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Deep Learning-based Educational User Profile and User Rating Recommendation System for E-Learning

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Abstract

In the current era of online learning, the recommendation system for the eLearning process is quite important. Since the COVID-19 pandemic, eLearning has undergone a complete transformation. Existing eLearning Recommendation Systems worked on collaborative filtering or content-based filtering based on historical data, students' previous grade, results, or user profiles. The eLearning system selected courses based on these parameters in a generalized manner rather than on a personalized basis. Personalized recommendations, information relevancy, choosing the proper course, and recommendation accuracy are some of the issues in eLearning recommendation systems. In this paper, existing conventional eLearning and course recommendation systems are studied in detail and compared with the proposed approach. We have used, the dataset of User Profile and User Rating for a recommendation of the course. K Nearest Neighbor, Support Vector Machine, Decision Tree, Random Forest, Nave Bayes, Linear Regression, Linear Discriminant Analysis, and Neural Network were among the Machine Learning techniques explored and deployed. The accuracy achieved for all these algorithms ranges from 0.81 to 0.97. The proposed algorithm uses a hybrid approach by combining collaborative filtering and deep learning. We have improved accuracy to 0.98 which indicate that the proposed model can provide personalized and accurate eLearning recommendation for the individual user.

Keywords: E-Learning; Recommendation System; Machine Learning; Deep Learning**.**

1- Introduction

To improve eLearning recommendation systems, it is critical to offer relevant data [12],[14],[17]. A customized eLearning recommendation system [11] is necessary to promote the acceptability of eLearning among students in all parts of India. Some of the drawbacks or issues in the recommendation framework are a cold start, reliable information would not be provided, searching from vast data, similar phrases are used for different reasons, and data relevance [25]. We are attempting to solve these concerns in our work.

Online education [1] is now widely utilized around the world, allowing young people to learn at their own pace while being safe at home. To satisfy the necessity, the proposed framework is introduced. The data science application for education is this type of recommendation system.

Information overload, adequate information, and reliable information delivered to learners are currently difficulties in eLearning [10]. A standard eLearning site should be available to students. eLearning has been around for a long time, and it provides a lot of benefits for students. It is founded on teaching values. The system presented in this study will aid in distance education.

Online degrees, distance learning courses, and online certifications are offered by many schools, universities, enterprises, and organizations throughout the world to promote eLearning. Many online courses and certifications are offered and announced by open courseware for MIT, Learndirect.com, NPTEL (National Enhanced Learning Technology Program), MOOC NPTEL (Massive Open Online Courses) [4].Companies, on the other hand, as they get to this higher level of personalization, increase the amount of information that buyers must process before

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selecting which goods match their demands. The suggested approach is one of the answers to the problem of knowledge overload.

The majority of the decision-making in the recommendation framework is based on historical data or user's information.[15][25]. The recommendation framework has proposed a lot of work since the mid-1990s. Students who use eLearning are well aware that proposing systems is both a learning opportunity and a challenge [10]. The recommendations in the eLearning recommendation system are based on user feedback. There are two perspectives on this. The system is partially converted to manual by forcing students to rate courses; second, the system is automated by inferring learning from students' study patterns or click-stream activity. The suggested rating scores are expressed as a ratio of real study hours to total course hours and are converted to explicit rating values on a scale of 1 to 5.

The objectives of this paper are:

1.Proposal of a novel recommendation system model for online course recommendation with a hybrid approach consisting of the collaborative learning and deep learning approach.

2.To improve accuracy as compared with the current approaches.

The remainder of the paper is organized as follows. Section 2 defines the related work. Section 3 explains the proposed model and methodology section 4 explains experimentation and results. Section 5 concludes the paper and its future scope.

2- Related Work

In the paper [1], the author, Dr. Wahab Ali, suggested that the teachers who are using online learning platforms for teaching students should use technology and instruments to promote, during exceptional times mainly. He called for online and remote learning during the Pandemic as a necessity during lockdowns and social isolation.

