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Addressing Linguistic Challenges in Arabic NLP: A Comprehensive Study on Content-Based and Collaborative Filtering Techniques for

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A B S T R A C T

Efficient algorithms need to detect Arabic-speaking users and provide them with content that promotes cultural exchange and knowledge acquisition. This study proposes an enhanced Arabic Article Recommendation System (AARS) grounded on semantic analysis techniques strengthened by the BERT model. The system aims to promote recommendation relevance and accuracy, a process frustrated by the complexity of the Arabic language brought about by dialectical variations and diacritical presence. To mitigate these challenges, the method takes a light normalization step for removing noise and redundant characters, followed by a morphological dialect stemmer to extract root forms and improve semantic representation. In addition, the proposed system integrates cultural, personal, and contextual dimensions—such as user interests and preferences—to make context-aware recommendations. Empirical results confirm the effectiveness of the approach in recalling and presenting relevant content and thereby enhancing user satisfaction and involvement. In addition to its theoretical significance, the system also offers economic benefits to content providers and advertisers by enabling personalized, targeted suggestions. Future work will entail model refinement and exploring advanced methods to further promote stability and adaptability in the face of future computational demands and challenges

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1. Introduction

2. The exponential growth of digital content has created an urgent need for intelligent recommendation systems (RS) capable of filtering and delivering relevant information to users. While effective solutions have been developed for several widely used languages, Arabic presents unique challenges due to its complex morphology, flexible grammatical structures, and wide dialectal variations. These linguistic characteristics hinder straightforward application of conventional recommendation approaches, making the development of efficient Arabic Article Recommendation Systems (AARS) a critical research direction. This study addresses these challenges by exploring advanced semantic analysis techniques and deep learning models to enhance the accuracy, contextual relevance, and overall effectiveness of Arabic content recommendations [1]. The place of recommendation systems is certainly significant and they are indispensable for enhancing customer attention, satisfaction and loyalty within a range of areas such as e-Commerce, social networks and content delivery platforms. From the user input and interaction profile, RS is capable of predicting the user's choice and subsequently provide product alternatives that would be most suitable for the user. Nevertheless, these systems experience several challenges among them being data sparsity, the cold-start problem and the characteristics of the Arabic language. That can cause some challenges, which require rather powerful solutions derived from natural language processing or NLP and machine learning in particular [3]. This research aims to provide a systematic approach on how the emerging limitations on Arabic article recommendation systems can be conquered through the application of NLP model; the BERT. The current paper seeks to enhance the degree of semantic analysis of Arabic text by using BERT in order to improve the chance of recommending relevant results. The integration of BERT does not only assist in reading and interpreting Arabic complexities as well as recognizing pragmatic features but also assist in extraction of context required features which can highly influence users' preference. This research entails several critical steps which include data collection and preparation in addition to feature extraction and both, collaborative and content-based filtering. Basically and from our baseline models, a detailed comparison of the propose approaches will also be conducted in order to have a clear understanding of the proposed approaches effectiveness and stability in delivering quality recommendations. Furthermore, this study will also establish the other possible future pitfalls and challenges of current AARS in other to identify other future related AARS research areas [4].

3. Thus, it is the goal of this work to make some improvements to the Arabic article recommendation system that is challenging by Arabic language and culture. By applying technologies in NLP & recommendation algorithms, and by adopting this ontological approach of this research, it aims at improving on delivery of meaningful content targeted at Arabic users and in the process improving the interaction that users have with content. [6].

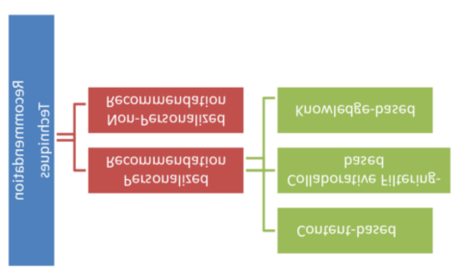

Fig. 1 Recommendations Techniques

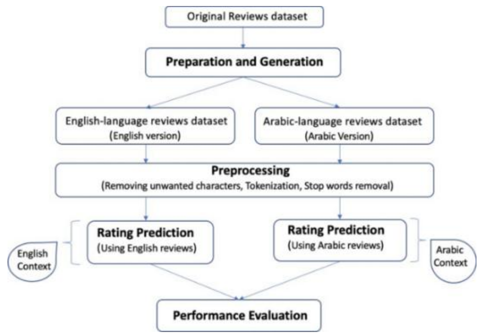

Fig. 2 Original Reviews Dataset

Table 1 Arabic Article Recommendation Systems [7]

