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An Advanced Real-Time Job Recommendation System and Resume Analyser

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***Abstract*— The increasing complexity and abundance of information in resumes have created confusion and challenges for both candidates and recruiters. An effective resume screening is crucial for students looking for job opportunities as they can demonstrate their skills and qualifications to potential employers and is essential for the recruiter. This study focuses on implementing a resume screening and job recommendation system using Graph Neural Network based on domain adaptation approach and Natural language processing. The goal is to extract latent features from job posts and resumes using GNN and NLP techniques, including Named Entity Recognition (NER). Furthermore, the system leverages the GloVe word embeddings for tokenizing and encoding textual information, enhancing semantic understanding. In addition, the system evaluates the resume score based on the job description using advanced techniques such as cosine similarity and TF-IDF to assess the relevance of keywords and phrases between the resume and job description. By considering the job roles matched to the resume it also recommends the latest jobs posted on different websites using web scraping. In conclusion, this study demonstrates the effectiveness of the GNN-based domain adaptation method can make more accurate in resume screening and job recommendations.**

***Keywords*— NLP, GNN, Domain Adaption, Job recommendation and Resume Analyzer.**

I. INTRODUCTION

Resume screening and Job recommendation systems plays a vital for both candidates and recruiters. Due to increasing in technologies a large number of jobs are created and new trends comes into market every day. For a candidate to apply for a job, it is crucial to understand which work roles are compatible. And also, it is difficult to evaluate the resume and job description manually whether the resume is matched for particular job role or not. So, to make the process better and quicker an AI based resume analyzer and Job recommendation system is needed for the candidate.

Many of the traditional algorithms proved their efficiency in resume classification, but they require labelled data, which is scarce and difficult to obtain. Additionally, the current contextual embedding methods are not comfortable for dealing with large size resumes. This paper suggests an approach using domain adaptation technique based on a graph neural network to categorise resumes without needing labelled resumes and retraining the model to handle these issues [1]. The enrolment process for organizations has changed due to the internet, with online job listings attracting a wide range of candidates. However, this has also brought about difficulties like the submission of several irregular and diverse resumes [5]. Utilizing machine learning algorithms and web scraping techniques to streamline various tasks, including skill assessment, resume screening, job notifications, and interview arrangement. This system encompasses functionalities like conducting virtual practice interviews, automated appointment scheduling, and administering a pre-interview questionnaire, all while monitoring applicants' backgrounds [4].Traditional text representation methods suffer from sparse and high-dimensional representations, while deep learning models like CNN and RNN have limitations in capturing global word co-occurrences. Graph Neural Networks (GNNs) have emerged as a promising approach for text classification, as they can capture global information through message passing over graphs [6]. The advancement of communication and information technology has paved the way for the internet to become a prominent tool for securing employment during college campus recruitment periods. A novel hybrid job recommendation approach is employed within college recruitment systems, integrating collaborative filtering and user profile-based filtering. This approach exhibits greater accuracy when compared to conventional recommendation systems [11][12].

LLMs' comprehensive contextual data and semantic representations allow for the analysis of behaviour graphs and the discovery of patterns and linkages. It introduces a meta path prompt constructor to encode the interaction information of the graph into natural language prompts. The framework, called GLRec (Graph-understanding LLM Recommender), is fine-tuned with LoRa in a constructed instruction dataset to optimize the quality of job recommendations. Using Large Language Model can enhance the screening process and recommendation systems [8]. With the help of Large

Language Models (LLMs) and Generative job Recommendation based on Large language models (GIRL) can creates personalized job descriptions for job seekers based on their Curriculum Vitae (CV). The generated job descriptions serve as references for job seekers. They also bridge the semantic gap between CVs and job descriptions, improving the performance of traditional discriminative models [9].

