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Article

Intelligent Student Mental Health Assessment Model on Learning Management System

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Abstract: A learning management system (LMS) is a software or web based application, commonly utilized for planning, designing, and assessing a particular learning procedure. Generally, the LMS offers a method of creating and delivering content to the instructor, monitoring students' involvement, and validating their outcomes. Since mental health issues become common among studies in higher education globally, it is needed to properly determine it to improve mental stability. This article develops a new seven spot lady bird feature selection with optimal sparse autoencoder (SSLBFS-OSAE) model to assess students' mental health on LMS. The major aim of the SSLBFS-OSAE model is to determine the proper health status of the students with respect to depression, anxiety, and stress (DAS). The SSLBFS-OSAE model involves a new SSLBFS model to elect a useful set of features. In addition, OSAE model is applied for the classification of mental health conditions and the performance can be improved by the use of cuckoo search optimization (CSO) based parameter tuning process. The design of CSO algorithm for optimally tuning the SAE parameters results in enhanced classification outcomes. For examining the improved classifier results of the SSLBFS-OSAE model, a comprehensive results analysis is done and the obtained values highlighted the supremacy of the SSLBFS model over its recent methods interms of different measures.

Keywords: Learning management system; mental health assessment; intelligent models; machine learning; feature selection; performance assessment

1 Introduction

A learning management technique (LMS) is software for delivering, creating, and managing e-learning content. The organization uses LMS and interrelated software to deal with its online learning program. This earlier LMS which includes Blackboard and Moodle is simplification tool to organize instructor-led online courses. The software was quite straightforward. It is comprised generally of determined class models and assignment-submission features. Mostly, class involves written course material and pre-recorded classroom lectures. LMS helps to learn manager handles the whole life cycle of the learning procedure within a company [1]. They are an important mechanism for other companies that wanted to run a complete online learning program. With increasing pressures in life and present fierce competition, college student mental health problems [2] becoming clearer, and the mental health condition [3] is of major concern.

Persons with serious mental illnesses or disorders are enforced to drop out of school, append to school [4], commit suicide, self-harm, and breaking the law from limitless stream amongst college student. It can be urgent and critical for enhancing college student complete quality, especially cultivate exceptional social talents, the psychological quality [5], predict psychological status, and improve mental health education. The college student is excellent member of the youth population, represents a higher intelligent group, and has the psychological status that is crucial. They are in a serious transitional time in their maturity and development. They confront several problems during this time, together with socialization and emotions [6]. When they aren't appropriately managed, it might result in anxiety, depression, and other mental problems. This is very dangerous to college students' growth. It is common to come over the instance of exceptional college students failing to handle the final suicide because of psychological problems [7].

The mental problem affects each aspect of college student, have an effect on their educations and employment might severally threaten their health condition. The recurrence of campus tragedy illustrates that psychological problems amongst college students have advanced to the point. With this regard, we must examine the prediction and assessment of college students' psychological status [8]. Recently, due to the tremendous growth of smart technology [9] including neural networks [10], has outstanding efficiency for non-linear issues like college students' psychological status calculation. Currently, several methods are designed for classifying psychological conditions. This strategy is employed for data classification and in few instances, it is combined with other methodologists for hybrid models. Also, Feature Selection (FS) is a part of the procedure of data classification. It is a process of selecting set of features from original feature.

This article develops a new seven spot lady bird feature selection with optimal sparse autoencoder (SSLBFS-OSAE) model to assess students' mental health on LMS. The SSLBFS-OSAE model involves a new SSLBFS model to elect a useful set of features. In addition, OSAE model is applied for the classification of mental health conditions and the performance can be improved by the use of cuckoo search optimization (CSO) based parameter tuning process. For examining the improved classifier results of the SSLBFS-OSAE model, a comprehensive results analysis is performed on benchmark dataset.

2 Literature Review

The researchers in [11] studied connections and forecasts that to be amongst levels of mental health from the college students, for instance, psychological capital (PsyCap), moderate mental health and languishing, and flourishing. In order to this cross-sectional, exploratory analysis survey approach is utilized to data gathering and to analyze of outcomes the sequence of descriptive, correlation, ANOVA, and several regression analyses are completed. The researchers in [12] scrutinized student acceptance of and purpose for utilizing LMS to university education in Turkey utilizing extended Technology Acceptance Model (e-TAM). The TAM is extremely utilized from several domains of technologies acceptance from the last years and has been recognized as extremely suitable to determine factors that influence the purpose for utilizing and adopting e-learning platforms at university. Zheng et al. [13] estimated 104 mental health apps on Google Play and App Store by executing sentiment analysis (SA) of 88125 user's analyses utilizing ML technique, afterward conducted thematic study on the review. It is apply and relate the efficiency of 5 classifiers utilizing supervised ML approaches which are extremely utilized to resolve classifier problem.

Oyebode et al. [14] inspected how organizational support affects LMS self-efficacy, technical support, and faculty-perceived benefit. The empirical analysis dependent upon responses in 379 instructors at many universities is performed. The basic formula modelling was implemented for developing and assessing the measurement method, and analyzing the connections amongst the features from the basic pattern. Maqsood et al. [15] concentrate on offering education with educational method with mode of deliveries utilizing digital solution with novel paradigm approach. It integrates the statistical information compared with the Pakistani Ministry of Health coronavirus epidemic for drawing the outcomes. The precautionary measure containing social distance is named to abrupt closure of educational institution, exit the digital solutions as initial means of continuities from educational actions. Ren et al. [16] designed for evaluating the psychological influence of COVID-19 when school reopening and exploring utilize machine learning (ML) the issues which control anxiety and depression amongst students. The SMOTE is employed for counteracting the imbalance of recovered information. The Akaike Information Criterion (AIC) and multivariate logistic regression (MLR) are executed for exploring vital factor influencing.

