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An automatic college library book recommendation system using optimized Hidden Markov based weighted fuzzy ranking model

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ABSTRACT

An automated book recommendation system has becoming a necessary role in increasing the efficacy and user experience of college library. The number of books in the library is very large, and it is difficult for students to choose the appropriate book from each department efficiently. The manual selection of books is time-consuming, and an automatic library book recommendation system is highly required. Therefore, this research proposes a novel ranking-based hybrid recommendation system for assisting each student in different department to select required books with minimal time. Initially, pre-processing is done to label each department name, which can effectively reduce the time complexity. Then, weighting is provided for each book using a timestamp based on the days the book was issued between the date of issue and return. After, Pearson correlation coefficient (PCC) is computed to find the similarity between the department and the corresponding books. Finally, the Hidden Markov-assisted Chaotic Artificial Humming Bird with Discriminant Analysis and weighted fuzzy ranking (HMCAHB_DA-WFR) model is proposed to classify the books according to the department accurately based on the generated ranks and provides better recommendation to the students. The proposed method is implemented in PYTHON software, and a real-time dataset is utilized from Bhilai Institute of Technology, Durg. The proposed method obtains a better accuracy of 99.2%, Kappa of 97.6%, MAE of 0.074, NMCC of 98.7%, FPR of 0.0085% and FNR of 0.034%. The attained simulation results prove the efficiency of proposed method over other existing methods.

1. Introduction

In growing countries, the availability of the Internet and technology have provided significant convenience for improving self-learning activities. It has an issue that the person could not find relevant books based on the requirement for specialized or personalized study. To resolve this problem, a recommendation system is introduced which has the ability to learn resources based on the precise collection of relevant information (Vineela et al., 2021; Saleem et al., 2021). A recommender system is a part of information filtering systems for predicting user preferences or ratings (Chanaa, 2022). Also, this system improves the quality of decision-making system (Qian et al., 2019; de Souza Pereira Moreira et al., 2021).

The recommender system is classified into varied types: collaborative filtering-based, content-based, and hybrid approaches (Qian et al., 2019; Ramakrishnan et al., 2020; Mounika and Saraswathi, 2021; Kommineni et al., 2020; Gao et al., 2023). Collaborative approaches are further classified into item-based and user-based collaborative filtering. In the item-based approach, two items were combined, and the similarity score between them is estimated with cosine distance, Jaccard distance and Pearson's correlation. In a user-based approach, the similarity between two users is combined, and the scores are generated. Active recommendations can be performed based on the calculation of score values (Ramakrishnan et al., 2020; Kommineni et al., 2020). The content-based system correlates with the user profile and item contents effectively (Shah, 2019), (de Souza Pereira Moreira et al., 2021; Kommineni et al., 2020). Such item contents can be described as a group of descriptive attributes. The model-based approach is either item-based or user-based, and in this approach, the prediction of rating value depends on the weighted average of several users' recommendations. In addition, the memory-based technique is based on a machine-learning algorithm (de Souza Pereira Moreira et al., 2021; Kommineni et al., 2020; Li et al., 2019).

The proposed research deals with the college library book recommendation mechanism in which students can explore for books based on their demand (Tian et al., 2019). This recommendation is mainly based

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on the feedback of other students (Devika et al., 2021). Here, the feedback is considered in the form of comments or ratings that available in the database. In general, online book recommendation process faces a complex issue in exhibiting the correlation among books (Rana and Deeba, 2019). When, the students or any other users explore for purchasing a specific book, the recommendation system can suggests some books which have been acquired from the information database involving other student's interests. The recommender system predicts user interest based on several AI-based approaches such as clustering, classification, deep learning, and regression applied at an abstract level (Chanaa, 2022). In recent years, Deep learning (DL) and Machine Learning (ML) approaches are becoming more popular in detection and classification tasks (Hasib et al., 2023a,b; Hasib et al., 2023a,b; Hasib et al., 2022). Because of their great features, several studies used such approaches in recommendation system (Ijaz, 2020). The DNN-based approaches learn unsupervised data with high-level feature extraction (Maharana et al., 2021). Thus, the learning approaches are highly suitable for recommending appropriate books to the students (Wu et al., 2023a,b). Also, Latent Factor models are introduced in recent studies for aiding both recommendation system and handling high dimensional data (Wu et al., 2023a,b; Wu et al., 2023a,b; Wu et al., 2023a,b).

Every year, a large number of books are introduced to the library. When the number of books in the library is high, it is difficult for the user to select the appropriate book from many candidate books. At the same time, several books are not used, and it causes a waste of resources. This is due to the problem associated with information overhead. To tackle this, it is required to rely on the information filtering approach. It is categorized into search mechanism and recommendation approach. The former uses the keyword for finding the book based on user requirements (Alharthi et al., 2018). The recommendation approach automatically recommends books to a user. The personalized recommendations are suggested based on interest, behaviour and information. The personalized recommendations meet the user's needs but also help the user to explore new hobbies. The recommendation system resolves the issue of selecting the book, in which the library resource utilization rate is improved (Ifada et al., 2019). However, the existing methods faced several issues while recommending suitable library books to the students like data sparsity, lack of content knowledge, low scalability and diversity, cold start issues, etc. Thus, the proposed study introduced a hybrid recommendation system by integrating content-based and collaborative filtering-based approaches for effective accuracy performance.

Research questions:

a) How can an effective college library book recommendation model be designed for the demanded users?
b) How to provide a robust department-wise classification mechanism in the recommendation system?
c) Can a system be accurate enough to perform classification tasks and fuzzy ranking in the recommendation system domain?
d) How does the proposed model manage the challenges and risks associated with the classification stages to result in optimal outcomes?
e) How effectively does the hyperparameter tuning process support the proposed recommendation model?
f) How does the proposed system overcome the computational complexity issues?

For book recommendation, various methods have existed in previous studies. Several studies used Artificial Intelligence (AI) methods to enable book recommendations. For enhancing prediction accuracy, SAI methods are highly preferred. Some of the general AI methods that are supportable for recommendation systems are fuzzy methods, evolutionary algorithms, deep learning, machine learning, genetic algorithms and neural networks. Recently, the machine learning-based K-means Cosine Distance function has been used for recommending books to the demanded users (Sarma et al., 2021). This K-means Cosine Distance function has the ability to remove unwanted boring books. However, the mentioned method only recommends a minimum amount of books for a specific query due to the inability to cluster the books. To solve this issue, the proposed study used an optimized Hidden Markov Model (HMM) along with Discriminant Analysis (DA) for classifying books department-wise. On the other hand, CNN-based AI is preferred in some existing papers for making effective book recommendations (Wadikar et al., 2020). The developed CNN method provides better outcomes, but it is highly troubled by complexity issues. Thus, by considering this problem, the proposed study optimally fine-tunes the parameters of the HMM model using a modified bio-inspired optimization algorithm. Similarly, Long Short-Term Memory (LSTM) and Deep AutoEncoder (DAE) based deep learning methods are used in the existing works for recommending books to the required users (Hou, 2022). This method has the ability to learn the features effectively. However, such complex models need additional processing time while recommending books. This issues have solved in this proposed work by utilizing DA along with the proposed Hidden Markov-assisted Chaotic Artificial Humming Bird (HMCAHB) method. Because of the great efficiencies in the AI methods, the proposed study preferred AI methods for the book recommendation process. The major contributions of the proposed work are given below:

- To provide a hybrid recommendation system (HMCAHB_DA-WFR) for attaining personalized recommendations with the inclusion of a time component.
- To enable labelling-based pre-processing to enhance the possibility of success by providing appropriate recommendations and tackling the issue related to data analysis and information retrieval.
- To conquer timestamp-based weighting using issue date, receive date and the number of times the book is issued and to find similarities between books and corresponding departments using PCC.
- To propose an HMCAHB_DA-WFR based hybrid recommendation model for classifying and ranking the books based on corresponding departments respectively.
- To verify its efficiency, evaluate and analyze the performance like accuracy, MAE, Kappa, and run time of the proposed system.

The rest of the section is determined as follows: Section 2 presents the literature survey of a recently published papers related to proposed study. Section 3 demonstrates a detailed description of the proposed recommendation system. Section 4 evaluates the results and discussion of this work. Section 5 provides the conclusion of proposed work along with a valuable future scopes.

2. Literature review

Some of the recent work that carried on recommendation system using different mechanisms are provided as follows.

2.1. Library book recommendation systems

Riccardo Rubei et al. (2022) developed EvoPlan for upgrading third parties library with the consideration of software artefacts. The relevant migration data was extracted and encoded with graph-based representation. Multiple upgrade plans were upgraded with a migration graph considering the main population. This approach was evaluated on a curated dataset with information retrieval metrics such as precision, recall, F-measure, etc.

Malik et al. (2022) have presented an improved book recommendation system by analyzing various current recommendation methods and performance evaluation metrics. In general, a book recommendation system is mainly employed by books e-commerce sites. Thus, this existing review article surveys several machine learning methods that are used for recommending suitable books to the required users. For designing an effective book recommendation system, six methods were developed: clustering, content-based, opinion mining, collaborative filtering, association and hybrid technique. Here, hybrid methods are generated by the integration of several techniques. This existing review article clearly revealed the purpose of the book recommendation system.

