International Journal of Scientific Research in Engineering & Technology
Volume6, Issue6 (November-December 2026), PP: 203-210.
https://www.doi.org/10.59256/ijsreat.20260606028
www.ijsreat.com
ISSN No: 2583-1240

Smart Interviewer: An Adaptive Intelligence and Analytical Suite

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To Cite this Article: *Sivakumar Eswaran[1], Jayanthi D[2*], Vidhya V[3], "Smart Interviewer: An Adaptive Intelligence and Analytical Suite", International Journal of Scientific Research in Engineering & Technology, Volume 06, Issue 06, November-December 2026, PP:203-210.*

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Abstract: *Smart Interviewer, an innovative AI-driven solution, to redefine job interviews by addressing the challenges of limited interview exposure for students and streamlining the time-consuming hiring process for employers. The existing methods utilize Long Short Term Memory (LSTM) and Bidirectional Encoder Representations using Transformers (BERT) models, which focus on sequential data but struggle with very short or long text. In contrast, the proposed solution seamlessly extracts data from a variety of resumes, both structured and unstructured, spanning short to lengthy texts. The interview commences based on the candidates' skills extracted from their resumes, generating tailored questions for assessment. The personalized dashboards provide users with insightful performance analytics, while the employers benefit from a streamlined hiring process, facilitated by detailed user performance metrics. This holistic approach transforms the interview process for both candidates and employers alike.*

Keywords: *AI Interview, Candidate Assessment, Skill Extraction, Automatic interview assessment..*

I. INTRODUCTION

Smart Interviewer is an innovative solution aimed at revolutionizing the job interview process through the power of Artificial Intelligence. Smart Interviewer encompasses a range of cutting-edge technologies and modules. This platform extracts vital information from resumes, adapts interview questions contextually, assesses responses for semantic coherence and provides real-time feedback on performance. By seamlessly integrating these components, the system seeks to address the challenges faced by both candidates and employers during the interview process, streamlining workflows, enhancing candidate evaluation, and ultimately improving hiring outcomes. Through the implementation of advanced AI techniques, Smart Interviewer aims to deliver a more efficient, fair, and insightful interview experience for all stakeholders involved. Smart Interviewer transcends traditional interview paradigms, promising enhanced efficiency, fairness, and effectiveness in candidate evaluation. By leveraging the power of AI, Smart Interviewer aims to revolutionize recruitment practices, empowering both candidates and employers to make informed decisions and ultimately leading to better hiring outcomes.

II. RELATED WORK

The traditional interview process often faced numerous challenges. In the current setup, interviews are typically conducted manually, demanding significant time and effort from both interviewers and candidates. Assessments tend to be subjective, leaving ample room for bias in candidate evaluations. Moreover, scheduling interviews, particularly for remote or international candidates, posed logistical hurdles. The lack of automation of prolonged interview durations added to administrative burdens. Additionally, feedback mechanisms were limited, making it tough for candidates to receive constructive input. The goal of Smart Interviewer is to revolutionize interviews through AI-driven skill analysis, optimizing question generation, and enhancing engagement with candidates.

There are different approaches to extract skillsets from resumes. B. Gunaseelan et al., [1] introduced a system utilizing multi-level classification techniques to extract detailed resume segments like skill sets, experience, and education. Their approach accurately identified skill sets, accommodating variations in spelling and punctuation for improved flexibility. The study utilized the scikit-learn module to implement the classifier algorithm. They constructed multiple classification models, incorporating techniques such as K-Nearest Neighbors (KNN), Support Vector Machine (SVM) with RBF kernel, and ensemble methods including Bagging, Random Forest (RB), Gradient Boosting (GB), Extreme Gradient Boosting (XGB), Ada boost, and LightGBM. D. Vukadin et al., [3] proposed a Natural Language Processing system to address the challenge of Curriculum Vitae (CV) parsing. Their system utilized interconnected Machine Learning models to effectively extract and classify key sections of documents, including personal information, education, employment history, and skills. Their model extracted and classified key sections of a document, such as personal information, education, employment history, and skills, while also identifying specific details like names, dates, organizations, positions, and competency levels for individual skills. However, their model encountered limitations with tabulated data, indicating the need for additional multilingual and tabular datasets to improve performance.

