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An AI-Driven Resume Parsing And Ranking System Using Natural Language Processing For Automated Talent Shortlisting

A Structured NLP and NER-Based Framework for Fair, Explainable, and Scalable Recruitment Automation

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Abstract: The existing system for screening and ranking resumes is done manually in which recruiters rank resumes based on their company policies. It is not only time-consuming but also prone to human error and often influenced by biased opinions. Automated-resume screening has grown in popularity as it is more efficient and accurate. The main goal of this system is to help recruiters and job-seekers to recruit and get recruited, respectively. Not only we develop our system that does what traditional AI-based resume rankers do but also gives valuable insights and detailed analysis of our users that could improve their resumes ultimately making them more deserving candidates for that job position.

Keywords: Intelligence, Machine Learning, Resume Parse, Weighting Filter, RegEx, NLP

I. INTRODUCTION

It's often hard for recruiters to compare different candidates fairly, especially when each person has a different background, resume format, and way of showing their experience. This can make it difficult to choose the right person for the job. To solve this, the system compares candidates based on three main things: their experience, education, and skills and achievements. It checks how well a candidate's background matches the job by looking at their past roles, degrees, and the skills they've picked up over time. It doesn't just look at what they've done, but also how relevant and useful their experience is. The system also gives extra attention to things like certifications, career growth, and how well a person might fit into the company's culture. Overall, it helps pick the best candidates by giving a clear and fair comparison across all the important areas.

II. OBJECTIVES

The goal is to create an AI-based resume ranking system that differentiate the candidate on the basis of the candidate's education, technical skills, skills compared to job requirements and experience in the industry. Having a simple user-friendly interface for complex procedures and being an effective and accurate bridge between rightful candidates and recruiters are the main objectives.

II.A PROBLEM DEFINITION AND CONTRIBUTIONS

This study investigates the need to eliminate bias and inconsistencies in the automatic estimation and ordering of applicants' resumes (as a group), according to job descriptions as defined by the hiring organizations, and be able to do this at a large scale. The group of resumes is represented by the symbol R, and contains n candidate resumes (i.e., r1, r2, ..., rn). The job description is represented by the letter J, and is a structured representation of all the required and preferred skills, the minimum education, and the minimum experience needed for the job. The goal of the system proposed in this project is to generate a rank for each resume (i.e., S(ri, J)), with the candidates who are the most closely matching the job description (as per current market expectations) being given a higher ranking than those candidates that are less closely matched. Additionally, the system will provide recruiters and candidates with detailed analytical reports about their respective strengths and weaknesses, as well as possible career development paths.

This document highlights the main contributions of this project, with three major areas of impact. First, we have established an end-to-end Natural Language Processing (NLP) and Named Entity Recognition (NER) based method for extracting relevant information from resumes written in semi-structured formats. We are able to identify key pieces of information (entities) such as SKILLS, EDUCATION, and EXPERIENCE, and convert them into a common standard for use in automated analysis. Secondly, the system provides recruiters and candidates with two different types of Skills Reports: a Comparison Skills Report compares the candidate's SKILLS to those outlined in the specific Job Description, while an In-Demand Skills Report compares the candidate's SKILLS to those currently being sought by employers throughout the job market in order to give both the recruiter and candidate a better understanding of where they sit relative to the rest of the market. Thirdly, the project proposes a Configurable Scoring Model that combines Skill Match Score, Experience Match Score, Education Match Score, and Cultural Fit Score into an Overall Match Score using tunable weights that allow the recruiter to adjust how the Overall Match Score ranks candidates relative to their organizational goals. Finally, we address the Fairness and Ethical implications of using Artificial Intelligence (AI) to screen candidates; specifically we address the exclusion of sensitive demographic identifiers, the potential for bias in the underlying training data, and the importance of Maintaining Transparency and Conducting Periodic Audits of algorithmic behaviour.

III. LITERATURE REVIEW

1. Smart Resume Parser and Analyzer Using AI

(2024) introduces an Ai-based Resume Parser Analyzer designed for the recruitment process by automating resume screening, extracting essential information, and providing feedback.

