An Effective Online Learning Course Recommendation Using Improved Deep Active Convolutional Neural Network Based Sentiment Analysis and Ranking

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Abstract: *Online learning platforms are used to discover the optimal learning courses for learners according to their interests and knowledge. An effective methodology is needed to suggest effective learning courses according to Sentiment Analysis (SA). It is difficult to handle large user feedback manually, so the recommendation system is utilized. The recommender system should be developed with high efficiency in filtering information. Also, it requires efficient access and resolves the issue of information overload. In order to solve this issue, effective deep learning-based approaches for online course ranking were presented in this paper. The input dataset used for this work contains the information on the online course. Initially, the input text data is pre-processed using different effective pre-processing approaches. Afterwards, features such as Improved Term Frequency-Inverse Document Frequency (ITF-IDF), Bag of Words (BoW), and glove word embedding are extracted to enhance the classification performance. Further, the Modified Rain Optimization (MRO) algorithm is utilized for feature selection by reducing the redundant features. Finally, an Improved Deep active Convolutional Neural Network (IDCNN) is presented for online course preference SA. Here, the Adaptive Beetle Antennae optimization algorithm (ABA) is utilized for weight optimization in the proposed IDCNN. This enhanced IDCNN predicts effective online courses by using SA as positive, negative, and neutral. Finally, the optimal learning course ranking is performed through the Jaccard similarity approach. This final recommendation through ranking improves the quality of the selection process for an online course. The presented methodology is implemented in the Python programming language. The experimental results proved that the presented approach attains enhanced performance on different performances like accuracy (98.17%), precision (98.23%), F1-score (98.19%), Root Mean Squared Error (RMSE) (0.21), Kappa (97.06%), recall (98.21%), and Area Under the Curve (AUC) (98.17%).*

Keywords: *Text pre-processing, feature extraction, feature selection, optimization, sentiment analysis, online learning, recommendation*.

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1. Introduction

Electronic learning (E-learning) has gained extensive advancements in all fields, especially in education. Nowadays, education is based on e-learning. This technology provides course information and guidance to individuals online [46]. E-learning signifies an effective solution to the non-stop demand of life-long learning. It is an inspiring way to learn life-long skills, provided by the constructive integration of new skills.

Moreover, e-learning makes learning more interactive compared to the distance learning strategy. The internet and its services assist users, and the tracking procedures are certainly combined with the educational and technical aspects of dynamic learning [10]. The major aim of the e-learning recommender system is to suggest a series of items to learners. This recommends only the most effective courses to the learners [5, 48]. Nowadays, e-Learning accomplishes the integrated learning process to clarify new concepts and subjects and to learn advanced technologies in different approaches [24]. Many online course platforms, such as Massive open online courses (MOOCs), Khan Academy, etc., are available for different subjects [24]. Online learners are not familiar with selecting online courses. They can improve their online course selection by analyzing the reviews of students using effective learning approaches [13].

Online education is an important context for attracting great attention to people. With the increasing population, people want to learn online, and e-learning platforms help to adapt and advance the way in suggesting courses to learners [3, 21]. The associated platforms are intended as social networks where the thoughts concentrate on particular topics regarding the quality of course contents, tutors' skills, etc. Numerous Sentiment Analysis (SA) methods used to predict the students' opinions are intended to suggest content or emphasize insufficiencies in courses [11]. The social network and communication dynamics interfere with the SA, and this analysis is useful for knowing the learner's satisfaction with the courses. Based on users' reviews, online courses effectively predict advanced learning courses and provide details about particular courses. The SA approach predicts the positive and negative data about the courses. The new learners must choose an optimal learning course [14, 15].

Recommendation systems are used to find the services and products that meet users' respective needs and preferences. In past decades, recommendation systems have been widely used in social platforms with large amounts of internet data. The course recommendation framework recommends an appropriate course for the user according to the user's interests. Currently, various methodologies are utilized to recommend courses. Online course recommendations are the most important way to aid students in selecting relevant courses. Course recommendation systems are designed to assist students in selecting courses that align with their academic goals, interests, and needs. These systems can be particularly beneficial for students with varying requirements, such as those needing specific guidance due to differing academic backgrounds, career aspirations, or personal interests [17, 56].

The recommendation system is used for personalized learning through an accurate recommendation of courses and feedback to the learners. In the recommendation process, a system analyzes and compares the individual characteristics to the community. The optimal list evaluation of recommendations saves an amount during the data search process. The recommendation process can increase the possibility of studying courses according to their interest in quality platforms [1]. Online course learning can cut the time spent learning. Recommendation frameworks filter courses based on user's interests and needs from multiple sources. The framework simplifies the process of recommendation and attains relevant information. The recommendation system can provide the course list in a priority order [45].

In online learning, social media plays an important role in students' choices of courses [52]. Online course evaluation plays a crucial role in both course selection for students and teaching effectiveness for educators. However, current evaluation methods have faced criticism for overlooking the needs of learners and for being inefficient [57]. Different methodologies are used in the existing studies to predict learners' satisfaction with the course. The SA on online learning systems is intended to predict the user's preference for a topic. This has advanced considerably and is broadly utilized to adapt learning experiences. Different machine techniques, such as Support Vector Machine (SVM) [40], decision tree, and random forest [28, 37], are presented to recommend better courses for new learners based on SA. Moreover, deep learning techniques such as Recursive Neural Network (RNN), Convolutional Neural Network (CNN), and Long-Short Term Memory (LSTM) are presented [55]. However, the accurate suggestion of optimal e-learning courses is still in demand, and this needs effective methodology [4, 7].

In an e-learning setting, deep learning techniques-based systems can successfully recommend associated actions before attempting new learning sections. This provides customized references for learning resources that depend on the learning interests and learning paths of individuals in online learning programs [30]. The collaborative Multi-Armed Bandit (MAB) technique is used to deal with the arrival of individuals and insufficient feedback from the online recommender. Individuals collaboratively recommend the implicit social relationship or explicitly known terms [54]. The high-quality recommendation system has three components: a candidate generation module, a diversity promotion module, and a scope restricted module [23]. The online learning platform challenges users to pick relevant learning materials and courses based on their interests and requirements. To improve the skill and knowledge of learners, several viewpoints are considered to develop an intelligent based system. It can be attained with semantic recommendations with virtual agents for seeking relevant courses [2].

- **Motivation**

The investigation of online learning courses is important to acquire a valuable understanding of the quality of online courses. Effective analysis is needed to select the online course appropriately. The handling of reviews conveyed by the users would be difficult if they were handled manually. It is unrealistic to handle large amounts of feedback from e-learning platforms. To address this issue, current research has used machine learning algorithms and deep learning models to assess user reviews, sentiments, and methods automatically. These techniques fundamentally enhance different interactive online course learning platforms by combining automatic feedback analysis. Hence, the proposed approach performs the SA in online educational courses presented in recent research and supports the new learners by providing an overall understanding of online courses through SA research. The major contributions of the presented methodology are described as follows.

1. Different effective pre-processing techniques are utilized to pre-process the text data of online course information. Using this pre-processing approach minimizes the dimensionality of input data, and the text is prepared for the task of the recommendation system.
2. Different effective features are extracted to analyze online course learners' sentiments accurately. Here, effective features such as Improved Term Frequency-Inverse Document Frequency (ITF-IDF), glove word

embedding, and Bag of Words (BoW) features are extracted. With efficient feature extraction, the accuracy of the proposed model is improved with less duration.
3. The dimensionality of features is reduced with the Modified Rain Optimization (MRO) feature selection approach, which avoids the redundant features present in the data.
4. Efficient SA is presented as positive, negative, or neutral for online learning courses, with an improved deep learning-based framework Improved Deep active Convolutional Neural Network (IDCNN). Moreover, the network's performance is improved by using an adaptive optimization algorithm.
5. Then, the proposed system performance is compared with the techniques that are currently in use to prove the efficiency of the proposed system.

The rest of the manuscript is organized as follows: Section 2 describes the current literature reviews, section 3 provides a detailed description of the presented approach, section 4 describes the experimental results, and their discussions and the paper are concluded in section 5.

2. Related Work

Kastrati *et al*. [27] presented a weakly supervised framework for attributes-based sentiment examination on students' reviews of MOOCs. This developed framework automatically predicts the sentiment or the polarity of students' opinions on courses. This effectively reduces the necessity of manual annotation information for all the deep learning-based approaches. The automatic aspect-based sentiment evaluation tends to enhance the performance of the deep learning technique.

Ayyub *et al*. [6] introduced different features for SA using machine learning approaches. Moreover, the presented work analyses the introduced features with ensemble classifiers for the performance examination of techniques in SA. Here, N-gram and TF-IDF features were utilized for the analysis. Additionally, multi-layer Artificial Neural Network (ANN) classifiers with different activation functions like Rectifier, Tanh, and Maxout were utilized for the performance. The SA was evaluated using the Word2vec and Glove features.

