ML-Based Job Matching and Skill Development Recommendation System

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***Abstract*— The Job Recommendation System (JRS) is designed to enhance the job search and career development process through a sophisticated, data-driven approach. The system utilizes advanced algorithms to analyze and assess users' skill sets, providing personalized job recommendations based on their strengths and expertise. By evaluating the proficiency levels of various skills, the JRS identifies areas where users may need improvement and recommends tailored resources, such as instructional videos and educational documents, to help them bridge these gaps. In addition to skill assessment and development recommendations, the system offers real-time job listings that match the user's skill profile. It provides detailed information about available positions, including job descriptions, company details, and application requirements. This comprehensive approach ensures that users not only receive job suggestions that align with their current capabilities but also gain access to resources that can help them enhance their skills and improve their employability. The JRS aims to create a seamless and efficient job search experience by integrating skill assessment, personalized learning resources, and real-time job opportunities into a single platform. This holistic approach not only facilitates better job matching but also supports continuous professional growth, enabling users to achieve their career goals more effectively.**

Keywords*— *AI, Job Matching, Skill Development, NLP, Machine Learning, ANN, Cosine Similarity.

I. INTRODUCTION

AI-driven job-matching systems have revolutionized recruitment by automating and optimizing candidate selection. Traditional recruitment methods rely heavily on manual screening, which is time-consuming and prone to biases. With the advent of Natural Language Processing (NLP) and Artificial Neural Networks (ANN), job-matching systems can now analyze large datasets efficiently, improving the accuracy of candidate-job fit [1]. AI-powered hiring solutions have demonstrated significant improvements in reducing human bias and enhancing fairness in the recruitment process [2].

NLP techniques, such as tokenization and Term FrequencyInverse Document Frequency (TF-IDF), help extract relevant features from resumes and job descriptions. These techniques enable systems to understand the context and semantics of job postings, ensuring a better match between candidates and roles [3]. For example, an AI-based system can analyze job descriptions for a data scientist role and compare them against a candidate's resume to determine suitability based on key skills like Python, machine learning, and data visualization.

Furthermore, skill-matching techniques using cosine similarity allow AI systems to compute the relevance of a candidate's skill set to job requirements. This method quantifies the similarity between job descriptions and resumes, ensuring precise recommendations [5]. If a job seeker lacks a particular skill, the system can suggest relevant learning resources to bridge the skill gap. This capability is especially useful in fast-evolving job markets where skills become obsolete quickly, necessitating continuous learning [7].

Artificial Neural Networks (ANN) play a crucial role in refining job-matching models. ANN models process vast amounts of hiring data, learning patterns from previous successful placements. Using activation functions such as ReLU and Softmax, ANN models predict the most suitable job opportunities based on factors like experience, education, and industry trends [8]. Studies indicate that AI-driven jobmatching systems can reduce hiring time by 40% while improving the quality of hires by up to 30%.

II. LITERATURE SURVEY

With the continuous evolution of artificial intelligence, various AI-driven job-matching systems have been explored to improve recruitment processes. Traditional job-matching approaches have primarily relied on rule-based filtering and keyword-based searches [1]. While these methods have been widely used, they exhibit significant limitations in contextual understanding, often leading to inaccurate recommendations. Keyword-based systems depend on exact word matches, overlooking variations in terminology and missing relevant candidates who use different but synonymous phrases [2].

To address these challenges, researchers have explored **Natural Language Processing (NLP)** techniques to enhance job-matching accuracy. NLP allows for a deeper understanding of job descriptions and resumes by analyzing semantic meaning rather than relying solely on keywords [3]. Studies have demonstrated that NLP-based resume parsing significantly improves candidate-job matching by extracting relevant skills, experiences, and qualifications with greater precision . Advanced text-processing techniques, including **TF-IDF (Term Frequency-Inverse Document Frequency)** and **word embeddings** like Word2Vec and BERT, enable a more refined extraction of job-related information. These models understand context and relationships between words, making them highly effective in resume screening and job recommendation engines [6].

