Automated Learning Style Prediction using Weighted Neutrosophic Fuzzy Soft Rough Sets in E-learning Platform

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Abstract

Neutrosophic fuzzy logic (NFL) is a prolongation of classical FL that integrates the neutrosophic conception that handles the indeterminacy concept. This method offers a more comprehensive and flexible architecture to handle inconsistent, uncertain, and indeterminate data, which makes it especially helpful in complicated reasoning and decision-making scenarios where classical FL might be defeated. A learning scheme, which is made from the internet and computer as the main components, is called as an e-learning platform. Although the training might happen on or off campuses, utilizing the internet is an integral part of online learning. In the meantime, to significantly augment the education standard, it is essential to forecast the learning style of the user through supervision and feedback. Nonetheless, it averts the intrinsic relationship amongst e-learning behaviors. There might be technological difficulty ranging from network connectivity issue to users memorizing their username and password while executing and developing an educational program. The learning style prediction in e-learning network is complex one and therefore we recommend a new methodology which employs web mining method for the feature extraction and log files of students from the e-learning network. This study develops an Automated Learning Style Prediction using Weighted Neutrosophic Fuzzy Soft Rough Sets (ALST-WNSFSRS) technique in E-learning Platform. The ALST-WNSFSRS technique mainly aims for the prediction of automated learning styles. Initially, the information is gathered from the Kaggle websites and utilizing a web mining method the feature from the web and log files are pre-processed. The preprocessed information is scrutinized to discover the pattern of approach to learning and later investigated the pattern. Then, the feature patterns are clustered by the fuzzy c-means (FCM) clustering technique and later utilizing the WNSFSRS method, the approach to students learning is anticipated. To improve the performance of the WNSFSRS technique, glowworm swarm optimization (GSO) algorithm is used. The performance of the ALST-WNSFSRS technique is compared with existing models and the results reported the supremacy of the ALST-WNSFSRS technique interms of different measures

Keywords: Learning Style Prediction; E-Learning; Glowworm Swarm Optimization; Neutrosophic; Fuzzy Logic

1. Introduction

The real-world is occupied of vagueness, imprecision, and uncertainty. In our everyday life, we mostly deal with vague ideas quite than precise ones [1]. Dealing with imprecision is a huge issue in numerous fields like medical science, economics, environmental science, social science, and engineering. In present scenario, model vagueness has become more interesting for several authors [2]. Numerous traditional models like fuzzy set (FS), probability theory, vague set, rough set, intuitionistic fuzzy set (IFS) and interval mathematics are famous and efficiently model uncertainty [3]. Soft set (SS) method appeals numerous authors because it contains a massive range of applications in numerous areas like as decision-making, smoothness, probability theory, data analysis, predicting, measurement theory, and operations research [4]. Currently, several authors work to hybridize the dissimilar methods with SS and attained outcomes in various related models.

DOI: https://doi.org/10.54216/IJNS.250109
Received: February 09, 2024 Revised: April 12, 2024 Accepted: June 17, 2024

E-Learning is an appropriate learning approach, states to the distribution of data and knowledge to anyone, anytime and anyplace to decrease time, work, and price [5]. The main objective of e-learning are essentially 5-fold such as intelligent tutoring, personalized learning, flexibility, knowledge development, and constant valuation of learners' growth in e-learning [6]. Furthermore, the victory or failure of the e-learning structure is certain by numerous factors such as distribution of learning objects, related data retrieval, learning objects, performance assessment, knowledge management, and the impact of learning styles which differ from one to another learner [7]. The style of learning is a specific method in which an individual studies. Huge models and tools, such as interviews, questionnaires, and expose of profile data have been recognized in the earlier to forecast the learning styles of the learners over any type of atmosphere. These kinds of models for classification might be appropriate for the conventional classroom setting location [8]. On the other hand, the state of e-learning is entirely dissimilar owing to the features of invalidated face to face communications, understanding of body language, constant progress observing, efficient motivation, and enhanced self-efficacy. The learning styles vary depend upon dual significant factors such as dynamic and static factors and these factors are distinguished based on numerous features [9]. Depend upon the dimensions, the learning method and style models are correlated. So, particular models should be used to categorize the distinct learning styles and to suggest appropriate e-contents obtainable in the e-learning servers to the learners who are studying over web environments [10].

This study develops an Automated Learning Style Prediction using Weighted Neutrosophic Fuzzy Soft Rough Sets (ALST-WNSFSRS) technique in E-learning Platform. Initially, the information is gathered from the Kaggle websites and utilizing a web mining method the feature from the web and log files are pre-processed. The preprocessed information is scrutinized to discover the pattern learning method and later investigated the pattern. Then, the feature patterns are clustered by the fuzzy c-means (FCM) clustering technique and later utilizing the WNSFSRS method, the approach to students learning is anticipated. To improve the performance of the WNSFSRS technique, glowworm swarm optimization (GSO) algorithm is used. The performance of the ALST-WNSFSRS technique is compared with existing models and the results reported the supremacy of the ALST-WNSFSRS technique interms of different measures.

2. Literature Works

Hussain et al. [11] presents a new model that interprets unlabeled student feedback employing multi-layer topic modelling and also employs the Felder–Silverman Learning Style Method (FSLSM) method for detecting learning style automatically. This technique comprises learners giving answers for 4 FSLSM-based questionnaire on logging into the e-learning system, which are weighted utilizing the FL. This technique later evaluates the characteristics and activities of the learners by employing web usage mining models, identifying their learning series into particular styles with an innovative DL method. Furthermore, the technique evaluates the textual feedback employing Dirichlet allocation (LDA). Benabbes et al. [12] introduces a new data-based technique for retrieving the behaviours of the learning by implementing traces of their activities depending on the FSLSM model. The learners are classified into groups by their stage of preference for global/sequential, utilizing an unsupervised cluster technique. Later, a classifier technique custom-made for the needs was given training and built on the style of learning and their present contextual, a learning object suggestion list is also presented.

