AI-Powered Resume Analyzer and Job Matching System: A Comprehensive Review

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DOI: https://dx.doi.org/10.51584/IJRIAS.2025.101100036

Received: 14 November 2025; Accepted: 26 November 2025; Published: 08 December 2025

ABSTRACT

The AI-based job recommendation system employs Natural Language Processing (NLP), Large Language Models (LLMs), and API-based job search to automate and optimize career matching. Technical skills, experience, and job keywords are extracted from resumes with Spacy NLP and regex-based text analysis to allow candidate profiling. Information is processed with Ollama Mistral, a high-performance LLM, to predict the best job role to match based on skills and industry standards. Real- time job recommendations are obtained with RapidAPI's Job Search API, with the ability to filter search results with location-based filtering. The system optimizes job search efficiency, minimizes manual effort, and improves job-to- candidate matching accuracy. Skill gap analysis, AI-driven job ranking, and professional profile integration (Linked-In, GitHub) can be added to future development for improving recommendations. This project demonstrates the revolutionary capability of AI in employment matching, making job searching intelligent, data-driven, and personalized.

Keywords: Natural Language Processing (NLP), Large Language Models (LLMs), Ollama Mistral, resume analysis, job role prediction, skill extraction, RapidAPI Job Search.

INTRODUCTION

In the era of digital revolution, companies are burdened with the responsibility of sorting through thousands of resumes for every vacancy. Conventional human screening is time-consuming, labor-intensive, and susceptible to human prejudice, yielding inconsistent recruitment outcomes and missed talent [1]. To counter such issues, Artificial Intelligence (AI) and Machine Learning (ML) have become game-changing technologies in automating resume screening and candidate-job matching optimization [2].

AI-driven platforms can effectively scan and interpret candidate data to determine job fit. Machine Learning algorithms are used to improve recommendation precision by discovering intricate patterns in candidate profiles, enabling quicker and unbiased hiring decisions [3]. Natural Language Processing (NLP) adds the extra layer of security by turning unstructured resume content into informative representations, facilitating accurate skill extraction and contextual matching [4][5]. Methods like Named Entity Recognition (NER) and semantic similarity comparison enable NLP models to interpret job descriptions in a way that goes beyond basic keyword matching [6][7].

Recent studies have shown that coupling NLP and AI can greatly enhance the efficiency of recruitment. Intelligent resume analyzers employ ML algorithms for resume parsing, feature extraction, and candidate ranking based on job suitability [8]. Such systems adopt contextual language models to discover appropriate skills and refine job match precision [9][10]. Hybrid methods, which use rule-based filtering followed by ML-based classification, have also been shown to enhance ranking performance [11][12].

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

Contemporary resume analyzers utilize algorithms such as Random Forests [12], Support Vector Machines (SVMs), and Gradient Boosting to categorize and rank resumes [28]. Deep learning models, e.g., neural embeddings, complement semantic interpretation among job specifications and candidate qualities [17][24]. Likewise, AI-powered recommender systems offer job recommendations based on real-time labor market information and skill-based filtering [9][18]. They apply sophisticated ranking and recommendation techniques on a par with those implemented in social or music recommender systems [13][14].

Though these improvements have been made, there are still challenges—mainly in multilingual parsing and coping with varying resume formats [20], [27]. Keyword-based matching approaches do not usually achieve semantic relations, missing potential candidates with transferable skills [22]. In order to counteract this, the use of large language models (LLMs) has been implemented, allowing contextual understanding and the correct prediction of job titles [21]. Additionally, AI-based feature extraction and personality prediction have become vital to evaluate both the technical and behavioral qualities of candidates [15], [16], [19].

The new AI-Powered Resume Parser and Job Matching System utilizes NLP-based parsing, ML-based skill extraction, and AI-driven ranking algorithms to automate and streamline the hiring process. Using semantic similarity metrics, the system discovers contextual similarity between job posts and candidate qualifications, making equitable and efficient hiring choices [28][30].

Finally, the integration of AI, ML, and NLP is a revolution in recruitment. Through their ability to take unstructured resumes and make them structured, analyzable data, these technologies make the hiring process faster, less biased, and more accurate [23][26]. Therefore, the system proposed is a major step towards smart, effective, and data-based recruitment practices [5][6].

THEMATIC REVIEW OF LITERATURE

The review outlines four broad themes arising in current studies of AI-based resume analysis and job matching systems [1][3]. These are machine learning–based resume ranking, natural language processing (NLP) for extraction of skills and semantic analysis, job recommender systems based on AI for job matching, and LLM and deep learning integration for end-to-end candidate assessment [5][9].