eature	**Traditional Recommendation Systems**	**Advanced Recommendation Systems**
Data Sources	Primarily rely on user interaction data (e.g., ratings, clicks)	Utilize a wider range of data sources, including social media interactions, demographics, and contextual information
Algorithms	Primarily use collaborative filtering and content-based filtering	Employ more advanced algorithms, such as deep learning models and hybrid approaches
Personalization	Focus on user-item interactions	Consider a broader range of factors, including user preferences, demographics, and context
Real-time Recommendations	Limited ability to provide real-time recommendations	Can deliver real-time recommendations based on user behavior and current events
Cultural Sensitivity	May not fully consider cultural nuances and sensitivities	Incorporate cultural factors to provide more relevant and appropriate recommendations
Ethical Considerations	May face challenges related to bias and fairness	Prioritize ethical considerations, such as privacy protection and bias mitigation
Integration with Other Technologies	Limited integration with emerging technologies	Integrate with technologies like generative AI, blockchain, and AR/VR for enhanced capabilities
Future Trends	Focus on improving accuracy and efficiency	Explore new frontiers, such as generative AI, ethical AI, and social impact

4. Related Works

5. For clarity, the activities related to recommendation systems (RS) in this study rely on memory-based and model-based collaborative filtering with similarity measures, and Aygün and Okyay (2015) [8] highlighted

the need to add a new parameter based on data age or time.Thus, it is possible to take the age difference and the preference of the users to be more effective in the decisions here in as granted. On the aspect of the age parameters, we have incorporated a Pearson similar it y measure, which considers both the age of the user and the generation gap. For the purpose of better analysis and evaluation we applied these on the MovieLens 100K dataset. Regarding the accuracy and the reliability of the MAE the result was 0. They found accuracy of retrieved recall to be equal to 0. 740397 which is 7412/1000 almost equal to 7412 while precision was equal to 0. Altogether M1 was 7331, F1 was 0.7620. To compare, the authors in Al Hassanieh et al. (2018) [9] have used all these similarities on the same dataset and also on samples of the same dataset containing only 100 records. To tackle the problem of having less amount of data, two measures of similarity have been defined. The new measure used – the WPCC was computed as weight and frequency Pearson's product moment correlation coefficient. This research study therefore uses a frequency weight as a weighted space measure the Pearson correlation scale. Regarding the two testing algorithm namely FPCC and WPCC, experiment following has been noted from the MovieLens 1OOk data set and about 10 % users having Error Mean Absoulte of nearly 1 and Root Mean Square Error of nearly 1. 002. Following the test collection analysis built with the Naíve Bayes algorithm, Shuxian and Sen (2019) confirm hypotheses based on the MovieLens dataset. Hence for the purpose of depicting the targeted user of the receiver, comparable analysis was done on the score of such user for deriving similar matrix. Having said that a specificity of 0. 72, a sensitivity of 0. 89 and an overall recall ratio of 0. Consequently, the accuracy of it is at 78% and F1-score of 0. 83 are obtained, when the number of recommended movies is set 10. And the methods of sampling for data testing are 4-6 randomly selected people. To avoid these issues, Selvi and Sivasankar put forward A modified fuzzy c means clustering method in 2019[11].

6. To this end, they propose a new approach, known as modified cuckoo search (MCS), to improve the maximum data points in each cluster while providing a useful recommendation. An actual experiment based on the material mentioned above The considered RS is evaluated with the assistance of the MovieLens dataset. For the purpose of validating the reliability of the proposed MCS algorithm, the resultantly obtained cognitive map is examined against benchmarking optimization function using certain global optimization techniques such as swarm intelligent particle swarm optimization and cuckoo search. Sejwal and Abulaish [12] presented a recommendation technique that involves recommending videos to users using their proposed model known as Particle Swarm Optimization with Principal Component Analysis, or PSO-PCA. The above described filtering approaches should complement the problem of data scarcity in the following manner. Local neighborhood collaborative filtering is used instead of generality for this purpose in this work. Hence, to address the absence of sufficient data to support the study, we adopt the LDOS-CoMoDa dataset. In this work, we have used the PCA method which is normally used in recommender systems to measure the effectiveness. Specifically, the LDOS-CoMoDa is the selected dataset For above dataset, 75% data is used for training the system and used Above left out data is used for rating the degree of accuracy of above recommended strategies. For analytical purposes, this model computed mistakes in statistics using three metrics: and the mean absolute error (MAE), the mean standard error (MSE), the root mean squared error (RMSE) and the recall, accuracy and the F measure. The proposed model is 93% accurate which is highly efficient ACC: Thus, in their study performed in 2021, Boppana & Sandhya [13] suggested the approach that seems to be able to perform at least a primitive role as the contribution to some-not-sore recommendation system. These perception data are normally collected from tens of entailing internet facilities . The keyword search from the reviews has also been done by crawling and preprocessing the reviews that has been posted by the users. Data analysis was also carried out with the help of Natural Language Tool Kit for the programming language –Python abbreviated as NLTK. In the present section, I corrected each of the stage of preparation and included the parts of the text worked over throughout the process into the reviews. The degree density for negative, neutral and positive user feedback is presented as follows: All the above have been well implemented to reach the goal. Lastly, for taste we use DRNN (Deep Recurrent Neural Network) because it incorporates prefabricated user choice. This was achieved with the help of training the initialized neural network model with data from the NSW-Restaurant Rich dataset at specific parameter definition points of the model. If we compared this model with other models and analyzed on the basis of the criteria of confidence and recall it has got an accuracy of 99. 6 % than any other deep. In this paper, Manimurugan and Almutairi (2022) [14] proposed Context Aware Collaborative Filtering and Principal Component Analysis for recommending videos to the users (PCA).

