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Learning style prediction of e-learner using hybrid optimizer-based neural network

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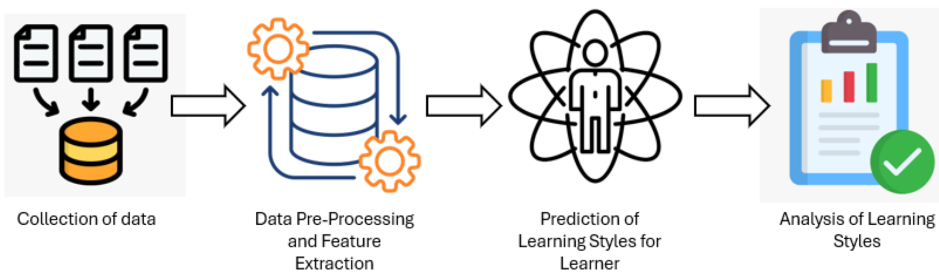
Article

ABSTRACT



The Learning Style prediction model in e-learning systems has gained immense attention in education. In the current scenario, the major demand for online platforms is to provide a substantiated interface that acclimatizes the learning styles of the learners. People learn in different ways, and their preferences can change over time. The accurate prediction of learning style can raise the learners' learning gain. This Research proposed a technique to predict the learning styles, by capturing the interaction behavior of the learner. The learning styles are predicted and grounded on the uprooted features using a Neural Network. It is trained and classified using a hybrid optimizer which is a fusion of Squirrel Search (SS) and Rider Optimization Algorithm (ROA). Felder-Silverman Learning Style Model is used to map the learner's learning styles. Eventually, the pupil and course ID, learning style, course completion status, and test score data are recorded to find the correlation. The proposed hybrid optimizer-based model provides superior performance compared to techniques with an accuracy of 0.95 and a maximal correlation of 0.406.

Keywords: Felder-Silverman Learning, Learning Styles, Optimization, E-learning, Squirrel Search and Rider Optimization Algorithm

INTRODUCTION

A Learning Style refers to the means used by different learners during learning. It is a method of acquiring knowledge by an individual using their preferred method." Learning styles can be characterized, grouped, and distinguished from various perspectives. They are generally designed in a way to give guidance to learning and teaching. In recent years, online education has been honoured as a support tool for instructors and experimenters as it gives the comfort of using it anywhere and anytime. It can overcome the limitations of time and space. Like traditional learning methods, online education also depends on effective communication of an individual's knowledge. An educator makes use of Bloom's knowledge base classification to outline the objectives of the course used to construct instructing contents and activities. Many times, the instructor makes use of these objectives to find student's accomplishments. Online education developed quickly in the previous period and changed into a sample of mastering.[1] For learners' evaluation in an online learning framework, the evaluation feature is needed.[2] The broadly used comparison approach in distance instructing and gaining knowledge is online examination.[3]

According to Bloom, there are three domains of learning. These are cognitive (knowledge), affect (emotions), and psychomotor (physical skills). Unfortunately, in the present scenario of online learning, only the cognitive domain is taken care of. As far as online education is concerned psycho motor skills are not much required. Every student must have a different way of learning. Learning Style pertains to the varied methods by which students sock up and process information. Catering to personal patterns can enlarge learners' likelihood of success and satisfaction. Most of

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the E-learning courses just focus on the records broadcast, especially, the course content, and neglect learners' learning mindset, emotions, and learning styles. Each learner has a different learning style but unfortunately, existing online learning systems evaluate all the learners in the same way. Learners' learning depends on his or her learning style and affective states. If we can incorporate the prediction of learners' learning styles in online learning platforms and provide the content accordingly, it will surely enhance the student's inspiration toward better learning. It will also increase learners learning gain.

There are a variety of models which include Visual-Auditory-Kinesthetic-Tactile (VAKT models), and the Felder-Silverman learning style model. The majority of them describe the learners as progressive means who are directly involved, emotional who interact with others, observational who watch, listen, and explore, and who analyze the subject matter through group discussion.

In the present scenario, online learning has been described as less emotional and distant. There are chances that E-learning systems don't give continuous input to the student. At such a point, a student doesn't get the benefit of getting actual remarks from the trainer to enhance the overall progress of grasping things. Yet, this type of structure must additionally provide remarks regarding the learner's learning styles due to the fact it noticeably impacts the student's inspiration toward higher learning. In classroom teaching, one can understand learners learning and preparation through interaction and body language. But this becomes very challenging when we make use of a computerized setup. Different approaches like questionnaires, facial expression recognition, gesture recognition, and so forth have been used for the prediction of learning styles. Here we propose a framework that focuses on the determination and of learning styles of learners in online learning. We have used the web usage log to predict learning styles as it is beneficial as compared to other techniques.[4,5] In a remote online educational setup, a teacher needs to evaluate individual learners' learning styles and accordingly adapt his/her assessment approach and give content for further learning. There is a need for a framework that catches and handles information to forecast learning styles. This system should be usable and effective for the learner as well as teacher.

