JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Implementation of Hybrid Recommendations for Movies

Akshat Kothiyal
Student, Department of Electronics & Communication Engg, Nitte Meenakshi Institute of Technology, Bangalore, Karnataka, India

Ankit Kumar
Student, Department of Electronics & Communication Engg, Nitte Meenakshi Institute of Technology, Bangalore Karnataka, India

Dhanush N
Student, Department of Electronics & Communication Engg, Nitte Meenakshi Institute of Technology, Bangalore, Karnataka, India

Prajna K B
Assistant Professor, Departmentof Electronics & Communication Engg, Nitte Meenakshi Institute Of Technology, Bangalore,Karnataka, India

Abstract

In the basics of today's digitally growing world, recommendation system plays a very important role in the media and entertainment industry. Streaming service providers like Netflix, YouTube, Amazon Prime, etc. are making tremendous use of recommendation systems in order to endorse their content to the users. A recommendation system is a type of information filtering system that intends to anticipate the rating or preference a user may assign to a certain item. The selection of a proper dataset and algorithms are the two most important pillars of a recommendation system. This prototype focuses more on content and collaborative-based approach which later shifts its focus to a hybrid model.
Mathematical modelling like Cosine Similarity and Single Value Deposition (SVD) is used in this project. Designing a user interface is also a part of this project where the user can display the results.

Keywords— Cosine Similarity, SVD, Recommendation system

1. Introduction

As the technology sector grew, the information age increased the amount of data produced on a daily basis. These types of available data were trained and tested by data scientists for the purpose of data mining and data processing. One of the fields associated with this data mining is called Recommender Systems. A recommendation system is a subclass of information filtering systems that attempt to predict the rating or preference a user might give to an item. In simple terms, it is an algorithm that recommends related items to users. Almost every aspect of the digital world uses recommendation systems. "Suggested Videos" on YouTube, "People you may know" on Facebook, "Games, Books, and Apps suggested for you" on Google Play Store, etc. are all examples of recommendation systemsthat consider the user's past/history and suggest results which the user may be interested in future. Recommendation systems help service providers by boosting their sales and better marketing of the products and help users in selecting items and decision-making. They have proven to increase the ease for the users in decision making. In the e-commerce world, they are proven to enhance revenue and are effective means of selling more products. Companies like Netflix, amazon have seen a large growth in their sales due to recommendation systems. Recommender systems handle the matter of data overload that users commonly encounter by providing them with personalized, exclusive content and repair recommendations. Recently, varied approaches for building recommendation systems are developed, which might utilize either collaborative filtering, content-based filtering, or hybrid filtering. Driven by the machine-controlled configuration, coordination, and management of machine learning prognosticative analytics algorithms, the advice system will sagely choose that filter to use for a selected user's specific situation. It facilitates marketers to maximize conversions and average order worth. Recommender systems will forecast user ratings, even before they need to provide one, creating them an efficient tool. Mainly, a recommendation system processes information through three phases as follows:

- Information collection phase
- Learning phase
- Prediction/recommendation phase

2. Literature Survey

In the paper by Neha Mamgain et al., sentiment analysis of people's viewpoints is carried out with respect to the top schools in India. In this paper, the authors have performed pre-processing techniques like an extension of internet language and exclusion of identical tweets. For spelling correction, the Bayes theorem is used by the authors. Also, the comparison is carried out between the outcomes using the following ML algorithms: Naive Bayes, Support VectorMachine, and an Artificial Neural Network model [2].

In the paper by Cailin Hu et al., the authors have tried to tackle the low precision of User-Based Collaborative filteringby proposing three improvements. First and foremost, the mean score was improved for the calculation of similarity. Also, the number of common things between two users was used to influence the validity of likeliness, and hence modification factor was added to weaken the pseudo alike errors. At last, the personal information registered by users was utilized to compute similarity based on user attributes. Based on the experimental results the paper concludes that Advanced Collaborative Filtering provides users with more accurate restaurant recommendations and improves the accuracy of similarity calculation [4].

The research paper by Reena Murali et al. focuses on the implementation of a real-time recommendation system usingApache Spark, a platform used for stream computing. The major aim of this recommendation system is to recommendTV channels to the users. The system designed implements a self-adaptive approach for model building. The designedrecommendation system uses the algorithms provided by Spark Machine Learning Libraries (Spark MLLib). A large amount of data in the system is managed by the Lambda architecture data processing method [5].

Saurabh Bhaulikar et al., come up with the idea to implement collaborative filtering by using geographical Latitude and Longitude instead of ratings given by users. They also stated that it is not convenient to make use of user ratings in order to recommend airlines as customers focus on multiple parameters like quality of service, customer satisfaction, etc. Authors filtered flights that are traveling between a source and destination locations and stored themin a temporary database. Also, users should create their profile in a database which will also store in a database [14]. The filtered flights from the database are then compared to the user database which will finally be recommended to users [6].

The paper by Bruno Almeida Pimental et al. proposes and has experimentally investigated the meta-learning approachthat uses a clustering algorithm as a learning technique in a recommender system. Three types of meta-features are considered for an experimental framework in the paper. The paper concludes with a study to analyze the importance of the meta-features to find relevant data partitions [8].

The research paper by Rachmadian Trihatmaja et al. focuses on overcoming the issue of too many recommendationsin the case of the CF recommendation system, by implementing the combination of the outlier labelling method, clustering, collaborative filtering, and association rule mining with a model of recommendation item selection basedon support value. Also, the paper concludes that the precision of CF implementation results can be improved by a unique value attribute in the selection item selection process[9].

Madhuri Kommineni et al., execute a recommendation system using a user-based collaborative filtering algorithmwhere they make use of Good reads books dataset which contains data about books, authors, and titles along with ratings. After pre-processing, they are making use of cosine-similarity, Pearson correlation, and Jaccard similaritymeasures to recommend books with more accuracy and consistency[12].