7. Two broad aspects that are captured in most of the traditional recommendation system models are content analysis and collaborative filtering whereby user input is dealt with by the recommendation systems decisions. Still there are some limitations but I find some weakness in data shortage in some of the filtering methods. Lacking such a method, the authors of this piece employ another strategy called neighborhood-based collaborative filtering to solve the issue. The LDOS-CoMoDa dataset is used for the performance evaluation in this work. In this work, the PCA method is designed to compute the similarity among the users and over the attributes for the video recommendations system effectively. The main aim is to improve the present context-aware recommendation model by integrating a collaborative filtering that uses PCA. In addition to the more consequential first seven dimensions, the set has 12 other context attributes. Nevertheless, if all possible contextual variables will be included into the system the result will be a very complicated system and it will take much more time to maintain this system, so only six contextual variables were used only. Thus, effective testing can employ only 25 % of the data, while the training can take place using 75 % of it. During this work, these statistical errors were assessed concerning the mean absolute error (MAE), the mean standard error (MSE, mean RMSE, recall, accuracy, and the f-measure based on the following methodology. The credits of the suggested model have been set at 86.70% accuracy having 93.84% of the precision and 78.54% of the recall in F-measure. The new model that was suggested by Parthasarathy and Devi; In (2022) [15] is named enhanced BIRCH where hyper parameters tuning is incorporated to the original BIRCH algorithm in order to increase the group formation step. By applying gradient boost classification wherein being highlighted that comprises a fairly broad area of coverage, the presented model provides a good quality of a new user movie recommendation. In this study, the proposed model is tested using the Movielens dataset, and four measures, including MAE, precision, recall, and f-measure, are used for the evaluation of the results. The experiments made allowed us to conclude that the proposed model of movie recommendation had better efficiency compared to current widespread technologies used today. The proposed model Got an MAE of 0.52 for the Movielens 100k and 0.57 for Movielens 1M.

8. On the recall wise, the proposed model was also 0.86 whereas on the rating scale it was 0.83 which outperformed all the existing movie recommendation approach on Movielens 100k dataset in terms of f-measure of 0.86. In make recommendation system, Wang et al. (2023) [16], these user elements are translated into certain categories. And in this setup, shortest connection between the nodes are take into account. Because there is so much data and multiple sets of user elements need reformatted data, different relationships are used to do so. The study was conducted using IMDb, an online resource intended for movie and TV show collection. Expected evaluations are normally computed to be greater than zero, for example if the user enters few number of rating. If the given user preferences deviate the maximum expected value is equal to 1, that is what is achieved by this component. The last lists of each category represent works with the final rate of 0 and 1 on average taken from the top ten films. The information important to each of the studies presented in Table 2.1 comes from prior research.

9. Table 2.1: Related Work information details.

Researcher and year	Dataset	Method	Challenges
Aygün and Okyay (2015) [8]	MovieLens	Pearson similarity	generation gap
Al Hassanieh et al. (2018) [9]	MovieLens	Different similarity measures	Data Sparsity Reduction
Selvi and Sivasankar (2019) [11]	Movie Lens	Collaborative filtering	The proposed method helps recommender systems deal with sparse data and increase their accuracy, two major problems.
Shuxian and Sen(2019) [10]	MovieLens and Facebook	Deep belief used for categorization (DBN) Network and Monarch Butterfly Optimization	helps recommender systems deal with sparse data
Sejwal and Abulaish (2020) [12]	LDOS-CoMoDa	Context-based rating prediction and Context-aware	Data Sparsity Reduction
Boppana and Sandhya (2021) [13]	NYC Restaurant Rich	Web crawling and Deep recurrent neural network	When making suggestions utilizing data from different domains, it's important to take into account the perspectives of those affected.
Manimurugan and Almutairi (2022) [14]	LDOSCoMoDa	Principle component analysis (PCA). CAC	Data sparsity is an issue for these filtering approaches. This work use neighborhood-based collaborative filtering as an alternative to more traditional approaches.
Parthasarathy and Devi (2022) [15]	movie lens	deep belief network	Data Sparsity Reduction
Wang et al. (2023) [16]	IMDb	Collaborative Recommendation System Based on Multi-Clustering	The difficulty arises when trying to use a distance value to describe consumers' tastes across many genres, such as "horror" and "adventure."