Aymane et al. [13] introduces an overall model that incorporates an AI-enabled adaptive learning technique. By employing the k-means cluster model, the method combines leaners with identical leisure interests. The Gradient Boosting Regressor approach is utilized for anticipating the performance of the study, with survey data and prior accomplishments. Also, the model integrates sustainability practices, maximizing the utilization of the resource in computation and data storage for promoting eco-friendliness. The model also employs ANN and decision tree algorithm (DTA) techniques for predicting individual learning styles and to personalize educational content delivery. In [14], a novel model is proposed. A range of features namely the overall posts and time were taken into account for modelling learning engagement. This methodology also implemented the BiLSTM approach with FastText word embedding for detecting the emotions of the learners. Later, an unsupervised cluster technique depending on the novel dataset was utilized for clustering the learners into clusters.

Sayed et al. [15] introduced an ensemble technique for classifying learners depending on their learning activity clicks by incorporating ML techniques such as SVM, KNN, LR, and RF with semantic association, which is later employed for assisting map learning action with VAK learning style. This assist in classifying learners, and to determine the method of learning. In [16], the estimation of the emotions of the learning specifically frustration emotion is precisely and automatedly accomplished by employing the data collected from learning management systems (LMS) technique by implementing the Takagi sugeno fuzzy inference engine. The encouraging messages that are implemented for transmitting the data to the learners are depending on regulatory fit theory. Various types of numerical assessments are carried out in this study for further evaluation.

DOI: https://doi.org/10.54216/IJNS.250109
Received: February 09, 2024 Revised: April 12, 2024 Accepted: June 17, 2024

3. The Proposed Model

In this paper, we have proposed a new ALST-WNSFSRS technique in E-learning platform. The ALST-WNSFSRS technique mainly aims for the prediction of automated learning styles. It contains different kinds of processes are involved. Fig. 1 illustrates the entire flow of ALST-WNSFSRS technique.

A. Preprocessing

Initially, the information is gathered from the Kaggle websites and utilizing a web mining method, then feature from the web and log files are pre-processed. This stage is comprised to exchange or encrypt the information and simply expressed by ML techniques. The major intention is to forecast the data features exactly by the projected work. Besides, it also vacuums the information for the mandatory format.

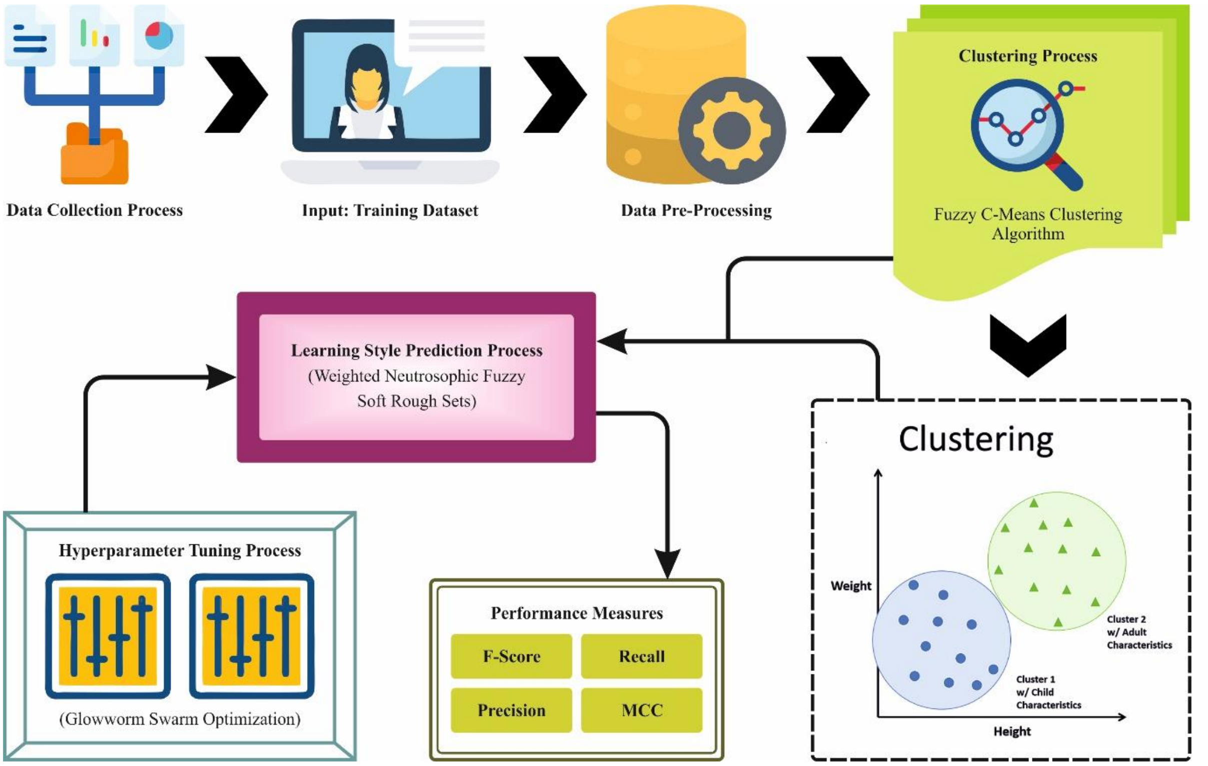

Figure 1: Overall flow of ALST-WNSFSRS technique

B. FCM Clustering Model

Then, the feature patterns are clustered by the FCM clustering technique. All the points are belongs to the cluster, instead of fully belongs to single cluster in fuzzy clustering [17]. In FCM All the points have a weight connected to the specific cluster, hence the point will not sit "in the cluster" and a weaker or stronger relationship to the clusters can be defined as the inverse distance to the cluster center. The procedure of FCM is given as:

Consider a k number of clusters.

Initialization: Arbitrarily initialize the k-means connected to the cluster and calculate the possibility that all the data points xi are a member of the cluster.

Iteration: Revaluate the cluster centroid as the weighted and given the membership possibilities of every data point

Termination: Repeat until iteration or convergence is attained.