Sarma et al. (2021) have utilized a machine learning algorithm for enabling a personalized book recommendation system. This existing study generated an efficient mechanism for performing book recommendations to online users, where a clustering approach was utilized to rate a book. After that, similarities of each book were identified and recommended a new book. For measuring the cosine similarity function and distance, the K-means cosine distance function was used, and it assisted in computing the relation among book clusters. This existing study has used ten varied datasets to prove this developed method's efficacy. For each dataset, the performance of the developed approach is measured, and the graphical representation of the developed model's accuracy is plotted by analyzing the receiver operating characteristics (ROC) curve. The simulation results evaluation shows that the established automated book recommendation system was highly superior to the common user-based recommendation system.

Wadikar et al. (2020) have established a Convolutional Neural Network (CNN) for recommending books to the demanded users. Here, a subject-based book recommendation was developed by using a CNN method. The designed recommendation system will allow the users to view and explore books, and by using CNN, the highly purchased books were listed. Also, the top-rated books are suggested depending on the subject name provided as the input. In this existing study, n-dimensional feature vectors are obtained to obtain better recommendation outcomes. Also, the significance of each word to a document is measured by utilizing Term Frequency-Inverse Document Frequency (TF-IDF) weights. Here, the TF-IDF was generated with the aid of the sklearn vectorizer scheme. This existing study used a book covers dataset for the simulation purpose, and the developed CNN method recommends the most corresponding book covers depending on the provided input book cover.

Hou et al. (Hou, 2022) have introduced deep learning models for performing personalized book recommendations for university libraries. The developed method enabled recommendations depending on properties and laws of user storage in the university library. This study initially utilized LSTM and then DAE for the recommendation process. In this, the LSTM is used to improve the ability of DAE to obtain robust temporal features. Also, the final softmax layer is aided in attaining the book recommendation outcome of the present user. Based on the real library lending data, the developed approach was validated. In addition, the attained performance of this developed approach was compared with other existing methods, and the analysis proves the effectiveness of this existing work.

Shi et al. (2023) have designed a library book recommendation system using CNN with a factorization machine (FM). This existing study initially analyses the difficulties in real library book recommendations and then generates an approach by considering feature combinations. Here, the students' demands were fetched by leveraging the attention module for varied categories of books from their history of borrowing. Also, the varied interests of students are learned by FM unit in which the context-aware features also get extracted. In this existing study, the high-order relations among feature maps are fetched through CNN and are attained by the outer product among feature embedding. For simulation, this study used a real-time dataset gathered from one university, and the obtained results prove the ability of this developed method.

2.2. Different learning schemes for recommendation systems

Delshad Fakoor et al. (Shakoor et al., 2021) described Gaussian Mixture Model clustering by considering the Pearson correlation coefficient and scores distance. It was introduced to predict the score in a machine learning-based recommendation system. In the information filtering technique, the user data was clustered by the recommender system, which represents the factors for accurate prediction by computing similarity between cluster members. The movie Lens dataset was evaluated, and the performance was compared with the previous recommender systems, such as Pearson correlation coefficients, K-means, similarity criteria, and fuzzy C-means algorithms.

GM Harshvardhan et al. (2022) proposed an unsupervised Boltzmann machine-based time-aware recommendation system (UBMTR) that extracts hidden features from the movie rating database when the rating was made. Using the time and rating, the binary values result with a contrastive divergence algorithm, and the samples were obtained from the Monte Carlo Markov Chain. There was a correlation between requested content and temporal conditions. The temporal information was incorporated with Boltzmann machines, which adopt pattern completion to deal with missing information. The raw data were encoded into latent variables to handle unbalanced and unstructured data.

Sunny Sharma et al. (2021a) proposed a personal recommender system using deep learning for related video recommendations based on the number of views and likes. It was based on additional objectives like enhanced transaction and user satisfaction by measuring the requirement and evaluating the intentional result. It was expensive to apply it to a real group of users and computing consequences. SPRS framework assisted a user in discovering information with user desire. Overloaded search space has been focused on enhancing the accuracy of a personalized recommendation system.

Hu et al. (Hu et al., 2023) developed a federated learning based recommendation system for constructing a privacy preserving mechanism. The traditional privacy preserved recommendation system utilized cryptographic algorithms for attaining more security. In this study, a locality sensitive hashing (LSH) was employed to generate recommendation system and exhibit secures the information under recommendation system against attackers. The result analysis shows that the utilized model attain better outcomes than other comparable methods.

2.3. Fuzzy based recommendation systems

Seyed Ebrahim Dashti1 et al. (Dashti and Sarafraz, 2021) proposed integrating a collaborative refinement technique with a fuzzy neural network associative exploration approach (Anfis). The hybrid recommender system provided the two-dimensional space of ancillary information, which reflects user preferences and items. The popular and popular user-specific items were considered for building the recommender system with approaches such as content-based and collaborative refinement. It was experimented on an actual Movielens 1M 6040 dataset and evaluated with mean error metric. The simulation results proves the effectiveness of this developed study.

Karthik et al. (Karthik and Ganapathy, 2021) have presented the fuzzy based recommendation system for estimating the interests of customers through sentimental analysis and ontology in e-commerce. Here, the utilized fuzzy logic is responsible for recommending suitable products to the user's present demand. The product's sentimental score is analyzed using a novel approach and the ontology alignment is used for generating decisions. An experimental analysis of the developed recommendation system exhibits superior performance than other previous methods. Table 1 shows the comparison of various state-of-the-art works.

Problem statement: The recommendation system was used to provide qualitative data to resolve the task of mapping between the user and the product. The recommendation system has the issue of poorly including implicit data. The recommendation system requires a vast amount of data for making decisions. It must capture and analyze the user data before providing recommendations. The more items with user preference have the possibility of making good recommendations. The attributes of the user can be varied based on the user's preferences. So, each attribute has different importance at varying times. In addition, the user preferences also varied with respect to the specific period and user desires. Using the conventional recommendation system, user reactions tend to be modified and unpredictable. Hence, a novel recommendation

Table 1
Comparison of different methods from varied studies.

Author	Purpose	Methods	Performance metrics	Limitations
Karthik et al. (Karthik and Ganapathy, 2021)	Prediction of customer's interests in e-commerce	Fuzzy-logic-based product recommendation system	Prediction accuracy	Time complexity is increased while calculating the product's sentimental scores.
Shambour et al. (Shambour, 2021)	Multi-criteria based recommendation	Deep Feedforward Neural Networks	MAE, RMSE	Failing to gather more information sources and quality of recommendation is influenced.
Dudekula et al. (Dudekula et al., 2023)	Program recommendation for smart television users	CNN	Precision, recall, F-measure, accuracy	Precision and recall values are not as much improved due to various complexities.
Ali et al. (Ali et al., 2022)	Affording recommendation system to e-learners	E-Learning Recommendation Architecture (ELRA)	Student performance level, Teacher performance level, Manager performance level, Dissatisfaction level	Failed to verify the progress of learners and teachers. Thus, the quality of courses in the online learning environment is not assured.
Pavitha et al. (Pavitha et al., 2022)	Providing effective movie recommendation	Support Vector Machine (SVM) and Naïve Bayes (NB)	Accuracy, precision, recall, AUC	Difficulty in learning the features and thereby attained insufficient accuracy results.

system is required to resolve the problem related to implicit data. To the best of the knowledge, the proposed method overcomes all the existing techniques' drawbacks and effectively shows outstanding performance.

3. Proposed methodology

The proposed system provides a personalized recommendation for each department user based on a hybrid recommendation system. The recommendation system is based on a ranking, which makes the system more objective. The hybrid recommendation system improves accuracy and provides scalability. Initially, the input dataset is pre-processed, and weighing is provided for each book attribute. Then, they are classified using the proposed hybrid recommendation system for each department. Then, the score is estimated, and the recommendation list is generated according to the score obtained by each book.

Fig. 1 signifies the workflow of the developed method. Initially, the input dataset is labelled based on the department name. The labelling minimizes the processing complexity of dealing with specific data. Thus, it improves the performance of a recommendation system. The accuracy of a recommendation system can be improved with the pre-processing approach. After pre-processing, TPCC is proposed to provide weight for each book based on the time stamp, such as the number of times the book is issued, the issue date and the return date. It computes the similarity between the department and the corresponding book based on an optimal criterion. After weighing that, an HMCAHB_DA-WFR based technique is introduced in which the book of each department has to be classified, and the scoring is provided separately for each book. The fuzzy-based scoring provides an optimal prediction by considering the features and data uncertainty. In the proposed work, the hybrid recommendation system can be modelled by integrating the content-based filtering system called Hidden Markov-Discriminant Analysis (HMDA) and collaborative filtering system named WFR. Finally, the recommendation list for all departments is generated based on the score of each book produced with fuzzy ranking. This recommendation list is useful for the candidate to select the required books.