The education organizations intend to give quality content to the scholars. The advanced system is required to make use of learning data and search the factors that influence learners' progress. The obtained information is employed to predict learners' progress. However, the prediction of getting to know the overall performance of scholars is a complicated venture due to the fact of indispensable infrastructures and custom-made necessities of distinct individualists. The aforesaid problem and limitations in the present approach are considered for devising a proposed learning styles forecasting model.

The goal is to find an E-learner's learning style. At first, courses, like Data Structures (Course 1), Data Base (Course 2), and Human Computer Interface (Course 3) are considered for the experimentation. These subjects are categorized as per complexity as High, Medium, and Low. Then, said courses are studied by the students through LMS. Based on the studying behavior, an interaction log is recorded. Every file includes information regarding course and topic Number, lecture type, amount of time given, and the marks scored in the examination of each student. Then, the features are extracted from it. Depending on the extracted feature, the learner's learning style prediction is performed. A hybrid optimizer-based neural network is used for prediction. The styles of learning are forecasted grounded on the uprooted features by making use hybrid optimizer-based Neural Network. It classifies the learners. FSLSM is utilized to map the learning styles. Eventually, the pupil and course ID, learning style, course completion status, and test score data are taken to find the correlation.

Other sections of this paper have: Section 2 contains a description of learning styles forecasting techniques used before along with the challenges. Section 3 describes the proposed technique for learning style forecasting with a hybrid optimizer-based neural network. The analysis of methods is presented in Section 4. Section 5 includes Statistical analysis of methods and Section 6 gives the conclusion.

LITERATURE SURVEY

Every student has a different learning style, but unfortunately, current online learning frameworks assess all students equally. Students' learning depends on various factors including their learning style and emotional states. To overcome this challenge there is a need to develop a system for the prediction of learning styles from the interaction behavior of learners.

As shown by Sabine G *et al.*, the model consists of an adaptive course generator and a generator of adaptive effective tactics.[6] For understanding learning styles surveys, polls, and programmed approaches were used. Emotional states were known from expressions and by using signals that record pulse and heartbeats. Learning styles were predicted based on this learner log using a k-means clustering algorithm.[7] Its result was compared with the survey outcome and the two techniques produced roughly comparable results. FSLSM was used for learning style mining.[8] Kolekar *et al.* used Artificial Neural Networks (ANN) and web utilization mining to detect learning styles using the FSLSM model.[9] There were two important aspects to their review, viz. a) the computer component of gathering learning skills and b) a framework for identifying learning styles. Researchers extracted facial features and location from the image and classified them into six different emotions. Strategies like Discrete Wavelet Transform, Gabor channel, and Histogram of Oriented Gradients were used for grouping this data.[10] The outcome showed that HOG achieved better answer with a Support Vector Machine (SVM) with 85% accuracy.

Farman Ali Khan *et al.* have prepared a framework for the learning style prediction of learners.[11,12] Various approaches used for capturing learner's learning behavior from their activities were focused on them.[13] Different techniques used to predict emotions, when E-learner goes through the lessons on online portals like intrusive and non-intrusive are mentioned. Kamilia Rahmah *et al* have done qualitative research with a descriptive approach.[14] They have described problem-solving supported by APOS theory (Action, Process, Object, Schema) in the form of Kolb's learning style. Data is collected using Kolb's learning style questionnaire, tests, and interviews. Collected data is analyzed and they have concluded each learning style is useful for solving certain stages of problems by considering APOS theory. Darmayanti, R. *et al.* have developed digital comic learning media. After analyzing data, it has been observed that the students have appreciated comics as a medium of learning.[15] Eka Dewi Fithrotunnisa *et al.* have tried to understand the difference between students' learning styles. Here authors have used a causal-comparative technique using a purposive sampling technique. Here authors have collected data from 30 students who are further classified into three categories through tests. Data is analyzed using linear regression. After analysis, it has been observed that a maximum number of students have visual learning styles and a comparatively number of students have kinesthetic and auditory learning styles. [16]

