ISSN: 0976-3104
SPECIAL ISSUE: COMPUTER SCIENCE

ARTICLE

ANT COLONY OPTIMIZATION BASED FEATURE SELECTION AND DATA CLASSIFICATION FOR DEPRESSION ANXIETY AND STRESS

S. T. Arokkiya Mary[1*], L. Jabasheela[2]

[1]*Department of Computer Applications, Research and Development Centre, Bharathiar University, Coimbatore, INDIA*

[2]*Department of Computer Science, Panimalar Engineering College, Chennai, INDIA*

ABSTRACT

In the recent days, Depression, Anxiety and Stress (DAS) became a common health issue appears over all parts the world. Several measures are available to compute the level of DAS and DAS-21 is the effective one amongst the other measure. Recently, machine learning and bio-inspired algorithms are employed to handle classification problems in an efficient way. To further enhance the classification performance, FS process is carried out in prior to classification process. It eliminates the unwanted and irrelevant features and chooses the significant features to model the classification system. In this paper, the significance of FS approaches (ACO and PSO) in the ant-miner based classification task of DAS is investigated. Ant-miner is the well-known classification algorithm which leads to efficient results for several kinds of classification task. This paper proposes a novel DAS model by the integration of FS methods with ant miner based classification model. The results are evaluated by validating the proposed method against a dataset collected by our own. The performance measures used in this study are accuracy, sensitivity, specificity, Kappa coefficient, F-score, False Discovery Rate (FDR) and False Omission Rate (FOR).

KEY WORDS
Ant miner, FS, Classification, Genetic algorithm, Particle Swarm Optimization

Received: 16 July 2018
Accepted: 11 Sept 2018
Published: 18 Sept 2018

***Corresponding Author**
Email:
arokya25@yahoo.co.in

INTRODUCTION

Based on World Health Organization (WHO), mental stress is commonly present in all parts of the world [1]. Some disorders like schizophrenia, bipolar disorder, depression, anxiety and stress (DAS) are some of the major dementia connected illness is also the causes of persons lives with disable nature. DAS are the well known diagnoses in health care and related to around 24% of diagnoses [2]. The significance of perceiving and handling depression and anxiety can't be downplayed as these constraints can bring a considerable decrease in personal satisfaction. This may show as confined support in the working environment, decline in normal health and disappointment in family or social life [3-5]. People with anxiety issue are more averse to take an interest in the workplace in contrast with people with disabilities and long-term health troubles [6], while depression are probably going to be less gainful at work or need to lessen the amount of work they perform.

Depression has been accounted for as an important imperative risk factor for suicide. An investigation by Suominen, Henrikkson, Suokas et al [7] revealed that 38% of suicide attempters has suffered from depressive issue while 75% were tested to have a depressive disorder (e.g. significant depression, depressive issue not generally indicated). Along with the individual load linked with depression and anxiety, there are also extensive financial costs to the community. In addition, DuPont and his team [8] recommend that the best effect comes from indirect costslike profitability in the working environment. The effect of unprocessed depression and anxiety on the capability to function is accounted for to be equivalent or more prominent than that of other basic medical issues, for example, coronary illness or joint pain [9]. Appropriate and sufficient handling of these conditions is essential as early recognition may prompt better result for the people concerned. Various researchers have evaluated distinctive models to distinguish the connection amongst depression and anxiety. In view of conventional ideas, anxiety and depression do not vary from each other and sometimes the conditions which present at the same time. This is because of the way that the models include anxiety and depression enfolds some common symptoms. Due to the interconnection between depression and anxiety, few investigations are made to find whether the emotional status of these differ from each another. As a result, some studies employed factor examination to compute discriminant validity of scale items. From the outcome of factor analysis, obviously the interconnection is at the middle level between anxiety and stress, however DAS are not quite the same as one other [10].

There are different factors which impact DAS and some of the reasons are sickness, pregnancy, scholarly advance, web-based social networking, debilitated understudies, disabled students, etc. of these issues are important to give treatment and diminishing the inability from the environment [11]. Distinctive measuring scales are available to calculate the levels of DAS and some of them include Beck Depression Inventory (BDI), the Beck Anxiety Inventory (BAI), the Hospital Anxiety and Depression Scale (HADS), the Center for Epidemiological Studies Depression (CES-D), and the Depression Anxiety Stress Scales (DASS). DASS is the most commonly used measuring scale and it has two forms namely DASS-21 and DASS-42.