3.1. Pre-processing and timestamp based weighting

In the initial stage, the labelling is performed for the department name, i.e., ECE, mechanical, EEE, civil and computer science as 1,2,3,4 and 5, respectively. This labelling can minimize computation complexity and easily identify books belonging to particular departments accurately. After labelling, each book is assigned a timestamp based on the number of times students issue the book, issue date and received date. The timestamp is determined by assigning a particular value to each book based on recent activities. It is based on the chronological difference between the days taken between the issue date and the received date. Finally, each book's values are arranged in ascending order using the timestamp. Then, the similarity is calculated between the department and the book using the Pearson correlation coefficient (PCC). PCC is one of the popular method used for analysing the correlation between two variables. In general, the computation of PCC is very simple and provides proper relationship among two sets of data. Because of reduced computation, PCC is highly efficient than other similarity metrics. Also, PCC has the ability to normalize the data which are in different scales and assists to smoothen the training process. Thus, the proposed study prefers PCC for finding the similarity between departments and books to make effective recommendation process.

The PCC evaluates the similarity between two vectors representing the number of days for all students for two books. It can be mathematically formulated as,

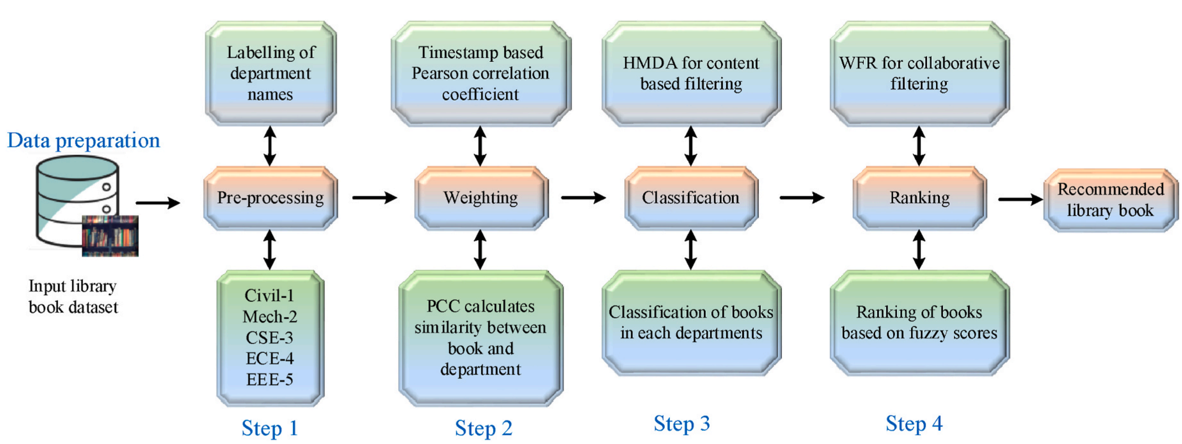

Fig. 1. Initial hypothesis of the proposed work.

$$PCC_{(x,y)} = \frac{\sum_s (n_{sx} - \hat{n}_x)(n_{sy} - \hat{n}_y)}{\sqrt{\sum_s (n_{sx} - \hat{n}_x)^2 \sum_s (n_{sy} - \hat{n}_y)^2}} \tag{1}$$

Here, n_{sx} implies the number of days in which the book x utilized by a student s, $\hat{n}_x$ signifies the mean number of days in which the book x is utilized, n_{sy} implies the number of days in which the book y utilized by a student s and $\hat{n}_y$ signifies the mean of a number of days in which the book y is utilized.

3.2. Proposed HMCAHB_DA-WFR model for book recommendation

The book recommendation is one of the essential processes, especially in a library where students struggle to choose a book efficiently. Only a few studies have been undertaken in accurately classifying and ranking recommended books. However, those techniques are highly suffered due to errors and time-consuming processes. To overcome this issue, this article proposes an effective hybridized HMCAHB_DA with the WFR model for recommending the book based on the received date, issue date and due date. Here, the parameters of the HMM model are optimally tuned using a CAHB-based bio-inspired algorithm. CB filtering is performed in HMCAHB_DA, and the book is finally accurately classified according to the department. In WFR, collaborative filtering is performed, and finally, ranking is performed by calculating the score of each book under a different branch.

3.2.1. Proposed content-based filtering with HMCAHB_DA technique

The HMM is the supervised statistical probabilistic learning model based on the hidden Markov states from the observed states. The HMM model works similarly to the CB filtering algorithm. The CB filtering helps the students select books based on other students' preferences with similar interests. For this, the timestamp weight and labelled departments are given as input to the HMM model. The mathematical interpretations of HMM for observed and state sequences are explained in detail below:

$P_{1,t}$: Till the time t, the Markov sequence state (input Markov state sequence) $P_{1,t} = [P_1, P_2, ..., P_t]$;

$Q_{1,t}$: Till the time t, the observed sequence state (predicted sequence outcome) $Q_{1,t} = [Q_1, Q_2, ..., Q_t]$;

Z: State space of the Markov model in which $Z = [0, 1, ..., x-1]$ and here, x indicates the total varying states in the state space;

$$V_{i,j}^T = \begin{cases} 0 \quad if \quad i \neq j \\ null \quad i = j \end{cases} \quad i = 1, ...m; \quad j = 1, ...,n \tag{6}$$

P_T: Markov states at the specific time T where, $P_T \in Z$;

Q_T: The number of observations takes place at a time T, where, Q_T implies the continuous random vector;

π: Initial Markov state based on probability distribution where, $\pi_x = P(P_1 = x)$;

S: Transition probability matrix (transition from one state to another state at single training) where, $S = P(P_{T+1} = y|P_T = x)$;

$\alpha_x(q)$: The outcome distribution for the observed sequence in single training is given by, $\alpha_x(q) = P(Q_{T+1} = q|P_T = x)$;

m: Inner Markov states of marginal probability distribution where, $m_x = P(P_T = x)$;

$F_x(q)$: Observation to state classifier for predicting the hidden states within the HMM using $F_x(q) = P(P_T = x|Q_T = q)$;

Based on the rule of probability function, the below interpretations must be satisfied for single training:

Table 2
Hyperparameters.

Epochs	50
Best num states	5
Covariance type	Diagonal
Number of hidden states	5

$$\sum_{x=0}^{u-1} \pi_x = 1, \quad \sum_{x=0}^{u-1} m_x = 1, \quad \sum_{x=0}^{u-1} s_{x,y} = 1, \forall y \in Z \tag{2}$$

The observation based on the conditional probability is evaluated using the Bayesian rule, and it can be mathematically interpreted as,

$$P(P_T = q|Q_T = x) \quad \alpha \quad \frac{P(P_T = x|Q_T = q)}{P(P_T = x)} \tag{3}$$

In order to improve the efficiency of HMM, its parameters are optimally tuned by using the Chaotic Artificial Humming Bird (CAHB) approach. Table 2 shows the hyperparameters of the proposed model.

The utilized CAHB algorithm is one of the bio-inspired optimization algorithms used for solving complicated optimization issues. Because of the better convergence speed in the Artificial Humming Bird (AHA) approach, the proposed study adopts this algorithm, and the inclusion of chaos helps to enhance the efficiency of the AHA approach further. Here, CAHB is used to fine-tune the parameters of HMM for making better classification outcomes. This CAHB approach optimally tunes the parameters based on the following fitness function.

$$Fitness = Max(Accuracy) \tag{4}$$

The steps involved in the CAHB approach are initialization, guided foraging, territorial foraging and migration foraging. The total population of parameters are initialized in the first step, which is given as follows,

$$y_i = L + rand.(U - L) \quad i = 1, ..., m \tag{5}$$

Where, U and L mentions the upper and lower boundaries for n^{th} dimensional issue, the random vector ranges from 0 to 1 is denoted as $rand$ and the position of i^{th} parameter is signified as y_i. The visit table of parameters is initialized as,

Where, $i = j$ and $V_{i,j}^T = null$ mentions that the search agents pick parameters as their particular parameter source. The terms $i \neq j$ and $V_{i,j}^T = 0$ represents that the j^{th} parameter source has been visited by the i^{th} search agent in the present iteration. In the proposed work, the CAHB approach fine-tunes the parameters based on the following migration strategy.

$$y_{wor}(t+1) = L + rand.(U - L) \tag{7}$$

Where, y_{wor} represents the parameter source with the inefficient nectar re-filling rate in the initial population. In AHB, the exploration and exploitation stage is managed by using the sinusoidal chaotic map and is expressed as,

$$z_{p+1} = K. \quad z_p^2 \; Sin(\pi zp) \tag{8}$$

Where, K represents the control parameter and the study used $K = 2.3$ and $z_0 = 0.7$. This can be mathematically expressed as,

$$z_{p+1} = \sin(\pi z_p) \tag{9}$$

Thus, by using CAHB, the parameters of the HMM model are optimally tuned, and the result of the optimized HMM is given as input to the discriminant analysis, which is also supervised learning. The major role of this DA is to convert high-level data into low-level data and make the similar class near and unequal class away from the space. The input and output of the optimized HMM model are given as input to the DA technique.

