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DEEP LEARNING ENABLED COURSE RECOMMENDATION PLATFORM

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ABSTRACT

E-learning platforms have gained much recognition in the field of teaching and learning especially after the outbreak of Covid 19. Many aids have been produced considering the demand for the online platform. One such aid is Learning Management System (LMS). However, prediction performance of the learner is challenging in LMS. Enabling a student to select a course, the function of Course Recommendation system is vital. In order to rectify the deficiencies in the existing system, intelligent system is recommended as it helps selecting a personalized set of data from a mass volume of information. Main objectives of this research are deep learning is considered for increasing the accuracy, the performance should be boosted with the proposed hybrid optimization technique, effectively perform the learning style prediction using random forest for achieving a more accurate recommendation of the course, to analyze the performance of the developed Taylor-CSO algorithm for ensuring accuracy and True Positive Rate (TPR) and True Negative Rate (TNR). Thus this research is an attempt to propose feasible methodologies on learning style-based performance prediction and course recommendation in E-Khool learning platform using deep learning algorithms. This research will fill in the existing research gaps in field of deep learning algorithms in electronic platforms

KEYWORDS: Course Recommendation, Deep Learning, E-Khool and Electronic Learning,

1. INTRODUCTION

Due to the tremendous development of the Internet, E-learning platforms have nowadays considered as the most promising platform that assists students to develop their skills to attain successful outcomes in intended learning. In fact, the learning platform also supports educational organizations to establish e-learning programme by designing new mechanisms to offer their educational related materials (Aissaoui, et al., 2019). E-learning has facilitated the process of learning different courses for more than 81 million students and has set the diverse skills across the world. While comparing with the existing educational pattern, E-learning offers a cost-affordable and free learning approach to student without the atmosphere of classroom effect. In most of the countries that are still developing, e-learning platforms have been utilized as another resource to common learning rooms by professionals, instructors, and tutors (Hassan, et al., 2019). With rapid growth in the number of students, services, and resources in e-learning platforms, one of the effective and feasible methods to enhance student's learning performance is data driven learning analysis (Wang, et al., 2019). Leaning style is considered as one of the significant characteristics that causes severe impacts on learning attainement of a given learner as it facilitates the system to customize the learning methods based on learner choices (Aissaoui, et al., 2019). Generally, learning style is termed as the valuable option for the learners to learn. Every individual has their own style in learning way that helps them to progress them effectively and also differ from one sceanrio to another. Usually, the learner's learning style is used to determine the capacity of the learner and the way of acquiring knowledge in several methods in a learning system.

In fact, learning style is characterized by many factors, like notes, exams, course contents, tutorials, assignments, and exercises and the pattern in which the course is arranged and presented, the way of presenting the information to the learners, the communication mechanism between learners, like discussion, chat rooms, and e-mail systems. Learning style is also termed as the representation of student's behaviors, and attitudes that determines the individual's way of learning (Aissaoui, et al., 2019). The learning system is utilized by different learners with various background, capabilities, skills, choices, interests, requirements, and learning way. The limitation of determining the learner's learning capabilities, and acquiring latest knowledge and skills has been receive much and more attention among the researchers for the past few years. In order to tackle such limitations, there is a demand for determining the individual's learning styles and guide the learner to select the courses according to the learner's learning capabilities and makes them to fit (Al-Masri and Curran, 2019). Nowadays, there has been an increasing attention concentrated by the learner's, like learning styles (Viola, et al., 2006), involving the effect of learning performance, and how learner should be assisted by flexible techniques. There is variety of mechanisms to estimate the learning style of student's. But some of the researchers quote that there is no sufficient proof to justify integrating leaning resources into common educational practice (Pashler, et al., 2008), hence this discrepancy between evidence and practice has stimulated disagreement, and few have represented the learning style as 'myth' (Newton and Miah, 2017). However, all such discussions are based on evidence and experiments in conventional classrooms and are cost affordable (Li and Zhou, 2018).

A Course Recommendation system guides the students to select the appropriate course and the personalized environment will have the potential to attract the learner to such system. A recommender system is defined as an intelligent system suggests a personalized set of data excerpted from a mass volume of information. Generally, the recommender system extracts the data based on user rating or suggestion on some element called collaborative filtering and the data based previous user's preference is called as content-based filtering. Content-based filtering suggests the courses preferred by same persons previously (Isinkaye, et al., 2015; Pritam, et al., 2019; Mondal, et al., 2020). However, this can be a very complex process as it consumes lot of time and includes accessing every platform, searching of accessible courses, carefully grasping the syllabus of every course and then selecting the course that is most suitable for the student (Apaza, et al., 2014 ; Klasnja-Milicevic, et al., 2018). Today, Artificial Intelligence is said to be a boon to most of the application fields and the deep learning technology is the most frequently used technology among the researchers. It provides better performance in feature extraction process, and can utilize a complicated framework to distinguish the internal structure of information. In fact, the deep learning research faces a lot of hurdles in the field of artificial intelligence. Deep learning techniques, such as Convolutional Neural Networks (CNNs), Stacked denoising autoencoders (SDAs), Deep Belief Networks (DBNs), and recurrent Neural Networks (RNNs) (Mikolov, et al., 2010) have attained better results in natural language semantics, image processing, text classification, and speech. Moreover, deep learning technology has also received good results in the field of recommendation systems (Zhang, et al., 2019).