C. Prediction using WNSFSRS

Consider point in objects or space, in which the common component Y, represented by y [18]. Neutrosophic set (NS) S in Y is indicated by the membership functions including TS (truth), IS (indeterminate) and FS (false). (TS(y), IS(y) and FS(y)) membership values would have non-standard or real-standard subset of $[0^{-}, 1^{+}]$. The grade of $TS(y)$, $IS(y)$ and $IS(y)$ could be of any values without constraint. The description is given below:

DOI: https://doi.org/10.54216/IJNS.250109
Received: February 09, 2024 Revised: April 12, 2024 Accepted: June 17, 2024

$$T_S(Y) \to]0^-, 1^+[\quad (1)$$

$$I_S(Y) \to]0^-, 1^+[\quad (2)$$

$$F_S(Y) \to]0^-, 1^+[\quad (3)$$

The object y represents a NS - S as $y = y(T, I, F) \in S$. The T, I, F may be the subset of real-standard or non-standard$[0^-, 1^+]$. T denotes truth membership; I refers to indeterminacy and F indicates the false membership of the NS- S. From mathematical modeling, neutrosophic generalize the concepts of intuitionistic fuzzy, classical fuzzy and interval FSs. However, the NS is explicitly defined in the area of science and engineering.

Lately, the NS is integrated to the rough set for determining unevenness and its interval as neutrosophic rough set. The approximation of FS is constructed according to the crisp approximation that leads to the concept of fuzzy rough set. Hence, the concept is introduced with NS for providing the knowledge from different datasets. The neutrosophic is integrated to the rough set for handling indefinite information with approximations namely lower and upper. Hence, the graph is created based on the conception of the hybrid mechanisms. It constructs self-complementary di-graph for rough NS in decision making case. NS is basic to obtain single-value neutrosophic set (SVNS), which is an improvement of intuitionistic FS, where 3 membership values namely truth, false and indeterminacy are not related, and the value belongs to closed interval. Through the relation coefficient, decision making is performed. Also, the complex, crisp proportional calculation is expanded with the COPRAS-SVNS for taking multiple criterion decision.

If $\mathcal{F}$ in MADM signifies the DMs familiarity in conflict with the features instead of the evaluation value, define lower and upper boundary functions of $\mathbb{R}(\mathcal{F})$ should be altered consequently [19]. Consequently, the new description is:

Description 12. Consider X as a universe. C as a set of attributes (parameter) regarding the object in X, $NFS\{X\}$ as the group of each NFSS over the universe X, $\mathbb{R}$ as a NFSS relationship from universe X to C (viz., $\forall c \in C \subseteq C, \mathbb{R}(c) \in NFSS$ (X)) , ψ as a map: $C \to NPSS\{X\}$. Next, $(\psi, C, \mathbb{R})$ is called as a NFRS Approximation Space. For $\mathcal{F} \in NFS(C)$, the upper and lower estimate of $\mathcal{F}$ is described by the following expression:

$$\underline{\mathbb{R}}(\mathcal{F}) = \left\{\left(x, \underline{\mu}(x), \underline{\eta}(x), \underline{v}(x)\right) \middle| x \in X\right\} \quad (4)$$

$$R(\mathcal{F}) = \{(x, \bar{\mu}(x), \bar{\eta}(x), \bar{v}(x)) | x \in X\} \quad (5)$$

Where

$$\underline{\mu}(x) = \min_{c\in C}\left(\mu_{\mathbb{R}}(x,c) \cdot \min\left(\mu_{\mathcal{F}}(c), \left(2 - \eta_{\mathcal{F}}(c) - \nu_{\mathcal{F}}(c)\right)\right)\right), \quad (6)$$

$$\underline{\eta}(x) = \max_{c\in C}\left(\eta_{\mathbb{R}}(x,c) \cdot \max\left(\eta_{\mathcal{F}}(c), \left(2 - \mu_{\mathcal{F}}(c) - \nu_{\mathcal{F}}(c)\right)\right)\right), \quad (7)$$

$$\underline{v}(x) = \max_{c\in C}\left(\nu_{\mathbb{R}}(x,c) \cdot \max\left(\nu_{\mathcal{F}}(c), \left(2 - \mu_{\mathcal{F}}(c) - \eta_{\mathcal{F}}(c)\right)\right)\right). \quad (8)$$

and

$$\bar{\mu}(x) = \max_{c\in C}\left(\mu_{\mathbb{R}}(x,c) \cdot \max\left(\mu_{\mathcal{F}}(c), \left(2 - \eta_{\mathcal{F}}(c) - \nu_{\mathcal{F}}(c)\right)\right)\right), \quad (9)$$

$$\bar{\eta}(x) = \min_{c\in C}\left(\eta_{\mathbb{R}}(x,c) \cdot \min\left(\eta_{\mathcal{F}}(c), \left(2 - \mu_{\mathcal{F}}(c) - \nu_{\mathcal{F}}(c)\right)\right)\right), \quad (10)$$

$$\bar{v}(x) = \min_{c\in C}\left(\nu_{\mathbb{R}}(x,c) \cdot \min\left(\nu_{\mathcal{F}}(c), \left(2 - \mu_{\mathcal{F}}(c) - \eta_{\mathcal{F}}(c)\right)\right)\right). \quad (11)$$

Where $0 \le \underline{\mu}(x) + \underline{\eta}(x) + \underline{v}(x) \le 3, 0 \le \bar{\mu}(x) + \bar{\eta}(x) + \bar{v}(x) \le 3$

Next,

$$\mathbb{R}(\mathcal{F}) = \left(\underline{\mathbb{R}}(\mathcal{F}), \overline{\mathbb{R}}(\mathcal{F})\right) \quad (12)$$

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Received: February 09, 2024 Revised: April 12, 2024 Accepted: June 17, 2024

$$= \left(x, \left(\underline{\mu}(x), \overline{\mu}(x)\right), \left(\underline{\eta}(x), \overline{\eta}(x)\right), \left(\underline{v}(x), \overline{v}(x)\right)\right) \quad (13)$$