Let's assume the input feature matrix as, $U = \{u_1, u_2 \ldots u_i \ldots\}$ where, u_i indicates the i^{th} sample feature vector, and the mean feature vector $\alpha_j (j = 1, 2 \ldots k)$ for the i^{th} sample can be mathematically interpreted as

$$\alpha_j = \frac{1}{M_j} \sum_{a \in A_j} a \qquad j = 1, 2 \ldots p \tag{10}$$

Here, p indicates the total samples present in the training set, M_j implies the j^{th} number of samples, A_j represent the j^{th} sample class. The covariance matrix of the class samples can be mathematically formulated as,

$$C_j = \sum_{a \in A_j} (a - \alpha_j)(a - \alpha_j)^T \qquad j = 1, 2 \ldots p \tag{11}$$

The low-level feature vector in the DA can be represented as, d and the consecutive feature vector is represented as, $b_1, b_2 \ldots b_d$. Hence, the final matrix will be in the form $n \times d$ in a matrix B. Based on the condition, the smallest distance between the book and a department is determined, and it can be interpreted as,

$$\arg \max_{B} \left(\frac{B^T K_b B}{B^T K_w B} \right) \tag{12}$$

Here, K_w indicates the matrix within class samples and K_b implies the matrix between class samples.

$$K_b = \sum_{j=1}^{p} \sum_{a \in A_j} \left((a - \alpha_j)(a - \alpha_j)^T \right) \tag{13}$$

$$K_w = \sum_{j=1}^{p} M_j (\alpha - \alpha_j)(\alpha - \alpha_j)^T \tag{14}$$

Here, α indicates the mean of a sample vector.

In DA, the nearest neighbour algorithm is utilized to classify the book based on the labelled department. To find the nearest neighbour, three major steps are followed and it is given below.

- Provide the training matrix set $X = \{[a_1, b_1], [a_2, b_2] \ldots [a_M, b_M]\}$ where, $a_i \in A \subseteq R^n, b_i \in B = \{l_1, l_2, \ldots, l_c\}$ in which a implies the training sample feature, n represents the feature dimension, b demonstrates the training sample type, l denotes the training label samples and c determines the number of categories present in the training sample.
- Estimate the cosine similarity between the training and testing samples. Assume the two points as $x(x_1, x_2 \ldots x_n)$ and $y(y_1, y_2 \ldots y_n)$ in a n^{th} space dimension. The cosine similarity between x and y can be mathematically interpreted as,

$$\cos(x, y) = \frac{\sum_{b \in B} N_{x,b} N_{y,b}}{\sqrt{\sum_{b \in B} (N_{x,b})^2 (N_{y,b})^2}} \tag{15}$$

Here, $N_{x,b}$ indicates the number of days the book b is utilized by x, $N_{y,b}$ indicates the number of days the book b is utilized by y and B demonstrates the total number of books present in a particular department.

- Based on the outcome of cosine similarity, the closed point of a sample is determined in the training set, and the sample class of a is finalized based on the nearest category sample. At last, the classification of books is performed based on department-wise efficiency.

3.2.2. Collaborative filtering-based WFR approach for recommended book ranking

After finding the cosine similarity, the nearest neighbour of that particular category is ranked based on the obtained value of a book. The WFR works based on collaborative filtering that considers the number of days the particular student utilizes the book. The CF filtering recommends the books based on the experience of other users. Traditional fuzzy rule (Garg and Rani, 2020) is a very complex and time-consuming process; hence, this study introduces a novel weighted fuzzy ranking rule that ranks the books based on the calculated score.

In WFR, initially, the particular score given to each book based on the department gets converted into different fuzzy numbers and generates the fuzzy matrix for each department. Here, the score is considered as, not used: score$<$10, average: 10 $\leq$ score$<$20, good: 20 $\leq$ score$<$35 and recent: score$>$35. Then, measure the average score of each fuzzy number and de-fuzzification is performed. Then, the normalized weight is evaluated for each book, and finally, the aggregated score is calculated for each department. This score is considered the overall rating of books under each department. Fuzzification, membership function and de-fuzzification are the three major blocks in fuzzy system. Fuzzification is the process of converting the set if inputs into fuzzy sets through linguistic variables of fuzzy, membership function and fuzzy linguistic terms. The membership function is employed in both the process of fuzzification and de-fuzzification. The membership function represents the degree of satisfaction of students for a book. Finally, de-fuzzification is performed to attain a set of given input data depending the membership function.

In weighted fuzzy, a membership degree function is assumed to be between 0 and 1 and is referred to as a fuzzy set. Let's assume the fuzzy set be S has the membership function β_M and the membership value of p is represented as, $\beta_M(p)$. In WFR, the fuzzy membership function $\beta_M(p)$ has different interpretations based on the student's preference. The fuzzy set considers only the continuous value between 0 and 1 for $\beta_M(p)$, and it can be mathematically interpreted as,

$$\beta_M(p) = \begin{Bmatrix} 1 \quad if \quad p \quad belongs \quad to \quad M \\ 0 \quad if \quad p \quad not \quad belongs \quad to \quad M \\ 0 < c < 1, \quad if \quad p \quad partially \quad belongs \quad to \quad M \end{Bmatrix} \tag{16}$$

In WFR, instead of considering the user's feedback, the number of days the student utilizes the book is considered the linguistic term. Using triangular membership functions, the number of days is fuzzified based on the student's preference. The linguistic terms can be categorized into five types: highly preferable, preferable, less preferable, fairly preferable, and no preferable. The degree of recommendation is present in the fuzzy variable membership function.

To maximize accuracy, normalized weight is evaluated based on fuzzy number de-fuzzification. The process of obtaining an individual number from the entire fuzzy set is termed de-fuzzification and is done after performing fuzzification. The linguistic terms in the fuzzy aid in providing a particular rate to each student's preferences department-wise. Selecting highly recommended from different books is given in a set $[b_1, b_2, b_3, ...b_n]$. The ratings of each book are determined as D_{xy}, and the average of all fuzzy numbers under different ratings can be mathematically interpreted as,

$$D_{xy} = \frac{1}{k} \otimes (D_{x1} \oplus D_{x2} \oplus ..... \oplus D_{xk}) \tag{17}$$

Using triangular fuzzy number, the average fuzzy score matrix is obtained, and it can be mathematically interpreted as,

$$T = \frac{(x+2y+z)}{4} \tag{18}$$

The normalized weight is calculated based on dividing the de-fuzzification score of an individual book by the total number of books present in the particular department. The total aggregated score for each book under each department is calculated using an additive approach between the de-fuzzified fuzzy number and normalized weight for each book given by the active students. It can be expressed as,

$$S = [DF_{xy}] [w_y] \tag{19}$$

Here, DF_{xy} represents the de-fuzzified score and w_y indicates the normalized weight of each book. The total score of each book is given in matrix format by multiplying the de-fuzzified score and obtaining normalized weight. Thus, based on the computed scores, the WFR methods ranks each books. Algorithm 1 demonstrates the pseudocode for the proposed method.

Algorithm 1. Pseudocode of the proposed method

```
Pseudocode of the proposed method
Input: Real-time library book dataset;
Output: Classification and ranking of recommended books in the library;
Do labelling for each department
Label as civil-1, Mech-2, CSE-3, ECE-4, EEE-5;          //pre-processing stage
Perform timestamp weighting
Calculate the number of days between issue data and return data;
If the number of days is high
Weight is high;
Else
Low weight;
End if                                                   //timestamp weighting
Perform similarity calculation between book and department using equation 1;
Do classification using HMCHAB_DA based content filtering
For content-based filtering
Input: Timestamp weighting and department labels;
Output: Department-wise books
//Derive the mathematical interpretation for state sequence in the HMM model
Obtain the probability distribution for predicting in Markov state sequence using equation2;
Obtain the predicted observed sequence (books) using the Bayesian rule using equation 3;
Observed weight and score labels are given as input DA;
Obtain the input feature vector using equation 4;
Obtain the covariance matrix of each department using equation 5;
Set the condition between the book and the department using equation 6;
Calculate the distance between books and departments and within the books using equations
7 and 8;
Evaluate the similarity between books and similarity using equation 9;
End for                                     //HMCHAB_DA content based filtering
Do WFR-based CF filtering
For CF filtering
Input: Number of days, books, departments;
Output: Ranking of recommended books for departmental wise;
Assume the fuzzy set using equation 16;
//Provide fuzzy number based on the ratings of each book
Interpret the fuzzy numbers under different ratings using equation 17;
Calculate the average fuzzy score matrix using equation 18;
Multiply de-fuzzified fuzzy number and timestamp weight using equation 19;
Do ranking based on the obtained final score
//Repeat the same process for each department
End for
End do                                      //WFR-collaborative filtering
```

4. Results and discussion

The proposed recommender system approach will be implemented with the Python working platform and compared to an existing approach with performance metrics such as accuracy, MAE, kappa score, and run time. For experimentation, the proposed study collects the real-time dataset from the Bhilai Institute of Technology, Durg. In this real-time data, both student dataset and faculty dataset are available. Amongst that, the proposed study used student dataset for enabling college library book recommendation process. The utilized dataset involves totally 12 features and is mentioned in Table 3. From the total

Table 3
Available features in dataset.

