Journal of Intelligent Systems and Internet of Things
Vol. 14, No. 02, PP. 115-126, 2025
DOI: https://doi.org/10.54216/JISIoT.140210

Social Media Platform Based Evaluation of Teaching Style on Online Education System using Heuristic Search with Stacked Sparse Autoencoder Model

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Abstract

As online education has become increasingly prominent, the primary objective of this study is to evaluate students' opinions of online classes taught by teachers with no prior experience in online teaching, focusing on their teaching style, teaching efficiency, and pedagogy in the online classroom. Online teaching is a kind of teaching system that depends on network management technology. It concludes the teaching method by the process of live courses or recorded courses employing software containing special online teaching environments and any APP software employed for teaching. Social media, with its massive pool of user-generated content and instant feedback, offers a great opportunity to calculate teaching styles in online class management. Therefore, this study offers a Social Media Based Evaluation of Teaching Style in Online Education Systems using Heuristic Search (SMBETS-OESHS) Algorithm. The main objective of the SMBETS-OESHS technique for evaluate teaching styles in online education systems using insights derived from social media platforms. At primary stage, the SMBETS-OESHS model takes place linear scaling normalization (LSN) is implemented for scaling the input data. Next, the bayesian optimization algorithm (BOA) based feature selection process can be employed to allow for the detection of the most relevant features from the data. In addition, the SMBETS-OESHS model exploits stacked sparse autoencoder (SSAE) technique for classification process. In order to achieve optimal performance, the SSAE model parameters are fine-tuned using the improved beetle optimization algorithm (IBOA), ensuring robust evaluation accuracy. The experimental validation outcome of the SMBETS-OESHS algorithm undergoes and the performances are examined over various measures. The simulation outcome stated that the enhanced solution of the SMBETS-OESHS system over the recent techniques.

Received: March 16, 2024 Revised: June 20, 2024 Accepted: October 14, 2024

Keywords: Online Education System; Social Media; Heuristic Search; Stacked Sparse Autoencoder; Information and Communication Technology

1. Introduction

Decisive thinking and innovation of students rise with advanced educational models as per the global decisions on higher studies in the 21st century. Inventive learning tactics and innovations are very vital in order to prepare the student's study [1]. Generally, in the learning–teaching procedure, there are three vertices i.e., communication technology over digital devices, teaching, and advanced habits in teaching. In the initial vertex, the professor is said to be an implementer and delivers sources and utensils to students and aids them in progressing novel skills and knowledge. The project-based learning aids students as well as teachers to boost combined learning by conversing exact subjects [2]. Cognitive individuality is created between the students. In order to advance global learning, instructors want to update them. It is highly probable when university researchers and professors set a space for novel instructive methods in dissimilar regions [3]. Unlike conventional classrooms, virtual classrooms provide a limitless option for presenting teaching advanced tactics. The next vertex denotes the usage of Information and Communication Technology (ICT) devices for endorsing new teaching. Learning management system (LMS) aids in learning, evaluation, teaching, testing, and educational administration [4]. Depending upon the study and the need to enhance online learning knowledge, there is a necessity for variations in the enterprise and distribution of distance learning programs that integrate social learning where students can create educational discourses in both oral and written methods collaboratively [5].

To attain higher stages of interaction and student fulfilment, numerous fluctuations should be executed in a novel social media model for online course projects and distribution [6]. The general social media for online classes comprises podcasting, blogs, virtual environments, and social networking. Social networking websites include technology, social traits, and higher-level social systems that involve students with interactivity and enable advanced levels of knowledge transfers in the courses [7]. The thought of engaging students in the online classroom utilizing the addition of targeted social media devices and verified it with a contrast of courses that did not include social media. Over the procedure of reinforcing cognitive growth on every level and peer contact, the gravity of deeper learning and the growth of higher cognitive abilities arise, particularly with twenty-first-century learners [8]. As an outcome, students who existed in the higher level Social Media course exposed stronger capabilities to engage in the assignments essentially and 85% of students generally endured on task throughout every lesson. There are numerous vital factors observed in the literature review, which are essential to insert social media in the online classroom [9]. There would be the likelihood of enlarging the level of interaction from main discussion threads and journals to cooperative social dialogues and conversations utilizing Facebook, Twitter, and other social networking tools [10].

This study offers a Social Media Based Evaluation of Teaching Style in Online Education Systems using Heuristic Search (SMBETS-OESHS) Algorithm. At primary stage, the SMBETS-OESHS model takes place linear scaling normalization (LSN) is performed to scale the input data. Next, the Bayesian optimization algorithm (BOA) based feature selection process can be deployed to allow for the detection of the most relevant features from the data. In addition, the SMBETS-OESHS model exploits stacked sparse autoencoder (SSAE) technique for classification process. In order to achieve optimal performance, the SSAE model parameters are fine-tuned using the improved beetle optimization algorithm (IBOA), ensuring robust evaluation accuracy. The experimental validation outcome of the SMBETS-OESHS algorithm undergoes and the performances are examined over various measures.