Liu *et al*. [36] developed a technique for sentiment recognition on online course reviews by utilizing a Multi-swarm Particle Swarm Optimization (MPSO) approach based on feature selection. A large number of features in the process will affect the performance of sentiment prediction in online course learning. Moreover, the redundant features affect the performance of machine learning techniques. The presented MPSO approach reduces the redundant based text features and selects the effective discriminant features for further processing. This subsequently enhances the performance of sentiment recognition in online course reviews.

Hew *et al*. [20] developed a supervised machine learning technique based on SA and hierarchical linear modelling features to examine online courses. The features were extracted using hierarchical linear modelling for MOOCs. These features were utilized to determine students' perceptions of online courses. This suggests the learners choose the optimal learning courses. However, there is still a possibility of improvement in performance examination.

Huang *et al*. [22] investigated the interaction patterns of students as well as the dynamic learning of sentiments. Here, different learning tasks were performed to learn students' sentiments. These sentiments were demonstrated as a periodic feature during online learning. Moreover, a four-phase model was utilized to predict online learning based on students' SA.

Troussas *et al*. [50] developed intelligent educational software for enhancing computer interaction by providing sufficient learning materials to learners. It combines technological and pedagogical techniques for delivering complicated learning materials to students. It was attained by integrating component display theory with content-based filtering and multiple-criteria decision analysis with personalized learning material. The research focuses on the characteristics of students, and it was utilized by the under graduated university students during the period of COVID-19 for learning Java programming.

Chrysafiadi *et al*. [9] described a solution for adaptive e-assessment for creative adaptive tests. For each test item, the representation structure and rule based fuzzy reason was included for the personalized test of each student. For each test item, description, possible answers, correct answers and metadata with several characteristics such as level type learning objective and error categories are assessed by considering the learner's age. It permits the system to check the requirements of the learner. The amount and complexity level of test items were added with the Revised Bloom Taxonomy using a rule-based fuzzy approach.

Krouska *et al*. [32] analyzed the learner's intention with Mobile Game-based Learning (MGbL) for providing educational practices during COVID-19. It was utilized for programming language instruction in higher education. MGbL provides teaching and learning benefits from a technical or pedagogical perspective. Krouska *et al*. [31] presented MGbL applications with Genetic Algorithms (GA) for recommending each student to play with the competitors. Considering the learning mode, present knowledge, misunderstandings, and previous knowledge, appropriate equality status was discovered using GA.

Troussas *et al*. [49] suggested an intelligent tutorial application over Facebook for programme learning. The learning outcomes were enhanced with pedagogical tools of adaptivity and assessment. The integrated tutoring system made use of the Facebook platform's potential. The knowledge gap of the student was covered with query solving of unknown procedures by offering an intelligent Virtual Coach offering. The virtual coach provided tailored assistance based on the revised Bloom Taxonomy for student assessment.

Hasan *et al*. [18] described an AI-based fault diagnosis model. To capture the significance of invariant characteristics, the statistical feature extraction approach and wrapper-based feature selection were introduced. A feature filtration approach was considered for dealing with multicollinearity issues. It occurs due to the presence of correlated features. This approach reduces the dimensionality by removing the collinear feature information from the data. The final feature pool obtained was classified using the K-nearest neighbour algorithm.

Table 1. Comparison of existing approaches.

Article used	Approach used	Novelty	Result obtained
Weakly supervised framework for aspect-based SA on students' reviews of MOOCs [27]	DNN based sentimental learning CNN+FastText	Aspect-based sentiment analysis was presented with a supervised learning approach	F1-score=93.3
exploring diverse features for sentiment quantification using machine learning algorithms [6]	multi-layer feed-forward ANN using diverse activation functions	Word embedding features are explored with sentimental quantification. Diverse activation functions such as Rectifier, Maxout and Tanh were compared with different classifiers.	Absolute Error (AE)=0.092, Relative Error (RE)=9.21, Normalized Absolute Error (NAE)=0.092.
Sentiment recognition of online course reviews using multi-swarm optimization-based selected features [36]	MSPSO	Emotional features were selected to generate multi-diverse particle swarms for cross-training subsets.	For positive subjective samples, precision=88.1, recall=88.2, F-measure=88.1. For negative subjective samples, precision=88.3, recall=88.1, F-measure=88.1, AUC=90.3.
What predicts student satisfaction with MOOCs: A gradient boosting trees supervised machine learning and SA approach [20]	Machine learning with sentimental analysis	MOOCs were randomly chosen to quantitatively analyze the data. A sentimental analysis and a supervised machine learning-based framework were developed to examine large datasets. Learner level and course level factors predict MOOC.	The variance associated with course=0.024, Standard Deviation (SD)=0.160. The variance associated with individual=0.424, S.D.=0.651. P-value<0.01, F1-score=0.8138
Investigating students' interaction patterns and dynamic learning sentiments in online discussions [22]	Lag sequential analysis and quantitative content	Learning tasks are performed with an asynchronous discussion platform to analyze dynamic learning sentiments and interaction platforms.	For 1658 learning tasks, the learning statistics of 100 were achieved.
Improving learner-computer interaction through intelligent learning material delivery using instructional design modeling [50]	Component display theory, along with multiple-criteria decision analysis and content-based filtering	Intelligent techniques and instructional theory were combined to provide adequate learning materials to learners.	p-value=$1.1\text{x}10^{-10}$
Combination of fuzzy and cognitive theories for adaptive e-assessment [9]	Cognitive and logic theories of fuzzy	Adaptive e-assessment is provided by blending fuzzy theories.	Mean=9.20, S.D.=12.73
Mobile game-based learning as a solution to COVID-19 era: Modeling the pedagogical affordance and student interactions [32]	partial least squares structural equation modeling (PLS-SEM)	MGbL usage of learner's intention was investigated by modelling pedagogical use of technology and interactions.	Average Variance Extracted (AVE)=0.691, composite reliability (CR=0.857), Cronbach's Alpha=0.780
Applying GAs for recommending adequate competitors in mobile game-based learning environments [31]	GAs	MGbL applications with GA for tutoring	Mean=5.92, alpha value=0.05, P-value= 285869e^{-06}
Intelligent and adaptive tutoring through social networks for higher education [49]	i-Learn c# tutorial application	The capacities of the Facebook platform were extended, and intelligent virtual coach offerings were provided with solving and knowledge queries.	Mean=7.41, SD =1.4497, t-statistics=1.6487, p-value=1.49e^{-07}
An explainable AI-based fault diagnosis model for bearings	Stockwell transformation coefficient, wrapper-based feature selector, spearman's rank correlation coefficient, and K-NN	The idea of explainability was introduced for the first time in the field of bearing fault diagnosis	Classification accuracy of 100% with the Case Western Reserve University (CWRU) bearing dataset and 97.0% with the experimental dataset.
ALBERT-based personalized educational recommender system: Enhancing students' learning outcomes in online learning [42]	ALBERT	able to comprehend the semantic meaning of learning materials, student profiles, and interactions while also capturing contextualized word representations	Highly scalable and high inference speed.
BERT-enhanced SA for personalized e-commerce recommendations [26]	CF-BERT	SA and collaborative filtering work together to provide accurate and customized suggestions.	Accuracy-91%
SA and summarization of restaurant reviews using T5 and ChatGPT [16]	T5 and ChatGPT	To evaluate how well they captured the important details and opinions mentioned in the evaluations.	BLEU score-50.72% T5, 54.87% ChatGPT

Iwendi *et al*. [25] introduced a pointer-based item-to-item collaborative filtering recommendation system. A machine learning-based approach is presented to provide a better course recommendation to users. Furthermore, user evaluations and comments are incorporated to examine recommendations without modifying content. The developed scheme of recommendation was totally based on pointers. The recommendation was provided based on the comments and reviews of other users. Here, the word2vector process was utilized to split the user comments into negative, positive or neutral. The pointer-based model performs well, but the data set was not effective for performance validation.

To discover the right content, online learners have to filter through a huge array of instructional resources. Nanda *et al*. [42] provide a personalized educational recommender system based on A Lite Bidirectional Encoder Representations from Transformers (ALBERT) to enhance student learning. The enhanced Bidirectional Encoder Representations from Transformers (BERT) algorithm, called ALBERT, is able to comprehend the semantic meaning of learning materials, student profiles, and interactions while also capturing contextualized word representations. The suggestions for tailored learning made by the ALBERT-based recommender system are assessed in this study. A varied group of students from various educational domains is assessed in order to determine learning results. Academic performance, engagement, and information retention are evaluated both before and after the recommender system. To increase recommendation accuracy, learner engagement, and tailored learning, the recommender system makes advantage of ALBERT's model optimization.