The score function is given below:

$$S\big(\mathbb{R}(\mathcal{F})\big) = \underline{\mu}(x) + \overline{\mu}(x) - \underline{\eta}(x) - \overline{\eta}(x) - \underline{v}(x) - \overline{v}(x). \quad (14)$$

$$\underline{\mathbb{R}}(\mathcal{F}) = \{(a_1, 0.04,0.85,0.60), (a_2, 0.04,1.02,0.22), (a_3, 0.08,0.24,0.36)\};$$

$$\overline{\mathbb{R}}(\mathcal{F}) = \{(a_1, 0.45,0.06,0.01), (a_2, 1.28,0.03,0.00), (a_3, 0.09,0.00,0.01)\}.$$

Moreover, $S(a_1) = -1.03, S(a_2) = 0.05, S(a_3) = 0.3$, then $S(a_3) > S(a_2) > S(a_1)$.

Hence, the last sorting is $a_3 \succ a_2 \succ a_1$.

If dissimilar parameters $c(c \in C)$ have dissimilar weights, then the NFSS becomes a weighted NFSS.

Description 13. Consider X as a universe. C as a set of attributes (parameter) with the weight w_C regarding objects in X, $NPS\{X\}$ as the group of each NFSS , $\mathbb{R}$ as a NFSS relationship to C $\big(\forall c \in C \subseteq C, \mathbb{R}(c) \in NFSS(X)\big)$, and ψ as a map: $C \to NFSS\{X\}$. Next, $(\psi, C, \mathbb{R}, w_C)$ is a weighted NFSS. For $\mathcal{F} \in NPS(C)$, the upper and lower estimate of $\mathcal{F}$ is given below:

$$\underline{\mathbb{R}}(\mathcal{F}) = \left\{\left(x, \underline{\mu}(x), \underline{\eta}(x), \underline{v}(x)\right) \middle| x \in X\right\} \quad (15)$$

$$\overline{\mathbb{R}}(\mathcal{F}) = \left\{\left(x, \overline{\mu}(x), \overline{\eta}(x), \overline{v}(x)\right) \middle| x \in X\right\} \quad (16)$$

Where

$$\underline{\mu}(x) = \min_{c \in C}\left(w_c \cdot \mu_{\mathbb{R}}(x,c) \cdot \min\left(\mu_{\mathcal{F}}(c), \left(2 - \eta_{\mathcal{F}}(c) - v_{\mathcal{F}}(c)\right)\right)\right), \quad (17)$$

$$\underline{\eta}(x) = \max_{c \in C}\left(w_c \cdot \eta_{\mathbb{R}}(x,c) \cdot \max\left(\eta_{\mathcal{F}}(c), \left(2 - \mu_{\mathcal{F}}(c) - v_{\mathcal{F}}(c)\right)\right)\right), \quad (18)$$

$$\underline{v}(x) = \max_{c \in C}\left(w_c \cdot v_{\mathbb{R}}(x,c) \cdot \max\left(v_{\mathcal{F}}(c), \left(2 - \mu_{\mathcal{F}}(c) - \eta_{\mathcal{F}}(c)\right)\right)\right). \quad (19)$$

And

$$\overline{\mu}(x) = \max_{c \in C}\left(w_c . \mu_{\mathbb{R}}(x,c) \cdot \max\left(\mu_{\mathcal{F}}(c), \left(2 - \eta_{\mathcal{F}}(c) - v_{\mathcal{F}}(c)\right)\right)\right), \quad (20)$$

$$\overline{\eta}(x) = \min_{c \in C}\left(w_c . \eta_{\mathbb{R}}(x,c) \cdot \min\left(\eta_{\mathcal{F}}(c), \left(2 - \mu_{\mathcal{F}}(c) - v_{\mathcal{F}}(c)\right)\right)\right), \quad (21)$$

$$\overline{v}(x) = \min_{c \in C}\left(w_c . v_{\mathbb{R}}(x,c) \cdot \min\left(v_{\mathcal{F}}(c), \left(2 - \mu_{\mathcal{F}}(c) - \eta_{\mathcal{F}}(c)\right)\right)\right). \quad (22)$$

Now, $0 \le \underline{\mu}(x) + \underline{\eta}(x) + \underline{v}(x) \le 3, 0 \le \overline{\mu}(x) + \overline{\eta}(x) + \overline{v}(x) \le 3$

$$\mathbb{R}(\mathcal{F}) = \left(\underline{\mathbb{R}}(\mathcal{F}), \overline{\mathbb{R}}(\mathcal{F})\right) \quad (23)$$

$$= \left(x, \left(\underline{\mu}(x), \overline{\mu}(x)\right), \left(\underline{\eta}(x), \overline{\eta}(x)\right), \left(\underline{v}(x), \overline{v}(x)\right)\right). \quad (24)$$

$$S(\mathbb{R}(\mathcal{F})) = \underline{\mu}(x) + \overline{\mu}(x) - \underline{\eta}(x) - \overline{\eta}(x) - \underline{v}(x) - \overline{v}(x). \quad (25)$$

Consider that $\underline{\eta}, \overline{\eta}, \underline{v}$ and $\overline{v}$ parameters increase, the value of assessment functions become closer to negative or zero, this doesn't enable mathematical comparisons and calculations. Thus, the assessment function should be accordingly increased. The novel assessment function is given below:

Description 14. The score function can be given by:

DOI: https://doi.org/10.54216/IJNS.250109
Received: February 09, 2024 Revised: April 12, 2024 Accepted: June 17, 2024

$$S(\mathbb{R}(\mathcal{F})) = \underline{\mu}(x) + \overline{\mu}(x) + \left(2 - \underline{\eta}(x) - \underline{\nu}(x)\right) + \left(2 - \bar{\eta}(x) - \bar{\nu}(x)\right) \tag{26}$$

$$= 4 + \underline{\mu}(x) + \overline{\mu}(x) - \underline{\eta}(x) - \bar{\eta}(x) - \underline{\nu}(x) - \bar{\nu}(x)\,. \tag{27}$$

Instance 5. Still analyse the data in Instance 3 with the vector of weighted $w = \{0.50,0.25,0.15,0.10\}^T$, the upper and lower boundaries and score function is given below.

