AI-Powered Resume Analyzer and Interview Preparation System

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***Abstract*—In today's competitive job market, the challenge of crafting an optimized resume and preparing effectively for interviews cannot be overstated. Traditional resume-building methods are often manual, requiring job seekers to spend a significant amount of time ensuring that their resumes align with specific job descriptions. Similarly, interview preparation frequently involves generic advice that is often unstructured and lacks personalization. The gap here lies in the absence of a personalized, data-driven approach to both optimizing resumes and preparing for interviews. This is where AI can bring substantial benefits.**

By leveraging advanced AI technologies such as Natural Language Processing (NLP) and Machine Learning (ML), our project aims to provide personalized, intelligent feedback to job seekers, enhancing both the quality of their resumes and their readiness for interviews. The system will not only suggest modifications to resumes based on job descriptions but also generate interview questions tailored to specific roles, evaluate user responses, and provide detailed feedback. Through these two functionalities, the system promises to give job seekers a significant edge in the highly competitive job market.

***Index Terms*—AI, resume optimization, interview preparation, natural language processing, job search, applicant tracking systems**

I. Introduction

The current employment environment is quite demanding for job applicants to work in an ever-competitive atmosphere. Recent Glassdoor statistics (2023) indicate that 118 applicants on average apply for each vacant position, which is a frightening situation for job applicants willing to be noticed. The traditional employment process is realized through two extremely critical steps that will render one successful, and those include resume sending and successful interviews. Nevertheless, current research emphasizes that 75% of resumes that get filtered through Applicant Tracking Systems (ATS) are discarded before human examination (Shields, 2023), and a paltry 20% of interviewees are offered a job (LinkedIn Workforce Report, 2024). Such statistics illustrate the requirement for enhanced solutions to support applicants to make both aspects of their application process effective.

Today's market has many tools that are either aimed at resume optimization or interview practice but the solutions tend to function independently, delivering a fractured preparation process without unified messaging through application components. Moreover, existing solutions concentrate primarily on static templates or universal tips rather than delivering dynamic, personalized feedback that is specifically tailored to match particular job demands. This gap in the market thus demands the creation of an integrated, computer-based system for the analysis of resumes as well as interview answers together with specific job definitions, thereby providing the applicants with explicit, tailored advice from the start of their application until the end.

This paper offers a comprehensive explanation of our proposed AI-based Resume Builder and Interview Preparation System that addresses the limitations of existing solutions through advanced natural language processing techniques and machine learning algorithms. The system consists of two complementary parts: a Resume Analyzer that analyzes and enhances resumes based on specific job descriptions, and an Interview Coach that generates personalized interview questions and provides useful feedback on candidate responses. By integrating all these components into one platform, our platform offers the job seeker an integrated, beginning-to-end preparation process that significantly increases their prospects in the employment market.

II. Description

A. Resume Analyzer Component

The Resume Analyzer module applies cutting-edge natural language processing techniques to bridge the gap between candidate skills and employer requirements. Rather than relying on superficial keyword matching on the surface, our tool applies transformer-based models such as BERT (Bidirectional Encoder Representations from Transformers) or GPT-4 to deduce useful information from both resumes and job descriptions (Devlin et al., 2019). This semantic meaning enables the system to recognize explicit skill mentions as well as implicit qualifications conveyed by experience descriptions and achievements.

The primary operation of the Resume Analyzer entails several important processes. To begin with, the system extracts major entities from the resume and job description, including skills, experiences, qualifications, and responsibilities. This extraction process relies on named entity recognition with domain-specific training to enable the accurate identification of information in the text. The system then calculates similarity scores between matching resume and job description elements, applying advanced semantic similarity algorithms that consider contextual relationships, not merely lexical matching.