SI.no	Features
1	Member code
2	Title
3	Issue date
4	Due date
5	Rec date
6	Section
7	Course
8	No_of_days
9	Branch
10	Subject
11	Book_type
12	Semester

Table 4
System configuration of the proposed method.

System Specifications		
S No.	Parameters	Configuration
1	Processor	Intel® Core™2 Duo CPU @3.00 GHz,2.99 GHz
2	Installed RAM	8.00 GB (7.84 GB unstable)
3	System type	64-bit operating system,×64-based processor
4	Pen and touch	No pen or touch input is available for this display

data, 38,373 of data are used for training the proposed model and 9594 data are used for testing purpose.

Thus, by utilizing the real-time data, the proposed study performs library book recommendation process. The system configuration of the proposed method is tabulated in Table 4.

4.1. Performance metrics

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{20}$$

Here, TP indicates the true positive value and FP depicts the false positive value.

$$Kappa = \frac{M \cdot \sum_{i=1}^{l} P_{ii} - \sum_{i=1}^{l} (P_{i+} \cdot P_{+i})}{M^2 - \sum_{i=1}^{l} (P_{i+} \cdot P_{+i})} \tag{21}$$

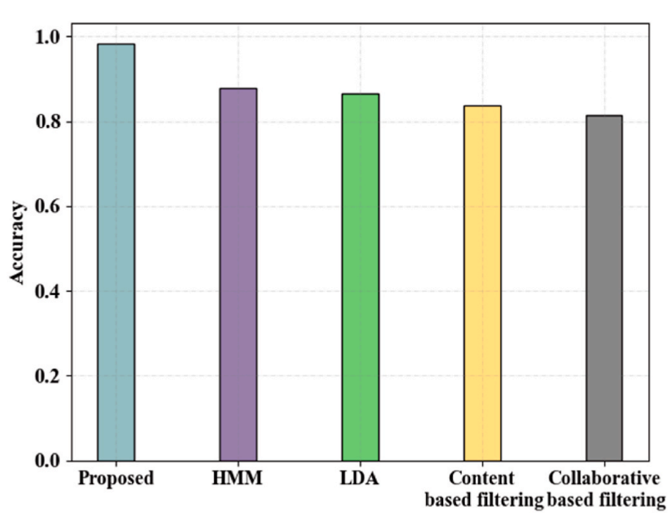

Fig. 2. Analysis of accuracy performance.

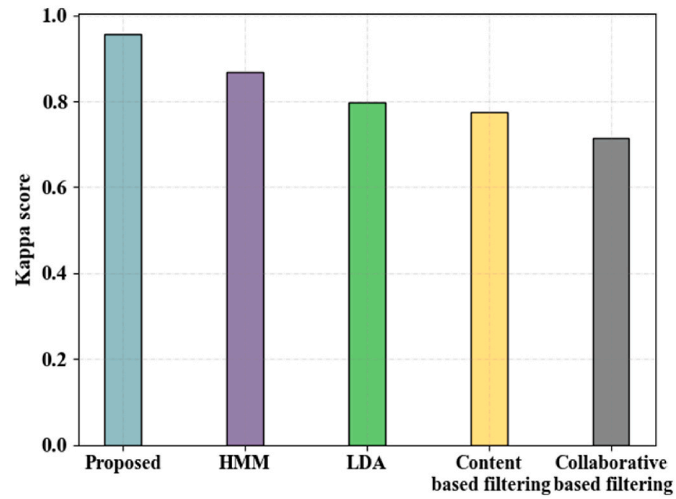

Fig. 3. Analysis of kappa performance.

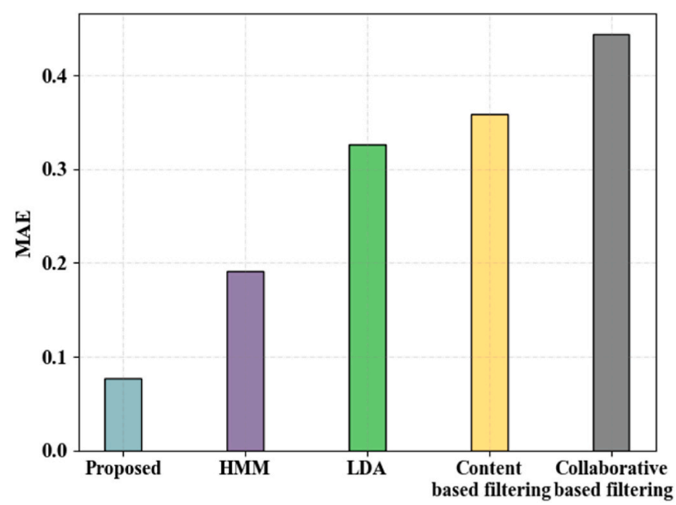

Fig. 4. Analysis of MAE performance.

Where M denotes the total books in each department, the total departments are represented as l, the parameter P_{ii} is denoted as the matrix's diagonal element, and the sum of the entire rows is represented as P_{+i}.

$$MAE = \frac{|(a_i - a_p)|}{N} \tag{22}$$

Here, MAE mentions mean absolute error, a_i represents actual values, N denotes the mean of total books present in each department, a_p depicts the predicted books.

$$FPR = \frac{FP}{TN + FP} \tag{23}$$

Where, FPR represents the false positive rate, FP depicts the false positive value and TN mentions the true negative value.

$$FNR = \frac{FN}{FN + TP} \tag{24}$$

Where, FNR denotes false negative rate, FN mentions false negative value and TP indicates the true positive value.

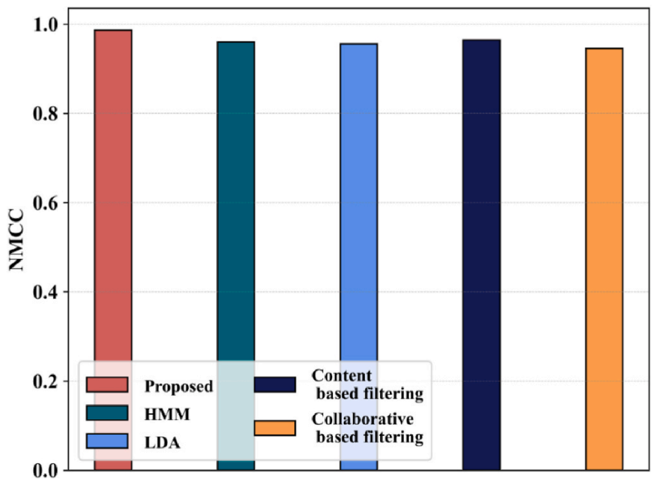

Fig. 5. NMCC comparison analysis.

4.2. Performance evaluation of the proposed method with a conventional technique

In this section, the performance achieved by the proposed method is given in a graphical illustration. To prove the proposed method's efficiency, some conventional techniques like hidden Markov model (HMM), linear discriminant analysis (LDA), conventional CF technique and conventional CB filtering are employed for comparison. HMM is one of the statistical model used to analyze the hidden variables from the specific set. Because of the better ability in HMM, the proposed study prefers this model as the baseline method. On the other hand, LDA also chosen as the baseline method due its beneficial characteristics. Moreover, the conventional CF and CB filtering methods are widely utilized in recommendation system and hence such techniques are also considered as the baseline methods. In order to find the robustness of proposed study, the aforementioned efficient methods are utilized for comparison. In this work, the mentioned existing techniques also implemented and compared the results with proposed model for proving the effectiveness. Separate results have been analyzed both monthly and weekly to recommend the library books effectively.

Fig. 2 demonstrates the comparative analysis of accuracy performance. From the graphical interpretation, the proposed method outperforms better performance compared to existing techniques. It is also noted that the LDA and traditional CB filtering show almost equal performance, and CF based recommendation system shows a very low performance compared to other techniques. The proposed method utilizes both CB and CF recommendation systems and effectively achieves accurate performance in each department. Traditional CB filtering-based recommendation system selects the books based on similar preferences from other users. With only CB filtering, the students cannot view the past ratings given to each book. While considering only CF recommendations, high-level books are recommended based on previous ratings given by other users. However, this filtering system cannot recommend similar books belonging to a particular department. The proposed method uses a hybrid recommendation system that can accurately recommend the book under each department. The existing HMM, LDA, CBF and CF and proposed HMCAHB_DA-WFR based recommendation system obtain the accuracy of 95.7%, 93.5%, 92.8%, 90.8% and 99.2%, respectively.

The kappa performance is illustrated in Fig. 3. It is observed that the proposed hybrid recommendation system shows high performance compared to other conventional techniques. The existing HMM, LDA, CBF and CF and proposed hybrid recommendation system obtain the kappa score of 86.7%, 79.8%, 77.5%, 71.3% and 97.6%, respectively. By analyzing the ratings given by past students, the existing predicted outcome does not match the actual values, resulting in a high error.

