.100	0.100	0.102	0.100	0.108	0.101	0.101	0.106	0.104	0.087
	M	Min	0.122	0.116	0.126	0.125	0.129	0.127	0.127	0.130	0.129	0.108
		Max	0.146	0.128	0.137	0.146	0.155	0.148	0.148	0.191	0.182	0.110
		Avg	0.112	0.105	0.112	0.111	0.118	0.115	0.115	0.116	0.116	0.100
	A	Min	0.119	0.111	0.120	0.119	0.126	0.120	0.120	0.132	0.123	0.106
		Max	0.114	0.108	0.114	0.115	0.124	0.118	0.118	0.126	0.120	0.103
		Avg	0.119	0.118	0.089	0.096	0.214	0.092	0.085	0.116	0.094	0.088
Execution Time	M	Min	25.10	5.85	7.60	5.26	22.11	3.91	3.91	14.79	5.90	1.85
		Max	39.28	14.93	7.77	5.81	23.03	7.66	7.66	11.99	6.02	2.11
		Avg	32.38	8.87	7.67	5.59	22.61	5.74	5.74	11.23	5.95	1.95
	M	Min	32.27	6.19	7.79	5.98	23.80	4.24	4.24	13.37	6.25	2.14
		Max	45.40	23.19	9.32	8.46	29.69	15.61	15.61	30.08	6.43	3.40
		Avg	36.36	10.81	8.37	6.65	25.24	7.78	7.78	16.84	6.36	2.51
	A	Min	26.76	6.08	7.68	5.79	23.10	4.04	4.04	12.36	6.04	2.05
		Max	40.58	16.62	7.97	6.40	24.55	8.90	8.90	15.91	6.14	2.27
		Avg	33.40	9.45	7.84	5.99	23.64	6.10	6.10	13.20	6.10	2.14

agents has been varied from five to ten. The graphs have been drawn between several iterations versus the best values scored for the algorithms.

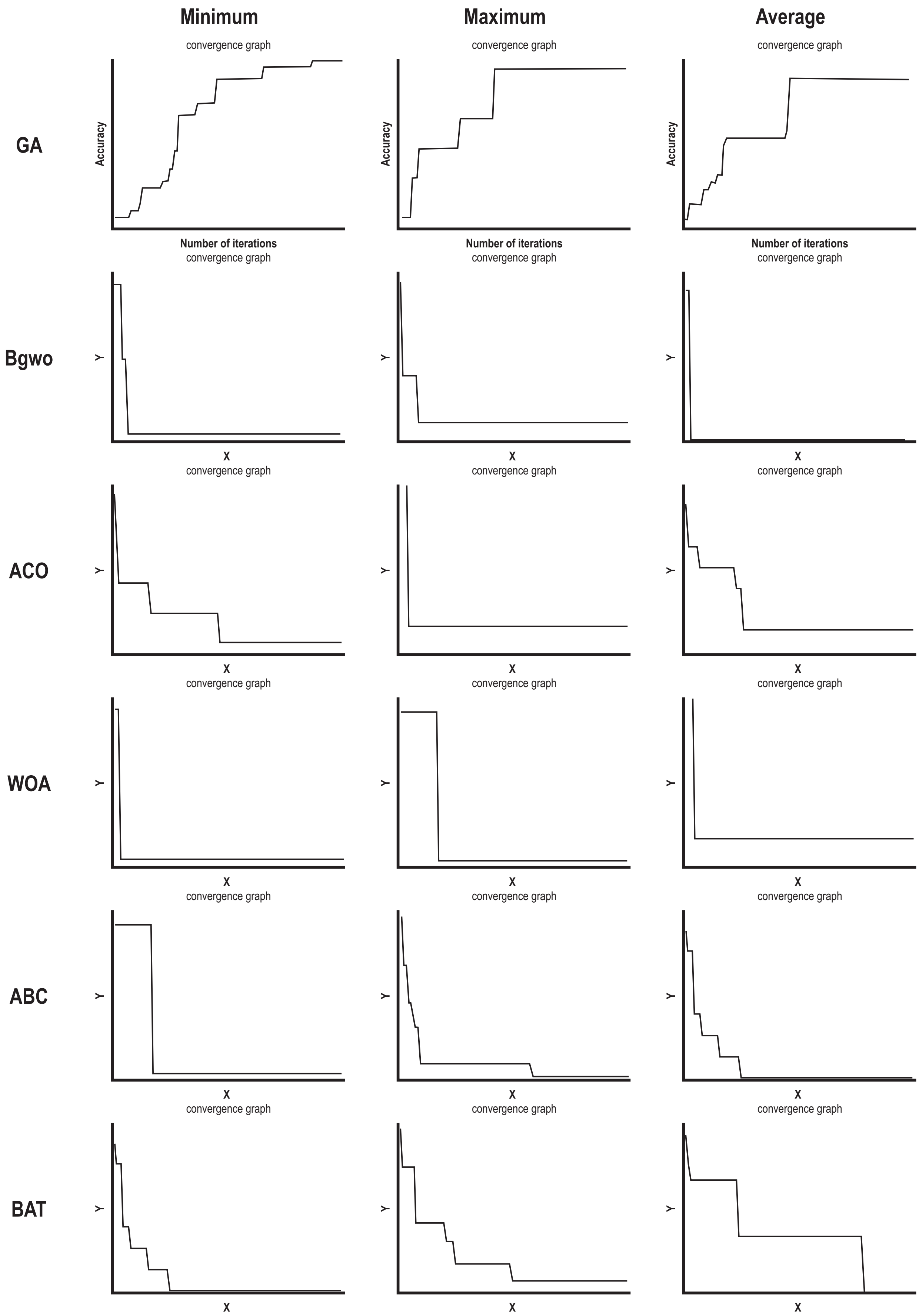
It is verified from Figure 3, that independent of the number of agents used, the excellent solution can be determined using the hybrid approach of RCM-WOA. The fusion of the evolutionary algorithm (GA) and swarm intelligent meta-heuristic algorithm (WOA) is the key reason for the same. The outcomes for the psychological disorder diagnosis (depression and anxiety) problem revealed that the use of restricted crossover and mutation operations of GA in the hybrid meta-heuristic algorithms (RCM-WOA) effectively balanced both the issues of exploration and exploitation.