10. Methodology

This section provides the extensive approach taken for constructing and evaluation Arabic article recommendation systems (AARS) with a focus on employing the emerging NLP tool, the BERT. The methodology is structured into several key phases: data cleaning, data preparation and transformation, recommendation system deployment and measurement methods.

3.1 Data Acquisition

The first activity in the presented methodology is th e data collection that is presented in a diverse format which includes Arabic articles. Hence this data is obtained from various sources including news sites, blogging sites or scholarly databases in order to have an adequate flow of Arabic over different sites. The data acquisition process includes: Web scraping: As part of it, bots are employed to gather articles from such websites while adhering to the service's policies. Data Curation: The collected material is then purged to filter out junk posts or, in other words, such articles that are not useful to the target audience.

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3.2 Data Preprocessing

Consequently, data cleaning in its broader sense is an initial preprocessing by which the raw text data are to be prepared. Given the complexities of the Arabic language, the preprocessing steps are tailored to address specific linguistic challenges: Preprocessing: This involves the following; removal of stop words, stemming, lemmatization, transliteration, removal of non Arabic element like punctuation, hyphenation etc. The basic concept is that to retain only the Arabic script since the word 'Allah', and few other Islamic words or terms or phrases are in Arabic. Normalization: Normalization process attempts to return to one base form the many different forms of the same word. This includes: Diacritics Removal: It is wise and common for diacritics to be removed in Arabic text, and this confuses everyone most of the time. It also normalizes as it akes a point to use the bare roots of words As. Mapping Variants: Some of the words are stemmed or reduced to the root to provide profuse meaning of that particular word. Tokenization: It involves breaking down the text into individual item of information, while it refers to word or other piece of importance, with commensurate attention paid to Arabic morphological analysis. This step also has a significance towards the next phase on feature extraction and analysis. Stop Words Removal: Negations such as Arabic stop words that have no contribution to the information content in the text are also removed in order to bid more value to the dataset. Stemming: Filtering term stemming algorithm is used where the words are chopped off their roots and is most efficient in Arabic due to derivational characteristics [17].

3.3 Feature Extraction

Feature extraction is a process that takes very much importance in feature extraction in order to transform the result of the preprocessed text for recommendation models. The following techniques are employed: TF IDF: Term Frequency–Inverse Document Frequency:This numerical approach quantifies the significance of a word within a document in relation to its distribution across the entire corpus. In this case it helps to obtain the main terms that characterize the articles. Word Embedding: Like in the case of BERT model all the data is preprocessed using advanced embedding's with the general aim of finding semantic relations between the words. The same serves to give a detailed meaning and understanding of the meaning of a word or term in Arabic text. Semantic Analysis: Additional text processing techniques like LSA and topic modeling is then used to extract other features for the articles that make up other themes and topics from the collected articles.

3.4 Implementation of Recommendation Algorithms

The core of the methodology involves implementing various recommendation algorithms, focusing on both collaborative filtering (CF) and content-based filtering (CBF) approaches: Collaborative Filtering: This approach has to do with the interaction data of users; with the aim of identifying articles of like-minded users with that of the targeted users. Two main types of collaborative filtering are employed: User Based CF: It involves recommending objects based on the similarity of the users and tells the user a list of similar users as well as the articles they liked. Item-Based CF: This method recommends articles based on the fact that the articles with which the user has interacted are similar to other articles. Content Based Filtering: It recommends articles based on features of the articles in question. For better classification and semantic analysis of the content this step involves also the integration of the BERT model for a better recommendation to the users based on their profile/behavior.

3.5 Evaluation Metrics

To assess the performance of the recommendation systems, a comprehensive set of evaluation metrics is employed: Precision: Represents the amount of all articles that has been recommended are actually relevant to the subscriber. Recall: Measures the quality of recommendations by calculating the value that defines the ratio between relevant domain articles and the number of articles recommended by the system. F1-Score: The F-measure of precision/reCall which means a set can provide a good result of the system in one parameter but at the same times harm the opposite parameter at the same level. Mean Squared Error (MSE): Performs the assessment of credibility of the predicted and actual ratings in collaborative filtering environment. User Satisfaction Surveys: By obtaining feedback in the form of qualitative data from the users, their satisfaction levels in terms of the specific recommendations is evaluated to gather sufficient data about the usefulness of the system [18- 21].