DAS investigation models with novel ideas are presented and few of the conventional approaches are not widely used. In the meantime, the prior models are not applicable for the variations in the levels of DAS. In the recent years, numerous approaches are developed to classify DAS and are found in the literature. These strategies are utilized for data classification and in some of the cases it is integrated with other methods for hybrid approaches. Feature Selection (FS) is also a part in the process of data classification. It

IIOAB JOURNAL
ISSN: 0976-3104

is a procedure of choosing subset of features from raw features. It removes the redundant and irrelevant features along with the reduction in computational complexity of the system. The advantages of FS methods are less execution time, transparency, minimizing the number of measurements, etc. and so on. The goal of FS algorithm is to make the system less complex and to maximize the efficiency of the learning algorithm. The FS can be formulated as a combinatorial optimization problem and the function selection is a dataset. The design variables are the addition (1) or the elimination (0) of the features. A complete selection of features would measure several combinations (2^N, where N represents the number of features). It is hard to compute in case of more number of features and it becomes impossible. It is computationally complex; when the number of features is big, then it become impossible. Some of the metaheuristic algorithms used for FS are Ant Colony Optimization (ACO), GA, Particle Swarm optimization (PSO), simulated annealing, etc. are employed for effective results.

This paper investigates the significance of FS approaches (ACO and PSO) in the ant-miner based classification task of DAS. Ant-miner is the well-known classification algorithm which leads to efficient results for several kinds of classification task. This paper proposes a novel DAS model by the integration of FS methods with ant miner based classification model. The results are evaluated by validating the proposed method against a dataset collected by our own. The performance measures used in this study are accuracy, sensitivity, specificity, Kappa coefficient, F-score, False Discovery Rate (FDR) and False Omission Rate (FOR).

RELATED WORK

This section summarizes the state of art methods to investigate DAS in different dimensions. In [12], an examination is one to analyze the satisfaction level and ensuring the recommendation of giving internet-delivered treatment DAS for university students. The result of the examination demonstrates that the DAS level is diminished among students who experienced the proposed learning 4 times in a month. [13] performed a study to explore the state of DAS on high school girl students in Saudi Arabia by the use of DASS-42. Among the samples (N=545), just 26% of young ladies are not having DAS and half of the young lady's experiences atleast two disease in DAS. The outcomes portray the centrality of naming essential care doctors to protect young ladies, approve and mend psychological instability. [14] inspects the interconnection between otherworldly wellbeing and DAS in the patients experience from heart problems. A sample (N=150) is gathered from Ardabil clinic in the year of 2014. The outcome of this study recommends that the rise in spiritual health automatically reduces the level of DAS levels in heart failure patients. It suggests the necessity of forming medical communities to give mandatory spiritual healthcare. [15] led an examination to decide the intermediate responsibility to handle the measure of addicting to video game and psychological maladjustment. A survey (samples N=552) is performed over internet by the use of CAES scale, DASS-21 and BACQ. The results indicate that a solid connection between them the higher inclusion in computer games can lead to higher risk of addiction. [16] performed a study to assessment to anticipate the likelihood of DAS for Type II diabetes patients (N=2508) in 12 open medicinal services associations in Malaysia. DASS is utilized and gotten the likelihood of DAS indications 11.5%, 30.5% and 12.5% separately. It is clear that the occurrence if DAS is observed to be high for Type II diabetics. [17] carried out a procedure o compute the DAS levels of mechanical representatives in Bangalore, India utilizing DASS-21. From the acquired outcomes, it is clear that 36% of workers experience the ill effects of uneasiness.

[18] presented a method to identify the defects and analyze fundamental depressive disease in online networking. Initially, Crowdsourcing is utilizing to gather Tweets by the use of a default psychometric tool. A statistical classifier is developed to evaluate the risk of depression, before the reported onset. It gives an approach to design new tools to determine the severity levels of depression which will be helpful for individual persons and hospitals. [19] performed an investigation to assess the DAS level on Nepal medical undergraduate students (sample N=538) by DASS and SPSS is employed as a statistical tool. In addition to DASS, some additional questions are also added in the questionnaire. The results demonstrate that the students suffer from DAS and the respective percentage is 29.9%, 41.1% and 27%. [20] carried out a study to evaluate the DAS among the undergraduate physiotherapy students. This study is done based on the data gathered from 267 students and the results reported that the DAS level is high. So, it is suggested to give promotions and healthcare to the physiotherapy students. [21] investigated the rate of ADHD-related traits among young adults in an Australian university, and to study whether higher endorsement of ADHD-related symptoms is linked with self-reported symptoms of DAS, and autistic-like traits.