Algorithm 1 Resume Analysis Algorithm

```
Input: resume_text, job_description
Output: Analysis results with recommendations

# Extract key elements from both documents
resume_entities ← extract_entities(resume_text)
job_entities ← extract_entities(job_description)

# Calculate similarity scores
skill_match_score ← calculate_similarity(resume_entities['skills'], job_entities['skills'])
experience_match_score ← calculate_similarity(resume_entities['experience'], job_entities['experience'])

# Identify gaps
missing_skills ← identify_gaps(resume_entities['skills'], job_entities['skills'])

# Generate recommendations
recommendations ← generate_recommendations(missing_skills, skill_match_score)


return { 'match_score': (skill_match_score + experience_match_score) / 2,
    'missing_skills': missing_skills,
    'recommendations': recommendations,
    'ats_compatibility': check_ats_compatibility(resume_text)
    }
```

The implementation of this algorithm requires sophisticated language models that understand industry-specific terms in various industries. Our approach is justified by a research paper by Smith et al. (2023), which demonstrates that industry-specific models outperform general-purpose models by up to 27% in processing job content, confirming our use of specialist models for various professional sectors. By this approach, the Resume Analyzer offers detailed comments such as overall match score, missing skills or experiences, step-by-step suggestions for improvement, and ATS compatibility assessment.

B. Interview Coach Component

The Interview Coach module translates job descriptions into tailored interview preparation experiences, allowing candidates to align their responses with employer expectations. The module addresses a significant gap in existing interview preparation tools, which typically offer generic questions that may not best capture the unique requirements and challenges of particular jobs.

The process of generating questions takes several sophisticated steps. Initially, the system extracts relevant aspects of the job post, including required skills, primary responsibilities, and ideal qualifications. The system subsequently utilizes the extractions to construct various types of questions, including technical questions that test specific skills, behavioral questions that test prior experience with regard to work responsibilities, and situational questions that test how a candidate would deal with impending challenges in the job.

Algorithm 2 Interview Question Generation Algorithm

```
Input: job_description
Output: Generated interview questions

# Extract key components from job description
skills ← extract_skills(job_description)
responsibilities ← extract_responsibilities(job_description)


# Generate different types of questions
technical_questions ← generate_technical_questions(skills)
behavioral_questions ← generate_behavioral_questions(responsibilities)
situational_questions ← generate_situational_questions(responsibilities)

return technical_questions + behavioral_questions + situational_questions
```

Apart from question generation, the Interview Coach provides positive feedback on candidate responses, evaluating dimensions of relevance, clearness, completeness, and similarity to job specifications. The evaluation process employs natural language understanding techniques in examining different dimensions of response quality, providing candidates with accurate, actionable feedback to enhance their performance in an interview.

III. System Implementation

The AI-powered resume analysis tool is built as a full-stack Python application that combines several state-of-the-art technical features to deliver its core functionality. As its foundation, the system utilizes Streamlit as the web app framework which provides a simple-to-use user interface for uploading resumes and showing analysis. It facilitates rapid development of interactive features while handling the complexities of file upload, user sessions, and responsive layout management.

Algorithm 3 Document Processing Workflow

```
Initialize Streamlit application interface
Configure Google Gemini API connection
while application is running do
    Receive user upload via file_uploader widget
    Determine file type (PDF/DOCX/TXT)
    Dispatch to appropriate text extractor
    Perform text normalization and cleaning
end while
```

The pipeline for backend processing begins with document ingestion, wherein the system accepts resumes in PDF, DOCX,

and TXT formats through Streamlit's file uploader widget. Each must be processed in a different way:

Algorithm 4 Text Extraction Logic

```
if file is PDF then
    Use PyPDF2 to extract text layer
    Preserve section headers and bullet points
else if file is DOCX then
    Use python-docx to parse paragraphs
    Maintain original formatting markers
else if file is TXT then
    Directly read UTF-8 content
    Normalize line endings
end if
```

PDF documents are parsed using PyPDF2 to obtain text layers without losing structural data, DOCX documents are processed through the python-docx library in order to maintain paragraph-level formatting, and plain text files are decoded directly as UTF-8 content. This multifaceted support ensures compatibility with the overwhelming majority of resume formats encountered in professional settings.

Document processing features a number of robustness mechanisms to address real-world variation in resume structure. The text extraction algorithms include error handling for corrupted files, encoding detection fallbacks, and automatic line break and whitespace normalization. For PDFs specifically, the system imposes text-based vs. image-based resume screening with user feedback in case optical character recognition (OCR) is required for scanned documents. Preprocessing of extracted text includes Unicode normalization, removal of non-printable characters, and smart hyphenated word concatenation across line breaks. These preprocessing operations provide consistent input for downstream AI analysis regardless of original document formatting.