2. Literature Review

Hussain et al. [11] present a new technique, which interprets unidentified student feedback utilizing multilayer topic modelling and executes the Felder Silverman Learning Style Method (FSLSM). This model contains learners responding to four FSLSM-based queries depending upon classification into the e-learning platform and delivering personal data, which are biased utilizing fuzzy logic. Then, the study examines behaviours of learners and actions utilizing the web usage mining models, sorting their education systems into exact styles with an innovative DL method. Tian et al. [12] construct a learning concern classification method depending upon TCNN-GRU DL, gather new datasets from online social media sites to execute interest of learning labelling and classification, and then utilize the TCNN-GRU method for defining the consumers learning interest trend. On this basis, the idea of learning interest index is additionally projected. Imran et al. [13] concentrated on the assessment of online education method, which was assumed throughout the COVID-19 pandemic. Due to this reason, reviews or sentiments of students were gathered from the Twitter platform about the learning field. To mechanize the procedure of evaluation, a hybrid technique can be employed as a knowledgebase of opinion words besides ML and boosting technique with n-grams.

Rif'an et al. [14] use qualitative models utilizing a descriptive case study method, especially in the framework of graphic qualitative study. Purposive sampling has been used in this study. Interviewing and documentation techniques are also employed. Teachers use dissimilar teaching models like learning videos earlier the class starts, dubbing projects, and homework to create video projects. Alsayat and Ahmadi [15] present a novel model utilizing supervised learning and text-mining approaches with the help of the ensemble learning technique. A boosting model, AdaBoost, is employed in Artificial Neural Networks (ANNs) for ensemble learning to enhance its performance. The study employs ANN method, dimensionality decrease, and Latent Dirichlet Allocation (LDA) for written data analysis. Principal Component Analysis (PCA) is employed for the reduction of data dimensionality.

Nguyen et al. [16] project a method to define students' learning forms to build modified online programs. Also, the study tackled an effectual model to classify learning style and assess how student’s learning style affect an outcome. To modify appropriate content and education procedures for every student, ML models were employed in order to perceive students' learning styles and categorize them depending on the VARK method. In [17], the authors proposed a theoretical structure depending upon knowledge acceptance and leadership model. It was employed in order to recognize preservice learning leaders' SMKI and their outcome on ALD to contract with a learning crisis. Besides, SMKIs are reinforcing ALD, indirectly and directly, utilizing FCs and SMKB. Similarly, the pupils of higher education were considered pre-service leaders who were registered in management programs and educational leadership.

3. Proposed Methodology

In this study, we offer a novel SMBETS-OESHS methodology. The main objective of SMBETS-OESHS technique for evaluate teaching styles in online education systems using insights derived from social media platforms. Fig. 1 represents the entire procedure of SMBETS-OESHS methodology.

3.1. Data Normalization using LSN

At primary stage, the SMBETS-OESHS model takes place LSN is performed to scale the input data. LSN is a pre-processing approach deployed to standardize data by altering it to regular scale that is mainly useful in assessing teaching styles in online education systems. By guaranteeing that each feature like sentiment scores, engagement metrics, and feedback ratings, are on a similar scale, LSN improves the comparability of social media data. Additionally, LSN gives enhanced model solutions by enabling the training of ML techniques, as it permits quicker convergence and optimum generalized. Eventually, the application of LSN supports educators in gaining clearer insights into how various teaching styles resonate with students in the digital learning environment.