II. Related Work

Chung, Y. C., & Kuo R J. [1] introduced an domain adaptation approach, utilizing a graph neural network framework for the automated classification of resumes within database systems. The primary goal is to uncover underlying characteristics of job postings, enabling the categorization of resumes without the need for labelled resume data. The outcomes revealed that the suggested method had a high accuracy of 81%. But one of the major limitations observed in this proposed method is difficult to enhance the model's performance, such as studying the autocorrelation of occupational groups and classifying resumes into proper categories. Spoorthi, M., Kuppala, M., Karpe, V. S., & Dharavath, D. [2] presents an automated resume classification system that incorporates deep learning models for the categorization of resumes, focusing on the skills mentioned within each resume. The system employs an ensemble learning approach, where the accuracy of the system is contingent upon the quality of the training data. It's worth noting that the system's effectiveness could be compromised if the training data lacks accuracy or carries biases. Gu, Y., Wang, Y., Zhang, H. R., Wu, J., & Gu, X. [3] suggest an innovative approach to text classification called Text-MGNN, which leverages Graph Neural Networks (GNNs) to classify text by considering multiple levels of granularity while also incorporating a topic-aware perspective. It is evaluated on three real-world datasets and outperforms 11 baseline methods. The proposed method archives 97% accuracy with R8 dataset and with R52 it archives 94% accuracy. Silva, G. L. L., Jayasinghe, T. L., Rangalla, R. H. M., Gunarathna, W. K. L., & Tissera, W.[4] developed an system that helps to identify the skills and generate resumes. The objective is to use machine learning algorithms and web scraping technology to automate processes like skill matching, shortlisting of resumes, and scheduling interviews.

Ransing, R., Mohan, A., Emberi, N. B., & Mahavarkar, K. [5] employ machine learning techniques, including K-Nearest Neighbour (KNN), Linear Support Vector Classifier (Linear SVC), and XGBoost, to construct a ranking system aimed at suggesting more suitable resumes based on textual job descriptions. They introduce a two-tiered stacked model of base models, which yields promising outcomes when contrasted with using individual models and got an accuracy of 85 %. Furthermore, the authors note the potential for performance improvement by incorporating deep learning models such as Long Short-Term Memory (LSTM), Recurrent Neural Networks (RNN), or Convolutional Neural Networks (CNN). Tripathi, R. C[6] proposed method designed to streamline the labour-intensive and equitable screening process through intelligent automated resume analysis and recommendations and got 87% accuracy. Sridevi, G. M., & Suganthi, S. K. [7] developed AI based system that predict a suitable candidate. Additionally, four clusters derived from the job description were utilised to measure similarity and correspond to primary skills. Three classifiers, such as Adaboost, linear regression, decision trees, and XGBoost are used to determine candidate suitability. The Jaccard similarity measure is used to evaluate the suitability between a Job Description (JD) and a Candidate Resume (CR).

Wu, L., Qiu, Z., Zheng, Z., Zhu, H., & Chen, E. [8] have introduced Large Language Models (LLMs) as a way to comprehend behavioural graphs and apply this comprehension to enhance recommendations in the context of online recruitment. They have also presented a novel framework known as GLRec, which integrates Large Language Models (LLMs) with behavioural graph comprehension to elevate the quality of job recommendations. Their assessment of the framework's performance utilizes the AUC metric.. Zheng, Z., Qiu, Z., Hu, X., Wu, L., Zhu, H., & Xiong, H. [9] proposed a novel approach called Generative job Recommendation based on Large language models for job recommendation systems with Large Language Models (LLMs) to generate personalized job descriptions for job seekers. And evaluates the performance of the GIRL approach using two different metrics: AUC and Log Loss. Du, Y., Luo, D., Yan, R., Liu, H., Song, Y., Zhu, H., & Zhang, J. [15] devised an interactive approach for completing resumes, addressing the constraints associated with the synthetic generation of Large Language Models (LLMs) and the use of Generative Adversarial Networks (GANs) in refining representations of subpar resumes. This method incorporates an alignment multi-objective learning framework tailored for job recommendation.

Li, S., Li, K., & Lu, H. [10]examine the potential bias in deep-learning-powered automated resume screening tools, specifically in the use of word embedding for low-dimensional vectors. The use of different values of the boundary parameter (τ) and the regularization parameter (λ) to evaluate the performance of the bias mitigation method. Zhu, Y. [11] proposed a hybrid approach for job recommendation algorithm for college employment systems. Shaikym, A., Zhalgassova, Z., & Sadyk, U. [12] design a job recommendation system and evaluated using a hybrid approach. The system uses advanced techniques and algorithms. Sharma, M., Choudhary, G., & Susan, S. [13] introduced a method for efficient classification of resumes. Also introduce Elite bag-of-words, a text vectorization technique for the vectorization of resumes and compare its performance with other existing bag-of-words approaches. Petersheim, C., Lahey, J., Cherian, J., Pina, A., Alexander, G., & Hammond, T. [14] introduced a comparative evaluation of resumes from various domains. Their findings indicated that students were 7.4% more inclined than recruiters to advance resumes to the next stage. Additionally, students spent an average of 7.2 seconds less time reviewing each resume. Furthermore, they observed that for each incremental point increase in GPA, there was a 26.6-28.5% higher likelihood of a resume being advanced.

