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# Effectiveness of English Online Learning Based on Dual Channel Based Capsnet

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**Abstract:** Web-based learning systems have quickly developed, by giving students a broader access to wide range of courses. However, when presented with a huge number of courses, it might be difficult for users to rapidly discover the ones they are interested in, from a large amount of online educational resources. As a result, a course recommendation system is crucial to increase users' learning benefit. Presently, numerous online learning platforms have developed a variety of recommender systems using conventional data mining techniques. Still, these methods have several shortcomings, like adaptability and sparsity. To solve this problem, this study provides a deep learning based English course recommendation system with the extraction of features using a dual channel based capsule network (CapsNet). This network extracts all the important features about the courses and learners and suggests suitable courses for the learners. To evaluate the proposed model's performance, several investigations are performed on a real-world dataset (XuetangX) and outperforms existing recommendation approaches with an average of 91% precision, 45% recall, 55% f1-score, 0.798 RMSE, and 0.671 MSE. According to the experimental findings, the proposed model provides better and more reliable recommendation performance than the conventional approaches. According to the experimental findings, the proposed model provides better and more reliable recommendation performance than the conventional approaches.

**Index Terms:** CapsNet, English, deep learning, personalized learning, XuetangX, online courses.

## 1. Introduction

Educational courses are essential to the distribution of knowledge in both online and traditional classroom settings since they represent a common sort of learning materials and objects. As a result of online education and the internet's rapid expansion, learners are no longer comfortable with the basic comprehensive set of courses and prefer to select appropriate courses they are fascinated in through online learning networks [1-3]. These are continually transforming traditional educational approaches.

According to the Education Informatization 2.0 action Plan, which was announced by the Ministry of Education in 2018, "the fundamental mission of developing moral teaching around a new path is to speed up, upgrade and to develop ethical qualities in education. Moreover, the "Online + education" concept is promoted as a result of the advancement of information technology, particularly the advancement of intelligent systems. It creates the way for the application of innovative mechanisms and creates personalized, digital, intelligent, lifelong, and education networks [4-7].

These systems have the benefits of free courses, extensive information, and flexible options while still being able to offer high-quality, specialized teaching courses, a comprehensive syllabus, and accompanying projects [8-11]. However, the rapid expansion of platforms and courses causes "information overload," making it difficult for users to make decisions about which courses to take when they have access to so many options. Also, choosing their favorite course in online involves a difficult and time-consuming process [12-15]. Therefore, it is critical to assist users in easily selecting the appropriate course based on their interests. Moreover, Traditional recommendation algorithms cannot learn the deep features of users or courses.

In addition, many e-learning cities now suggest learning materials that are concentrated on particular e-learning platforms, failing to adequately take into account user preferences, requests, and flexibility [16-18]. In addition, it needs a significant amount of time and effort for students to sort through the numerous learning resources related to their interests to find the ones they need and enjoy the most. This requires students to have certain information validation and inspection skills, which is difficult for students in general and even more difficult for newcomers.

Additionally, existing recommendation systems that use memory-based models can infer user preferences from past actions like selecting, ranking, and watching. They are unable to figure out why users behave the way they do. Second, the conventional strategy suffers from cold-start issues, in which new users do not have historical information that the algorithm could utilize to create recommendations. Furthermore, these systems can't recommend anything until a user rates their preferences [19, 20]. The previously created recommendation system also has the drawback of not taking into account detailed data about the user's most pertinent courses. The classification of users' particular needs and areas of interest by combining various data characteristics and creating important course-related information is very important to suggest suitable courses. This serves as a reason for creating an effective strategy to deal with information overload and create English online learning course recommendation system.

As a result, this study suggests a unique deep learning-based English course recommender system based on Dual Channel Capsule Network (Dual CapsNet) that can precisely capture high-level user behaviors and course attribute characteristics. This technique contains several advantages such as the connectivity among layers of the Capsule Networks requires fewer variables and is highly stable. Furthermore, compared to other deep learning algorithms, Capsule Networks converge with less iteration. Thus, the Dual CapsNet technique is implemented to address the issue of confusion caused by the availability of educational materials in the online world and assist students in quickly acquiring personalized learning resources.

The important aspects of the paper are listed as follows,

- A dual CapsNet-based deep learning recommendation system is implemented to properly and effectively examine the association between courses based on all the available course-related data.
- To address the issues of information overload and data sparsity, the suggested approach in this work successfully learns the interaction features between user actions and course attributes.
- This study performs several tests using real-world education datasets to show the suggested model's performance in comparison to the conventional suggestion approach.

