AI Generative personalized interview preparation problem

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***Abstract*—Effective document processing and interactive AI-powered support have become crucial in the age of AI- driven automation. This study introduces a document processing system based on Streamlit that combines text-to- speech (TTS) and natural language processing (NLP) technologies. The system uses FAISS vector databases, Google Gemini AI, and LangChain to extract and process text from PDF and DOCX files and provide intelligent query-based answers. It also provides text-to-audio conversion, making the experience more accessible. Personalized document analysis is guaranteed by a safe user authentication system. Our method improves automated content summarization, interview preparation, and resume processing. By providing an intelligent and user-friendly document analysis system, the suggested solution shows increased efficiency in document interaction.**

Keywords— ***Document Processing, AI, Streamlit, LangChain, Google Gemini AI, NLP, Text-to-Speech, FAISS, Resume Analysis, Authentication.***

I. INTRODUCTION

Efficiently processing and extracting valuable information from papers has become essential in today's digital world. Intelligent document processing solutions are becoming more and more in demand, whether it is for professionals handling documents, researchers analyzing big datasets, or job seekers getting ready for interviews. Conventional techniques for manually extracting and evaluating document content are laborious, prone to mistakes, and not scalable. Natural language processing (NLP) and artificial intelligence (AI) techniques have become effective tools for automating document processing in order to overcome these difficulties. This allows users to intelligently extract, evaluate, and interact with textual material. The project provides interactive tools for job seekers in addition to document analysis, such as an ATS score checker that assesses a resume's compatibility with applicant tracking systems, a technical question generator that creates AI-powered interview questions, and a mock test generator for self-evaluation.

The AI-powered document processing system presented in this paper was developed with Google Gemini AI, Streamlit, LangChain, and FAISS vector databases to provide an effective, interactive, and user-friendly method of document handling. Users can convert text to speech for improved accessibility, extract insightful text, and create AI-powered insights by uploading PDF or DOCX files. Using their uploaded resumes, candidates can receive context-aware AI-generated answers to frequently asked interview questions, which is especially helpful for resume analysis and interview preparation. The suggested method combines FAISS (Facebook AI Similarity Search) to improve information retrieval and document understanding. Based on the content that has been retrieved, the system may produce customized and pertinent responses thanks to Google Gemini AI embeddings. For users who prefer audio- based interactions, the text-to-speech (TTS) features enabled by gTTS and Pygame also offer an audible representation of the extracted text, enhancing accessibility. In addition to document analysis, this system includes a secure authentication module that guarantees user interactions are private and safe. Users can obtain AI-driven insights catered to their individual needs after logging in and uploading their papers. Applications such as resume screening, content summarizing, AI-assisted document review, and automated interview preparation will find this solution especially helpful due to its dynamic and interactive document processing capabilities. This study examines the technological implementation, methods, and architecture of this

AI-driven document processing system. We offer information on how to employ vector databases, NLP methods, and sophisticated AI models to revolutionize document interaction and eventually improve productivity, usability, and user engagement. We illustrate how well the system performs accurate text retrieval, context-aware response generation, and interactive document processing through experimental assessment and real-world use cases.

II. LITERATURE SURVEY

It is critical in the quickly changing employment market to match educational pathways with new professional prospects. A resume-based re-education framework that is effective and dynamically adjusts to changes in the market was proposed by Ashrafi et al. [1], guaranteeing that candidates' abilities stay current. Expanding on this basis, other research projects have investigated AI-powered approaches to improve job matching and career recommendations. The Gemini MultiPDF Chatbot was created by Kaif et al. [2] and uses big language models to process numerous documents, allowing for thorough career assistance.

In a similar vein, Muludi et al. [3] used a retrieval-augmented generation technique, using large datasets to improve job recommendations. To expedite resume analysis and candidate-job matching, Xu et al. [4] presented ChatUIE, a chat-based unified information extraction system that makes use of massive language models. The potential of AI in urban career services was highlighted by Sanaei et al. [5], who presented a deep multisensor dashboard within the Web of Things architecture for smart city applications.