Lamiyah Katt Analysis et al. created an online grocery recommender that recommends products based on item-based collaborative filtering. In item-based recommendation, a profile is created of an individual user which consists of details of the product consumed by the user. This recommender recommends the items which are similar to the items that have been used by the user in past. This is implemented by creating a correlation matrix which helps to check therelationship between the observed data. For this, the Singular Value Decomposition (SVD) method can be implemented [14].

T. Sasipraba et al., implemented a hybrid recommendation system that uses the features of content-based filtering andcollaborating filtering together to make the prediction of movies. For implementation, the Movielens dataset has beenused. They have found that the hybrid model outperforms purely content-based and purely collaborative in performance comparison. The performance is compared based on precision, recall, and accuracy [15].

Priyadharshini A et al. proposed a crop recommendation system using different machine learning algorithms like Linear regression and Neural networks using Pandas, NumPy, TensorFlow, Keras, and Scikit learn libraries and Python as a programming language. The dataset has been taken from government websites and Kaggle which includesmini datasets like the Yield dataset, Cost of Cultivation dataset, Modal price of crops, Standard price of crops, and Soil nutrient content dataset. After pre-processing of data, the dataset is trained using different machine learning models. The results show that Neural Network has more accuracy in comparison to others [17].

3. Methodology

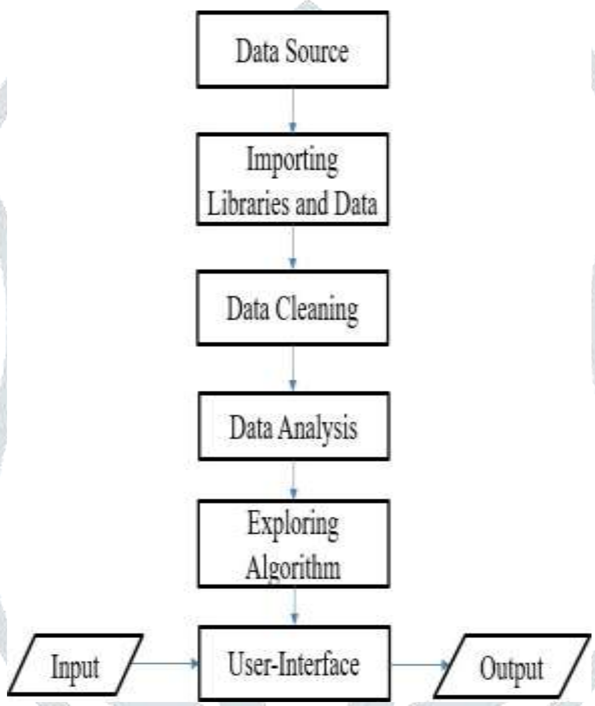

Fig 3.1. Design Flow-Chart

3.1 Data Source:

Data is obtained from the TMDB dataset, accessible on the Kaggle website which is publicly available. Itconsists of 5000 movies. The dataset is consisting of 8 CSV files.

3.2 Libraries Imported:

Libraries like NumPy, Pandas, OS, AST, Flask, Request, and Collections are imported into theimplementation of algorithms.

3.3 Data Cleaning:

Data were cleaned for missing data and null values. During this process, many stop words like ‘and’, ‘the’,‘is’, ‘are’,etc. are removed to organize the data. This step helps in removing redundancy and duplicates.

3.4 Data Analysis:

This process involves merging different CSV files based on a particular column and forming one big final data frame which is further used by the model to generate results. The dataset contains many features like title, genre, casting, crew, overview, movie ID, original language, production company, revenue, release date, etc. But all features are not required for the recommendation system. This data analysis process is used to filter out these features. For this project,we have considered features such as genre, title, cast, crew, movieID, keyword, and overview.

3.5 Exploring Algorithm:

We have considered some important features such as genre, title, cast, crew, movie ID, keyword, and overview. Outof the above features, a few of them will be merged. This step helps in reducing redundancyand duplicates.

3.5.1 Content-Based Approach:

Content-based filtering is a machine learning technique that uses similarities in features to make decisions. The mathematical modelling technique which we have used is cosine similarity. In order to obtain vectors for cosine similarity mathematical modelling, we perform text vectorization. Text vectorization is a technique in which the text is converted to vectors. In text vectorization, we use the “Bag of Words” technique. In text vectorization, we concatenate all the tags to make a string that contains million words which is called large text. From this large text, weobtain five thousand most commonly used words. In-text vectorization we do not consider stop words such as ‘And’, ‘To’, ’The’ etc. For achieving the filtering out of the stop words we are using the count- vectorizer class which is available in Scikit-library.

3.5.2 Collaborative Filtering

Collaborative filtering is a technique used to anticipate the things that a user could like based on evaluations given tothat thing by different other users who have an alike taste to that of the target user.

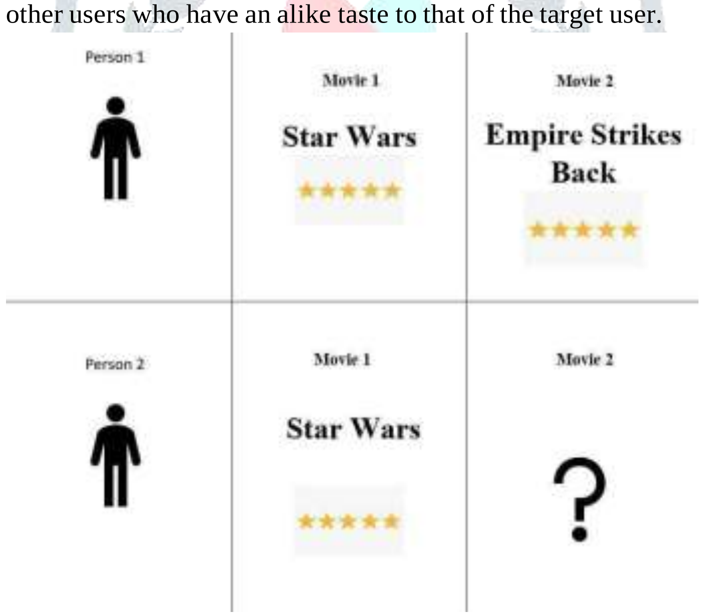

Fig 3.2 Collaborative filtering

In the above figure, person 1 likes both movies movie 1 and movie 2 and rated both movies 5 stars. Similarly, person 2 likes movie 1 and rated it 5 stars which suggest that person 1 and person 2 have a similar opinion regarding the movie. Based on these reviews, user-based collaborative filtering mightsuggest movie 2 to person 2. This is how a user-based recommendation system works.