2. REVIEW OF LITERATURE

Muhammad Awais Hassan et al.(Hassan, et al., 2019) devised a model that offered personalized gamification experience amongst each student considering the system interactions, which outcomes in increased motivation, increased interaction, and decreased drop-out ratio.

Xizhe Wang et al. (Wang, et al., 2019) devised a predictive model for effectual learning feature extracting, learning performance predicting and result reasoning. Here, a general learning feature quantification method was utilized for converting the raw data from e-learning systems into groups of independent learning features. Thereafter, a weighted avg-pooling was selected inspite of typical max-pooling in a convolutional GRU network for learning performance prediction. At last, an improved parallel xNN was offered to explain the prediction results.

Chao Li and Hong Zhou (Li and Zhou, 2018) devised hybrid Neural Network (NN) model which combined a Convolutional Neural Networks (CNN) and Gated Recurrent Unit (GRU) based Recurrent Neural Networks (RNN) in to discover individual learning style dynamically. The model was trained using learners' behavior data and adapted to predicting their learning styles.

Aleksandra Klasnja-Milicevic et al. (Klasnja-Milicevic, et al., 2018) devised the suitability of different techniques for adapting tag-based recommendations in e-learning platforms. The most suitable model ranking, on the basis of tensor factorization technique, was enhanced to gain the most effective recommendation results.

Ouafae El Aissaoui et al. (Aissaoui, et al., 2019) devised a generic approach for detecting learning styles in an automated manner. In fact, this technique does not relied on a particular LSM. This work comprises two major steps. First was extraction of learning sequences using learners log files considering the web usage mining. Secondly, the extracted learners' sequences were classified.

Shaimaa M. Nafea et al. (Nafea, et al., 2019) developed recommender algorithm for machine learning that combined students actual rating and learning styles for recommend personalised course learning objects (LOs).

Boran Sekeroglu el al. (Sekeroglu, et al., 2019), devised two datasets for prediction and classification of student performance. Eighteen experiments was carried out and outcomes suggested improved students performances.

Sadiq Hussain et al. (Hussain, et al., 2019) devised classification techniques like Artificial Immune Recognition System v2.0 and Adaboost, to discover students' performance prediction. Here, the maximal classification rate was 95.34% generated by the deep learning.

Table 1: SUMMARY OF REVIEW OF LITERATURE

Authors	Methods	Advantages	Disadvantages
Muhammad Awais Hassan et al. (Hassan, et al., 2019)	Felder Silverman Learning Style Model (FSLSM)	This method increased the communication with the system and decreased the drop-out ratio.	Failed to offer the feedback depending on the student learning type.
Xizhe Wang et al. (Wang, et al., 2019)	Conv-GRU and Parallel-xNN (P-xNN)	Achieved effective learning performance prediction.	Failed to accomplish some aspects of learning, such as sentiment analysis, trend prediction, and generation of learning path.
Chao Li and Hong Zhou (Li and Zhou, 2018)	Convolutional Neural Networks (CNN) and Gated Recurrent Unit (GRU) based Recurrent Neural Networks (RNN)	Effective identification of learning style of user's.	The approach was unable to provide adaptive learning system.
Aleksandra Klasnja-Milicevic et al.	Collaborative tagging	Provided accurate understanding about the	Failed to measure the impact of prior learner

(Klasnja-Milicevic, et al., 2018)	technique	learning content.	experience.
Ouafae El Aissaoui et al. (Aissaoui, et al., 2019)	Felder-Silverman Model and Fuzzy C-Means clustering algorithm.	Obtained accurate results and effectively handled the uncertainty of data.	The accuracy of the detection of learning style was low.
Shaimaa M. Nafea et al. (Nafea, et al., 2019)	Felder-Silverman learning style model (FSLSM) and Rating prediction algorithm	Provided best prediction accuracy. Effectively managed the cold-start and rating sparsity issues.	Dataset was too small.
Boran Sekeroglu et al. (Sekeroglu, et al., 2019)	Machine learning algorithms	Provided accurate results.	Failed to include large datasets.
Sadiq Hussain et al. (Hussain, et al., 2019)	Recurrent Neural Network (RNN)	Achieved effective identification of poor performers.	Computational time was high.

3. RESEARCH GAPS

The approach developed in (Liyanage, et al., 2016), successfully identified the learning style of the students and provided materials according to their learning style that enhanced the learning capacity of the students. The major obstacle in this method is that it had the capability to test on few numbers of learners. Felder Silverman Learning Style Model (FSLSM) developed in (Hassan, et al., 2019), was highly desirable because of the appropriate selection of adaptive gamification components and activities that considerably increased the factors, such as course completion, communication in the E-learning course, and interest, but it failed to motivate the students using adaptive gamification elements. In (Lau, et al., 2019), the Artificial Neural Network (ANN) effectively evaluated the student's performance, but still this approach resulted poor classification of students based on their gender. Though the MOOCRC method introduced in (Zhang, et al., 2019), achieved better recommendation efficiency and faster convergence speed, it failed to offer the student's performance based on their learning style.