The rest of this essay is planned as follows. The related work is summarized in Section 2. The proposed recommendation framework is presented in Section 3. The results of experiments and tests are given in Section 6. This paper is concluded in Section 7.

## 2. Literature Review

To improve the matching degree of course recommendation system, a dynamic collaborative filtering algorithm-based strategy is utilized by Wang and Fu [21]. To improve scalability and information sparsity of the recommendation system, slope one algorithm and dynamic k-nearest neighbor strategy was implemented with the collaborative filtering algorithm. The unscored value was calculated using the Pearson correlation coefficient to determine how similar the data is among learning users or project resources in the network. To analyze the effectiveness of the suggested technique, traditional binary particle swarm optimization and random coefficient-based particle swarm optimization techniques were compared in terms of recommended coverage, mean absolute error, convergence, and Parameter sensitivity performance metrics.

Xu and Zhou [22] presented deep learning based course recommendation system for online learning. In this work, course titles were converted from text to vector by using Word2vec approach. Then, the features were extracted from the course video file using ResNeXt-50 based technique. The visual feature was the average of all frame vectors. Additionally, Librosa was used to extract five acoustical features. Then, each learner's play and view records these courses were integrated with the learner's personal information and create 2–dimensional vectors. Finally, these vectors were processed by LSTM to recommend the final course list for users. In this approach, the authors only considered the course title, they do not consider other attributes such as description of the course, and reviews.

Ren et al. [23] suggested the multimodal course recommendation system which includes many phases such as pre-processing, extracting the features, profiling, and recommendation list. Initially, multimedia datasets were employed as the model's input; also, user statistical profiles, explicit feedback, and implied responses are taken into account. From the input data, the features were extracted using Resnet-16 based technique. Afterwards, the extracted features were processed using LSTM with attention mechanism. For performance assessment, Normalized Discounted Cumulative Gain, recall, hit ratio, and Area under the Curve was used as the performance metrics and compared to our proposed approach, this approach attains least values. Moreover, this technique requires longer time for training.

For a personalized learning system, Zhu [24] created a parallel neural network based on a neural collaborative filtering (NCF) model to acquire user and project perspective vectorization. Afterwards, the features were extracted using the multilayer perceptron (MLP) with the double layer attention mechanism which customize the weights assigned to the components of the historical connection series and improve the recommendation capacity. However, the error rate of this approach is higher than the proposed approach.

Chen et al. [25] presented a double-layer network based dynamic clustering collaborative filtering to improve the accuracy of the recommendation system. In this network, one layer used to retrieve characteristics of users and another layer used for items. Afterwards, dynamic evolutionary clustering was introduced to divide users into several groups. At last, user similarity among every community was utilized to retrieve top-N suggestion lists and score prediction. Three datasets were implemented for investigation trials, and several indicators were utilized to analyze the approach's capability. But, compared to our proposed approach, the results are not satisfactory. It achieves low precision, recall and f1-score values compared to our proposed technique.

Hao and Yang [26] suggested a strategy for recommending online learning resources that is attention-based and deep collaborative. This system incorporates all available online learning resources across the platform and adds an attention mechanism to assign weight to the materials. The feature extraction layer extracts nonlinear and linear interactions among the students and the course using MLP and generalized matrix decomposition. A deep neural network interacts with the attributes after calculating the attention of every characteristic size using softmax, and the prediction results can then be achieved by repeated training.

## 3. Proposed Methodology

An English learning recommendation system is designed and implemented using a Dual capsnet based deep learning framework that utilizes various modal data on the user and course. Initially, the input data are preprocessed and then forwarded to Dual Capsnet based network for feature extraction. In this dual capsnet, one layer is used to extract the features about user information. It analyzes user profiles, feedbacks and personal interest and then extracts significant features from the data. Another layer in the Capsnet is used to extract the feature about course information such as course title, description and reviews are analyzed and feature extraction is conducted. Finally, the fusion process is conducted on the extracted features of two parallel layers and the suitable courses recommendation list is suggested for users based on the final features. The overall process of this course recommendation framework is shown in Fig. 1.

### *3.1. Data preprocessing*

These data must be converted into vector representation since they cannot be entered into the network directly because they are not all in digital form. For example, the category of online courses and student details are not in digital form. Therefore, we utilized word2vec technique to convert these details into vector representation.