Using SA to integrate textual data, like reviews, has become more important. However, interpreting and analyzing unstructured review data efficiently comes with its own set of difficulties. As a result, Karabila *et al*. [26] suggest a recommendation system that combines SA with collaborative filtering to provide accurate and customized suggestions. This method consists of three primary steps:

1. Building a hybrid collaborative filtering-based recommendation model.
2. enhancing the RS's product selection process with BERT insights for improved recommendation accuracy in the e-commerce space.
3. developing a BERT-fine-tuned model for precise sentiment categorization.

Gund *et al*. [16] address the need for text summarization in restaurant reviews by combining SA and natural language processing technologies. Businesses find it difficult to get valuable data from internet reviews. Reviews were categorized into good, negative, and neutral attitudes using SA. For summarization tasks, ChatGPT and the refined T5 model were employed and assessed using the ROUGE measure. The evaluation shows how effective the process is at summarizing. Both models performed well, according to the results, with the T5 model obtaining encouraging ROUGE-1 ratings. The comparison of existing approaches is given in Table 1 above. The comparison of existing approaches is given in Table 1. The existing approaches have been used by machine learning, deep learning, and artificial intelligence-based approaches, utilizing learner information and dynamic learning procedures. Pre-processing feature extraction and classification strategies are used in the existing model but not optimized. The inefficient handling of large datasets by machine learning or other existing algorithms results in inefficiency in online learning. Recent advanced deep learning algorithms are needed to improve the accuracy and efficiency of e-learning. In the existing techniques, there is still a possibility of performance improvement. Many techniques are presented in existing studies, but the system's efficiency is the same in all existing approaches. This work presented an effective SA based online learning course prediction using an IDCNN to improve the accuracy of online learning.

3. Proposed Methodology

This paper presented an optimal recommendation for an online learning course by utilizing deep learning-based SA and ranking the optimal learning course. At first, the input text data is pre-processed with the tokenization, stop word removal, spelling correction, stemming and lemmatization processes. Afterwards, effective features like BoW, ITF-IDF and glove word embedding are extricated from the pre-processed text data. Subsequently, MR optimization methodology is utilized to choose the most important features and reduce their dimensionality. Afterwards, an improved deep convolutional neural network framework is utilized in SA to accurately categorize the input text data into positive, negative and neural classes. Finally, the Jaccard similarity approach is calculated between the user query data and the categorized positive class data. This results in the optimal learning course based on the attained similarity score. The schematic diagram of the presented methodology is depicted in Figure 1.

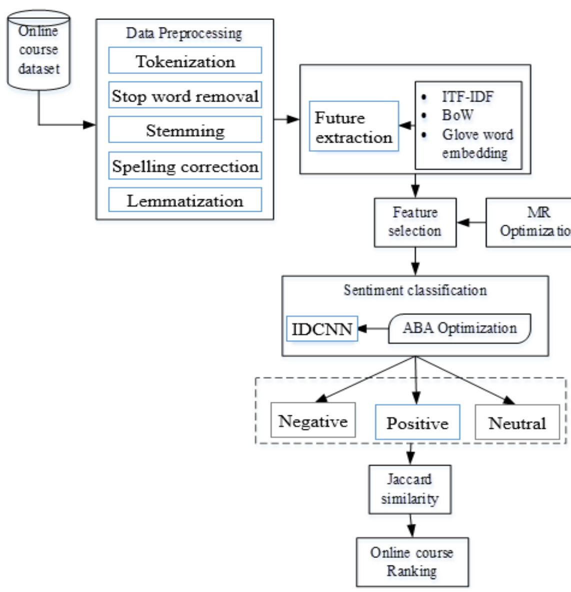


Figure 1. Schematic diagram of the presented methodology.

3.1. Pre-Processing

Initially, the input online course data taken from the dataset is utilized for processing. The text form of input data is pre-processed using the different text pre-processing approaches: stop word removal, tokenization, Stemming, spelling correction, and lemmatization. These approaches effectively pre-process the text data and make it suitable for further processing. The pre-processing approaches are described in the subsequent sub-sections. With pre-processing, the dimensionality of the data is minimized, and it is well prepared for the recommendation task.

3.1.1. Stop Word Removal

Stop words are the general words that are not important for SA. The process of eliminating the stop words reduces the dimensionality of the data. The example stop words are "The," "an," "At," "a," "that," and so on. In SA, removing these words does not change the meaning of the phrase.

3.1.2. Tokenization

It is the process of breaking long paragraphs into broken texts known as tokens. This process breaks the large paragraphs into smaller sentences and further breaks the sentences into tokens. Tokens are chunks of words.

Example:

Input: "PYTHON programming language"
Output: (PYTHON) (programming) (language)

3.1.3. Stemming

It is the process of converting the various tenses of words into their general base form. This process is important to eliminate the unnecessary computation of words. Moreover, this stemming process will reduce the size of words. Some examples of the stemming process are "arguing" to "argue." The example stemming process is provided in Table 2.

Table 2. Example stemming process.

Words	Stemming
Swimming	Swim
Playing	Play
Thinking	Think
Arguing	Argue

3.1.4. Spelling Correction

This process is utilized to correct errors in spelling. This process is utilized for data cleaning. This process predicts the misspelt words and results in the corrected version of the words. The incorrect spelling of the words changes the correct meaning of the words.

Example: "b4" to "before," "tmrw" to "tomorrow."

3.1.5. Lemmatization

It is merging two or more words into a single word. This pre-processing approach predicts the morphology of words. Moreover, this process removes the ending words like "impressed" to "impress," "catch" to "caught," and so on. In the proposed work, TreeTagger is used as an independent component of the speech tagger.

3.2. Feature Extraction

This section extracts effective features using ITF-IDF, BoW, and Glove word embedding. These effective features enhance prediction performance and are described in the subsequent sub-sections. By using feature extraction, the accuracy of the classification task is improved with less duration.

3.2.1. Bag of Words

This feature extraction process characterizes the word occurrence count in the considered document. This feature extraction process converts the text data into numeric vectors. The quantitative numbers obtained are determined by the number of times each word appears in the document. The example of a bag of words matrix representation for the pre-processed tweet is provided in Table 3.

Table 3. BoW matrix generation.

The online learning course recommendation effect process suggests an optimal course	online	1
	learning	1
	course	2
	recommendation	1
	effect	0
	process	0
	suggest	0
	Optimal	1

The BoW vector is comprised of different vectors of words. This feature vector contains all the information about the words.

3.2.2. ITF-IDF

The presented ITF-IDF is the improved form of the TF-IDF feature vector. This feature extraction process provides the feature vector of the important texts. This feature vector is computed by multiplying the term frequency and the inverse document frequency feature. The TF-IDF feature is extracted by utilizing the subsequent Equation (1),

$$Tf - Idf = Tf \times \log(Idf) \tag{1}$$

here, Tf signifies the term frequency and Idf signifies the inverse document frequency. Here, the term frequency is computed through the subsequent Equation (2),

$$Tf_{l,p} = \frac{M_{l,p}}{\sum_k M_{k,p}} \tag{2}$$

Moreover, the inverse document frequency is computed through the subsequent Equation (3),

$$Idf_l = \log\left(\frac{M}{Df_k} + 1\right) \tag{3}$$

here, $M_{l,m}$ signifies the number of words in the document ($\overline{d}_p$), and the denominator part signifies the total count of words that appeared in the document $\overline{d}_p$. Idf_l signifies the total count of the documents with the word (W_l) and M signifies the total amount of data in the dataset. Moreover, the weight factor is computed through the subsequent Equation (4)

$$\overline{W}_F = \frac{\overline{F}}{\overline{F}_T} \tag{4}$$

here, $\overline{W_F}$ signifies the weight factor, $\overline{F}$ signifies the feature class and $\overline{F_T}$ signifies the total extracted features. Moreover, the computed weight factor using Equation (4) is updated in the subsequent Equation (5) to attain the improved TF-IDF feature vectors. Then, the improved TF-IDF is computed through the subsequent Equation (5),

$$Tf - Idf = \frac{M_{l,p}}{\sum_k M_{k,p}} \times \log\left(\frac{M}{Df_k} \times \overline{W}_F + 1\right) \tag{5}$$

here, *ITf–Idf* signifies the improved TF-IDF feature vector; the first term signifies the *TF* feature vector; the second term signifies the IDF feature and $\overline{W_F}$ signifies the weight factor. An improved TF-IDF feature extraction provides better performance when differentiating the features.