4. Mathematical Equation

This model has the same basic idea behind it of segmenting a document into sentences; however, here we assume that the semantically relevant information is concentrated in specific sentences in the longer text, so testing relations between all words in a document is not required. In contrast, we implemented a BERT-based similarity matching algorithm capable of recognizing high-relevance sentences and passing them as input to the BERT model that is can perform the required classification task. The highly relevant sentences were selected by employing a maximum marginal relevance, MMR similarity algorithm as shown by Equation 1. The sentence lengths are between 30 to 150 tokens

$$MMR = argmax\ Di \in X\left[\lambda Sim_1\,(D_i, S) - (1-\lambda) maxDi\epsilon\ c(D_i, D_j\right]\ Eq.1$$

Where S is the sentence vector and Di is the document vector related to S. X is a subset of documents in our dataset we already selected and λ is a constant in range of for diversification of results. The $Sim1$ and $Sim2$ are the similarity function which can be replaced by cosine, Euclidean, Jacard and any other distance similarity measures. In our model we have used the proper cosine similarity that explained by equation 2cosine similarity that explained by Equation 2

$$\frac{cos^{-1}\left(\frac{\sum_{i=1}^{n} u_i \times u_i}{\|u\|2\times\|u\|2}\right)}{\pi}\ Eq.2$$

It was because of this that we could build our recommender system using collaborative filtering, which is really a process of transforming this training dataset into a matrix of product features. To predict products that a certain user has not rated, we would need some metric that identifies similarities between users, user-based, or between items, item-based. One of the most common metrics is cosine similarity, as shown in Eq (3).

$$s(d_a, d_{1)} = \frac{\sum_f w_{ff}.w_{fa}}{\sqrt{\sum_f w_{ff}^2}.\sqrt{\sum_f w_{fa}^2}}\ Eq.\ 3$$

where wji and wja are components of vectors dada and didi, respectively. Next, we perform a cosine similarity-based prediction of ratings. The ratings of either the most similar items (in item-based approach) or users (in user-based approach) were utilized to anticipate the rating of a current user for a particular item that has not yet been rated.

$$Pff = r_t^- + \frac{\sum_u s(i,u)(r_{ff} - r_t^-)}{\sum_u \|s(i,u)\|}\ Eq.\ 4$$

where: PijPij is the predicted rating for item j by user i. rijrij denotes the rating provided by user i for item j. $\underline{r}i$r¯i is the average rating by user i. (i,u)s(i,u) denotes the similarity between users i and u.

$$Put = \frac{\sum_f r_{uf}.s(i,j)}{\sum_f x(i,j)}\ Eq.4$$

where: puipui is the predicted rating for user u and item j. rujruj denotes the actual rating that user u gave to item j. (i,j)s(i,j) denotes the similarity between items j and i.

Equation (5) is for user-based, and Equation (6) is for item-based collaborative filtering. Algorithm 2: Content Based Filtering Input: Target user's profile, preprocessed items to be recommended. Output: Recommendations. Steps: 1. Generate target user's contextual profile vector 2. Generate items' content vector 3. Generate similarity matrix between all items contents and target user profile using the following equation

$$\mathbf{Sim}(\mathbf{v_c^-}, \mathbf{v_m^-}) = \frac{\sum_{i=1}^{n} c_i \times \sum_{i=1}^{n} m_i}{\sqrt{\sum_{i=1}^{n} c_i^2} \times \sqrt{\sum_{i=1}^{n} m_i^2}} \text{ Eq.5}$$

Cosine Similarity (Equation 3): This equation is crucial for measuring the similarity between users or items in collaborative filtering. By quantifying the cosine of the angle between two vectors, it effectively captures the degree of similarity based on user ratings or item features. The choice of cosine similarity is particularly appropriate in high-dimensional spaces, such as those encountered in recommendation systems, where the sparsity of data can lead to misleading distance measures. The equation's structure allows for straightforward computation and interpretation, making it a popular choice in the field.

Prediction Equations (Equations 4, 5, and 6): These equations outline the process of predicting user ratings for items that have not yet been rated. They leverage the similarity scores derived from the cosine similarity measure to generate recommendations. The formulation emphasizes the collaborative nature of the approach, where the ratings of similar users or items are aggregated to provide a personalized recommendation. This methodology highlights the importance of user behavior patterns and the underlying assumption that users with similar tastes will rate items similarly.

Marginal Relevance (MMR) (Equation 1): The MMR equation introduces a diversification aspect to the recommendation process, balancing relevance and novelty. By incorporating a parameter (λ) that adjusts the trade-off between relevance and diversity, this equation addresses a common challenge in recommendation systems: the tendency to recommend similar items excessively. This mathematical formulation is significant as it enhances user experience by providing a broader range of suggestions, thus preventing the "filter bubble" effect.