3 The Proposed Model

This article has developed a new SSLBFS-OSAE model to assess students' mental health on LMS. The SSLBFS-OSAE model is mainly intended to determine the proper health status of the students with respect to DAS. The SSLBFS-OSAE model encompasses SSLBFS model to elect features, SAE based classification, and CSO based parameter optimization. Fig. 1 depicts the overall process of SSLBFS-OSAE technique.

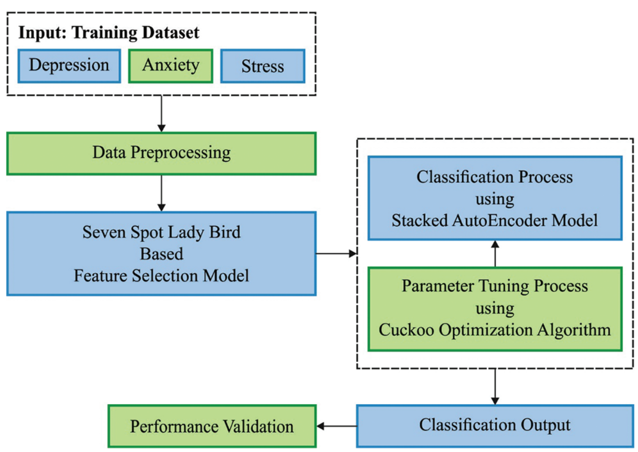

Figure 1: Overall process of SSLBFS-OSAE technique

3.1 Design of SSLBFS Technique

At the preliminary stage, the input data is passed into the SSLBFS algorithm to choose an optimal subset of features. The SSLB model simulates the foraging behavior of SSLB to resolve multi-dimension and multi-modal optimization issues. The major stages of the SSLB are given below [17].

Step 1. (Divide patches). assume that the searching space (environment) is a D-dimension space. The *ith* dimension space is separated into n_i subspaces and the entire dimension space is separated into $n = \Pi n_i$ subspaces (patches).

Step 2. (Population Initialization). assume that SSLB is processed as a point in a D-dimension patch. The *ith* ladybird is characterized as $X_i = (x_{i1},\ x_{i2},\ \ldots,\ x_{iD})$, whereas X_i denotes a latent solution to the enhanced question.

When m indicates the number of SSLB initialized with arbitrary location in a patch, the population size of SSLB is N, $N = m \times n$.

Step 3. (Calculate fitness). For all the particles, estimate the optimization fitness in a D-dimension patch.

Step 4. (Choose the optimal ladybirds). The present fitness calculation of ladybirds was compared to the fitness values of optimal past location (*sbest*). When the present value is superior to the preceding one, set *sbest* value is equivalent to the present value, and the *sbest* location is equivalent to the present location.

Step 5. (dispersion). In the SSLB, when a location doesn't enhance in a predefined amount of cycles, a novel location is generated in the patch whereby *gbest* present, which replaces the abandoned location. The novel location is generated nearby the *gbest* for sharing the data of the optimal ladybird in the entire particle. When the abandoned location represents X_i and $j \in \{1,\ 2,\ \ldots,\ D\}$, the SSLB discovered a new location $X_i^{'}$:

$$x_{i,j}^{'} = x_{gbest,j} + (\varnothing w) \tag{1}$$

Whereas w denotes the neighborhood space of gbest and ($\varnothing$ denotes an arbitrary value among [−1, 1].

Step 6. (update position). The location of ladybird is upgraded based on its preceding movement. When a ladybird has conducted widespread searching, the location of the ladybird is altered by:

$$V_i(t) = c * r_1 * (S_i(t) - X_i(t)) + \varepsilon_1 \tag{2}$$

$$X_i(t+1) = X_i(t) + V_i(t),\ |V_i(t)| \le V_{\max} \tag{3}$$

Afterward intensive search, a ladybird switched to wide searching. The location is upgraded based on below equation:

$$V_i(t) = c * r_2 * (L_i(t) - X_i(t)) + \varepsilon_2 \tag{4}$$

$$X_i(t+1) = X_i(t) + V_i(t),\ |V_i(t)| \le y_{\max} \tag{5}$$

In (2) and (4), r_1 and r_2 denotes two arbitrary numbers within 0 to 1, c positive constant is utilized to adjust the searching phase and searching direction in all the iterations. In Eqs. (3) and (5), the velocity of the ladybird in all the dimensions are constrained to the maximal velocity $V_{\max}$, that decide the searching accuracy of the ladybird in a solution space. When $V_{\max}$ is higher, the ladybirds probably fly through the optimum solution. But when the $V_{\max}$ is lower, the ladybird falls into the local searching region and has no approach to implement with the global searching.

$$V\_max = 0.2(ub - lb) \tag{6}$$

Whereas *ub* and *lb* denote the upper and lower limits. Next, adapt it here to clamp the particle velocity on all the dimensions.

Step 7. (Inspect end criteria). When the end criteria are fulfilled, i.e., the SSLB accomplished the maximal iteration, the SSLB is ended; or else, return to Step 3.

Consider a dataset with size $N_S \times N_F$ where N_S denotes total sample count and N_F indicates feature count. The major aim of the FS issue is to elect a feature subset S from available features (N_F) where $S < N_F$. The SSLBFS technique derives an objective function with the minimization of error rate, as given below.

$$Fit = \lambda \times \gamma_S + (1 - \lambda) \times \left(\frac{|S|}{N_F}\right) \tag{7}$$

where γ_S denotes classification error by the use of S and $|S|$ indicates total chosen feature count. λ can be utilized for balancing $\frac{|S|}{N_P}$ and γ_S.