3.2.3. Glove Word Embeddings

The Glove feature vector is an important feature for representing words. The Glove words representation framework is generated as a log-bilinear regression framework. This feature extraction model combines the matrix's global factorization and the local context window to provide the word representation. The word matrix is represented as $\overline{Y}_{kl}$. Every component in the $\overline{Y}_{kl}$ matrix signifies the appearing word frequency k in the word context l. The word constraints in glove feature extraction are described in the subsequent Equation (6),

$$\overline{Y}_{kl} = \overline{w}_k^t \overline{w}_F \tag{6}$$

here, $\overline{W}_l$ signifies the feature vector of the main word, $\overline{W}_l$ signifies the feature vector of the word context, and the glove feature is attained through the subsequent Equation (7),

$$\overline{G}_{v_F} = \log(\overline{Y}_{kl}) \tag{7}$$

here, $log(\overline{Y}_{kl})$ signifies the logarithmic function of the glove feature. This logarithmic function eliminates the divergences when evaluating the glove feature vector matrix.

3.3. Feature Selection

This section uses modified rain optimization to select the important features [41]. This feature selection process reduces the dimensionality of the features by removing the redundant features. The feature selection through the optimization approach is described in the subsequent sub-section. The proposed feature selection process resolves the issue of multicollinearity with correlated features. In order to generate a reduced feature set, feature filtration is applied in which bias-free results have been obtained. By eliminating the collinear feature from data, the entire dimensionality is minimized. The reduced feature set has minimal description length and non-overlapping information to produce unbiased classification results [8].

3.3.1. Modified Rain Optimization

This optimization is motivated by the nature of falling rain from the higher position to the lower position. This optimization methodology is utilized to reduce the dimensionality of the features. The rain optimization approach is initialized with the population of features.

This modified rain optimization methodology is initialized with the extracted features set, and it is described in the subsequent Equation (8),

$$\widetilde{M}_s = \{\overline{f}_{n,1}, \overline{f}_{n,2}, \overline{f}_{n,3}, \cdots \overline{f}_{n,k\}} \tag{8}$$

$$n \in \{1,2,3, \ldots . \hat{f}\} \tag{9}$$

here, $\widetilde{M}_s$ signifies the set of features. The optimal set of features is chosen by utilizing the presented MR optimization approach by decreasing the size of features, and it is described in the subsequent Equation (10),

$$\hat{f}_n = \overline{D}_{uniform}[\overline{U}_n, \overline{L}_n] \tag{10}$$

here, $\overline{D}_{uniform}$ signifies the uniform distribution, $\overline{U}_n$ signifies the upper bound data and $\overline{U}_n$ signifies the $\overline{L}_n$ lower bound data. Subsequently, the data locations are updated arbitrarily through the subsequent Equation (11).

$$\overline{P}_f = \overline{P}_{arbitrary}(\overline{I}_{initial} * \overline{I}_{\max}) \tag{11}$$

here, $\overline{P}_f$ signifies the optimal position of features, (*) function signifies the size of the unit vector, $\overline{P}_{arbitrary}$ signifies the arbitrary position, $I_{initial}$ signifies the initial iteration, and I_{max} signifies the maximum iteration. Moreover, the optimal position according to the nearest point ($\overline{Np}$) is utilized for the better selection of the feature set, and it is characterized by the Equation (12),

$$\overline{O}_F\left(\overline{Np}_{pk}^{m}\right) < \overline{O}_F\left(\overline{f}_{pk}^{m}\right), \qquad m = 1,2,3, \ldots . . M_p \tag{12}$$

here, $\overline{O_F}$ signifies the optimal set of features according to the priority of significant features from higher to lower. The final feature ranking for the selection of features is described in Equation (13),

$$\hat{F}_{rak} = \overline{O_F}|\overline{I}_{\max} - \overline{O_F}| \tag{13}$$

here, $\overline{I}_{\max}$ signifies the maximum number of iterations, $\overline{O_F}$ signifies the optimal set of features, and F_{rnak} signifies the raked features. The optimal selected feature is the ranked feature attained above the threshold (T_h) value, and it is characterized as $\hat{F}_{rak} > \overline{th}$. The feature vector above the generated threshold value is considered an important feature. This process decreases the size of the features set by eliminating unimportant features. This optimization process results in the optimal features based on the calculated priority based on this optimization.

A droplet's radius steadily lowers if it is terminated at the least position, improving the result 's accuracy. The fitness function, which is defined as follows, determines which qualities are nominated as the best.

$$fitness = \min(CF) \tag{14}$$

where, *CF* stands for the cost function. The MRO a technique uses opposition-based learning to fine-tune Remora Optimization Algorithm (ROA) since the random feature selection in ROA tends to skew the overall detection accuracy. Meta-heuristic techniques often employ opposition-based learning to improve performance by identifying the best solution for a given situation. Opposition-based learning, which finds an ideal solution in the opposite direction of the current answer and produces better results, is used to increase convergence and reduce time consumption. As a result, the convergence rate increases, and the solution approaches the ideal solution. Simultaneously estimating the original and matching opposing solutions is the primary goal of opposition-based learning. The matching solution that corresponds to it may be described as follows:

$$Z_i' = UB + LB - Z_i, \qquad Z_i \in [UB, LB] \tag{15}$$

The lower and upper bounds corresponding to search space are represented as *UB*, and n *LB* respectively. By cutting down on time consumption, this selection model also improves model performance. Opposition-based learning enhances search space exploration and exploitation, which raises the ROA for feature selection. Through the addition of opposing solutions to the current population, the learning method helps the algorithm avoid local optima and explore different places. By evaluating both potential and competing solutions, this approach speeds up convergence and guarantees a better balance between investigating new areas and focusing on promising ones.

3.4. Sentiment Classification Using IDCNN Framework

The IDCNN [34] is used to classify the online course into positive, neutral, and negative categories. Moreover, the Adaptive Beetle Antennae (ABA) optimization algorithm updates the IDCNN framework's optimized weights. This IDCNN classifier categorizes online courses by the SA into positive, negative and neutral. The presented IDCNN is comprised of a convolutional layer, max pooling, and fully connected layers with deep learning. The structure of the IDCNN is depicted in Figure 2.

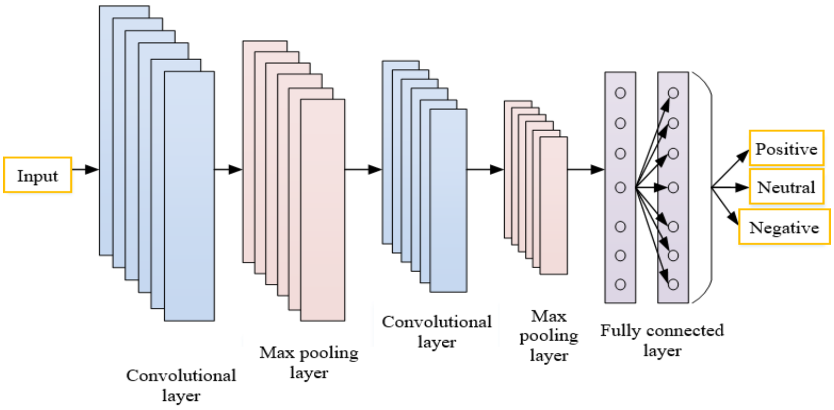


Figure 2. Structure of presented IDCNN.

3.4.1. Convolutional Layer

This layer performs the convolution operation among the input data and the weight matrices. In this layer, feature vectors are generated through this convolution operation. The operation of convolutional is described in the subsequent Equation (16),

$$\overline{Y} = \overline{X} * \overline{w}_m \tag{16}$$

here, $\overline{Y}$ signifies the output data of the convolutional layer, $\overline{X}$ signifies the input selected feature vectors to the Improved Convolutional Neural Network (ICNN) framework and $\overline{w}_m$ signifies the set of weights.

3.4.2. Weight Optimization Using ABA Optimization

The weights of the ICNN framework are updated optimally through the ABA optimization methodology. This ABA optimization approach is based on the behaviour of foraging. This approach finds the local intensity of the data to get the optimal weights. Initially, the location and the orientation parameters are generated arbitrarily, and they are normalized as per the subsequent Equation (17),

$$\tilde{B} = \frac{R(\overline{d}, 1)}{\|R(\overline{d}, 1)\|} \tag{17}$$

here, $\overline{d}$ signifies the spatial dimension, R signifies the arbitrary function. After the initialization of parameters, the special coordinates are computed for the left and right sides of the antenna, and it is described in Equations (18) and (19).

$$\overline{Z}_{Rk} = \overline{z}^{k} + p_0 \times \frac{\tilde{B}}{2} \tag{18}$$

$$\overline{Z}_{Lk} = \overline{z}^{k} + p_0 \times \frac{\tilde{B}}{2} \tag{19}$$

here, $\overline{z}^{k}$ signifies the location of beetle antennae at k^{th} iteration, $\overline{Z}_{Rk}$ signifies the location of right-side data at k^{th} iteration. $\overline{Z}_{Lk}$ signifies the location of left side data at k^{th} iteration and p_0 signifies the initial positions of the beetle. As per the position of data based on their directions, fitness is evaluated, and the data is chosen based on the minimum fitness value. Subsequently, the location of the beetle is updated, and it is described in subsequent Equation (20),

$$\overline{z}^{k+1} = \overline{z}^{k} + \rho^{k} \times \overline{B} \times \overline{sign}\left(\overline{F}(\overline{Z}_{Rk}) - (\overline{Z}_{Lk})\right) \tag{20}$$

here, ρ^k signifies the step factor, $\overline{sign}$ signifies the sign function and the value of ρ^k is generally equivalent to 0.95. The optimal weights are attained through this optimization and updated in the presented ICNN framework to enhance performance. The ABA algorithm is found to be simple and process with fewer parameters, which makes the proposed model integrate the ABA for weight optimization. This is performed to reduce the complexity of the proposed recommendation model. Further, this model can obtain the best solution in less time duration, which reduces the overall processing time of the proposed recommendation model.