Wosiak, A. [16] create a system specifically designed for Polish resume documents, with a primary focus on optimizing the IT recruitment process. The system's goal is to enhance candidate screening and selection by improving efficiency and accuracy. Pimpalkar, A., Lalwani, A., Chaudhari, R., Inshall, M., Dalwani, M., & Saluja, T. [17] implement NLP techniques to enable resume selection and identification, with a focus on analysing resumes. It consists of machine learning algorithms like SVM and Random forest that gives accurate results of 82% in resume classification. Pant, D., Pokhrel, D., & Poudyal, P. [18] developed an automated screening system tailored for software engineering position resumes. This system harnesses natural language processing, word matching, character positioning, and regular expression techniques. During a random test involving ten distinct resumes, the system successfully extracted and summarized 70.59% of the skills mentioned in those resumes. Venkataramana, A., Srividya, K., & Cristin, R. [19] introduces BART, a Deep Learning model, to address this challenge. BART merges encoder and decoder components and employs an attention mechanism to highlight key data features. It's compared with other models, including BERT, T5, and Roberta, to evaluate its efficiency in handling large datasets. Harsha, T. M., Moukthika, G. S., Sai, D. S., Pravallika, M. N. R., Anamalamudi, S., & Enduri, M. [20] proposed an architecture of the project follows the MVC design pattern, with the code divided into different parts based on their functionality. Lamba, D., Goyal, S., Chitresh, V., & Gupta, N. [21] introduced the Smart Resume Selector (SRS), an integrated system designed for classifying resume categories based on resume-to-job matching. Srividya, K., Bommuluri, S. K., Asapu, V. V. V. K., Illa, T. R., Basa, V. R., & Chatradi, R. V. S. [22] introduced hybrid model merges extractive summarization methods like Luhn and Textrank with the abstractive Pegasus model. Evaluation based on ROGUE scores compares its performance to that of BERT, XLNet, and GPT2, revealing enhanced outcomes compared to existing models, thereby improving the summarization process's efficiency.

III. METHODOLOGY

The **Fig.** *3* shows the proposed method's framework. To develop a comprehensive resume screening and job recommendation system that has advanced natural language processing and graph neural network techniques to enhance the efficiency and accuracy of the job matching process. This system aims to provide a tailored and data-driven approach to assist both job seekers and recruiters by predicting job categories, calculating matching scores, offering job and skill recommendations, and continuously updating job listings.

A. Dataset Description

There are 2 different datasets used in this system and those datasets are collected from Kaggle. The first dataset, referred to as the Resume Dataset, serves as the foundation for a Graph Neural Network (GNN) model designed for resume classification. This dataset contains 962 records with two essential fields Category and Resumes. It is primarily employed to predict job categories based on the provided resumes. On the other hand, the second dataset is Jobs on Naukri.com, has a broader scope, aimed at developing a Job and Skills Recommendation System. This dataset is considerably larger, comprising 27,010 records and encompassing seven fields like Job Salary, Job Experience Required, Key Skills, Role Category, Functional Area, Industry, and Job Title Category in addition to the Resumes field. This dataset is leveraged to offer job recommendations and skill matching based on job listings, making it a valuable resource for enhancing the recruitment and job search experience.

B. Data Preprocessing

Data preprocessing plays a pivotal role in getting raw text data ready for analysis in the context of the provided datasets. This multifaceted process involves systematically applying various techniques to prepare raw text data for analysis, model training, and information extraction. It starts with text cleaning, which involves removing special characters and punctuation, ensuring that the text is free from elements that might interfere with tokenization. Additionally, text is converted to lowercase uniformly to prevent fragmentation of words based on case variations. Tokenization, the segmentation of text into individual tokens or words, lays the groundwork for meaningful analysis by structuring the text data. Stopwords removal comes next, eliminating common and low-information words. Stemming and lemmatization, other fundamental preprocessing steps, standardize words by reducing them to their root form. These techniques enhance text consistency and ease further analysis.