MATERIALS AND METHODS

PSO based FS

In this study, ant-miner algorithm is employed for data classification purposes of DAS. To enhance the classification results of the ant miner, two FS approaches include ACO and PSO is used to prefer the feature sunset and remove unwanted features from the applied dataset. The overall workflow of the FS methods employed in ant miner algorithm is discussed below

PSO is one of the evolutionary algorithm introduced by Kennedy and Eberhart in 1995 [22]. PSO is devised from the inspiration of social behavior of bird flocking and fish schooling. The fundamental idea of PSO is to optimize the knowledge using social interaction in the population where thinking is private as well as social. In PSO, it is assumed that every solution is identified as a particle in the swarm. Each particle owns a position in the search space, which is given by a vector $x_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$, where *D* is the dimensionality of the search space. The particles travel in the search space to search the optimal solutions. Therefore, the velocity of each particle is denoted as $v_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$. For the duration of movement, every particle performs position and velocity updation on the basis of its experience and its neighbors. The best preceding location of the particle is termed as personal best *pbest*, and best location attained by the population is termed as global best *gbest*. By the use of*pbest* and *gbest*, PSO performs searching process of finding optimal solutions by position and velocity updation of every particle using Eq. (1) and (2).

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \qquad (1)$$

$$v_{id}^{t+1} = w * v_{id}^{t} + c_1 * r_{1.} * (p_{id} - x_{id}^{t}) + c_2 * r_{2.} * \left(p_{gd} - x_{id}^{t}\right) \qquad (2)$$

where *t* represents t^{th} iteration in the evolutionary process, $d \in D$ denotes the d^{th} dimension in the search space. *w* is inertia weight, *c*1 and *c*2 are acceleration constants. *r*1 and *r*2 are random values uniformly distributed in [0, 1]. *Pid* and *pgd* represents the components of *pbest* and *gbest* in the d^{th} dimension. The velocity is limited by a fixed maximum velocity, *v*max, and *vt*+1 *id* $\in[-v\max, v\max]$. The algorithm terminates when a predefined condition is satisfied, which can be a better fitness value or a fixed maximum number of iterations.

ACO based FS (ACO-FS)

For a feature set of size n, the FS technique helps to discover a minimal feature subset of size s (s<n), while keeping higher accuracy to represent original features. A partial solution is to represent any ordering between the features of the solution. In the meantime, the forthcoming feature to be selected should not be impacted by the past feature annexed to the partial solution [23]. In any case, there is no need that the solutions of a FS problem ought to be of equivalent size. The mapping of FS problem to ACO algorithm includes:

- Graph representation,
- Heuristic desirability,
- Pheromone updation and
- Solution construction

Graph representation

To begin with, the FS difficulty should be redefined as an ACO problem. Generally, ACO algorithm desires the problem to be represented in the form of graph. In this Fig, the nodes indicate features and the edges constitute the selection of next features. The optimal feature subset is chosen by the procedure of ant traversal through the graph where less number of nodes visited will fulfill the traversal termination condition. Every node is associated together to permit any feature can be chosen. The ant is initially at node F_1 and the options of the path to append subsequent features are represented by dotted lines. It picks a feature F_2utilizing transition rule, next it picks F_6, F_3, F_8 and F_9. On arriving F_4, the present subset $\{F_1, F_2, F_6, F_3, F_8, F_9\}$ is found to fulfill the traversal termination condition. The ant stops its transversal and provides the selected subset of features as a candidate for data reduction. The final chosen subset is denoted by solid lines. Utilizing the reformulated diagram, the transition rules and pheromone rule updation of traditional ACO algorithms can be engaged. For this situation, every feature has its individual pheromone and heuristic value.

Heuristic desirability

The basic element of ACO algorithm is a constructive heuristic to produce solutions in a probabilistic way. A solution construction begins with a null partial solution. Subsequently, at each construction process step, the current partial solution is extended by including a feasible solution element from a collection of solution components.