3.2 Design of OSAE Model

Next to the election of useful features, the classification process is carried out by the design of SAE model. Auto encoder (AE) makes use of weights for encoding input vector x to representation vector h, refers to latent variable [18]. It exploits a collection of generative weights for decoding vector representation vector to an approximate restoration of the input vector $x^{'}$. It mainly intends in the reconstruction of input data in an unsupervised manner, i.e., with no use of labels whereas the input and output dimensions are required to be identical. The encoder part of the AE model receives $x \in \mathbb{R}^m$ as input and mapped it to the latent parameter $h \in \mathbb{R}^n$:

$$h = f(Wx + b) \tag{8}$$

where f indicates activation function, like sigmoid, $s(x) = 1/1 + e^{-x}$ or rectified linear unit (ReLU), $Wandb$ implies weight matrix and bias. The decoder part mapped h to $x^{'}$ for reconstructing x with alike dimensionalities.

$$x' = f'(W'h + b') \tag{9}$$

where $f^{'}$, $W^{'}$, and $b^{'}$ denotes respective variables of the decoding unit which is distinct from the encoding unit. The training of AE takes place in the minimization of reconstruction error such as mean square error (MSE), as given below.

$$E(x,\ x') = \|\mathrm{x} - x'\|^2 \tag{10}$$

where x is generally averaged over n training instances. Autoencoder imposes sparsity regulation limitation to the hidden unit is named sparse autoencoder. A neuron is assumed to fire when the output value is close to 1 and it is considered to be inactive when the output value is closer to 0. Then to add a limitation thus output would be nearer to 0. Consider the normal activation of hidden state j as follows

$$\hat{\rho} = \frac{1}{k}\sum_{i=1}^{k} h_j \tag{11}$$

Then estimate $\hat{\rho}_j = \rho$ in which ρ represents the sparsity proportion variables that is a smaller positive value almost equivalent to zero. For imposing this limitation, add a penalty term according to Kullback-Leibler (KL) divergence as follows

$$\sum_{j=1}^{k} KL(\rho||\hat{\rho}) \tag{12}$$

Whereas

$$KL(\rho||\hat{\rho}_j) = \rho \ \log \ \frac{\rho}{\hat{\rho}_j} + (1-\rho) \ \log \ \frac{1-\rho}{1-\hat{\rho}_j} \tag{13}$$

denotes the Kullback-Leibler divergence. By including KL divergence term 4, the cost function becomes

$$J_{SAE} = \frac{1}{2}\sum_{i=1}^{N} \|x_i - \hat{z}\|^2 + \frac{\lambda}{2}(\|W\|^2 + \|W'\|^2) + \beta\sum_{j=1}^{N} KL(\rho||\hat{\rho}_j) \tag{14}$$

In which β denotes the weight of sparsity regularization term. By reducing the cost function, enhancing variables W, $W^{'}$, b and $b^{'}$.

In order to effectually tune the parameters involved in the SAE model, the CSO algorithm can be exploited. Cuckoo is a smart reproduction approach which contains the female placing her fertilizing eggs from the nest of other species for replacing parents unwittingly increase her brood. In some cases, the cuckoo eggs from the nest were exposed and alternate parents threw them away or left the nest and begins their individual brood away [19]. CSO algorithm is a novel meta-heuristic technique to resolve optimized issues that are dependent upon the obligate brood parasitic performance of any cuckoo species from group with Lévy flight (LF) performance of any birds and fruit flies. During this event of CSO algorithm, the walking step of cuckoos are defined as the LFs. The LF is a random walk (RW) in that stages are determined with respect to the step-length that are particular probability distributing, with direction of steps being isotropic and arbitrary. The LFs are a class of RW whereas the jump is distributed based on power law,

$$y = x^{-\beta}, \tag{15}$$

where $1 < \beta < 3$ and so is an infinite difference. The connection amongst light and LFs have been successfully executed for improving and optimizing search. During the case of CSO algorithm, the walking step of cuckoos is defined as LFs. In order to simplify in describing CSO algorithm, the subsequent 3 idealized rules are used.

1) All the cuckoos lay only one egg at once and locate their egg from a chosen nest at arbitrary.
2) An optimum nest with maximum quality of eggs is transferred over to next generation.
3) The amount of existing host nests are set, and the egg placed by cuckoos are exposed by host bird with probability $p_a \in [0, 1]$. During this method, the host bird is also throwing eggs to leave or away from the nest, and constructing an entirely novel nest. In order to simplify, this final assumption was estimated by fraction p_a of n nests that are moved by novel nests (with novel arbitrary solution).

In CSO algorithm, all the eggs from a nest signify the solution, and cuckoo egg refers the novel solution. The purpose is to utilize the novel and potentially optimum solution (cuckoo) for replacing not-so-good solutions from the nest. During the easiest method, all the nests have 1 egg. The technique is extended to further difficult cases whereas all the nests have several eggs signifying the group of solutions. If they create novel solutions $x^{(t+1)}$ for, approximately, the cuckoo i, an LF was executed

$$x_i^{(t+1)} = x_i^{(t)} + \alpha \oplus L\hat{e}vy(\lambda), \tag{16}$$

where $\alpha > 0$ has the step size that can be connected to scale of problem of the interests. Generally, it is utilized $\alpha = 1$. The above equation has fundamentally the stochastic formula to RW. Generally, an RW has a Markov chain who's next status or place is only dependent upon present place (the primary term from the above formula) and the transition probability (the secondary term). The product $\oplus$ implies entrywise multiplication. It is entrywise product was same as individuals utilized from PSO, however, the RW utilizing LF is further effectual from exploring the searching space as their step length is very long time from the long run. The LFs fundamentally offer an RW, but the arbitrary step length was drawn in Lévy distribution.

$$L\hat{e}\,vy(\lambda) \sim u = t^{-\lambda}(1 < \lambda \leq 3), \tag{17}$$

which is an infinite difference with infinite mean. At this point, the steps fundamentally procedure an RW method with power-law step-length distributing with big tail. The number of novel solutions is created by Lévy walk nearby optimum solutions attained so far; it is speed-up the local searching. But, the substantial fraction of novel solutions are created by distant field randomized and whose places can be enough away in the existing optimum solutions; it can ensure that system isn't be trapped as to local optimal. Fig. 2 depicts the flow of COA.