3.4.3. Max Pooling Layer

This layer decreases the size of extracted features. The max pooling operation considers the maximum value of the data in each chosen window. Moreover, this layer avoids the occurrence of over fitting issues between the data. This layer operation is described in Equation (21),

$$\overline{O}_{pooling} = Max(P_w), w - each\ window\ \ O_{pooling} \tag{21}$$

here, P_w signifies the data in every window, $O_{pooling}$ signifies the output of the pooling layer and *Max* signifies the maximum value.

3.4.4. Fully Connected Layer

This layer converts the data of 2D data to the 1D feature vector. In this layer, the final output class is predicted. The input of this layer is the flattened form of data values. According to that flattened data, the output class is decided. Here, the softmax function is incorporated to attain the accurate class probability. This layer results in accurate output classes. The softmax activation function predicts the scores and results in the output class. The softmax function is described in the subsequent Equation (22),

$$\overline{Z}_k = \frac{\exp(y_k)}{\sum_{k=1}^{M}(y_k)} \tag{22}$$

here, y_k signifies the input feature vector for the softmax function $\overline{Z}_k$ signifies the output classes and "*exp*" signifies the exponential term.

3.4.5. Dropout for the Reduction of Overfitting Issue

The input and recurrent connections are eliminated from the activation to decrease the overfitting in the networks. An adaptive beetle antennae optimization algorithm updates the weights during network training. This process can solve the issue of overfitting and increase the output performance. The range considered for the dropout is between 0 and 1. Here, 1 represents the no connection, and 0 represents the no dropout. The predetermined dropout rate is 0.5 to attain good results.

3.5. Online Course Recommendation by Ranking

The Jaccard similarity-based ranking approach is utilized to rank the positive category online courses to provide the final online course recommendation. The Jaccard similarity is computed among the classified items and the user query for the final ranking of the online course. The top-ranking courses are suggested as optimal courses for the learners. The Jaccard similarity measure is computed through the subsequent Equation (23),

$$\overline{S}_{jaccard}(\overline{l}, \overline{m}) = \left|\frac{\overline{l} \cap \overline{m}}{\overline{l} \cup \overline{m}}\right| \tag{23}$$

here, $\overline{S}_{jaccard}$ signifies the Jaccard similarity, $\overline{l}$ signifies the user query and $\overline{m}$ signifies the data item, $\overline{l} \cap \overline{m}$ signifies the total quantity of data present in both sets and $\overline{l} \cup \overline{m}$ signifies the similar data in either group. This computation score is utilized to rank the online learning course. The top-ranking courses are considered optimal learning courses and are recommended as optimal quality online courses. The positive category online courses are ranked according to the calculated similarity score, and the course with the highest score is recommended as an optimal course for the learners.

Since Jaccard similarity only considers the intersection of sets rather than the frequency of elements when working with binary data or situations where the presence or absence of elements is more important than their magnitude. It is found superior to dice and cosine similarity. This makes Jaccard similarity perfect for set comparison tasks like collaborative filtering, where the goal is to identify shared features rather than their weights. This advantage is leveraged in the proposed model for final ranking. This has a major role in enhancing the efficiency of the proposed recommendation model.

4. Results and Discussions

This section examines the experimental results of the presented online course recommendation. The performance of the presented methodology is compared with the existing approaches in regards to accuracy, precision, recall, F1-score, classification error, Kappa, Area Under the Curve (AUC) and Root Mean Squared Error (RMSE). The presented methodology is implemented in the Python programming language. Moreover, the performance of the presented approach is examined with the online course dataset for the recommendation.

4.1. Dataset Description: E-Learning Course Dataset

The presented approach is analyzed with the e-learning course dataset [19]. This dataset contains various learning courses like Java, data science, Python, database, Graphics, machine learning, algorithms, HTML, and C++. Moreover, detailed descriptions of these languages are available in the dataset. Moreover, user comments about the courses with user IDs are present in the dataset. The available courses are categorized into positive, negative, and neutral cases according to the methodology presented. The training and testing data are considered from the dataset in the 70% and 30 % ratios, respectively.

4.2. Performance Metrics

This section describes various performance evaluations like accuracy, recall, F1-score, precision, RMSE, Kappa and AUC. The performance of the provided approach is evaluated using these performance metrics, which are derived in the following subsections.

4.2.1. Accuracy

This performance metric is utilized to predict the proportion of correct classification. It is the proportion of the corrected identified class to the total number of classes. It is computed through the subsequent Equation (24),

$$A_Y^{''} = \frac{\bar{t}_+ + \bar{t}_-}{\bar{t}_+ + \bar{t}_- + \bar{f}_+ + \bar{f}_-} \tag{24}$$

here, $A_Y^{''}$ signifies the accuracy performance, $\bar{t}_+$ signifies the true positive, $\bar{t}_-$ signifies the true negative, and T_N signifies the total number of positive data.

4.2.2. Kappa Statistic

This measure is utilized to evaluate the degree of probability amongst classified data. It is assessed through the expressed Equation (25),

$$\bar{K}_S^{''} = \frac{\bar{P}_0' - \bar{P}_C'}{1 - \bar{P}_C'} \tag{25}$$

here, $\bar{K}_S^{''}$ signifies the kappa measure, $\bar{P}_0'$ signifies the calculated accuracy, and $\bar{P}_C'$ signifies the probability change in the accuracy.

4.2.3. Precision

This measure estimates the accurately predicted positive data amongst all the considered positive data. It is computed through the subsequent Equation (26),

$$\bar{P}^{''} = \frac{\bar{t}_+}{\bar{t}_+ + \bar{f}_+} \tag{26}$$

4.2.4. Recall

This performance measure has computed the proportion of positive data between the true positive and false negative classes. It is computed through the subsequent Equation (27),

$$\bar{R}_L^{''} = \frac{\bar{t}_+}{\bar{t}_+ + \bar{f}_-} \tag{27}$$

4.2.5. F1-Score

This performance measure is the harmonic mean value of the recall and the precision measure. It is computed through the subsequent Equation (28),

$$\bar{F}1_{score} = 2 * \frac{\bar{P}^{''} \times \bar{R}_L^{''}}{\bar{P}^{''} + \bar{R}_L^{''}} \tag{28}$$

here, $\bar{F}1_{score}$ signifies the F1-score performance, $\bar{P}^{''}$ signifies the precision measure, and $\bar{R}_L^{''}$ signifies the recall measure.

4.2.6. AUC

This measure evaluates the trade-off between the true and the false positive rate. This provides positive class data among the negatives. The greater the output value of this measure, the more efficient the suggested strategy. It is computed through the subsequent Equation (29),

$$\overline{a_{uc}} = \frac{1}{2}\left(\frac{\bar{t}_+}{\bar{t}_+ + \bar{f}_+} + \frac{\bar{t}_-}{\bar{t}_+ + \bar{f}_+}\right) \tag{29}$$

4.2.7. RMSE

This performance is employed to evaluate the error variance among the predicted value obtained by the classifier and the original data. It is evaluated through the expressed subsequent Equation (30),

$$\overline{R_{MSE}} = \sqrt{\frac{1}{K}\sum_{l=1}^{K}\left(\bar{P}_y(l) - \bar{T}_y(l)\right)} \tag{30}$$

here, $\overline{R_{MSE}}$ signifies the RMSE performance, $\overline{P_y}(l)$ signifies the probability predicted class l, and $\overline{T_y}(l)$ signifies the true probability.

4.2.8. Mean Reciprocal Rank (MRR)

The MRR is a metric to evaluate systems that return a ranked list of answers to queries.

For every query, the reciprocal rank is computed by $1/rank$, where *rank* represents the position of the high ranked answer (1, 2, 3...*N*), *N* represents the returned answer in a query. If no accurate answer is returned in a query, then the rank of the reciprocal is zero. The MRR is computed by an Equation (31)

$$MRR = \frac{1}{P}\sum_{k=1}^{P} {}^{1}/_{rank_k} \tag{31}$$

here, *MRR* represents the MRR *P* represents the multiple queries.