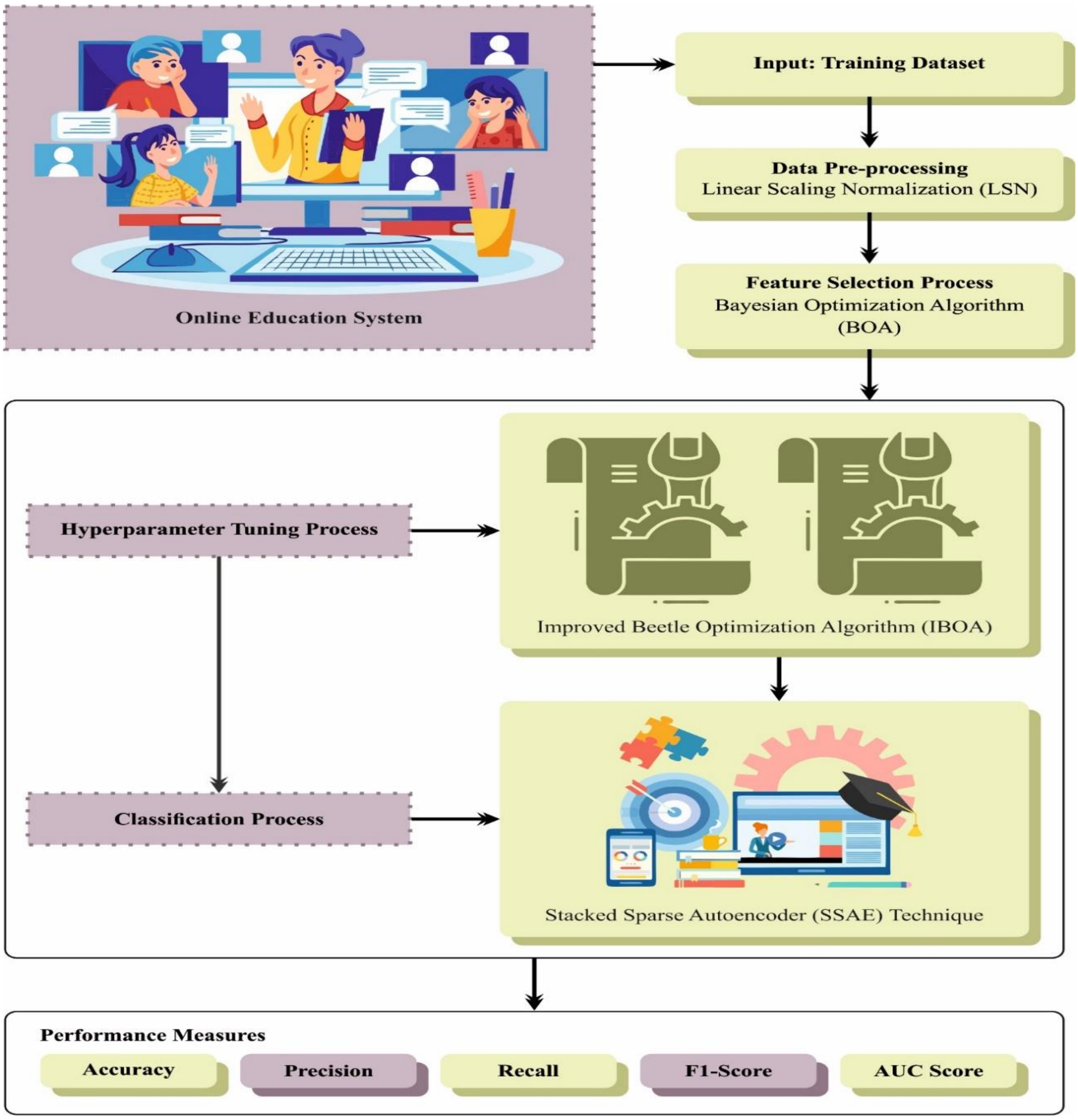

Figure 1. Overall process of SMBETS-OESHS methodology

3.2. BOA based Feature Selection

For feature selection process, the BOA can be employed to allow for the identification of the most relevant features from the data. The alternative method, otherwise known as the objective function (OF), iteratively upgrades the computation of the OF by optimizing loop parameters from the previous iteration, thus achieving parameter upgrades and probabilistic method correction [18]. The formulation can be represented below:

$$f(x) \sim GP\big(m(x), k(x, x')\big) \tag{1}$$

whereas $f(x)$ signifies the evaluating OF value equivalent to the sample; x denotes the model under the training set; $X = (x_1, x_2, \dots \dots, x_n)$ means the sample-set; $m(x)$ and $k(x, x')$ signifies the mean covariance functions, respectively.

$$H = -\sum_{b=1}^{B}\sum_{c=1}^{C}\tau_{bc}\ln\omega_{bc} + \lambda\sum_{j=1}^{2}\rho_j^2 \tag{2}$$

whereas B signifies the sample count; C is the class counts; τ_{bc} shows whether the b sample constitutes the class c; ω_{bc} denotes the output outcome of classifications; λ signifies the regularizing co-effcient; ρ_j^2 is the parameter that studied from the layer of network; and j denotes feature maps. The function of mean can be represented below:

$$m(x) = E[f(x)] \tag{3}$$

whereas E denotes a Gaussian distribution.

To respond to the problem of imbalanced sample owing to recurring samples at local optima, the acquisition function can be utilized to choose an optimum sample in the alternate method. Over the growth, the following acceptable sample point is recognized.

$$I^* = \mathrm{argmax}_{i\epsilon I}\,\varphi_i(x, A) i \in I \tag{4}$$

Whereas, A denotes the observed data set and φ_i signifies the acquisition function.

To attain optimum sample acquisition, the acquisition function of UCB can be used in this study with the formulation presented below:

$$\varphi_{uCB}(x, A) = \mu(x) + \beta\delta(x) \tag{5}$$

whereas $\delta(x)$ and $\mu(x)$signify the covariance and mean function of the alternate method OF and following distribution, correspondingly and β is the fine-tuning constraint.

The fitness function (FF) developed in the BOA is intended to balance among the adopted feature counts from all the performances (lowest) and classifier accuracy (highest) executed through these chosen features, Eq. (6) exemplifies the FF for measuring outcomes.

$$Fitness = \alpha\gamma_R(D) + \beta\frac{|R|}{|C|} \tag{6}$$

Whereas, $\gamma_R(D)$ implies the classifier rate of errors of arrangef for classifier. $|R|$ defines the amount of adopted subset and $|C|$ signifies the entire feature counts in the database, α and β demonstrate the 2 constraints equivalent to the prominence of classifier quality and subset length.

3.3. Classification using SSAE Model

In addition, the SMBETS-OESHS model exploits SSAE technique for classification process. An autoencoder (AE) is an unsupervised learning NN method, which studies the feature of raw data automatically and contains three layers such as input, output, and hidden [19]. The encoding system is made of a hidden layer (HL) and an input layer. While the decoding system is made of HL and output layer. The encoding system excerpts the feature from the new data, whereas the decoding system reinstates input data over the feature.