The main purpose of this tool is to increase the accuracy of the candidate filtering process compared to traditional screening methods. The system integrates Named Entity Recognition, Regular Expression Matching, and Structured Resume Parsing to provide coverage for various formats and layouts of resumes.

This AI resume parsing tool also provides feedback to the candidates by identifying skills on their resume that are missing or can be added, which will allow recruiters and candidates to be more informed when making a decision.

2. Resume Parsing Framework for E-recruitment

Sajid et al. (2022) introduced a resume parsing framework designed to overcome hindrances associated with the extensive range of resume formats encountered in the electronic recruitment system. Traditional methods such as rule-based and supervised techniques struggle to differentiate font styles, colours and layout structures. These inaccuracies hinder the effective data mining, particularly in extracting crucial and relevant information and ranking applicants. To address these issues Named entity recognition (NER) framework is used to extract critical data.

The authors propose to use an ontology to enhance the skill extraction process by clustering related competencies and thus improving the downstream matching and ranking of candidates. The authors of this project concluded that the extraction quality of resumes is much greater with a layout-aware parsing process than when it is conducted using a rule-based approach alone. The authors also indicated that this enhanced quality of extraction is particularly beneficial when processing resumes that have complex layouts.

3. Procedural Justice and Fairness in Automated Resume Parsers

(2023) highlighted the ethical concerns around bias in resume parsing systems. Their study explores the candidates' perspectives on fairness, equality, and transparency in AI-based resume screening. They find that while AI can reduce human bias, it often lacks fairness for minority groups. The authors propose guidelines for enhancing fairness and inclusivity in these systems.

Recent research on AI-powered ranking systems for resumes has included the use of Natural Language Processing (NLP) and machine learning (ML) to determine the matching score between resumes and job descriptions based on semantic similarity, as opposed to solely on matching keyword counts. These resume ranking systems use vector representations of a candidate's resume and a job description to find matching candidates, presenting the list of ranked candidates to recruiters. To evaluate this type of ranking, researchers use the following metrics: precision, recall, F1-score, and precision@k, and they find that AI-powered ranking systems significantly reduce manual effort while improving the quality of shortlisted candidates.

4. Resume Analyzer and Recommender System Using Python

An AI-driven tool to automate and enhance resume evaluation using NLP and machine learning. It extracts, analyzes and ranks candidate information based on predefined job criteria through a user-friendly Streamlit interface.

Deep learning methods of developing frameworks for resume parsing (such as DeepResume), and hybrid transformer-based approaches to resume parsing, have combined traditional Named Entity Recognition (NER) and Transformer models (such as BERT, SBERT, and DeBERTa) with the use of NLP processing pipelines to offer layout-aware segmentation and more advanced methods of entity extraction for parsing resumes. These types of systems have increased the ability to identify complex relationships in resumes, such as those involving multi-sentence experiences and those containing multiple skills. The experimental results show that hybrid systems offer at least a twofold increase in extracting accuracy for most entity types (e.g., skills, education, and employment history) compared to using only classical NER and regular expression methods.

5. Raising Questions of AI-Driven Resume Screening's Fairness, Transparency, and Bias

Several studies have explored issues of fairness and transparency in AI-based resume screening, pointing out that models developed on historical hiring data may be vulnerable to perpetuating or amplifying already existing demographic bias. Researchers have recommended the use of bias-aware machine learning techniques as well as developing fairness metrics such as demographic parity and equal opportunity to assess the impact of AI systems on various groups and recommend conducting regular audits of the impact of AI-driven resume screening on minority groups. Also recommended are establishing policy and procedures that exclude the use of sensitive characteristics.

IV. METHODOLOGY

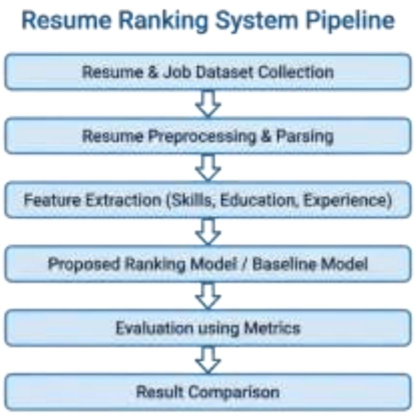

Figure 1 illustrates the overall experimental workflow of the proposed AI-based resume ranking system, from dataset collection to performance evaluation.