To meet market expectations, Krishnan et al. [6] introduced Skill Mount, a machine learning-based platform for individualized career skill development. Using LinkedIn data scraping and sophisticated resume analysis, Kumar et al. [7] highlighted the significance of AI in career advancement by providing customized job recommendations. By using Resspar, an AI-driven resume parsing and recruitment platform, Abisha et al. [8] have demonstrated how natural language processing and generative AI may be integrated into recruitment systems. Manish et al. [9] concentrated on using big language models to optimize resume parsing, improving the precision of candidate-job fit evaluations.

An AI-powered algorithm was presented by Mishra et al. [10] for intelligent CV recommendations, giving job seekers useful feedback. Patel and Gupta's [11] AI-powered job matching system is another innovation that matches user profiles with job advertisements to increase hiring effectiveness. To improve the match between candidates and jobs, Kang and Lee [12] suggested a framework for resume analysis that makes use of ranking algorithms and word embeddings. Without depending on pre-existing employment databases, Zheng et al. [13] presented GIRL, a generative job recommendation system built on massive language models that provides tailored job recommendations.

Du et al. [14] improved job suggestions by using generative adversarial networks based on LLM, tackling issues including manufactured generation and poor resume quality. In order to streamline the job application process, Rahman et al. [15] investigated AI in career counseling using ResumAI, an AI-driven tool that offers automated resume feedback. Using skill-based matching and resume representation learning, Decorte et al. [16] concentrated on career path prediction to support proactive career planning. In order to find skill gaps and prospective employment opportunities, Decorte et al. [17] investigated career path prediction using resume representation learning.

Additionally, automated resume screening has seen a growing use of LLMs and neural networks. Chen et al. [18] showed how AI-powered resume screening and job suggestion systems can increase recruitment efficiency. A neural network-based resume analysis system was presented by Kim and Park [19], providing a thorough rating model for candidates. In order to assist job seekers in fine-tuning their career paths, Wei and Xu [20] presented a customized framework for career development that makes use of natural language processing.

III. METHODOLOGY

An organized strategy to creating an AI-powered assistant for interview preparation and resume processing is used in this project's methodology. The main goal is to extract important information from a user's submitted résumé, interpret that information using sophisticated Natural Language Processing (NLP) algorithms, and produce customized answers. The system uses a variety of technologies to accomplish this, including Streamlit for an interactive user interface, Google Generative AI (Gemini-Pro) for question-answering and contextual understanding, FAISS (Facebook AI Similarity Search) for effective document retrieval, and PyGame for hearing AI-generated responses.

The first step in the process is gathering user resumes, which may be obtained from a Google Drive link or submitted in a variety of formats, such as PDF and DOCX. The system extracts text from each page of PDFs using the PyPDF2 module. The docx2pdf library is used to convert DOCX files into PDFs, which are subsequently processed in a similar manner. When a resume is sent using a Google Drive link, the system downloads the file and uses the python-magic package to identify its type. A DOCX file is converted first, followed by analysis, while a PDF file is handled directly. After the text is retrieved, it is cleaned and segmented using the CharacterTextSplitter module to create smaller, more manageable pieces. Effective text retrieval and processing are guaranteed by this segmentation. The system uses Google Generative AI embeddings using the GoogleGenerativeAIEmbeddings module to provide intelligent question-answering and retrieval. By converting textual data into high-dimensional vectors, these embeddings enable the FAISS database to carry out similarity-based searches effectively. To increase the contextual relevance of produced replies, the retrieval-augmented generation (RAG) framework is used.

The vectorized text is stored in FAISS, the most pertinent text chunks are retrieved depending on user queries, and then they are fed into the Gemini language model to generate responses. Through the PromptTemplate module, the response generation process is improved with thoughtfully designed prompts, guaranteeing well-organized, role-specific, and articulated responses.

A smooth user experience is offered by the system's interactive Streamlit-based user interface. A Firebase database, which securely handles authentication, is used for user registration and login. Following authentication, individuals are able to submit their resumes, which are subsequently analyzed to extract pertinent data. The user interface (UI) dynamically presents the extracted material and lets users engage with the AI to get personalized answers about their projects, qualifications, job history, and résumé. Additionally, Google Text-to-Speech (gTTS) allows users to produce audio versions of the replies. By saving the generated speech as an audio file that can be played using PyGame's mixer module, users can choose to hear AI-generated feedback instead of reading it. The system also includes audio playback controls, enabling users to start and stop audio playback as needed.