Pheromone updation

When all the ants found the solutions, the pheromone evaporation of all nodes is initiated and each ant *k* deposits a quantity of pheromone as given in Eq. (3),

$$\Delta\tau_i^k(t) = \begin{cases} \phi\cdot\gamma\left(S^k(t)\right) + \frac{\phi(n-|S^k(t)|)}{n}, & \text{if } i \in S^k(t) \\ 0 & \text{otherwise} \end{cases} \qquad (3)$$

where $S^k(t)$is the feature subset produced by ant *k* at t^{th} iterative and $|S^k(t)|$ indicates the length, ϕ and φ are the two parameters to control the relative weight of classifier performance and feature subset length,

$\phi \in [0,1]$ and $\varphi = 1-\phi$. Basically, adding new pheromone by ants and pheromone evaporation are represented by the rule as given in Eq. (4) is applied to all the rules:

$$\tau_i(t+1) = (1-\rho)\tau_i(t) + \sum_{k=1}^{m} \Delta_i^k(t) + \Delta\tau_i^g(t) \quad (4)$$

where m is the number of ants at every iteration and $\rho \in (0, 1)$ is the pheromone trail decay coefficient. The main usage of pheromone evaporation is to keep away from stagnation, each ant experience pheromone updation and the best ant lays more pheromone on nodes of the best solution. It leads to the exploration of ants around the optimal solution in the subsequent iterations.

Solution construction

The process begins with the generation of number of ants and is deployed in a random way. Next, the number of ants to lay on the graph is set equivalent to the number of features available in the data. The ant starts from the process of path construction from different features. From the initial positions, they transverses the nodes in a probabilistic way until the termination condition satisfies. The consequential subsets are gathered and analyzed for optimal one. On the identification of optimal subset, then the procedure terminates and the best feature subset is noted. When the conditions unsatisfied, then the pheromone will be updated and generates a new set of ants to repeat the process.

ANT-MINER based DAS Classification

Once the features are chosen by ACO and PSO algorithm, ant miner applied for the classification of DAS. Using ant miner algorithm [24], the ants determine the shortest path from source to destination. The ants choose the possible paths using a probability function. It is derived by the amount of pheromone present in the path and heuristic function. When ants visited all the feasible paths, the path containing more amount of pheromone and the heuristic value with higher possibility will be elected. On choosing a path by ant, the pheromone value initiates to rise. When adequate number of ant follows one path, it will become a candidate rule and it is considered as a discovered rule when the quality is good enough.

Structural representation

Basically, ACO follows the foraging principle of real ant colonies. An attribute is denoted as $Attribute_i$ where i indicate the series of the attribute and Va_{ij} represents the non-continuous attribute value. The subsequent level of the attribute fall into a class and the value of class are indicated by CL_k, where k is the series value in the class. The ant rises from the nest as a source and chooses a value for each attribute. Upon visiting all attributes, it takes a value for the class and consumes the food as a destination [30]. For rule discovery, sufficient amount ants should takes the similar path which is explained below and shown in [Fig. 1].