$\underline{\mathbb{R}}(\mathcal{F}) = \{(a_1, 0.0040, 0.1500, 0.2800), (a_2, 0.0040, 0.1500, 0.0700), (a_3, 0.0080, 0.0750, 0.1400)\}$; $\overline{\mathbb{R}}(\mathcal{F}) = \{(a_1, 0.2250, 0.0120, 0.0010), (a_2, 0.3750, 0.0075, 0.0000), (a_3, 0.4500, 0.0000, 0.0010)\}$; $S(a_1) = 3.7860$;

$$S(a_2) = 4.1515;$$

$$S(a_3) = 4.2420;$$

Clearly, $(a_3) > S(a_2) > S(a_1)$, hence the last ordering is $a_3 \succ a_2 \succ a_1$.

Generally, dissimilar DMs have dissimilar decision weights in chaotic multiple attribute group decision making (CMAGDM), hence its overall assessment function is given below.

Definition 15 the overall assessment function for the CMAGDM is (a_i):

$$\mathbb{S}(a_i) = \sum_{k=1}^{l} \tau_k \, S_k(a_i) \tag{28}$$

Where $S_k(a_i)$ refers to the k^{th}DM's scores for the i^{th} alternatives $(i = 1, \dots, m;\ k = 1,2, \dots, l)$; τ_k refers to the weight of $k^{th}DM(\tau_k \geq 0, \Sigma_{k=1}^{l} \tau_k = 1)$.

D. Parameter Selection

To improve the performance of the WNSFSRS technique, the GSO algorithm is used. The GSO is a dual-dimension workplace where every imitation agent is transport a light and takes its opinion, recognized as the range of local resolution [20]. To define Luciferin's location, it is essential to reflect its value of objective. The agents with greater level of intellect are probable to fly to superior locations. A neighbor with luciferin power bigger than its size is in the range of local decision will be spread-out near when the agent identifies. As per to the neighbors number, there is a dissimilar local decision bound. When there are less and huge neighbors, there will be upsurge and reduction in threshold, respectively. Anyway if the neighbor is nominated, the agent constantly modifies its way of drive. As luciferin stages upsurge, a neighbor becomes more eye-catching. Furthermore, most agents are situated in numerous positions simultaneously. There are 3 main stages to GSO such as luciferin upgrade stage, motion stage, and the decision threshold stage.

Luciferin upgrade stage:

Luciferin is upgrades as per to the gloss function value. Every glowworms start with the similar luciferin stage, but it differ with the activity level in the glowworms existing condition even if every glowworms contain the similar luciferin level in the early iteration. An individual opinion of the radiation and temperature levels at an exact position defines the luciferin value. Every glowworm upsurges its luciferin level also to its preceding level. Luminescence values have been deducted from preceding one in order to pretend decline in the radiance. The upgraded instruction of Luciferin value is as:

$$L_g(d+1) = (1-\rho)L_g(d) + \gamma J_g(d+1) \tag{29}$$

Where, $L_g(d)$ signifies the Luciferin level of a glowworm; J_g denotes an objective function; ρ denotes luciferin decline constant $0 < \rho < 1$ and γ refers to the luciferin improvement constant.

Movement stage:

This stage contains every glowworm that defines the neighbor movement with a greater luciferin level than over the usage of a probabilistic device. To appeal glowworms, neighbors who produce a bright light are gorgeous. The prospect of every glowworm g affecting near a neighbor h is computed below:

$$P_{gh} = \frac{L_h(d) - L_g(d)}{\sum_{n \in K_g(d)} L_n\,(d) - L_g(d)} \tag{30}$$

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Here, $h \in K_g(d), K_g(d) = \{h; E_{g,h}(d) < P_E(d); L_g(d) < L_h(d)\}$ denotes the set of neighborhood. $\beta_E(d)$ designates the range of variable neighborhood related at time d. $E_{g,h}(d)$ represents the Euclidean distance among glowworms h and g at time d. Let the glowworm g picks a $h \in K_g(d)$ with $P_{gh}(d)$ set by Eq. (30). So, glowworm movement is defined below:

$$y_g(d+1) = y_g(d) + S(y_h\left(\frac{y_h(d) - y_g(d)}{\|y_h(d) - y_g(d)\|}\right) \tag{31}$$

Whereas $\|\|$ denotes the operator of Euclidean norm and S signifies the size of step.

Decision range upgrade:

Each agent was related with a neighborhood whose circular range r_e^g is active $0 < r_e^g < r_S$. The luciferin device has a array of radial denoted as r_S. If glowworms are dependent merely on local data, the peaks number taken will differ as per to the sort of radial device. Agents whose devices are proficient to cover the whole searching space to the global optimal. As an outcome, defining a neighborhood range is appropriate for dissimilar function designs are challenging without any understanding about the function of objective. As a common regulation, the objective function with least inter- peak distance larger than re were preferred over with least inter-peak distances lesser than re. So, GSO identifies manifold peaks by using a range of adaptive neighborhood in a multi-modal function state. If the below mentioned regulation is utilized, solution seems to be much decreased:

$$r_e^g(d+1) = \min\left\{rS, \max\left\{0, r_e^g(d) + \beta(kd - |Kg(d)|)\right\}\right\} \tag{32}$$

The above given calculation has been stated as an amount of neighbors parameter kd and constant parameter β. Fig. 2 signifies the flowchart of GSO.