### *3.2. Feature extraction using Dual CapsNet*

Sets of embedded neurons are referred to as capsules in deep learning, and a CapsNet is made up of these capsules. Three components make up the two-lane Dual CapsNet design. There are 2-D capsule network channels in the first section. Here, the feature of user details is extracted from one channel, while course details are extracted from another. The second stage is called the fusion stage, and it combines the features taken from two 2-D capsule channels. The third stage is the output component, which combines three FC layers to provide the users' final list of chosen courses.

In this network, these two parallel 2-D capsule networks contain the same process. The first two layers in this architecture include 16 and 32 kernels, each measuring 5 by 5, with a stride of 1. The output from the second layer is subjected to maximum pooling with a stride of two. In the third layer, 128 filters with a stride of 1 and a size of 9×1 are present. The major capsule, which is in the fourth layer and contains 32 separate capsules, is applied to each capsule using a filter with a size of 9×1 and a stride of 2. The convolutional operation (16 convolution channels, 2 filters per convolution, ReLU activation), which uses 2 convolutional units with a 33 kernel and a stride of 2, is used in each Primary capsule.

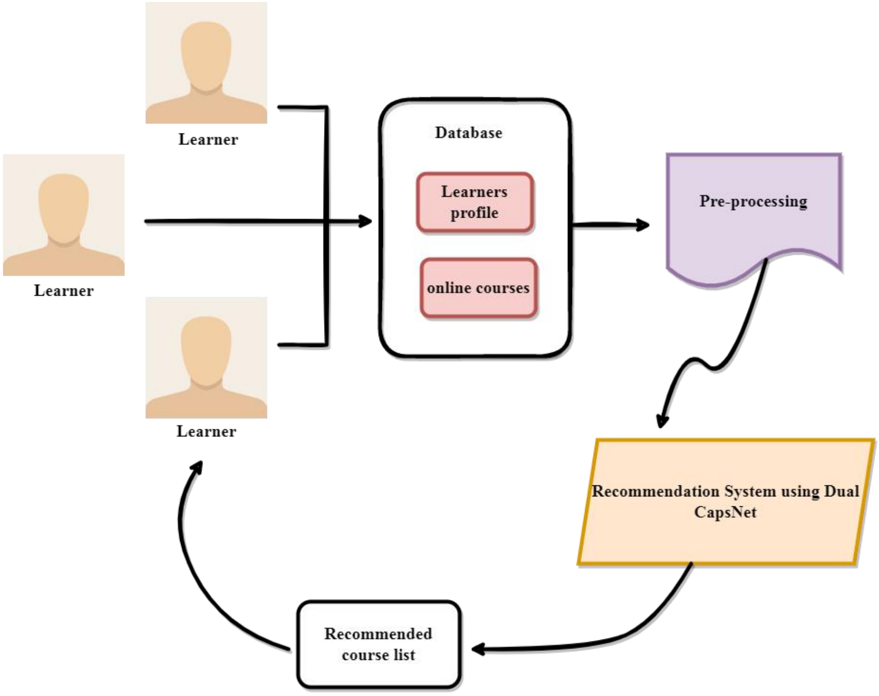



Fig. 1. System Architecture

The dynamic routing algorithm process is used to forward the capsules in the primaryCaps layer to the featureCaps layer. The individual opinions of each capsule are calculated using the trainable weights W of dynamic routing. $W_{ij}$ has a dimension of 8 ×16 if j ∈ [1, $N_{class}$] represents the index of the 16-dimensional output capsules and i∈ [1, $N_{PC}$] represents the index of the 8-dimensional primary capsule's dimension. The primary capsule's individual assessment of the output capsule's j is provided by

$$\hat{v}_{j/i} = v_i \times W_{ij}^{DC} \tag{1}$$

Where $v_i$ represents the i-th primary capsule. We obtain an output block with shape $N_{class\times 16}$ for each primary capsule i. Routing weights Rb, or a different kind of weight dimension $N_{PC} \times N_{class}$, are taken into account for the procedure of dynamic routing. They are used to combine many viewpoints to create the final output capsule. The separate opinions $\hat{v}_{j/i}$are combined to create the featureCaps output using the coupling coefficients $CC_{ij}$. The coupling coefficients $CC_{ij}$ are provided by

$$CC_{ij} = \frac{exp\,(Rb_{ij})}{\sum_k exp\,(Rb_{ik})} \tag{2}$$

Sixteen capsules are included in the featureCaps, and each of them acquires parameters from the primaryCaps layer. The concatenation approach is employed to combine the outcomes from the two featureCaps.