A. System Architecture

The proposed system will use a modular pipeline to convert raw resumes into ranked candidate lists and analytical reports based on a Job Description. The pipeline includes multiple steps: Document ingestion, Text extraction & Cleaning, Entity recognition & Normalization, Feature Engineering, Scoring & Ranking and Report Generation. At a high level, all candidate resumes (in formats including PDF & Word) will be submitted by the candidate or collected via external sources. These resumes will subsequently be run through the pipeline to create a structured profile of the candidate (through the use of structured data) and a score for the recruiter to interpret. The Document Ingestion section receives candidate resumes from multiple sources (i.e. job portals, email submissions, and applicant tracking systems). The File Handling module checks the source of each file for the proper file type, removes any corrupted files, and passes all valid resumes into the queue to be processed. Text Extraction uses the appropriate parser for each file type to extract plain text from PDF and Word format resumes, preserving as much of the resume structure as possible (i.e. the major headings and bullet points). Once the plain text has been extracted from each resume, the text is normalized to prepare it for further analysis in the pipeline. The normalization process will include; converting the text to lower case, removing all boilerplate content, tokenizing the text, and segmenting the text into sentence structures (i.e. identifying the beginning and end of a sentence). After the Document Ingestion and Text Extraction phases are complete, the extracted and cleaned resumes will be passed to the Entity Recognition and Normalization phases for extraction of Semantics and Structure.

1. Data Collection

The data collection process for Ai-resume links to various materials, including online job boards and career platforms, professional networking platforms, applicant tracking systems (ATS), and other online resources. The resumes are collected in various formats such as pdf, microsoft word, plain text file, portfolio, etc; depending on the job requirements and applicant's personal preferences.

2. Data Extraction and Analysis

The system processes resumes in pdf format, transforming them into structured text format. Named Entity Recognition (NER) model identifies and classifies entities such as name, CGPA, location, skills, etc.

2.1. NLP and NER Pipeline

The entity recognition and extraction (NER) of unstructured resume text converts it into structured resume fields. An NER model will either be pre-trained or fine-tuned for this purpose. NER models identify entities: Candidate Name, Candidates Contact Information (Phone# etc.), Academic Degree(s), School(s), Date(s), Job Title(s), Company(ies), Skill Phrase(s), etc. The normalized text is processed through the NER model, which assigns entity labels to tokens in the normalized text, and aggregates together these entity labels into large segments representing Education Entry(ies), Work Experience(s), and Skills Listings. This allows the information extracted from the resumes to be disaggregated into separate segments, thus eliminating the need for formatting assistance or manual templates to separate out the different semantic sections of the resume. After entity detection occurs, there is a normalization step to standardize the extracted information. All Skill Phrases are mapped to a Controlled Vocabulary/Skills Ontology so that any semantically similar skills (ex. "C-language","C-programming","C dev") are treated as one canonical skill. Job Titles are mapped to Normalized Role Categories and Seniority Levels, and Degree Names are Mapped to Standard Levels such as Diploma, Bachelor's, Master's, Doctorate. Dates are parsed, extracted, and stored as Structured-TimeStamps so experience duration can be calculated. By normalizing, sparsity is decreased, improved accuracy of matching occurs, and consistent scoring can be accomplished when candidates are being evaluated using various job profile types.

2.2. Feature Engineering

During the feature engineering step, a variety of features will be created for each candidate's resume and the job post(s) they apply for using a combination of the normalised entities for each element. These features include: an identification of overlapping skills between the candidate(s)' resume(s) and employer(s)' post; a list of required skills from the job post that is missing from the candidates' resumes; a count of the preferred skills the candidates that can be seen in their resumes; and a total number of years of relevant work experience across multiple organisations. The above-mentioned aggregation of work history will allow for the identification of how many years the candidate has been working in their respective field, by grouping multiple work experience entities by date of employment (start date and end date) and determining if the corresponding job description, job title matches the field/industry that the candidate is being applied for. In addition to these items, other measurable education elements can include the highest degree of education held, the field of study and whether or not the candidate meets/exceeds any minimum academic degree requirements for the job. Information that demonstrates cultural fit, behaviour fit, or any other signals relevant to behaviour could also be recorded as features. For example, stable work history may be reflected in the average length of time held in each position, while a candidate demonstrating rapid advancement may have been promoted within the same company, or have moved from a junior (entry) position to a senior position. Lastly, sections of the resumes that are free-form text (e.g., career objectives, summaries, project descriptions) may be examined for the presence of keywords or sentiments that reflect a connection to the value of the Company, or the soft skill attributes required to perform successfully in the job. All of these features will be combined into a structured feature vector to be used with the scoring model.