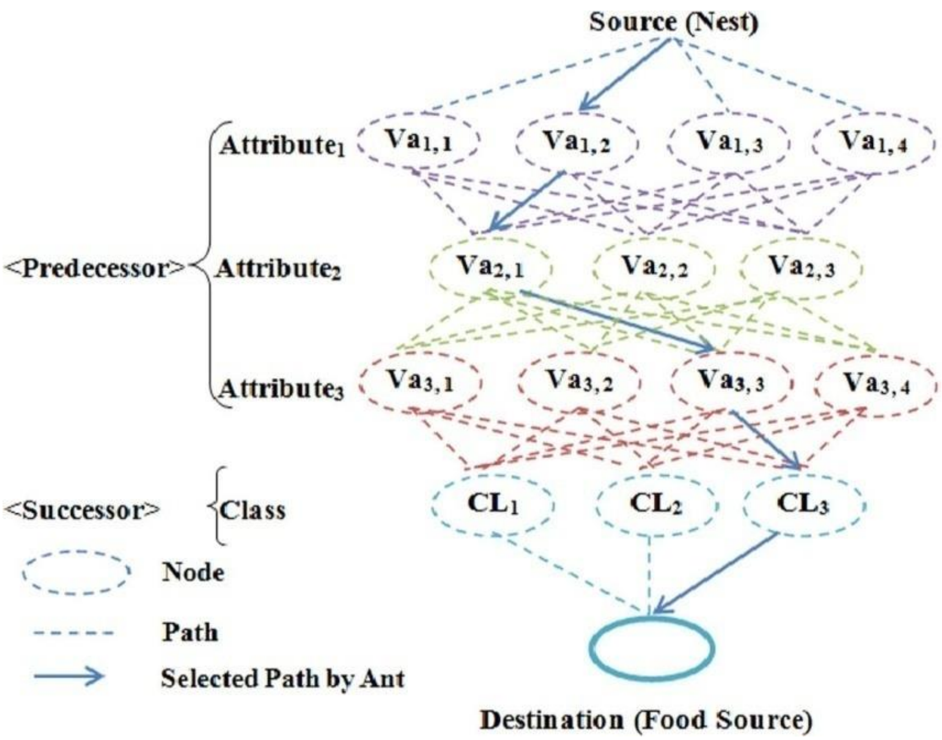

Fig. 1: Structural representation of ACO based classification.

IIOAB JOURNAL
ISSN: 0976-3104

Rule structure

The classification based rule structure of ant-miner algorithm is: IF <antecedent > THEN <descendant>.

Rule generation

Sequential covering method is employed by ant-miner algorithm to recognize the list of classification rules. At first, the number of discovered rules in the rule list is set to zero and the training set hold the collection of discovered rules. The discovery of classification rules in each repetition of WHILE loop parallel to a number of executions of the REPEAT-UNTIL loop leads to shifting of a classification rule list and eliminates from training set. This process continues until maximum threshold value reaches the number of uncovered training cases. At the start, Ant_t set with zero rules and incremented by one term to its available partial rule until any of the below conditions satisfied
(1) Any value lesser than predefined threshold can be appended to the rule
(2) When the ants utilize all the attributes earlier, rule generation will be terminated. The artificial ants select an attribute value to create rules by the probability function Eq. (5).

$$P_{xy} = \frac{\eta_{b_{xy}} \cdot \tau_{b_{xy}}}{\sum_{x=1}^{a}(z_x) . \sum_{y=1}^{b}\left(\eta_{xy} \cdot \tau_{xy}(t)\right)} \qquad (5)$$

where, P_{xy} represents the likelihood function,η_{xy}represents the value of a problem-dependent heuristic function and $\tau_{xy}(t)$represents the amount of pheromone at iteration t.

Rule pruning: This procedure aimed to eliminate the unnecessary rules generated by ants in every step. It helps to improve the rule quality generated by the ants and the rules will be simple. Eq. (6) gives the rule quality lies between, $0 \leq Q \leq 1$.

$$Q = \frac{TP}{(TP + FN)} * \frac{TN}{(FP + TN)} \qquad (6)$$

where, TP-True Positive, TN- True Negative, FP-False Positive and FN-False Negative.

Pheromone Updating: It represents the quantity of the evaporation of ant pheromone in the real world. Artificial ants execute pheromone updating process to find the simpler rules. Due to positive feedback procedure, the errors in the heuristic measure will be corrected and leads to enhanced classification accuracy and is equated in Eq. (7).

$$\tau_{xy}(t = 0) = \frac{1}{\sum_{x=1}^{a} bx} \quad (7)$$

where, η_{xy} represents the value of a problem-dependent heuristic function, a is the 'n' number of attributes, b_i *is* the possible values that associated attribute a_i.

PERFORMANCE EVALUATION

To validate the effective results of the proposed method, it is validated using a dataset, which contains 938 samples collected from college students from Puducherry, India using DASS-21 measure to assess the level of DAS among them. The dataset consists of a total of 938 instances, 7 features and 5 classes. The dataset description is tabulated in [Table 1]. For experimentation, WEKA is used as a simulation tool. The performance of the proposed method are compared with PSO based FS in the classification process using ant miner. The experimental results are compared with one other using different performance measures namely accuracy, sensitivity, specificity, Kappa coefficient, F-score, FDR and FOR.

Table 1: Dataset description

S. No	Dataset	No. of Instances	No. of Features	No. of Classes
1	Depression	938	7	5
2	Anxiety	938	7	5
3	Stress	938	7	5

The comparative results of the ACO based feature section methodologies are tabulated in [Table 2-4] for depression, anxiety and stress and are illustrated in [Fig. 3-5]respectively. From [Table 2], it is apparent that the classification performance without FS is poor than other methods. By contrast, the classification results of the PSO based FS methodology achieves better performance than without FS. In the same way, the ACO based FS with classification shows superior performance than other compared methods. However, out of 7 features, PSO algorithm selects four features whereas the proposed ACO algorithm selects only three features. For depression dataset, the proposed method attains maximum closest performance with a higher accuracy of 97.56, sensitivity of 93.86, specificity of 99.23, F-score of 96.78, FOR of 6.56, FDR of 2.45 and kappa value of 93.47 respectively.