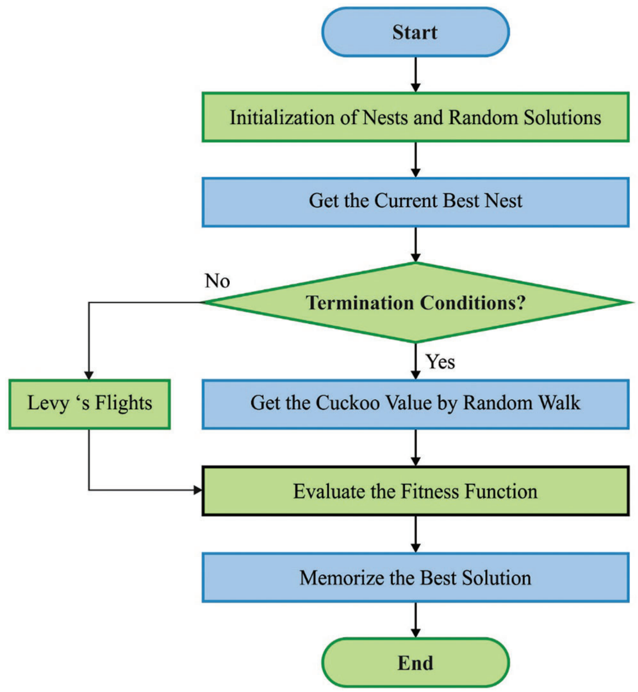

Figure 2: Flow of cuckoo optimization algorithm

4 Experimental Validation

The performance validation of the SSLBFS-OSAE model takes place using the benchmark DAS dataset from UCI repository. Each of the three sub datasets contains 938 instances, 7 features, and 5 classes. Fig. 3 shows the correlation matrix of the test dataset.

Tab. 1 and Fig. 4 highlights the FS outcomes of the SSLBFS technique with existing techniques in terms of best cost (BC) and chosen features. The results indicated that the SSLBFS technique has gained effectual outcomes with minimal BC under all datasets. For instance, with depression dataset, the SSLBFS technique has reached to lower BC of 0.0076 whereas the GGWO, GWO, ACO, and PSO techniques have attained higher BC of 0.0083, 0.0187, 0.0259, and 0.0351 respectively. Meanwhile, with anxiety dataset, the SSLBFS technique has attained reduced BC of 0.0142 whereas the GGWO, GWO, ACO, and PSO techniques have offered increased BC of 0.0173, 0.0190, 0.268, and 0.0391 respectively. Eventually, with stress dataset, the SSLBFS technique has accomplished minimal BC of 0.0329 whereas the GGWO, GWO, ACO, and PSO techniques have reached maximum BC of 0.0457, 0.0782, 0.0829, and 0.0973 respectively.

Fig. 5 provides the accuracy and loss graph analysis of the SSLBFS-OSAE approach under three datasets. The outcomes outperformed that the accuracy value tends to increase and loss value tends to decrease with an increase in epoch count. It can be also experimental that the training loss is low and validation accuracy is higher under three datasets.

Tab. 2 reports the comparison study of the SSLBFS-OSAE model on the test depression dataset. The table values indicated the betterment of the SSLBFS-OSAE model over the existing models.

Fig. 6 investigates the $prec_n$, $reca_l$, and $accu_y$ of the SSLBFS-OSAE model with existing models on depression dataset. The results reported that the SSLBFS-OSAE model has offered ineffectual outcome with lower values of $prec_n$, $reca_l$, and $accu_y$. At the same time, the LR and MLP models have reached moderately enhanced values of $prec_n$, $reca_l$, and $accu_y$. Along with that, the IFSSML-DAS, BSO-

LSSVM, and ACO models have accomplished reasonable values of $prec_n$, $reca_l$, and $accu_y$. However, the SSLBFS-OSAE model has shown effectual outcome with the higher $prec_n$, $reca_l$, and $accu_y$ values of 0.9882, 0.9981, and 0.9911 respectively.