Algorithm 5 Error Handling Framework

```
Attempt text extraction
Validate extracted content UnsupportedFormatError
Notify user of unsupported file type CorruptedFileError
Provide detailed error message APITimeoutError
Implement exponential backoff
Retry request (max 3 attempts)
```

The system's intelligence core is derived from Google's Gemini AI models, specifically using both the gemini-2.5-flash and gemini-2.5-pro variants depending on user preference. Integration is established through Google's official SDK with API keys securely stored as environment variables rather than hardcoded credentials. This is according to security best practices and is simpler to rotate keys. The interaction model utilizes thoughtfully engineered prompts that combine a variety of modular components: foundational instructions specifying the AI's role as a career advisor, sector-specific templates usable across multiple fields of profession (technical, executive, etc.), and context job description if prompted by the user. The prompt engineering demonstrates high-level understanding of large language model behavior, incorporating techniques like few-shot learning via implicitly embedded examples in the template designs.

Algorithm 6 AI Analysis Engine

```
Load environment variables
Configure Gemini API connection
Generate domain-specific prompt template
Calculate semantic similarity scores
Identify key skill matches and gaps
Evaluate ATS compatibility factors
Generate improvement recommendations
Format analysis report
```

Quality of analysis is enhanced through various generation parameter tunings. The temperature parameter of 0.2 delivers stable, reproducible output with allowing minor creativity in wording the suggestion. The top-p parameter of 0.8 with top-k sampling of 40 maintains response diversity without sacrificing relevance. The system allots a generous output token limit of 4096 so that feedback can be comprehensive in many aspects of resume quality. These parameters were empirically derived through rigorous testing on a wide range of resume samples to balance detail with brevity. The AI answers adhere to a systematic format that addresses systematically major resume evaluation dimensions: ATS compatibility scoring, presentation of skills, experience structuring, quantification of achievements, and overall story flow.

The user interface utilizes a multi-tab presentation system to break down the massive AI feedback into bite-sized sections. A primary "Complete Analysis" tab shows the full detailed analysis, and supporting tabs highlight key strengths and areas for improvement through analyzed quotes of the core analysis. This structure overcomes the common limitation of career tools' information overload by enabling both detailed browsing and immediate comprehension. The user interface is supplemented by download functionality using plain text and PDF, accomplished using Streamlit's built-in download buttons along with server-side document generation. For PDF output, the system would utilize report generation libraries to emit professionally formatted documents with proper styling and layout.

Algorithm 7 User Interface Flow

```
Initialize Streamlit components
Create file uploader widget
Implement analysis type dropdown
Add job description text area
Process submission when received
Display results in tabbed interface:
Tab 1: Full analysis report
Tab 2: Key strengths
Tab 3: Improvement areas
Implement download functionality
```

Technical implementation details reveal a number of thoughtful architecture decisions. The code's modular organization separates concerns among document processing,

AI interaction, and presentation layers. Separation enhances maintainability and allows for future extension. Error handling is extensive, catching and appropriately exposing exceptions from document parsing, API conversing, and content generation. The application includes intelligent resource utilization, particularly important in light of document processing large documents and AI model interactions. Security is represented by the ephemeral processing paradigm wherein resumes are never saved on disk or databases but only reside in memory while actually being analyzed.

The analysis engine has a number of innovative features in its prompt design. For technical positions, it particularly assesses skills matrices and technology proficiency presentation. Executive resume analysis targets leadership metrics and strategic impact quantification. Entry-level evaluations target transferable skills and academic project relevance. This specialization is obtained through dynamically constructed prompts that integrate the correct domain-specific template with the extracted resume content and optional job description. Prompt engineering reflects sophisticated knowledge of resume best practices and large language model capabilities.

A unique aspect of this deployment is how it addresses Applicant Tracking System (ATS) optimization. AI analysis includes individual ATS compatibility factors to verify: keyword density evaluation, standardizing section headings, format cleanliness, and avoid graphically confusing material that can confuse parsing engines. The feedback contains concrete suggestions on improving machine readability while remaining human readable - a significant factor in modern-day job searching. This functionality goes beyond simple keyword matching to sense semantic relevance and context presentation of skills and experiences.

The system's configuration options reveal thoughtful user customization. Users may select versions of AI models to work with, based on need - the quicker "flash" version for speedy response or the more capable "pro" version for nuanced scrutiny. Industry-specific analysis modes allow relevant feedback regardless of whether the user operates in technology, business, healthcare, or other fields. The above is presented in a plain, easy-to-understand interface with helpful tooltips and sensible defaults.