3.6 User-interface

In addition to the implementation of the recommendation system and generating results on the console, we aim to develop and integrate a simple user interface, we have opted for a web app as our user interface. Web- app is application software that is running on a web browser rather than on a local operating system of the device. It helpsto deliver the service and the functionality to the users through the world wide web over an active internet connection.To make the results appear more user-friendly and interactive, the web app is made to run on the google collab platform, it is designed using HTML and CSS. Python package named “Flask” which is popularly used for developing web apps has been used, and the app is integrated to the method, which is previously defined that producesthe recommendation results, thus letting the results appear on the web app. The web app is further made interactive, where users can click on their interesting titles which the recommendation system generates as recommendations, then click the user makes, is counted by the web app and is made onto a separate page called the trending page, whereall the trending list of movies is stored and updated as the user starts interacting with the system, this trending page is shown to the new users, and a personalized recommendation based on their previous ratings is generated by the recommender system for the old user and displayed on a new redirected page.

4. Implementation

4.1 Dataset Description:

A dataset in machine learning is a collection of data pieces that can be treated by a computer as a single unit for analytical and prediction purposes. To implement a project successfully, we should always choose a dataset that gives us better andmore effective results. For the implementation of this project, we have chosen the TMDB dataset which contains 8 CSVfiles.

4.2 Pre-processing of Dataset:

We have used a movie dataset that contains title, genre, casting, crew, overview, movie ID, original language, production company, revenue, release date, etc. But all these parameters are not required for a recommendation system. We have chosen a few important parameters such as genre, title, cast, crew, movie ID, keyword, and overview. Out of the above parameters, a few of them will be merged. This step helps in reducing redundancy and duplicates. After pre-processing we have tags present in the form of strings. To implement content-based, we need to convert the text (strings) into the form of a vector. **Text vectorization**is a technique in which the text is converted to vectors.

4.2.1 Content-Based approach:

Content-based filtering is a machine learning technique that uses similarities in features to make decisions. The mathematical modeling technique which we have used is Cosine Similarity.

Feature Extraction and Mathematical Modelling

Cosine similarity is the measure of similarity between two vectors of an inner product space. It is measured by the cosine of the angle between two vectors and it is often used to measure document similarity in text analysis. To obtainvectors for cosine similarity, we perform text vectorization.

Text Vectorization is a technique in which the text is converted to vectors. In-text vectorization we use the “Bag of Words” technique. In-text vectorization, we concatenate all the tags to make a string that contains millions of words which is called large text. From this large text, we obtain 5000 most commonly used words. In-text vectorization, wedo not consider stop words such as ‘And’, ‘To’, ’The’ etc. For achieving the filtering out of the stop words we are using the count-vectorizer class which is available in Scikit-library.

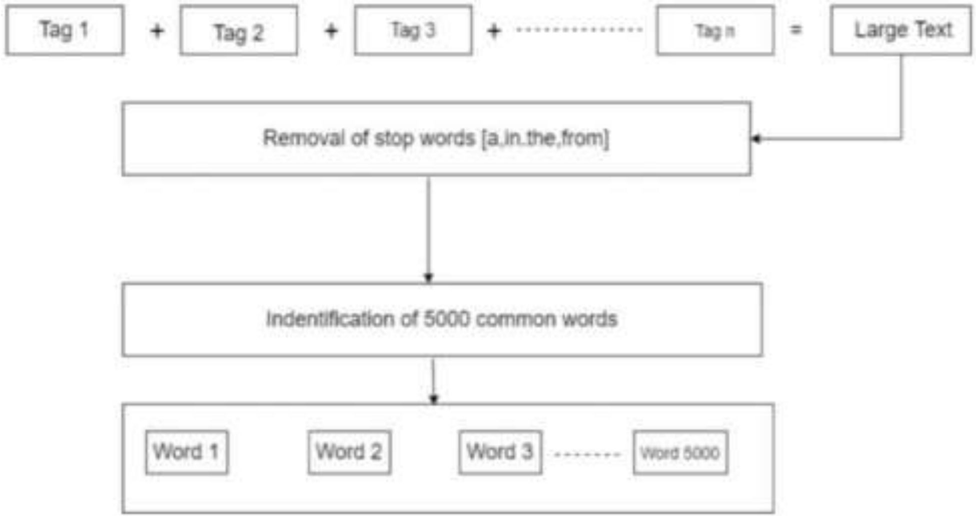

Fig 4.1. Feature Extraction of a content-based approach

We have 5000 words and 5000 movies which are represented in matrix form.

	W1	W2	W3	....	W 5000
MOVIE 1	3	0	1	....	5
MOVIE 2	2	4	3	....	4
. . .	. . .	. . .	. . .	....	. . .
MOVIE 5000	3	4	3	....	2

5000 X 5000

REPRESENTS VECTOR IN 5000 DIMENSIONS

Fig 4.2. Matrix representation of feature extraction

To understand in a better way let’s consider a matrix of 5000 x 2 where 5000 is the number of movies and 2 isthe number of words.