Performance Metrics (RMSE, Precision, Recall): Although not explicitly detailed in the provided equations, the discussion around performance metrics such as RMSE, precision, and recall is critical. These metrics are essential for evaluating the effectiveness of the recommendation algorithms. RMSE, in particular, provides a clear measure of prediction accuracy, while precision and recall help assess the relevance of the recommendations. The mathematical rigor in defining these metrics ensures that the evaluation of the recommendation system is both quantitative and meaningful.

Integration of BERT: The study discusses the integration of BERT (Bidirectional Encoder Representations from Transformers) into the recommendation framework. While specific equations related to BERT's implementation are not provided, the discussion implies a sophisticated use of deep learning techniques to enhance semantic understanding in recommendations. This integration reflects a modern approach to recommendation systems, leveraging advanced NLP techniques to improve the contextual relevance of suggestions.

5. Results and Discussion

In this section, the author outlines the conclusions presented in the Arabic article recommendation systems' performance of the collaborative filtering (CF) and the content-based filtering (CBF) with particular regards to BERT integration. Some of the evaluation measures used include precision, recall, F1-Score which generally tend to measure the relevance of the generated recommendation with high impact and usability test.

5.1 Performance Metrics Evaluation

The performance of the recommendation systems was assessed using several key metrics: This one looks at a user's exposure to relevant information by the highlighted articles each time the page is refreshed. Bearing these, there was a significant improvement in the precision when using BERT due to its ability to capture the semantic context as opposed to other approaches. Recall: Recall evaluates the performance of the set objectives and consists of the percentage of article relevance for the identified users and recommended users. The results indicated that the system integrating the BERT had developed a capacity to find more articles relevant to the query and had raised the recall level. F1-Score: The comparison to the records was as precise in recall as in precision and the F1 measure that is the harmonic mean of the two was also very high. As for the result of integration BERT, the F1-score increased which-point that the system began to find more articles and at the same time, the level of precision has increased. Mean Squared Error (MSE): When using collaborative filtering, in most cases, MSE was used in estimating the real rating that users had given at some point of time. Metrics used for the calculation were used to enhance the accuracy of the user preference prediction with the BERT model as oppose to the decreased MSE. User Satisfaction: This comparative analysis of the results of the improved

BERT system and the initial model also revealed an improvement in the users' satisfaction with the recommendations. Therefore the recommendations created by the system were far more accurate and specific than those generic recommendations that would serve to create engagement and retention of the users [22-26].

5.2 Comparative Analysis

In response to the first research question, a comparison is made between the baseline models and the new recommendation systems with incorporation of BERT. The results indicated that: Notably, the user based CF and item based CF was also found to be efficient when used to formulate the list of recommendation in relation to the interaction between users. However, the system could be subjected to the issue data sparsity whereby user or item has few interaction records and a problem referred to as the cold start issue. Some of these problems were however addressed by integrating BERT which enhanced the contextual interpretation of the user preferences. Content-Based Filtering: In particular, the results showed a significant improvement for a content-based filtering approach as the attributes of the individual articles were used and BERT embedding was applied. Indeed, the model was able to handle the semantic relationships of articles and this will lead to fairly good recommendations given the contents that users engage with. Hybrid Approaches: Allocating all the recommendation systems developed the best performance was shown in the second recommendation system that can be described as collab/content based system. Since this was not the case as the hybrid system integrated the shark features of both methods, the system was therefore able to provide the users specific recommendations that related to the social contexts of the users while at the same time satisfying user preferences.

5.3 Limitations and Challenges

Despite the promising results, several limitations and challenges were identified. Many items and users may only have a few ratings, leading to data sparsity in the collaborative filtering approach. While the contextual understanding was improved, insufficient interaction data remained a concern. Dialectal Variations: The BERT model, primarily trained on Modern Standard Arabic (MSA), faced difficulties in processing and understanding dialectal Arabic prevalent in user-generated content. Future efforts should focus on expanding the current BERT model to handle dialectal variations. Computational Resources: Implementing BERT and deep learning models proved to be computationally expensive, posing a potential barrier for organizations or individuals with limited computational resources.