4.2.9. Mean Average Precision (MAP)

The mean average position of multiple queries is calculated by the subsequent Equation (32).

$$MAP = \frac{\sum_{p=1}^{P} AvgQ(p)}{P} \tag{32}$$

here, *P* represents the number of queries, *AvgQ*(*p*) represents the average position for a given query *p*.

4.2.10. Normalized Discounted Cumulative Gain (NDCG)

NDCG metric is used to measure the quality of ranking. Here, the NDCG is calculated based on the significance of items. Here, the NDCG metric calculation is expressed by the subsequent Equation (33).

$$NDCG = {}^{DCG}/_{IDCG} \tag{33}$$

here, *p* signifies the number of queries. The NDCG metric is used to evaluate the performance of recommendation quality through the ranking process. The NDCG is based on the actual and the ideal weight values of gains. The *IDCG* is computed by the subsequent Equation (34),

$$IDCG = \sum_{k=1}^{M(ideal)} \frac{H_k^{ideal}}{log_2(k+1)} \tag{34}$$

here, IDCG represents the (Ideal Discounted Cumulative Gain). The discounted count gain of ideal orders is calculated based on the gain value. Furthermore, Discounted Cumulative Gain (DCG) is calculated by the subsequent Equation (35).

$$DCG = \sum_{k=1}^{M(actual)} \frac{H_k^{actual}}{log_2(k+1)} \tag{35}$$

The NDCG metric ensures the ranking quality performance and provides the top search results in ascending order. It is the proportion of discounted cumulative gain to the idealized discounted cumulative gain.

4.3. Performance Analysis

In this section, the performance of the presented approach is compared with the existing approaches. The examined confusion matrix of the presented methodology is portrayed in Figure 3.

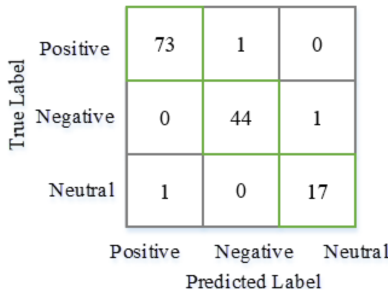


Figure 3. Confusion matrix of the presented approach.

Figure 3 provides the confusion matrix of the presented approach with three classes: positive, negative and neutral. The generated confusion matrix is utilized to predict performance evaluations. Furthermore, Table 4 shows a performance analysis of the provided approach in terms of accuracy. In the confusion matrix, the number of positives is 73, the number of negatives is 44, and the neutral is 17. While considering three classes, the number of positives is high, and the neutral classes are low. In addition to that, the average of negative classes has been obtained.

Table 4. Performance on accuracy.

Technique	**Accuracy (%)**	**Recall (%)**	**Precision (%)**	**F1-score (%)**
Fuzzy logic+SS	97	86	89	87
Dictionary based approach	82	62	78	69
AFINN	74	65	70	67
SS+ opinion documents	91	85	80	82
Proposed	98.17	98.21	98.23	98.19

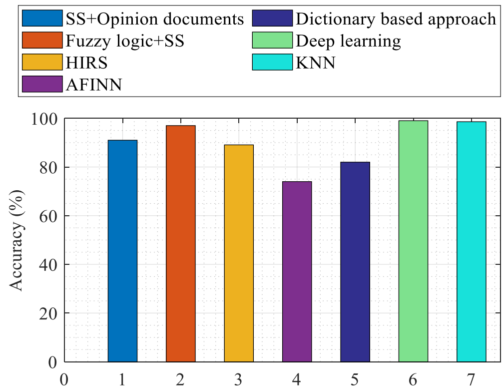


Figure 4. Performance comparison of accuracy.

In Table 4, the performance comparison on accuracy is provided. The presented approach attains a significant improvement in accuracy performance. This proved that the presented approach is more accurate (98.17%). Moreover, the performance comparison on accuracy is depicted in Figure 4. The accuracy obtained for the recommendation system is in the range of 70% to 100%. The proposed fuzzy logic and Semantic Similarity (SS) based approach gained an accuracy value above 97%. The dictionary-based approach and other approaches are below 85%.

In Figure 4, the performance of the presented methodology is compared with the existing methodologies. The developed approach attains better performance in accuracy (98.17%) than the existing fuzzy logic with SS (97%), dictionary-based approach (82%), AFINN (74%), and SS with opinion document (91%) approach [38]. Moreover, the recall performance comparison is depicted in Figure 5.

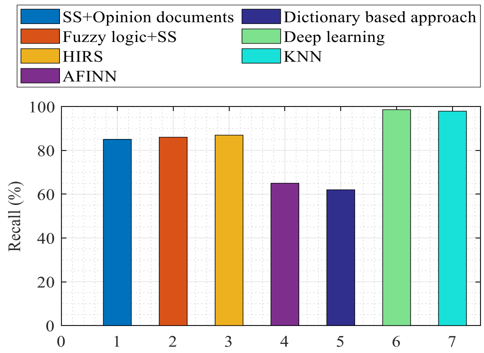


Figure 5. Performance comparison of recall.

Figure 5 provides a performance evaluation of the presented methodology regarding the recall. This illustrates the presented approach attained an improved recall (98.21%) performance than the existing different approaches like existing AFINN (65%), fuzzy logic with SS (86%), dictionary-based approach (62%), Hierarchical Information Retrieval System (HIRS) (89.9%), SS with opinion document (85%), and K-Nearest Neighbors (K-NN) (98%) [38]. The recall value of the proposed and existing recommendation system achieved a recall value of 60 % to 99%. While considering the proposed fuzzy based system, a recall value above 86% was obtained. But in the case of other approaches, it is less than or equal to 85%.

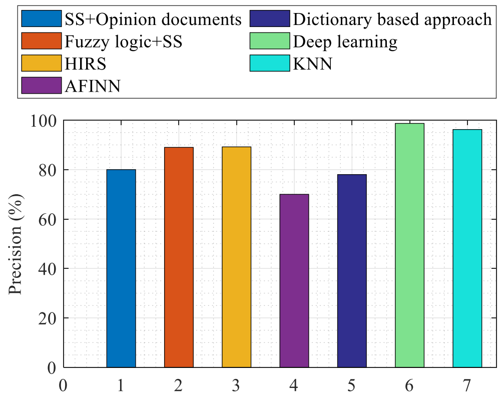


Figure 6. Comparison analysis of precision.

Furthermore, the performance evaluation on the precision measure is illustrated in Figure 6. The precision result of the recommendation system has reached values up to 98.19%. Compared with the existing recommendation system, SS-based and proposed approaches are higher than 82%. The remaining approaches are in the range of 70%.

In Figure 6, the performance examination of the precision measure is illustrated. This proved that the presented methodology achieved higher precision performance than the other existing dictionary-based approaches (78%), AFINN (70%), fuzzy logic with SS (89%), and SS with opinion document (80%) [38]. Then, the F1-score performance is illustrated in Figure 7. The F1-score is greater than 65% for all systems, including the suggested system. Dictionary based and AFINN has the F1-score of 65 % to 70 %. It is lower than the proposed and SS based techniques.

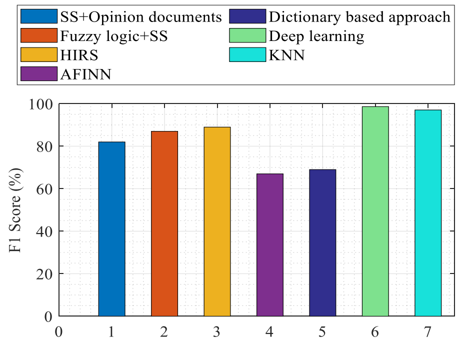


Figure 7. Comparison analysis on F1-score.

In Figure 7, the performance analysis of the F1-score is depicted. This proved that the presented methodology attains an improved performance on recall than the existing dictionary-based approach (69%), SS with opinion document (82%), AFINN (67%), and fuzzy logic with SS (87%) [38].

Furthermore, the performance examination on Matthews Correlation Coefficient (MCC) is mentioned in Table 5.

Table 5. Performance on MCC measure.

Methodology	**MCC (%)**
EELR	84.6
Proposed	**96.24**

Table 5 demonstrates the performance comparison on MCC. This proved that the developed approach attains 96.24% MCC, higher than the existing approach, like EELR (84.6%) [51]. Moreover, the performance examination on the Kappa measure is provided in Table 6. The Kappa and AUC measure is compared with the existing approaches such as Sequential Minimal Optimization (SMO), Naive Bayes, J48, logistic, Instance-Based K-nearest neighbor (IBK), Java Repeated Incremental Pruning to produce error reduction (JRip), and WekaDeeplearning4J.

While comparing the performance with Kappa, the proposed values are much higher, and the existing results are lower than 50 % in most approaches.

