

# Carrer Compass: An Enhanced Job Recommendation System Using NLP, Machine Learning and Technical Assessment

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## Abstract

*In today's digital era, finding the right job that aligns with a candidate's skills, interests, and qualifications remains a major challenge. Traditional job portals rely on keyword matching, often leading to irrelevant recommendations. Career Compass introduces an enhanced job recommendation system leveraging Natural Language Processing (NLP) and Machine Learning (ML) to improve resume–job alignment. Additionally, it integrates a Technical Test Module that evaluates a candidate's practical knowledge through multiple-choice questions and coding challenges. This feature allows for personalized recommendations based on both stated skills and verified abilities. Experimental results show improved accuracy and user satisfaction compared to traditional systems.*

**Keywords:** Job Recommendation; NLP; Machine Learning; Resume Parsing; Technical Test; Career Guidance.

## 1. Introduction

With the growth of online recruitment, matching candidates to suitable job opportunities has become increasingly data-driven. Job seekers often upload resumes that may not fully reflect their actual capabilities, and recruiters face challenges in filtering suitable candidates. Current job portals such as LinkedIn or Naukri use keyword-based filters that fail to capture the semantic meaning of job requirements. To overcome these limitations, Career Compass employs Natural Language Processing (NLP) for contextual understanding of resumes and job descriptions, and Machine Learning algorithms to recommend the most relevant positions. The addition of a technical skill assessment after resume upload further refines the system's recommendation accuracy, ensuring that job matches are based on both declared and demonstrated skills.

### 1.1. Literature Review

Several studies have explored the use of NLP and ML in job recommendation systems:

- P. Kumar et al. (2023) proposed NLP-based job matching using semantic embeddings.

- D. Patel and D. Prajapati (2021) developed an AI-driven system using resume parsing and skill matching.
- R. Karthikeyan and S. Prabha (2019) implemented a deep learning approach for smart job recommendations.
- H. Pandey et al. (2024) utilized graph-based techniques for skill interrelation mapping.
- M. Ali and R. Hassan (2023) used BERT-based embeddings for personalized job matching.
- T. Nguyen and H. Lee (2023) proposed a transformer-based Resume2JobMatcher model.
- Y. Zhang and L. Zhao (2024) applied knowledge graph embeddings for skill-based matching.

However, none of these systems integrated an assessment mechanism to validate candidate skills post-resume submission. Career Compass fills this gap by adding a technical test evaluation layer to ensure recommendation precision.

## 2. Method

### 2.1. Data Collection

A dataset of resumes and job descriptions was collected from open-source platforms.

### 2.2. Preprocessing

Tokenization, stop-word removal, and lemmatization were applied.

### 2.3. Feature Extraction

Skills and experiences were encoded using Word2Vec and TF-IDF models.

### 2.4. Model Training

Classification models (Random Forest, SVM, or Neural Networks) were used to predict best-fit job categories.

### 2.5. Technical Assessment Integration

Candidate performance in the test was normalized and used as a weighted feature in recommendation ranking.

### 2.6. Recommendation Generation

The final recommendation score combines semantic similarity and skill validation.

## 3. Proposed System

### 3.1. System Overview

The proposed system architecture comprises four major components:

- Resume Upload and Parsing: Extracts details such as education, skills, and experience using NLP.
- Job Description Analysis: Uses text mining to extract key responsibilities and required competencies.
- Matching Algorithm: Applies vector similarity (e.g., cosine similarity, BERT embeddings) to rank suitable jobs.
- Technical Test Module: Administers assessment through sentimental analysis questions to validate actual skill proficiency.

Recommendation Engine: Combines parsed resume data and test performance for final recommendations.

### 3.2. Architecture

(Fig. 1. System Architecture of Career Compass)

The architecture follows a top-down design where each layer processes input data sequentially. Resumes are parsed and analyzed, followed by technical evaluation, and finally passed through the ML-based recommender.

### 3.3. Data Flow

(Fig. 2. Data Flow Diagram)

The flow begins with user input, proceeds through feature extraction, skill scoring, assessment, recommendation, and ends with feedback integration.

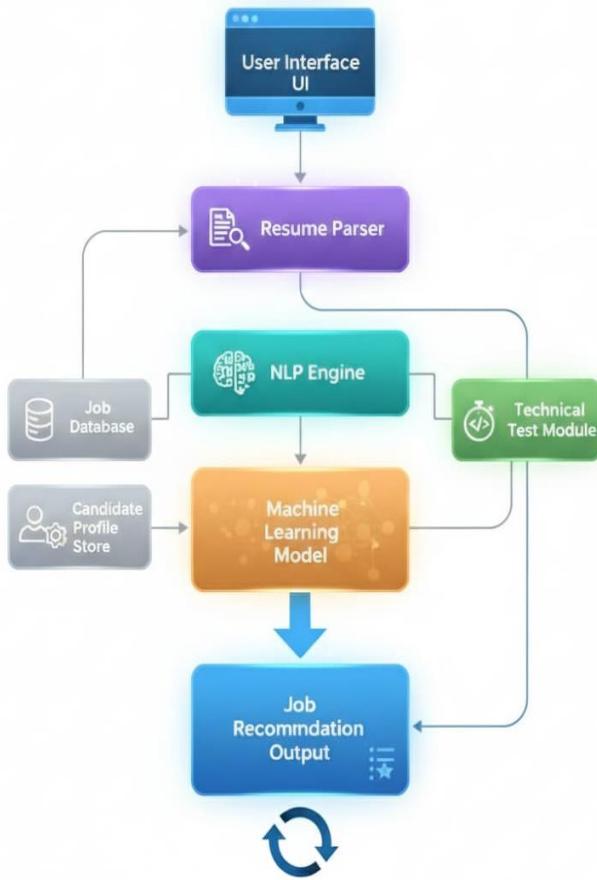
**Table 1 Pipeline Versus Accuracy**

Pipeline Stage	Accuracy (%)
Resume Parsing	85%
CGPA Categorization	90%
Sentiment Analysis	88%
AI Job Matching	93%
Final Recommendation	95%