	W1	W2
MOVIE 1	3	0
MOVIE 2	2	4
. . .	. . .	. . .
MOVIE 5000	3	4

5000 X 2

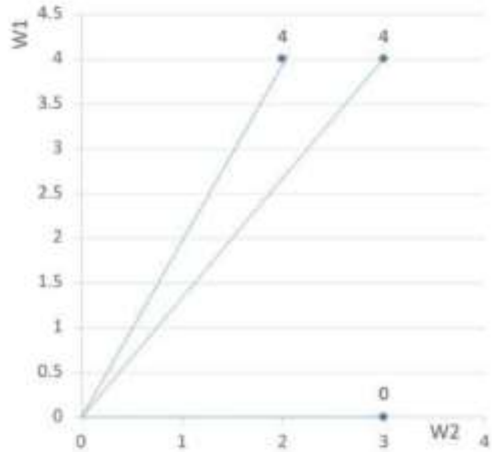

Fig 4.3. Matrix and graphical representation of feature extraction

Let's consider W1 is action and W2 is comedy. The matrix shows that W1 (action) is repeated thrice and there is no presence of W2 (comedy) in the tags of movie 1. A similar procedure is repeated in other movies. The graph shows the representation in the form of vectors. Now we find the distance of each vector from everyother vector which can be done by using cosine similarity.

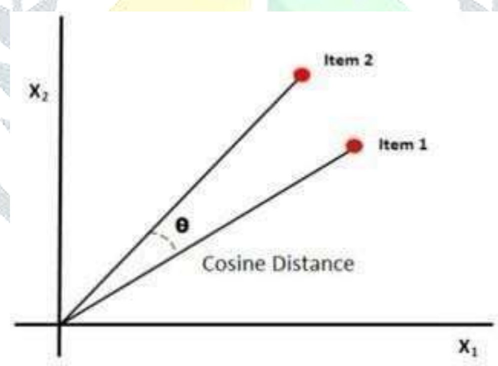

Fig 4.4. Graphical representation of Cosine Similarity

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}},$$

Fig 4.5. Equation of cosine similarity

The lesser the value of the angle between the two vectors, the greater will be the similarity between them.

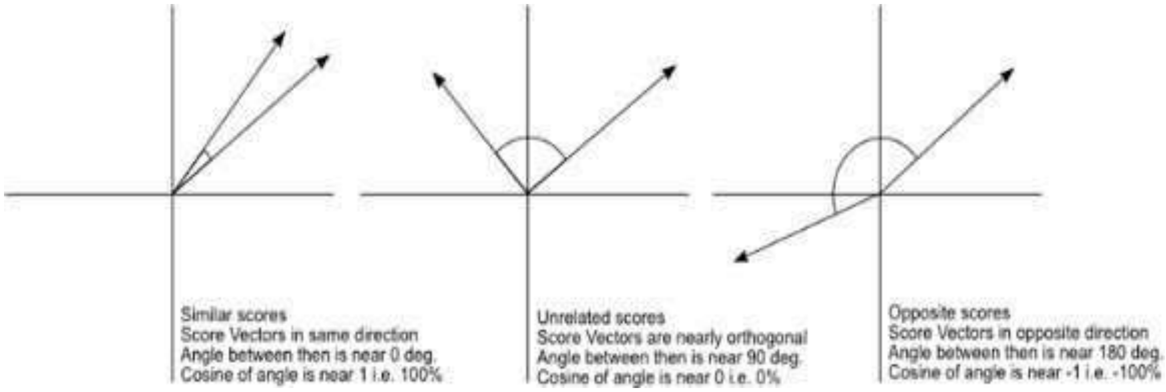

Fig 4.6. Graphical representation of vectors

4.2.2 Collaborative Filtering:

Collaborative filtering is a technique used to anticipate the things that a user could like based on evaluations given tothat particular thing by different other users who have an alike taste to that of the target user. In the context of the recommender system, the Singular Value Decomposition (SVD) is used as a collaborative filtering technique.

Singular Value Decomposition

Machine learning typically employs the Singular Value Decomposition (SVD), a dimensionality-reduction method fromlinear algebra. In the SVD matrix factorization technique, the number of features in a dataset is decreased by switchingfrom an N- to a K-dimensional space (where K<N). Each row in the matrix represents a user, and each column is a pieceitem. The ratings that users provide to items make up the matrix's elements.

A matrix can be divided into three additional matrices using the singular value decomposition, as shownbelow:

$$A = USV^T$$

A is a *m x n* utility matrix.

U is a m x r orthogonal left singular matrix, which represents the relationship between users and latentfactors.

The latent factor strengths are expressed by the diagonal matrix S, which has the dimensions r x r.

The similarity between items and latent components is shown by the diagonal right singular matrix V,which has the dimensions r x n.

The characteristics of the items, such as the movie's genre or title, are the latent factors in thissituation.

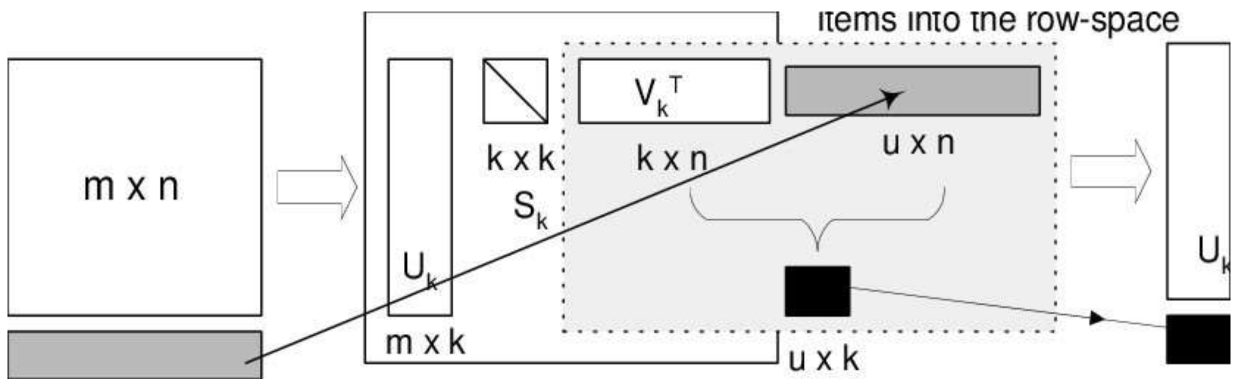

Fig 4.7 Schematic diagram of the SVD folding-in technique

5. Results

Table 5.1 MAE Values

MAE VALUES					AVERAGE
0.67702835	0.68111889	0.68211658	0.6818615	0.6728424	0.678994
0.6773526	0.67821474	0.67508912	0.6741587	0.6768229	0.676328
0.67631654	0.68102294	0.6785669	0.6767839	0.6762866	0.677795

MAE – Mean absolute error, is a measure that gives the mean absolute difference between the predict valueand true value in a dataset.