$X = [X_1, X_2, \cdots, X_n]^T$ denotes an input, n means the amount of nodes from the input layer, signifying the dimension of sampling data. The hidden feature h of new data X attained over the encoded system was computed below:

$$h = f(WX + b) \tag{7}$$

Here, h denotes the parameter of feature obtained by encoding; f signifies an activation function of $Sigmoid$ in the encoding procedure; W and b represent the weight and bias, correspondingly; the size of W is signified by$s \times n$, whereas s indicates the size of the feature parameters.

The decoding was employed in order to rebuild the new input data, and the rebuilt data Y is gained after decoded the unseen feature h, as below:

$$Y = U(W'h + b') \tag{8}$$

Here $Y = [Y_1, Y_2, \cdots, Y_n]^T$ denotes an output data; U means a sigmoid activation function employed in the decoding procedure; W' and b' indicate weights and biases employed, correspondingly; and $w' = W^T$.

The AE utilizes stochastic gradient descent and backpropagation (BP) techniques to enhance the set of parameters $\theta = \{W, b, W', b'\}$ and to minimalize errors among input and output data. Generally, the function of mean square error (MSE) is definite as a loss function that has been formulated below:

$$J_{MSE}(\theta) = \frac{1}{m}\sum_{i=1}^{m}\frac{1}{2}\|X^{(i)} - Y^{(i)}\|^2 \tag{9}$$

Here, m denotes the amount count of training sample; $Y^{(i)}$ and $X^{(i)}$ represents an output and original data of the ith sample, correspondingly

The sparse autoencoder (SAE) has been built by inserting a term of sparse penalty to the AE cost function. The SAE can acquire additional intellectual and illustrative compression features and contain high possible.

$$J_{spare}(\theta) = \beta \sum_{j=1}^{s} K\,L(\rho \| \hat{\rho}_j) \tag{10}$$

$$KL(\rho \| \hat{\rho}_j) = \rho \log_2 \frac{\rho}{\hat{\rho}_j} + (1 - \rho)\log \frac{1 - \rho}{1 - \hat{\rho}_j} \tag{11}$$

$$\hat{\rho} = \frac{1}{m}\sum_{i=1}^{m}\left(a_j X^{(i)}\right) \tag{12}$$

In Eq. (10), β denotes the factor of sparse penalty, which is employed in order to control the weight in the loss function; s refers to the size of HL; $\hat{\rho}_j$ means an average activation value of HL; and ρ specifies the sparse parameter.

Eq. (11) is the comparative entropy calculation formulation employed in order to evaluate the grade of deviation among the dual distributions.

The Eq. (12) computes an average activation value of HL, whereas a_j refers to an amount of activity in jth unit of HL.

$$J(\theta) = J_{MSE}(\theta) + J_{sparse}(\theta) \tag{13}$$

The above mentioned Eq. (13) is the SAE loss function. In that, the 1st term is MSE function and the 2nd term is the sparse penalty. Fig. 2 illustrates the structure of SSAE.