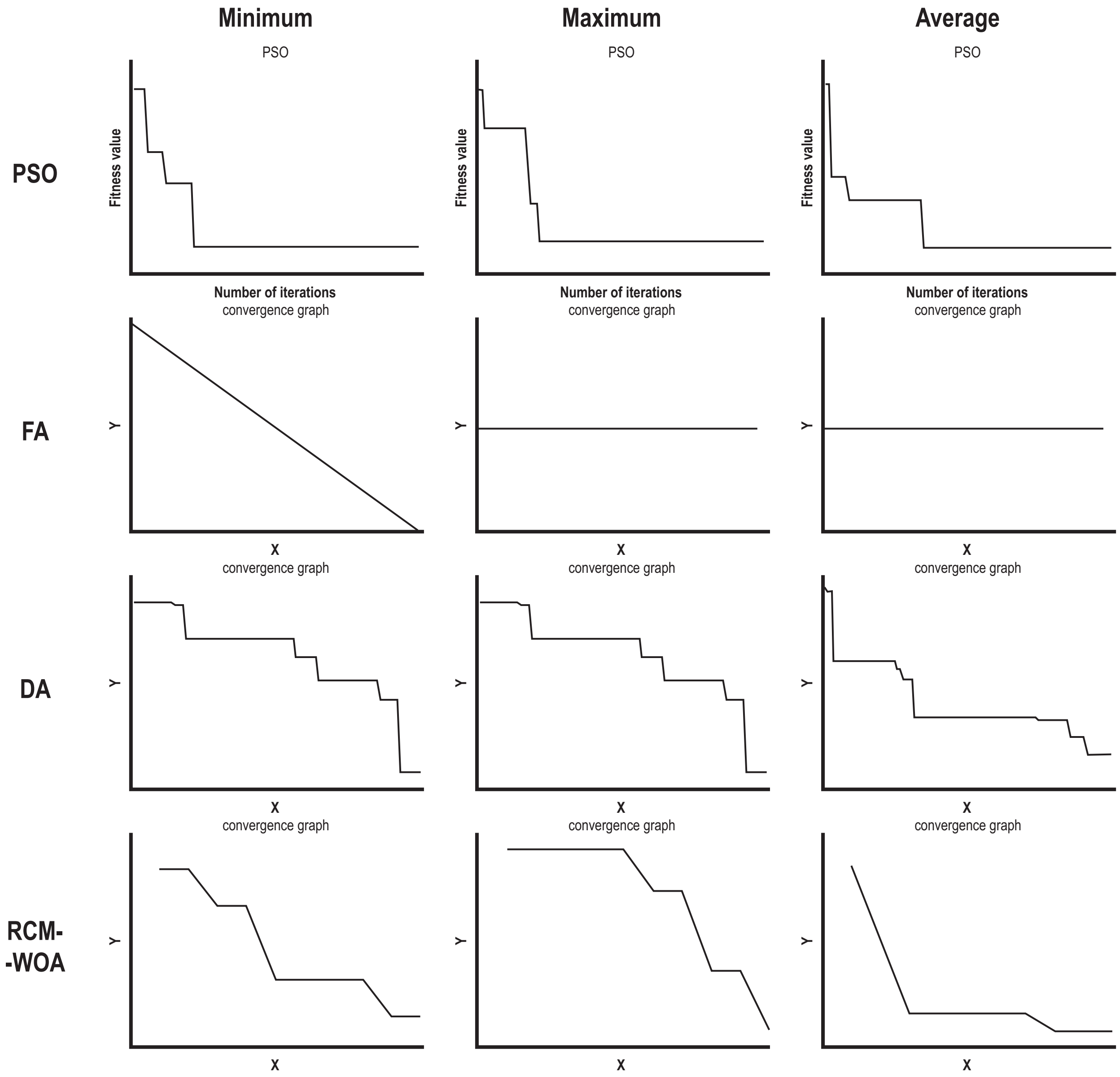
Wilcoxon's rank-sum test (Sharma, 2015) is used to examine whether the suggested RCM-WOA algorithm is significantly better than other algorithms such as GA, bGWO, ACO, WOA, ABC, BAT, PSO, FA, and DA or

