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Research paper

Job Recommendation System

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Abstract

Online recruitment platforms have led to a surge in job applications, creating challenges for companies in managing and reviewing them efficiently. With the exponential growth of online job postings and user profiles, the challenge of matching the right job to the right candidate has become increasingly complex. Job recommendation systems aim to streamline this process by leveraging advanced algorithms to suggest relevant job opportunities to job seekers based on their skills, experience, and preferences. Our proposed technique performs better in terms of personalized job recommendations to different users based on their profiles.

Keywords: *Recommendation System; Hybrid Model; Machine Learning; Natural Language Processing; User Profile; Skill-based.*

1. Introduction

In today's dynamic and ever-evolving job market, the need for efficient and effective job recommendation systems has become increasingly evident. As individuals navigate through the wide range of career options available, they are often overwhelmed with an excessive amount of information, making it challenging to identify suitable employment opportunities. The primary objective of a job recommendation system is to streamline the job search process by providing personalized recommendations tailored to each user's unique profile. By analysing various factors such as a user's educational background, work experience, skills, and interests, these systems can accurately match individuals with relevant job openings, thereby saving time and effort while increasing the likelihood of finding a fulfilling career opportunity. The benefits of job recommendation systems extend beyond just facilitating job searches for individuals. Employers also stand to gain significant advantages from the implementation of these systems. By leveraging sophisticated algorithms to sift through vast amounts of candidate data, employers can identify the most qualified candidates efficiently and expedite the hiring process. Furthermore, job recommendation systems contribute to the overall efficiency and productivity of the job market by reducing friction in the matching process between job seekers and employers. By leveraging technology to automate and optimize the recruitment process, these systems enable companies to fill vacancies more quickly and with greater precision, ultimately driving organizational growth and success.

In this paper, we explore the landscape of job recommendation systems, examining various approaches, methodologies, and algorithms employed in existing research. By synthesizing insights from a comprehensive review of literature and analysing real-world case studies, we aim to gain a deeper understanding of the challenges and opportunities in this domain. Additionally, we propose novel strategies and techniques to enhance the performance and effectiveness of job recommendation systems, ultimately contributing to the advancement of this critical area of research and practice.

2. Related work

This paper proposes a graph-based recommendation system to address the challenges faced by companies due to the high volume of applications. Utilizing techniques such as node embedding and feature representation, including node2vec, Graph SAGE, and GCN, the system aims to predict connections between job seekers who have applied for similar positions. By analyzing job seekers' application behavior, the system identifies relationships between candidates and facilitates the identification of qualified individuals for open positions. [2] This paper proposes a system aimed at enhancing job searches by using deep learning algorithms such as Long Short-Term Memory (LSTM). By analyzing job postings and candidate profiles, the system classifies and transforms them into numerical vectors using the doc2Vec method to preserve semantic meaning. The objective is to improve talent matching and job recommendations by enhancing the efficiency and effectiveness of talent and job searches. [3] This paper uses the Deep Semantic Structure Algorithm (DSSM) to enhance job recommender systems. Addressing challenges such as cold start and scalability issues encountered in existing systems, DSSM focuses on semantic representation and deep learning techniques. By learning from sparse data and capturing complex relationships between job descriptions and candidate profiles, DSSM aims to improve recommendation accuracy and outperform traditional models. The paper presents experimental results comparing DSSM with existing models using various datasets, demonstrating its effectiveness in offering prom-