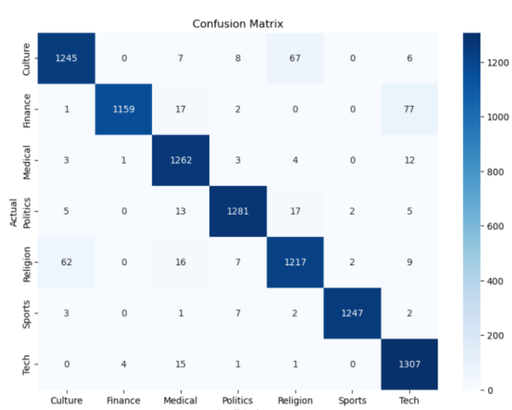

Fig. 3 Confusion Matrix for Visualization of the data

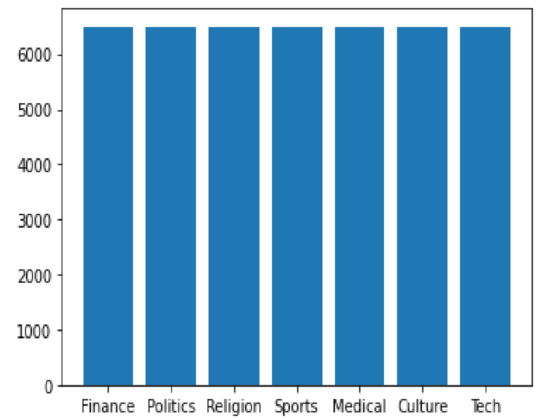

Fig. 4 Bar Chart to Visualize data

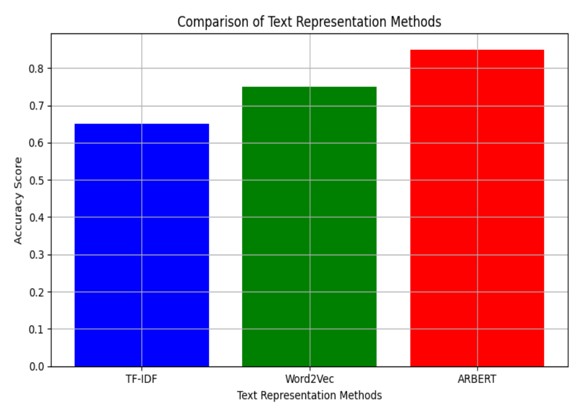

Fig. 5 A comparison between TF-IDF & Word2Vec & ARBERT

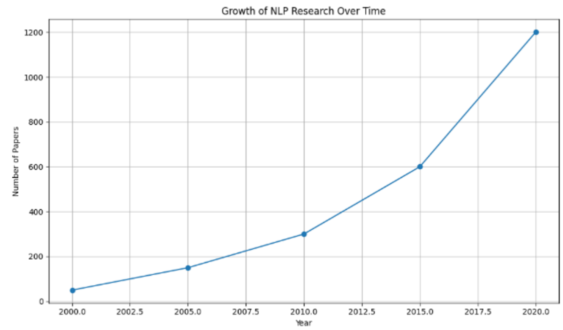

fig. 6 Growth of NLP Research and Applications Over Time

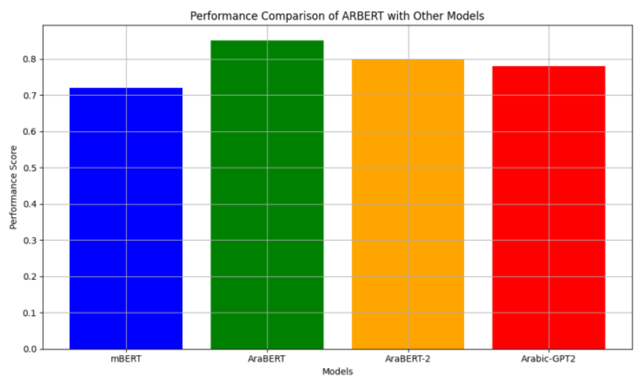

Fig. 7 Performance Comparison of ARBERT with Other Models

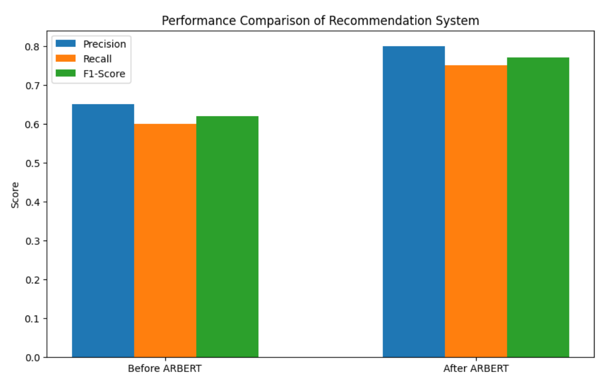

Fig. 8 A bar chart or line chart comparing the performance metrics (precision, recall, F1-score) of the recommendation