Raj et al, have done a literature review of content recommendation systems in personalized learning environments. Such systems suggest appropriate learning resources based on learner attributes which improves the learning outcomes. Here, the authors have summarized many elements of recommender systems, like learner attributes and recommendation algorithms. It has been noted that cognitive characteristics of learners, like acquisition preferences and styles, are more frequently utilized than characteristics like social standing or trust. It has been noted that this type of work typically uses a combination of two or more recommendation systems. [17]

Elena Guillermina *et al.* have developed a system to measure the effects on student engagement by considering students' learning styles while creating an adaptable online environment. Here authors have described and compared an adaptive learning environment that considers learning styles with an existing e-learning technique. The online survey was conducted to gather data. It has been observed that reading comprehension is an issue. It may be resolved by students by using the internet to improve their learning via self-learning.[18]

For a group of kids with learning difficulties, Monika Thapliya *et al.* have supplied differentiated mastering surroundings in the domain model of a smart tutoring system. In this case, the authors have created a model that aids in identifying the afflicted domains. Different learning environments are developed here. In this case, a differentiated environment for the acquisition is created with a multiple-criterion decision analysis approach.[19] Through the mediating influence of student happiness, the authors of the research examined the connection between the 4Cs and performance effectiveness. Students in Thailand provided the data, which was then examined. The 21st-century learning model and student performance effectiveness have been demonstrated to be significantly mediated by student satisfaction.[20] The difficulties faced by students and professors during the COVID period have been examined by Vian Ahmed and Alex Opoku using the framework of the Emergency Management Life Cycle. In this study, the authors gathered information on the difficulties, solutions, and effective methods of online delivery from students and instructors through interviews and questionnaires. Following examination, it was shown that using technology-supported tools improved students' experience of learning.21

The Felder-Silverman Learning Style Model is differentiated due to its robustness and practicability while addressing differences in learning styles. Its distributed acceptance and empirical support, make it a desirable choice for researchers.30

The quick shift towards online education presented both students and instructors with a variety of difficulties in terms of learning and competence. Despite these difficulties, they discovered that teachers with strong communication abilities and a flexible teaching approach contributed favorably to a sudden transfer online. Soni Sweta *et al.* have collected data using Moodle. They have created a Bayesian Network Dynamic Dependency Adaptive Model for predicting learning styles. They have used highly correlated dependent variables for the prediction of the learning styles.[22] They also have used the face expression recognition method for detecting the emotions of learners. Real-time pictures of the learner were captured for this purpose and CNN was utilized.[23,24] Biometric information was used for learning style detection.[25] Here authors have collected data using eye trackers and accelerometers. Based on it learning styles are predicted. Huong et. al has directed recent developments, challenges, and opportunities while integrating learning styles with the e-learning portal.[26]

Sayed, W.S.et al. proposed a model for an adaptive E-learning platform that addresses diverse learning styles by combining the VARK model and gamification. Authors have used Deep Q-Network Reinforcement Learning and rule-based decision-making and found enhanced learning outcomes. However, there is a scope for testing this model for the data collected from real students for the different supervised models.[38]

Researchers in the paper have presented a framework using a Weighted Sum Model and an Artificial Neural Network (ANN) to recommend collaborative activities. They have utilized the Gardner and Korth framework to identify learners' styles. This model needs to be tested on a wider range of learning contexts and subjects beyond programming languages.[39]

Even though there is a lot of work done in this area, there are few gaps that need to be addressed. Those gaps include

i. Habit of procrastination

ii. Dynamic Nature of Learning

iii. Validity and Reliability of Assessment Tools

iv. Need for various optimizers for training classifiers

A) Importance of Optimization in Neural Networks:

Optimizers have a crucial function in the functioning of neural networks. Understanding their mechanisms would aid in selecting the most suitable optimizer for a given application. In the realm of deep learning, loss serves as an indicator of the model's performance at a given point in time. Consequently, this loss is utilized to train the network to improve its performance. Essentially, a lower loss value corresponds to better model performance. The optimizers aim to update the characteristics of the neural net, such as the weights of neurons and learning rate, to reduce losses. It plays a crucial role in minimizing losses and achieving the most precise outcomes possible. Over the past few years, various optimizers have been explored, each offering its advantages and disadvantages. These include Gradient Descent

(GD) and its variants, AdaDelta, Nesterov Accelerated Gradient (NAG), Adam, etc.

B) Impediments of the existing optimizers:

Each of the above optimizers has its Benefits and impediments. A few of the impediments are listed below.