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ising results through its emphasis on semantic structure and utilization of advanced learning methods.[4] This paper introduces an intelligent job recommendation system utilizing machine learning techniques. Employing word embedding-based recommendation techniques, the system matches job seekers with suitable positions based on their profiles, gathering and analyzing data on candidates' educational and professional backgrounds as well as job openings from various sources. By providing personalized job suggestions, the system aims to streamline the job search process, benefiting both employers and job seekers. [5] This paper explores the utilization of machine learning and text mining for real-time job vacancy recommendations and talent matching at large job fairs. Employing methods such as term frequency matrix and similarity calculation, the study analyzes online discussions to understand trends and develop a system capable of efficiently matching job seekers with job vacancies. This system conducts personalized competitiveness and personality trait analysis based on electronic resumes submitted by applicants, providing job vacancy recommendations to applicants and generating talent recommendation lists for companies. [6] JobFit assists HR in efficiently identifying the best-fit candidates for job roles. In today's competitive job market, where job satisfaction and productivity are paramount, JobFit utilizes recommender systems, machine learning techniques, and past data to predict candidate suitability. By analyzing job requirements and applicant profiles, it generates a score, providing a sorted list of recommended candidates. This streamlines the recruitment process, enabling HR to focus on screening and interviewing a smaller pool of candidates.[7] This paper proposes an approach to creating an effective job recommender system using the Apriori algorithm. By restructuring and organizing the employment information based on the algorithm's findings, the system aims to optimize the quality and relevance of job recommendations. The Apriori algorithm is utilized to scan the database, identify frequent items, and filter out non-frequent items to obtain a frequent item set, which serves as the basis for the recommended employment information. [8] It introduces IHGCN (Improved Heterogeneous Graph Convolutional Network) as a solution to enhance job recommendations for job seekers on online recruitment platforms. IHGCN constructs a heterogeneous resume graph and treats job recommendation as a multi-class classification problem. By introducing a novel labeling classification standard for early job seeker resumes, IHGCN learns node representations from the graph to improve recommendation effectiveness. [9] it addresses the growing importance of social networks, particularly in the context of job portal websites. The research objective is to develop a framework that suggests job opportunities to candidates based on the compatibility between job descriptions and candidate profiles. The paper employs various machine learning algorithms to achieve this goal, with the Random Forest Classifier yielding the best accuracy score. [10] The paper proposes a system that utilizes data from multiple job portals to match candidates with suitable job opportunities. By employing dynamic ontology creation and similarity measures, personalized recommendations based on skills and experiences are generated. The system aims to address challenges faced by both employers and job seekers, facilitating successful job matches. [11] The paper proposes a hybrid job recommendation system merging content-based and collaborative filtering through Statistical Relational Learning (SRL). By addressing the challenge of integrating these approaches without extensive feature engineering, it offers a principled approach to balance precision and recall. [13] used a hybrid model of large language models, TF-IDF and cosine similarity for job recommendations. [14] used Google Gemini Artificial Intelligence along with LinkedIn web scraping for personalized job recommendations. [15] used Machine Learning and Natural Language Processing for personalized job recommendations. [16] used Artificial Intelligence, Natural Language Processing, and web scraping to get exact matches for jobs according to the profiles of candidates. [17] used Naïve Bayes technique in collaboration with a graph-based model for personalized job recommendations and profile building. Table 1 shows the summarized literature review. Recent advancements in transformer-based models like BERT and its successors, such as RoBERTa and DeBERTa, have also demonstrated improved contextual representation in job recommendation tasks [13] [14]. These models enable a deeper semantic understanding of candidate profiles and job descriptions.

2.1. Synthesis and comparative analysis of techniques

The reviewed literature reveals a variety of methodologies for job recommendation systems, each with distinct strengths and limitations. For instance, DSSM [3] demonstrates high semantic understanding but faces cold-start issues due to sparse user data. In contrast, IHGCN [8] excels at modelling heterogeneous interactions but may struggle with scalability and computational complexity. Graph-based techniques like Node2Vec [1] and ontology-driven models [10] offer structural insight and contextual mapping, respectively, though they often lack adaptability in real-time applications. Deep learning approaches such as LSTM [2] offer strong performance on sequential data but require significant computational resources. These trade-offs highlight the need for hybrid and ensemble models—like those proposed in this study—that aim to combine semantic understanding, structural mapping, and scalability.