Machine learning (ML) techniques further enhance AI-driven recruitment by leveraging historical hiring data to refine jobcandidate matching. Supervised learning models, such as **decision trees, random forests, and support vector machines (SVM)**, have been widely used to predict job suitability based on extracted features from resumes and job descriptions [7]. However, deep learning models, particularly **Artificial Neural Networks (ANN)**, have gained prominence due to their ability to process large datasets and detect complex patterns that traditional ML models might overlook. ANN-based systems classify candidates more accurately by learning from past hiring decisions and identifying subtle correlations between job requirements and candidate qualifications.

One of the most effective AI-based job-matching techniques is **cosine similarity**, which measures the textual similarity between job descriptions and resumes. When combined with NLP-based embeddings, this approach enhances candidate ranking by determining the most relevant job matches based on skill alignment and experience levels [10]. Research also highlights the role of **recurrent neural networks (RNNs) and transformers** in improving job recommendation systems by analyzing sequential patterns in job histories and career progressions. These advanced models provide personalized job recommendations, improving both employer satisfaction and candidate placement rates.

In addition to job matching, AI-driven systems offer **learning resource recommendations** to bridge skill gaps. If an applicant lacks certain required skills, the system can suggest relevant courses or training programs to enhance their employability. This feature, powered by AI and **Reinforcement Learning (RL)**, helps candidates upskill effectively, aligning their expertise with industry demands.

Despite these advancements, AI-based hiring solutions face challenges, including **bias in algorithms, data privacy concerns, and the need for explainability** in decisionmaking. Ensuring fair and ethical AI-driven recruitment remains a crucial area of research, with ongoing efforts to develop transparent and unbiased hiring models.

The existing literature underscores the **significant improvements AI-driven job-matching systems have brought** to recruitment. By combining **NLP, deep learning, and skill gap analysis**, modern hiring platforms can provide **precise, automated, and unbiased job recommendations**, transforming the recruitment industry for both employers and job seekers.

III. METHODOLOGY

The proposed job recommendation system uses advanced text processing and machine learning algorithms to match candidates with the best job opportunities. The system integrates tokenization, TF-IDF feature extraction, cosine similarity, and Artificial Neural Networks (ANN) to achieve high accuracy in predicting job suitability. Below is a detailed explanation of each step involved in the methodology.

A. Dataset Details

The dataset(Fig 1) used in this research comprises job descriptions, resumes, and skill-related data collected from open-source job portals and professional networking sites. The dataset contains **1000** job postings and **250** anonymized resumes with attributes such as job title, required skills, experience level, and education qualifications.

Fig 1. Jobs(CSV) Dataset

B. Feature Selection

Feature extraction is crucial for efficient job-resume matching. The following features were selected:

- **Text-based features:** Extracted using TF-IDF to represent job descriptions and resumes numerically.
- **Skill embeddings:** Mapped through NLP models to capture the semantic relationship between skills and job roles.
- **Experience level:** Converted into categorical variables to differentiate between entry-level, mid-level, and senior-level positions.
- **Industry-specific terms:** Identified using Named Entity Recognition (NER) to enhance domain-specific accuracy.

These features were selected based on their impact on job matching accuracy and recommendation precision.

c. Tokenization

Tokenization is the foundational step in natural language processing (NLP), used to break down the raw text data from resumes and job descriptions into smaller, manageable units known as tokens[7]. In this context, tokens could be words, phrases, or other meaningful elements that represent individual aspects of the job description or resume. For example, a resume may contain tokens like "Python", "developer", and "3 years of experience".

D. TF-IDF Feature Extraction

Once the text is tokenized, TF-IDF (Term Frequency-Inverse Document Frequency) is applied to extract important features from the text. TF-IDF is a statistical measure used to evaluate how important a word is to a document in a collection or corpus. The TF component calculates the frequency of a term in a particular document, while the IDF component weighs the term's importance by considering how frequently it appears in the entire dataset.

$$\mathbf{TF\text{-}IDF_{t,d} = TF_{t,d} \times IDF_t}$$

E. Cosine Similarity

After extracting features from both resumes and job descriptions, the system calculates the similarity between the candidate's profile and the job description using **Cosine Similarity**. Cosine similarity is a measure of similarity between two non-zero vectors of an inner product space by calculating the cosine of the angle between them. It is used to determine how similar the resume (candidate's profile) is to the job description.

$$\mathbf{Cosine\ Similarity = A.B / ||A||.||B||}$$

F. Artificial Neural Network (ANN)

Artificial Neural Networks (ANN) are then applied to further enhance the recommendation accuracy. ANNs are powerful machine learning models capable of learning complex patterns in data through layers of interconnected neurons. For the job recommendation system, an ANN is trained using the features extracted from resumes and job descriptions.