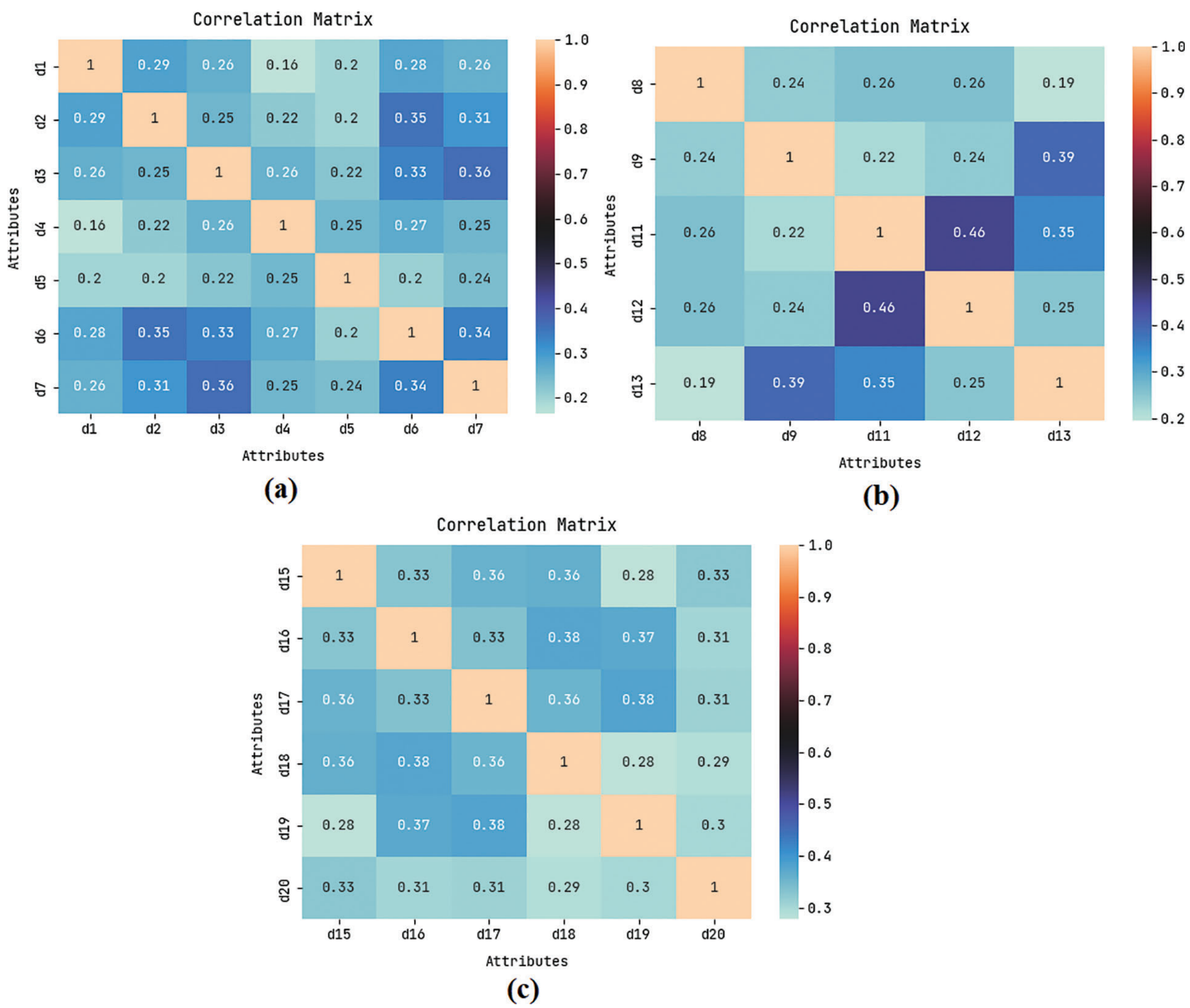

Figure 3: Correlation matrix a) Stress b) Depression c) Anxiety

Table 1: Selected features of existing with proposed algorithm on applied dataset

Methods	Best cost	Selected features
Depression dataset		
SSLBFS	0.0076	1, 3, 5
GGWO	0.0083	2, 3, 6
GWO	0.0187	1, 2, 5

(Continued)

Table 1 (continued)

Methods	Best cost	Selected features
ACO	0.0259	4, 6, 2
PSO	0.0351	6, 3, 1, 7
Anxiety dataset		
SSLBFS	0.0142	1, 4, 6
GGWO	0.0173	2, 3, 5
GWO	0.0190	1, 3, 7
ACO	0.0268	4, 6, 7
PSO	0.0391	1, 2, 6
Stress dataset		
SSLBFS	0.0329	2, 3, 6
GGWO	0.0457	1, 2, 6
GWO	0.0782	1, 3, 4
ACO	0.0829	1, 5, 7
PSO	0.0973	1, 2, 4, 6

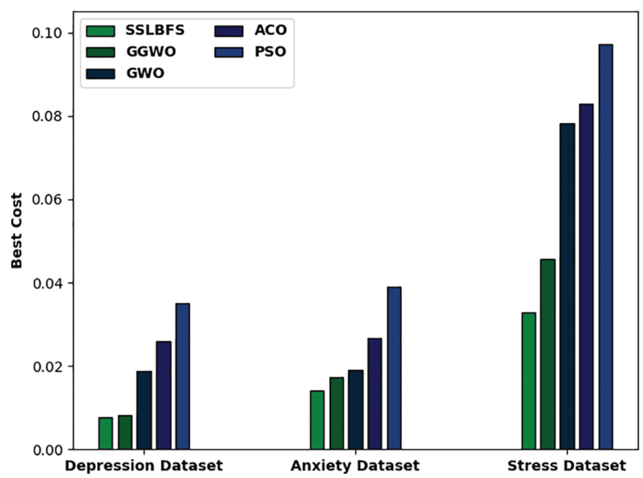

Figure 4: Best cost analysis of SSLBFS technique

Fig. 7 examines the F_{score} and *kappa* of the SSLBFS-OSAE method with existing models on depression dataset. The outcomes reported that the SSLBFS-OSAE model has offered ineffectual outcomes with lower values of F_{score} and *kappa*. Besides, the LR and MLP models have reached moderately improved values of F_{score} and *kappa*. Along with that, the IFSSML-DAS, BSO-LSSVM, and ACO models have accomplished reasonable values of F_{score} and *kappa*. Lastly, the SSLBFS-OSAE method has shown effectual outcome with the higher F_{score} and *kappa* values of 0.9908 and 0.9854 correspondingly.

Tab. 3 demonstrates the comparison study of the SSLBFS-OSAE method on the test anxiety dataset. The table values indicated the betterment of the SSLBFS-OSAE technique over the existing approaches.