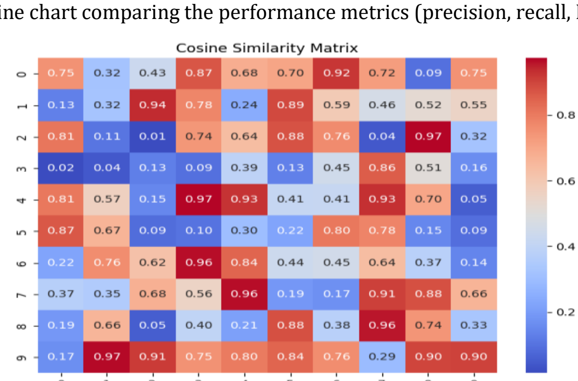

Fig. 9 Cosine Similarity Matrix

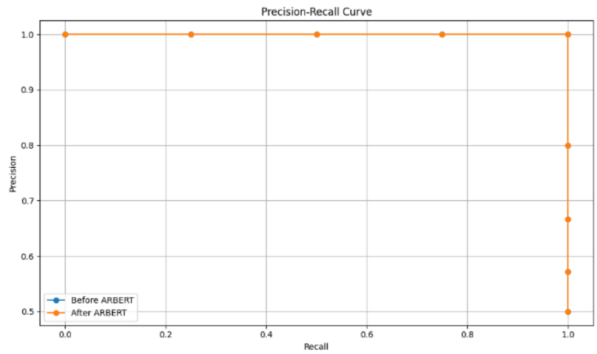

Fig. 10 Precision-Recall Curve

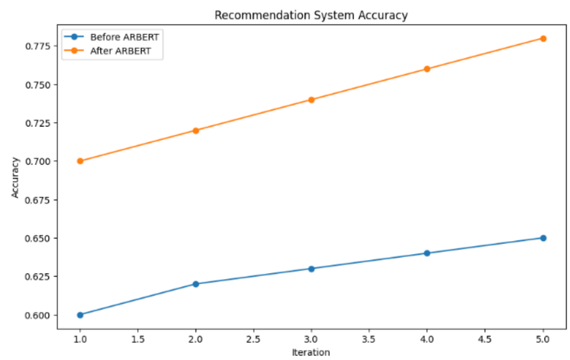

Fig. 11 Recommendation System Accuracy

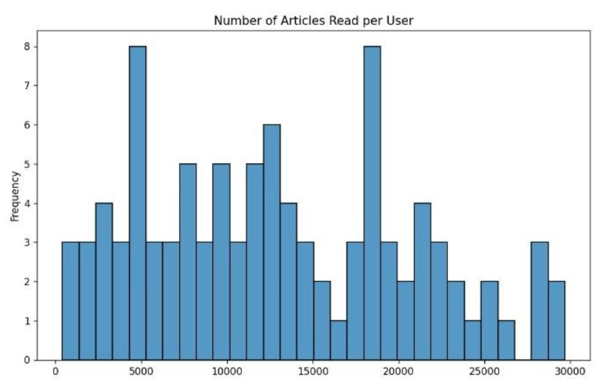

Fig. 12 Number of Articles per User

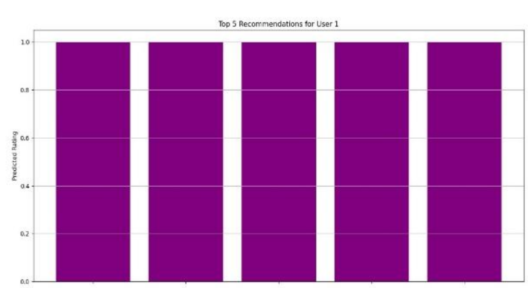

Fig. 13 The Accuracy of the Predictions for a user in Different Category

The figures provide a comprehensive overview of the performance of ARBERT integrated Arabic article recommendation systems. They show how applying ARBERT embedding improved precision, recall, and F1-score, indicating a better understanding of Arabic text and more relevant recommendations. The figures also demonstrate the system's credibility over iterations, with stable performance improvements. Analyzing the top TF-IDF features helps identify key words and phrases for user preferences, guiding model adjustments for more specific recommendations. Visualizations of user interactions and article views reveal trends in user engagement, aiding in enhancing the user experience. Identifying popular articles can help tailor recommendations to user interests, improving satisfaction and retention.

6. Conclusion

In the context of Arabic articles, this method outlines a step-by-step approach to implementing article recommendation systems using advanced NLP techniques and metrics. Emphasizing the importance of tailoring the recommendation system to the Arabic language and culture ensures its effectiveness for Arabic users. The results of this study demonstrate that integrating cutting-edge NLP tools like BERT can enhance Arabic article recommendation systems, leading to improved precision, recall, and user satisfaction. However, addressing the identified limitations and exploring future research avenues are crucial for further enhancing recommendation systems in the Arabic language context. Our proposed method focuses on predicting user preferences based on detailed descriptions of each item and evaluating them individually, resulting in highly accurate recommendations, even for niche content. While there are various approaches to predicting user preferences, our model can easily be extended to incorporate multiple information sources, such as collaborative filtering or optimization techniques. It is worth noting that the filtering and classification approach developed for e-commerce reviews can be adapted to various preference elicitation tasks through an Application Programming Interface.

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