Intelligent Feature Subset Selection with Machine Learning based Risk Management for DAS Prediction

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Abstract

In the current epidemic situations, people are facing several mental disorders related to Depression, Anxiety, and Stress (DAS). Numerous scales are developed for computing the levels for DAS, and DAS-21 is one among them. At the same time, machine learning (ML) models are applied widely to resolve the classification problem efficiently, and feature selection (FS) approaches can be designed to improve the classifier results. In this aspect, this paper develops an intelligent feature selection with ML-based risk management (IFSML-RM) for DAS prediction. The IFSML-RM technique follows a two-stage process: quantum elephant herd optimization-based FS (QEHO-FS) and decision tree (DT) based classification. The QEHO algorithm utilizes the input data to select a valuable subset of features at the primary level. Then, the chosen features are fed into the DT classifier to determine the existence or non-existence of DAS. A detailed experimentation process is carried out on the benchmark dataset, and the experimental results showcased the betterment of the IFSML-RM technique in terms of different performance measures.

Keywords: Risk management, Machine learning, Feature selection, DAS, Prediction model, Classification.

1. Introduction

Machine learning methods were widely employed as decision making support tools in the difficult environments of healthcare information analyses. The dominance of psychological disorders is continually growing particularly in youth and children populations [1, 2]. The similar relates to stress disorder that is identified as the popularly established psychological diseases nevertheless of age. But, to predict knowledge psychological health mechanism depends on data mining, and ML methods have fascinated slight consideration from the study fields. Initial efforts were dedicated to the prognoses of dementia [3] via demographic data, neurophysiological tests, panic disorder [4], social psychosis [5], bipolar disorders, etc according to sleep quality and neuroimaging information from wearable medicinal devices [6-8].

Nowadays, in epidemic scenarios, people often complaining about pressure, anxiety, and stress, main depressing disorders are usually viewed as primary psychological disorders over the world. While somebody seems to have strong feelings like distress and sadness for a longer time, they may possess primary depressing disorders [9, 10]. It has higher impact on physical and psychological actions to the one suffers from it; similarly, there is a high risk of irresponsibility [11]. The person who suffers from MDD tends to feel unconcerned in doing the activity they liked formerly. Besides, it affects their mood and behaviors, and find trouble in everyday actions. Most people decease by punishing itself are establish to have psychological disorder i.e., curable, generally because of depressions. The suicidal rates are

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assumed to be 15% amongst depressive people [12, 13]. The most important depressing disorders are curable psychological disorders which perform while the persons are anxious due to many causes of ones' life comprising hormonal change [14].

Main depressing disorders are called comorbid, i.e., medicinal conditions which tend to appear, and it is a difficult process for identifying either the person is suffering from MDD or not. In several instances, the person who is distressed will be unwilling to check professionals due to the under-trained resource and workforce; it is complex to diagnosing and endure additional treatments [15]. Therefore, in this work, they have attempted to employ ML methods for distinguishing among non-depressed and depressed persons. Alternatively, it would be complex for diagnosing this distressed person as the work's stylishness wouldn't permit one to understand the actuality. Hence, there is a need for bringing a scheme which can permit to investigate itself with no human interference. In [16], predictions of the existence of mental difficulties like stress, anxiety, and depression were created through 8 ML processes to information acquired from the online DASS42 tools. The 5 diverse seriousness stages of stress, anxiety, and depression are anticipated by 8 processes. The systems are gathered into 4 classes: tree based, probabilistic, KNN, and NN. A hybrid classification algorithm has been employed to predict diverse seriousness levels of stress, anxiety, and depression.

Mutalib [17] presents identifying factors in mental health problems among selected higher education students. This study aims to classify students into different categories of mental health problems, which are stress, depression, and anxiety, using machine learning algorithms. The data is collected from students in a higher education institute in Kuala Terengganu. The algorithms applied are DT, NN, SVM, NB, and LR. Srividya et al. [18] proposed different ML procedures like SVM, DT, NB, KNN, and LR for identifying psychological conditions of targeted groups. The response attained from the targeted groups for the developed questionnaire has been initially subjected to unsupervised learning techniques. The label attained because of clustering has been authenticated by calculating the MOS. These CHs are later employed for building classifiers to forecast the psychological state of a person. Vincent et al. [19] aim are to examine the IT staff are commonly working with target. The ANN, i.e., modelled insecurely such as brain, has demonstrated recently which could execute optimal compared to classification algorithm. This work has executed the multilayer neural perceptron and experiment with the BP method through the sample information gathered from IT professionals.