In the proposed recommendation system, the high-level latent properties of the courses and users are captured by the two parallel 2-D capsule networks in the same dimensions. Then, this module merges the high-level latent aspects of user actions and course attributes that were learned by the fusion module. The output layer (reconstruction sub-network) then receives the concatenated feature matrix. This layer is made up of two fully connected layers with dimensions of 512 and 1024 and ReLU activation functions, as well as a final FC layer with dimensions of 2304 and softmax activation. The proposed paradigm primarily emphasizes implicit feedback which uses a binary class label. In other words, this model's output is the chance of the user taking a course they haven't yet. The network ultimately suggests the best courses to learners in the order of the highest probability values.

Finally, it is possible to think of the projected label as a user's potential for engaging with a course. The sigmoid activation function is used to limit the estimated label's range to between 0 and 1. The following definition applies to the loss function:

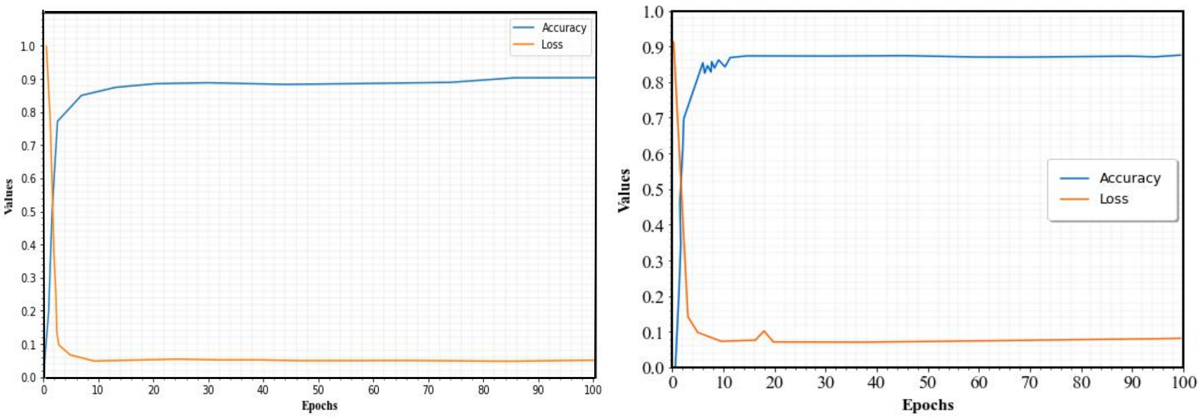
$$L(x_{ij},\hat{x}_{ij}) = \sum_{(i,j)\in\chi} (x_{ij} - \hat{x}_{ij})^2 + \frac{\lambda}{2}\|\Theta\|^2 \tag{3}$$

Here, to avoid overfitting, the regularization parameter $\lambda$is utilized. The predicted and actual values are represented by $\hat{x}_{ij}$and $x_{ij}$ correspondingly and the set of parameters are denoted by$\Theta$. Moreover, a training dataset that includes both positive and negative feedback is also indicated by$\chi$

## 4. Result and Discussion

In this section, several experiments are performed to illustrate the value of the suggested strategy. The datasets utilized in this investigation are first briefly discussed. The key assessment metrics are then presented. The experimental results are then compared using several change detection approaches once a comprehensive analysis has been completed. All tests are run on a computer equipped with an Intel Core i7 processor, 32GB of RAM, an Nvidia GTX 1080Ti GPU, and a Windows 10 operating system. All of the experiments involving the suggested strategy are carried out using Keras with a Tensorflow backend.

Eighty percent are used as training sets while twenty percent of the datasets are used as test sets for the model evaluation. Every sample in either the training or test set is a series that depicts a user's history of click-related actions. We hold out the most recent clicked notion as the objective during training for every sequence in the training set. The remaining concepts are also considered historical clicked topics. We randomly choose X topics that a learner hasn't ever interacted with previously as false negatives for each good instance. During the experimental process, the input data (XuetangX dataset) is initially preprocessed using word2vec approach, then the CapsNet model is trained using the pre-processed data to extract the features from the data and produce the recommendation of suitable course list. After the training process, the testing phase is conducted and the results are evaluated using the several performance metrics. Figs. 2a and 2b displays the training and testing accuracy and loss of the suggested technique respectively. On the XuetangX dataset, training occurs faster, as seen in the figure. The proposed model's training process also seems to be more consistent and efficient. Moreover, the testing loss and accuracy plots indicate that the proposed model is not overfitted with input data which indicates that the model can deliver a satisfactory result with fewer epochs.