- The time needed to finish a single age is enormous, contrasted with the GD calculation.
- Takes quite a while to converge.
- May trap at local minima
- Involve enormous memory to compute the gradient on the complete data
- The update is very noisy.
- Takes a more extended chance to converge
- The hyperparameter should be chosen manually
- The learning rate is continually diminishing causing slow training.

By looking at these impediments, it is found that there is a need to have an algorithm for training the neural networks that can overcome a few of the listed impediments. Fig. 1 shows a review of research on Learning Styles. Work that is already done by the researchers and challenges are listed.

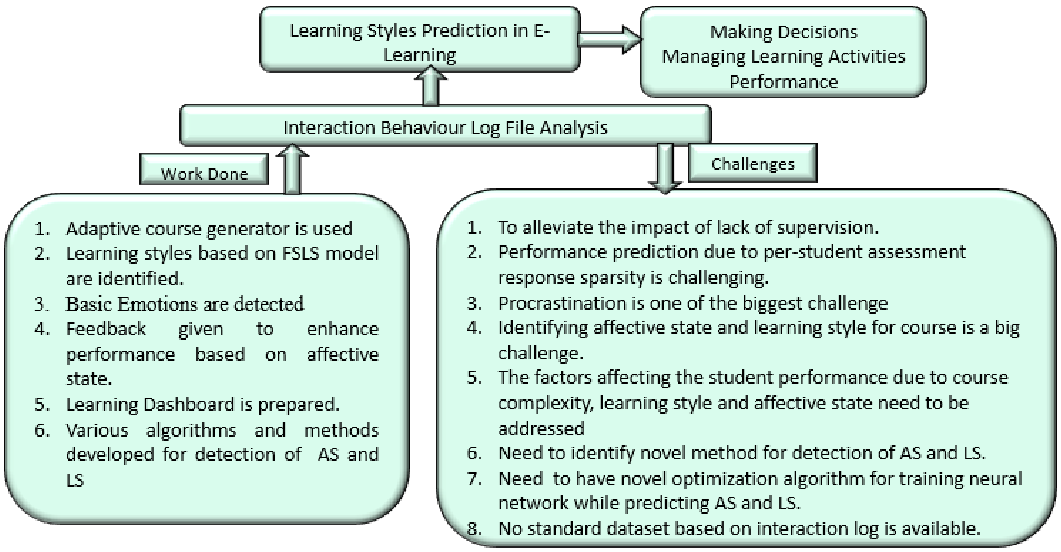

Figure 1. Review of Research on Learning Styles

Proposed Hybrid Squirrel-Rider-based Neural Network for Prediction of Learning Style

Adaptive online learning platforms are among those that prioritize knowledge acquisition. The system is developed using the learning styles that involve inspiration for structuring the courses. The goal of the research is to devise a method for the prediction of learning styles. First of all three courses such as DSF (Course 1), DBMS (Course 2), and HCI (Course 3) are considered for experiment. The above-mentioned courses are categorized as per their complexity as High, Medium, and Low. Then, said subjects are learned by the students through LMS. Based on the studying behavior, an interaction log is recorded. Every file includes the topic Number, lecture type, time spent, and exam marks of each student. Then, the features are taken out from it. Depending on the extracted feature, the learning style of the learners is predicted using a NN.[27]

A neural network is trained utilizing the proposed Squirrel-Rider hybrid optimizer. This hybrid algorithm is formulated through the integration of Squirrel Search and Rider Optimization Algorithm.[28,29] This hybrid optimizer-supported neural network effectively predicts the learning styles. Eventually, the pupil and course ID, learning style, course completion status, and test score data are taken to find the correlation. The proposed methodology consists of the four phases viz. i. Data Collection ii. Preprocess data and extract features iii. Prediction of learning styles of learner and iv. Finding a correlation between learning style with a score on an exam and completion of the course.

1. Data Collection:

A learning Management system is used for the collection of interaction data of the students. Data is collected as a log file for the three different courses with varied complexity such as DSF (Course 1), DBMS (Course 2), and HCI (Course 3) for around 100 students.

Here every course has five units and each Unit has topics with ten lectures which contains videos, document, PDF, PPT, and exams having twenty questions each. The log recorder records the learner's behavior

2. Feature Mining:

After preprocessing the collected data, features are extracted from it. The following eight features are extracted for every student and every subject daily.

FEA1: The amount of lectures done.
FEA2: The quantity of written material covered (PDF/doc/PPT).
FEA3: The number of videos explored.
FEA4: The quantity of topics explored.
FEA5: It signifies learning time.