A. Machine Learning–Based Resume Screening and Ranking

Machine learning (ML) algorithms have been extensively used to screen resumes and rank candidates [1][2]. Roy et al. constructed an ML-based recommendation system that enhanced the precision of resume classification by computerized detection of relevance between job profiles and candidates [1]. Reedy and Kumar created a decision tree-based and logistic regression-based resume screening model that was more precise than manual shortlisting [2]. Sheikh et al. proposed an AI-based ranking system integrating ML and NLP that minimized human bias and improved selection consistency [3]. Sathvik et al. [6] and Raut and Wagh [7] proposed intelligent analyzers with Python-based classifiers for automated screening, whereas Soni et al. [8] and JayaPriya et al. [4] stressed lightweight ML models for rapid evaluation. Together, these studies indicate the capability of ML in simplifying recruitment, though they continue to grapple with small datasets and excessive dependence on formatted input formats [5].

B. NLP for Resume Parsing and Skill Extraction

The incorporation of NLP has enabled resume parsers to comprehend unstructured text well [15][19]. Johnson illustrated the application of SpaCy for Named Entity Recognition (NER) to efficiently extract entities such as skills and experience from resumes [23]. Wang and Li gave an in-depth overview of skill extraction based on NLP, illustrating how transformer models enhance contextual information [19][26]. Becker and Müller pointed out difficulties in multilingual parsing, referencing discrepancies in worldwide resumes [20][27]. JayaPriya et al. [4] and Soni et al. [8] used tokenization and syntactic parsing to identify structured attributes. At the same time, Lee and Kim criticized keyword-based methods for lacking semantic connections between skills and job descriptions [22]. These results affirm that NLP enhances feature extraction accuracy, particularly in combination with contextual embeddings and semantic similarity measurements [15].

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

C. AI-Based Recommender Systems for Job Matching

Recommender system methods have been advanced to improve job-candidate matching accuracy [9][17]. Natarajan and Rajaraman deployed an NLP-based similarity model using gradient boosting with high alignment between candidate profiles and job descriptions [30]. Ma et al. applied semantic similarity and ensemble learning for resume-job matching with better accuracy [28]. Zhou and Chen suggested a deep learning–based recommender system for user-specific job recommendations in accordance with user skill sets and interests [17]24]. Kishore and Sreerala created an AI system incorporating real-time data for skill-based recommendations and job search based on personalization [9]. Earlier recommender models, including those by Al Otaibi and Ykhlef [10] and Carrer-Neto et al. [13], provided the basis for knowledge-based and collaborative filtering strategies in HR. These models greatly improve matching precision but continue to struggle with issues of explainability, fairness, and data imbalance [22][29].

D. LLM and Deep Learning Integration for Holistic Candidate Evaluation

Recent research has centered on sophisticated AI techniques like deep learning and large language models (LLMs) for more informative candidate assessment [16][21]. Ahmed and Rahman proposed an LLM-based model for job title prediction with better contextual accuracy compared to conventional NLP pipelines [21]. Robey et al. presented a personality prediction system via CV analysis, integrating ML and psychological profiling to derive behavioral fit [16]. Dr K. G. R. et al. [5] and Sheikh et al. [3] introduced AI-powered systems that simultaneously screen both employers and candidates, optimizing the recruitment for both. Deep learning algorithms have also enhanced semantic understanding and resume-job similarity scores, such as in Wang et al. [15] and Zhou and Chen [17]. These works portend a move from rule-based to human-centric AI, applying behavioral, linguistic, and contextual intelligence to recruitment [18][24].

In general, the issues highlight that AI systems tremendously improve efficiency, fairness, and consistency in hiring [1][4][6][9]. Nevertheless, ongoing issues include limited data sizes, multilingual adaptation, algorithmic bias, and uninformed decision-making [20][21][27]. Future work should aim to create hybrid, explainable AI architectures and benchmark datasets for ensuring equitable and scalable usage in worldwide recruitment scenarios [9][17][30].