MAE is calculated by:

$$MAE = 1/n * \Sigma|y_i - \hat{y}_i|$$

where:

- Σ is a symbol that means "sum"
- y_i is the observed value for the i^{th} observation
- $\hat{y}_i$ is the predicted value for the i^{th} observation
- n is the sample size

Table 5.2 RMSE Values

RMSE VALUES					AVERAGE
0.87757036	0.86657815	0.85856629	0.87670624	0.87535747	0.870955
0.85294761	0.86096552	0.87682075	0.87990287	0.83148991	0.860425
0.88226398	0.85676122	0.83441285	0.8587991	0.85378753	0.857204

RMSE - Root means square error, is one of the most widely used methods, to assess the quality of predictions. It depicts the proximity of the predictions and the true values using Euclidean distance. In order, to calculate RMSE,it is important to calculate the residual for each data point. Residual is the difference between the predicted valuesand true values.

RMSE is calculated by using the formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(f_i - o_i)^2}$$

Where:

- ∑ is the summation of all values
- f is the predicted value
- o is observed or actual value
- (fi — oi) 2 are the differences between predicted and observed values and squared
- N is the total sample size

These are negative-oriented scores, which means that the lower values are better. A model with the RMSE score lying in the range equal to or less than 0.5 is considered to have the most accurate predictions. The models with RMSE scores lying in the range of 0.5 and 0.85 tend to give moderately accurate predictions and the RMSE values above 0.85 are considered to be the worst score for a model.

The result of the content-based approach (Fig 5.1) and hybrid approach (Fig 5.2) at the console level areshown below:

```
recommend('The Dark Knight Rises')
```

	original_title	vote_average
6981	The Dark Knight	8.3
6218	Batman Begins	7.5
524	Batman	7.0
1134	Batman Returns	6.6
7659	Batman: Under the Red Hood	7.6
132	Batman Forever	5.2
7582	Defendor	6.5
8265	Batman: The Dark Knight Returns, Part 1	7.7
9121	İtirazım Var	7.1
8001	Batman: Year One	7.1
4544	Q & A	6.6
2752	Death Wish	7.0
9024	Batman v Superman: Dawn of Justice	5.7
1864	The Siege	6.1

Fig 5.1. Output of content-based approach

```
# Recommendations for user with id 1
hybrid(1, 'The Exorcist')
```

	Title	Vote Average	TMDb Id	Estimated Prediction
7203	Ponyo	7.5	12429	2.991438
7441	Mary and Max	7.8	24238	2.945316
5373	Dark Water	6.7	12205	2.925234
2229	The Sixth Sense	7.7	745	2.867434
8081	Kokowaah	6.4	53174	2.850054
1663	One Magic Christmas	5.7	13380	2.826156
3789	I Never Promised You a Rose Garden	7.9	66092	2.805663
7822	Confessions	7.6	54186	2.778723
1115	Breaking the Waves	7.2	145	2.776095
1848	Beloved	5.9	39437	2.766958
267	Priest	6.4	40156	2.747017
8169	People Like Us	6.6	98548	2.736181
5298	The Virgin Spring	7.8	11656	2.659678
2300	Alice Sweet Alice	6.4	23761	2.651771
4888	Leap of Faith	5.1	12772	2.642807

Fig 5.2. Output of hybrid approach

Fig 5.3. Home page of User-Interface (web-app)

Fig 5.3 represents the homepage of the user interface (web app) which displays the result. There are twooptions availableon this page:

a. Recommend to old user
b. Recommend to new user

These given options can be explored by the users according to their convenience.

Here, old users mean that the dataset already contains required information like user-id, ratings, etc. of that user and, new user means that this particular user has visited this interface for the first time and there is no history saved in the dataset about them.

When a user clicks on option I, i.e., recommend to the old user, a new page will open displaying the recommendations based on the past activity. Suppose he/she has rated 'n' number of movies. Let's take n = 20. Then, outof these 20 movies, any random movie will be selected among the top 10 rated movies by him/her. The recommendation which will be displayed on the interface, in this case, is based on this randomly selected movie by the system.

When a user clicks on option II, i.e., recommend to a new user, since the system doesn't have any past information about this new user. So, the system cannot recommend movies based on past activity. In spite, it will display some trending movieswhich are created by the system based on programming.

Now, suppose a user with user-id 1 clicks on option 1. Shown below is displaying some of therecommendations based onthe movie 'THE RING'.