(a)Training accuracy and loss

(b) Testing accuracy and loss

Fig. 2. Training and testing accuracy and loss of the proposed approach

Regarding parameter settings, the learning rate is 0.001, the quantity of iterations is 100, and the batch size is 16. Adaptive Moment Estimate (Adam) is a method of optimizing the adaptive learning process. The Adam optimizer is renowned for its speedy convergence and low memory usage. It uses a first-order gradient.

### 4.1. Dataset Description

To test the methodology, we used data from a real-world MOOC platform in China called XuetangX (available at http://www.xuetangx.com). In this study, classes from several years will be treated equally. There are 3,708,461 members, 7327 lessons, 96,950 recordings, and 140,446,950 relationships among the 2527 ideas that make up this system. Students who had enrolled in fewer than three courses were excluded to guarantee that the sequence suggestion made sense. Finally, the dataset contains 82,535 students, 1,302 courses, and 458,454 events.

*4.2. Performance metrics*

To evaluate the proposed personalized English learning system, several performance metrics were used. They are Root Mean Squared Error (RMSE), MAE (mean absolute error), precision, recall, F1-score, Hit ratio (HR) and Area Under the Curve (AUC) which are described in the following equation.

$$F1 = \frac{2\times precision\times recall}{precision+recall} \tag{4}$$

$$precision = \frac{No.of\ courses\ in\ the\ label}{No.of\ recommended\ courses} \tag{5}$$

$$recall = \frac{No.of\ courses\ in\ the\ label}{No.of\ all\ courses\ in\ the\ label} \tag{6}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{x}_i - x_i)^2} \tag{7}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|\hat{x}_i - x_i| \tag{8}$$

Here, the actual and predicted rating in the test set is denoted by x and $\hat{x}$ correspondingly. The AUC metric is analyzed based on the True Positive and False Positive rates. The courses that the recommender suggests for a certain learner and are also in the test set for that learner are considered true positives. False positives are courses suggests for a learner but are absent from the user's test vector.

To compute the error among the projected and actual ratings for the various models, the RMSE and MAE are used. For each learner, we created the top K courses for the suggestion list. A hit was declared if the test item appeared in the top K list. The HR is calculated using the below formulas when N represents the number of test data.

$$HR@K = \frac{\#No\ of\ Hits@K}{N} \tag{9}$$

*4.3. Experimental results*

This section discusses the outcomes of the investigation analysis. On a real-world dataset, many trials are performed with several recommendation list sizes, and Table 1 displays the HR outcomes of the models based on the recommendation list size. From the table, it is observed that the size of the recommendation list increased, and HR for all methods also increased. Moreover, when comparing the proposed approach to other methods using various recommendation list sizes, it consistently outperformed them. The graphical representation of Table 1 is presented in Fig.3.

Table 1. Comparison of the proposed approach in various hit ratios

| Techniques | Dataset | HR@50 | HR@100 | HR@150 | HR@200 |
|---|---|---|---|---|---|
| Deep Neural Network [22] | Private | 5.21 | 13.67 | 21.52 | 29.34 |
| LSTM+Attention [23] | Private | 7.71 | 15.85 | 24.90 | 31.27 |
| Deep collaborative filtering [26] | Private | 6.13 | 14.32 | 22.64 | 30.11 |
| Proposed approach | XuetangX | 9.25 | 17.22 | 26.65 | 34.79 |

The illustration shows that the suggested strategy produces a superior outcome that is noticeably superior to alternative approaches. The key reason is that the suggested approach can fully use the input's significant dimensions and temporal properties. Compared to all the techniques, the hit rate of Deep Neural network (DNN) little lower, which means it provides the very least information about the course.

Recall, Precision, and F1 are employed in this study to measure recommendation accuracy, and their findings are evaluated with those of Teaching Evaluation Network-Tensor Factorization (TENTF) [25] and Dynamic Clustering Collaborative Filtering with Double Layer Network (DCCF-DN) [27]. In Table 1, recommendation number 2 to 10 is selected for analysis. From the table, it is observed that the proposed approach is effective to some extent when compared to other techniques. The graphical representations of precision, recall, and f1-score findings are displayed in Figs. 4, 5, and 6 respectively.