The authors of the paper [6] suggested different approaches to analyzing trainers' and trainees' understanding of digital learning. Also, the authors addressed the technique of execution of digital learning. Their focus is on the active learning mode of the students during the digital learning phase, which includes the creative performance of the students and education system during the outbreak of COVID-19, to overcome the confusion of ongoing academic disruption and bring back the educational activities in place.

A hybrid real-time incremental stochastic gradient descent (RI-SGD) technique for implicit feedback Matrix Factorization recommendation system was developed in the study [16]. The study's numerical data revealed that the RI-SGD approach could reach almost the same recommendation accuracy. The proposed method can be utilized to improve the accuracy of various collaborative filtering algorithms in the future.

This paper [30] introduces a method that combines knowledge graph and collaborative filtering. They used the semantic information of the items and fused it with a collaborative filtering algorithm to recommend the course. The side information like social media, multimedia is used as parameters. User interests have not been considered herein our model we are considering the User Interests.

The Educational Data Mining technique is employed to handle academic management problems in this paper [31], and the Singular Value Decomposition (SVD) classifier is used to provide course information for students' optional course recommendations based on their grades. The accuracy of the advice is worse here because SVD has an issue with data density. The accuracy can be increased using the proposed method.

In this paper [31] Educational Data Mining algorithm is used to solve the academic management problems and a Singular Value Decomposition (SVD) classifier is used for giving course information for a recommendation of elective courses to the students based on their grades. Accuracy of recommendation is less here as SVD has a problem with the density of the data. Using our method, the accuracy is improved.

The authors of this paper [23] employed the Apriori and SPADE algorithms to select courses based on course history similarities. We increased the accuracy by combining the user's profile with the course ratings provided by users.

Similarly, the challenges in eLearning Recommendation Systems [13] are:

1. Existing work shows that User profile-based recommendation systems for eLearning are having an accuracy of less than 0.98. The comparison with the existing systems is shown in Table 1.
2. Current results have not utilized all the available information like mining users and item profiles, implicit feedback, contextual information, and review texts.
3. Scalability for the recommendation system is one of the problems.
4. Taking User's interests into consideration and Users' Ratings is also required for better accuracy in a recommendation.

In contrast to most current eLearning recommendation systems, such as [3],[6],[12], which only

used explicit feedback rating values in their recommendation method, the proposed approach considers multidimensional attributes of an education-based user profile and rating values in its recommendation method. The proposed system uses a user profile and ranking based on education for recommendation purposes, as well as deep learning [26][28] to improve recommendation accuracy.
To demonstrate the efficacy of the proposed method, it was tested against existing recommendation algorithms. Precision, recall, F1-score, and accuracy [9] are employed as performance indicators.

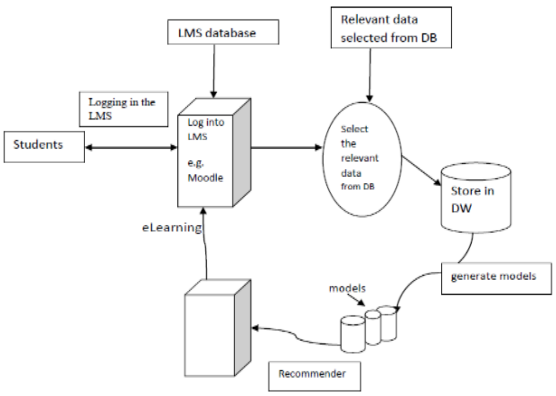
3- Proposed Methodology

The system architecture depicted in Fig.1 accepts User Profile data from Institutes or educational institutions as input data. The data is stored in the dataset through Learning Management Systems (LMS). The relevant data stored in the database is considered for the recommendation model. The information seeker's attention is drawn to the precise profiling technique [3]. User profiling [19] is used to develop recommendations for knowledge seekers using a hybrid approach that combines collaborative filtering with content-based filtering [16]. The proposed algorithm is as:

Algorithm:

Input: User Profile and User Rating Dataset
Output: Course Recommendation
1. Dataset is built from Engineering Students Profile.
2. Do stemming the field keyskills.
3. Tokenize the keyskills generated from step 2.
4. Remove the predefined frequent words,from tokenized keyskills.
5. Use TF-IDF to categorize and filter courses.
6. Extract Feature Vector, apply K-means algorithm and find out clusters.
7. Use the deep learning method to train the model.
8. Perform testing on new user profiles and predict the course recommendation list for the user.