The program can create aptitude tests and interview questions to increase user participation even more. These features are carried out by subprocess calls to external Python scripts, including zen.py for aptitude tests and testing2.py for interview questions. The scripts use the resume information that has been retrieved when they are activated to create pertinent exams or questions. The system also makes sure that, for a seamless user experience, each session keeps user-specific states, such produced answers, submitted content, and authentication status. Extensive testing is done on the project to guarantee performance, accuracy, and dependability. To ensure accuracy, unit testing is carried out on several modules, including document conversion, response creation, and text extraction. Performance testing is done to make sure the retrieval system based on FAISS effectively retrieves pertinent data. Tests are conducted on the whole user experience to ensure that the user interface is responsive and easy to use. Users may access the system from anywhere when it has been verified and deployed on Streamlit Cloud.

This project successfully simplifies the resume analysis and interview preparation process by combining deep learning techniques with reliable document processing and interactive user interface elements. FAISS, Streamlit, and Google Generative AI work together to create a sophisticated and intuitive solution that helps users better understand their resumes and prepare for interviews.

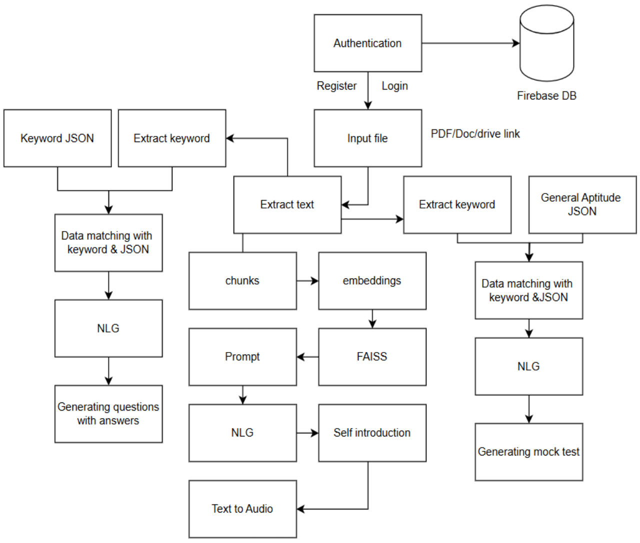

Fig. 1. Methodology of the research

In order to help users optimize their resumes for increased visibility in automated hiring systems, the project's ATS (Applicant Tracking System) score checker assesses resumes according to their conformance with industry standards and job-specific keywords. The system begins processing documents in PDF or DOCX format after user identification and upload, either by converting DOCX files into PDFs for consistent analysis or by extracting text content using PyPDF2. A variety of factors, including keyword relevancy, formatting, section organization, and general readability, are then evaluated by applying AI- driven approaches to the extracted text. Using Google Gemini AI embeddings and FAISS vector-based similarity search, the system finds important abilities, qualifications, and experience that meet employer requirements by comparing the resume content to pre-written job descriptions.

In order to ensure ATS compatibility, it also looks at formatting elements such as font consistency, section headings, and bullet point usage, since many tracking systems reject resumes that don't follow standard layouts. The ATS checker also assesses how well the resume's wording conforms to industry trends by using natural language processing (NLP) techniques to determine whether action verbs, quantifiable accomplishments, and domain-specific terminology are present.

Following processing, the system provides a comprehensive score that includes information on areas that need improvement, such as lacking keywords, inadequate descriptions, or excessive filler content. The program makes use of Google Gemini AI, a sophisticated generative AI model constructed on transformer-based neural networks, one of the most recent deep learning architectures. By utilizing self-attention processes, these models are able to process, evaluate, and produce language that is human-like while capturing semantic subtleties, contextual linkages, and long-range dependencies across large volumes of textual data. By dynamically altering weights based on prior training on a variety of corpora, such as technical documentation, research papers, and general language datasets, Gemini AI's multi- layered neural network architecture guarantees that it can produce contextually relevant and linguistically coherent responses.