Table 1: Related Works

References	Name of the research papers	Data source	Technique	Performance A: Accuracy P: Precision R: Recall F: F-score
[1]	Job Seeker Recommendation for Employers: A Graph-Based Recommendation Approach Using Node Embedding	Kariyer.Net data	Graph Algorithm	A:77.53 P:76.79 R:76.04 F:75.89
[2]	Job Recommendation Based on Recurrent Neural Network Approach	Multiple job portals	RNN - LSTM	A:96.89 P:98.6 R:98.64 F:98.04
[3]	Enhanced DSSM (deep semantic structure modelling) technique for job recommendation	Naukari.com Careerbuilder.com	Semantic modelling	A:89.2 P:91.8 R:85.3 F:90.6
[4]	Designed Framework for Advanced Intelligent Job Recommendation System	LinkedIn, Indeed, Glassdoor	Word Embedding	A:87.53 P:86.9 R:86.43 F:85.8
[5]	Based on the application of AI technology in resume analysis and job recommendation	Multiple job portals	Term Frequency Matrix	A:78.76 P:77.42 R:84.17 F:79.43
[6]	JobFit: Job Recommendation using Machine Learning and Recommendation Engine	Multiple job portals	Bayesian Ridge and Linear regression	Linear Regression A:95.91 P:94.57 R:95.33 F:95.48 Bayesian Ridge A:95.34 P:95.5 R:96.01 F:95.66
[7]	Analysis of University Students Employment Recommendation System Based on Apriori Algorithm	Multiple job portals	Apriori Algorithm	A:94.17 P:94.07 R:95.22 F:94.96
[8]	An improved heterogeneous graph convolutional network for job recommendation	LinkedIn	Heterogeneous Graph Convolutional Network	A:85.93 P:90.11 R:88.73 F:87.02
[9]	Prediction of recommendations for employment utilizing machine learning procedures and geo-area-based recommender framework	LinkedIn	Machine Learning Classifiers	Logistic Regression A:86.15 P:1.0 R:86.1 F:94.1

				KNN A:87.95 P:92.5 R:91.2 F:91.0 Stochastic Gradient A:72.25 P:77.1 R:64.1 F:70.8 SVM A:86.15 P:1.0 R:86.1 F:94.1 Naïve Bayes A:86.74 P:99.1 R:87.1 F:92.8 AdaBoost A:86.15 P:1.0 R:86.1 F:94.1 Random Forest A:95.58 P:99.7 R:96.5 F:97.9
[10]	Concept Based Dynamic Ontology Creation for Job Recommendation System	Multiple job portals	Feature extraction, Similarity measures, and Ontology mapping.	A:97.53 P:96.79 R:96.04 F:94.89
[11]	Combining content-based and collaborative filtering for job recommendation system: A cost-sensitive Statistical Relational Learning approach	Multiple job portals	Statistical Relational Learning	A:84.95 P:82.9 R:84.2 F:81.70
[12]	Intelligent job matching with self-learning recommendation engine	Multiple job portals	Ontology-based inference techniques, combined with a self-learning engine	A:94.95 P:92.25 R:93.82 F:92.60
[13]	A Hybrid Approach for Job Recommendation Systems	Multiple job portals	Large Language models, TF-IDF and cosine similarity	Similarity score: 0.88
[14]	AI for Career Growth: Advanced Resume Analysis and LinkedIn Scraping for Personalized Job Recommendations	LinkedIn	Artificial Intelligence	Not mentioned
[15]	AI Powered Job Recommendation System	Multiple job portals	Machine Learning, Natural Language Processing	Not mentioned
[16]	Development of a Recommendation System for Resume Tracking and Job Suggestions	Multiple job portals	Artificial Intelligence, Natural Language Processing	Not mentioned
[17]	Intelligent Hiring Software- Job Recommendation System and profile builder	Multiple job portals	Naïve Bayes, Graph Based	P: 85 R: 78
[18]	ML-Based Job Matching and Skill Development Recommendation System	Multiple job portals	Artificial Neural Networks	A: 89.3 F: 89