Table 2: Classification results with depression dataset

Method	Selected Features	Accuracy	Sensitivity	Specificity	F-score	FOR	FDR	Kappa
None	All	77.51	85.21	52.33	86.62	14.44	13.98	35.09
PSO	6,3,1,7	91.42	88.67	93.12	89.55	10.11	11.45	81.67
ACO	4,6,2	97.56	93.86	99.23	96.78	6.56	2.45	93.47

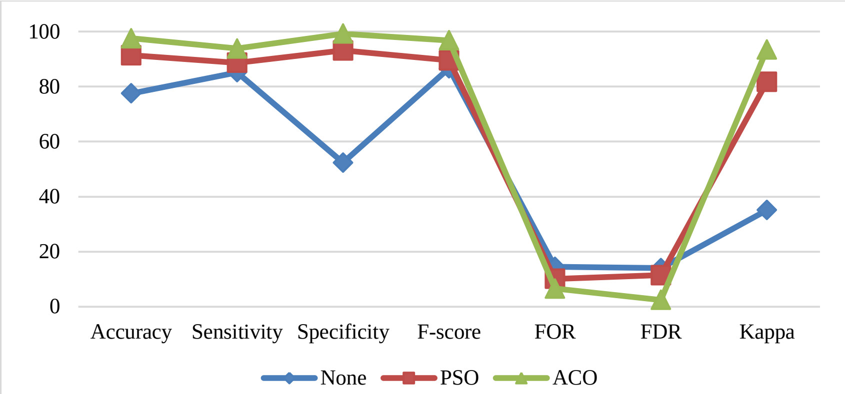

Fig. 2: Comparative analysis of classification results for depression dataset.

Table 2] demonstrates the classification performance for anxiety dataset. The table values depicts that the worse performance is achieved when no FS mechanism is involved. The classification performance is significantly improved by the inclusion of FS methods. Here, the PSO FS method outperforms the classification performance when no FS is employed. But, it fails to achieve better performance when compared to ACO based FS. Similarly to depression dataset, for anxiety dataset, out of 7 features, PSO algorithm selects four features whereas the proposed ACO algorithm selects only three features. For anxiety dataset, the proposed method attains maximum closest performance with a higher accuracy of 93.78, sensitivity of 92.31, specificity of 94.76, F-score of 91.06, FOR of 7.36, FDR of 12.14 and kappa value of 84.76 respectively.

Table 3: Classification results with anxiety dataset

Method	Selected Features	Accuracy	Sensitivity	Specificity	F-score	FOR	FDR	Kappa
None	All	89.78	83.3	93.69	85.41	14.01	13.22	74.72
PSO	2,3,4,1	91.68	89.71	93.76	88.51	10.42	12.67	79.68
ACO	1,3,2	93.78	92.31	94.76	91.06	7.36	12.14	84.76

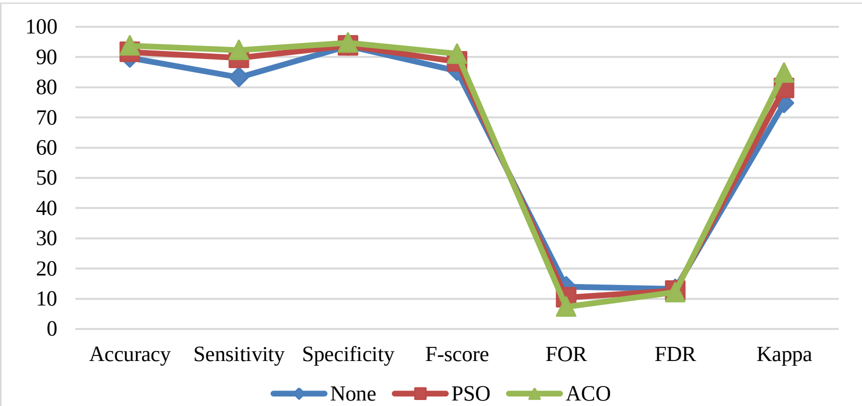

Fig. 3: Comparative analysis of classification results for Anxiety dataset.