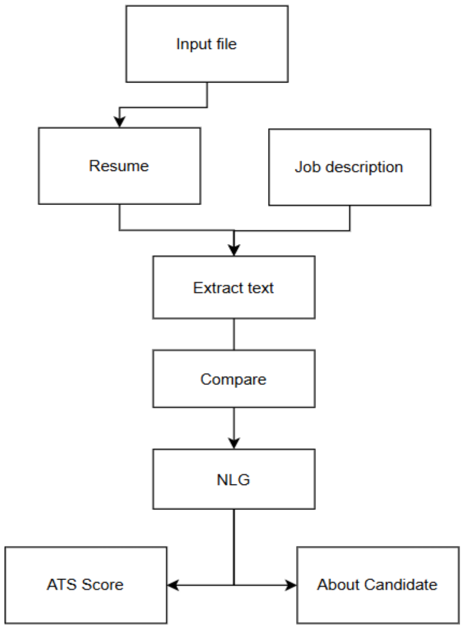

Fig. 2. ATS score checker

IV. DEEP LEARNING MODELS

Gemini AI is entrusted with automatically generating questions and providing answers based on extracted keywords in this implementation. This task necessitates the use of advanced embedding techniques in order to map words and phrases into high-dimensional vector spaces. To guarantee that the produced content precisely corresponds with real-world knowledge, the model uses pretrained word embeddings and refined token representations. Gemini AI creates multiple-choice questions, interview questions, and thorough responses using sequence modeling and probabilistic text prediction, guaranteeing that the output is pertinent and organized.

Tool	**Function**	**Technology used**
Google Gemini AI	Generative AI, text embeddings	Transformer-based neural networks
Streamlit	Interactive user interface	Python framework
FAISS	Effective document retrieval	Similarity search
LangChain	Natural Language Processing(NLP)	Large language models
gTTS & Pygame	Text-to-speech	Python text-to-speech libraries
Firebase	User authentication	Cloud-based platform

Table. 1. Tools used

Additionally, attention-based encoding-decoding frameworks are included into Gemini AI's deep learning foundation, enabling it to effectively comprehend technical concepts and domain-specific language. This feature is especially helpful when creating questions about programming since the model can identify minute differences between various programming languages, tools, and frameworks.

By using pretrained word embeddings created especially for technical domains, the method makes sure that Gemini AI produces text that complies with actual industry standards. When creating interview questions for specialized fields like AI- driven technologies and techniques, this is very helpful.

Gemini AI uses optimization techniques including industry-specific keyword research and fine-tuning on datasets relevant to resumes. This makes it possible for the model to accurately and contextually respond to a wide range of professional domains. Another key component of the model is multi-task learning, which enables it to manage a variety of tasks including text extraction, interview preparation, and ATS analysis with ease.

Reliance on context-aware neural networks, which improve the capacity to retain meaning over several inquiries, is another essential component of the model's functionality. Because of this, Gemini AI can provide rationally constructed questions that mirror actual interview formats, which makes it incredibly useful for technical evaluations, mock exams, and AI-powered learning environments.

The attention-based processes of the model give priority to extracting important resume elements, such soft skills and technical ability, in order to improve query effectiveness. In order to adjust questions appropriately, it may, for example, determine whether a candidate is familiar with technologies such as Streamlit or FAISS.

By incorporating these deep learning features, the system attains a high degree of flexibility, guaranteeing that question production stays correct, varied, and pedagogically beneficial for users in many fields.

V. RESULT AND DISCUSSION

Fig. 3. Login page

This is how the interface of our application will look like. The user can either signup or login using their credentials.