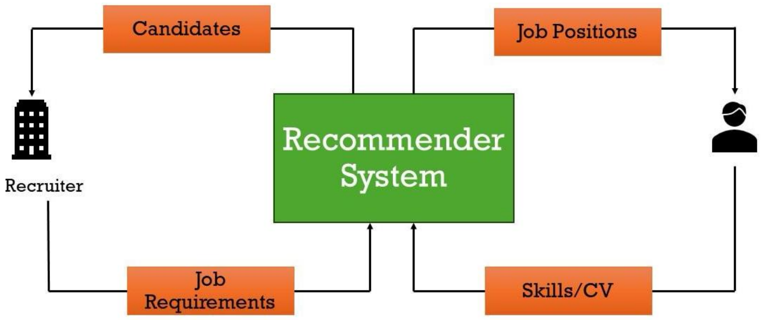

Fig. 1: Working of Recommendation System.

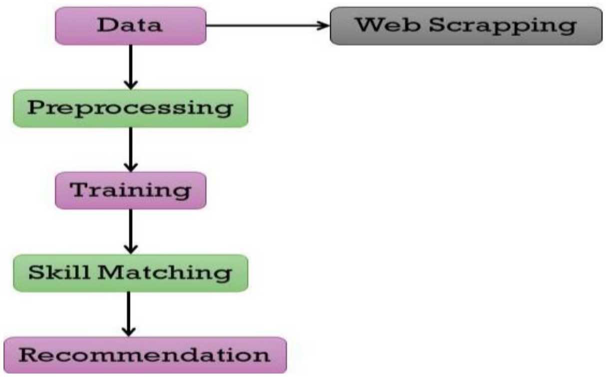

Fig. 2: Recommendation Process.

3. Techniques used for job recommendation

In research that took place initially, job recommendations was using multiple machine learning and NLP techniques. The following are some of those techniques used in traditional approaches:

Apriori algorithm- it is a data mining technique used for association rule mining in large datasets. It works by identifying frequent item sets and generating association rules based on their occurrence patterns. Here, it could be applied to analyze the historical data of applicants. By identifying frequent patterns among successful job placements, the system can recommend similar jobs to applicants based on their profiles.

Bayesian Ridge- it is a probabilistic regression technique that utilizes Bayesian inference to estimate the parameters of a linear regression model. It incorporates prior knowledge about the distribution of the coefficients into the regression process, providing a robust method for handling multicollinearity and noisy data. Here, it could be applied to model the relationship between candidate attributes and job suitability scores.

Graph algorithms- they analyze and process data represented as graphs. It can help identify relevant connections between job seekers and job opportunities based on their attributes and interactions within the system. Node2vec employs random walks to generate node embeddings, capturing both local and global graph structures. Graph SAGE learns node representations by aggregating features from a node's neighborhood, enabling scalable and expressive graph modeling. GCN extends traditional convolutional neural networks to graph-structured data, leveraging graph topology to perform node classification and link prediction tasks.

Heterogeneous Graph Convolutional Network is an advanced graph neural network architecture designed to handle heterogeneous graph data, where nodes and edges may represent different types of entities and relationships. HGCN extends traditional GCNs, allowing for more expressive and accurate modeling of complex relationships. Here, it can be utilized to capture diverse interactions, enabling more effective recommendations.

Linear regression is a statistical technique that models the relationship between a dependent variable and one or more independent variables. It assumes a linear correlation between these variables and uses the least squares method to minimize the discrepancy between observed and predicted values. This method can be employed to forecast job candidate suitability based on their attributes.

Logistic regression is a statistical technique used for binary classification, where the dependent variable has two possible outcomes. It estimates the probability that the dependent variable falls into a specific category based on one or more independent variables. This method can be utilized to predict the probability of a candidate's suitability for a job based on their attributes.

