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ResuMatch: AI-Powered Resume-Job Description Matching System

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***Abstract*—The goal of ResuMatch is to introduce a modern, fair, and intelligent recruitment support system that automates the process of mapping candidate resumes to job descriptions using advanced artificial intelligence techniques. The system focuses on improving hiring accuracy while reducing the man- ual screening effort typically performed by HR professionals. It leverages semantic text representation models, section-wise resume extraction logic, and weighted matching algorithms that compare skills, experience, and qualifications against role-specific requirements. Unlike traditional keyword-based screening, ResuMatch performs contextual interpretation to identify relevant competencies even when presented using different wording styles.**

A core emphasis of this work is on transparency, interpretability, and unbiased evaluation. The system produces structured match outputs, including similarity scores, critical skill gaps, and categorized strengths, supporting objective decision-making for recruiters. Furthermore, candidates benefit from improvement-oriented feedback, enabling them to refine their resumes and enhance eligibility for future opportunities. The implementation pipeline integrates automated text extraction, NLP-based normalization, vector embedding generation, scoring logic, and visual dashboards for HR users and academic placement cells.

ResuMatch includes robust preprocessing, domain-wise skill mapping, relevance weighting strategies, and evaluation of matching consistency across varied resume formats. The system is deployed through an interactive interface that displays section-wise match insights, missing technical areas, and role-fit recommendations. By combining intelligent matching, transparency, and user-focused interpretability, ResuMatch offers a practical AI-based hiring framework that enhances decision reliability, reduces bias, and redefines modern resume-job alignment workflows.

***Index Terms*—AI resume matching, hiring automation, NLP, matching algorithm, skill extraction**

I. Introduction

The way companies hire has changed quickly from manually checking resumes to using automated, data-driven systems. This change happened because there are more job applicants than ever before, and the skills needed for jobs keep changing all the time. In the past, recruiters made decisions based on their own opinions and by looking for certain keywords in resumes. This often led to inconsistent decisions, personal biases, slower hiring processes, and missing out on talented people [1][2]. As more job boards and online platforms emerged, companies started getting hundreds or even thousands of applications for a single job, making the old way of screening nearly impossible [3].

Recent research shows that just matching keywords isn't enough to determine how well a resume fits a job because similar skills can be expressed in different ways. For example, phrases like “developed backend services” and “implemented REST API modules” have the same meaning, but traditional systems can't recognize that. Now, modern approaches rely more on understanding the meaning behind the words, the context in which they're used, and mapping skills rather than just matching words [4][5].

Artificial Intelligence (AI) is now a key tool in smart hiring. It uses natural language processing, document representation through embeddings, and similarity calculations to match candidates and jobs better. AI-powered systems can automatically extract information from resumes, identify job requirements, measure experience levels, and assign scores to show how well a candidate fits the role [8][9]. These systems help make hiring decisions more accurate, reduce manual work, and ensure more consistent results [10].

Although current studies have developed resume-parsing techniques, semantic similarity models, and ranking algorithms, many systems still lack transparency, skill-gap reporting, and clear explanations for both recruiters and job seekers [11][12]. There are also ongoing concerns about fairness in automated hiring, as biases based on demographics or unfair ranking patterns can affect outcomes [13]. Research shows that using explainable evaluation methods, fair scoring, and neutral skill prioritization can help reduce these issues [14][15].

ResuMatch is an AI-based system designed to address these challenges. It extracts structured information from re- sumes, simplifies job requirements, and calculates similar- ity based on skills, experience, education, and the meaning behind the words. It helps identify a candidate's strengths, missing skills, and actionable recommendations, leading to more transparent and understandable hiring decisions, unlike basic filters [16][17]. ResuMatch works through a detailed process that includes text preprocessing, natural language processing, embedding-based similarity evaluation, and visual tools tailored for HR professionals, academic institutions, and consulting firms [18].