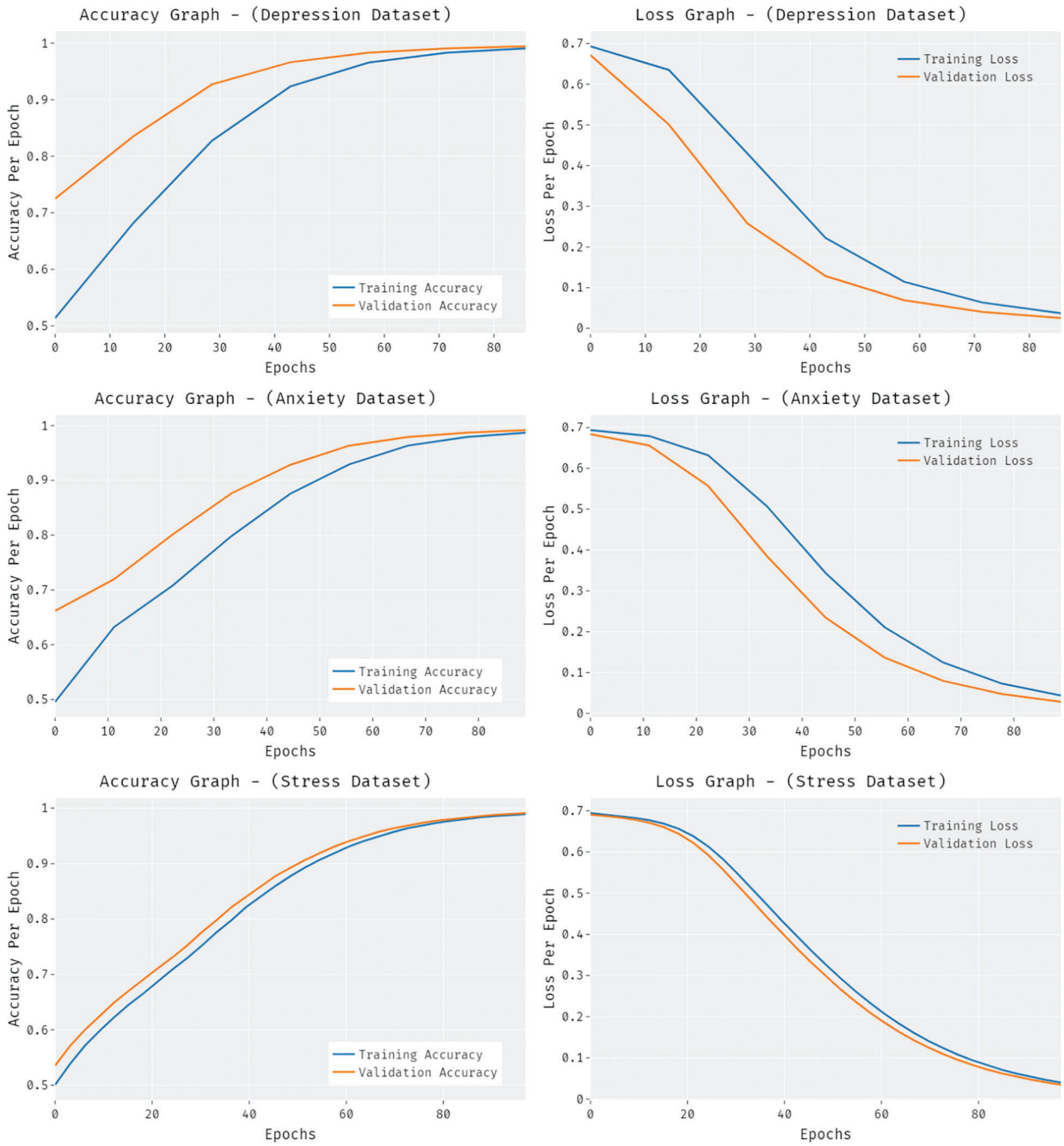

Figure 5: Accuracy and loss analysis of SSLBFS-OSAE technique under three datasets

Fig. 8 investigates the $prec_n$, $reca_l$, and $accu_y$ of the SSLBFS-OSAE model with existing methods on anxiety dataset. The results reported that the SSLBFS-OSAE model has offered ineffectual outcome with lower values of $prec_n$, $reca_l$, and $accu_y$. In addition, the LR and MLP approaches have reached moderately enhanced values of $prec_n$, $reca_l$, and $accu_y$. Along with that, the IFSSML-DAS, BSO-LSSVM, and ACO techniques have accomplished reasonable values of $prec_n$, $reca_l$, and $accu_y$. Eventually, the SSLBFS-OSAE model has exhibited effectual outcome with the higher $prec_n$, $reca_l$, and $accu_y$ values of 0.9812, 0.9921, and 0.9888 correspondingly.

Table 2: Result analysis of SSLBFS-OSAE technique on depression dataset with recent approaches

Methods	$Prec_n$	$Reca_l$	Acc_y	F_{score}	Kappa
SSLBFS-OSAE	0.9882	0.9981	0.9911	0.9908	0.9854
IFSSML-DAS	0.9742	0.9957	0.9847	0.9875	0.9691
BSO-LSSVM algorithm	0.9540	0.9934	0.9812	0.9747	0.9686
ACO algorithm	0.9380	0.9917	0.9724	0.9729	0.9383
LR algorithm	0.9085	0.8971	0.9083	0.9263	0.7130
MLP algorithm	0.9401	0.9425	0.9350	0.9131	0.8253
J48 algorithm	0.8041	0.8300	0.8272	0.8351	0.4915
RepTree algorithm	0.7619	0.8104	0.8180	0.7941	0.4275
CART algorithm	0.7410	0.8041	0.7978	0.7805	0.3878