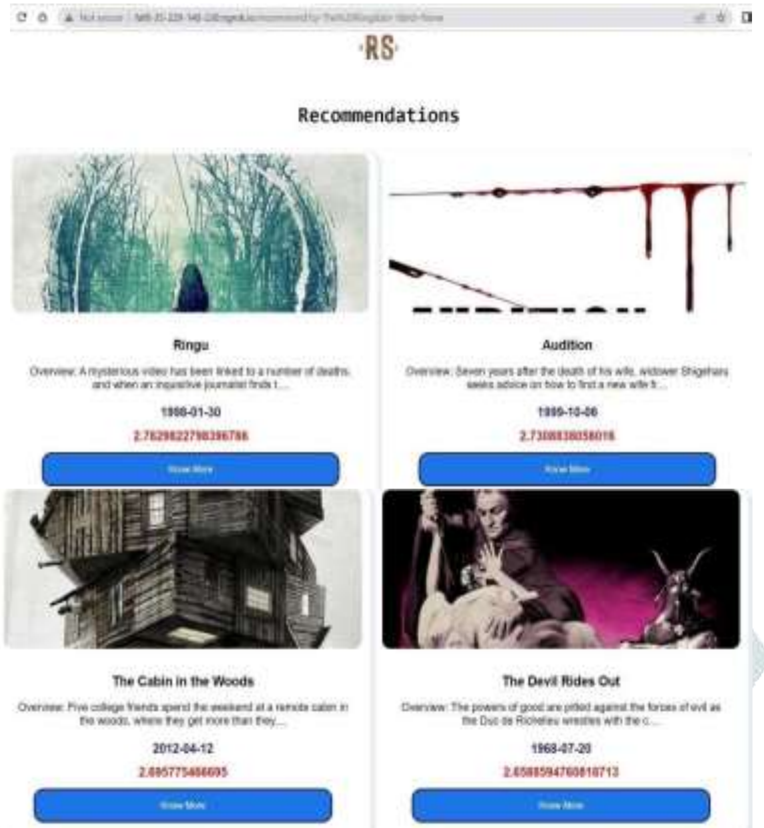

Fig 5.4. Old user recommendation page

The displayed page also contains 1 option i.e., Know More, which on click will redirect to TMDB websitewhich willshow information about the movie.

Fig 5.5. Know More Page

Suppose any new user clicks on option 2 (fig 5.3). A trending page will open and display some movies.

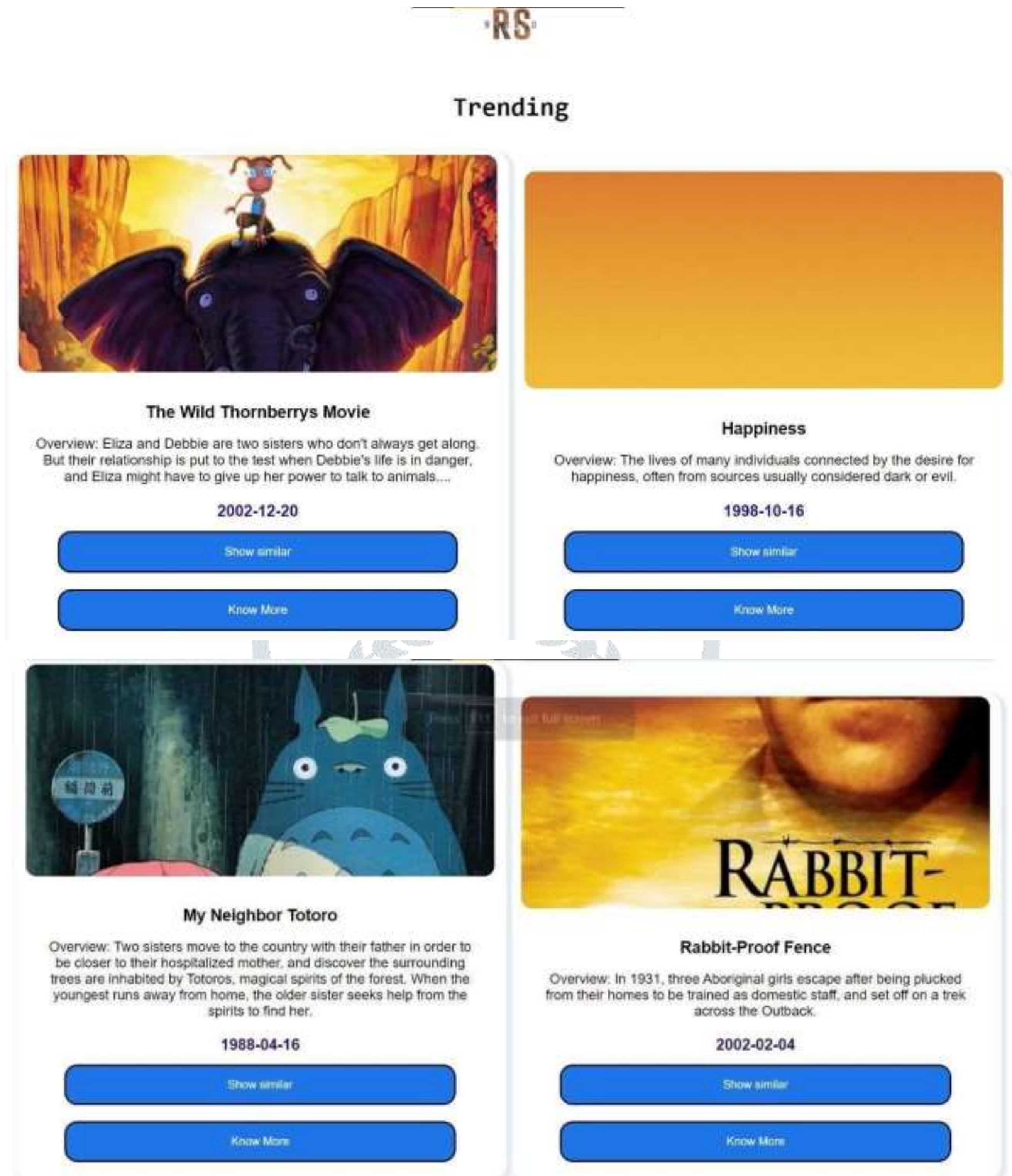

Fig 5.6 Trending Movies

These recommendations have again two options:

(I) Show similar – which on click will recommend more movies similar to that movie.

(II) Know more – which on click will redirect to the TMDB website which will display anyinformation about thatmovie.

Suppose any user clicks on 'show similar' of the movie 'HAPPINESS' (fig 5.6), a new page opens (fig 5.7) andwill displaysome recommendations based on the movie 'HAPPINESS'. Besides this, if any user clicks on anymovie, it means that the user is interested in that movie. At the same time, any clickon any movie will affect the trending lists. In this case, a user clicks on the movie 'HAPPINESS'. Fig

5.8 shows the impact when a user clicks on the movie 'HAPPINESS'.