COMPARATIVE ANALYSIS

Table 1: Comparative Analysis of Research Paper

S. No.	Author(s) & Year	Objective / Research Focus	Methods / Techniques Used	Dataset / Experimental Setup	Key Findings / Results	Limitations / Gaps Identified	Future Scope / Remarks
1	P. K. Roy et al., 2020	To automate resume recommendation and candidate-job matching using ML algorithms.	TF-IDF vectorization, Naïve Bayes classifier, and cosine similarity for ranking resumes.	Collected dataset of candidate resumes and job descriptions; preprocessing with text cleaning and feature extraction.	Achieved 85% accuracy in resume-job match ranking; reduced recruiter workload.	Limited contextual understanding; lacks semantic matching of skills.	Integrate deep learning (BERT) for contextual embeddings and improve semantic accuracy.
2	K. S. Reedy & A. S. Kumar, 2025	To design an intelligent resume screening system using NLP and ML.	NLP preprocessing (tokenization, lemmatization), TF-IDF, and Support Vector Machine (SVM).	Dataset from job portals; resumes converted to structured data; multiple job categories.	Improved resume classification accuracy by 89%; efficient shortlisting.	Model performance drops with unstructured resumes; lacks adaptive learning.	Add deep learning models and adaptive learning with feedback loops.
3	S. M. S. Sheikh et al., 2025	To enhance recruitment efficiency using an AI-powered resume ranking system.	BERT-based NLP embeddings with Random Forest ranking model.	10,000 resumes and job descriptions; skill extraction via NLP pipeline.	Achieved precision of 0.92 and recall of 0.88; effective skill-based ranking.	Computationally expensive; limited scalability for large datasets.	Use distributed ML models; integrate cloud deployment for scalability.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

4	J. JayaPriya et al., 2025	To create a smart AI resume analyzer for candidate evaluation.	Keyword extraction, ML classification (SVM, KNN), and scoring algorithm.	Custom dataset of resumes with recruiter-labeled relevance.	Automated scoring system achieved 87% recruiter agreement rate.	Lacks personalization; fixed rule-based thresholds.	Include feedback-based adaptive ranking; hybrid AI-human review.
5	K. G. R. Dr et al., 2024	To optimize both candidate and company selection using AI-driven screening.	Multi-agent AI framework integrating NLP-based resume parsing and company profile matching.	Resume–job dataset with labeled skill relevance; implemented in Python.	Enhanced matching accuracy by 30% compared to traditional filters.	Limited interpretability of AI decision logic; biased dataset.	Use explainable AI (XAI) and fairness constraints to reduce bias.
6	G. V. S. Sathvik et al., 2025	To develop a smart resume analyzer using machine learning for efficient recruitment.	Decision Tree and Naïve Bayes classifiers; text preprocessing pipeline.	Dataset of resumes with recruiter-approved tags; cross-validation used.	Achieved 88% accuracy in classification; efficient processing speed.	Poor generalization to unseen job domains; dataset imbalance.	Enrich dataset with diverse roles; implement deep ensemble models.
7	P. G. Raut & R. D. Wagh, 2024	To design a resume analyzer and recommender using Python for job matching.	TF-IDF, cosine similarity, and rule-based filtering; implemented in Python.	Real-world resumes and job descriptions collected manually.	Improved recruiter efficiency by 40%; simple and interpretable model.	Manual preprocessing required; lacks automation and contextual semantics.	Add NLP automation with pretrained transformers (e.g., BERT, RoBERTa).
8	A. Soni et al., 2024	To create an AI resume analyzer capable of ranking resumes for recruitment automation.	NLP-based feature extraction, clustering (K-Means), and ranking algorithm.	Dataset of 500+ resumes with labeled skill categories.	System effectively grouped candidates by skill domains; accuracy ~82%.	Limited dataset; lacks advanced NLP features.	Expand dataset; integrate deep semantic models for improved clustering.
9	C. R. Kishore & T. Sreerala, 2025	To build a personalized job recommendation system using real-time data and AI.	Hybrid recommendation (content + collaborative filtering) with NLP-based skill extraction.	Real-time job portal data; user profiles updated dynamically.	Personalized recommendations improved user engagement by 35%.	Real-time latency; integration with external APIs challenging.	Deploy on scalable cloud infrastructure; use streaming data frameworks.
10	S. T. Al Otaibi & M. Ykhlef, 2012	To survey and analyze job recommender systems across domains.	Literature review and taxonomy of job recommender approaches (content-based, collaborative, hybrid).	Review of 60+ recommender systems and datasets.	Highlighted key algorithms and evaluation metrics for job recommender design.	Outdated models; lacks coverage of recent AI/NLP methods.	Update survey with deep learning-based and transformer models for job matching.