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Received: February 09, 2024 Revised: April 12, 2024 Accepted: June 17, 2024

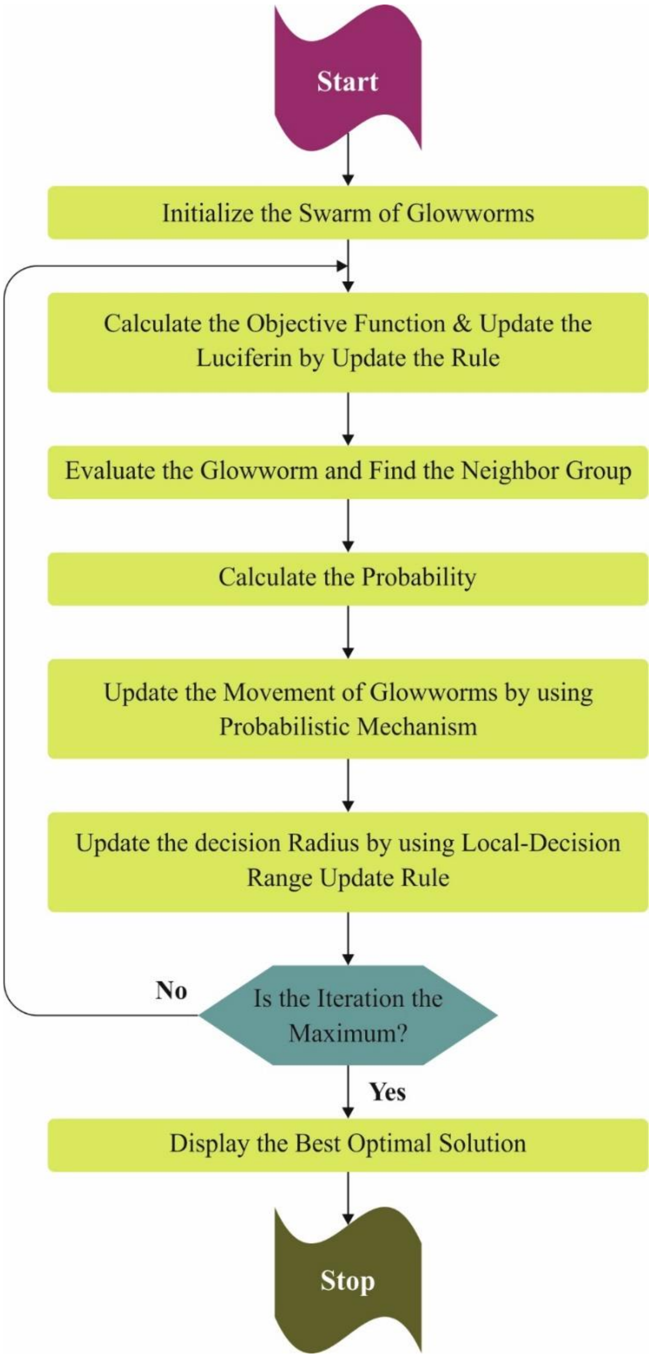

Figure 2: Flowchart of GSO

The GSO method makes a fitness function (FF) to achieve improve performance of classifier. It defines a positive numeral to signify the superior solution of the candidate. In this research work, the classifier rate of error minimization is measured as FF and set in Eq. (33).

$$fitness(x_i) = ClassifierErrorRate(x_i)$$
$$= \frac{no.of\ misclassified\ instances}{Total\ no.of\ instances} * 100 \qquad (33)$$

4. Performance Validation

In this part, the performance of ALST-WNSFSRS technique is compared with existing models. In Table 1, a comparative analysis of ALST-WNSFSRS technique with existing methodologies [21].

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Fig. 3 defines the comparative outcome of ALST-WNSFSRS technique interms of $accu_y$. The experimental outcome of ALST-WNSFSRS technique has exhibited better performances compared with other approaches. Based on $accu_y$, the ALST-WNSFSRS technique has higher $accu_y$ of 97.86% where the FSLSM, BILBCI, hybrid filtering, FCM, and SCA-WMQSVM approaches have lesser $accu_y$ of 87.02%, 82.68%, 77.42%, 78.66%, and 95.69%, respectively.

Table 1: Comparative analysis of ALST-WNSFSRS model with existing methods

Models	$\boldsymbol{Accu_y}$	$\boldsymbol{Reca_l}$	MCC
FSLSM	87.02	87.52	89.55
BILBCI	82.68	88.13	83.02
Hybrid Filtering	77.42	86.61	82.36
FCM Model	78.66	89.66	82.36
SCA-WMQSVM	95.69	95.45	94.78
ALST-WNSFSRS	97.86	97.28	97.40

Fig. 4 describes the comparative result of ALST-WNSFSRS system in terms of $reca_l$. The experimental outcome of ALST-WNSFSRS approach has shown better performance compared with other techniques. Based on $reca_l$, the ALST-WNSFSRS method has greater $reca_l$ of 97.28% whereas the FSLSM, BILBCI, hybrid filtering, FCM, and SCA-WMQSVM techniques have smaller $reca_l$ of 87.52%, 88.13%, 86.61%, 89.66%, and 95.45%, respectively.

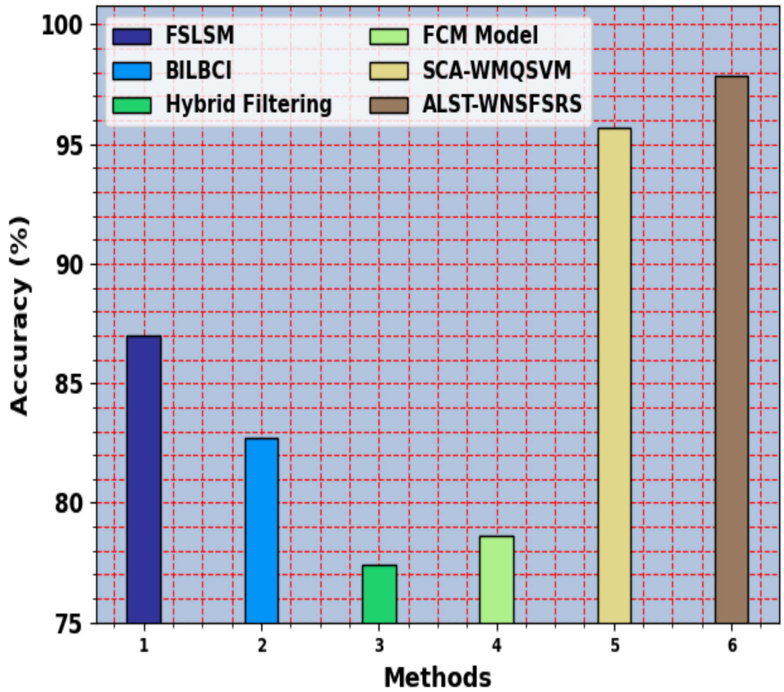

Figure 3: $Accu_y$ outcome of ALST-WNSFSRS model with existing methods

DOI: https://doi.org/10.54216/IJNS.250109
Received: February 09, 2024 Revised: April 12, 2024 Accepted: June 17, 2024