FEA6: The number of exams given
FEA7: It gives frequency ID.
FEA8: It represents the frequency of sign_in.

Features are selected based on the learning styles identified by Felder Silverman. According to Felder Silverman, the learning styles of students are categorized into four classes Sensing-Intuitive, Active-Reflexive, Visual-Verbal, and Sequential-Global.

3. Learner's learning style prediction using a Hybrid Squirrel-Rider-based Neural Network

LS has a crucial importance in learners learning. The prediction of LS is helpful in educational settings and it is related to enhancing learning outcomes. Here, the projected Hybrid Squirrel-Rider-supported Neural Network is formulated for the learning style prediction of learners regularly. Based on the uprooted features, the classifier forecasts the learner's learning styles. Neural Network is trained with the proposed Hybrid Squirrel-Rider algorithm and it is obtained by combining ROA and SSA. This classifier predicts the learning styles efficiently depending on the given features. The details of the classifier, its training, and the generated output are given as follows.

Architecture of Neural Network

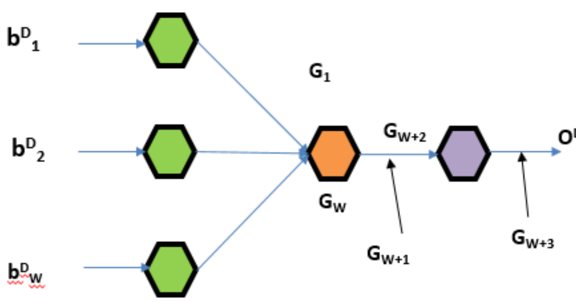

Figure 2 Neural Network Architecture

This classifier consists of the input, hidden, and output layers with neurons. The input given to the neural network is expressed as,

$$b^D = \{b_1^D, b_2^D, \ldots, b_\omega^D, \ldots, b_W^D\}$$

Where W indicates several features. The categorization is carried out using weights. The weight of hidden layers neuron is given as, $G = \{G_1, G_2, \ldots, G_W\}$

Gw+1 expresses the bias posed by the neuron of the hidden layer. Gw+2 expresses the weights of the neurons in the output layer. Gw+3 gives a bias to the output layer. So, the classifier output is evaluated using the following function given as,

$$O^D = G_{W+2} * \left[\log sig\left(\sum_{\omega=1}^{W} b_W^D * G_W + G_{W+1} \right) \right] + G_{W+3}$$

Where,
$\log sig$ symbolize log-sigmoid transfer function. It computes output based on a given input,

b_W^D denotes input of with neuron; G_W represent the weight of with neuron and
G_{W+2} Indicates output weight, G_{W+1} and stands for biases.

Training of Neural Network using proposed Hybrid Squirrel-Rider Algorithm

The learning style prediction is done using a neural network which is trained using a hybrid Squirrel-Rider algorithm. It is the fusion of SSA and ROA.

In the squirrel search algorithm (SSA), Squirrels are initially randomly located. SSA is obtained by dynamic foraging behavior and effectual way of locomotion (gliding) of squirrels. SSA acquires global optimum solutions and provides constant accuracy. It also can effectively search space exploration. According to this algorithm in the forest, it is assumed that three different types of trees exist in the forest acorn nuts tree, normal tree, and hickory nuts tree. Then, each squirrel quests for nutrients and makes use of their present resources optimally by demonstrating a run-time foraging behavior. It consists of three cases i. Squirrels at present on acorn trees may go to the hickory tree. ii. Squirrels at present on normal trees may go to the acorn nut trees and iii. Squirrels who have consumed acorn nuts move from normal to the hickory tree.

According to SSA, the position update equation of squirrels is given as,[29]

$$P_{e+1}(h,j) = P_e(h,j) + d_r \times B_d (P_e(f,j) - P_e(h,j)) \quad (1)$$

Where, $P_e(f,j)$ show squirrels on acorn nut tree. $P_e(h,j)$ shows squirrel position which is on a hickory nut tree, random gliding distance is d_r, and the gliding constant is B_d.

After rearranging the equation 1, we get equation 2 as bellows

$$P_e(h,j) = \frac{P_{e+1}(h,j) - d_r B_d P_e(f,j)}{1 - d_r B_d} \quad (2)$$

According to the Rider Optimization Algorithm, four types of riders exist. The motivation behind ROA is rider groups, who change the location to acquire a common target position. They are viz. i. Bypass rider ii. Overtake rider iii, Follower rider, and iv Attacker rider. Each of these riders tries to win the race by reaching the leading position. They use different strategies to become the winner.