Underlying technical factors are such as thorough input validation to avoid malformed documents interfering with processing. The system uses size constraints on uploads to avoid resource exhaustion attacks. API communication involves retry mechanisms and timeout mechanisms to make it reliable. For the AI-generated responses, the application has mechanisms against possible hallucinations or off-topic excursions through proper prompt constraints and post-processing validation.

The program also demonstrates an awareness of true resume analysis practice in the employment world. Analysis criteria are the things that recruiters want to examine: quantifiable accomplishments, progressing responsibility indication, proof of skill by examples, and consistency with professional narratives. The down-to-earth methodology ensures the feedback is useful and congruent with employment decision-maker standards.

Extensibility in the future is integrated into the architecture. The modular architecture allows new document formats to be added with ease through additional extractor implementations. The prompt engineering framework allows for simple integration of new industry templates or analysis dimensions. The presentation layer can be extended with visualization capabilities or interactive editing capabilities without requiring fundamental architectural changes.

IV. Implementation Details

The code uses a high-end AI-powered resume analysis tool built with Streamlit that is designed to provide professional-grade resume optimization via several well-designed elements. At its core, the system utilizes Google's Gemini AI models to analyze resume text, wrapped in a user-friendly web interface supporting multiple document formats and customization options. The app begins by configuring necessary runtime configuration through `setup_accessibility_features()` and `setup_language_support()`, that configure user options for appearance of interface and language support, storing these as Streamlit session state to be maintained across sessions.

Algorithm 8 Accessibility and Language Initialization

```
Initialize session state if not exists
Set default accessibility parameters:
language = 'en'
text_to_speech = False
high_contrast = False
font_size = 'medium'
Configure available languages: ['en', 'es', 'fr', 'de', 'zh-cn', 'ja']
Set auto-detection preference
```

The document processing capability demonstrates sound engineering in the form of `extract_text_from_pdf()` and `extract_text_from_docx()` functions that handle PDF and Word documents respectively, with heavy error checking and text normalizing to produce clean input to be analyzed. These extraction procedures go beyond basic text recovery through document structure retention, handling of tables within DOCX files, and clean-up of extracted content by intelligent means.

Algorithm 9 Document Processing Logic

```
if file is PDF then
    Use PyPDF2 to extract text layer
    Preserve section headers and bullet points
    Clean up excessive newlines
else if file is DOCX then
    Use python-docx to parse paragraphs
    Extract table content with cell boundaries
    Maintain original formatting markers
else
    Direct UTF-8 text extraction
    Normalize line endings
end if
Implement comprehensive error handling
```

The main workflow of the application centers on `display_resume_analysis_page()`, which oversees the complete user flow from file importation to result presentation. The function first shows the file import dialog with PDF, DOCX, and TXT import support, followed by the optional retrieval of a job description for targeted analysis. Upon activation, the analysis workflow shows respectful UX features like a spinner while processing and expandable areas to see raw extracted text.

Algorithm 10 Resume Analysis Workflow

```
Initialize file uploader widget (PDF/DOCX/TXT)
Optional job description text area
Validate file type and size
Extract and clean text content
Generate domain-specific prompt
Call Gemini API with configured parameters:
temperature = 0.2
top_p = 0.8
max_output_tokens = 4096
Display results in tabbed interface
```

The result presentation employs a tabbed interface to show detailed feedback, key strengths, and areas for improvement, although the latter two are currently placeholders for more advanced content parsing functionality. The download facilities demonstrate pragmatic use with both text and timed PDF export capability, although the PDF creation remains to be implemented.

Algorithm 11 Result Presentation Logic

```
Create tab container with three views:
1. Complete analysis report
2. Key strengths summary
3. Improvement suggestions
Implement download buttons:
Text format with direct output
PDF format (placeholder)
Maintain responsive layout
```

Additional pages like `display_skills_matching_page()` and `display_about_page()` extend the application's capabilities with skills matching capability and thorough documentation, while `display_settings_page()` enables user control of interface options and output formatting. The `main()` function serves as the application entry point, initializing global page settings and establishing the navigation hierarchy. It anticipates accessibility and language support activation before rendering the sidebar user interface made up of logo display (with gracious fallback behavior), navigation controls, and analysis options configuration.