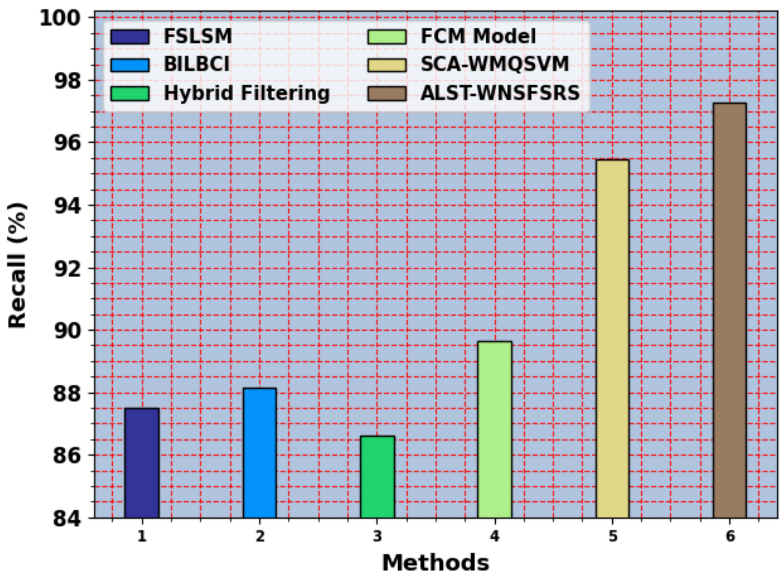

Figure 4: $Reca_l$ outcome of ALST-WNSFSRS technique with existing methods

Fig. 5 describes the comparative outcome of ALST-WNSFSRS system in terms of MCC. The experimental result of ALST-WNSFSRS approach has displayed better performances compared with other methods. Based on MCC, the ALST-WNSFSRS approach has greater MCC of 97.40% whereas the FSLSM, BILBCI, hybrid filtering, FCM, and SCA-WMQSVM techniques have lesser MCC of 89.55%, 83.02%, 82.36%, 82.36%, and 94.78%, correspondingly.

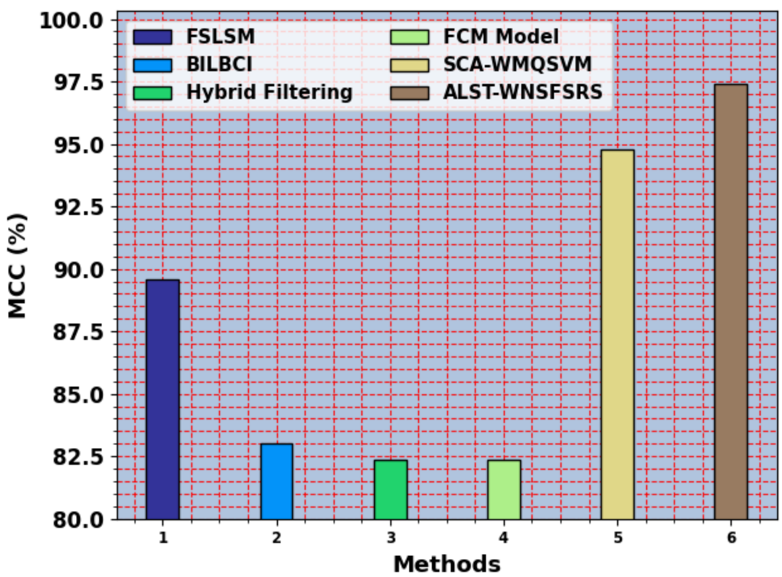

Figure 5: MCC outcome of ALST-WNSFSRS technique with existing methods

In Table 2 and Fig. 6, a detailed performance analysis of ALST-WNSFSRS technique with existing systems are given. The simulation outcome implied that the BILBCI model has exhibited poor performances over other approaches. Likewise, the FSLSM and hybrid filtering methods have outperformed somewhat improved solutions. In addition, the FCM and SCA-WMQSVM approaches have demonstrates reasonable outcomes. Finally, the ALST-WNSFSRS approach has depicted superior performance with maximum $prec_n$ of 98.08%, $reca_l$ of 99.38%, and F_{score} of 98.08%, respectively.

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Table 2: Performance analysis of ALST-WNSFSRS technique with existing systems

Performance (%)			
Methods	$Prec_n$	$Reca_l$	F_{Score}
FSLSM	88.37	77.69	84.16
BILBCI	82.87	84.81	80.60
Hybrid Filtering	86.75	89.02	78.01
FCM Model	89.67	91.28	89.67
SCA-WMQSVM	94.52	96.14	96.14
ALST-WNSFSRS	98.08	99.38	98.08