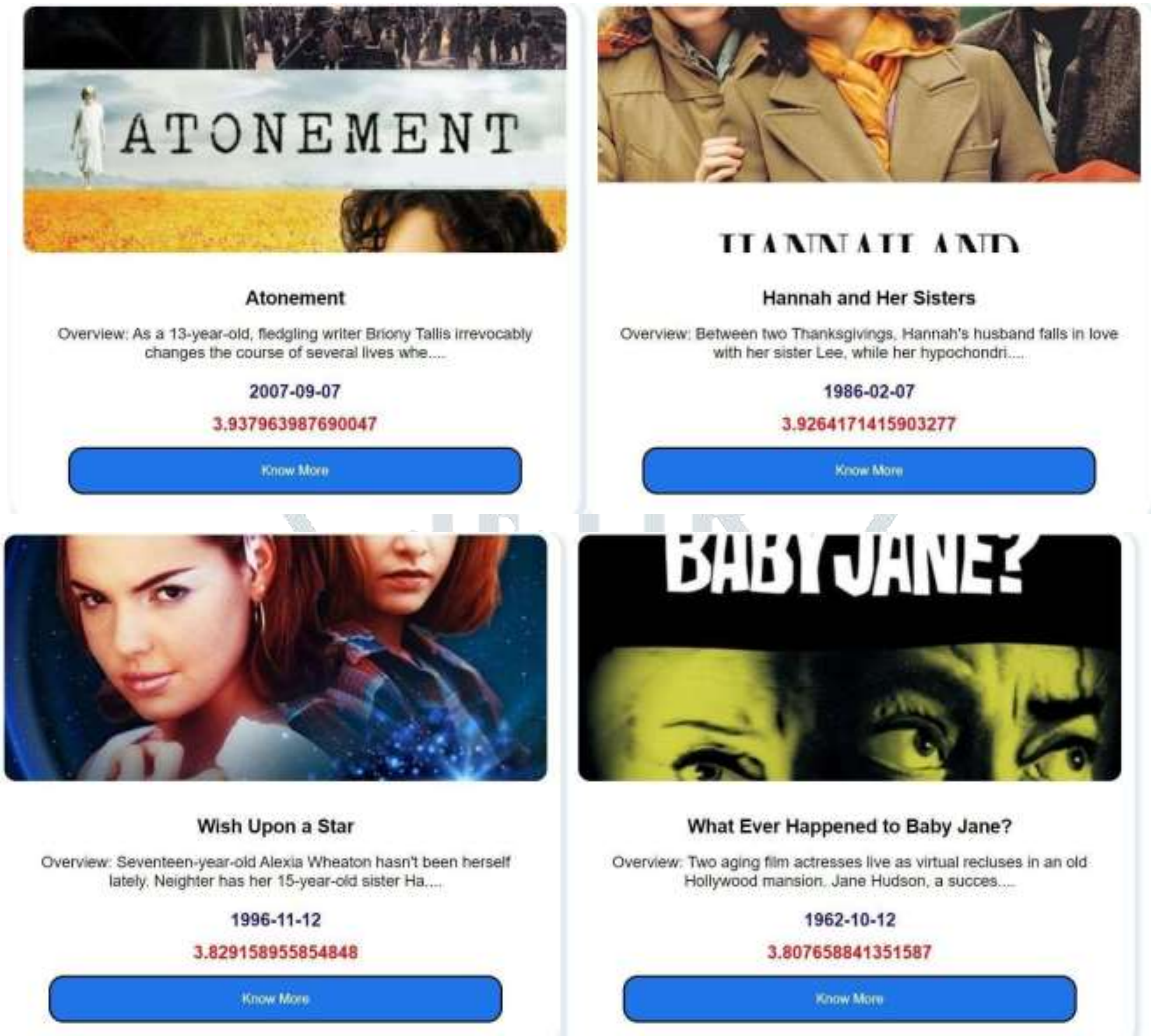

Fig 5.7. Trending page 2

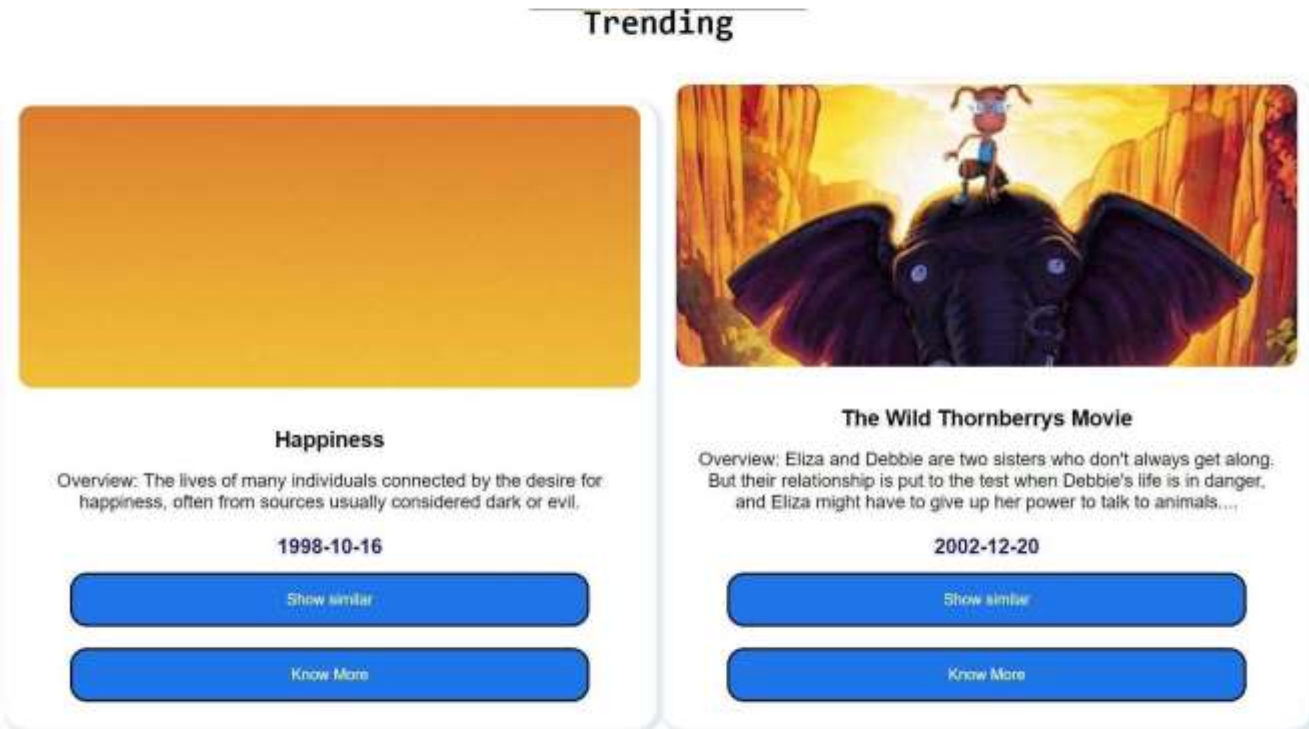

Fig 5.8. Trending page 3

.