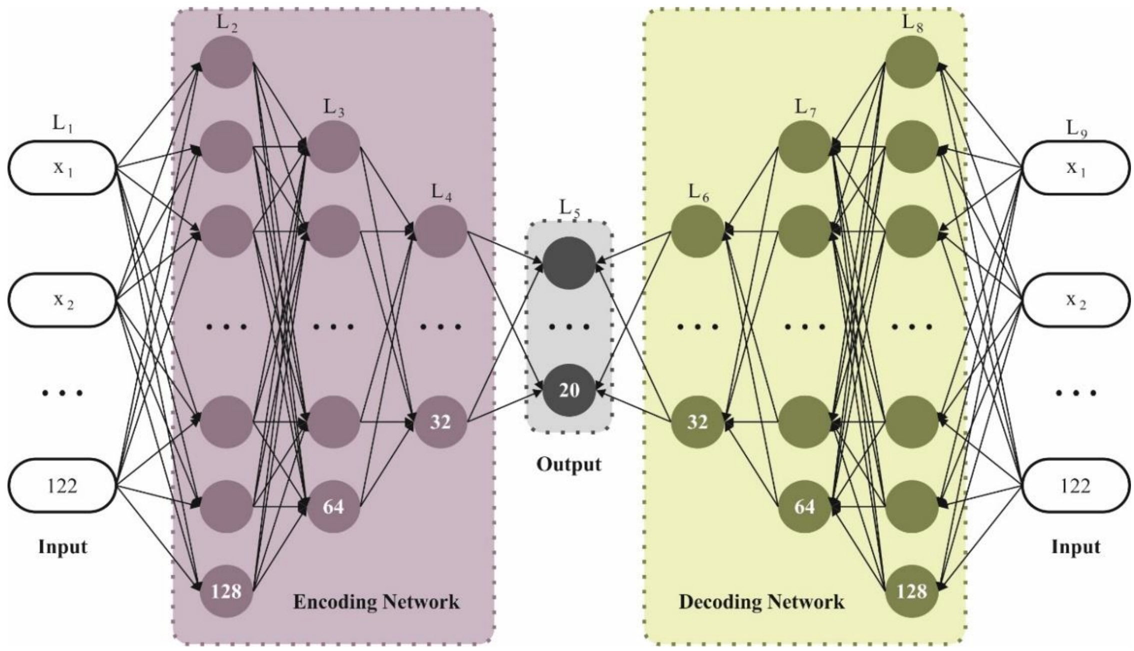

Figure 2. SSAE Architecture

3.4. Parameter Optimizer

In order to achieve optimal performance, the SSAE model parameters are fine-tuned using the IBOA, ensuring robust evaluation accuracy. The DBO is a new swarm intellect technique to tackle complex optimization issues [20]. This method appeals to stimulation from the exclusive existence tactics of dung beetles. It attains optimizer goals by pretending their 5 behaviours such as dancing, reproduction, ball rolling, stealing, and foraging. Conversely, in real application, the DBO even meets numerous challenges. These comprise lower population range inadequate global exploration ability and a trend of being stuck in local goals. To tackle these limits, the conventional DBO has been developed with three features that are mentioned below.

Population Initialization Depend upon Latin Hypercube Sampling

In order to tackle the problem of decreased range affected by randomly distributed early population in DBO technique, the Latin hypercube sampling (LHS) is used to initialize of population. LHS certifies complete analysis of the variable range over hierarchical sample. It assurances that each and every area covers sampling point, improving population uncertainty and consistency. This technique considerably enhanced the diversity of population. The complete process of this model has been mentioned below:

- Let the sample space be d-dimensional with a size of sampling N.
- Split the interval $[x_l, x_u]$ of every variable size x_i into N equivalent part, resultant in $N \times d$ intervals.
- Make a number at random in every separated interval, creating an $N \times d$ sample matrix S.
- In matrix S, organize every column at random, then successively pick only one numeral from every column in order to create a sample vector.
- Do again step4 till N sampling vectors are produced, establishing the last population.

Over this technique, LHS certifies an even distribution of sample points in every variable diversity. Simultaneously, it upsurges the chance of population initialization. This significantly improves diversity of population and also permits the technique to discover the search space in a superior way. As an outcome, the likelihood of discovering the global optimal has been enlarged.

Let the size of population be 30 and a 2D search space with every range size from$[0,1]$, Latin hypercube sampling evades the attention of samples detected in arbitrary initialization. These mains to an additional typical and various first population, so enhancing the model's search efficacy and optimizer performance.

Golden Sine Approach

The original DBO technique contains a restriction owing to the dung beetles linear rolling behavior. This action limits equally global and local search abilities. In order to tackle this problem, the Golden Sine Algorithm (Golden-SA) has been developed. The Golden-SA influences the function of sine in order to cross the unit cycle. This optimizer enhances the balance among exploitation and exploration. So, it improves the rolling performances of dung beetles in either local or global searches. The enhanced location upgrade formulation for the rolling behavior is mentioned below:

$$x_i(t+1) = x_i(t) \times |\sin(r_1)| - r_2 \times \sin(r_1) \times |c_1 \times X^b - c_2 \times x_i(t)| \quad (14)$$

In this formulation, the X^b signifies the location of global best; r_1 implies the randomly created value in the interval of $[0,2\pi]$; r_2 refers to a generated number at random in the interval $[0,\pi]$; c_1 and c_2 refers to the coefficients of golden section, computed below:

$$c_1 = a \times (1-g) + b \times g \quad (15)$$

$$c_2 = a \times g + b \times (1-g) \quad (16)$$

While, $g = 0.618$ means the golden ratio; a and b denote original values for the golden ratio, usually fixed to $a = -\pi$ and $b = \pi$. This development efficiently improves the model's global search ability and local search accuracy, considerably raising the likelihood of discovering the global optimal.

Cauchy-Gaussian Mutation Approach

The DBO technique inclines to drop into local goals in the advanced phases of iterations. To resolve this problem, the Cauchy-Gaussian mutation approach was developed. This technique initially picks the individual with the finest present fitness for mutation. Next, it equates the locations after and before the mutation. A better location has been selected for the following iteration. As a result, this technique improves diversity of population and enhances global search ability in the advanced phases of iteration. The mathematical formulation is mentioned below:

$$X_{new} = X^b \times [1 + \lambda_1 Cauchy(0,1) + \lambda_2 Gaussian(0,1)] \quad (17)$$

Here X_{new} denotes the location after mutation; X^b represents the present global best location; Cauchy $(0,1)$ means a randomly generated numeral by the Cauchy distribution; and Gaussian $(0,1)$ means a produced value at random by the Gaussian distribution. λ_1 and λ_2 represents the dynamic parameters, which are formulated below:

$$\lambda_1 = 1 - \frac{t^2}{T_{\max}^2} \quad (18)$$

$$\lambda_2 = \frac{t^2}{T_{\max}^2} \quad (19)$$

While t and $T_{\max}$ denotes a present and maximum iteration count, respectively. When the iteration evolves, λ_1 progressively reduces while λ_2 rises. This device permits the method to evade from the local goals in the later phases, harmonizing global exploration and local exploitation abilities. The IBOA produces an FF for achieving better classifier proficiencies. It solves a positive integer to exemplify the good efficiency of candidate outcomes. In this case, the decrease of the classifier rate of errors can be assumed that FF.

$$fitness(x_i) = ClassifierErrorRate(x_i)$$

$$= \frac{No.of\ misclassified\ instances}{Total\ no.of\ instances} * 100 \quad (20)$$

4. Result Analysis and Discussion

The experimental validation outcome of the SMBETS-OESHS approach can be examined using a benchmark dataset available in the Kaggle repository [21]. It contains 900 samples under three classes are shown in Table 1. The total number of features is 22. From these, 13 features were selected: Number of Subjects, Gender, Home Location, Level of Education, Internet facility in your locality, Device type used to attend classes, Study time (Hours), Time spent on social media (Hours), Average marks scored before pandemic in traditional classrooms, Engaged in group studies?, Clearing doubts with faculties in online mode, and Performance online.