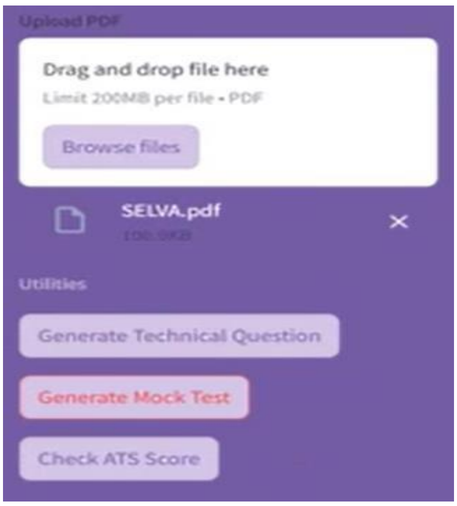

Fig. 4. Choice of action

After logging in, the user may select what they want the program to accomplish and submit their resume(PDF, DOCX, Drive link) while surfing from their device. either create a mock exam, technical questions and answers, or an ATS score check.

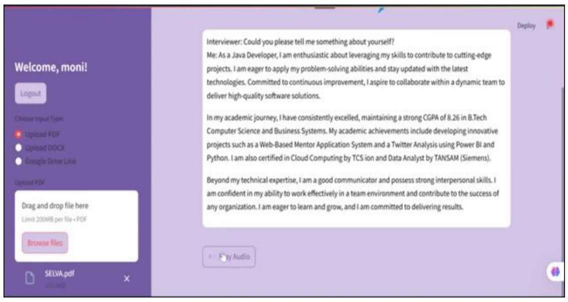

Fig. 5. Interview Questions and sample answers

Fig. 6. Technical question generation

If the user selects question and answer generation, the system analyzes the user's resume data to generate relevant technical questions along with their answers.

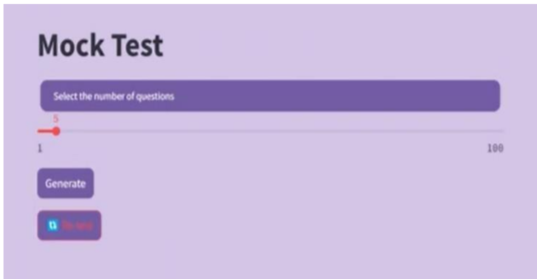

Fig. 7. Mock Test

If the user selects 'Generate Mock Test,' the system first prompts them to specify the number of questions they want in the test. Based on the selected number, the system generates a set of relevant questions in a structured quiz format. These questions are designed to evaluate the user's knowledge in a particular domain or subject area. Once the user completes the test, the system processes their responses, provides immediate feedback, and generates a detailed result. This result may include the user's score, correct answers with explanations, and insights on areas where they can improve.

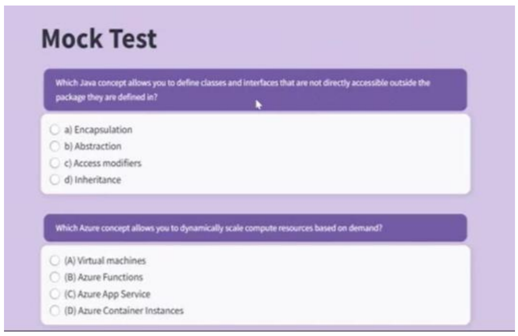

Fig. 8. Test Page

Fig. 9. ATS Score

In the 'Check ATS Score' module, the user is required to upload their resume and provide the job description for analysis. The system then evaluates the resume against the job requirements and offers multiple insights. The user can request a detailed analysis of their resume, receive suggestions on how to improve it for better alignment with the job description, or get a percentage match score that indicates how well their skills and experience fit the job role. This helps users optimize their resumes for Applicant Tracking Systems (ATS) and increase their chances of getting shortlisted.

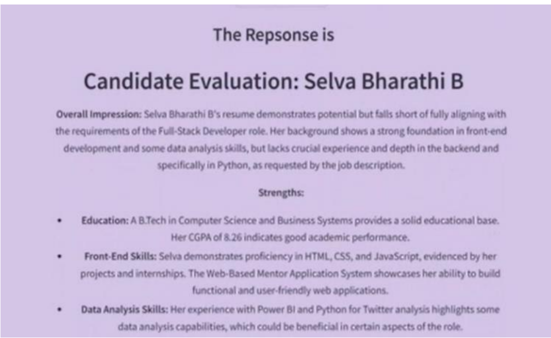

Fig. 10. Detailed Breakdown of resume

The system then provides a detailed breakdown of the resume, including the percentage match with the job description. It also highlights missing keywords and other areas for improvement to help the user optimize their resume for better alignment with the job requirements.