References

[1] Q. Liu, E. Chen, H. Xiong, C. H. Q. Ding and J. Chen, "Enhancing Collaborative Filtering by User Interest Expansion via Personalized Ranking," in IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), vol. 42, no. 1, pp. 218-233, Feb. 2012, doi: 10.1109/TSMCB.2011.2163711

[2] N. Mamgain, E. Mehta, A. Mittal and G. Bhatt, "Sentiment analysis of top colleges in India using Twitter data," 2016 International Conference on Computational Techniques in Information and Communication Technologies (ICCTICT), 2016, pp. 525-530, doi: 10.1109/ICCTICT.2016.7514636

[3] N. Kussul, M. Lavreniuk, S. Skakun and A. Shelestov, "Deep Learning Classification of Land Cover and Crop Types Using Remote Sensing Data," in IEEE Geoscience and Remote Sensing Letters, vol. 14, no. 5, pp. 778-782, May 2017, doi: 10.1109/LGRS.2017.2681128

[4] L. Li, Y. Zhou, H. Xiong, C. Hu and X. Wei, "Collaborative filtering based on user attributes and user ratings for restaurant recommendation," 2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), 2017, pp. 2592-2597, doi: 10.1109/IAEAC.2017.8054493

[5] B. K. Sunny, P. S. Janardhanan, A. B. Francis and R. Murali, "Implementation of a self-adaptive real time recommendation system using spark machine learning libraries," 2017 IEEE International Conference on Signal Processing, Informatics, Communication and Energy Systems (SPICES), 2017, pp. 1- 7, doi: 10.1109/SPICES.2017.8091310

[6] S. Bahulikar, V. Upadhye, T. Patil, B. Kulkarni and D. Patil, "Airline recommendations using a hybrid and location based approach," 2017 International Conference on Intelligent Computing and Control Systems (ICICCS), 2017, pp. 972-977, doi: 10.1109/ICCONS.2017.8250610

[7] V. Garg and R. Tiwari, "Hybrid massive open online course (MOOC) recommendation system using machine learning," International Conference on Recent Trends in Engineering, Science & Technology - (ICRTEST 2016), 2016, pp. 1-5, doi: 10.1049/cp.2016.1479

[8] R. Trihatmaja and Y. D. Wardhana Asnar, "Improving the Performance of Collaborative Filtering Using Outlier Labeling, Clustering, and Association Rule Mining," 2018 5th International Conference on Data and Software Engineering (ICoDSE), 2018, pp. 1-6, doi: 10.1109/ICODSE.2018.8705883

[9] S. Banihashemi, J. Li and A. Abhari, "Scalable Machine Learning Algorithms for a Twitter Followee Recommender System," 2019 Spring Simulation Conference (SpringSim), 2019, pp. 1-8, doi: 10.23919/SpringSim.2019.8732884

[10] B. A. Pimentel and A. C. P. L. F. de Carvalho, "Unsupervised Meta-Learning for Clustering Algorithm Recommendation," 2019 International Joint Conference on Neural Networks (IJCNN), 2019, pp. 1-8, doi: 10.1109/IJCNN.2019.8851989

[11] L. P. J. Rani, D. C. J. W. Wise, K. Ajayram, T. Gokul and B. Kirubakaran, "Course Recommendation for students using Machine Learning," 2020 International Conference on Electronics and Sustainable Communication Systems (ICESC), 2020, pp. 381-384, doi: 10.1109/ICESC48915.2020.9156012

[12] M. Kommineni, P. Alekhya, T. M. Vyshnavi, V. Aparna, K. Swetha and V. Mounika, "Machine Learning based Efficient Recommendation System for Book Selection using User based Collaborative Filtering Algorithm," 2020 Fourth International Conference on Inventive Systems and Control (ICISC), 2020, pp. 66-71, doi: 10.1109/ICISC47916.2020.9171222

[13] Y. Mahima and T. N. D. S. Ginige, "Graph and Natural Language Processing Based Recommendation System for Choosing Machine Learning Algorithms," 2020 12th International Conference on Advanced Infocomm Technology (ICAIT), 2020, pp. 119-123, doi: 10.1109/ICAIT51223.2020.9315570

[14] L. Khattar and G. Munjal, "Analysis of Online Grocery Recommendation Systems," 2021 11th International Conference on Cloud Computing, Data Science & Engineering (Confluence), 2021, pp. 741- 745, doi: 10.1109/Confluence51648.2021.9377058

[15] S. C. Mana and T. Sasipraba, "A Machine Learning Based Implementation of Product and Service Recommendation Models," 2021 7th International Conference on Electrical Energy Systems (ICEES), 2021, pp. 543-547, doi: 10.1109/ICEES51510.2021.9383732

[16] J. Chen and C. WU, "The Design of Cross-border E-commerce Recommendation System Based on Big Data Technology," 2021 6th International Conference on Intelligent Computing and Signal Processing (ICSP), 2021, pp. 381-384, doi: 10.1109/ICSP51882.2021.9409014

[17] P. A, S. Chakraborty, A. Kumar and O. R. Pooniwala, "Intelligent Crop Recommendation System using Machine Learning," 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), 2021, pp. 843-848, doi: 10.1109/ICCMC51019.2021.9418375