This study presents a system that improves the hiring process by making it more efficient, supporting unbiased evaluations, and raising awareness about the challenges in job seeking. The use of AI-driven profiling and contextual document matching, as demonstrated by ResuMatch, helps modernize the hiring cycle, reduce screening time, and make recruitment decisions more rational in real-world settings [19][20]. This research provides an in-depth overview of the existing literature, methodology, implementation, evaluation results, and possible future developments in scalable recruit- ment intelligence.

II. LITERATURE REVIEW

This part presents the existing work concerning AI-assisted recruitment, resume parsing, semantic job–candidate matching, fairness in automated hiring, and recommendation-oriented systems that offer feedback to applicants. The purpose of this study is to identify the problems that ResuMatch intends to solve by positioning it among other studies and pinpointing the gaps.

A. Traditional Resume Screening and ATS Systems

Normal hiring procedures are largely based on manual resume reading which is facilitated by primitive Applicant Tracking Systems (ATS) that conduct keyword-based filtering. Research reveals that pure keyword matching is a very weak method; one can easily manipulate it by just throwing keywords into resumes and it often does not work if the same skill is described with different words [1][2]. The first ATS instruments were concentrating on the surface-level features like whether certain skills, degree names, or years of experience were mentioned without taking into account the context [3].

Moreover, research suggests that recruitment processes involving a large volume of applicants, for example, campus drives or major job portals, are a source of overburden for recruiters and thus, human decision-makers. Consequently, fatigue, inconsistency, and time pressure in decision-making occur [1][4]. The manual screening process tends to select applicants with well-organized resumes and trusted educational backgrounds rather than objectively assessing skills, which leads to lost talents and poor explainability for denied candidates [5]. These constraints served as an incentive to transition to AI-powered resume comprehension and semantic matching.

B. Resume Parsing and Information Extraction

The most important condition of automated matching is the accurate conversion of unstructured resumes into structured data. The majority of works propose rule-based parsing, template-specific extraction, and section detection using handcrafted heuristics [2][6]. Although these methods yield decent performance on standardized formats, they have problems with various resume layouts, font mixing, and artistic designs.

Therefore, the current studies employ Natural Language Processing (NLP) and machine learning to divide resumes into semantically meaningful sections such as Skills, Experience, Education, Projects, and Certifications [2][7]. The models trained on a large corpus of resumes increase the performance of the extraction of job titles, organizations, dates, and skill entities [3][8]. For instance, some systems like Resume2Vec-style architectures, which are parsed, transform the resumes into vector representations that can be referred to by downstream matching models [3].

However, a lot of these methods either have a consistent structure as a premise or concentrate solely on extraction precision without taking into account the integration of end-to-end matching, interpretability, or feedback generation [6][9]. This is the reason behind the use of an integrated pipeline in ResuMatch, which is tightly coupled with parsing, representation as well as matching.

C. Job Description Understanding and Semantic Matching

Job descriptions (JDs) are the sources of information about the required skills, tasks, tools, and experience levels. Early methods considered JDs as mere collections of keywords and compared them to resumes through term frequency or TF–IDF scoring [4]. Such procedures do not consider semantics and thus, they punish candidates whose resumes contain different but semantically related terms.

The most recent publications prove significant gains in job–resume matching performance when using embedding- based representations. Semantic resume–job matching work is based on models such as BERT, sentence transformers, or domain-specific embeddings that help reveal deeper relationships between text spans [3][10]. By using these methods, both resumes and JDs are transformed into dense vectors from which similarity can be inferred by using cosine or other related measures, thereby making it possible to identify conceptual proximity such as “backend development” and “REST API implementation” even if the actual words are not similar [4][11].

Hybrid systems combine explicit skill extraction with embedding-based similarity to achieve a trade-off between interpretability and performance [7][12]. Several studies suggest that similarity can be differently weighted across various dimensions like skills, experience, education, and domain alignment rather than having just one single score without any differentiation [10][13]. ResuMatch is in line with this research by employing a weighted scoring technique that is performed over semantic representations of resume and JD sections.