Fig.1 System Architecture



3-1- Dataset

The data has been collected from the student profiles of Dr. Vishwanath Karad, MIT World Peace University (MITWPU), Pune. The data is collected from students through the Calyxpod tool. This data is for the year 2019-2020 for 5 different programs as mentioned in Table 2. Different User profile parameters considered are User Id, Specialization, Gender, Known Languages, Internship Experience, Projects, keyskills, Career Objectives, Certification.
As per the literature study, the parameters used for recommendations are students' grades, historical data, or User profiles [23]. We've used User Profile to determine the user's course requirements. Users Rating is also considered for recommendations. We were able to determine the course's quality as well as the user's grasp of the course by using ratings. Currently, this study only focuses on Engineering students. Engineering courses are fast and vast. For slow learners, the online courses will help to understand and speed up their studies. Further, this can be applied to another program as well.

Table 1: Summary of methods used for Course Recommendation System

Sr.No.	Authors and Year	Methodology	Parameters Used	Performance Measure
1	Zammer Gulzar, A.Anne Leema,Rerard Deepak(Dec 2017)[7]	Hybrid techniques are used N-Gram and Query Expansion approach and upgrade basic information retrieval technique along with the support of Ontology	User's personal information	Accuracy=0.95
2	Dussadee Praserttitipong and Wijak Srisujjalertwaja(Dec 2018)[31]	Education Data mining (EDM) and Singular Value Decomposition (SVD)	Student Grades	Accuracy=0.67
3	Raghad Obeidat, Rehab Duwairi, Ahmad Al-Aiad(Feb 2019)[23]	Apriori algorithm association rule mining and SPADE algorithm sequential pattern mining.	The similarity of student's course history	Rules Coverage using Apriori Algorithm Association Rule Mining =0.691
4	Gongwen Xu, Guangyu Jia, Lin Shi, Zhijun Zhang(Aug 2021)[30]	the algorithm based on knowledge graph and collaborative filtering	Side Information is used as social media, multimedia	Accuracy =0.96
5	Idowu Dauda Oladipo, Joseph Bamidele Awotunde, Muyideen Abdul Raheem Oluwasegun Osemudiame Ige Ghaniyyat Bolanle Balogun Adekola Rasheed Tomori Fatimoh Abidemi Taofeek-Ibrahim(Oct 2021)[8]	logistic regression model and deep recommender were used to classify students to recommend possible electives to them.	Students' previous grades	Accuracy=0.84
6	Our Method	K-means algorithm and Sequential deep learning algorithm	User Profile and User Rating	Accuracy=0.98

Table 2: Data Collection

Sr.No.	Specification of Data	Number of records
1	Computer Engineering	423
2	Electronics &Telecommunication	474
3	Mechanical	555
4	Civil	200
5	Chemical	233

Out of all the User Profile dataset parameters, the "keyskills" parameter is taken to decide the recommendation. The system is trained using all the records in the User Profiles dataset. Another dataset used for the recommendation is the User Rating dataset. This dataset is the matrix of User Id and Course Id. The User Id field is derived from the User Profile dataset. The Course Id comes from the list of courses. The course list is as shown in Table 3. There are a total of 20 courses we considered. Each course has a unique id, that is, course id. User Ratings from related clusters are taken into account when creating the User Rating dataset. The rating is given explicitly by the user in the range of 1 to 5 (1 is the lowest rating, and 5 is the highest rating).

3-2- Modelling Techniques

The proposed system's functioning is explained below.