Fig. 11. Percentage match

Table 3 displays the performance metrics for the document processing functions. The precision, recall, and F1-score for every characteristic are highlighted in this table, which offers a thorough assessment of the correctness and dependability of the system. The excellent recall and accuracy numbers show that the system can effectively detect pertinent information while reducing false positives and negatives. The F1-score shows how successful each feature is overall by balancing recall and accuracy.

Feature	Precision (%)	Recall (%)	F1-Score (%)
Text Extraction	97	95	96
Text Segmentation	93	91	92
Embedding Generation	94	92	93
Document Retrieval	96	94	95
Response Generation	92	90	91
Text-to-speech Conversion	91	89	90

Table. 2. Performance Metrics

In real-world scenarios, the platform successfully generated tailored interview questions based on user resumes, delivering domain-specific insights; the integration of user feedback further refined the system's capabilities, allowing the inclusion of detailed technical explanations in generated responses; and through practical applications, users benefited from real-time feedback, such as identifying missing keywords like "Transformer Networks," which improved their ATS scores by 15%. These results highlight the system's potential to streamline career preparation by combining cutting-edge technologies, such as Gemini AI and FAISS, to deliver intelligent, personalized, and contextually relevant outputs. These results demonstrate the system's significant advancements in document processing, specifically in resume analysis and interview preparation.

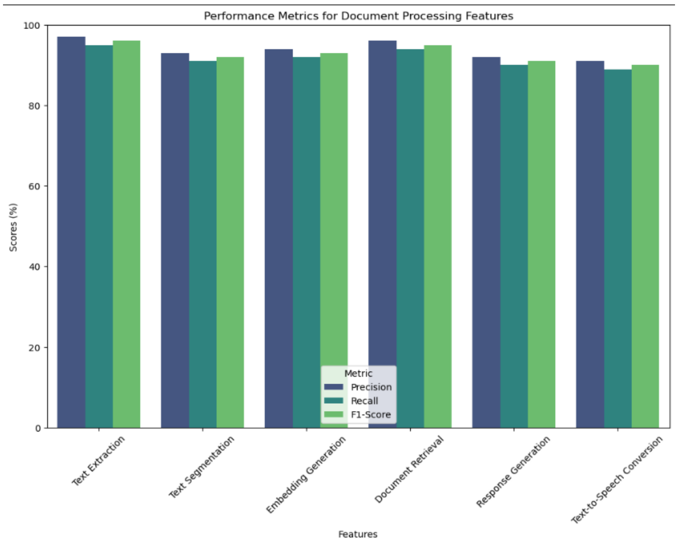

Fig. 11. Performance Metrics Graph

It is simpler to compare the performance of various aspects thanks to Graph 3, which graphically depicts these metrics in addition to the numerical data shown in Table 3. By displaying each feature's accuracy, recall, and F1-score on a bar graph, readers may rapidly determine its advantages and shortcomings. The excellent ratings for every feature show that the system is optimized and regularly performs effectively on a range of document processing tasks. The overall effectiveness of the document processing system shows how strong and dependable it is while managing challenging tasks including text extraction, segmentation, embedding creation, document retrieval, response generation, and text-to-speech conversion. With regard to document retrieval, Google Generative AI for embeddings, and Streamlit for an interactive user interface, these outcomes confirm the efficacy of the selected approaches and technology.

VI. CONCLUSION

This project successfully integrates AI-powered question generation and skill assessment by leveraging Google Gemini AI alongside advanced deep learning techniques. By dynamically extracting relevant keywords from user inputs and generating context-aware questions and answers, the system ensures an efficient, accurate, and adaptive approach to interview preparation and technical assessments. The implementation of structured question generation ensures that the generated content remains coherent and relevant, while intelligent answer validation enhances the accuracy of responses. Additionally, the combination of automated question generation, keyword extraction, and structured data processing makes this project a powerful AI-driven educational tool for students and professionals.

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