Feature engineering is paramount for advanced analysis, creating meaningful features or representations like TF-IDF vectors or word embeddings (e.g., Word2Vec, GloVe). These capture word importance and semantic relationships between words. Addressing class imbalances is vital when they exist, as seen with job categories. Techniques like oversampling or under sampling balance the dataset to mitigate class bias. Text length normalization ensures uniformity, which some NLP models require. Data splitting into training, validation, and test sets is standard practice for model evaluation and preventing overfitting. Noise reduction, including spell-checking and outlier removal, improves data quality.

In both datasets, text cleaning and normalization are integral to creating a consistent and error-free dataset for analysis. Moreover, in the context of resume classification, Part-of-Speech (POS) tagging plays a crucial role in the identification of words. POS tagging involves labelling words in a text corpus with their corresponding parts of speech, such as nouns, verbs, adjectives, etc. In the context of the Resume Dataset, POS tagging can assist in identifying and categorizing words and phrases based on their roles within a resume as shown in **Fig.** *1*.

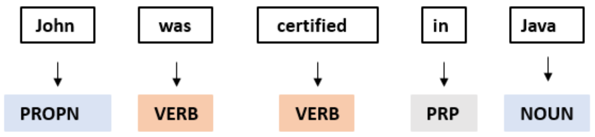

Fig. 1. POS Tagging Example.

C. Model Implementation for predicting Job Role

After completing data preprocessing, the dataset is divided into training, testing, and validation subsets to facilitate the resume screening procedure. Two models, namely K-Nearest Neighbours (KNN) and Support Vector Classification (SVC), are trained on this meticulously prepared dataset. To optimize their performance, we conduct a thorough fine-tuning of the hyperparameters. However, the outcomes of these model implementations do not yield substantial contextual insights during the resume classification task. While these models do exhibit proficiency in managing the pre-processed textual data, they fall short when applied to unlabelled data, failing to capture the nuanced contextual meaning present within the text. This underscores the imperative need for more advanced approaches in resume screening, ones that can accurately decipher and categorize resumes based on their content.

The advanced deep learning model like GNN, has an advantage of maintaining Contextual information in the data. To implement GNN, for tokenizing and embedding the text data, GloVe (Global Vectors for Word Representation) is used. It loads pre-trained GloVe word vectors, which provide pre-trained word representations. An embedding matrix is built using GloVe with capabilities for encoding, decoding, and embedding the text data into numerical formats, setting the stage for the upcoming Graph Neural Network (GNN) methodology as shown in **Fig.** *3*. This crucial component operates on node embeddings and edge weights, facilitating the flow of information and message-passing among nodes within the graph.

The TextLevelGNN Model serves as the core of the text classification module within the GNN framework. The model receives inputs of node sets (text data), neighbour sets (graph connections), and public edge masks, establishing the foundation for its message-passing operation is shown in **Fig.** *3*. In GNN Model there are multiple layers, each responsible for capturing and propagating information through a graph structure. Starting from an initial node feature matrix, GNN layers perform operations that combine node features, such as weighted summation or attention mechanisms, to produce updated node representations. This process is repeated over multiple layers, enabling GNNs to capture complex dependencies and patterns in graph-structured data effectively and message passing between nodes is shown in **Fig.** *2*.

When implementing a GNN model, these layers are stacked sequentially to create the model architecture. The classification error, often measured using cross-entropy loss, plays a pivotal role. During the training phase, the model's parameters are fine-tuned to minimize this error. The process involves iteratively adjusting the weights and biases of the GNN through techniques like backpropagation and gradient descent.

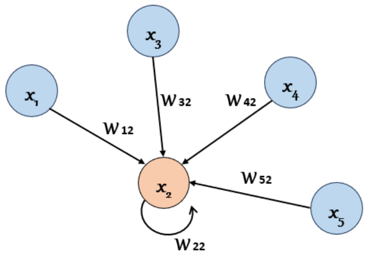

Fig. 2. Message passing in GNN.