Let the system be the set, S = {I, O, F}

$I: Set\ of\ Inputs = \{U1, U2, \ldots. Un, K1, K2 \ldots. Kn, R1, R2, \ldots.. Rn\}$

Where

$U1, U2, \ldots., Un = set\ of\ User\ Profiles$

$K1, K2, \ldots Kn = set\ of\ keyskills\ taken\ from\ User\ Profiles$

$R1, R2, \ldots.., Rn = Ser\ of\ User\ Ratings$

$O: Set\ of\ Outputs = \{RE1, RE2, \ldots. REn\}$

Where

$RE1, RE2, \ldots. REn = Recommendation\ list$

$F: Set\ of\ Functions = \{F1, F2, F3, F4\}$

where

$F1: Feature\ Extraction$

$F2: Clustering\ by\ Kmeans$

$F3: Training\ the\ model$

F4: Recommendation model

3-2-1-Data Pre-processing and Feature extraction (Function F_1)

To obtain the vector representation of each word, the TF-IDF (Term Frequency-Inverse Document Frequency) approaches [5] are used. TF-IDF is a traditional method used in the recommendation system.TF-IDF has the first item as Term Frequency (TF) can be represented as $tf_{t,d}$ where t is the word count, and d is the document where the counted word has appeared. $tf_{t,d}$ gives us a number that tells how many times the word t appears in document d. Their sub vectors compared each other, and similarity measure Euclidean distance is used. Tf-Idf weights are used to compare User Profiles. Term Frequency (TF) represents as $tf_{t,d}$.

The equation of TF weight is as

$$tf_{t,d} = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}} \tag{1}$$

where $f_{t,d}$ is term count in a document

The equation of IDF weight is as

$$idf = \log \frac{N}{df_t} \tag{2}$$

Tf-Idf weight is

$$W_{t,d} = 1 + \log 10 tf_{t,d}\ X \log \frac{N}{df_t} \tag{3}$$

Where N is the total number of documents.

Table 3: Course List

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Course ID	Course Name	Course ID	Course Name
1001	Core JAVA	1011	LINUX
1002	CPP	1012	PHOTOSHOP
1003	Data Structures	1013	CAD-CAM
1004	Python	1014	AuTOCAD
1005	C	1015	3D-modelling
1006	Mysql	1016	Project Managemnet
1007	Embedded C	1017	Hypermesh
1008	SQL	1018	D-A-U-E
1009	MATLAB	1019	Staad-pro
1010	Arduino	1020	Tekla

Each word in the dataset is converted into a vector. The input for the next function is the feature vector acquired from the F1. To extract the feature vector, the frequency matrix is computed first, then using frequency matrix term frequency (TF) is calculated, and inverse document frequency (IDF) is computed. The pseudo-code of the feature extraction is shown below.

```
ComputeFrequencyMatrix(userKeySkills):
    freqMatrix ← {}
    stopwords ← SET(stopwords.words("English"))
    ps = PorterStemmer()
    for each user in userKeySkills:
        freqTable ← []
        keyskills ← wordTokenise(userKeyskills)
        for each keyskill in keySkills:
            keyskill ← keyskill.lower()
            keyskill ← ps.stem(keyskill)
        if keyskill in stopwords:
                continue
            if keyskill in freqTable:
                freqTable[keyskill] ← freqTable[keyskill] + 1
            else:
                freqTable[keyskill] ← 1
        freqMatrix[user] ← freqTable
    return freqMatrix

ComputeTf(freqMatrix):
    tfMatrix ← {}
    for each user, freqTable in freqMatrix.items():
        tfTable ← []
        userKeyskillsCount ← length(freqTable)
        for each keyskill, count in freqTable.items():
            tfTable [keyskill] ← count / userKeyskillsCount
        tfMatrix[user] ← tfTable
    return tfMatrix
        idfTable ← []
        for each keyskill in freqTable.keys():
        idfTable[keyskill] ← math.log10(totalUsers / countUsersPerKeyskill[keyskill])
        idfMatrix[user] ← idfTable
    return idfMatrix

ComputeTfIdf(tfMatrix, idfMatrix):
    tfidfMatrix ← {}
    for each (user, freqTable) in zip(tfMatrix.items(), idfMatrix.items()):
        tfidfTable ← []
  for each (keyskill, value) in zip(tffreqTable.items(), idffreqTable.items():
            tfidfTable [keyskill1] ← (tfvalue . idfvalue)
        tfidfMatrix[user] ← tfidfTable
    return tfidfMatrix
```