Table 4. p-value

	GA	bGWO	ACO	WOA	ABC	BAT	PSO	FA	DA
Accuracy	1.2E-08	1.7E-14	9.8E-08	8.3E-09	8.6E-06	2.0E-08	2.6E-07	3.4E-07	3.6E-08
Sensitivity	4.5E-15	1.6E-08	2.6E-14	9.2E-17	7.9E-13	3.7E-16	1.8E-1	6.7E-25	6.1E-20
Specificity	1.8E-08	1.5E-02	3.0E-09	2.8E-09	2.0E-12	4.6E-12	2.6E-20	9.3E-10	2.2E-17
Precision	4.1E-13	2.8E-16	7.7E-12	1.9E-09	3.7E-10	6.4E-1	3.9E-14	1.3E-08	1.7E-07
Recall	4.5E-07	2.7E-19	2.4E-08	5.1E-07	7.3E-06	3.8E-09	1.5E-07	2.9E-03	3.9E-01
F-measure	7.4E-09	3.4E-19	6.5E-2	8.3E-08	2.3E-11	8.1E-06	3.7E-13	2.1E-02	6.0E-06

Figure 3. Convergence graphs of Dataset





not. The performance of RCM-WOA on six performance metrics (accuracy, sensitivity, specificity, precision, and recall) was compared to each of the other algorithms at a 5% significance level.

The p-values produced by the test are shown in Table 4, where p-values less than 0.05 indicate that the null hypothesis is rejected. On the other hand, underlined p-values (higher than 0.05) indicate that there is no statistically significant difference between the compared data. Fortunately, in maximum cases, the p-values are less than 0.05. These results represent that the outcomes produced using RCM-WOA are significant i.e. the results obtained using RCM-WOA are better than GA, bGWO, ACO, WOA, ABC, BAT, PSO, FA and DA.

CONCLUSIONS

In this research, nine emerging swarm intelligence-based meta-heuristic techniques ((Genetic algorithm (GA), binary Grey Wolf Optimizer (GWO), Ant Colony Optimization (ACO), Particle Swarm Optimization, Artificial Bee Colony (PSO), Firefly Algorithm (FA), Dragonfly Algorithm (DA), Bat Algorithm (BAT) and Whale Optimization Algorithm (WOA)) have been employed to find the optimal set of features used to diagnose depression and anxiety among humans. To avoid local optima and to maintain the balance between exploration and exploitation, a new hybrid feature selection technique called the Whale Optimization Algorithm with restricted crossover and mutation*(WOA-RCM).* This method has been designed by hybridizing WOA with GA (crossover and mutation). The performance of ten swarm intelligence-based meta-heuristic algorithms has been evaluated using different performance metrics such as accuracy, sensitivity, specificity, precision, recall, f-measure, error rate, execution time and convergence curve. For the collected dataset, the best rate of accuracy, sensitivity, specificity, precision, f-measure, error rate and execution time reached utilizing the proposed method RCM-WOA is 0.914, 0.855, 0.984, 0.857, 0.843, 0.057 and 1.85 respectively. RCM-WOA outperforms all nine soft computing techniques in terms of performance (viz. GA, GWO, ACO, WOA, ABC, BAT, PSO, FA and DA). For each of the five datasets, the rate of improvement in accuracy ranges between 1% and 3%.

In future, the association of these disorders needs to be mined at various granular levels. Furthermore, research into the usage of a binary or chaotic variation of various nature-inspired computing systems in the diagnosis of various human psychological diseases is required. Likewise, the effect of a random walk, levy flight and feature selection is still needed to examine as far as different human psychological disorders are concerned. Also, the effectiveness of these algorithms can be evaluated for other human psychological as well as neurological disorders such as Schizophrenia, Insomnia, Parkinson's, Alzheimer's, Mania, Autism etc.

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