D. Job Recommendation and Candidate Ranking Systems

Research work point out the employment of ranking and recommendation models for linking candidates with suitable job roles through embedding based similarity and hybrid scoring strategies [9][10]. Certain methods rank candidates based on a single suitability score or learning to rank models to estimate match likelihood and interview fit [11]. Nevertheless, the majority of these systems offer scant interpretability and do not explicitly provide reasons for the ranking results, thus the recruiters are left wondering why particular profiles are ranked higher [12]. ResuMatch solves this problem by delivering score decomposition and reason based matching to facilitate openness.

E. Fairness, Bias, and Ethical Issues in Hiring Systems

Automating recruitment raises the issue of algorithmic bias, in particular, when models reflect patterns from historical hiring data [1][13]. Research works underline the importance of neutral feature selection, fairness metrics, and explainable evaluation criteria as means to avert discriminatory decisions [14]. While many solutions accept the problem of fairness, implementing systems that explicitly provide features to disclose or alleviate the hidden bias is scarce [17]. ResuMatch addresses the problem by concentrating on skill specific signals instead of demographic features and by revealing the evaluation components.

F. Skill Gap Awareness and Feedback Oriented Systems

Current publications argue that recruitment systems have to reveal the lack of competencies so that applicants can work on their readiness for the job [12][19]. The frameworks for gap identification can be utilized for training recommenda- tions, course suggestions, or project based development [18]. ResuMatch is moving along the same path; it announces the missing skills, matched strengths, and offers improvement guidance instead of merely filtering candidates.

G. Summary of Research Gaps

The literature review has uncovered significant gaps that lead to the omission of:

- The lack of systems that integrate end to end parsing, semantic matching, and structured insights [8][11].
- The decision making process in ranking is hardly transparent, which reduces the trust of both applicants and recruiters into the decisions made [12][17].
- Very few implementations of candidate centric evaluation are available, thus most of the feedback given is rejection only [18][19].

ResuMatch plays a role by bringing together semantic similarity, weighted scoring, explainability, and improvement oriented features into one comprehensive framework.

H. Resume Format Variability

Open research points out that the main factors causing lower resume parsing accuracy are those very aspects that differently formatted resumes have: different kinds of formatting, non standard section ordering, and different linguistic expressions of candidates. In contrast to the tightly organized technical docs, resumes are usually decorated with creative ways of presenting info, such as multiple columns, icons, tables, and templated designs, which all contribute to the limited efficiency of rule based ATS parsing techniques [4][6][9]. Studies show that it is quite common for the company to find the information relating to certification, project description, or domain expertise typically hidden in the narrative sentences, thus it becomes very difficult to extract them by means of keyword based heuristics [10][11]. In consequence, these problems were solved only by the semantic encoders and contextual segmentation that understand the content rather than depending on the position or format [14][15]. ResuMatch is moving in the same way by leveraging section wise similarity scoring and context aware extraction, thus providing accurate retrieval even when resumes are not in a standard structure.

III. Proposed Methodology

The proposed methodology automates how candidate resumes are matched with job descriptions by aligning through structured extraction, semantic representation, and weighted matching. Four major stages make up the entire pipeline: resume processing, job description processing, embedding based representation, and suitability score computation.

A. System Overview

The process starts with the intake of candidate resumes along with a job description. Unlike traditional ATS systems that depend on the presence of keywords, the suggested method relies on semantic understanding and, thus, concep- tually similar terms still yield relevant matches. Moreover, the system also determines a strength and weakness breakdown, thereby making it easier to both recruiters and applicants for the interpretation process.

B. *Resume Processing*

The resumes that are uploaded undergo the conversion process from PDF or DOCX to plain text. Then the texts go through the normalization that includes formatting removal, stop word filtering, section identification, and token refining. The approach recognizes segments like Skills, Experience, Education, and Projects by using contextual patterns as opposed to fixed templates. The identified entities are recorded in structured fields to facilitate standardized comparison of various resume formats.