3-2-2- Clustering using K-Means Algorithm (Function F2)

The feature vector is taken from the User Profile. This feature vector is fed into the K-means clustering algorithm [24] to determine which cluster the User Profile belongs to. To determine the set of K clusters, the K-means clustering technique is utilized. Every data point is assigned to the closest center, with the total number of such assignments reduced to a minimum. For low-dimensional data, the K-means clustering algorithm is utilized because it is simple and fast. It outperforms other hierarchical clustering methods in terms of computing speed. It also results in tighter clusters [24].

3-2-2-1-Elbow method to find optimal clusters

Both distortion and inertia elbow methods [27] are applied using the dataset and calculated the value of k. Fig.2 depicts the elbow to finalize the value of k using distortion. On the X-axis value of k and the Y-axis, the distortion value is displayed. Fig.3 depicts the elbow to finalize the value of k using inertia. On the X-axis value of k and Y-axis, the inertia value is displayed. The distortion is measured as the sum of the square distances of the respective clusters from the cluster centers. The Euclidean distance metric is used. Inertia is the number of square sample distances to the center of their nearest cluster to calculate distortion. Then using Euclidean distances between centroids and their items, the total intra-cluster variation is calculated.

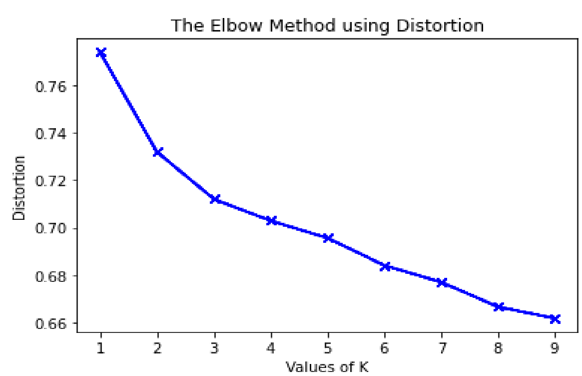

Fig. 2 The elbow method uses distortion

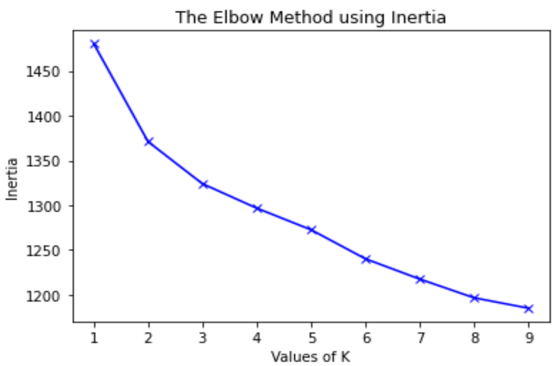

Fig.3 The elbow method uses inertia

The K value of the K-means algorithm can find out using the above elbow method. Once the K value is finalized, the clusters from the available feature vector are calculated using the standard K-Means algorithm. Euclidean Distance similarity measure [11] is used to find the similarity index in the K-Means algorithm.

The equation of Euclidean Distance similarity measure is:

$$d(\mathbf{p},\mathbf{q}) = \sqrt{\sum_{i=1}^{n}(q_i - p_i)^2} \tag{4}$$

where p,q= two points in Euclidean n-space

q_i,p_i=Euclidean vectors, starting from the origin of the space (initial point)
n= n-space
The K-Means algorithm returns the clusters which the following model uses for training purposes.

3-2-3-Training the Model (Function F_3)

The model is trained using a deep learning-sequential model [2]. Fig.4 depicts the suggested system's sequential model. A sequential model is a series of layers that process input and output it through the output layer. It has a sequence of layers.