Term frequency matrix- it is a representation where rows represent documents and columns represent terms, indicating the frequency of each term within each document. It's commonly used in NLP tasks like text classification and information retrieval. Here, job descriptions and resumes help to quantify the relevance of candidates to job postings based on the frequency of relevant terms.

Recurrent Neural Networks are a class of neural networks designed to handle sequential data by maintaining a hidden state that captures information about past inputs. Long Short-Term Memory is a type of RNN architecture that addresses the vanishing gradient problem, enabling the model to retain information over long sequences. Here, the LSTM model could analyze sequential data such as user interactions over time, for personalized recommendations based on historical behavior and preferences.

Random Forest- it is an ensemble learning method that constructs multiple decision trees during training and then combines the outputs of the individual trees. It works by bagging or bootstrapping samples from the dataset and randomly selecting subsets of features at each split in the tree. It can be used to predict the suitability of candidates for particular roles by considering various attributes.

Support Vector Machine- it is a method used for both classification and regression tasks. It identifies the hyperplane that optimally separates classes in the feature space, maximizing the margin between them. SVMs can manage both linear and non-linear data by employing kernel functions to transform the data into a higher-dimensional space. This technique can be used to classify candidates based on their attributes and preferences.

KNN- it is a supervised learning algorithm used for classification and regression tasks. It works by identifying the K closest data points to a given query point using a distance metric, like Euclidean distance, and making predictions based on the majority class or average value of these nearest neighbors. This approach can be used to recommend similar job opportunities or candidates based on their attributes or preferences.

Stochastic Gradient Descent- it is an optimization algorithm used in training ML models, particularly in large-scale and online learning settings. It iteratively updates the model parameters by computing the gradient of the loss function concerning a subset of training examples (mini-batch) and adjusting the parameters in the direction that minimizes the loss.

Ontology mapping it refers to a formal representation of knowledge within a specific domain, typically organized in a hierarchical structure that defines concepts, relationships, and properties. It provides a standardized way to describe entities and their interconnections, enabling effective knowledge sharing and reasoning.

4. Overview of evaluation metrics

Accuracy Score: It represents the ratio of correctly classified instances to the total instances evaluated, giving an overall performance measure. However, it may not be reliable for imbalanced datasets where one class predominates.

Precision: It indicates the ratio of correctly predicted positive instances out of all predicted positives, highlighting the model's reliability in positive predictions, especially critical when the cost of false positives is high.

Recall: Also known as sensitivity, it measures the proportion of correctly predicted positive instances out of all actual positives, reflecting the model's ability to capture all relevant instances, crucial when missing positives is costly.

F-score: This is the harmonic mean of precision and recall, balancing both metrics. It is particularly useful for imbalanced datasets, with values ranging from 0 to 1, where higher values denote better performance in both precision and recall.

5. Challenges in the job recommendation system

The efficacy of job recommendation systems hinges on their ability to efficiently match job seekers with suitable opportunities amidst vast and dynamic employment landscapes. However, existing systems grapple with several significant challenges that hinder their effectiveness and scalability. These challenges span from limitations in data utilization due to hardware constraints to the oversight of critical aspects such as feature engineering and real-world performance evaluation. One significant challenge arises from the immense volume of job applications on platforms. However, due to hardware limitations, current implementations often analyze only a limited timeframe of data, potentially neglecting valuable insights from longer-term trends. Moreover, the existing framework focuses on applying deep learning models to enhance job recommendations; it overlooks the critical aspect of feature engineering, which can significantly impact model performance.

Another notable issue lies in the lack of consideration for real-world performance and scalability of proposed recommendation systems. Understanding how these systems perform under different conditions and their ability to handle large datasets or high traffic volumes is crucial for assessing their practical utility and effectiveness. Additionally, the need for improved inferences using statistical smoothing methods suggests a gap in optimizing feature selection approaches, which could potentially enhance the accuracy and robustness of recommendation systems.