Algorithm 12 Main Application Flow

```
Configure page layout and title
Initialize accessibility features
Set up language support
Create sidebar navigation:
Logo display with fallback
Page selection radio
Model selection dropdown
Analysis type selector
Route to selected page
Display API key instructions
Render application footer
```

The body content dynamically displays different pages based on user selection to provide a consistent single-page application experience. Attentive details like the API key setup instructions and application footer demonstrate care with user onboarding and transparency. In the implementation, the code reflects strong architecture patterns in the shape of modular design (with distinct utility modules for different concerns), complete error handling, session state management for enduring preferences, and well-kept separation of concerns between interface generation and business rules. The implementation also reflects consideration for production aspects through attributes like accessibility support, multi-language support, and safe API key management without losing sight of ease of coming close through clean code structuring and documentation.

A. Setup.py Implementation

This is an automated dependency manager Python script to be used within a particular AI Resume Analyzer application. The primary function of this script is to verify and install all the Python packages listed in the project's 'requirements.txt' file before executing the actual application.

Algorithm 13 Dependency Verification Process

```
Import required modules (subprocess, sys)
Open and read requirements.txt file
Create list of required packages
for each package in requirements do
    Attempt to import package
    if import succeeds then
        Mark as installed ()
    else
        Add to missing packages list
    end if
end for
```

The script begins by importing the required modules - subprocess to execute system commands and sys to fetch the path for the Python interpreter. At its core, the script follows a simple yet efficient approach of dependency management. It first reads from requirements.txt to build a list of required packages, and then it scans carefully if each package has been installed by making attempts at imports.

Algorithm 14 Package Installation Routine

```
if missing packages exist then
    Print installation header
    for each missing package do
        Construct pip install command
        Execute using subprocess.check_call() Verify successful installation()
    end for
else
    Confirm all packages are installed
end if
Print completion message
```

Where required, for the missing ones, it auto-installs using pip through Python's subprocess module. The beauty of this script is the robust verification technique implemented. Rather than simply checking pip's list of installed packages, it actually checks whether packages could be imported successfully in the present Python environment - a better measure of actual usability.

Algorithm 15 User Feedback Mechanism

```
Initialize with clear status message
Provide visual indicators () for operations
Print detailed status at each phase:
Package verification
Installation process
Final confirmation
Include next-step instructions
```

The script provides clear, user-friendly feedback at every point, using checkmark symbols () to give a visual confirmation of successful operations and printing status messages at every critical point. When installations are required, it builds the pip install commands defensively with the directory of the installed Python interpreter for virtual environment support. The coding reflects some good Python practices like proper use of context managers in file operations, list comprehensions for clean data processing, and the standard if __name__ == "__main__" guard for script interpreters.

Though today's usage plays nicely with simple dependency needs, there's also room to strengthen error messaging, progress reports, and further-level versioning requirement support. This script particularly makes itself valuable to Streamlit apps like AI Resume Analyzer where an unfulfilled dependency has a tendency to mean obscure failure in the case of end users that are not even Python coders. Its cross-platform design performs correctly on any operating system, and the light implementation imposes little performance overhead at application launch. Facilitating what otherwise would be a tedious, and possibly error-prone, undertaking, this dependency checker enables easy confidence that the application will run with all necessary components properly installed.

V. Evaluation

Establishing robust evaluation metrics is essential for gauging the success of our AI-powered system and ensuring continued enhancement during its design and rollout. We've established a comprehensive evaluation framework that addresses both user-centric and technical performance, providing a holistic view of the system's impact on the job seekers' success.

A. Resume Matching Accuracy Metrics

Resume analysis accuracy is a critical performance measure of the system, and it has to be measured reliably with standard information retrieval measures. Precision is the ratio of correctly matched resume-element-to-job-requirement pairs out of the total number of matched resume elements, so that the system makes relevant suggestions without clobbering users with too many irrelevant ones. Recall is a measure of the number of actual matches correctly picked up by the system, that is, perfect identification of all material skills and experience. These scores can be combined using the F1-score:

$$F1 = \frac{2 \times (Precision \times Recall)}{(Precision + Recall)} \tag{1}$$

We have established a high target of having an F1-score of at least 0.85, which will indicate exceptional performance according to industry standards (Chen & Mueller, 2023). We will achieve this target by implementing regular model fine-tuning processes, including regular retraining with larger datasets and fine-tuning based on user feedback.