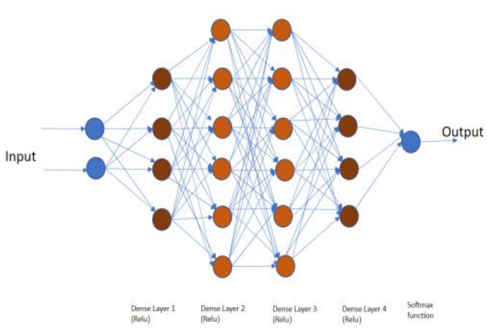

Fig.4: Deep Learning Sequential model

In the first dense layer,50 neurons and the relu() activation function is used. It is a rectilinear activation function. Mathematically, it is defined as y= max (0, x). It returns 0 if it gets negative input. For positive input, it gives the same value back. In the output layer the SoftMax() function[18] is used as activation function. It specifies the probability for each node in the output layer; when these probabilities are added together, the result is 1. That is, the result is between 0 and 1.

Softmax function is

$$\sigma(Z)_i = \frac{e^{Zi}}{\sum_{j=1}^{K} e^{Zi}} \; for\ i = K\ and\ z = (Z_1, \dots \dots Z_K)\epsilon\mathbb{R}^K \tag{5}$$

$\sigma = softmax\ function$

$Z = input\ vector$

e^{z_i} =standard exponential function for an input vector

K= number of classes in K-means

e^{Z_j}=standard exponential function for output vector

In the second dense layer, 30 neurons, in the third layer 20, and the fourth layer10 neurons and relu() activation function is used in all these layers. After creating the model, an object is created that can perform training actions at each iteration. In compiling the model Stochastic Gradient Descent (SGD) optimizer [21], categorical cross-entropy [29] loss function is used because the multi-class classification and accuracy metric is used. The model is trained for 1000 iterations. In the end, the model performance analysis is done using loss and accuracy.

3-2-4-The Recommendation Model (Function F_4)

A recommendation list of courses is shown in Table 2. Then the next step is to read the User (individual user) Profile who is willing to use the proposed eLearning model. It reads a single user profile to which the course is to be recommended. The steps in section 3-2-1- will be carried out on the selected single user profile, and the feature vector is extracted from that profile. It needs to be found that the cluster would fit perfectly using this feature vector. A trained model will be used to find the predicted cluster that is the cluster to which that record belongs. The keyskills available to the user will be subtracted from the cluster's keyskills, and the user would be recommended for the remaining courses. There may be more than the one suggested coue out of which the user can choose for one of the courses. From the recommended course list, a user is recommended a single course and dataset User Rating considered as mentioned in the dataset. The mean of User Rating will be calculated, and the course having maximum mean will be recommended to the user, using the User Rating dataset and recommendation list. Step 3.2.1 is applied to U1 (feature vector of a single user). The trained model from step 3.2.3 can be used on the feature vector U1 to get the predicted cluster. This is the cluster number from which cluster the user belongs. To get the recommendation list, subtract the keyskills of the user and the matching class. The result of the subtraction is the recommended list of courses which is depicted in the Venn diagram in Fig.5.

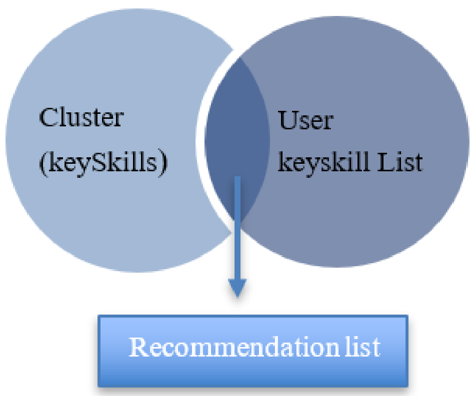

Fig.5 Venn diagram for a recommendation list

4- Results and Discussion

We investigated with the aid of a small educational illustration from eLearning. The execution of the algorithm mentioned above is performed using the datasets mentioned in the dataset section. The eLearning recommender model is implemented with the various Machine Learning Algorithms [20]. All the Machine Learning algorithms are executed, and results are determined for comparison with the proposed method. There are four classes for the mentioned dataset using K-means clustering algorithms, as shown in Table 4. The performance measures result is depicted in Table 5. Total