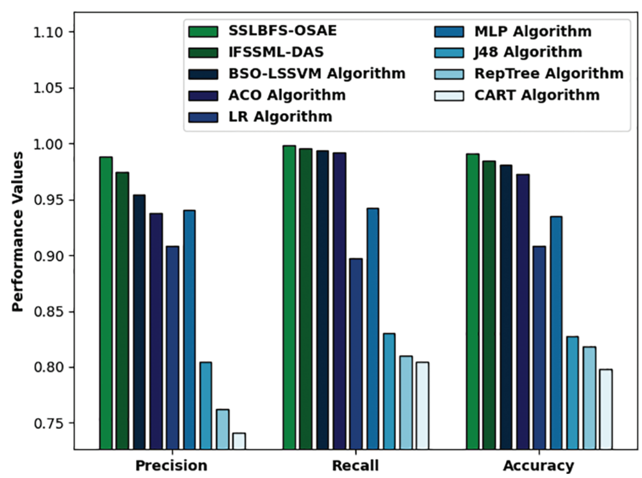

Figure 6: Comparative analysis of SSLBFS-OSAE technique under depression dataset

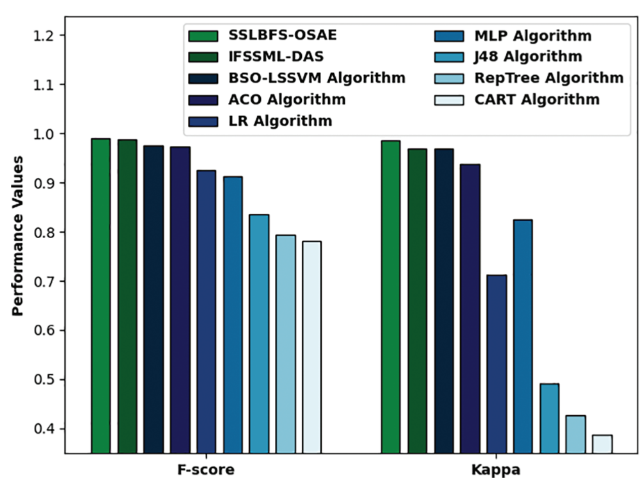

Figure 7: F_{score} and kappa analysis of SSLBFS-OSAE technique under depression dataset

Table 3: Result analysis of SSLBFS-OSAE technique on anxiety dataset with recent approaches

Methods	$Prec_n$	$Reca_l$	Acc_y	F_{score}	Kappa
SSLBFS-OSAE	0.9812	0.9921	0.9888	0.9904	0.9873
IFSSML-DAS	0.9687	0.9877	0.9828	0.9621	0.9585
BSO-LSSVM algorithm	0.9422	0.9688	0.9565	0.9411	0.9294
ACO algorithm	0.9272	0.9532	0.9406	0.9161	0.8455
LR algorithm	0.9317	0.9227	0.9224	0.9204	0.7381
MLP algorithm	0.9535	0.9534	0.9727	0.9489	0.8550
J48 algorithm	0.8411	0.8564	0.8595	0.8396	0.4667
RepTree algorithm	0.8098	0.8596	0.8522	0.8234	0.3804
CART algorithm	0.8586	0.8855	0.8840	0.8696	0.5178

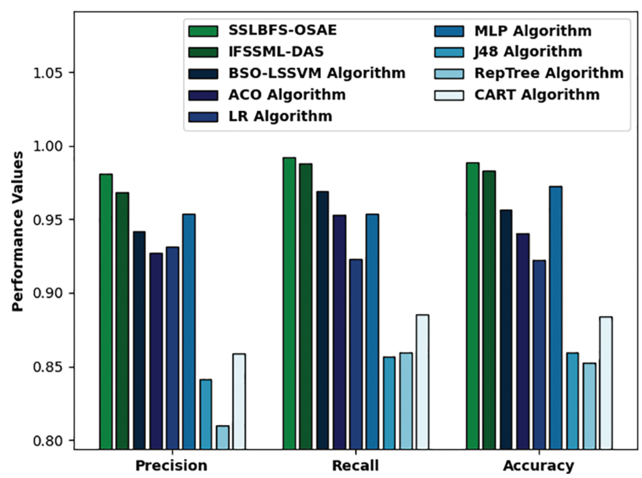

Figure 8: Comparative analysis of SSLBFS-OSAE technique under anxiety dataset

Fig. 9 illustrates the F_{score} and *kappa* of the SSLBFS-OSAE system with existing techniques on anxiety dataset. The results portrayed that the SSLBFS-OSAE model has offered ineffectual outcomes with lesser values of F_{score} and *kappa*. Followed by, the LR and MLP techniques have attained to moderately higher values of F_{score} and *kappa*. Besides, the IFSSML-DAS, BSO-LSSVM, and ACO algorithms have accomplished reasonable values of F_{score} and *kappa*. At last, the SSLBFS-OSAE method has illustrated effectual outcome with the higher F_{score} and *kappa* values of 0.9904 and 0.9873 correspondingly.

Tab. 4 demonstrates the comparison study of the SSLBFS-OSAE approach on the test stress dataset. The table values referred the betterment of the SSLBFS-OSAE technique over the existing models [20].

Fig. 10 examines the $prec_n$, $reca_l$, and $accu_y$ of the SSLBFS-OSAE algorithm with existing models on stress dataset. The results reported that the SSLBFS-OSAE system has offered ineffectual outcome with lower values of $prec_n$, $reca_l$, and $accu_y$. Simultaneously, the LR and MLP methods have reached moderately enhanced values of $prec_n$, $reca_l$, and $accu_y$. Moreover, the IFSSML-DAS, BSO-LSSVM, and ACO models have accomplished reasonable values of $prec_n$, $reca_l$, and $accu_y$. However, the SSLBFS-OSAE approach has shown effectual outcome with the higher $prec_n$, $reca_l$, and $accu_y$ values of 0.9894, 0.9889, and 0.9910 correspondingly.