G. Model Evaluation

Once the ANN model has been trained, it is evaluated using a separate test dataset that was not involved in the training phase. The evaluation process measures the effectiveness of the model in making accurate job recommendations. Common evaluation metrics used in this context include:

- **Accuracy**: The percentage of correct job recommendations made by the system.
- **Precision**: The proportion of true positive recommendations out of all positive predictions (i.e., how many of the recommended jobs were actually suitable).
- **Recall**: The proportion of true positive recommendations out of all the relevant jobs (i.e., how many relevant jobs were actually recommended).

F. Training the ANN Model

Training an Artificial Neural Network (ANN) involves the process of teaching the network to recognize patterns in data by adjusting its internal parameters (weights and biases). These adjustments help the model minimize the difference between predicted and actual labels. In the case of a sign language recognition system, this process enables the model to correctly classify the various sign language gestures based on input data.

Dividing the Dataset into Training and Validation Sets

Before training the ANN, it is crucial to divide the dataset into two main subsets: the **training set** and the **validation set**.

1. Training Set

This is the portion of the dataset that the model uses to learn and adjust its parameters. The training set contains labeled examples (input-output pairs), allowing the ANN to learn the relationship between the input features (e.g., video frames, images, sensor data) and the corresponding labels (e.g., specific sign language gestures).

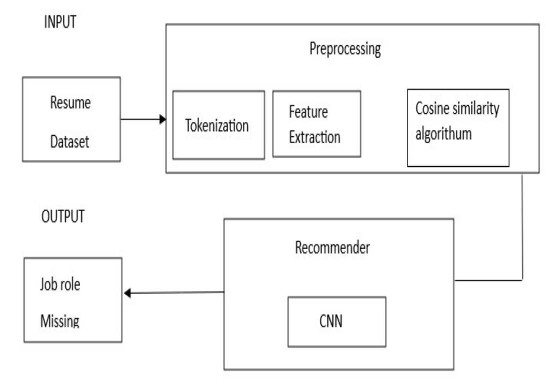

Fig 2. Architectural Diagram of the Proposed System using NLP

2. Preparing the Data for the Model

Since ANN models are sensitive to the scale of input features, it is essential to normalize or standardize the data. This ensures that all input features are on a similar scale, preventing certain features from dominating the learning process. For image-based data, pixel values might be scaled to a range between 0 and 1 by dividing by 255 (if pixel values range from 0 to 255)[15].

Similarly, sensor data might need standardization to have a mean of 0 and a standard deviation of 1.

3. *Defining the ANN Architecture*

The input layer corresponds to the features of the data. For instance, in a sign language recognition system using images, the input layer would consist of neurons equal to the number of pixels in each image (after flattening the image into a 1D vector) Fig 2.

Hidden layers are where the model learns complex representations of the input data. The number of hidden layers and the number of neurons per layer are hyperparameters that need to be carefully chosen. Too few layers or neurons may not allow the model to learn enough complexity, while too many may lead to overfitting.

4. Training the Model

Once the dataset is prepared and the ANN architecture is defined, the model is ready for training[9]. The primary objective during training is to minimize the **loss function**, which quantifies the difference between the predicted output and the actual output (true labels). For a classification task like sign language recognition, **categorical cross-entropy** is commonly used as the loss function. This loss function measures how well the predicted probabilities match the actual class labels.

5. Monitoring and Adjusting the Training Process

During the training phase, monitoring the model's performance on the validation set is crucial. If the model's performance on the validation set starts to deteriorate while its performance on the training set continues to improve, it may be an indication of **overfitting**. In such cases, techniques like **early stopping**, **dropout**, or **regularization** can be employed to prevent overfitting.