Table 1: Details on database

Classes	No. of Samples
Good	200
Bad	200
Average	500
Total Samples	**900**

Fig. 3 depicts the classifier performances of the SMBETS-OESHS method in test database. Figs. 3a-3b illustrates the confusion matrices with proper detection and classification of 3 classes on 70%TRASE and 30%TESSE. Fig. 3c demonstrates the PR investigation, signifying maximal outcome under 3 classes. Eventually, Fig. 3d represents the ROC outcome, demonstrating capable solution with superior value of ROC under 3 classes.

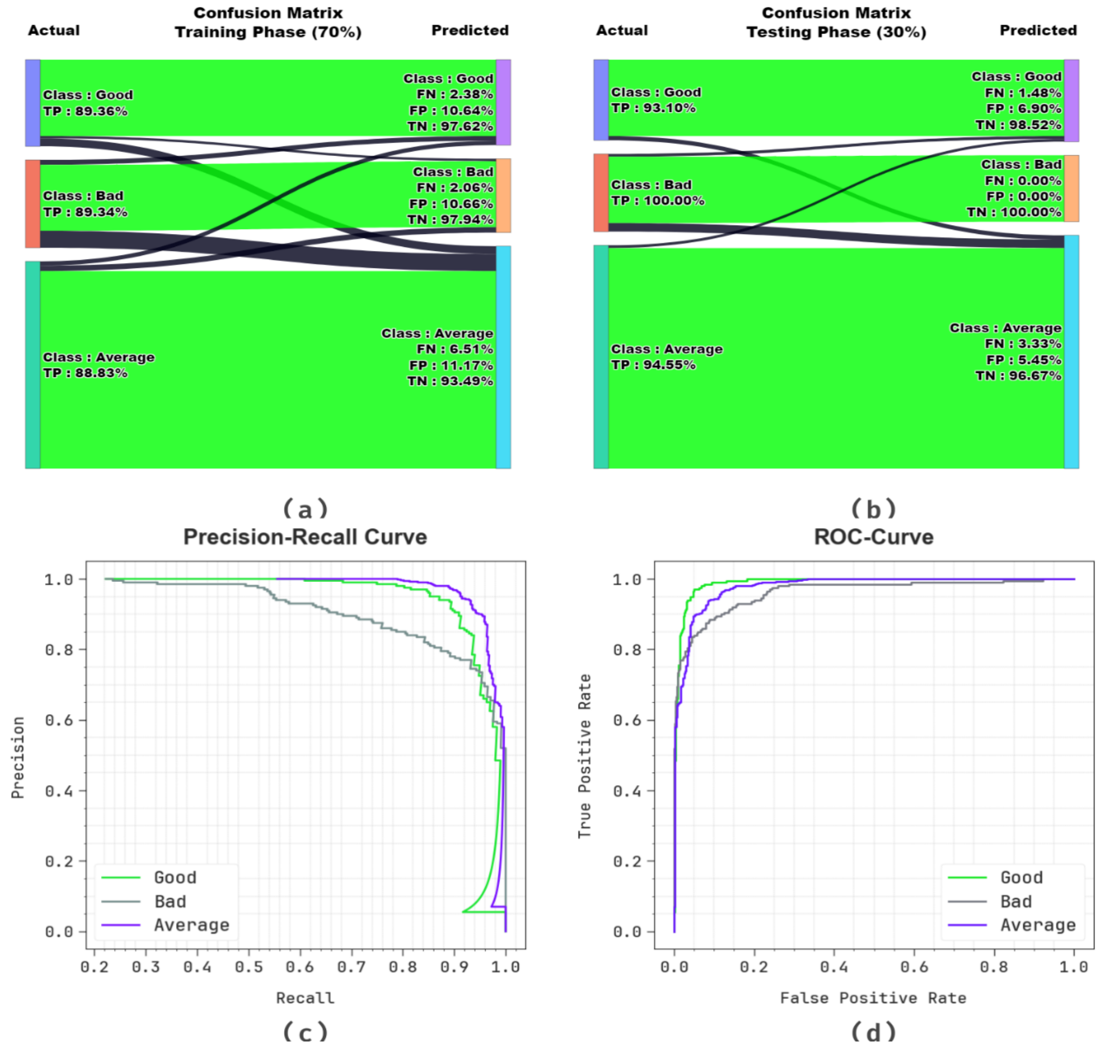

Figure 3. (a-b) 70%TRASE and 30%TESSE of confusion matrices, (c) PR curve, and (d) ROC curve

In Table 2 and Fig. 4, the overall classification outcomes of the SMBETS-OESHS algorithm with 70%TRASE and 30%TESSE are depicted. The table values indicate that the SMBETS-OESHS system has accurately recognized all three classes. With 70%TRASE, the SMBETS-OESHS technique offers average $accu_y$ of 92.70%, $prec_n$ of 89.18%, $reca_l$ of 86.20%, $F1_{score}$ of 87.45%, and AUC_{score} of 89.77%, respectively. Followed by, with 30%TESSE, the SMBETS-OESHS methodology achieves average $accu_y$ of 96.79%, $prec_n$ of 95.88%, $reca_l$ of 92.98%, $F1_{score}$ of 94.22%, and AUC_{score} of 94.84%, correspondingly.