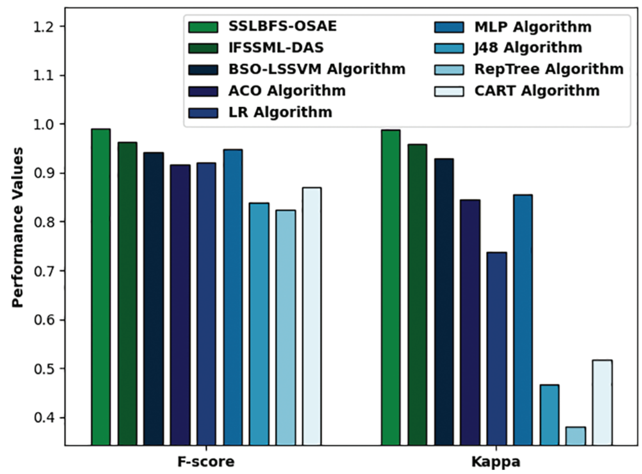

Figure 9: F_{score} and kappa analysis of SSLBFS-OSAE technique under anxiety dataset

Table 4: Result analysis of SSLBFS-OSAE technique on stress dataset with recent approaches

Methods	$Prec_n$	$Reca_l$	Acc_y	F_{score}	Kappa
SSLBFS-OSAE	0.9894	0.9889	0.9910	0.9876	0.9900
IFSSML-DAS	0.9864	0.9847	0.9653	0.9531	0.9646
BSO-LSSVM algorithm	0.9610	0.9629	0.9428	0.9340	0.9318
ACO algorithm	0.9258	0.9424	0.9259	0.9184	0.8430
LR algorithm	0.9110	0.9045	0.9108	0.9051	0.7189
MLP algorithm	0.9338	0.9398	0.9462	0.9424	0.8320
J48 algorithm	0.8058	0.8255	0.8133	0.8079	0.4230
RepTree algorithm	0.7702	0.8074	0.8101	0.7812	0.3643
CART algorithm	0.8619	0.8820	0.8918	0.8685	0.5362

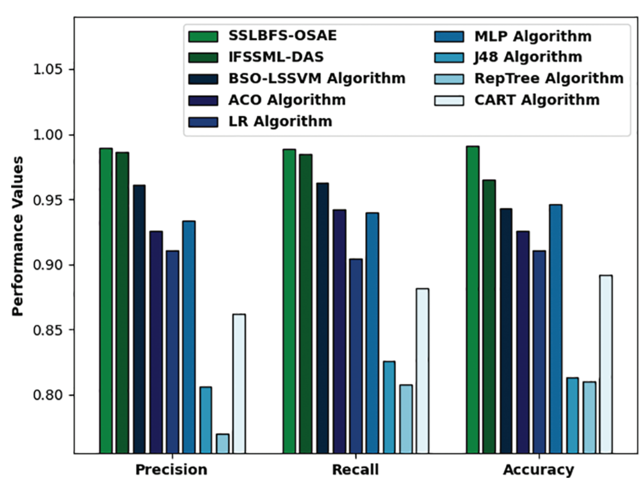

Figure 10: Comparative analysis of SSLBFS-OSAE technique under stress dataset

Fig. 11 defines the F_{score} and *kappa* of the SSLBFS-OSAE method with existing techniques on stress datasets. The results exposed that the SSLBFS-OSAE model has obtainable ineffectual outcome with lower values of F_{score} and *kappa*. Likewise, the LR and MLP techniques have reached moderately enhanced values of F_{score} and *kappa*. Furthermore, the IFSSML-DAS, BSO-LSSVM, and ACO approaches have accomplished reasonable values of F_{score} and *kappa*. Finally, the SSLBFS-OSAE method has exhibited effectual outcomes with the higher F_{score} and *kappa* values of 0.9876 and 0.9900 respectively. After examining the above mentioned results and discussion, it is evident that the SSLBFS-OSAE model has outperformed the existing ones with improved classification performance on LMS.

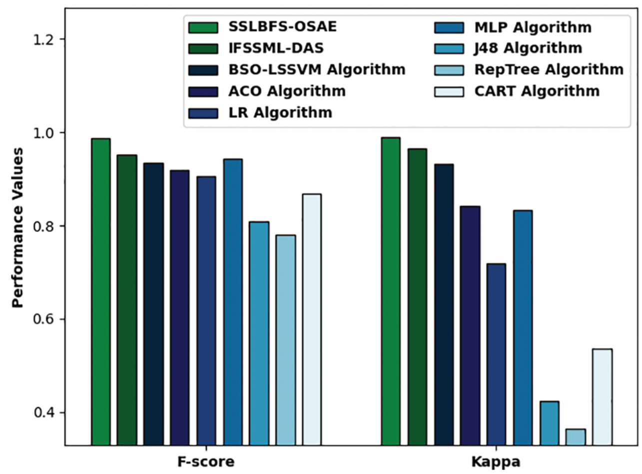

Figure 11: F_{score} and kappa analysis of SSLBFS-OSAE technique under stress dataset

5 Conclusion

This article has developed a new SSLBFS-OSAE model to assess students' mental health on LMS. The SSLBFS-OSAE model is mainly intended to determine the proper health status of the students with respect to DAS. The SSLBFS-OSAE model encompasses SSLBFS model to elect features, SAE based classification, and CSO based parameter optimization. The design of CSO algorithm for optimally tuning the SAE parameters results in enhanced classification outcomes. For examining the improved classifier results of the SSLBFS-OSAE model, a comprehensive results analysis is performed on benchmark dataset. The comparative result analysis highlighted the supremacy of the SSLBFS model over its recent methods interms of different measures. Therefore, the SSLBFS-OSAE model has the capability of determining the mental condition of the students. In future, the presented SSLBFS-OSAE model can be deployed in higher educational institutions.

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