This paper designs an intelligent feature selection with ML based risk management (IFSML-RM) for DAS prediction. The IFSML-RM technique follows a two-stage process namely quantum elephant herd optimization based FS (QEHO-FS) and decision tree (DT) based classification. At the primary level, the QEHO algorithm utilizes the input data to select a useful subset of features. Then, the chosen features are fed into the DT classifier to determine the existence or non-existence of DAS. A detailed experimentation process is carried out on benchmark dataset and the experimental results showcased the betterment of the IFSML-RM technique interms of different performance measures.

2. Materials and Methods

In this study, a new IFSML-RM technique is derived to predict and classify DAS. The IFSML-RM technique follows a two-stage process namely QEHO-FS and DT based classification. The detailed working of the IFSML-RM technique is shown in Fig. 1 and the detailed processes are offered in the succeeding portions.

2.1 Design of QEHO-FS Technique

The input data is fed into the QEHO-FS technique to pick an optimum subset of features. EHO methods depend largely on behaviours of elephants that is recently proposed for global optimal. This method doesn't make use of the previous individuals in the consequent updating process. While significant information in the earlier individuals is wholly used in optimization manner, the solutions quality would be significantly improved. The main contribution of this study is to improve the EHO update procedure whereas the EHO update operators were used. According to the EHO operators, the interrelated operation is determined consequently.

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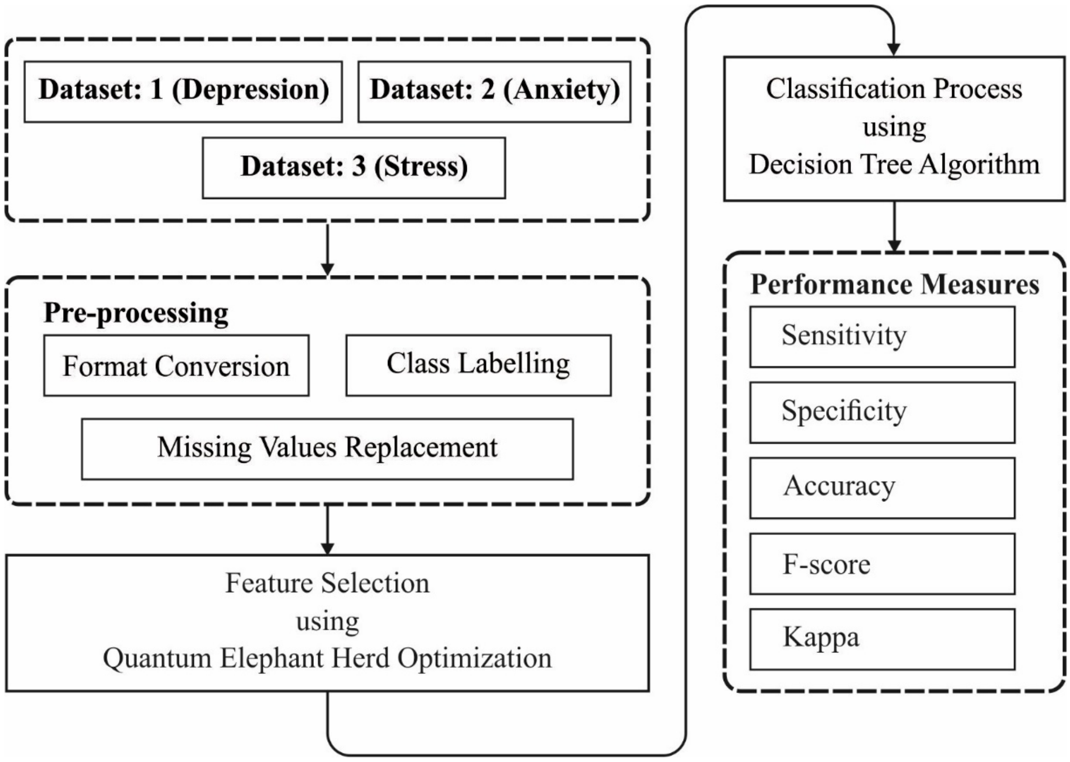

Fig. 1. Block diagram of IFSML-RM technique

The updated principles of important EHOs are proposed by [20. Considers an elephants clan i.e., denoted by ci. Later, the future location of elephants, j, in the clans are increased as (1),:

$$x_{new,ci,j} = x_{ci,j} + \alpha \times \left(x_{best,ci} - x_{ci,j}\right) \times r, \quad (1)$$