Table 2: Overall classifier of SMBETS-OESHS system with 70%TRASE and 30%TESSE

Classes	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{Score}$	AUC_{Score}
TRASE (70%)					
Good	94.92	89.36	88.11	88.73	92.52
Bad	92.22	89.34	75.17	81.65	86.25
Average	90.95	88.83	95.32	91.96	90.54
Average	**92.70**	**89.18**	**86.20**	**87.45**	**89.77**
TESSE (30%)					
Good	97.41	93.10	94.74	93.91	96.43
Bad	97.04	100.00	85.45	92.16	92.73
Average	95.93	94.55	98.73	96.59	95.35
Average	**96.79**	**95.88**	**92.98**	**94.22**	**94.84**

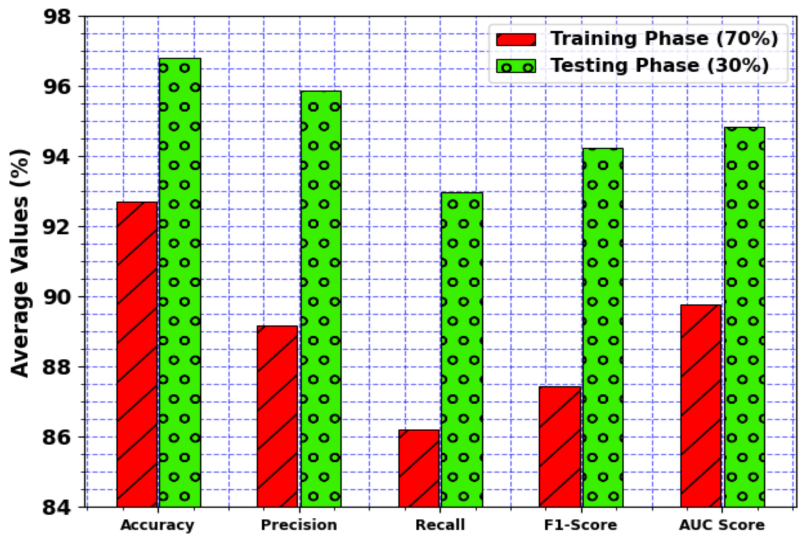

Figure 4. Average of SMBETS-OESHS algorithm with 70%TRASE and 30%TESSE

In Fig. 5, the TRA $accu_y$ (TRAAC) and validation $accu_y$ (VLAAC) curves of the SMBETS-OESHS approach are shown. The $accu_y$values are evaluated under the range of 0-30 epochs. The outcome exhibited that the TRAAC and VLAAC outcome shows a trend of rising that reported the competence of SMBETS-OESHS approach with higher solutions under distinct iterations. Following, the TRAAC and VLAAC kept closed across the epochs that point out lesser overfitting and display superior outcomes of SMBETS-OESHS approach, encouraging continuous prediction on hidden samples.