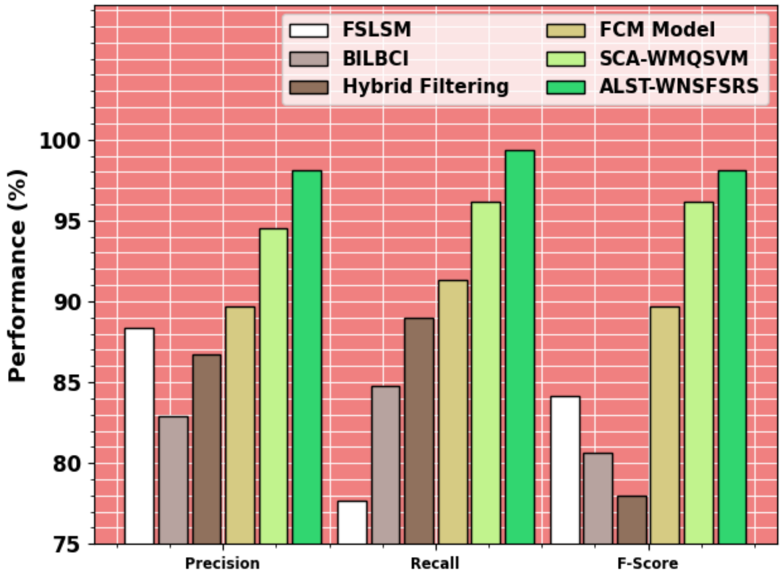

Figure 6: Performance analysis of ALST-WNSFSRS technique with present systems

In Table 3 and Fig. 7, a detailed time analysis of ALST-WNSFSRS method with current models are given. The simulation outcome implied that the FCM technique has displayed poor performances over other methods. Similarly, the FSLSM and hybrid filtering models have outperformed better solutions. Furthermore, the BILBCI and SCA-WMQSVM systems have establishes reasonable results. Lastly, the ALST-WNSFSRS technique has portrayed higher performance with smaller time of 0.91s.

Table 3: Time analysis of ALST-WNSFSRS model with existing systems

Techniques	Time in Seconds (s)
FSLSM	2.03
BILBCI	2.43
Hybrid Filtering	2.76
FCM Model	4.23
SCA-WMQSVM	1.87
ALST-WNSFSRS	0.91

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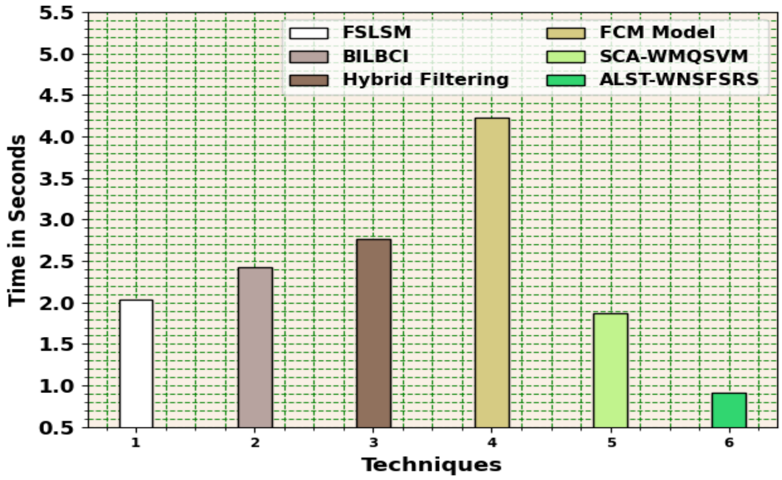

Figure 7: Time analysis of ALST-WNSFSRS model with existing systems

In Fig. 8, the ROC curve of the ALST-WNSFSRS model is studied. The results indicate that the ALST-WNSFSRS techniques reaches improved ROC outcomes over every class, representing major ability of discriminating the classes. This reliable trend of enhanced ROC values over several classes indicate the proficient performance of ALST-WNSFSRS technique on forecasting classes, highliging the strong nature under classification procedure.

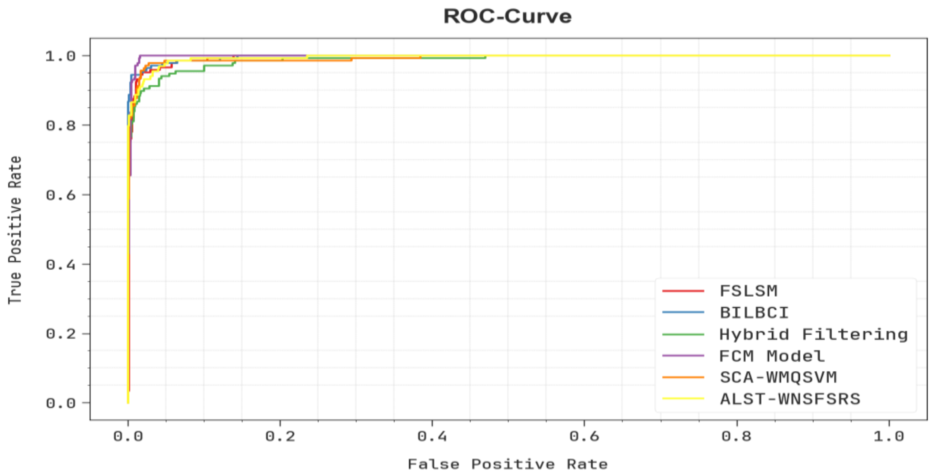

Figure 8: ROC curve of the ALST-WNSFSRS technique

5. Conclusion

In this paper, we have developed a new ALST-WNSFSRS technique in E-learning platform. The ALST-WNSFSRS technique mainly aims for the prediction of automated learning styles. Initially, the information is gathered from the Kaggle websites and utilizing a web mining method the feature from the web and log files are pre-processed. Then, the pre-processed information is scrutinized to discover the pattern learning method and later investigated the pattern. Then, the feature patterns are clustered by the FCM clustering technique and later utilizing the WNSFSRS method, the approach to students learning is anticipated. To improve the performance of the WNSFSRS technique, the GSO algorithm is used. The performance of the ALST-WNSFSRS technique is compared with existing models and the results reported the supremacy of the ALST-WNSFSRS technique interms of different measures

Funding: “The author gratefully acknowledges technical support provided by Faculty of Computing and Information Technology and Faculty of Tourism at King Abdulaziz University, Jeddah, Saudi Arabia”

Conflicts of Interest: “The authors declare no conflict of interest.”

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