D. Score prediction between Job description and Resume

After data preprocessing and tokenization, the next in the process is the calculation of the matching score between a job description and a candidate's resume. The textual information needs to be transformed into a numerical format to conduct this comparison. This conversion is accomplished through the application of the Count Vectorizer from scikit-learn, transforming the text data into a document-term matrix. This matrix serves as a representation of word frequency in each document, be it a resume or a job description. Subsequently, the generated matrix becomes the foundation for calculating the cosine similarity between these two documents.

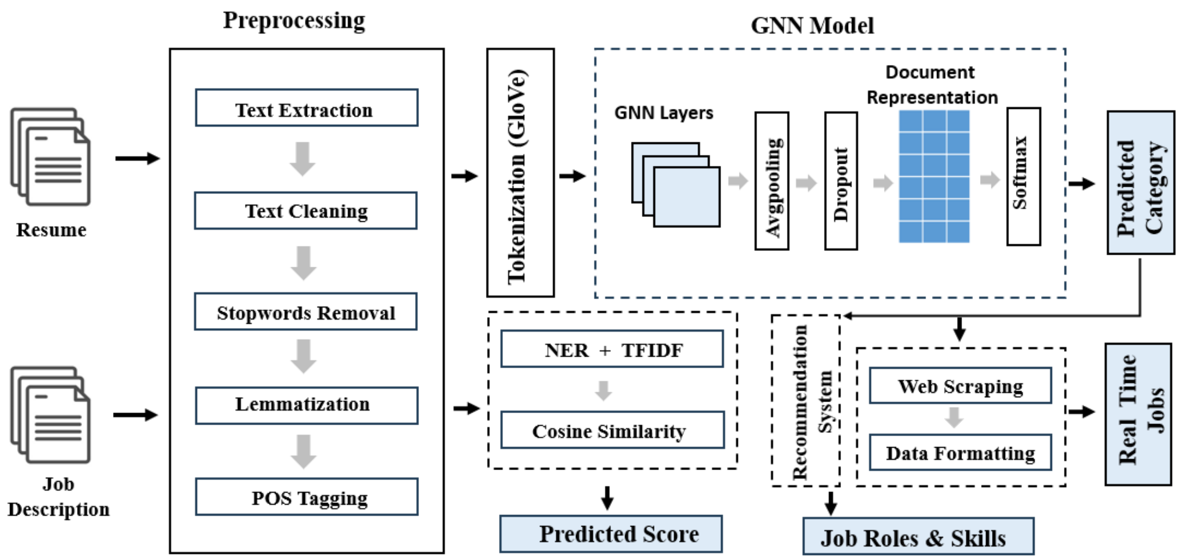

Fig. 3. Resume classification and Job recommendation system using Graph Neural Network.

Cosine similarity is a powerful metric utilized in this context to gauge the angle between the term frequency vectors of the resume and job description in a multi-dimensional space. This percentage-based matching score reflects the extent to which the candidate's qualifications match the job requirements, offering valuable insights for recruiters and job seekers is shown **Fig. *3***.

E. Jobs and Skills Recommendation System

The Job and Skill Recommendation System represents a crucial component within the broader framework. The process begins by taking the user's or job seeker's input category, which signifies their specific domain or job type of interest. It leverages a dataset of job listings augmented with key skills, encompassing essential details such as job titles, associated key skills, and job categories as shown in **Fig. *3***. These are the foundational elements that feed the recommendation engine.

To assess the relevance of job listings and key skills to the user's input category, the system employs TF-IDF vectorization. This technique converts textual data into numerical vectors, effectively quantifying the importance of each term in relation to the entire dataset of job listings. Furthermore, the recommendation system extends its utility beyond job listings by identifying and suggesting relevant key skills associated with the recommended job listings. To further enhance the recommendation system's accuracy and personalization, a hybrid approach is introduced. This hybrid recommendation system includes a variety of recommendation methods, such as collaborative filtering and content-based filtering. In this approach, user preferences, behaviors, and interactions within the platform can be factored into fine-tune recommendations. This not only empowers job seekers in discovering relevant job opportunities and understanding the key skills required in their chosen field but also assists employers in suggesting job titles and essential key skills.