Table 6. Performance comparison on Kappa and AUC measure.

Methodology	Kappa measure (%)	AUC (%)
SMO	43	69
Naive Bayes	43	81
J48	49	81
Logistic	44	84
IBK	37	65
JRip	51	77
WekaDeeplearning4J	43	83
Proposed	97.06	98.17

Table 6 provides the performance examination on AUC and Kappa measures. The presented methodology attains an improved performance compared to the existing methodologies. This showed that the developed methodology performs better than the existing approaches. Moreover, the performance examination on AUC is illustrated in Figure 8. The AUC computation is considered with an average value of 80%, and for the existing approaches, it is lower, and for the proposed approaches, it is higher than the existing results. The higher results of these metrics indicate the efficiency of the proposed approaches.

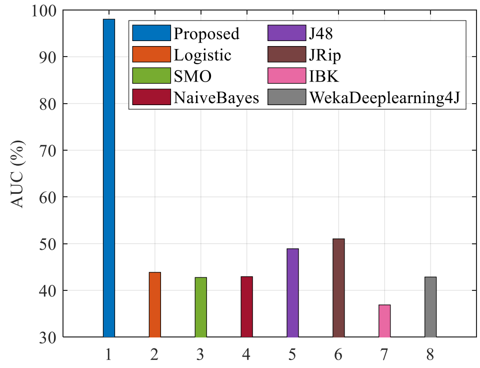


Figure 8. Performance comparison on AUC.

In Figure 8, the performance of the presented approach in regard to AUC is examined with the different approaches. This proved that the presented approach (98.17%) attains enhanced performance on AUC than the different existing logistics (84%), SMO (69%), Naive Bayes (81%), J48 (81%), JRip (77%), IBK (65%), and WekaDeeplearning4J (83%) [33]. Moreover, the performance of the Kappa measure is depicted in Figure 9.

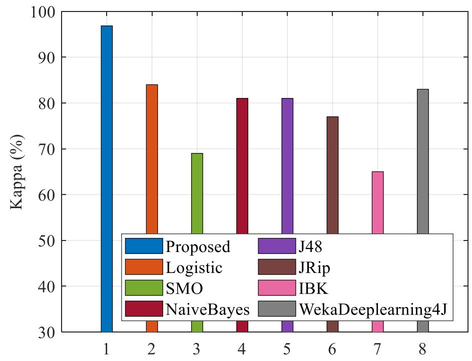


Figure 9. Comparison examination of Kappa.

In Figure 9, the performance examination on the Kappa measure is illustrated. This proved that the presented approach (97.06%) attained a significant improvement in Kappa performance than the different existing Naive Bayes (43%), J48 (49%), JRip (51%), logistic (44%), SMO (43%), IBK (37%), and WekaDeeplearning4J (43%) [33]. Moreover, the performance of classification error is depicted in Figure 10.

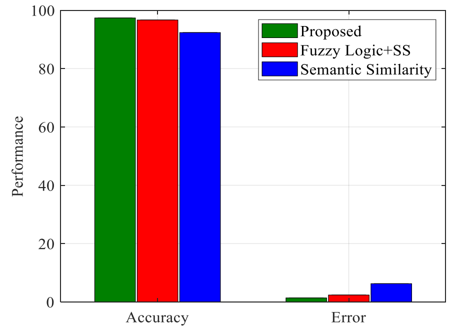


Figure 10. Performance comparison of classification error and accuracy.

In Figure 10, the performance of the presented methodology is compared with the existing approaches. The presented approach attains a lesser error value than the existing Semantic Similarity-based (SS) methodology and fuzzy logic with SS [38] approaches.

Furthermore, the performance examination of the RMSE measure is mentioned in Table 7.

Table 7. Performance examination on RMSE.

Methodology	RMSE
K-means	0. 8359±0.05
Random	0.8123±0.05
Collaborative filtering	0. 8374±0.05
NoR-MOOCs	0.7908±0.05
HIRS	0.826±0.05
ECF	0.38±0.05
ECBF	0.35±0.05
Proposed	0.02±0.05

In Table 7, the RMSE performance is provided with the comparison approaches. In this, the presented methodology achieves a lesser RMSE (0.21), which proves the significance of the presented methodology. Moreover, the RMSE performance is examined using the existing methodologies [29], as shown in Figure 11.

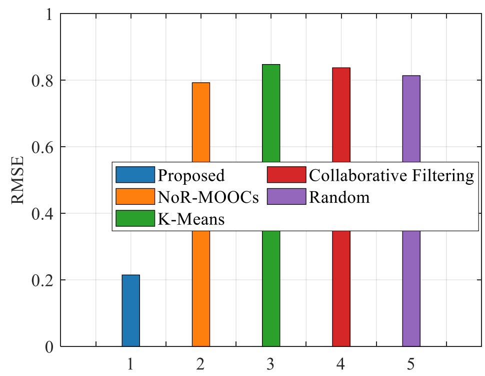


Figure 11. Performance comparison on RMSE.

In Figure 11, the presented methodology obtained a lesser RMSE value than the other existing methodologies. This proved that the presented approach attains the minimum error of the existing Collaborative filtering (0.83), random (0.81), Novel online Recommendation algorithm for Massive Open Online Courses (NoR-MOOCs) (0.79), and K-means (0.83) [29] schemes. The RMSE values are in the range of 0.21 to 0.83. The Approaches such as K-means, random and collaborative filtering range to 0.83, whereas NoR-MOOCs are below 0.7908. The lower RMSE is obtained with the proposed model, which is in the range of 0.21.

Table 8. Comparison with different word embedding approaches.

Word embedding approaches	Accuracy	Precision	Recall	F-measure
Word2vec	98.02	97.99	98.01	98.10
Glove	98.17	98.23	98.21	98.19
BERT	98.10	98.21	98.10	98.02
GPT	98.12	98.20	98.15	98.00

Different word embedding approaches, such as Word2Vec, Glove, BERT and GPT, are compared with the proposed approach in Table 8. Compared with different word embedding approaches, better results are attained with the Glove approach. Glove-based embedding outperforms other techniques.

Table 9. Performance of online recommendation system by varying ranking approaches.

Performance metrics	Jaccard similarity	Dice similarity	Cosine similarity
Accuracy	98.17	98.10	98.03
Recall	98.21	97.98	97.99
Precision	98.23	98.02	98.20
F1-score	98.19	97.99	98.10
MCC	96.24	96.21	96.15
Kappa measure	97.06	97.00	97.03
AUC	98.17	98.10	98.16
RMSE	0.21	0.25	0.30

The online recommendation is provided with the ranking of Jaccard similarity. The performance of the proposed work is evaluated using the Jaccard similarity-based ranking. By using other ranking methods, such as Dice similarity and cosine similarity, the performance of the proposed work is described in Table 9. When using other ranking approaches, the performance of the proposed approach is degraded, and there is a slight deviation from the performance obtained with the proposed Jaccard similarity measure.

By explicitly calculating the ratio of common items to all unique elements, Jaccard similarity offers a simple way to understand how sets overlap. Jaccard is appropriate for data of different sizes since it is not impacted by the size of the sets being compared, unlike cosine similarity, which can be influenced by vector magnitudes. The primary benefit of Jaccard similarity over Dice similarity is that Jaccard emphasizes punishing differences across sets more than Dice, which makes it more suited for situations where precisely identifying unique items and reducing false positives are essential.

In addition, performance validation is performed using different performance measures such as MRR, MAP and NDCG for top N recommendations. Moreover, accuracy, F-score and area under curve measures are used to analyze the sentiments since the F-score metric is utilized to predict the mean F-score of every class. In this section, the proposed methodology is compared with different existing approaches in terms of MRR, MAP and NDCG measures. Here, the SA is performed with F-score, accuracy and AUC measured to validate the sentiments. The proposed scheme attains better performance than the compared approaches. In this section, the proposed scheme is analyzed with and without sentiments.

Table 10. K-fold validation analysis.

Kfold	5	10	15	20
Accuracy (%)	99.78	99.69	99.52	99.23
Precision (%)	99.773	99.65	99.519	99.24
Recall (%)	99.75	99.66	99.52	99.2
F1 score (%)	99.76	99.68	99.54	99.23

The k-fold analysis for the proposed model is discussed in Table 10. The performance validation of the proposed scheme with existing approaches in regard to MAP, MRR and NDCG is given in Table 11.

Table 11. Comparison analysis of MRR, MAP and NDCG measures.