The ROA is greatly efficient and undergoes imaginary computing to solve the optimization issues, but contains less convergence. Each of these riders has its update equation as per the strategy it follows. The Overtaker rider uses the strategy of overtaking the other riders and has enhanced chances of winning the race. The updated equation of Overtaker rider is

$$P_{e+1}(h,j) = P_e(h,j) + \left[D_e^R(h) * P^L(L,j)\right] \quad (3)$$

Where, $P_e(h,j)$ is the position of the hth rider in jth coordinate, $D_e^R(h)$ stands for direction, j is a coordinate selector, P^L indicates the position of the leading rider, and L indicates the leading rider's index.

Substitute equation (2) with equation (3) and rearranging it, we get the final equation 4 of the hybrid Squirrel-Rider algorithm

$$P_{e+1}(h,j)=\frac{1-d_rB_d}{-d_rB_d}\left[\frac{-d_rB_dP_e(f,i)}{1-d_rB_d}+D_e^R(h)*P^L(L,j)\right] \quad (4)$$

After using this hybrid optimization technique, it is observed that this method performs learning style prediction with enhanced accuracy of classification. The training of neural networks is performed using the proposed optimizer. The learning style obtained using FSLSM is predicted using the Neural Network.[30] Here, the learning style of each student for each course is predicted.

Correlation study

The correlation analysis is performed to find the relationship of learning style with examination rating and completion of the course. Here every student's exam score and course completion status are calculated. The relationship of it with learning styles is identified. From the learning styles, one can understand the pattern of learning of a student which is very important for enhancing learning outcomes.[35] Students may have different ways of learning and if they get learning material suitable to their learning styles, their interest in learning may be enhanced and chances of dropout may decrease.[31,32] Here, the student and course ID, learning style, the score exam, and the completion status of the course are taken further for doing a correlation study.

Results and Discussion

The usefulness of the proposed Squirrel-rider-supported Neural Network is evaluated using accuracy and correlation. The comparison of the proposed algorithm against a few popular techniques is performed by changing courses and by changing student's performance categories.

1. Comparative analysis

An evaluation of methods with parameters like, accuracy and correlations are performed by changing courses of varied complexity. In addition to this, the analysis is done by changing the performance of the students.

2. Analysis using Case 1

The comparison of techniques for learning style prediction concerning accuracy is represented with different courses. Also, the correlation analysis of learning style versus examination rating and learning style versus course completion is done.[34]

Comparison of learning styles prediction techniques using accuracy for varied courses

Figure 3 shows the accuracy of prediction of learning styles using different techniques for varied courses. Considering Course 1, Course 2, and Course 3, the accuracy measured by the Squirrel-Rider supported Neural Network technique is 0.95, 0.901, and 0.885 respectively. It is more in comparison with the output received by other acknowledged techniques like RNN and NN. Figure 4 shows an analysis of different techniques using the correlation of learning style with scores of exams for varied courses. Concerning courses 1, 2, and 3, the correlation calculated by the proposed Squirrel-Rider-based Neural Network technique are 0.406, 0.326, and 0.22 respectively. It is more in comparison with the output received by other acknowledged techniques like RNN and NN.

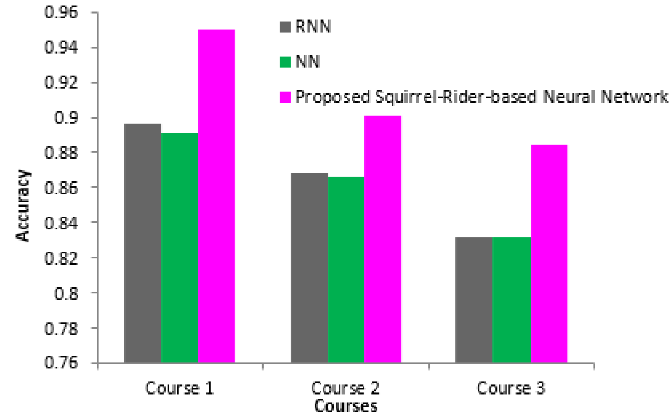

Figure 3 Comparison of learning styles prediction techniques using accuracy for varied courses

