

RESUME QR GENERATOR – RESUME ANALYZER

An AI-Powered NLP-Based Resume Analysis and Screening System

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Abstract: The AI Resume Analyzer using Natural Language Processing (NLP) algorithms is a cutting-edge tool designed to streamline and enhance the recruitment process. In today's competitive job market, employers and HR professionals are inundated with countless resumes, making the task of identifying the most qualified candidates a daunting and time-consuming challenge. This AI-powered solution leverages advanced NLP techniques to automatically evaluate and rank resumes, significantly improving the efficiency and effectiveness of talent acquisition. The system begins by extracting textual content from resumes, which can be in various formats such as PDF, Word, or plain text. The NLP algorithm then parses this textual data to identify and categorize key information, including candidate contact details, skills, work experience, education, and other relevant sections. Furthermore, it evaluates the quality and relevance of the content, considering factors like the match between the candidate's skills and the job requirements, the length and quality of the work experience, and the presence of industry-specific keywords.

Index Terms: AI Resume Analyzer, Natural Language Processing, Resume Screening, Recruitment Automation, QR Generator, Machine Learning.

I. INTRODUCTION

The introduction to an AI resume analyzer revolves around the theoretical underpinnings of this technology, shedding light on its role in streamlining the recruitment process. AI resume analyzers, at their core, leverage the power of artificial intelligence and natural language processing (NLP) to revolutionize the way companies sift through job applications and identify potential candidates. This technology is designed to provide a sophisticated layer of automation in the initial stages of the hiring process, thereby saving time, reducing biases, and enhancing efficiency.

The theoretical foundation of AI resume analyzers lies in their ability to understand and extract meaningful information from resumes, such as skills, qualifications, and experience. The AI Resume Analyzer employs machine learning models to assign each resume a numerical score, which reflects the candidate's suitability for the job. This score is based on a comparison of the resume's content to predefined job criteria and the characteristics of successful employees in the organization.

The advantages of this AI-powered system are manifold. It significantly reduces the time and effort required to screen resumes, ensuring that HR professionals can focus on more strategic and value-added tasks. Additionally, it minimizes the risk of human bias in the initial candidate selection process, enhancing fairness and diversity in hiring. Finally, the system can provide valuable insights to recruiters and organizations, allowing them to fine-tune job descriptions, identify skills gaps, and optimize their talent acquisition strategies.

II. METHODOLOGY

The methodology of an AI resume analyzer is a systematic approach that integrates artificial intelligence and natural language processing to streamline the recruitment process. This methodology typically involves several key steps.

In summary, the methodology of an AI resume analyzer involves data collection, machine learning model development, feature engineering, customization, integration, user feedback, and continuous improvement. The goal is to create a powerful and adaptable tool that enhances the efficiency and fairness of the hiring process while making it more data-driven and objective.

III. MODEL EVALUATION

In the Novachat system, evaluation ensures that the chatbot performs accurately, efficiently, and empathetically.

Dataset Splitting: The dataset is divided into training and validation sets to assess model performance during development.

Intent Classification Evaluation: The intent classifier is evaluated based on its accuracy in correctly identifying user queries, measured by comparing predicted intents with actual labelled intents.

IV. PLANNING

We are using the Waterfall model for our project estimation, consisting of the following six phases:

1. Requirement Gathering and Analysis: In this step various requirements needed for the project are identified, such as software and hardware required, database, and interfaces.

2. System Design: The system is designed to be easily understood by the end user, i.e., user-friendly. UML diagrams and data flow diagrams are designed to understand the system flow, system modules, and sequence of execution.

3. Implementation: In the implementation phase, the various modules required to successfully achieve the expected outcome are developed. With inputs from system design, the system is first developed in small programs called units, which are integrated in the next phase. Each unit is developed and tested for its functionality, referred to as Unit Testing.

4. Testing: Different test cases are performed to verify whether the project modules give the expected outcome in the assumed time. All units developed in the implementation phase are integrated into a system after individual testing, and the entire system is then tested for faults and failures.

5. Deployment of System: Once functional and non-functional testing is complete, the product is deployed in the customer environment or released into the market.

6. Maintenance: Issues that arise in the client environment are fixed through patches, and better versions are released to enhance the product. Maintenance ensures these changes are delivered to the customer environment.

V. CONCLUSION AND SCOPE

Resume Screening and Shortlisting: AI resume analyzers are primarily designed to assist HR professionals in efficiently screening and shortlisting candidates.

Keyword and Skill Matching: AI resume analyzers use natural language processing to extract and match keywords, skills, and qualifications from resumes with job requirements.

Scalability: AI resume analyzers are scalable and can handle a high volume of job applications, making them suitable for both small and large organizations.

Feedback and Reporting: Some AI resume analyzers offer insights and feedback on the effectiveness of job postings and recruiting strategies.

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REFERENCES

- [1] Amato, F., Boselli, R., Cesarini, M., et al. "Challenge: Processing web texts for classifying job offers," Semantic Computing (ICSC), 2015 IEEE International Conference on. IEEE, 2015: 460–463.
- [2] Cafarella, M. J., Banko, M., Etzioni, O. "Open information extraction from the web," US Patent 8938410, 2015-01-20.
- [3] Gaikwad, S. V., Chaugule, A., Patil, P. "Text mining methods and techniques," International Journal of Computer Applications, 2014, 85(17).
- [4] Gupta, R. "Journey from data mining to web mining to big data," arXiv preprint arXiv:1404.4140, 2014.
- [5] Gong, Yiguang, Mei Ping. "Research on a combined ontology-based text information extraction technology," Proceedings of 2010 International Conference on Broadcast Technology and Multimedia Communication, Vol. 4. International Communication Sciences Association, Hong Kong, 2010: 129–135.