Class 0	Html, MongoDB, embedded, core, Matlab, SQL, MySQL, python, java, CPP
Class 1	Revit, skills, communication, design, cad, data, PCB, programming, CPP, Matlab
Class 2	Cad, office, creo, Matlab, Solidworks, Ansys, proe, ms, CATIA, AutoCAD
Class 3	Python, android, javascript, PHP, SQL, MySQL, Java, CPP, CSS, HTML

8 Machine Learning algorithms [22] are used, as shown in Table 5.

Table 4: Classes/Cluster list

Precision (6), recall (7), F1-score (8) are employed as performance measurements [22]. True positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are the four parameters that are used to evaluate the model's overall predictive capability (9). The accuracy is defined as the ratio of appropriately recommended courses to the first n courses advised. The recall ratio is the number of correctly recommended courses divided by the total number of recommended courses (m).

$$Precision = \frac{TP}{TP+FP} \quad (6)$$

$$Recall = \frac{TP}{TP+FN} \quad (7)$$

$$F = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision}+\text{Recall}} \quad (8)$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (9)$$

Table 5: Analysis of Machine Learning Algorithm

Sr.No.	Algorithms Used for eLearning Recommendation System	Average accuracy (%)	Performance Measures				
			Classes	Precision	Recall	F1-Score	Support
1	K Nearest Neighbour	91	0	0.83	0.85	0.84	85
			1	0.94	0.93	0.94	389
			2	0.83	0.86	0.84	72
			3	0.89	0.87	0.88	78
2	Support Vector Machine	97	0	0.98	0.95	0.96	85
			1	0.97	0.98	0.96	389
			2	0.94	0.97	0.97	72
			3	0.95	0.97	0.96	78
3	Decision Tree	95	0	0.97	0.88	0.94	85
			1	0.97	0.96	0.97	389
			2	0.9	0.97	0.93	72
			3	0.89	0.96	0.93	78
4	Random Forest	97	0	0.96	0.94	0.95	85
			1	0.98	0.97	0.98	389
			2	0.91	0.99	0.95	72
			3	0.94	0.96	0.95	78
5	Naïve Bayes	60	0	0.25	0.96	0.39	85
			1	0.88	0.35	0.5	389
			2	0.6	0.93	0.73	72
			3	0.68	0.24	0.36	78
6	Linear Regression	97	0	0.95	0.94	0.97	85
			1	0.97	1	0.98	389
			2	0.96	0.92	0.96	72
			3	0.96	0.95	0.95	78
7	LDA	92	0	0.82	0.92	0.87	85
			1	0.98	0.91	0.94	389
			2	0.87	0.93	0.9	72
			3	0.8	0.95	0.87	78
8	Neural Network	96	0	0.94	0.93	0.93	85
			1	0.98	0.97	0.98	389
			2	0.93	0.96	0.95	72
			3	0.94	0.96	0.95	78
9	Our Proposed algorithm using Deep Learning	98	0	0.94	0.95	0.95	85
			1	0.99	0.98	0.98	389
			2	0.97	0.97	0.97	72
			3	0.96	0.97	0.97	78

Fig.6 shows the graph of precision values for all four classes/clusters of all the algorithms. A high precision value indicates that there is a low false-positive rate. Fig.7 depicts the plot of recall values for all the four clusters of all algorithms. A high recall value indicates that there is a low false-negative rate. Fig.8 depicts the plot of the F1-score for all clusters of all algorithms and projects that large score value results in a correct positive outcome and preserving it.

Fig.9 shows the plot of the accuracy of all algorithms. The proposed algorithm accuracy achieved is 0.98 which shows that the system correctly recommends the courses to a user by using the User Profile and User Ratings dataset.