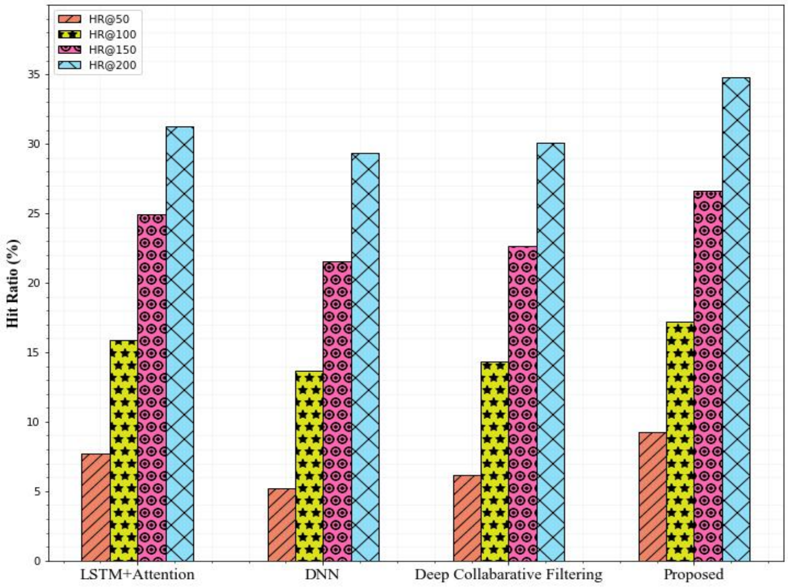



Fig. 3. Graphical representation of hit ratio comparison

Table 2. Comparison of recommendation results with existing techniques

| Techniques | Dataset | Metrics | 2 | 4 | 6 | 8 | 10 |
|---|---|---|---|---|---|---|---|
| DCCF-DN [25] | MovieLens − 100K | Precision | 91.14 | 90.20 | 89.61 | 89.04 | 88.59 |
| | | recall | 8.32 | 15.91 | 22.68 | 28.63 | 33.92 |
| | | F1-score | 15.18 | 26.88 | 35.95 | 43.02 | 48.72 |
| TENTF[27] | BIT-UASET | Precision | 81.12 | 73.11 | 68.97 | 51.65 | 43.69 |
| | | recall | 17.41 | 29.23 | 39.12 | 49.12 | 56.31 |
| | | F1-score | 28.16 | 41.67 | 54.78 | 60.32 | 73.11 |
| Proposed | XuetangX | Precision | 95.87 | 93.21 | 90.16 | 88.78 | 86.41 |
| | | recall | 23.45 | 35.15 | 48.67 | 51.36 | 63.98 |
| | | F1-score | 32.42 | 44.78 | 57.12 | 64.89 | 78.09 |

The precision values of various approaches have risen, as seen in Fig. 4 when iteration times have risen. In contrast, it can be seen from comparisons that the precision value of the system developed in this study is consistently greater than that of the standard approaches, with the highest precision value of 95.87 and the lowest value of 86.41. It demonstrates that the proposed methodology used in this study may advise the learner on the courses that are most suitable for their needs.

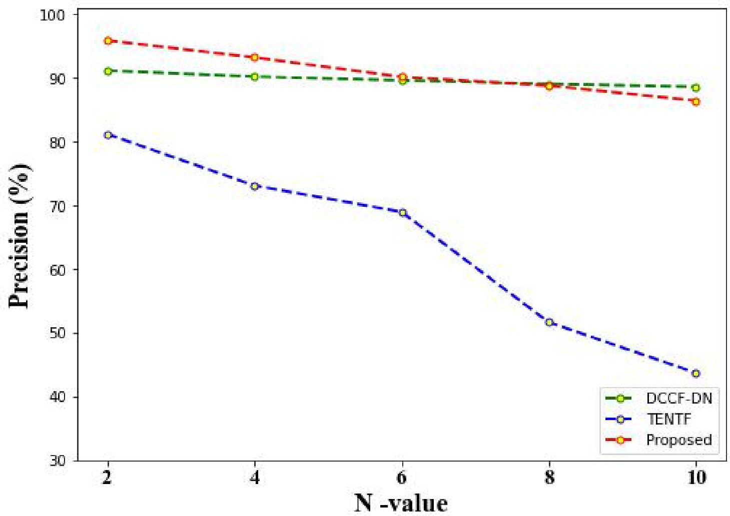



Fig. 4. Comparison of Precision with existing techniques

The proposed Dual CapsNet can bring together individuals with shared interests to form communities, and their advice is valuable when making decisions. Based on the expected score ratings, our suggested strategy suggests some potentially interesting content to the target user. As seen in Figs. 5 and 6, our suggested model surpassed other baseline techniques to achieve the best results in F1@N and Recall@N.