To assess the candidates' responses, semantic analysis is required to understand the context of the answers and assess their responses accordingly. L. Zhang et al., [6] introduced Semantic Graph Bidirectional Encoder Representations from Transformers (SG-BERT), a technique for long text analysis. SG-BERT extracted word and sentence features, constructed a semantic graph for emotional labeling, and utilized BERT for sentiment analysis. The long-text corpus had to go through one-hot word embedding before being fed into SG-BERT for sentiment extraction and subsequent semantic graph creation, which is utilized for classification training. However, challenges arose with ultra-long texts due to the reliance on BERT for classification learning, particularly when the semantic graph becomes overly extensive. Sarada Sreekumar and Shiji S [9] proposed a system that focused on two efficient semantic knowledge-based techniques, Harvesting and Analyzing Semantic Knowledge (HASK) and Semantic Enrichment (SE). Both these techniques considered semantic knowledge to comprehend short texts. The concluding phase of short text comprehension involved instance disambiguation and re-ranking concept clusters based on context information using the SE technique, comprising preprocessing, conceptualization, identifying co-occurring terms, and detecting the final concept.

Providing interview summary from the interview transcript is also vital to give feedback on how the candidate performed in the interview. Recently, text summarization has been undergoing significant evolution, with various approaches emerging to effectively summarize the text while preserving its context. A. Dilawari et al., [12] introduced a novel neural attention model for abstractive text summarization, aiming to produce concise and insightful summaries. Their system integrated both extractive and abstractive methods, incorporating linguistic features such as sentence position, numerical data count, and named entity tags to enhance summarization quality. Their two-stage system utilized attention mechanisms to highlight crucial information at both the sentence and word levels, achieving an impressive ROUGE score of 37.76% on the CNN/DailyMail dataset and garnering praise from human evaluators for producing high-quality summaries. These results addressed the challenges in abstractive text summarization. Mudasir Mohd et al., [13] introduced an advanced tool designed to condense text documents effectively while maintaining their essential meanings. The system addressed the challenges of unstructured textual data by employing semantic analysis that utilized the distributional semantic algorithms like Word2Vec to produce high-quality summaries surpassing many open-source summarizers. The system showcased SemanticSum's functionalities, developed in Python and utilizing machine learning libraries like scikit-learn, pytorch, and gensim, with a backend named The Summarizing Engine (TSE) and a user-friendly web interface.

Zhang et al. (2024) [14] investigated the capability of Large Language Models (LLMs) to assess personality traits and interview performance using Asynchronous Video Interviews (AVIs). The authors evaluated GPT-3.5 and GPT-4 by comparing their assessments with those generated by task-specific AI models and human annotators, using simulated interview responses from 685 participants. The study examined the validity, reliability, fairness and rating patterns of LLM-based assessments. The experimental results demonstrated that LLMs achieved comparable or even better zero-shot validity than task-specific AI models in predicting certain personality traits. Furthermore, the explanations generated by LLMs provided interpretable insights into personality assessments. However, the study also identified limitations, including inconsistent performance across personality traits, insufficient test–retest reliability and potential biases in automated evaluations. The authors concluded that although LLMs offer promising capabilities for automating personality and interview performance assessment, careful validation, fairness evaluation and human supervision are essential before deploying them in employment-related decision-making. This research provides a foundation for the proposed Smart Interviewer system to incorporate LLM-based response evaluation and analytical feedback while maintaining fairness and reliability.