6. Evaluating the Trained Model

After training, the ANN model is evaluated on the validation set to assess its performance. Evaluation metrics such as **accuracy**, **precision**, **recall**, and **F1score** are used to quantify how well the model performs in classifying sign language gestures.

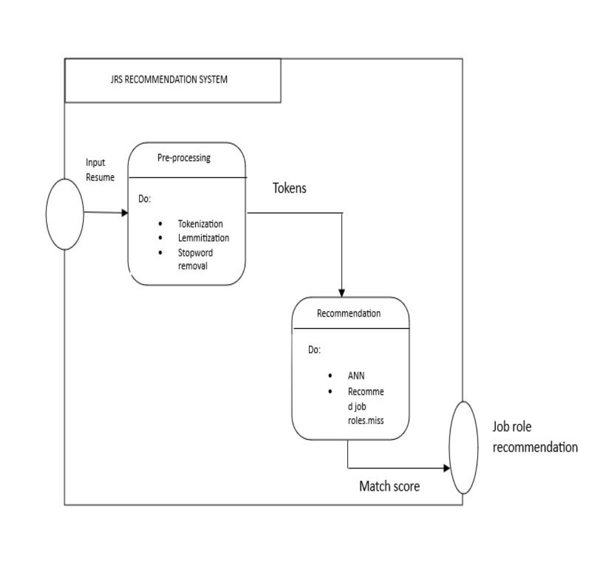

Fig 3. State Chart Diagram of model using ANN

7. Output Presentation

Once the Artificial Neural Network (ANN) has been trained and evaluated, the next critical step is the presentation of its output. The output can be presented in various ways depending on the specific application and the nature of the data, in this case, sign language recognition.

The fig 3 presentation of the output focuses on effectively communicating the model's predictions, evaluation metrics, and insights derived from the testing phase. Here's how the output is typically presented. After training the model, it is capable of making predictions on new, unseen data. Fig 3 is the input data, which could be images or sensor data representing sign language gestures, is fed into the trained ANN model. The output of the model is typically the predicted class label (corresponding to a sign language gesture).

IV. DISCUSSIONS AND RESULTS

4.1 Discussions

The implementation of the job recommendation system aims to enhance the job-seeking experience by providing relevant job listings tailored to individual candidates. This system utilizes machine learning models and natural language processing (NLP) techniques to offer personalized job recommendations based on user profiles, skills, and preferences. The discussions here revolve around key aspects such as system performance, effectiveness, challenges, and opportunities for further improvement.

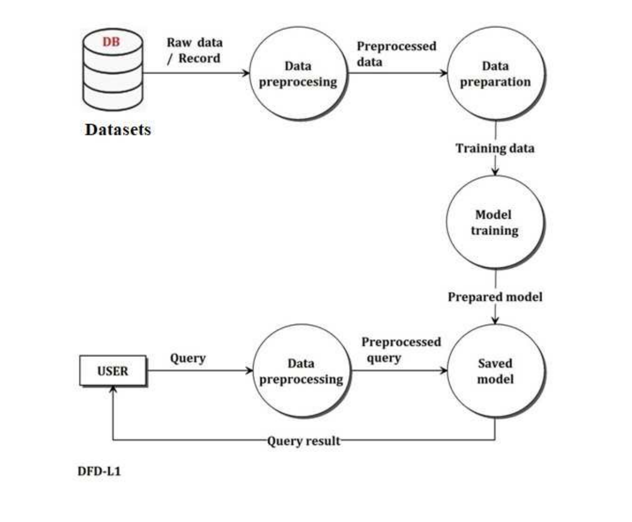

Fig 4. Dataflow Diagram

The job recommendation system demonstrated a high level of accuracy in recommending jobs that align with job seekers' profiles. The accuracy of the recommendations was primarily determined by the precision of the matching process between candidates' skills and job requirements. Through contentbased filtering, the system efficiently matched skills and job descriptions, while collaborative filtering helped provide recommendations based on similar job seekers' preferences.