a) Correlation Measure of learning style with a score of exam

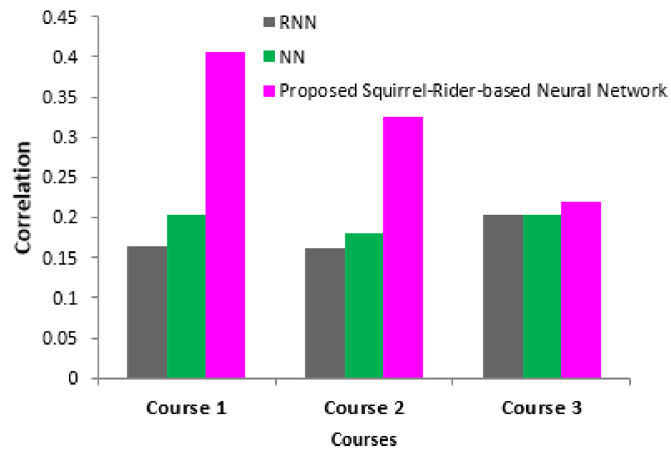

Figure 4 Correlation measure of learning style with a score of exams

b) Correlation Measure of learning style with completion of the course

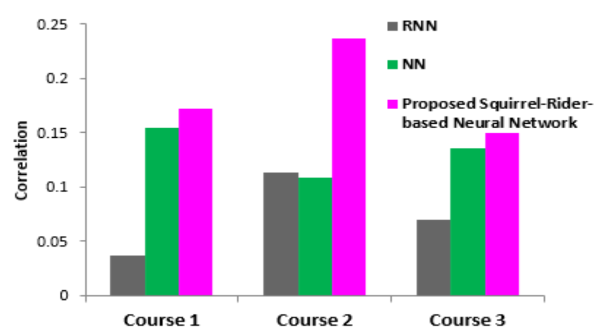

Figure 5 Correlation measure of learning style with completion of course status

Figure 5 shows an analysis of different techniques using a correlation of learning style with completion of course status for varied courses. Considering Course 1, course 2, and Course 3, the correlation measured by the proposed Squirrel-Rider-based Neural Network technique is 0.172, 0.237, and 0.15 respectively. It is more in comparison with the output received by other acknowledged techniques like RNN and NN.

5.5.2. Analysis with Case 2

The comparison of techniques for learning style prediction concerning accuracy is represented with varied student performance categories. Also, the correlation analysis of learning style versus examination rating and learning style versus course completion is done.

a) Comparison of learning styles prediction techniques using accuracy for varied student performance categories:

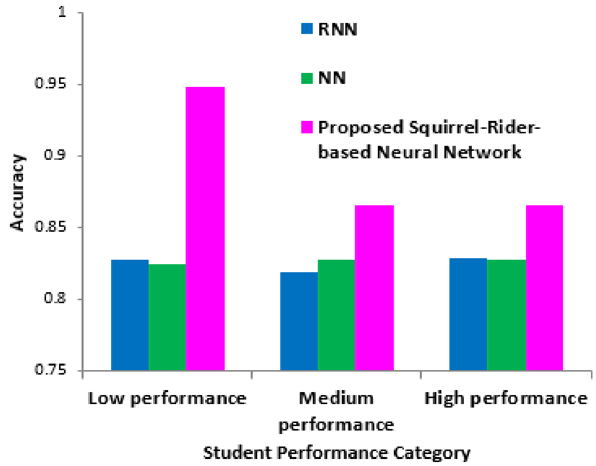

Figure 6 Comparison of learning styles prediction techniques using accuracy for varied student performance category

Figure 6 shows the accuracy of the prediction of learning styles using different techniques for varied student performance categories. Considering the Low, Medium, and High student performance categories, the accuracy measured by the proposed Squirrel-Rider-based Neural Network technique is 0.948, 0.866, and 0.866 respectively. It is more in comparison with the output received by other acknowledged techniques like RNN and NN.

b) Correlation measure of learning style with score of exam:

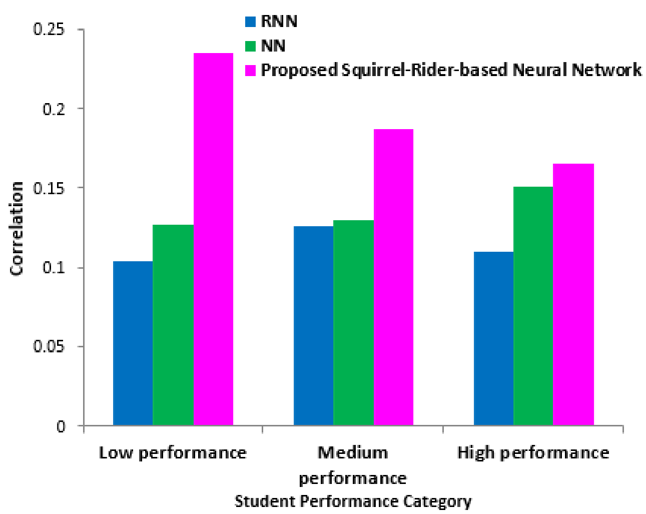

Figure 7. Correlation measure of learning style with a score of the exam

Figure 7 shows an analysis of different techniques using the correlation of learning style with the score of the exam for varied student performance categories. Considering Low, Medium, and High student performance categories, the correlation measured by the proposed Squirrel-Rider-based Neural Network technique is 0.235, 0.187, and 0.165 respectively. It is more in comparison with the output received by other acknowledged techniques like RNN and NN.