Koutsoumpis et al. (2024) [15] presented a machine learning-based approach for evaluating personality characteristics and interview performance through Asynchronous Video Interviews. The research investigated how different interview-related features, including verbal responses, facial expressions and voice characteristics, contribute to personality and interview performance predictions. The authors also examined the influence of trait-relevant interview questions on the accuracy of automated assessments. Their findings indicated that machine learning models could explain variations in personality and interview performance, with verbal features contributing more significantly than facial and voice features. The study further reported that asking questions specifically designed to assess particular personality traits improved the amount of personality-related information extracted from interviews. The authors highlighted the potential of algorithmic interview assessment while emphasizing the importance of evaluating bias and the validity of automated predictions. This work is relevant to the proposed Smart Interviewer system, particularly in developing competency-based question generation, NLP-based answer analysis and machine learning-based candidate performance evaluation.

Pentland et al. (2025) [16] proposed a structured design framework for developing automated job application systems using Asynchronous Video Interview (AVI) recordings. The study addressed the challenge of evaluating a large number of job applicants objectively while reducing the time and cost associated with traditional recruitment procedures. The authors emphasized the use of behavioural indicators that are difficult to manipulate and unbiased, validated training labels to improve the reliability of automated assessments. To demonstrate the proposed framework, they developed a prototype system for assessing general mental ability, which is considered an important predictor of job performance. The findings indicated that automated analysis of AVI recordings could provide more objective measures for evaluating candidates during the initial recruitment stage. The study concluded that AI-powered video interview systems can support efficient candidate screening when appropriate assessment criteria, validated data and fairness principles are incorporated. This research is relevant to the proposed Smart Interviewer system for developing automated candidate evaluation, competency scoring and analytical report generation, thereby reducing the dependency on manual interview assessment.

Szandała (2025) [17] investigated the effectiveness of Large Language Models (LLMs) in evaluating technical competencies of candidates during IT recruitment by comparing AI-based assessments with evaluations provided by human experts. The study considered three LLMs, namely ChatGPT, Google Gemini and Mistral, and compared their performance

with three experienced DevOps specialists. The experimental evaluation involved 21 candidates who responded to ten industry-oriented technical questions, covering areas such as cloud computing, infrastructure management, containerisation and CI/CD practices. Both human experts and AI models assessed the candidates' responses using a common five-point rating scale ranging from −2 to +2. Statistical techniques, including Fleiss' Kappa and one-way ANOVA, were employed to examine evaluation consistency and differences in assessment scores. The results indicated that AI models could evaluate candidate responses significantly faster than human experts, and the average assessment scores did not show statistically significant differences between human and AI evaluations. However, repeated evaluations revealed inconsistencies in AI-generated scores, particularly in ChatGPT, highlighting the challenges associated with the reliability of automated assessment. The study concluded that LLMs can effectively support technical candidate screening and competency evaluation but should complement rather than completely replace human expertise. The authors also emphasized the importance of fairness, transparency, regular performance audits and human supervision in AI-assisted recruitment. This research is relevant to the proposed Smart Interviewer system for implementing automated technical answer evaluation, competency-based scoring, performance analysis and intelligent feedback generation while maintaining human oversight in final candidate selection

Zhou (2026) [18] proposed a multimodal deep learning framework for automated employability assessment by integrating three major sources of candidate information: textual resumes, audio responses and video interviews. The proposed architecture combines BERT for extracting semantic information from resumes, wav2vec 2.0 for processing speech features, and EfficientNet with OpenFace for extracting visual and behavioural features from interview videos. An attention-based fusion mechanism dynamically assigns importance to different modalities, enabling the system to consider the most relevant information for individual candidates. The framework also incorporates SHAP-based explainable AI techniques and fairness-aware optimisation to improve the transparency and reliability of automated predictions. According to the reported experimental results, the model achieved an F1-score of 0.91 and an accuracy of 90.3% on a test dataset of 2,500 candidates, with improvements over unimodal and conventional multimodal approaches. The authors concluded that integrating textual, audio and visual information can improve employability assessment while providing interpretable and comparatively fairer predictions. This research is particularly relevant to the proposed Smart Interviewer system for integrating resume analysis, speech processing, video-based features and intelligent candidate performance analytics within a unified platform.