Whereas $x_{new,ci,j}$ means the updated position, and $x_{ci,j}$ suggests the previous location of elephants j in clan ci. $x_{best,ci}$ indicates matriarch of clan ci; epitomizes the rightest elephants in the clan. The scaling factors $\alpha \in [0,1]$ are used in calculating the matriarch of ci on $x_{ci,j}$. $r \in [0, 1]$ that belong to stochastic distributions which are able to provide the development in the population variance. It is noted $x_{ci,j} = x_{best,ci}$, represent a matriarch in a clan couldn't be increased as (1). This state is detached by upgrading the location of appropriate elephants by:

$$x_{new,ci,j} = \beta \times x_{center,ci}, \quad (2)$$

Whereas $x_{center,ci}$ on $x_{new,ci}$, is maintained by $\beta \in [0,1]$. The data reached from each individual in clan ci is used to develop a new individuals$x_{new,ci,j}$. The middle part of a clan ci, $x_{center,ci}$, is defined for dth dimensional with D calculation where D implies the general dimensions by:

$$x_{center,ci,d} = \frac{1}{n_{ci}} \times \sum_{j=1}^{n_{ci}} x_{ci,j,d} \quad (3)$$

In this method, $1 \leq d \leq D$ depict the dth dimensions, n_{ci} means the individual in ci, and $x_{ci,j,d}$ denotes dth dimensions of individuals $x_{ci,j}$.

Essentially, ME leave family member also live without help when they are mature. The procedure of isolation is labelled as splitting operators i.e., appropriate in solving the optimization problems. To enhance the search capacity of EHO method considers elephant through poor fitness to implement the splitting operators for each generation by (4).

$$x_{worst,ci} = x_{min} + (x_{max} - x_{min} + 1) \times rand \quad (4)$$

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Whereas x_{max} & x_{min} denotes the upper and lower bounds, respectively. $x_{worst,ci}$ indicates the poor elephants in clan ci. $rand \in [0, 1]$ indicates a kind of uniform and stochastic distributions from zero and one.

Meta heuristic method is a kind of elitism principle used by the objectives of securing optimum elephants from being demolished through a clan update and separate operator. Firstly, the best elephant must be secure and poor one should be exchanged by storing optimal elephants in the search method. It confirms that late elephant populations are good compared to prior ones. Accordingly, slower convergences are increased by resolving complex problems, and largescale optimization problems. Lately, some particulars are used to reuse the elephant's location and improve the search capability of EHO models.

QEHO algorithm is a new type of computational method which employs the model pertinent to quantum theories such as state superposition, quantum entanglement, and estimation. An important module of quantum computations is qubit. In two important conditions is $|0>$ & $|1>$ develops a qubit, i.e, signified as linear incorporation of two important conditions by.

$$|Q>= \alpha|0> +\beta|1>. \tag{5}$$

$|\alpha|^2$ means the opportunity to observe states $|0>, |\beta|^2$ suggests probability of observing states $|1>$, where $|\alpha|^2 + |\beta|^2 = 1$. A quantum are manufactured by n qubit. Due to the quantum superposition, all quantum's are made up of 2^n possible value. A n-qubit quantum are given by.

$$\Psi = \sum_{x=0}^{2^n-1} C_x |x>, \sum_{x=0}^{2^n-1} |C_x|^2 = 1. \tag{6}$$

Quantum gate is used for modifying the conditions of qubits such as Hadamard, rotation, NOT, etc. At first, the Rotation gates [21] are determined by mutational operators to make a successful quanta method and identify the global optimal solutions. The rotation gates are demonstrated by:

$$\begin{bmatrix} \alpha^d(t+1) \\ \beta^d(t+1) \end{bmatrix} = \begin{bmatrix} \cos(\Delta\theta^d) & -\sin(\Delta\theta^d) \\ \sin(\Delta\theta^d) & \cos(\Delta\theta^d) \end{bmatrix} \begin{bmatrix} \alpha^d(t) \\ \beta^d(t) \end{bmatrix} ford = 1,2,\ldots,n. \tag{7}$$

$\Delta\theta^d = \Delta \times S(\alpha^d, \beta^d), \Delta\theta^d$ denotes the rotation angles of the qubits, where Δ Y $S(\alpha^d, \beta^d)$ indicate the size and directions of rotation respectively.