Furthermore, existing systems often fall short in terms of personalization and scalability, with limited exploration of user feedback and alternative recommendation approaches beyond pre-trained models. Addressing these gaps could lead to the development of more effective and versatile recommendation systems with broader applicability and impact across various industries. Lastly, the paper identifies challenges related to the dynamic nature of employment trends and the importance of recommendation diversity in providing graduates with a range of employment options. By considering these factors and exploring recommendation diversity, future research can contribute to the development of more adaptive and comprehensive recommendation systems tailored to individual user needs and preferences.
In conclusion, the identified gaps and challenges in existing job recommendation systems underscore the pressing need for comprehensive solutions that address issues such as data volume limitations, real-world performance, feature engineering, and scalability. By enhancing inferences through advanced statistical methods, optimizing feature selection approaches, and prioritizing personalization and scalability, future research can pave the way for more effective and adaptable recommendation systems. Additionally, acknowledging the dynamic nature of employment trends and the importance of recommendation diversity can further enrich the capabilities of these systems, ultimately leading to more accurate, versatile, and user-centric job recommendation platforms with broader applicability and impact in the ever-evolving job market landscape.

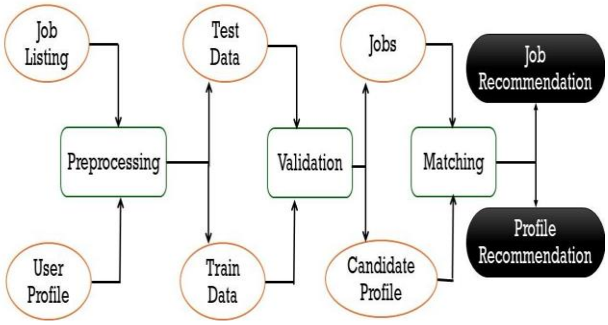

Fig. 3: Steps In Recommending Jobs to Candidates.

6. Proposed framework for job recommendation

Data will be gathered from job portals and websites, social media platforms, company career pages, etc. The dataset is preprocessed to remove irrelevant words and missing values. We convert labels to a binary format to simplify the problem. Data augmentation is used to increase diversity and balance job preferences. We have to divide the data into 2 parts: 80:20 for training and testing, respectively. Figure 3 and Figure 4 show the steps in recommending jobs to candidates and the Proposed Models, respectively.

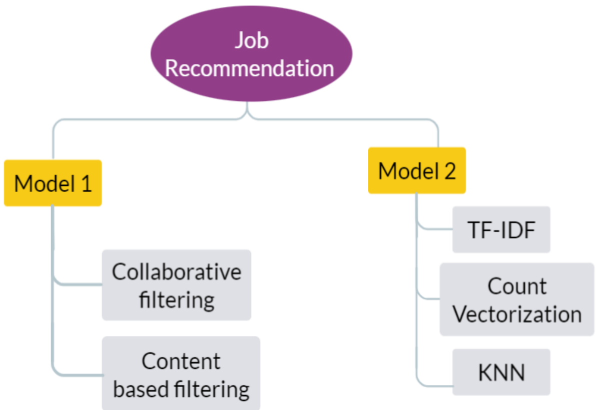

Fig. 4: Proposed Models.

We put forth an ensemble model as a solution to problems in job recommendation. Specifically, we have developed and extensively studied two ensemble models tailored to the job recommendation domain.

1) Collaborative filtering + Content based filtering
2) TF-IDF + Count Vectorization + KNN

The following is a comparative study of both models.

Table 2: Comparison of Models

	Model 1	Model 2
Technique	Collaborative filtering + Content-based filtering	TF-IDF + Count Vectorization + KNN
Technique Explanation	Collaborative filtering- It utilizes user behavior data to identify patterns and make personalized suggestions. By analyzing similarities between users' preferences and job listings, it matches users with relevant jobs. Content-based filtering- By analyzing features such as job titles, descriptions, and user preferences, it matches users with relevant job opportunities that align with their skills and interests.	TF-IDF- it captures the unique characteristics of each posting based on which it identifies jobs that align with the user's profile. Count Vectorization- it converts text into numerical representations by counting the occurrence of words in user profiles and job descriptions KNN- it classifies users based on the similarity in preferences of others.
Data Utilization	Relies on user-item interactions and item-item similarities.	Utilizes user profiles, job descriptions, and numerical features.