Panfilova et al. (2026) [19] introduced a modular AI-based interviewer agent that uses Large Language Models to conduct adaptive, semi-structured interviews. The proposed system was designed to analyse interviewees' responses, determine whether additional questions were necessary and automatically generate context-aware follow-up questions. The researchers evaluated six advanced LLMs using a standardized set of 54 interview questions and assessed their performance based on five important criteria: empathy, necessity of follow-up questions, context-awareness, openness and appropriate skipping of unnecessary questions. The evaluation involved expert annotations of more than 2,900 interview items, along with measurements of response generation time, questioning intensity and linguistic characteristics. The results revealed that different LLMs demonstrated different strengths, with some producing more empathetic questions, while others showed better contextual understanding and selective questioning capabilities. The study also highlighted the importance of maintaining conversational context, generating relevant follow-up questions and ensuring structured output from AI interview agents. The authors concluded that contemporary LLMs can perform several important interviewing functions when supported by suitable orchestration, memory management and evaluation mechanisms. This research directly supports the proposed Smart Interviewer system, particularly in implementing adaptive question generation, intelligent response analysis, contextual follow-up questioning and automated interview evaluation.

In summary, the traditional interview process has long grappled with challenges, including manual procedures, subjective evaluations, and limited feedback mechanisms. Various solutions have been proposed, from Natural Language Processing systems for CV parsing to advanced techniques like semantic analysis and text summarization. However, existing systems often lack integration and struggle with handling specific data types or contexts. This highlights the need for a comprehensive interview system that can overcome these limitations and provide a highly efficient and transparent assessment of candidates based on their performance. Smart Interviewer emerges as a solution to this imperative, aiming to transform the interview process through AI-driven skill analysis, optimized question generation, and enhanced candidate engagement. By integrating diverse techniques and addressing the deficiencies of existing systems, Smart Interviewer aims to establish a robust platform for effective candidate assessment and interview management.

III. PROPOSED WORK - SMART INTERVIEWER

Smart Interviewer introduces a cutting-edge system aimed at transforming the conventional interview process. By harnessing advanced technologies like Natural Language Processing (NLP), machine learning, and artificial intelligence (AI), Smart Interviewer seeks to optimize various facets of interviews, ranging from candidate evaluation to question formulation and feedback mechanisms. The system is composed of distinct modules, each designed to fulfill specific roles in streamlining the interview process. These modules encompass Skill Extraction, Adaptive Question Generation, User Input, Semantic Analysis, Interview Dashboard, and Interview Summarization.

Through the seamless integration of these modules, Smart Interviewer endeavors to deliver a comprehensive and efficient interview experience for both candidates and employers alike. By leveraging AI-powered skill analysis and customized question generation, the system ensures that interviews are tailored to each candidate's unique profile, thereby facilitating more precise assessments. Additionally, the incorporation of semantic analysis and interview summarization enriches the feedback process, enabling deeper insights into candidate performance. Overall, Smart Interviewer represents a significant advancement in interview technology, poised to simplify the hiring process and elevate candidate selection outcomes.

A. Design

In Figure 1, we present the intricate architecture of Smart Interviewer, a sophisticated integration of user interfaces, backend components, AI-powered modules, and data storage. This web-based platform seamlessly combines user engagement with the complexities of natural language processing, skillset analysis, and integration with external APIs to deliver a comprehensive and insightful interview experience. The security protocol begins with user authentication, meticulously validating credentials against the User Database. Once authenticated, users are prompted to upload or re-upload their resumes.

The Text Extraction & Skillset Analysis Module plays a pivotal role in parsing resumes, meticulously extracting a comprehensive list of skillsets, laying the groundwork for subsequent interview interactions. This skillset data forms the basis for question generation in the Adaptive Question Generation Module. Tailoring questions to extracted skillsets, this module dynamically adjusts difficulty levels based on candidate proficiency, ensuring a personalized and challenging interview experience. The Voice Engine transforms text-based questions into spoken language for user presentation, while user responses undergo speech-to-text conversion. The Semantic Analysis Module evaluates response correctness and coherence, generating detailed scorecards that offer users insights into their interview performance.