3. Evaluation

The evaluation process uses a detailed and well-rounded scoring method to review and sort resumes based on several important factors. At the core of this system is the Overall Match Score, which is calculated by combining scores from four key areas: Skill Match Score (how well the resume matches the required and preferred skills), Experience Match Score (how relevant the past work experience is), Education Match Score (the type and level of education), and Cultural Fit Score (how well the candidate's values align with the company's). Based on this overall score, resumes are grouped into three categories: High Match (score above 80% with strong alignment), Moderate Match (score between 60% and 80% with a mix of strengths and areas for improvement), and Low Match (score below 60% with major gaps).

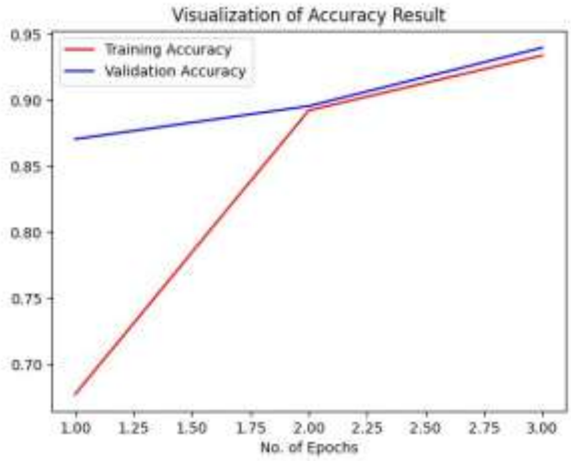

Fig. 2 illustrates the convergence behavior of the proposed model during training. The steady increase and close alignment of training and validation accuracy indicate effective learning and limited overfitting.

The system carefully reviews important aspects such as how skilled and relevant the candidate is for the role, how their career has progressed, how stable their job history is, how well their industry background fits the job, how compatible they are with the company culture, and how their skills meet current market needs. The evaluation produces clear match reports, analyzes the candidate's career path, highlights any skill gaps, offers suggestions for growth, and even explores other possible career directions. This approach ensures a complete and fair review of every resume, giving useful insights to both job seekers and employers.

3.1. Scoring and Ranking Model

There are four components in the scoring model that help recruiters decide if a candidate is suitable for the job: Skill Match Score, Experience Match Score, Education Match Score and Cultural Fit Score.

The Skill Match Score is based on how many of the candidate's skills match those listed in the job description. This includes normalising each candidate's skills and weighing the skills based on importance.

The Experience Match Score takes into consideration both the length of time the candidate has been working in similar positions and how relevant their previous work experience is to the position for which they are applying. Candidates with superior experience in a similar field will receive a high score while candidates who have long periods of inactivity or worked in jobs for only short amounts of time will receive lower scores.

Candidates are checked for minimum educational requirements, and additional educational credits can be given for advanced degrees or degrees that are particularly related to the occupation for which they are applying.

The Cultural Fit Score assesses how closely the candidate's career path, goals, and interests are to the mission and values of the company and the responsibilities of the job. The Overall Match Score is derived from the four scores listed above. This overall score is created by summing the subscores from above while taking into account the recruiters or company values for weighting. For example, a recruiter may choose to place a heavier emphasis on the Skill Match Score for highly specialised technical positions and a heavier emphasis on the Experience Match Score and Cultural Fit Score for leadership positions.

Once all of the job applicants have been evaluated and their Overall Match Scores computed, the resumes will be graded in descending order based on their respective scores, and this ranking will assist in creating the final list of shortlisted candidates. In addition, the rating of each applicant will be used to help explain the recruiter's decision-making process and to help candidates understand how each of the subscores contributed to the final match score.