How does it work?	By integrating these two techniques, the ensemble model achieves a more comprehensive understanding of user preferences and job attributes. This hybrid approach enables the system to capture both user-item interactions and item-item similarities, resulting in more accurate and diverse job recommendations.	TF-IDF and Count Vectorization transform textual data into numerical representations, capturing the importance and frequency of terms in user profiles and job descriptions. These features are then fed into the KNN algorithm, which classifies users based on the similarity of their preferences to those of neighboring users.
Limitation Mitigation	This approach mitigates the limitations inherent in each method, such as the cold start problem in Collaborative Filtering and the sparsity of data in Content-Based Filtering.	This approach mitigates the limitations, like the inability of TF-IDF and Count Vectorization to capture semantic relationships and the reliance of KNN on the nearest neighbors for classification.
Performance A: Accuracy P: Precision R: Recall F: F-score	A: 88.6 P: 88.46 R: 86.93 F: 87.8	A: 91.5 P: 90.23 R: 90.67 F: 91.54

- Scalability Considerations

The proposed Model 2 demonstrates greater scalability compared to Model 1, particularly when dealing with large-scale datasets. TF-IDF and Count Vectorization are computationally efficient and easily parallelizable, while KNN allows for fast approximation methods like KD-Trees. In contrast, Model 1's reliance on collaborative filtering may require frequent retraining as user-item interaction data grows. Thus, Model 2 is better suited for real-time applications where rapid updates and low-latency predictions are crucial.

7. Conclusion

In this research paper, we explored and analyzed various existing methodologies for job recommendation systems. We then proposed two hybrid approaches to enhance the accuracy and relevance of job recommendations. The first approach combines Collaborative Filtering (CF) with Content-Based Filtering (CBF), combining the benefits of both techniques to improve recommendation precision. The second approach utilizes TF-IDF (Term Frequency-Inverse Document Frequency) and Count Vectorization in conjunction with K-Nearest Neighbors (KNN) to offer a robust and scalable solution for job recommendation. Our experiments demonstrated that both proposed methods outperform traditional single-technique systems, highlighting the benefits of hybrid models. The CF + CBF approach excels in personalizing recommendations by considering both user preferences and item similarities, while the TF-IDF + Count Vectorization + KNN method effectively captures textual features of job descriptions and user profiles, leading to more accurate matching. Overall, our work contributes to the ongoing development of intelligent job recommendation systems, aiming to provide users with more relevant job opportunities and improve the overall job search experience.

8. Future work

Future research should explore transformer-based models such as BERT, which can significantly enhance semantic matching by understanding context within job descriptions and candidate profiles. For example, research can ask: "Can BERT reduce semantic mismatches in job descriptions for newly onboarded users?" Additionally, ethical concerns such as algorithmic bias—especially gender or racial biases in recommendations—must be critically evaluated. Explainable AI techniques could also be explored to enhance transparency for both employers and job seekers.

While our proposed methods show promising results, there is scope for future research to further enhance systems. Firstly, incorporating deep learning techniques such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs) could capture more complex patterns and relationships in the data, potentially improving recommendation quality.

Another area worth exploring is the use of advanced Natural Language Processing (NLP) techniques like BERT (Bidirectional Encoder Representations from Transformers) to better understand the semantic meaning of job descriptions and user profiles. This could improve the matching process by considering the context. By continuously iterating on these improvements, we can work towards developing more sophisticated, user-centric job recommendation systems that better meet the needs of job seekers and employers alike.

Conflicts of interest

The authors have no conflicts of interest to declare.

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