IIOAB JOURNAL ISSN: 0976-3104

From [Table 2], it is apparent that the classification performance with no FS shows worse performance than the compared methods. By contrast, the classification performance of the PSO based FS method accomplishes preferable performance than without FS. In the same way, the ACO based FS with classification shows superior performance than other compared methods. However, out of 7 features, PSO algorithm chooses four features whereas the proposed ACO algorithm selects only three features. For depression dataset, the proposed method attains maximum closest performance with a higher accuracy of 93.57, sensitivity of 93.31, specificity of 93.76, F-score of 91.06, FOR of 8.36, FDR of 10.14 and kappa value of 84.76 respectively. From the above experimental results, it is proved that the inclusion of ACO based FS process will enhance the classification performance of the ant-miner algorithm for DAS.

Table 4: Classification results with stress dataset

Method	Selected Features	Accuracy	Sensitivity	Specificity	F-score	FOR	FDR	Kappa
None	All	89.84	95.93	73.61	93.82	20.4	12.18	70.15
PSO	3,5,2,6	90.65	88.71	93.76	88.51	10.42	12.67	79.68
ACO	3,4,6	93.57	93.31	93.76	91.06	8.36	10.14	84.76

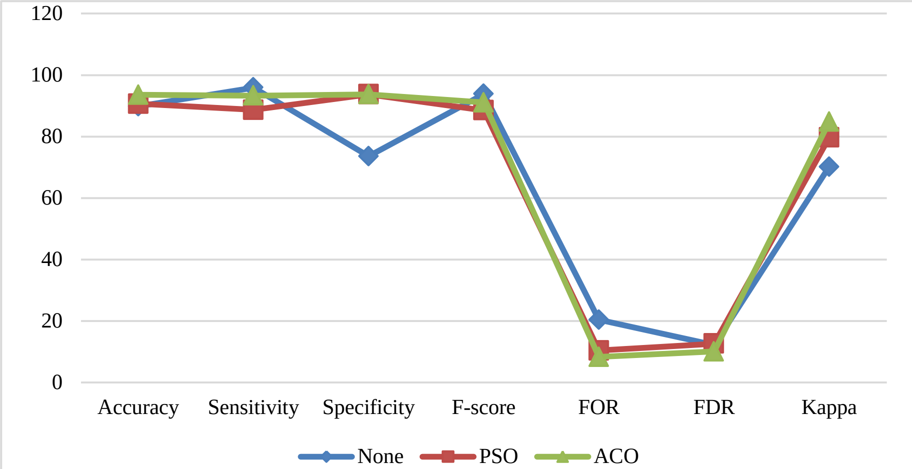

Fig. 4: Comparative analysis of classification results for Stress dataset.

CONCLUSION

This paper investigates the significance of FS approaches (ACO and PSO) in the ant-miner based classification task of DAS. It eliminates the unwanted and irrelevant features and chooses the significant features to model the classification system. The goal of this study is to examine the consequence of FS approaches in the ant-miner based classification task of SPP. The results are evaluated by validating the proposed method against a dataset collected by our own. The performance measures used in this study are accuracy, sensitivity, specificity, Kappa coefficient, F-score, FDR and FOR. The proposed method attains maximum closest performance with a higher accuracy of 97.56, sensitivity of 93.86, specificity of 99.23, F-score of 96.78, and kappa value of 93.47 respectively. From the experimental results, it is verified that the use of ACO in the FS for ant miner based data classification is superior than the PSO based FS.

CONFLICT OF INTEREST

No conflict of interest

ACKNOWLEDGEMENTS

This study is supported by UGC under grant number MRP-6524/16 (SERO/UGC)

FINANCIAL DISCLOSURE

None

REFERENCES

[1] World Health Organization. The World Health Report 2001: Mental health: new understanding, new hope. World Health Organization, 2001.

[2] Andrews G, Kristy Sanderson, Slade T, Issakidis C [2000] Why does the burden of disease persist? Relating the burden of anxiety and depression to effectiveness of treatment. Bulletin of the world Health Organization, 78(4): 446-454.

[3] Mendlowicz, Mauro V, Murray B. Stein [2000] Quality of life in individuals with anxiety disorders. American Journal of Psychiatry, 157(5): 669-682.