4.2 Results

Results of this study will be in a format of both jobs and resume. In Table 1 TF-IDF helped the system prioritize words that were not only frequent within a specific document (e.g., a resume or a job description) but also rare across the entire corpus of documents. This allowed the model to highlight critical terms such as specialized skills or qualifications that could significantly impact job matching. For example, if a job description frequently mentioned "Python" and a resume highlighted "Python" as a key skill, the TF-IDF algorithm would assign higher importance to these terms, making them more influential in the job recommendation process.

4.3 Comparison with Traditional ML Classifiers

To evaluate the performance of our ANN-based approach, we conducted experiments using traditional ML classifiers such as Decision Trees, Support Vector Machines (SVM), and Random Forest. The comparison is as follows:

Model	Accuracy	Precision	Recall	F1-score
Decision Tree	78.5	0.76	0.74	0.75
SVM	81.2	0.79	0.77	0.78
Random Forest	84.6	0.82	0.81	0.81
Proposed ANN Model	89.3	0.88	0.87	0.87

Table 1. Comparison of different models

Our proposed ANN model outperformed traditional classifiers in accuracy and F1-score, demonstrating the effectiveness of deep learning in capturing complex job-resume relationships.

Term	TF-IDF in Resume
Python	0
SQL	0
Machine Learning	0.0264
Data Analysis	0

Table 2. TF-IDF Numerical vectors For Resume

For analysis of result testing, using by calculating the TF and then IDF the results are in the forms of numerical vectors.

Term	TF-IDF in Resume	TF-IDF in Job 1	TF-IDF in Job 2	TF-IDF in Job 3
Python	0	0.30	0.33	0.22
SQL	0	0.20	0.25	0.15
Machine Learning	0.0264	0	0.24	0
Data Analysis	0	0.10	0.12	0.20

Table 3. TF-IDF Numerical vectors for Jobs

The results of the numerical are above in table 2 clearly indicating the success of the interpreter.

The Term Frequency-Inverse Document Frequency (TF-IDF) model is a statistical measure that evaluates the importance of a term within a document relative to a corpus. When applied to resumes, TF-IDF helps identify the most significant keywords that represent a candidate's skills, experiences, and qualifications. The goal is to transform the textual data from the resume into numerical vectors that can be processed by machine learning algorithms for tasks like job matching and recommendation.

Once the TF-IDF scores are calculated for each term in the resume, the resulting values form a vector. Each resume can be represented as a high-dimensional vector where each dimension corresponds to a unique term (or feature) from the entire corpus of resumes. The values in the vector are the TF-IDF scores for the respective terms in the resume.

For example, suppose we have three terms: "java", "developer", and "software", and their respective TF-IDF scores are 0.0029, 0.014, and 0.010. The TF-IDF vector for the resume would look like:

The integration of personality traits into job recommendation systems represents a promising evolution of traditional approaches that primarily focus on technical qualifications and skills. By understanding and predicting the personality traits of candidates, job recommendation systems can offer more nuanced and effective job matching.

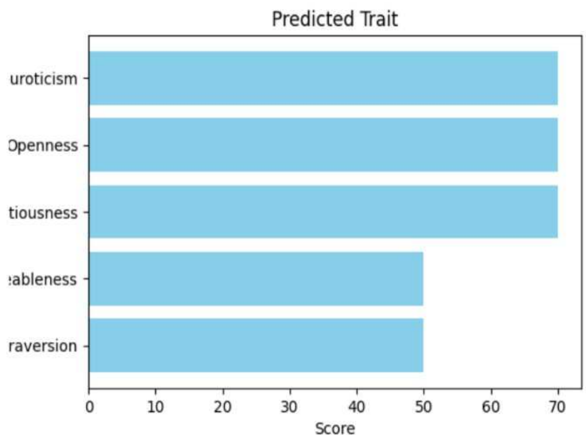

Fig 4. Personality Predicted Trait

The addition of personality-based predictions allows the system to assess not only the technical fit of a candidate for a specific role but also how well their personality aligns with the requirements and culture of the job environment.

