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AI-Powered Resume Analyzer and Career Assistance System Using Large Language Models

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***Abstract*—Increasing reliance on Application Tracking System (ATS) has created an array of complications for job seekers which include limited feedback, keyword dependency, or lack of personalization. Traditional tools often fail to provide detailed insights or actionable feedback. This leaves the users unsure of how to actually improve their resumes. This paper explores an AI-powered Resume Analyzer and chat assistance that uses large language models (LLMs) to evaluate user resumes and generate feedback. The system performs resume analysis by identifying strengths, weaknesses, and generating an ATS-style score based on predefined evaluation criteria. Furthermore, AI-driven chat assistance allows users to ask questions related to resume improvement, career guidance, ATS optimization. This work demonstrates a feasible alternative to traditional tools by integrating LLMs for personalized carrier assistance.**

***Index Terms*—Resume Analysis, Applicant Tracking System (ATS), Large Language Models (LLMs), Natural Language Processing (NLP), AI Chat Assistant, Career Recommendation Systems.**

I. INTRODUCTION

The rapid growth of digital recruitment platforms has significantly transformed the hiring process. Organizations rely on Application Tracking System (ATS) to automate the resume screening and candidate selection process. These systems allow organization to manage large amounts of candidates on predefined criteria. Although ATS platforms improve efficiency, they create challenges for job seekers who often receive little to no feedback on their resumes. Tradition ATS methods primarily use a rule-based filtering system based on keyword matching. These approaches fail to understand context and hence, may incorrectly reject qualified candidates. Furthermore, these systems do provide limited insight on resume improvement.

Natural Language Processing (NLP) and Large Language Models (LLM) have provided new possibilities for contextual document analysis and interactive feedback. NLP techniques allow systems to extract information from unstructured documents like resumes. LLMs provide contextual understanding and feedbacks. These advancements have enabled AI-driven systems to offer personalized feedback and interactive assistance. Recent research has shown the effectiveness on transformer-based approaches in text classification and AI applications. Unlike tradition ATS systems, LLMs provide contextual and valuable feedback along with points for improvement.

In this work, an AI-powered resume analyzer is proposed to provide intelligent resume evaluation. It allows authenticated users to upload PDFs, receive an ATS score along with their strengths, weakness, and interact with an AI chat for personalized guidance.

II. LITERATURE REVIEW

Several studies exploring automated resume screening and candidate matching using computational techniques. Malinowski et al. [1] proposed a bilateral recommendation approach for matching candidates with job opportunities, highlighting the importance of aligning both candidate preferences and recruiter requirements. However, these systems are based on structured data and hence, lack interpreting resumes with different layouts. To improve on this extraction regardless of layouts, NLP based approaches have been widely adopted. Gupta et al. [2] developed a resume parser using Natural Language Processing (NLP) to extract this information. While this improves data extraction, it lacks in generating actionable insights or feedback. Zhang et al. [3] showed the impact of character level convolution in understanding textual patterns. Alongside, the approaches discussed by Nielsen [7], this provides better semantic representation of textual data. However, these models lack flexibility in real-world applications and require extensively labeled datasets. A significant change in understanding natural language was brought about by the introduction of transformer-based architecture. Vaswani et al. [4] introduced the attention mechanism, this allows models to understand context more effectively. Building upon this, large language models such as GPT show better contextualization and better context appropriate responses [5], [10]. Modern iterations, like GPT-4, have more context understanding capabilities and can generate more context-aware responses [6]. Although these models provide powerful capabilities, many existing implementations raise concerns regarding data privacy and external dependencies. Furthermore, they focus more on parsing and matching rather than interactive feedback mechanisms. The proposed system combines resume analysis with an AI chat interface using an LLM. This integration enables both structured evaluation and real-time user interaction.