Fig. 4 imply the MAE analysis performance. The proposed method obtains low error from the graphical manifestation compared to other techniques. The MAE analyses the actual label and predicted outcome to estimate the error under each department separately and accurately produces the mean error. The graph shows that the traditional CF recommendation system shows higher errors than other recommendation systems. The existing HMM, LDA, CBF and CF and proposed hybrid recommendation system obtain the MAE of 0.19, 0.32, 0.35, 0.44 and 0.074, respectively. Fig. 5 shows the NMCC comparison of proposed and existing methods.

The above comparison shows the efficacy of the proposed model. As compared with other existing methods, the attained NMCC value of the proposed work is enhanced due to its higher efficiency. The NMCC values of proposed and existing HMM, LDA, CBF and CF methods are 98.7%, 96%, 95.6%, 96.5% and 94.6%. Fig. 6 shows the comparison of FPR and FNR of both proposed and existing works.

The graphical representation in FPR and FNR analysis reveals the efficacy of the proposed work. The attained FPR value of the proposed method is 0.0085%, and the existing HMM, LDA, CBF and CF methods are 0.026%, 0.04%, 0.044% and 0.057%. Whereas the attained FNR value of the proposed model is 0.034%, and the existing HMM, LDA, CBF and CF methods are 0.106%, 0.162%, 0.18% and 0.22%. Because of optimizing the parameters of HMM in the classification stage, the learning ability of HMM is enhanced, and it aids in attaining better results while classifying books department-wise.

4.3. Ranking of books in both month-wise and week-wise

In this section, the books ranked are analyzed both monthly and weekly efficiently. The proposed WFR method accurately ranks the books based on the score obtained from the fuzzy ranking. The detailed analysis of the simulation outcome is explained in detail below.

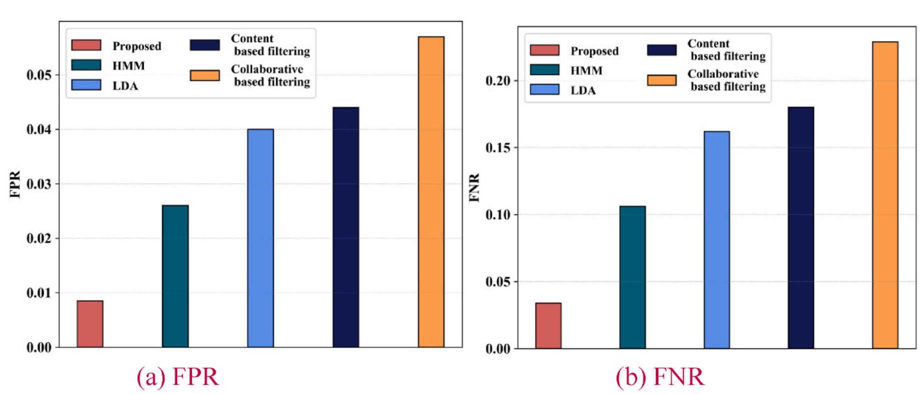

Fig. 6. FPR and FNR comparison over existing methods.

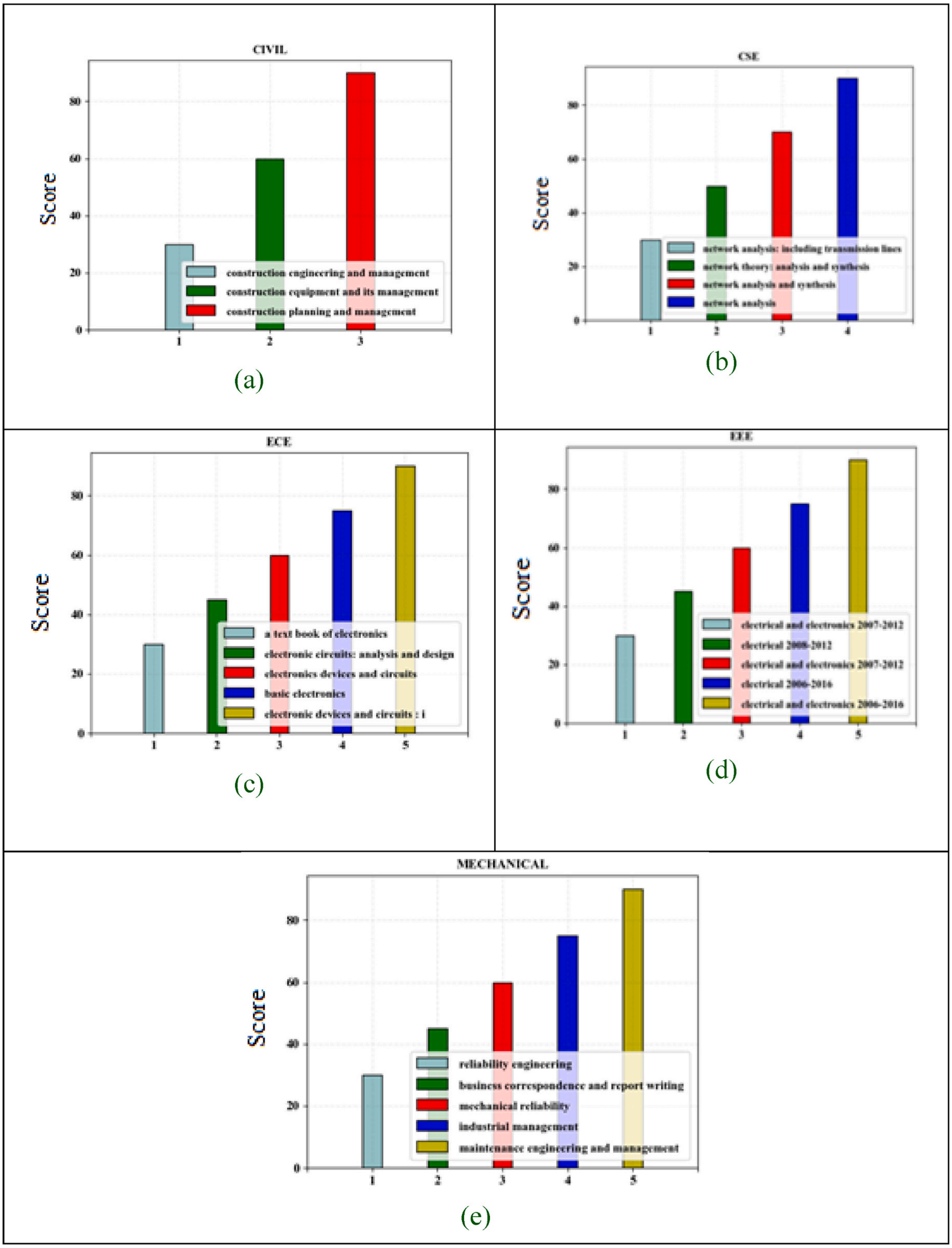

Fig. 7. Month-wise ranking of recommended books for all departments.

Fig. 7 represents the month-wise ranking of recommended books for civil, CSE, ECE, EEE and mechanical departments. The ranked books for each department are clearly illustrated in the graphical illustration. For the civil department, the book titled “Construction Planning and Management” obtained the highest score of 96, and the book titled “Construction Engineering and Management” obtained the lowest score of 27. In the same way, other departmental books are ranked based on the obtained fuzzy scores accurately.

Fig. 8 represents the week-wise ranking of recommended books for civil, CSE, ECE, EEE and mechanical departments. The ranked books for each department are clearly illustrated in the graphical illustration. By analyzing the mechanical department, the book named “Maintenance