In evaluating recommendation methods, the hybrid approach stands out as it combines collaborative filtering and content-based filtering, offering a more comprehensive and personalized experience for users.

F. Web Scrapping Real Time Jobs

By talking job role as input latest jobs suitable for the corresponding job role fetched from different websites using web scraping. The data can be retrieved by initiating GET requests to the designated job URLs, granting access to the most recent job postings. Following this, HTML parsing, facilitated by Beautiful Soup, structures, and navigates the web content, aiding in the precise identification of HTML elements housing the job listings. Once these listings are precisely located, the system extracts vital details, encompassing job titles, company names, locations, start dates, and application links. This gathered data is then structured into dictionaries for each job listing and amalgamated into a comprehensive list, thus delivering a real-time and organized compilation of job opportunities. This dynamic web scraping methodology empowers job seekers with the most up-to-date job listings, furthering their pursuit of meaningful employment prospects. Using Web scrapping we can recommend jobs using real time data that can be updated from different websites.

IV. EXPERIMENTS AND RESULTS

The complete process, shown in **Fig. *3***, illustrates the efficacy of the proposed method employing Graph Neural Networks (GNN) in accurately predicting job roles. The results of various models used in the system are comparison in **Table 1**. Performance metrics include precision, recall, f1-score, and accuracy are used for evaluating the system performance. Accuracy serves as a pivotal performance metric in evaluating the system's ability to precisely match job roles to resumes, thereby affirming its effectiveness in enhancing the recruitment process. The results shown in **Table 1** are proved the performance of GNN model.

TABLE 1. COMPARISON OF PERFORMANCE METRICS FOR VARIOUS MODELS .

Models	Performance metrics			
	Precision	***Recall***	***F1 – score***	***Accuracy***
KNN	0.9867	0.9745	0.9723	0.9745
SVM	0.9789	0.9612	0.9756	0.9712
GNN	**0.9886**	**0.9789**	**0.9799**	**0.9878**

This high accuracy underscores the system's robustness in categorizing resumes and job descriptions accurately for GNN Model is shown in **Fig.** *4*. Moreover, the system excels in additional aspects as well. The scoring prediction module ensures that matching scores between resumes and job descriptions.

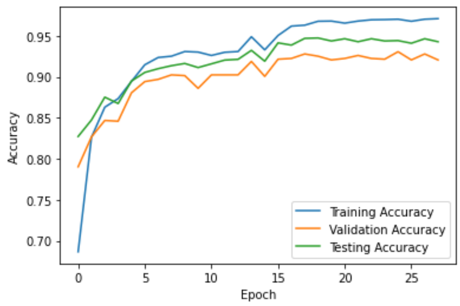

Fig. 4. Accuracy Graph for GNN Model.

Furthermore, the recommendation system leverages resume content and predicted job categories to offer tailored suggestions for job roles and essential skills, enhancing the career development of job seekers. Additionally, the real-time job web scraping component continuously updates the system with up-to-date job listings from various websites, maintaining an enriched and current job database. This guarantees that job seekers may access the most recent employment possibilities, supporting a successful and active job search process.

V. CONCLUSION AND FUTURE SCOPE

In summary, this approach introduces a robust resume screening and job recommendation system that effectively leverages advanced natural language processing and Graph Neural Networks (GNN). The system demonstrates exceptional prowess in predicting job categories, achieving a commendable 97% accuracy rate, and provides valuable insights for aligning resumes with job descriptions. The significance of this work lies in its potential to transform the job matching process, streamlining it and conserving time and resources for both job seekers and employers. Nonetheless, it's important to acknowledge certain limitations in terms of scalability and dealing with unstructured data. The execution time of the proposed algorithm is notably efficient, making it well-suited for this application. Its swift processing ensures timely resume screening and job recommendations, a critical factor in the dynamic job market, enhancing user experience and job matching efficiency.

However, there is a scope for this work that lays the foundation for a transformative path in the technology sector, providing students and job seekers with a novel approach to streamline their job search. One crucial extension involves integrating the system with direct outreach capabilities. After accurately predicting job roles, users can select target companies aligned with their career aspirations. The system can then facilitate direct communication by generating tailored email drafts addressed to the respective HR representatives of these companies, enhancing both time efficiency and the effectiveness of job applications.

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