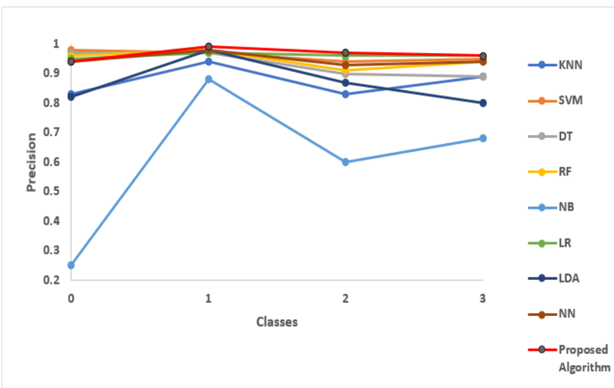

Fig.6 Plot of Precision

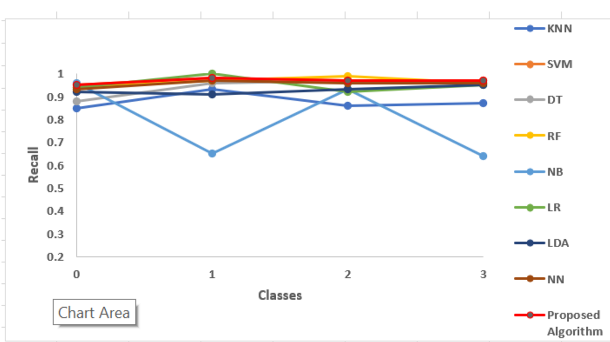

Fig.7 Plot of Recall

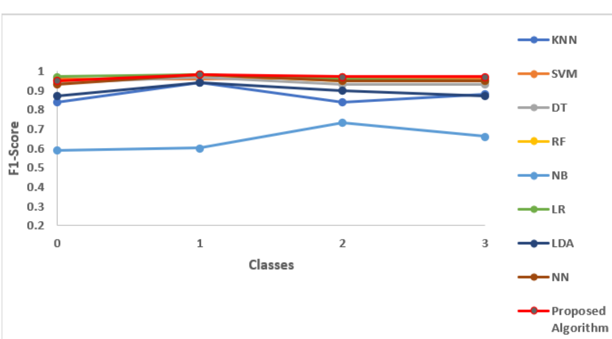

Fig.8 Plot of F1-score

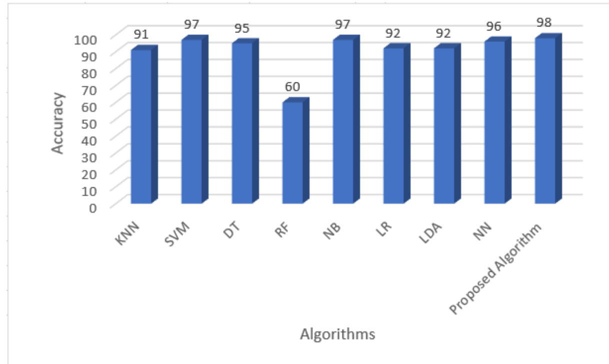

Fig.9 Comparison of accuracy

5- Conclusion and Future Work

To improve the accuracy and effectiveness for a proper recommendation of the course we proposed an eLearning Recommendation System based on collaborative learning and deep learning. The proposed system addresses the problems of collaborative filtering in the recommendation system algorithm which solely employs the users' history or grades data. To evaluate the performance of the proposed method, experiments on User Profile and User Rating between state-of-art methods and our method are conducted. Various machine learning algorithms are used to compare the results with the proposed method. The accuracy of machine learning algorithms is between 0.81 to 0.97 and we have improved the accuracy by using the proposed method to 0.98. The results suggested that the considered parameters in the dataset and deep learning approach provide more accurate results.

However proposed algorithm also has some limitations, which will not consider the weak topic of the user and do not consider implicit feedback of the user. It can be enhanced even more if implicit feedback-based recommendations are taken into account. Another limitation is the experimentation is done only on Engineering students. The model can further extend to any of the eLearning programs by modifying the course list.

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