Moreover, users receive condensed summaries and scorecards from the Text Summarization module, providing a quick overview of their strengths and weaknesses. The Interview Analytical Dashboard serves as a visual aid, presenting performance metrics to track and evaluate interview progress effectively. This multi-layered architecture ensures users benefit from an enriched, insightful, and dynamic interview experience, fostering more informed candidate evaluations.

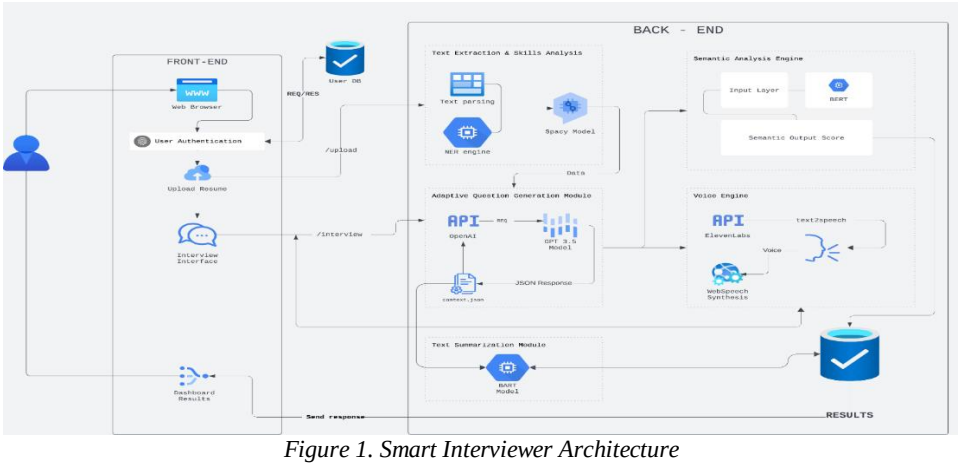


Figure 1. Smart Interviewer Architecture

B. Modules

1. User Authentication

At the core of the Smart Interviewer system lies a robust User Authentication architecture, powered by JWT (JSON Web Tokens) and MongoDB. This architecture ensures a secure and efficient process for verifying and managing user identities. JWT, known for its reliability in token-based authentication, enhances the security of user data. Complementing JWT is MongoDB, a NoSQL database renowned for its scalability and flexibility in storing and retrieving user information. Through the implementation of encryption techniques, sensitive data is safeguarded during transmission, bolstering user privacy and facilitating password reset and recovery functions. Together, these components instill confidence in the platform, striking a balance between security and user-friendliness.

2. Resume Parsing and Skillset Extraction

The Text Extraction & Skillset Analysis Module plays a pivotal role in the Smart Interviewer system, enabling the extraction of key information from resumes and providing a robust foundation for intelligent, context-aware interviews. This module hinges on the prowess of spaCy, a widely acclaimed natural language processing library. It utilizes a pre-trained spaCy model that has been meticulously fine-tuned for Named Entity Recognition (NER). The NER component proves to be the linchpin for identifying specific entities in the text, such as skills, college names, degree names, and other essential details.

Text Extraction

The process begins with the user uploading a resume document. Any format such as, PDF, DOC, or plain text is supported. Smart Interviewer employs PyMuPDF, a Python library specifically designed for extracting the entire details from the resumes. This tool is responsible for extracting textual content from the user's uploaded resume.

3. Identifying Skillset using Named Entity Recognition

Once text extraction is completed, the system employs spaCy, a widely used natural language processing library, for Named Entity Recognition (NER). Custom-trained NER models within spaCy are utilized to identify specific entities such as skills, college names, and degree information. These models detect entities based on patterns and linguistic context. The focus of the NER module is primarily on recognizing skills, including programming languages, tools, and technical expertise.

Identified skills are categorized using predefined classifications and stored in a database for future reference, enabling structured and organized skill analysis for interview questioning.

Identifying Skillset using Named Entity Recognition

In AI-driven interviews, personalization is key, with user skillsets extracted from resumes guiding question creation. The Question Generation Module, powered by FastAPI, facilitates seamless user interaction, with endpoints "/speak" and "/response" utilizing Large Language Models (LLMs) to generate tailored questions. These LLMs, honed to understand user skills, ensure engaging interviews, while a document.json file maintains conversation context for coherence.