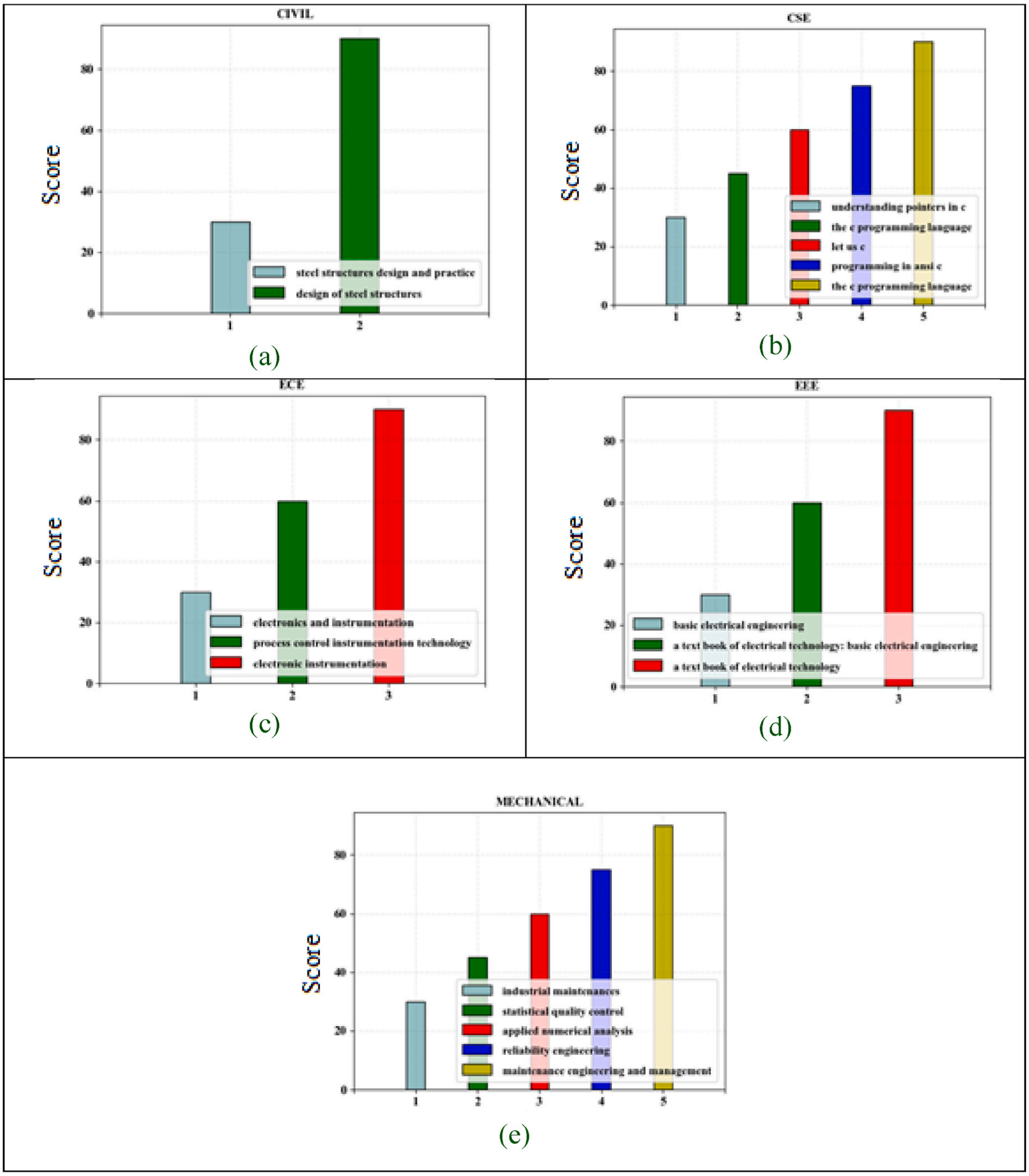

Fig. 8. Week-wise ranking of recommended books for all departments.

Engineering and Management" obtains the highest score of 96, and the book named "Industrial Maintenance" obtains the lowest score of 27. In the same way, other departmental books are ranked based on the obtained fuzzy scores accurately. Fig. 9 shows the loss curve of the proposed model.

The loss curve is also termed a training or error curve, which plots the training and testing error over the number of iterations or epochs of the proposed recommendation model. Here, the loss of the proposed model is analyzed by varying the epoch sizes from 0 to 300. The above graphical representation states that the attained loss in the proposed model is highly reduced in each epoch. Thus, the analysis states that the proposed model is more efficient in the book recommendation process. Fig. 10 illustrates the learning curve of the proposed model.

The learning curve has the ability to graphically depict how the proposed model is enhanced over time because of learning and improved proficiency. Here, the learning curve is determined by varying the learning efforts from 0 to 175. The performance of learning ability Fig. 11 shows the Precision@K comparison analysis over other existing methods.

The above graphical representation shows the results attained in the metric Precision@K, where the performance of the proposed model is compared with several existing methods. By varying the value of k from 0 to 50, the precision value also gets varied. However, the proposed method attained better precision value by varying the k value as compared with other existing methods. Table 5 illustrates the overall run time performance analysis. Here, the time complexity of both

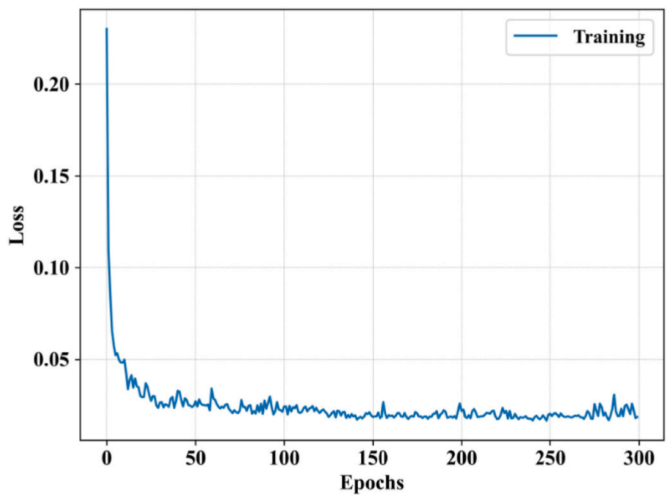

Fig. 9. Loss curve of the proposed model.

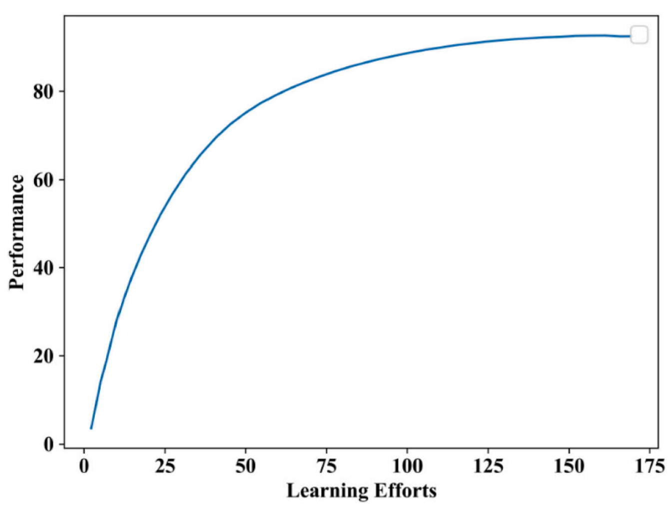

Fig. 10. Learning curve of the proposed model.

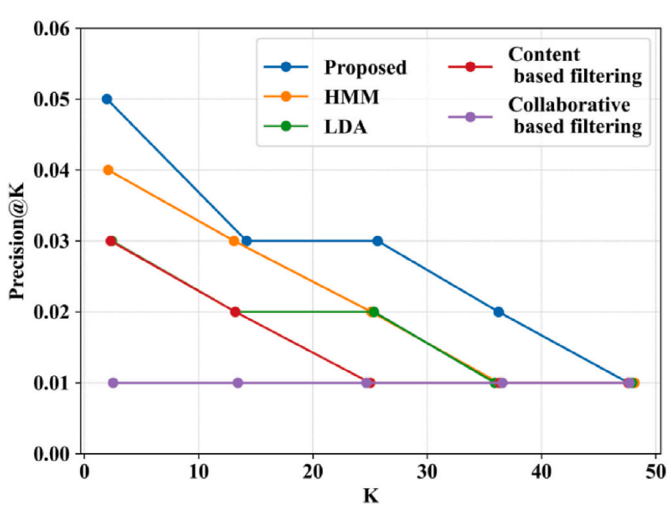

Fig. 11. Precision@K comparison analysis.

Table 5
Time complexity analysis.

Methods	Run time (sec)
Proposed (HMCAHB_DA-WFR)	**44.37**
HMM	52.68
LDA	54.7
Traditional CBF	54.9
Traditional CF	55.9
Support vector regression (SVR) (Gopikrishna and Ashwini, 2022)	197.26

Table 6
Performance obtained by existing techniques.

Performance measure	Techniques	Obtained outcome
Accuracy	SVR	94%
	LSTM	93%
	AE	95%
	Proposed (HMCAHB_DA-WFR)	**99.2%**
Kappa	SVR	81%
	LSTM	78.7%
	AE	85%
	Proposed (HMCAHB_DA-WFR)	**97.6%**
MAE	SVR	0.28
	LSTM	0.33
	AE	0.23
	Proposed (HMCAHB_DA-WFR)	**0.074**

proposed and existing methods are determined. Analysing time complexity in recommendation system is important for assuring scalability and cost-effectiveness of proposed model. By analysing the overall run time of proposed HMCAHB_DA-WFR model with other previous recommendation models, the strength of proposed work is revealed clearly. Thus, the attained reduced run time states that the proposed recommendation system achieved low time complexity and hence it is highly sufficient for college library book recommendation process.

Table 6 tabulates the performance obtained by existing techniques. From the table, it is clear that the proposed method obtains better performance compared to existing techniques. However, the existing studies consume high time and low accuracy performance due to low feature learning ability and increased over-fitting issues. In order to strengthen the effectiveness of the proposed work, the attained results are also compared with other datasets like Books.csv, Ratings.csv, Max_Rating.csv and Book_tags.csv. The mentioned datasets are attained from the Goodreads-books repository of Kaggle. These datasets are also implemented in this work, and the attained values are compared with the other existing methods. Table 7 shows the performance comparison of the proposed and other existing methods in varied datasets.