Sr No	Title of Paper	Publication Year	Virtue
1.	Matching people and jobs: A bilateral recommendation approach	2006	Proposed a system for matching candidates and jobs based on suitability.
2.	Resume parser using natural language processing	2019	Developed a resume parser using NLP to extract information from resumes.
3.	Character-level convolutional networks for text classification	2015	Introduced character-level convolutional neural networks for text classification tasks.
4.	Attention is all you need	2017	Presented the transformer architecture and attention mechanism, used in for modern LLMs.
5.	Language models are few-shot learners	2023	Introduced GPT-3, demonstrating that LLMs can use few-shot learning for tasks involving NLP.
6.	GPT-4 technical report	2023	Described GPT-4's reasoning and contextualization for complex tasks.
7.	Neural networks and deep learning	2015	Explained neural networks and deep learning techniques for intelligent data processing.
8.	Natural Language Processing with Python	2009	Provided practical NLP methods using Python for text processing and language analysis.
9.	Speech and Language Processing	2023	Presented techniques used in speech and natural

			language processing.
10.	Improving language understanding by generative pre-training,"	2018	Introduced generative pre-training for language understanding, which modern GPT based systems rely on.

III. METHODOLOGY/EXPERIMENTAL

Synthesis/Algorithm/Design/Method:

This system is designed to provide intelligent resume analysis and assistance with the interaction of Natural Language Processing (NLP), Large Language Models (LLM), and web technologies. It consists of multiple stages such as user interaction, text extraction, resume analysis, ATS score generation, and assistance. The workflow of this system is a modular pipeline where each component performs a specific task in the resume evaluation process.

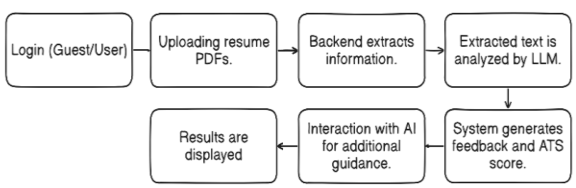

Figure 1: Work-Flow

The system supports two modes of access: authenticated user and guest mode. Registered users are able to upload resumes in PDF format and access the analytical features whereas guest users are limited to the AI chat functionality.

The resume analysis process extracts textual context from each page, formats inconsistencies and passes it to language model for evaluation.

After text extraction, the model evaluates this resume based on predefined criteria using prompt engineering that instruct the model on clarity, quality, relevance, and achievements. The model then generates feedback identifying strengths, weaknesses, and suggestions. Unlike traditional ATS systems that reply primarily on keyword matching, this system performs contextual analysis on the resume. This provides more meaningful feedback to users. The systems generates and ATS score from 0 to 100 to approximate of the resume's quality. This score is derived from the model's evaluation of factors, including resume structure, readability, keyword relevance, technical skills, and presentation quality. When the resume has been analyzed, the extracted information including context is shared with the AI chat which can further assist users in improving their resumes interactively.

IV. RESULTS AND DISCUSSIONS

This system was successfully implemented and tested in a local environment. It was evaluated based on functionality, responsiveness, usability, and the quality of resume analysis generated by the language model.

The system successfully supports both authenticated and guest-based access modes. Guest users were able to interact with the AI chat assistant without authentication.

The system was capable of generating meaningful feedback including strengths, weaknesses, and improvements. However, the ATS score varied slightly across repeated analysis. This was likely due to the probabilistic nature of the LLMs and differences in generated responses. The quality of extracted test also influenced response accuracy. Resumes with complex layouts or image-based texts resulted in incomplete extraction affected the quality of the feedback generated. Hence, the limitations of this system include:

- ATS scores were not fully deterministic due to the probabilistic nature of LLMs.
- Smaller language models often produced incomplete or inconsistent feedback.
- PDF text extraction depends on formatting of the document,
- Larger models require higher computational power and increased memory usage.

This demonstrates that LLMs can significantly improve the quality and interactivity of resume analyzers compared to traditional rule-based ATS approaches. By combining contextual analysis and conversations, this system offers more meaningful feedback.

V. CONCLUSION

This paper presented the design and implementation of an AI-powered Resume Analyzer. The system combines Natural Language Processing (NLP) and Large Language Models (LLM) to provide resume evaluation and interactive chat assistance. Unlike traditional ATS systems that rely on rule-based filtering, this system performs contextual analysis of resume content enabling personalized feedback. Repeated uses show that larger language models produced more consistent and context-aware evaluations compared to smaller models. However, certain limitations such as variability in ATS scoring and extraction quality were identified during testing.

Overall, the system demonstrates the feasibility of integration transformer-based AI models into resume analysis. This creates more interactive and user-centric assessment tool.

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