Techniques	MRR	MAP	NDCG
SVD	83.92	73.06	86.53
SVD with L-CNN	84.09	73.67	86.78
NMF	82.98	72.97	86.67
NMF with L-CNN	83.19	73.26	86.84
SVD++	84.24	73.48	86.84
SVD++ with L-CNN	84.24	73.82	86.89
Proposed	**88.87**	**79.45**	**91.02**

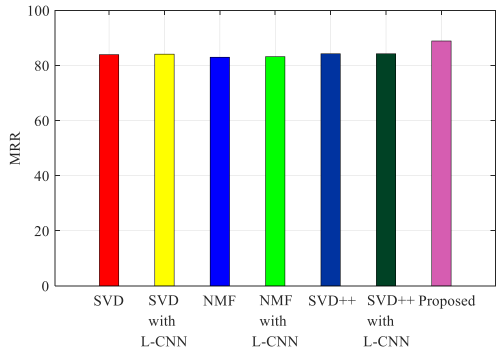


Figure 12. Comparison analysis of MRR.

In Table 11, the performance of the proposed methodology is compared with different existing approaches in terms of MRR, MAP and NDCG for top N recommendations. The proposed methodology attains better performance than the compared existing approaches. Furthermore, the proposed scheme is compared with different existing approaches such as Singular Value Decomposition (SVD), SVD with L-CNN (Convolutional Neural Network with Long short-term memory), Non-negative Matrix Factorization (NMF), NMF with L-CNN, SVD++ (a derivative of

SVD), SVD++ with L-CNN [12] in terms of various performance measures. The comparison analysis proposed scheme in MRR performance is illustrated in Figure 12.

Figure 12 compares the proposed scheme with different existing approaches with MRR metrics. Here, the proposed RS attains better performance than the compared existing approaches. Furthermore, the performance of MAP is compared with different existing approaches, as shown in Figure 13.

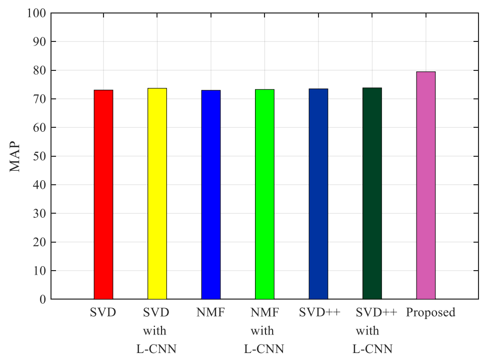


Figure 13. Comparison analysis of MAP.

In Figure 13, the performance is analyzed with the MAP metric. Here, the proposed methodology achieves higher MAP performance than the compared schemes such as SVD, SVD with L-CNN, NMF, NMF with L-CNN, SVD++, and SVD++ with L-CNN [12]. Furthermore, the performance analysis in terms of NDCG is depicted in Figure 14.

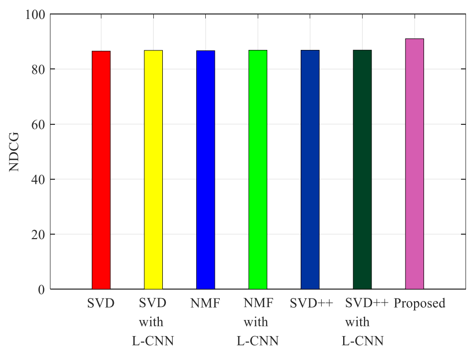


Figure 14. Performance comparison of NDCG.

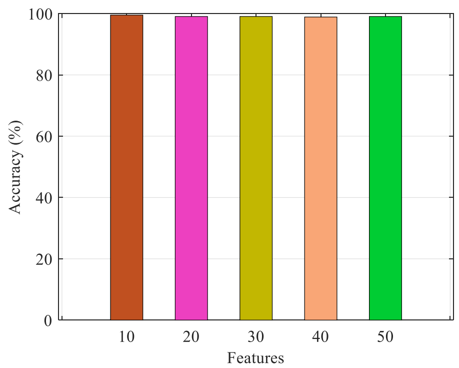
In Figure 14, NDCG performance is analyzed using different approaches. The suggested scheme obtains a higher NDCG outcome than the compared schemes. This proves that the proposed methodology performs better than the compared existing approaches. The analysis of response time for online course recommendation is given in Table 12.

Table 12. Comparison of response time.

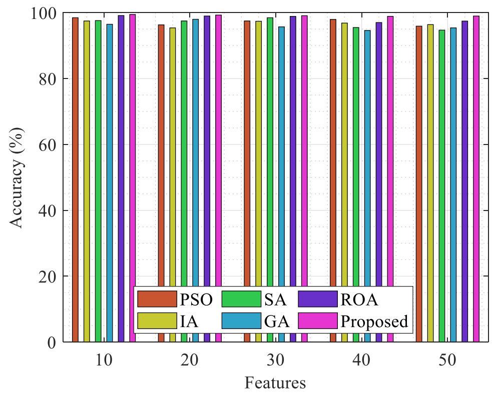
Techniques	Response time (ms)
Collaborative filtering	322
ISLA-learning	120
Proposed improved deep convolutional neural network	88

Table 12 compares the proposed response time with different approaches, such as Improved Supervised Learning Algorithm (ISLA) learning [45] and collaborative filtering [35]. The proposed online recommendation process is used to suggest accurate courses according to the interests of each individual. The proposed analysis is compared with different existing approaches in terms of different performance metrics. The proposed scheme proved that an accurate recommendation is achieved in less time.

By combining the recommendation system's techniques, the proposed system's performance is improved by tackling the drawbacks of the traditional recommendation system. The involvement of artificial intelligence-based approaches minimizes the issue of overfitting. The proposed neural network tests the multiple data time to perform better. As a result, better feature selection and classification are obtained, hence improving the recommendation system's accuracy.



a) Accuracy vs selected features.



b) Accuracy comparison with different algorithms.

Figure 15. Feature selection algorithm-based comparison.

The feature selection-based comparison is shown in Figure 15-a) and (b). The feature extraction stage is followed by feature selection, which helps to improve the proposed model performance. While the latter uses a classification method to choose the feature subset of the greatest quality, the former uses feature correlation criteria to choose the best feature subset at a reduced computational cost. Furthermore, the filter methods are relatively less reliable when working with high-dimensional data for feature selection. Researchers have recently focused a lot of emphasis on metaheuristic-based feature selection because of its superior global searching capabilities. Artificial Immune Algorithm

(IA) [53], Particle Swarm Optimization (PSO) [47], Simulated Annealing (SA) [43], and GA [39] are a few of the most often utilized algorithms. Due to their strong global searching capabilities and lack of reliance on prior knowledge of the search field, these algorithms exhibit notable performance even when applied to complicated tasks. However, it encounters the difficulty of an exponential rise in processing cost when the search space is enlarged. In order to get around the drawbacks of the current methods, a hybrid feature selection algorithm is suggested in this study. The ROA [44], a robust optimization technique that was just established, performs better when its exploration and exploitation phases are improved.

Table 13. Ablation study analysis.

Ablation study	Module 1	Module 2	Module 3	Module 4	Module 5
Accuracy (%)	99.81	99.35	99.07	98.83	99.68
Precision (%)	99.84	99.32	99	98.79	99.7
Recall (%)	99.85	99.33	99.02	99.8	99.69
F1 score (%)	99.86	99.37	99.05	99.82	99.52

The ablation study analysis for the proposed model is discussed in Table 13. In these 5 different modules are analyzed. The 5 modules are without pre-processing (module 5), without feature extraction (module 4), without feature selection (module 3), without ABA optimization (module 2), and proposed (module 1). This analysis shows the effectiveness of each step in the proposed framework. Each step has its influence in achieving better performance in the recommendation system. The model is found to be highly flexible and shows less processing time than other existing models.

5. Conclusions

This paper proposed a novel deep learning-based framework for online course ranking with SA. Initially, the input data is pre-processed with various text pre-processing approaches in which the dimensionality of the data is minimized. Afterwards, most discriminative features such as ITF-IDF, BoW, and Glove word embedding features are extracted, and the extracted features are optimally chosen through the MR optimization methodology. The proposed feature extraction improves the accuracy of the overall recommendation system by eliminating the presence of redundant features. Then, the IDCNN framework with ABA weight optimization is utilized to predict the positive, negative and neutral classes accurately. Finally, the optimal learning courses are ranked using the Jaccard similarity-based approach. The experimental results of the developed approach are examined with the various existing approaches.

Moreover, the presented approach proved that the performance of the presented methodology significantly enhanced in terms of different effective performance evaluations like accuracy (98.17%), precision (98.23%), recall (98.21%), F1-score (98.19%), RMSE (0.21), Kappa (97.06%) and AUC (98.17%). In future work, the presented work will be further improved with enhanced deep learning-based approaches and recommendations for more online courses for new learners. The proposed work is limited to the issue of scalability while increasing the number of users. In this work, different course languages are only recommended to learners, and it will be extended with the details of an institution to the learners. It can also be extended to perform a case study with real-time participants to estimate the system's usability and detect the areas of improvement for making the system more user-dependent.

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