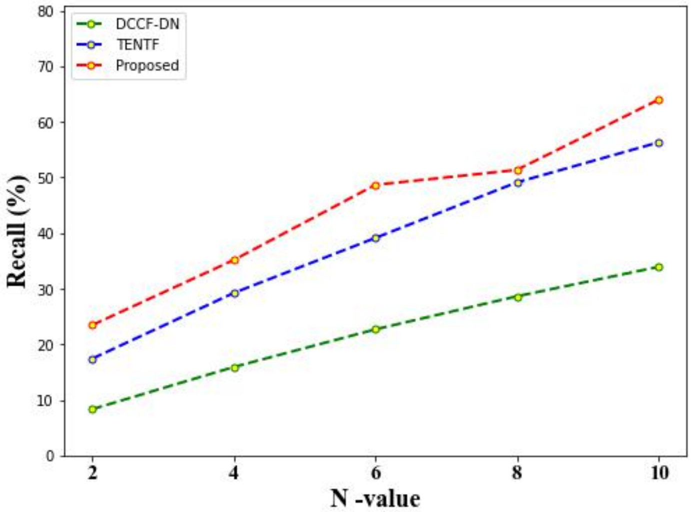



Fig. 5. Comparison of Recall with existing techniques

Particularly, the suggested model outperforms existing baseline models by maintaining a recall rate nearly above 70% when N varies from 2 to 10 (recall@10 = 63.98). On the other hand, the F1-score indication demonstrated that, when contrasted to existing techniques, the suggested framework obtained the greatest performance (F1@10 = 78.09). In other baseline models, the performance of TENTF is superior to DCCF-DN in terms of recall and f1-score. However, the DCCF technique has higher precision values than the TENTF technique. Since these values do not go beyond our suggested strategy. Moreover, the results of the proposed model's variants are demonstrating that each of the characteristics extracted from the input contributes to the recommender system to achieve the best outcomes.

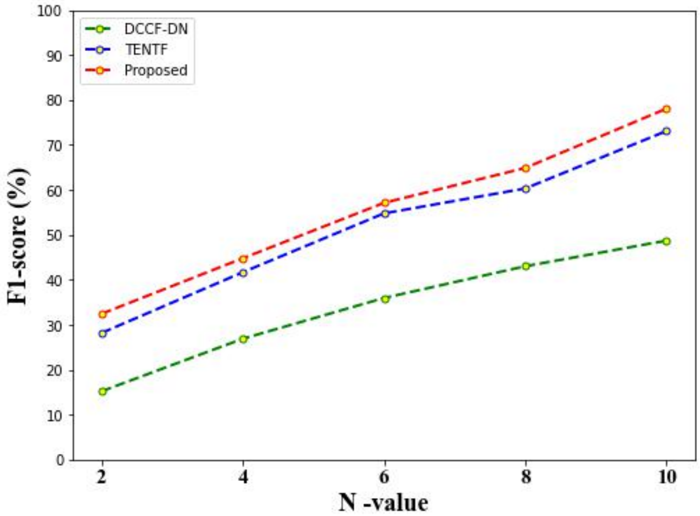



Fig. 6. Comparison of F1-score with existing techniques

To analyze the accuracy and reliability of the proposed approach, AUC is the important performance metric. In Table 3, the AUC value of proposed approach is compared with the existing techniques. Based on AUC, the proposed Capsnet outperforms all the existing techniques. Because, compared with our Capsnet, the deep neutral network fails to assess the sequence information. Moreover, pooling mechanism (average pooling) in DNN can reduce the overfitting but some crucial information could be lost during this process. Compared to this, our proposed approach preserves important features and provide better recommendation list than other techniques.

Table 3. AUC Analysis

| Techniques | Dataset | AUC |
|---|---|---|
| Deep Neural Network [22] | Private | 0.7903 |
| LSTM+Attention [23] | Private | 0.7989 |
| Multi-layer perceptron (MLP) [29] | XuetangX | 0.8595 |
| Multiple-layer graph convolutional network (MGCN) [30] | XuetangX | 0.8656 |
| Proposed approach | XuetangX | 0.9265 |

Compared to all other techniques, Multi-layer perceptron (MLP) and Multiple-layer graph convolutional network (MGCN) achieves comparable performance. In MLP, the output is depending on the dataset properties and it requires lot of computations. If the input data is very large, the network complexity is increased. The MGCN contains space complexity. It performed well only on limited data. But our proposed approach can handle large number of data and provide effective results due to its quick training time.