[4] Rapaport, Mark Hyman, Cathryn Clary, Rana Fayyad, and Jean Endicott [2005] Quality-of-life impairment in depressive and anxiety disorders. American Journal of Psychiatry, 162(6): 1171-1178.
[5] Waghorn, Geoff, David Chant, Paul White, and Harvey Whiteford [2005] Disability, employment and work performance among people with ICD-10 anxiety disorders. Australian and New Zealand Journal of Psychiatry, 39(12): 55-66.
[6] Greenberg, Paul E, Ronald C. Kessler, Howard G. Birnbaum, Stephanie A. Leong, Sarah W. Lowe, Patricia A. Berglund, and Patricia K. Corey-Lisle [2003] The economic burden of depression in the United States: how did it change between 1990 and 2000? Journal of clinical psychiatry, 64(12): 1465-1475.
[7] Suominen KM, Henriksson M, Suokas J, Isometsä E, Ostamo A, Lönnqvist J [1996] Mental disorders and comorbidity in attempted suicide. Acta Psychiatrica Scandinavica, 94(4): 234-240.
[8] DuPont RL, Rice DP, Miller LS, Shiraki SS, Rowland CR, Harwood HJ [1996] Harwood. Economic costs of anxiety disorders, Anxiety 2(4): 167-172.
[9] Schonfeld WH, Verboncoeur CJ, Fifer SK, Lipschutz RC, Lubeck DP, Buesching DP [1997] The functioning and well-being of patients with unrecognized anxiety disorders and major depressive disorder, Journal of affective disorders, 43(2):105-119.
[10] Rowe SK, Rapaport MH [2006] Classification and treatment of sub-threshold depression. Psychopharm Review, 41(5): 33-39.
[11] Goldberg DP [1995] Form and frequency of mental disorders across centers. Mental illness in general health care: An international study.
[12] Currie SL, McGrath PJ, Day V [2010] Development and usability of an online CBT program for symptoms of moderate depression, anxiety, and stress in post-secondary students. Computers in Human Behavior, 26(6): 1419-1426.
[13] Frazier P, Richards D, Mooney J, Hofmann SG, Beidel D, Palmieri PA, Bonner C [2016] Acceptability and proof of concept of internet-delivered treatment for depression, anxiety, and stress in university students: protocol for an open feasibility trial. Pilot and feasibility studies, 2(1): 28.
[14] Safavi M, Oladrostam N, Fesharaki M, Fatahi Y[2016] An Investigation of the Relationship between Spiritual Health and Depression, Anxiety, and Stress in Patients with Heart Failure. Health, Spirituality and Medical Ethics, 3(2): 2-7.
[15] Loton D, Borkoles E, Lubman D, Polman R [2016] Video game addiction, engagement and symptoms of stress, depression and anxiety: The mediating role of coping. International Journal of Mental Health and Addiction, 4: 565-578.
[16] Kaur G, Tee GH, Ariaratnam S, Krishnapillai AS, China K [2013] Depression, anxiety and stress symptoms among diabetics in Malaysia: a cross sectional study in an urban primary care setting. BMC family practice, 14(1): 69.
[17] Rao S, Ramesh N [2015] Depression, anxiety and stress levels in industrial workers: A pilot study in Bangalore, India. Industrial psychiatry journal, 24(1): 23.
[18] De Choudhury M, Gamon M, Counts S, Horvitz E [2013] Predicting depression via social media. ICWSM, 13: 1-10.
[19] Kunwar D, Risal A, Koirala S [2016] Study of depression, anxiety and stress among the medical students in two medical colleges of nepal. Kathmandu Univ Med J, 53(1): 22-6.
[20] Syed A, Ali SS, Khan M [2018] Frequency of depression, anxiety and stress among the undergraduate physiotherapy students. Pakistan journal of medical sciences, 34(2):468.
[21] Nankoo MM, Palermo R, Bell JA, Pestell CM [2018] Examining the rate of self-reported ADHD-related traits and endorsement of depression, anxiety, stress, and autistic-like traits in Australian university students. Journal of attention disorders, 1:1087054718758901.
[22] Kennedy J [2011] Particle swarm optimization. In Encyclopedia of machine learning, 760-766.
[23] Parpinelli RS, Lopes HS, Freitas AA [2002] Data mining with an ant colony optimization algorithm. IEEE transactions on evolutionary computation, 6(4): 321-332.
[24] Uthayakumar, J, Vengattaraman T, Dhavachelvan P. [2017] Swarm intelligence based classification rule induction (CRI) framework for qualitative and quantitative approach: An application of bankruptcy prediction and credit risk analysis. Journal of King Saud University-Computer and Information Sciences (In press).