User Input and Access to Large Language Model

The interview process begins with the user's input, which is collected through the '/speak' endpoint. The user's responses are logged, creating a starting point for the conversational flow. The power of OpenAI's Large Language Models is harnessed by the module to generate questions. These LLMs can process the user's skills and competencies, and then construct contextually relevant questions based on this understanding. Figure 2 shows the webpage to upload the resume of the candidate.

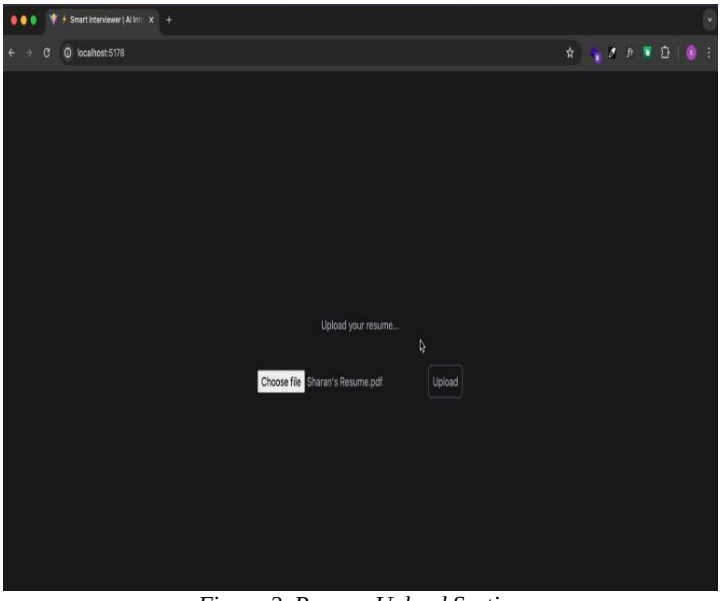


Figure 2. Resume Upload Section

JSON Response to preserve context

The '/response' endpoint receives the query and accesses the LLMs. In response, it swiftly returns a structured JSON response containing custom-tailored questions and potential answers. The conversation context is managed by the module using a document.json file. This file records the conversation's history, ensuring continuity and coherence throughout the interview process.

4. Voice Engine Module

The Voice Engine module stands as a crucial component within the Smart Interviewer system, playing a central role in delivering an immersive interview experience. This section delves into the vital contribution of Elevenlabs' text-to-speech services in ensuring authentic speech synthesis, underscoring the module's importance in elevating user engagement.

User Interaction using Whisper API

Within the Smart Interviewer application's frontend, users have access to a user-friendly interface for conducting interviews. Central to this user interaction is the Whisper API. This API allows users to respond to interview questions via speech, streamlining the communication process and making it more intuitive and accessible.

Elevenlabs API Integration

The Voice Engine module intertwines lifelike speech synthesis with heightened user engagement, enriching the interview experience. Through audio outputs resembling human speech, user engagement is notably elevated, fostering more authentic responses and enriching interview quality. This distinguishing feature positions Smart Interviewer as a standout in the AI-driven interview landscape. Powered by Elevenlabs' text-to-speech services, the Voice Engine achieves lifelike speech synthesis, enriching user interactions. Leveraging this advanced API ensures clear, articulate, and natural audio responses, enhancing user engagement and interview authenticity. Figure 3 shows how the user interacts with the system to provide answers for the questions.