RESEARCH GAPS AND CHALLENGES

Despite the advancements, several critical challenges and research gaps remain open in the field:

a. Algorithmic Bias and Fairness: A primary ethical concern is that AI systems can perpetuate or amplify historical biases present in the training data (e.g., favoring male-dominated terminology for certain roles) [2]. The lack of standardization in resume formats and the inherent complexity of deep learning models make bias detection and mitigation a persistent challenge [3][6].
b. Data Scarcity and Domain Specificity: Training sophisticated deep learning models requires large, high-quality, and richly annotated datasets [2]. Such domain-specific data is expensive and difficult to acquire, hindering generalization across different industries (e.g., healthcare versus finance) [1].
c. Lack of Standardization: The sheer variety of resume formats and linguistic expressions for the same skill set poses a challenge for consistently accurate parsing and NER [2]. Many systems struggle when documents contain complex layouts, graphics, or unusual section headings.
d. Model Explainability (XAI): AI systems are often perceived as "black boxes." For HR professionals, understanding why a candidate received a low score is essential for trust and accountability [2]. The

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

complexity of deep learning models makes providing clear, actionable explanations difficult, representing a significant barrier to widespread adoption.

FUTURE DIRECTIONS

Future research efforts in AI-powered resume analysis are focused on addressing the current limitations to create more robust, transparent, and globally equitable systems:

Integration of Explainable AI (XAI):

I. Developing visual and textual XAI modules that highlight the specific phrases or skills in a resume that led to a particular score or rank. This would improve user trust and provide actionable feedback to job seekers [2].

II. **Bias Mitigation and Fairness Metrics:**

Future systems must incorporate fairness-aware learning techniques and metrics (e.g., ensuring score consistency across different protected demographic groups) to actively remove learned bias from the models [3][6].

I. Advanced Multi model and Multilingual Processing: Expanding the capability to process non-textual elements (e.g., visual layout quality, use of images) and implementing robust support for multiple languages beyond English to create globally adaptable solutions [3].

II. Transfer Learning and Small-Data Techniques: Utilizing pre-trained large language models (LLMs) and focusing on few-shot or zero-shot learning to fine-tune systems effectively, even with limited, domain-specific labelled data [2].

III. Proactive Recommendation Systems:

Moving beyond simple matching to include features like skill gap identification and personalized course recommendations to help candidates proactively close their profile gaps, transforming the analyzer into a career guidance tool [4][6].

CONCLUSION

The AI-powered resume analyser and job matching system represents a transformative shift in the recruitment landscape, moving decisively away from subjective, manual processes towards data-driven, objective evaluation. Modern techniques leveraging Deep Learning and semantic similarity (BERT, SBERT) have provided unparalleled accuracy in contextual matching, far surpassing the limitations of traditional keyword-based methods (TF-IDF, SVM). However, the widespread adoption of this technology is contingent upon successfully navigating critical challenges related to algorithmic fairness, ensuring data diversity, and enhancing model explainability. Continued research into bias mitigation and XAI integration will be essential to ensure that future AI systems are not only efficient but also ethically sound and equitable, ultimately leading to better hiring outcomes for both organizations and candidates globally.

REFERENCES

1. Roy P.K, et al. (2020) “A Machine Learning Approach for Automation of Resume Recommendation System,” Procedia Computer Science, vol. 167, pp. 2318–2327.
2. Reedy K.S. and Kumar A.S. (2025) “Resume Screening System Using Natural Language Processing and Machine Learning,” Journal of Engineering Sciences, vol. 16, no. 6.
3. Sheikh S.M.S., et al. (2025) “AI-Powered Resume Ranking System: Enhancing Recruitment Efficiency through Natural Language Processing,” International Journal of Research Trends and Innovation, vol. 10, no. 5, May.
4. JayaPriya J., et al. (2025) “Smart AI Resume Analyzer,” International Journal of Scientific Research in Science, Engineering and Technology, vol. 12, no. 3, pp. 879–883.