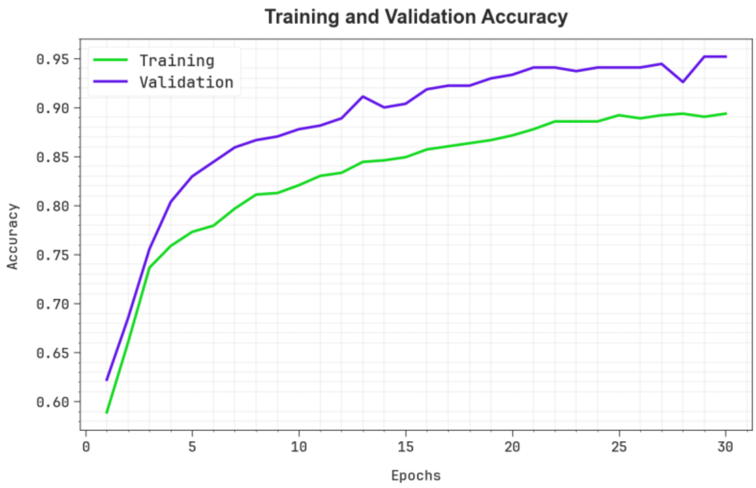

Figure 5. $Accu_y$ Curve of the SMBETS-OESHS algorithm

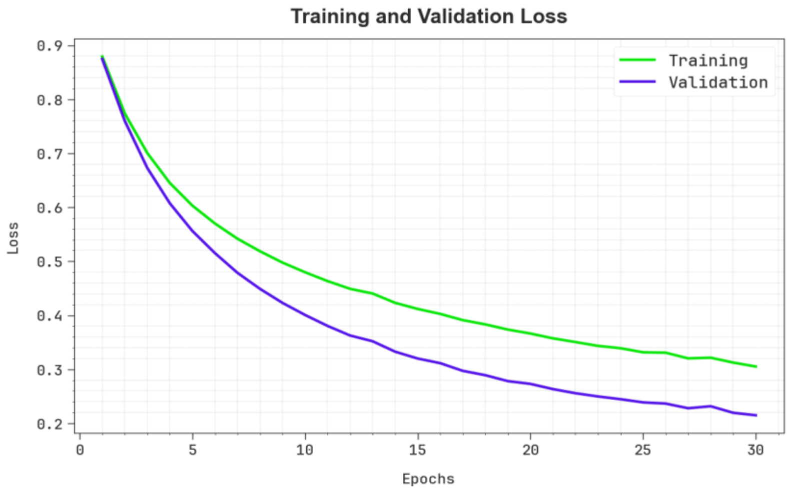

Figure 6. Loss curve of the SMBETS-OESHS algorithm

In Fig. 6, the TRA loss (TRALO) and VLA loss (VLALO) curves of the SMBETS-OESHS algorithm are exhibited. The loss values are estimated under an interval of 0-30 epochs. It is signified that the TRALO and VLALO outcomes outperformed a trend to reduce that notified the capability of SMBETS-OESHS approach in assessment of a trade-off among generalized and data fitting. The consecutive reduction in loss outcomes promises the greater solution of SMBETS-OESHS methodology and adjusts the prediction outcomes over time.

To demonstrate the optimal performance of the SMBETS-OESHS approach, a brief comparative outcome is made in Table 3 and Fig. 7 [22]. The table values implied that the Gaussian Naïve Bayes approach has outperformed lesser result with $accu_y$ of 82.15%, $prec_n$ of 90.88%, $reca_l$ of 81.65%, and $F1_{score}$ of 85.66%.

Table 3: Comparative outcome of SMBETS-OESHS technique with other methodologies

Algorithms	$Accu_y$	$Prec_n$	$Reca_l$	$F1_{Score}$
Random Forest	90.00	86.37	90.34	87.38
Support Vector Machine	82.75	84.87	83.28	83.95
Gaussian Naïve Bayes	82.15	90.88	81.65	85.66
Decision Tree	91.07	83.10	90.99	93.75
CNN Classifier	85.99	91.38	91.77	92.09
KNN Algorithm	94.08	83.67	86.82	83.63
XGBoost Model	88.81	81.98	89.69	82.62
SMBETS-OESHS	96.79	95.88	92.98	94.22

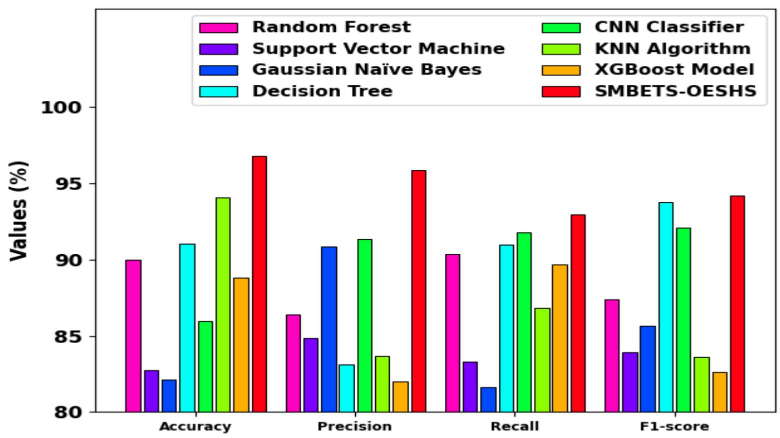

Figure 7. Comparative outcome of SMBETS-OESHS system with other methodologies

In the meantime, the SVM technique has tried to realize somewhat closer outcome with $accu_y$ of 82.75%, $prec_n$ of 84.87%, $reca_l$ of 83.28%, and $F1_{score}$ of 83.95%. Furthermore, the CNN, XGBoost, RF, DT, and KNN methodologies have displayed reasonable classification performances. Nevertheless, the SMBETS-OESHS technique demonstrates promising performance with $accu_y$ of 96.79%, $prec_n$ of 95.88%, $reca_l$ of 92.98%, and $F1_{score}$ of 94.22%.

5. Conclusion

In this study, we offer a novel SMBETS-OESHS methodology. The main objective of the SMBETS-OESHS technique for evaluate teaching styles in online education systems using insights derived from social media platforms. At primary stage, the SMBETS-OESHS model takes place LSN is performed to scale the input data. Next, the BOA based FS process can be employed to allow for the detection of the most relevant features from the data. In addition, the SMBETS-OESHS model exploits SSAE technique for the classification process. In order to achieve optimal performance, the SSAE model parameters are fine-tuned using the IBOA, ensuring robust evaluation accuracy. The experimental validation outcome of the SMBETS-OESHS algorithm undergoes and the performances are examined over various measures. The simulation outcome stated that the enhanced solution of the SMBETS-OESHS system over the recent techniques.

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