Table 4. Error Analysis

| Techniques | Dataset | RMSE | MAE |
|---|---|---|---|
| Double-layer CNN [24] | private | 0.843 | 0.722 |
| TENTF [27] | BIT-UASET | 0.959 | 0. 691 |
| DTNM [28] | CiaoDVD | 0.941 | 0.737 |
| Proposed | XuetangX | 0.798 | 0.671 |

In Table 4, the RMSE and MAE of proposed and existing recommendation algorithms are compared. These algorithms include the Double Layer Convolutional Neural Network (DLCN) [24], TENTF [27], and Double Trace Norm Minimization (DTNM) [28]. The table shows that the suggested algorithm's RMSE and MAR values are significantly higher than those of other strategies. The suggested method integrates information about students, online courses, and content descriptions; it offers more extensive information and tends to eliminate inaccuracies. As a result, the model presented in this work has some validity. Fig. 7 shows the graphic representation of Table 4.

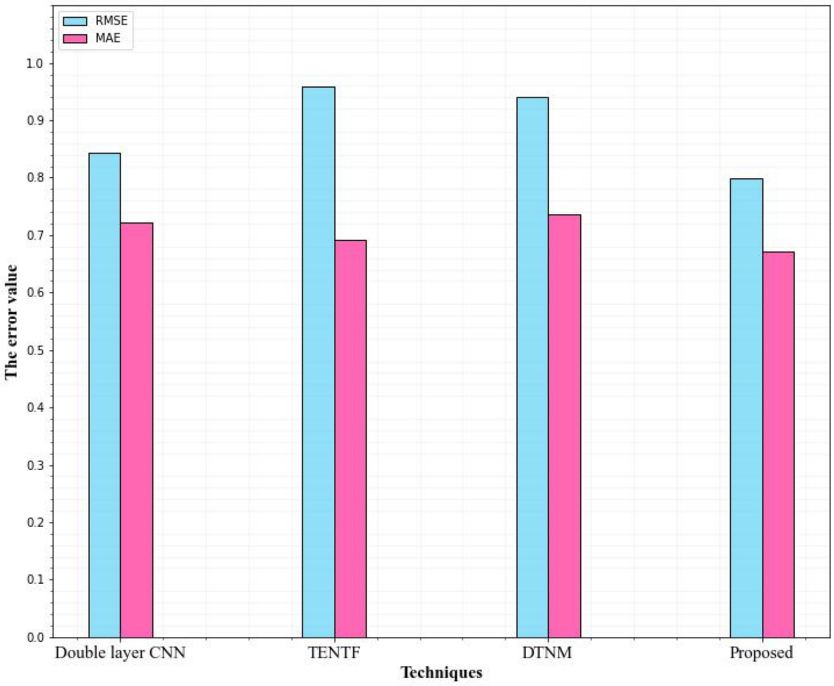



Fig. 7. Comparison of RMSE and MAE with existing techniques

The MAE value of the algorithm created for this research is comparatively low (0.671) when compared to other techniques. This indicates that the accuracy of the recommended system designed in this study is accurate. Additionally, when compared to other methods like CNN (0.843), TENTF (0.959), and DTNM (0.941), the suggested model gets the smallest RMSE value (0.798). Additionally, the performance of our suggested model has performed differently when unnecessary feature portions have been removed; indicating that the suggested features provide a favorable impact on the realization of the final forecast.

## 5. Conclusion

To address the issue of the current network platform's absence of accurate assisted course selection, this study suggested an effective online course recommendation system based on the deep learning technique. The dual capsnet is implemented in this framework to enhance the suggested approach's feature extraction capability and retrieve useful characteristics to produce a relevant course list that is more in accordance with learners' interests. Our experimental findings using real-world dataset demonstrate that the suggested recommendation model outperforms the existing techniques and obtains average values of 91% precision, 45% recall, 55% f1-score, 0.9265 AUC, 0.798 RMSE, and 0.671 MSE that demonstrate superior recommendation accuracy. Our research has practical consequences in online learning platforms that suggest appropriate courses to learners, and they don't need to waste time for selecting the right courses from lengthy lists of options. In future, we can research how to make use of more varied educational auxiliary data, such as student social activity, leverage scores, and learning preferences.

## Acknowledgements

We declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

## Authors' Contributions

The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

## Ethics Approval

This material is the authors' own original work, which has not been previously published elsewhere. The paper reflects the authors' own research and analysis in a truthful and complete manner.

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