From the above results, it is noticed that the proposed study obtains better results in each dataset as compared with other methods. Because of the great efficiency of the proposed model, the performance is enhanced, and it states that the proposed study is highly suitable for effective recommendation scenarios. For analysing the accurateness of proposed work, Root Mean Square Error (RMSE) is evaluated and compared with other recent methods. Table 8 shows the RMSE comparison of both proposed and existing methods. In Table 8, the RMSE value of proposed study is compared with other previous methods like Singular Value Decomposition (SVD), Content based filtering, collaborative filtering, hybrid filtering and K-Nearest Neighbour (KNN) (Arunruviwat and Muangsin, 2022). The result analysis in RMSE metric shows that the proposed method attained reduced RMSE value than other comparable methods. Thus, the analysis proves the strength of proposed HMCAHB_DA-WFR than others.

Table 7
Performance comparison in different datasets.

Datasets	Proposed (HMCAHB_DA-WFR)	HMM	LDA	Content-based filtering	Collaborative based filtering
	Accuracy	Accuracy	Accuracy	Accuracy	Accuracy
Real-time dataset from the Bhilai institute of technology, Durg	99.2%	95.7%	93.5%	92.8%	90.8%
Books.csv	98.07%	94.1%	92.3%	92.08%	89.76%
Ratings.csv	97.9%	95.2%	93.83%	92.24%	89.9%
Max_Rating.csv	98%	94%	91.67%	91.08%	90%
Book_tags.csv	98.2%	95.35%	93%	92.17%	89.97%

Table 8
RMSE comparison of proposed and other recent methods.

Methods	Attained RMSE
Proposed HMCAHB_DA-WFR	1.0246
SVD (Arunruviwat and Muangsin, 2022).	1.2676
KNN (Arunruviwat and Muangsin, 2022).	1.2247
Content based filtering	1.6945
Collaborative filtering	1.4137
Hybrid filtering (Arunruviwat and Muangsin, 2022).	1.2247

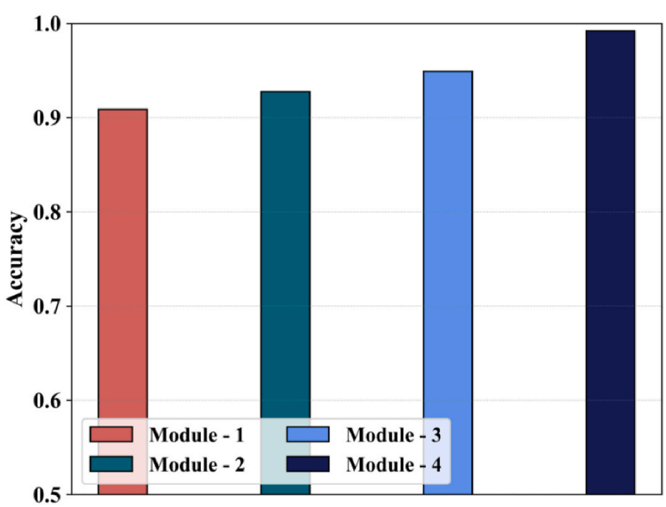

Fig. 12. Accuracy evaluation in ablation study.

4.4. Ablation study analysis

In this section, the ablation study analysis is performed for proving the effectiveness of each stages that generated in this proposed work. Here, the ablation study is conducted by four modules like module 1, module 2, module 3 and module 4. In module 1, the utilization of PCC in the initial stage is omitted and the accuracy value is computed. Similarly, module 2 skips the parameter tuning process of HMM using CAHB and the accuracy performance is evaluated. Module 3 neglects the DA mechanism in the proposed recommendation model. Finally, module 4 depicts the accuracy value attained in the proposed HMCAHB_DA-WFR model. Fig. 12 shows the evaluation of accuracy performance in ablation analysis.

From the above graphical representation in Fig. 12 clearly exhibits the need of each stages proposed in this work. Initially, the PCC method is excluded in the proposed model which provides reduced accuracy of 90.87% in module 1. Also, the purpose of utilizing CAHB in the proposed HMCAHB_DA-WFR model is revealed in module 2 because it attains reduced accuracy of 92.76%. While skipping DA in proposed HMCAHB_DA-WFR model, the accuracy value is gets reduced as 94.9%. But, the proposed HMCAHB_DA-WFR model attains better accuracy value of 99.2% because of the presence of effective methods in each stages. Thus, the analysis proves the need of each methods that generated in this study for recommending college library books.

5. Conclusion

The recommendation system is part of an information filtering system that aids in predicting the user's preference for any object. The main part of this study is to recommend books in the personalized library that helps the students choose books from the corresponding department. In the initial stage, labelling is performed for each department. Then,

Table 9
Contribution and limitations of existing and proposed methods.

Author	Method	Contribution	Result	Limitations
Sarma et al. (Sarma et al., 2021)	Machine learning algorithm based on K-means clustering with cosine functions	To offer an efficient mechanism for performing book recommendations to online users	Sensitivity-62.9%, specificity-66.1% and F1-score-65.6%	Need deep learning architecture to enhance the performance in terms of different evaluation metrics.
Wadikar et al. (Wadikar et al., 2020)	CNN	To effectively recommend books to the demanded user with better recommendation outcomes.	Viewing and searching books is better by providing the subject name as input	Training required more time, and it underwent an exploding gradient issue.
Hou et al. (Hou, 2022)	LSTM-DAE	To develop a personalized book recommendation system based on the properties and laws of user storage in the university library	Precision-54.3%, recall-52.8% and F1-score-53.2%	Requires more memory and increased computational complexity owing to their additional operations and parameters.
Shi et al. (Shi et al., 2023)	CNN-FM	To introduce a library book recommendation system based on feature interactions	Achieved better recall value to offer valuable recommendations depending on user preferences	Need to improve the extraction of high-order correlation for improving the recommendation results.
Dudekula et al. (Dudekula et al., 2023)	CNN	Program recommendation for smart television users	Precision-82.68%, recall, 81.57% and AUC-80.17%	Precision and recall values are not as much improved due to various complexities.
Proposed	HMCAHB_DA-WFR	Introducing a new AI mechanism for enabling college library book recommendation	Achieved better results in terms of accuracy- 99.2%, Kappa- of 97.6%, MAE-0.074, NMCC-98.7%, FPR-0.0085% and FNR-0.034%.	Cost-effective and requires more memory.

timestamp-based weighting is done for each book using the number of days calculated between return data and the number of times the book is issued. Then, PCC is performed to analyze the difference between the departments and corresponding books. Finally, the HMCAHB_DA-WFR technique is emphasized to classify and rank the book according to the department accurately. The proposed recommendation system is implemented on the PYTHON platform and uses a real-time dataset from the Bhilai Institute of Technology, Durg. In an experimental scenario, the proposed method obtains an overall accuracy of 99.2%, Kappa of 97.6%, MAE of 0.074, NMCC of 98.7%, FPR of 0.0085% and FNR of 0.034%, and an overall run time 44.37s. Table 9 illustrates the comparison of the proposed work with other existing methods.

The comparison analysis in Table 8 shows the ability of proposed method in real time scenarios. Because of achieving better recommendation results, it clearly states that the proposed study is highly suitable for real-time applications. Also, the proposed library book recommendation system in real-world applications can significantly improve the utilization of resources, user experience and helps future research endeavours for gaining more success in the field of recommendation system. In conclusion, the significance of proposed research results on real-time applications aids to improve several aspects of human lives involving the development of modern Artificial Intelligence (AI) systems.

5.1. Limitations of this study and effective future scopes

The proposed technique has various advantages in the offline library book recommendation system field under low time complexity. Because of the great efficiency, the proposed study has extended clinical significance. Hence, the future study will focus on utilizing this proposed model in medical sectors to recommend medicine, e-medical tests, diet plans, doctors, etc. Despite this, the proposed technique is only processed for Bachelor of Technology (BE) courses. In future, researchers need to process the same technique for other courses like MTech, MBA and MCA courses and analyze the performance for the same. In addition, the proposed recommendation system is very cost-effective and demands more memory space. Therefore, in the future, researchers must concentrate on introducing improved lightweight AI-based methods to reduce memory storage and improve computational performance. Also, the proposed study only uses book-related data to enable the recommendation process. Hence, the future study focussed on working on various domains, including music recommendation, course recommendation, movie recommendation and scientific article recommendation. Moreover, the proposed classification only classifies limited books in each classes hence a hybrid deep learning methods will be used in future works to classify more books in the recommendation system using varied datasets.

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Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

Consent to participate

All the authors involved have agreed to participate in this submitted article.

Consent to publish

All the authors involved in this manuscript give full consent for publication of this submitted article.

CRediT authorship contribution statement

Monika Verma: Conceptualization, Methodology, Software, Writing – original draft, Visualization. **Pawan Kumar Patnaik:** Formal analysis, Data curation, Review & Editing, Supervision, Project administration.

Declaration of competing interest

Authors do not have any conflict of interest to declare.

Data availability

No data was used for the research described in the article.

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