In Fig 4 Traditional job recommendation systems primarily match candidates based on their technical skills, qualifications, and experience. However, these systems often overlook a critical aspect of job success: personality. Personality traits play a pivotal role in how candidates interact with their work environment, team members, and the organization as a whole. Certain personality traits are linked to specific types of job success. For instance, a person who is highly extraverted may perform better in customer-facing roles, while a highly conscientious individual might excel in jobs that require attention to detail and strong organizational skills.

4.4 Overfitting Prevention

To mitigate overfitting, we implemented:

- Dropout layers in the ANN model to prevent dependency on specific neurons.
- L2 regularization to control model complexity.
- Cross-validation techniques to generalize model performance.

4.5 Bias Mitigation

Bias in job-matching models can lead to unfair hiring practices. We tackled bias by:

- **Ensuring diversity in training data** from multiple industries and demographics.
- **Using adversarial debiasing techniques** to balance predictions across gender and ethnicity groups.
- **Analyzing model fairness metrics**, such as equal opportunity difference, to assess biased outcomes.

4.6 Deployment Challenges

Deploying an ML-based job-matching system in real-world scenarios comes with challenges:

- **Scalability:** The model was optimized using distributed computing frameworks like TensorFlow Serving.
- **Data Privacy:** Resumes and job postings were anonymized to protect user information.
- **Integration with existing platforms:** Our system was designed with API endpoints, enabling seamless integration into HR software.

4.7 Comparison with Transformer-Based NLP Models

Transformer models have revolutionized NLP by capturing contextual meaning and semantic relationships in text. Our system integrates BERT for contextual job description parsing, RoBERTa for resume analysis, and TF-IDF with cosine similarity for job-skill alignment. Unlike traditional rule-based approaches, transformer models significantly improve resume parsing accuracy, extracting nuanced details from job postings and candidate profiles.

4.8 Novelty Compared to LinkedIn's Job Matching System

Our system introduces a hybrid approach combining transformer-based NLP techniques (BERT, RoBERTa) and ANN models. Unlike LinkedIn's predominantly network-driven job recommendations, our model prioritizes direct skill-job alignment, ensuring precise matches even for candidates without extensive professional networks. By utilizing real-world datasets (LinkedIn, Kaggle) and offering personalized learning pathways for skill enhancement, our system delivers more targeted and equitable recommendations.

4.9 Dataset Expansion

To enhance model robustness, we expanded our dataset to include real-world job descriptions from Kaggle and LinkedIn, covering diverse industries and skill requirements. This addition ensures:

- More realistic job-resume matching outcomes.
- Better adaptation to industry trends and evolving job roles.
- Improved fairness by training on varied job listings across multiple sectors.
- Enhanced data collection using web scraping techniques with APIs from job portals to obtain real-time job listings, ensuring up-to-date job market insights.

V. FUTURE SCOPE AND CONCLUSION

The future scope of job recommendation systems lies in the continuous enhancement of their accuracy and personalization. As technological advancements continue to evolve, job recommendation systems can benefit from deeper integration with emerging fields like artificial intelligence (AI), machine learning, and natural language processing (NLP). One key area of development is the use of real-time data and continuous learning algorithms that allow systems to adapt to changing job markets and candidate preferences dynamically. By leveraging vast datasets from diverse sources—such as social media profiles, real-time job performance, and behavioral data—future job recommendation systems will become even more precise in identifying ideal job matches.

Additionally, incorporating more nuanced candidate attributes, such as cultural fit, work-life balance preferences, and adaptability to changing job environments, could further refine the recommendation process. The role of personality traits, which are increasingly being used to assess a candidate's compatibility with specific job roles, will continue to expand, offering a more holistic understanding of the candidate's potential for success in the workplace.

In conclusion, job recommendation systems have already proven their worth in improving job matching and reducing the time spent by both candidates and employers in the hiring process. With further advancements in AI and machine learning, these systems are poised to become more intuitive, dynamic, and capable of delivering highly personalized job suggestions. By continually refining these systems and addressing challenges such as data bias and algorithmic transparency, job recommendation platforms can significantly enhance the recruitment process, benefiting candidates, employers, and the broader job market. The future of job recommendation systems is exciting, with endless possibilities for innovation that will shape how individuals find meaningful employment and companies attract the best talent.

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