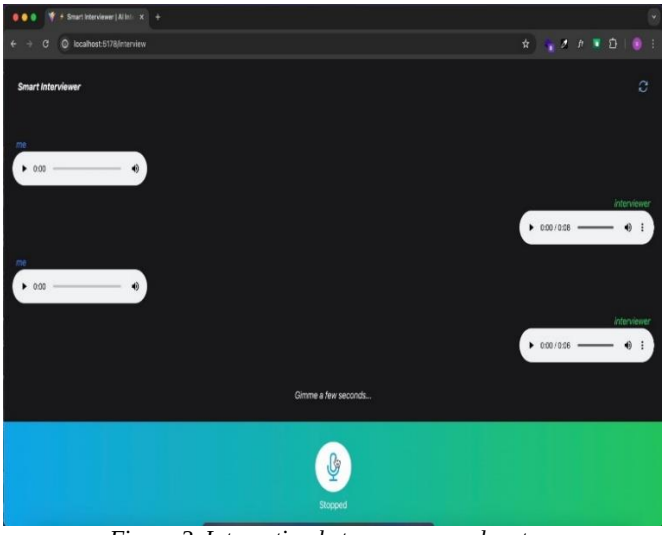


Figure 3. Interaction between user and system

5. Semantic Analysis

The Semantic Analysis Module in the Smart Interviewer system is a pivotal Natural Language Processing (NLP) component. Based on the BERT model fine-tuned with the SNLI-corpus 1.0, its primary objective is to predict the semantic equivalence of two text inputs.

BERT Embeddings

The BERT model provides excellent contextual embeddings of the input text but it lacks further adaptation to perform well on a specific task such as semantic analysis, and this is where the additional layers complement the BERT model in its drawbacks.

Bidirectional LSTM

The Bidirectional LSTM module is integral for capturing the sequential nuances within sentences, enabling the model to comprehend word order and context effectively. Pooling layers further enhance the model's capability by aggregating LSTM outputs through methods like Global Average Pooling and Global Max Pooling, capturing diverse aspects of semantic relationships. Regularization is enforced via the Dropout layer with a 0.3 dropout rate, preventing overfitting and promoting better generalization to new data. Finally, the Dense output layer employs softmax activation to deliver classification outcomes, with three output neurons corresponding to potential labels: "contradiction," "entailment," and "neutral."number

6. Text Summarization Module

The Text Summarization Module stands as a crucial feature, aimed at condensing extensive interview transcripts into clear and informative summaries. It acts as a guiding light, distilling essential information from lengthy discussions and delivering it in a succinct format. Additionally, the SAMSUM Corpus, boasting more than 16,000 chat dialogues with meticulously crafted summaries, enriches the module's capabilities with its wealth of annotated data. In Figure 4, the system summarizes the interview and provides the feedback to the user.

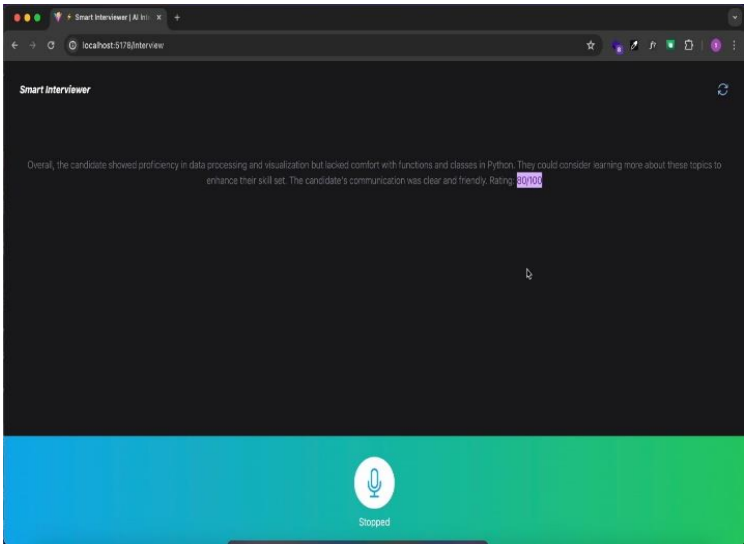


Figure 4. Candidate's Results

BART Embeddings

BART embeddings offer comprehensive contextual representations of input text, serving as the cornerstone for accurate summarization. While BART excels in capturing the nuances of language, additional layers are incorporated to fine-tune its performance for the specific task of text summarization.