3.2. Market-Trend Analysis and Reporting

In order to match candidates with specific jobs, we include a market trend analysis component in the system that allows us to compare the skills of candidates against real-time or periodically updated labor market data. This allows us to leverage aggregated statistics from both job postings and external Application Programming Interfaces (APIs) to identify which skills are currently in demand for a specific job title, technology stack, or geographic area. The system produces a Market Alignment Score for each candidate, which indicates how many of the trending skills are included in their recent projects or positions; thus allowing us to gauge not just the candidate's suitability for the open position but also their long-term potential in an overall job market. In addition, there is a Reporting Module that produces human-readable output for recruiters and candidates. The recruiter receives a Dashboard with their top-ranked candidates, a breakdown of respective candidate sub-scores and any critical missing skills or exceptional strengths as justification for their ranking. The candidate receives personalized feedback including their Overall Match Score and a summary of their strengths in specific skill, experience, education categories, and specific suggestions on how to either improve upon or acquire skills in demand; thus helping the candidate to transform the raw scores into actionable insights that make the system useful and transparent to real-world recruitment processes.

V. RESULTS AND DISCUSSIONS

To evaluate the efficacy of the given proposed system, a set of experiments are conducted on a collection of anonymized resumes and job descriptions from various technical domains. The dataset consists of multiple job postings, from software developer to network engineer roles, all associated with a pool of candidate resumes which were originally considered for those positions. Sensitive information including names, contact details, and precise organizations can be masked or replaced with neutral placeholders, which ensures that the evaluation is more focused on job-related attributes. A group of human recruiters or subject-matter experts can be asked to assign relevant labels or rankings to each candidate for a role, and these serve as a ground truth for measuring system performance.

The proposed method can be compared against baseline approaches that represent common practice in automated screenings. A simple keyword corresponding baseline might compute a score based mainly on the calculation of overlapping n-grams between resume and the job description, without sophisticated entity recognition or normalization. A stronger baseline can use TF-IDF vectorization for both resumes and job descriptions and the apply cosine similarity to estimate the relevance. The proposed framework, in contrast, leverages structured features extracted by NER and calculates interpretable subscores for skills, experience, and education. For each method, the standard classification and ranking metrics can be calculated, in particular, the precision, recall, F1-score, accuracy on the top selected candidates, and average precision, using the human annotations as a reference.

Experimental results can be recorded in tabular form, showing the performance across multiple job roles and evaluation metrics. Ordinarily, systems that incorporate structured entity-level information excel purely keyword-based baselines in identifying the most eligible candidates, especially when the resumes are heterogeneous in format and text. For instance, the proposed approach can be expected to display higher precision, meaning that a larger fraction of the highly ranked candidates are judged relevant by human experts, also while achieving better recall by missing fewer strong candidates. The decomposition into subscores also permits qualitative analysis: for some candidates, excellent skill matching, but weak education or limited experience may explain their position in the ranked list, providing a clear rationale that is often absent in black-box similar models.

Beyond overall accuracy, the experiments can investigate robustness and generalization. One study can test how the model behaves when resumes are rearranged, re-formatted, or contain missing sections, illustrating the advantage of NER-based extraction over brittle rule-based parsing. Another study can examine cross-domain generalization, training the scoring parameters on one job family and evaluating on another to observe whether the system remains reliable when skill and terminology distribution shift. These experiments help position the suggested system as a practical and extensible tool for real-world recruitment scenarios rather than one-off rule scripts.

VI. FUTURE SCOPE

The AI-powered resume ranking system offers enormous potential for future development to enhance the efficiency, fairness, and personalization of hiring. Some of these promising avenues include:

Incorporation with Real-Time Job Market Trends

Future releases can refresh skill requirements and industry trends through API integration with platforms such as LinkedIn or Glassdoor. This would enable candidate suggestions to be personalized in response to real-time market needs.

Inclusion of Multilingual Resumes

Expanding the parser to deal with resumes in various languages will bring the system within reach of a global user population and enhance diversity in international hiring practices.

AI-Powered Interview Readiness Scoring

The platform can be enhanced to determine a candidate's interview preparedness based on tone, wordings, and relevance of projects from their resume, providing advice and recommended areas of improvement.