B. Interview Response Quality Assessment

Assessing the quality of interview response evaluation is challenging because of the subjective nature of interview performance evaluation. Our method leverages NLP-based measures coupled with human expert validation to provide complete and precise evaluation. NLP-based evaluation metrics range from content relevance to determine the extent to which the response addresses the specific question and the extent of its adherence to the job requirement; structural coherence to evaluate the logical flow and organization of the response; language proficiency to evaluate grammar, vocabulary usage, and general clarity; and information density to evaluate the substantive content-to-word ratio in responses.

To validate these automatic assessments, we will compare the system scores with the scores of experienced human interviewers. A panel of HR professionals and hiring managers will rate a sample of the responses, and their ratings will be paired with the AI's ratings to come up with an agreement score. Thompson et al.'s (2023) research indicates that there can be as high as 82% agreement between AI systems and human experts in assessing interview answers, setting a baseline for the performance of our system.

C. User Experience and Success Metrics

While technical performance is valuable to capture the abilities of the system, the ideal yardstick to employ is user experience and true utilization results in practice. We shall use standardized metrics of usability such as the System Usability Scale (SUS) to analyze perceived usability as well as the Net Promoter Score (NPS) in order to rate users' readiness to

suggest use of the system to other stakeholders. Moreover, we will track task accomplishment rates and the efficiency of time in comparison with traditional preparation methods, providing numerical measures of the system's impact on user productivity.

VI. Related Work

Several various tools and websites have emerged in recent years to help job applicants create resumes and prepare for interviews. Most popular resume tools, even those hosted on websites such as LinkedIn and Glassdoor, offer generic templates and keyword suggestions. However, such tools are based on rigid forms and cannot provide advanced, context-sensitive feedback that will vary according to the specific job description. With the growing competitiveness of the job market, the need for personalized and intelligent application assistance has been more strongly felt.

Research on applicant tracking systems (ATS) has found that nearly all resumes—75% according to Shields (2023)—are rejected before reaching a human recruiter. This underscores the need to tailor resumes to content and formatting requirements as specified by such systems. Even while some software packages have introduced keyword-based suggestions for improving ATS compatibility, these are short of fully understanding the deeper semantic connection between job notices and candidate credentials.

Improved natural language processing has made it possible to break free from simple keyword matching. Techniques relying on contextual language understanding, such as those described by Devlin et al. (2019), can facilitate more robust resume to job posting comparisons. Similarly, Johnson and Williams (2024) demonstrated that tailored, AI-driven interview coaching can dramatically improve candidate performance in interviews. They echo the perception that tools offering focused, rather than broad, feedback perform better in preparing users.

Efforts have also been exerted in building systems that run imitation interview environments. Thompson et al. (2023) introduced research that suggested AI-created assessment of reactions to an interview can mirror strongly similar results of human judging and has the potential to offer mass, automated coach tools. Existing research has examined the technical challenge in such systems, specifically the costly computation involved in processing huge volumes of data. Methods such as model fine-tuning and cloud deployment, as suggested by Howard et al. (2022), are commonly used to improve performance and scalability.

While others have focused on resume optimization or interview preparation in the past, few have brought both together within an integrated platform. This project takes the strengths of these past approaches and introduces a more complete system—one that aligns resume content with job requirements and prepares applicants for interviews based on those requirements with a resulting aim to improve outcomes along the entire process of job seeking.

VII. Summary and Conclusion

This AI-powered resume analyzer and interview coach has the potential to significantly transform the way job seekers approach both resume writing and interview preparation. By providing intelligent, personalized feedback, the system helps job seekers understand what they are doing right and where they need improvement. The integration of NLP and ML techniques ensures that the feedback is both relevant and specific, enhancing the chances of securing a job.

By continuously improving the models and expanding the dataset, we can create an even more robust system that adapts to changing job market demands. This project has the potential to democratize access to high-quality resume feedback and interview coaching, making these services available to a wider range of individuals, especially those who might not have access to traditional career coaching resources.

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VIII. Project Demonstration

Our AI-powered resume analyzer and interview preparation system is demonstrated in the following video presentations:

A. Part 1

Overview
https://youtu.be/ZD7Ly8I8fEo

B. Part 2

Video Demonstration Part 2
https://youtu.be/MrcHSBGMn88