Encoder – Decoder Architecture

Employing an encoder-decoder architecture, the model utilizes BART as the encoder, capturing contextual details from the input text. The decoder then processes this information to craft clear and informative summaries. Integral to this process are attention mechanisms, which enable the model to concentrate on pertinent sections of the input text while composing the summary. Through the integration of additional layers, BART's inherent attention mechanisms are refined, ensuring the production of accurate and coherent summaries.

7. Analytical Dashboard Module

Interview analytics emerges as a potent resource, harnessing data-driven insights to refine the interview journey. This chapter delves into the integration of interview analytics within the project, emphasizing the modules employed, visualization techniques applied, and the benefits and limitations of analytics in interviews. Additionally, it offers conclusive reflections on the significance of interview analytics in optimizing recruitment processes. Here we use different graphs to visualize the trends like distribution of question difficulty, trend across history of interviews, and distribution of candidate's answers across different difficulty levels.

IV. RESULTS

The outcomes of the Smart Interviewer system demonstrate the effectiveness of its modules with Artificial Intelligence and user interactions. The discussion delves into the effectiveness of each component, considering factors such as user engagement, accuracy of skill extraction, question relevance, and overall interview experience.

Resume Parsing module parses the resumes and provides the skillset of the candidate accurately. It provides an **accuracy of 89%** and extracts the skillset of the candidate.

Semantic Analysis module compares two sentences and provides a label based on their semantic similarity along with the probability score. The labels are categorized into: affirmation, neutral and contradiction with **an accuracy of 87%.** This helps in understanding how the sentences are alike or different from each other.

Text Summarization module focuses on summarizing the entire interview transcript into a summary that provides the essential details of the interview. Currently the model is trained to provide only a two line summary of the entire transcript. It can be trained with a larger dataset to provide more detailed and accurate summary. This module is evaluated with ROUGE Score. ROUGE (Recall-Oriented Understudy for Gisting Evaluation) Score is a set of metrics used for evaluating automatic summarization and machine translation software in natural language processing. The ROUGE Score is calculated using Recall and Precision.

$$RECALL = \frac{Overlapping\ \ number\ of\ n-grams}{Number\ of\ n-grams\ in\ the\ reference}$$

$$PRECISION = \frac{Overlapping\ \ number\ of\ n-grams}{Number\ of\ n-grams\ in\ the\ prediction}$$

$$ROUGE = 2 * \frac{(Recall * Precision)}{Recall + Precision}$$

The ROUGE - L score is calculated by finding the longest common subsequence between the two sentences. Any ROUGE-L F1-score around 0.4 to 0.5 may be considered moderate. This module achieved the best ROUGE - L score in the 3rd epoch with a **ROGUE - L score of 0.43**. The generated length of the summary in that epoch was 30 words.

V. CONCLUSION AND FUTURE WORK

In conclusion, Smart Interviewer stands as a promising solution to the inefficiencies and limitations of traditional interview processes. By harnessing the power of AI-driven technologies, the system offers a comprehensive and efficient platform for conducting interviews, assessing candidates, and providing valuable feedback. Through the integration of modules such as skill extraction, adaptive question generation, semantic analysis, and interview summarization, Smart Interviewer aims to optimize the interview experience for both candidates and recruiters. The system's ability to personalize interviews based on candidate profiles, analyze responses for contextual understanding, and generate concise summaries underscores its potential to revolutionize the hiring process and improve candidate selection outcomes.

With the evolving technologies, Smart Interviewer can be further improved to perform more efficiently. One idea is to add features like emotion detection and sentiment analysis to give candidates a more personalized experience. The system could also made for interviews in different languages and for people with diverse backgrounds, making it useful for everyone around the world. Additionally, the system's technology can keep improving to make it even smarter and faster. The system can also be modified to automate question generation with RBT levels and enhance the analytics dashboard, so recruiters can quickly see how everyone is doing and compare top performers. The voice engine component of the system may also improve

its efficiency in translating the voice of Non-native English speakers. With these improvements, Smart Interviewer will be an even more valuable tool for hiring managers everywhere. By doing this, Smart Interviewer can help companies find the best people for the job, making the hiring process easier and more effective.

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