2.2 Design of DT Classifier

At this stage, the chosen features are passed into the DT classifier to determine the proper class labels for them. This study, it utilizes C5.0, a univariate decision tree technique which is profitable beneficiary of C4.5, broadly utilized and testing classifier technique. The whole explanation of this technique is over the extent of study, and the contributor is stated to [22] whole detailed. Now it summarizes the key elements of these techniques is defined in [22], concentrating specific consideration to these features which relate to evaluation of partition guidelines and selected features.

The significant component of decision tree estimate technique is the system utilized for estimation splitting on all inner nodes of the tree. For attaining, C5.0 utilizes a metric is known as *information gain ratio* that measures decrease in entropy of the information generated via splits. By these metrics, the testing on every node in a tree is chosen by the division of information which maximizes the decrease in entropy of the successor node. Provided a trained data set D consist of observations belong to m class $\{C_1, C_2, \cdots, C_m\}$, it requires testing T which divide D as n mutual exclusive subset $\{S_1, S_2, \cdots, S_n\}$. When it determines $f(C_i, D)$ which is equivalent to several cases in D belongs to classes C_i, and $|D|$ is equivalent to overall observation in D_1 next amount of data needed to recognize the classes for observations in D might measure by

$$info(D) = -\sum_{j=1}^{m} \frac{f(C_j, D)}{|D|} \times \log_2 \frac{f(C_j, D)}{|D|}. \tag{1}$$

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Since testing, T_1 which divides D as k results $\{D_1, D_2, \dots, D_k\}$, same amount might determine in which it counts entire data content later employing T is defined by

$$\text{info}_T(D) = \sum_{i=1}^{k} \frac{|D_i|}{|D|} \times \text{info}(D_i). \tag{2}$$

By these techniques, it measures the data obtained via partition D by T is expressed by

$$\text{gain}(T) = \text{info}(D) - \text{info}_T(D)\,. \tag{3}$$

This is also known as "gain criteria" which chooses the testing for that gain (T) is highest. Unsuccessfully, the gain (T) inclines to favors testing by huge number of splitting. To compensating for these results, gain (T) is expressed as

$$\text{spilt info}(T) = -\sum_{i=1}^{n} \frac{|D_i|}{|D|} \times \log_2\left(\frac{|D_i|}{|D|}\right) \tag{4}$$

attaining the split metrics

$$\text{gain}\; ratio(T) = \text{gain}(T)/\text{spiltinfo}(T). \tag{5}$$

By these architectures, D is recurrently splitting thus the gained ratio is maximized on every node of the tree. This process remains till every leaf node comprises individual observation from one class or else not gaining in information is produced via additional splits.

The outcome from this process is frequently huge and complicated tree which might over fitting to noises in trained information. When trained information comprises error, subsequently overfit the tree information in this way which results in low efficiency over invisible case. To minimalize these problems, the actual tree should prune to decrease classifiers error while information exterior of trained set is being categorized. To resolve these problems C5.0 utilizes error based pruning.

3. Experimental Evaluation

The performance of the IFSML-RM technique is validated using DAS dataset, which comprises 938 instances with 7 attributes and five classes under each dataset.

Table 1 and Fig. 2 demonstrates the results analysis of the IFSML-RM technique with other techniques [23] on the applied depression dataset. The results showcased that the IFSML-RM technique has accomplished maximum results over the other techniques. The DT classifier with no FS process accomplished a lower performance with the accu. of 0.7751, senst. of 0.8521, spec. of 0.5233, F-score of 0.8662, and kappa of 0.3509. In line with, the DT with PSO-FS model has obtained a slightly enhanced outcome with the accu. of 0.9142, senst. of 0.8867, spec. of 0.9312, F-score of 0.8955, and kappa of 0.8167. Followed by, the DT with ACO technique has resulted in a moderate performance with the accu. of 0.9756, senst. of 0.9386, spec. of 0.9923, F-score of 0.9678, and kappa of 0.9347. But the DT with QEHO algorithm has accomplished effectual outcome with the accu. of 0.9845, senst. of 0.9631, spec. of 0.9965, F-score of 0.9710, and kappa of 0.9589.