Bias Detection and Ethical Auditing

Incorporating modules to identify and counteract algorithmic bias would provide more fairness and inclusivity, consistent with recruiting AI ethics.

Gamification and Personalized Recommendations

For candidates, the site may include gamified feedback (such as skill badges) and personalized career suggestions based on resume analysis and trajectory prediction.

Integration with ATS and HRM Platforms

Smooth integration with Human Resource Management (HRM) and Applicant Tracking Systems (ATS) would make the workflow process smoother for big businesses.

Improved Cultural Fit Analysis with NLP

Enlarging cultural fit measures through advanced value- and sentiment-based keyword analysis could even better identify candidate-employer matching.

Resume Quality Enhancer Tool

Including an automated module that not only analyzes but assists in rewriting and optimizing resumes based on job positions would be useful to job applicants.

VII. FAIRNESS, ETHICAL CONSIDERATIONS, AND LIMITATIONS

AI systems that read résumés and decide who gets an interview raise serious questions about who is treated fairly, how the process is explained plus who is answerable when something goes wrong. Those systems decide who is placed on the shortlist, who receives a job offer and who moves up the career ladder - they must be used in a way that meets basic ethical standards.

Recruiting systems based on AI raise issues about transparency, accountability, and fairness, particularly when they are used to make significant decisions like hiring and promotions. When considering fairness in our proposed method, we used only features that were related to the job (e.g., skills, education, and experience) and did not include demographic variables (e.g., gender, age, ethnicity, and marital status). To also avoid using sensitive proxy variables (e.g., first names or pictures) or location information unless it was directly job-related, we made the design decision to restrict the input data to relevant job-related attributes. The goal of this design choice is to minimize the potential for repeated systematic discrimination and to encourage that selections are based primarily on qualification and merit.

However, while sensitive attributes are excluded from the input level, the potential still exists for bias in the system, due in part to historical data and job descriptions. For example, if the resumes used for tuning or validating the system are predominantly from one group of applicants, then the learned scoring behavior will reflect that group. Therefore, organizations using AI recruiting systems should regularly conduct fairness audits, where the selection rates, false positive and false negative rates across different demographic groups are compared using fairness metrics, such as demographic parity or equal opportunity, and these audits should occur where there is sufficient demographic data to facilitate the audit under the appropriate privacy and legal requirements. For organizations that detect disparities in these audits, mitigation measures may include re-weighting samples, adjusting decision thresholds, or employing fairness-aware learning objectives.

Trust between employers and job applicants can be developed by both parties knowing that employers will be able to assess them based on relevant skills and experience. The software generates an interpreted set of recommendations for each applicant based on their skills and experience, and uses that information in the applicant's report on their overall match to the job description. The applicant's report will include details about missing required skills and experience components and which skills and components contributed to their overall match score. Recruiters will verify that the applicant's report matches their expectations when they receive back recommendations generated by the software. The applicants will be given feedback about how to strengthen or adjust their qualifications for better alignment with job requirements and better match to the recruiter's expectations.

There are limits to this method of using the system to screen job applicants. Factors such as the availability of high-quality resumes, the type of job for which the applicant is applying, and the type of skills and experience required by the job are critical to the performance of the system; if the applicant's resume is sparse or poorly formatted, it may not be parsed correctly and may not provide an accurate assessment of their true abilities. Additionally, the system may have difficulty accurately assessing candidates applying to highly specialized jobs where the required skills are difficult to represent in general-purpose NLP models. The system primarily supports the analysis of English-language resumes; however, future updates can add the use of multilingual NER models and other non-English-language support. While this system will provide an effective and structured means of pre-screening job applicants, it is important to note that it will supplement, not replace, the hiring manager's ability to make hiring decisions and provide the hiring manager with the best candidates to interview.

VIII. CONCLUSION

Ai (NLP based regEx) is being used to help with resume screening and candidates shortlisting. This Ai tool is designed to help recruiters by making the screening process faster, more efficient and fair for all applicants regardless of their background. One of the biggest advantages is that it can easily manage a large number of applicants. RegEx is used to identify and match important keywords, skills and qualifications from resumes to what is listed in the job description.

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