C. *Job Description Processing*

Similar to the resume pipeline, the job description goes through the same NLP process to get the skills, tools, experience level, and qualifications required for the position. To interpret implicit requirements, the system also does some extra contextual mapping. For instance, ”backend development” is linked with API handling, server side logic, and database interaction. This helps ensure that partial or indirect statements are taken into account during matching.

D. *Embedding Based Document Representation*

In order to compare the resume and the job description in a substantial manner, both documents are transformed into dense vector representations. Embeddings capture semantic relationships and reduce linguistic variation. The embeddings for the different sections are obtained for skills, experience, and education, thus each dimension can be assessed separately rather than collectively. This leads to a deeper level of the match than a single score lexical similarity can provide.

E. *Multi Criteria Scoring Model*

A weighted scoring model is used to compute the overall suitability score. Each part is assessed separately and then combined:

- **S**kill Match Score
- **E**xperience Match Score
- **E**ducation Match Score
- **K**eyword/Role Score

The skill relevance gets the top weight, then the experience is weighted, thus ensuring that competency is still the main factor for the recommendations rather than just the way the information is presented.

F. *Output Generation*

The final phase yields three different output types:

- Overall match percentage
- Matched vs. missing skills
- Section wise scoring summary

On top of that, candidates get gap based suggestions like lacking certain tools, having an old tech stack, or not being sufficiently exposed to a domain which help them get better instead of just being turned down.

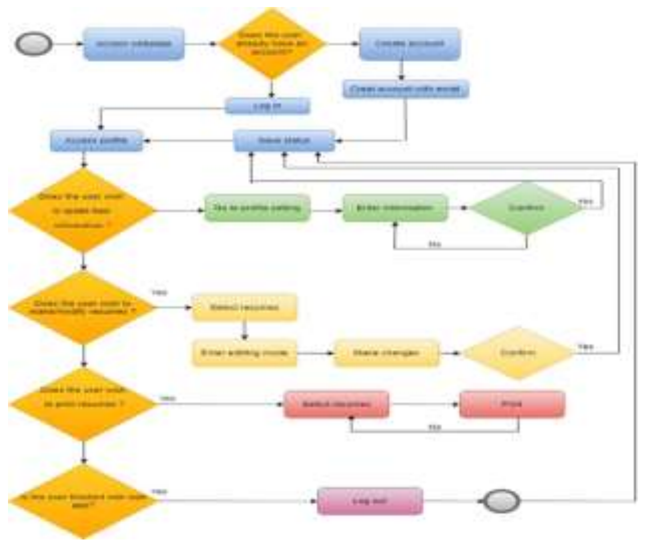

Fig. 1. User interaction and workflow process of the Resume-Job Matching System

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IV. CONCLUSION

This paper introduced ResuMatch, a AI powered system aimed at the automation and enhancement of resume job description matching. By adopting structured resume extraction, semantic comparison, and weighted scoring, the system goes beyond the constraints of manual screening and traditional keyword based methods. The model, through vector based similarity, figures out the real connection between two documents instead of just looking at the surface level overlap of keywords, thus allowing for the evaluation of candidates to be not only more accurate but also fairer.

ResuMatch explains the reason for the ranking in a very transparent way by pointing out the matched skills, the missing ones, and the experience that is in line. Apart from recruiters, applicants also get a lot of benefits as they receive clear and practical insights on how to increase their fit for the future roles. The experimental results showed that the screening process was done at a faster pace, there was more consistency in ranking, and the subjective evaluation was lessened.

Subsequent improvements may involve support for resumes in different languages, integration with ATS, and the creation of adaptive feedback modules. In brief, ResuMatch is a good example of how AI powered assessment tools can lead to greater trust, accuracy, and speed in the recruitment processes of today.

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