4. DEFINING RESEARCH PROBLEM

Even though the recommendation of course is devised and helped to analyze the information, but it failed to optimize algorithm by accuracy. Here, deep learning is considered for increasing the accuracy. In previous works, Apriori algorithm is devised, which helped the customers to offer best solution and boosted the technique to offer improved outcomes. However, the method lacks performance in E-commerce domain. The performance is boosted with the proposed hybrid optimization technique.

5. RESEARCH METHODOLOGY

The primary motive of this research will be to develop and design a newly proposed scheme called Taylor- Competitive Swarm Optimizer (Taylor-CSO) for effective learning style based performance prediction and course recommendation using E-Khool learning platform. The E-Khool LMS is a learning platform, which will be utilized for the creation of course and adding the learners. Initially, the log file with the records containing the course ID, topic ID, lecture type, time spent, and the exam score of the learners will be given as the input for the extraction of features. The features, such as time spent, lecture type, activity time & day, and entropy will be extracted from the log file. After the extraction of features, the Learning style prediction based Felder Silverman learning style model, where four learning style such as, active and reflective learners, sensing and intuitive learners, visual and verbal learners, and sequential and global learners will be considered using the random forest. Then, the learning preference will be identified based on similarity based computation model. Finally, the performance prediction based on learning style and learning preference will be done with the help of Deep residual neural network (Chen, et al., 2019). However, the Deep residual neural network will be trained using the proposed Taylor-CSO. The proposed Taylor-CSO algorithm will be developed by integrating the Taylor Series (Mangai, et al., 2014) and Competitive Swarm Optimizer (CSO) (Cheng and Jin, 2014). On the other hand, from E-khool LMS features like course review, course interestingness, and course buying sequence will be extracted. Furthermore, the course recommendation will be carried out using the same Deep residual neural network, which will be trained by the proposed Taylor-CSO algorithm. Moreover, the input log file will be simulated in the e-khool LMS platform and the implementation of the proposed method will be done in PYTHON tool. The performance analysis of the proposed Taylor-CSO will be done based on the evaluation metrics, like accuracy, TPR and TNR. The comparative analysis will be done with respect to the evaluation metrics, and the results of the proposed method will be compared with the existing techniques such as (Hassan, et al., 2019; Wang, et al., 2019 ; Li and Zhou, 2018) in order to reveal the performance improvement.

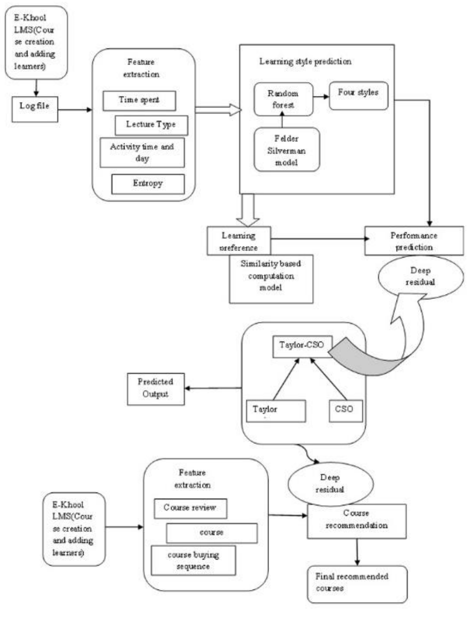

Figure 1: The block diagram of proposed method

6. CONCLUSION AND FUTURE SCOPE

This research present a newly proposed scheme called Taylor-CSO for effectual learning style based performance prediction and course recommendation considering the E-Khool learning platform. The E-Khool LMS is a learning platform, which are used for creating course and adding learners. At first, the log file with the records containing the course ID, topic ID, lecture type, time spent, and exam score of learners are given as an input for features extraction. The imperative features like time spent, lecture type, activity time & day, and entropy are mined using log file. After feature extraction, the prediction of learning style using Felder Silverman learning style model is done, wherein four learning style like active and reflective learners, sensing and intuitive learners, visual and verbal learners, and sequential and global learners are employed with random forest. Thereafter, the learning preference is discovered on the basis of similarity based computation model. At last, the performance prediction using learning style and learning preference are performed using Deep residual neural network (Chen, et al., 2019). However, the training of deep residual neural network is done proposed Taylor-CSO. The proposed Taylor-CSO algorithm is obtained by combining Taylor Series (Mangai, et al., 2014) and CSO (Cheng and Jin, 2014). On the other hand, from E-khool LMS features like course review, course interestingness, and course buying sequence are extracted. Finally, the course recommendation is performed with proposed Taylor-CSO-based Deep residual neural network. In future, additional datasets can be considered to check the feasibility of proposed model.

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