ISSN No. 2454-6194 | DOI: 10.51584/IJRIAS |Volume X Issue XI November 2025

5. K.G.R. Dr., et al. (2024) “AI-Driven Resume and Company Screening for Optimized Candidate and Company Selection Process,” TIJER, vol. 11, no. 4, Apr.
6. Sathvik G.V.S., Harshavardhan D., and Premalath J.S. (2025) “Smart Resume Analyzer Using Machine Learning,” IOSR Journal of Computer Engineering, vol. 27, no. 1, pp. 32–40.
7. Raut P.G. and Wagh R.D. (2024) “Resume Analyzer and Recommender System Using Python,” International Journal of Research Publication and Reviews, vol. 5, no. 6, pp. 6245–6253, Jun.
8. Soni A., et al. (2024) “AI Resume Analyzer,” International Journal of Engineering Research and Technology, vol. 13, no. 1, Jan.
9. Kishore C.R. and Sreerala T. (2025) “Personalized Job Search with AI: A Recommendation System Integrating Real-3Time Data and Skill-Based Matching,” International Journal of Engineering Research and Technology, vol. 14.
10. Al Otaibi S.T. and Ykhlef M. (2012) “A Survey of Job Recommender Systems,” International Journal of Physical Sciences, vol. 7, pp. 5127–5142.
11. Breaugh J.A. (2009) “The Use of Biodata for Employee Selection: Past Research and Future Directions,” Human Resource Management Review, vol. 19, pp. 219–231.
12. Breiman L. (2001) “Random Forests,” Machine Learning, vol. 45, pp. 5–32.
13. Carrer-Neto W., et al. (2012) “Social Knowledge-Based Recommender System,” Expert Systems with Applications, vol. 39, pp. 10990–11000.
14. Celma O. (2010) “Music Recommendation,” in Music Recommendation and Discovery, Springer, pp. 43–85.
15. Wang D., Su J., and Yu H. (2020) “Feature Extraction and Analysis of Natural Language Processing for Deep Learning English Language,” IEEE Access, vol. 8, pp. 46335–46345.
16. Robey A., et al. (2019) “Personality Prediction System Through CV Analysis,” International Research Journal of Engineering and Technology (IRJET), vol. 6, no. 2, Feb.
17. Zhou Y. and Chen B. (2023) “Deep Learning Approaches for Job Matching and Skill-Based Recommendations,” Machine Learning in HR, vol. 18, no. 1, pp. 33–50.
18. Singh R. and Verma P. (2019) “The Future of Recruitment: AI-Based Job Matching,” Journal of Emerging Technologies in HR, vol. 10, no. 2, pp. 60–80.
19. Wang X. and Li Q. (2022) “A Comprehensive Review of NLP for Skill Extraction in Resume Screening,” AI & NLP Research, vol. 25, no. 5, pp. 90–110.
20. Becker S. and Müller K. (2021) “Challenges in Multilingual Resume Parsing Using NLP,” Journal of Computational Linguistics, vol. 28, no. 4, pp. 200–220.
21. Ahmed T. and Rahman S. (2023) “Using LLMs for Job Title Prediction: A New Approach,” AI in Employment Research, vol. 15, no. 2, pp. 140–160.
22. Lee H. and Kim D. (2020) “Limitations of Keyword-Based Job Matching Algorithms,” International Journal of HR Tech, vol. 30, no. 2, pp. 150–165.
23. Johnson L. (2021) “Leveraging Spacy for Named Entity Recognition in Resume Screening,” AI and NLP Review, vol. 7, no. 3, pp. 210–225.
24. Zhou Y. and Chen B. (2023) “Deep Learning Approaches for Job Matching and Skill-Based Recommendations,” Machine Learning in HR, vol. 18, no. 1, pp. 33–50.
25. Singh R. and Verma P. (2019) “The Future of Recruitment: AI-Based Job Matching,” Journal of Emerging Technologies in HR, vol. 10, no. 2, pp. 60–80.
26. Wang X. and Li Q. (2022) “A Comprehensive Review of NLP for Skill Extraction in Resume Screening,” AI & NLP Research, vol. 25, no. 5, pp. 90–110.
27. Becker S. and Müller K. (2021) “Challenges in Multilingual Resume Parsing Using NLP,” Journal of Computational Linguistics, vol. 28, no. 4, pp. 200–220.
28. Ma Z., Wang Y., and Zhao Y. (2021) “Automated Resume Screening with Semantic Similarity and Gradient Boosting,” in Proceedings of the 2021 3rd International Conference on Cybernetics, Robotics and Control, 2021.
29. Mandviwalla M. and Kappelman L.A. (2021) “Automated Resume Screening Using Semantic Similarity and Machine Learning,” Journal of Information Systems Education, vol. 32, no. 1.
30. Natarajan R. and Rajaraman V. (2021) “Resume Analysis and Matching Using NLP Techniques,” in Proceedings of the 2021 International Conference on Smart Intelligent Computing and Applications (ICSICA), 2021.