Table 1 Classification Results with Depression Dataset

FS Methods	Selected Features	Accu.	Senst.	Spec.	F-score	Kappa
None	All	0.7751	0.8521	0.5233	0.8662	0.3509
PSO	6,3,1,7	0.9142	0.8867	0.9312	0.8955	0.8167
ACO	4,6,2	0.9756	0.9386	0.9923	0.9678	0.9347
QEHO	3,4,7	0.9845	0.9631	0.9965	0.9710	0.9589

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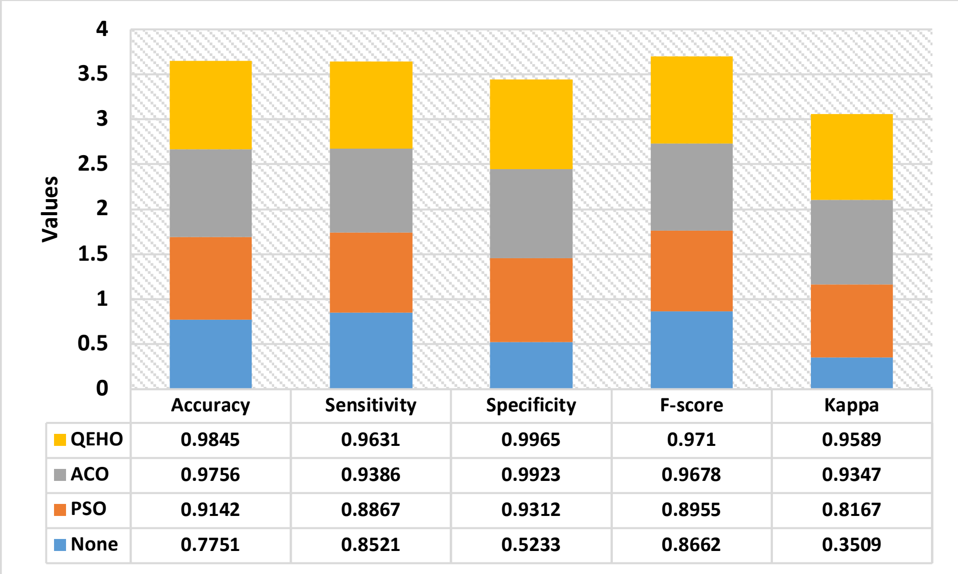

Fig. 2. Results analysis of IFSML-RM technique on depression dataset

Table 2 Classification Results with Anxiety Dataset

FS Methods	Selected Features	Accuracy	Sensitivity	Specificity	F-score	Kappa
None	All	0.8978	0.8330	0.9369	0.8541	0.7472
PSO	2,3,4,1	0.9168	0.8971	0.9376	0.8851	0.7968
ACO	1,3,2	0.9378	0.9231	0.9476	0.9106	0.8476
QEHO	1,2,5,7	0.9489	0.9309	0.9681	0.9432	0.9074

Table 2 and Fig. 3 exhibits the outcomes analysis of the IFSML-RM manner on the applied anxiety dataset. The results portrayed that the IFSML-RM approach has accomplished maximal results over the other approaches. The DT classifier no FS process accomplished a reduced performance with the accu. of 0.8978, senst. of 0.8330, spec. of 0.9369, F-score of 0.8541, and kappa of 0.7472. Likewise, the DT with PSO-FS model has obtained a slightly higher outcome with the accu. of 0.9168, senst. of 0.8971, spec. of 0.9376, F-score of 0.8851, and kappa of 0.7968. Next, the DT with ACO manner has resulted in a moderate performance with the accu. of 0.9378, senst. of 0.9231, spec. of 0.9476, F-score of 0.9106, and kappa of 0.8476. But the DT with QEHO methodology has accomplished effective results with the accu. of 0.9489, senst. of 0.9309, spec. of 0.9681, F-score of 0.9432, and kappa of 0.9074.

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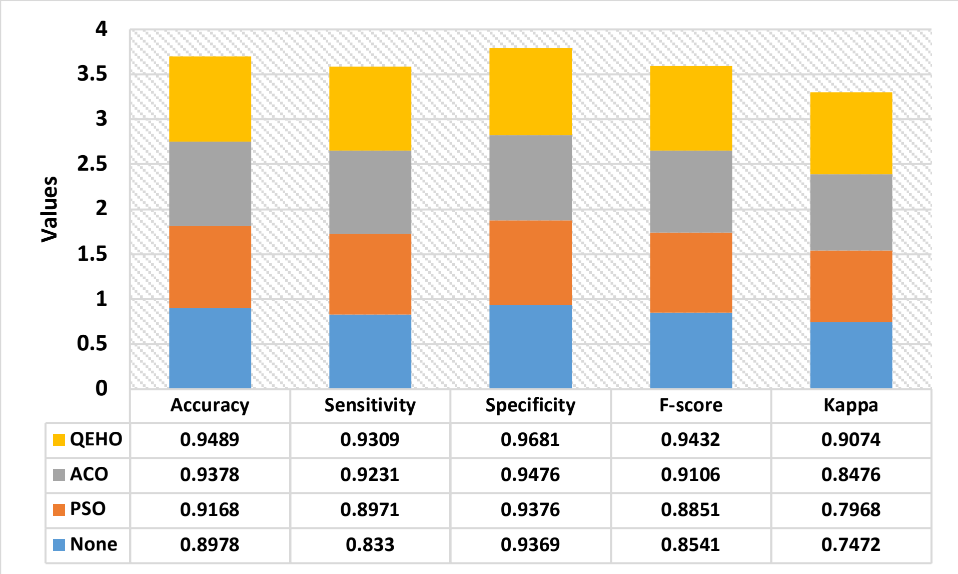