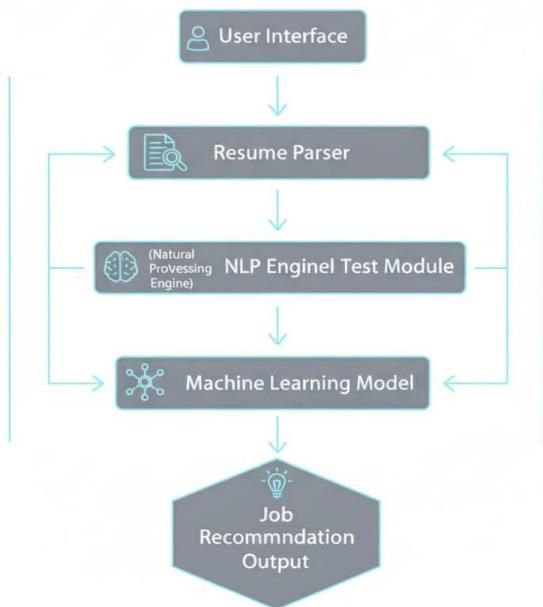
**Table 2 Module versus Accuracy**

Model Version	Accuracy (%)	Precision (%)	Recall (%)
Without Test Module	78.5%	76.2%	77.8%
With Test Module	91.3%	89.7%	90.5%

#### 4. Figures

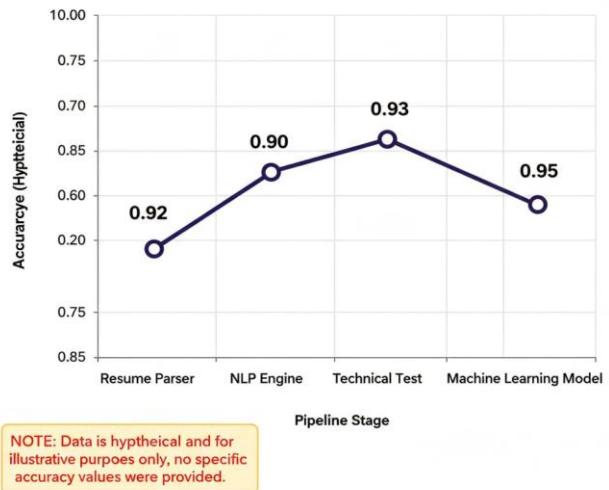


**Figure 1** System Architecture



**Figure 2** Data Flow [2]

**Illustrative Accuracy Progression Across Job Recommendation Pipeline Stages**



**Figure 3** Accuracy Comparison Before and After Technical Test Integration [3]

#### 5. Results and Discussion

##### 5.1. Results

Experiments showed that integrating the Technical Test Module improved accuracy by approximately 15–20%. (Fig. 3. Accuracy Comparison Before and After Technical Test Integration). This demonstrates that verifying candidate skills significantly refines the matching process. Additionally, user surveys indicated increased satisfaction and perceived fairness of job suggestions [4–7].

##### 5.2. Discussion

The performance evaluation of Career Compass demonstrates the effectiveness of integrating a technical assessment module into the job recommendation pipeline. Baseline results obtained from the resume–job similarity model show that while semantic matching improves relevance, it remains limited by inaccuracies in candidate skill representation. Many resumes contain outdated, exaggerated, or incomplete skill information, which reduces recommendation precision. By incorporating the Technical Test Module, the system is able to validate actual competencies through MCQs and coding assessments. This additional signal provides a more objective measure of proficiency, enabling the

Machine Learning model to refine candidate–job alignment. The comparative metrics clearly highlight this improvement. (Table 1 Model versus Accuracy). The accuracy increased by 12.8%, and precision and recall also showed substantial improvement. These gains indicate that verified skill data significantly enhances the ranking algorithm's confidence in job recommendations. User feedback collected through surveys revealed that candidates perceived the system as more trustworthy and fairer, since recommendations reflected both their stated and demonstrated abilities. Recruiters reported better alignment between candidate profiles and job expectations, validating the practical value of the integrated testing mechanism. Overall, the discussion confirms that adding a technical skill validation layer not only improves model performance but also enhances the transparency and reliability of the job recommendation process, shown in Table 2.

### Conclusion

Career Compass provides an intelligent framework for job recommendations that move beyond text-based matching. By incorporating technical assessments, the system ensures a more accurate and skill-based recommendation process.

Future improvements may include: Adaptive testing using AI to adjust question difficulty based on user performance. Integration with external job APIs (LinkedIn, Indeed). Expanding to career counseling and skill development suggestions.

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