c) Correlation measure of learning style with completion of the course:

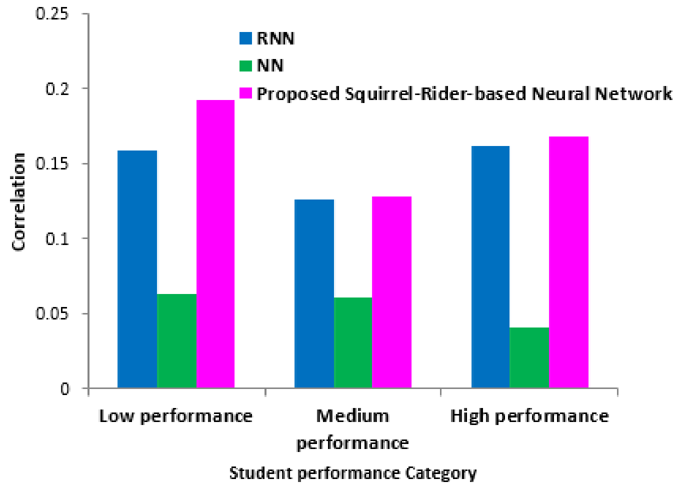

Figure 8 Correlation measure of learning style with completion of the course

Figure 8 shows an analysis of different techniques using the correlation of learning style with completion of the course for varied student performance categories. Considering the Low, Medium, and High student performance categories, the correlation measured by the proposed Squirrel-Rider-based Neural Network technique is 0.193, 0.128, and 0.168 respectively. It is more in comparison with the output received by other acknowledged techniques like RNN and NN.

The limitation of this study lies in the availability of the dataset. No standard interaction log dataset is available for the prediction of learning styles. This system may get tested for other datasets in the future.

4.1.2 Statistical Analysis:

The Proposed Squirrel-Rider-based Neural Network outperforms the other algorithms. If the Null Hypothesis is "The Squirrel-Rider-based Neural Network approach doesn't have a major effect on improving the prediction accuracy of learning styles". Results of the t-test applied on the Squirrel-Rider-based Neural Network and NN show that |t stat| > T Critical and P value < 0.05. So, the Alternate Hypothesis "The Squirrel-Rider-based Neural Network approach has a major effect on improving the prediction accuracy of learning styles" can be accepted. The outcome of the t-test is shown in Table 1.

Table 1: Outcome of t-Test of Squirrel-Rider-based Neural Network and NN

t-Test: Two-Sample Assuming Equal Variances	
Mean	0.902666667
t Stat	3.01108725724888
P(T<=t) one-tail	0.0065466360031096
t Critical one-tail	1.81246110219722

CONCLUSION

In this paper, a method for predicting learning styles is developed. Three courses are first used for the study: Data Structures, database, and Human-Computer Interface. For perceiving the course complexity survey was conducted and responses were collected from Computer and IT engineers and teachers.

These courses are taken by a variety of students, and the log file was made based on their study habits. The feature indicators are then retrieved and used for the neural network-based prediction of learning styles.

The neural network training is carried out with the proposed hybrid Squirrel-Rider optimizer and is developed by integrating SSA and ROA. Here, the prediction of styles of learning Active-reflective, Sensing-intuitive, Visual-verbal, and Sequential-global are performed. FSLSM is considered for the prediction of learning styles. Here, the Squirrel-Rider-based neural network classifier classifies learners into different dimensions. Finally, the pupil and course ID, learning style, course completion status, and exam score are considered for correlative study. The proposed Squirrel-Rider-based neural network outperformed other techniques with a high accuracy of 0.95 and a maximum correlation of 0.406 respectively. In the future other learning style models may be considered for prediction of learning styles. Also, multimodal approach that may take input in the form of facial expressions, sensor data may get developed.

CONFLICT OF INTEREST STATEMENT

The authors declared no conflict of interest the for publication of this work.

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