Fig. 3. Results analysis of IFSML-RM technique on anxiety dataset

Table 3 Classification Results with Stress Dataset

FS Methods	Selected Features	Accu.	Senst.	Spec.	F-score	Kappa
None	All	0.8984	0.9593	0.7361	0.9382	0.7015
PSO	3,5,2,6	0.9065	0.8871	0.9376	0.8851	0.7968
ACO	3,4,6	0.9357	0.9331	0.9376	0.9106	0.8476
QEHO	1,2,4,8	0.9502	0.9598	0.9432	0.9390	0.9007

Table 3 and Fig. 4 showcase the outcomes analysis of the IFSML-RM method on the applied stress dataset. The outcomes exhibited that the IFSML-RM manner has accomplished higher results over the other algorithms. The DT classifier with no FS process accomplished a decreased performance with the accu. of 0.8984, senst. of 0.95993, spec. of 0.7361, F-score of 0.9382, and kappa of 0.7015. Similarly, the DT with PSO-FS technique has gained a somewhat increased outcome with the accu. of 0.9065, senst. of 0.8871, spec. of 0.9376, F-score of 0.8851, and kappa of 0.7968. Along with that, the DT with ACO technique has resulted in a moderate performance with the accu. of 0.9357, senst. of 0.9331, spec. of 0.9376, F-score of 0.9106, and kappa of 0.8476. But the DT with QEHO methodology has accomplished performance outcomes with the accu. of 0.9502, senst. of 0.9598, spec. of 0.9432, F-score of 0.9390, and kappa of 0.9007.

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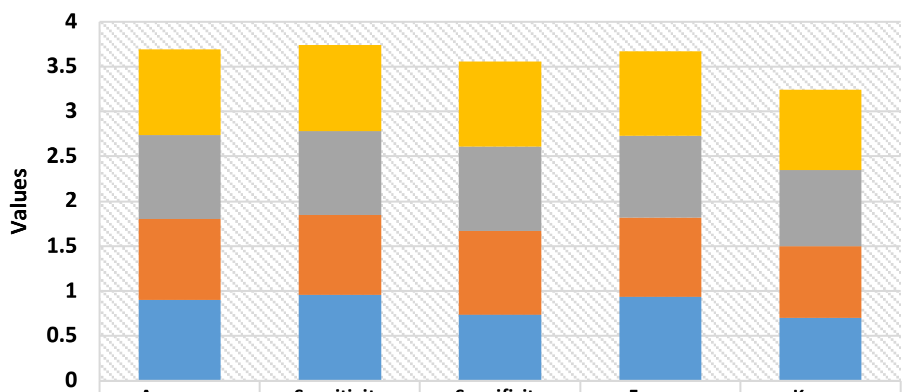

	Accuracy	Sensitivity	Specificity	F-score	Kappa
QEHO	0.9502	0.9598	0.9432	0.939	0.9007
ACO	0.9357	0.9331	0.9376	0.9106	0.8476
PSO	0.9065	0.8871	0.9376	0.8851	0.7968
None	0.8984	0.9593	0.7361	0.9382	0.7015

Fig. 4. Results analysis of IFSML-RM technique on depression dataset

4. Conclusion

This paper has introduced an effective IFSML-RM technique to predict and classify DAS. The IFSML-RM technique follows a two-stage process namely QEHO-FS and DT based classification. Firstly, the QEHO algorithm utilizes the input data to select a useful subset of features. Secondly, the chosen features are fed into the DT classifier to determine the existence or non-existence of DAS. A detailed experimentation process is carried out on benchmark dataset and the experimental results showcased the betterment of the IFSML-RM technique interms of different performance measures. Therefore, the IFSML-RM technique can be utilized as an appropriate tool for effective prediction of DAS. In future, clustering approaches can be designed to boost the DAS prediction outcomes.

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