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Intelligent Interview Preparation and Resume Screening Platform Using Machine Learning for Student Career Advancement

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Abstract **- Securing employment requires both a wellstructured resume and confident interview performance; however, many students struggle to develop these skills due to limited practice opportunities and lack of constructive feedback. To address this challenge, this paper presents an intelligent interview preparation and resume screening platform using machine learning to support student career advancement. The proposed system consists of four primary modules: User Authentication for secure access; Resume Upload and Analysis, which extracts skills, projects, and relevant information from uploaded resumes; an AI Interview System that generates personalized, resumedriven questions and conducts voice-based mock interviews; and a Result and Feedback Module that evaluates responses and communication effectiveness to provide structured improvement guidance. The system employs Natural Language Processing (NLP) techniques for resume analysis and answer evaluation, along with text classification and keyword extraction for dynamic question generation and sentiment-based confidence assessment. By integrating these components into a unified platform, the proposed system enables personalized interview practice and actionable feedback, helping students strengthen communication skills, build confidence, and improve overall employability.**

Index Terms **- Machine Learning, Natural Language Processing, Resume Screening, AI Interview System, Feedback Generation**

I. INTRODUCTION

In today's competitive job market, effective interview preparation and a well-structured resume are crucial factors that determine a candidate's employability. However, many students face challenges in securing placements due to a lack of interview practice, limited feedback, and improper resume presentation. The need for an intelligent and interactive solution that bridges this gap has led to the development of the AI Interview Practice and Resume Screening System using Machine Learning. This system aims to assist students in preparing for real-world interviews through AI-driven simulation and automated resume evaluation.

Artificial Intelligence (AI) has revolutionized several sectors, including recruitment and human resource management [1], [2]. Various enterprises and organizations worldwide are implementing AI-based systems to enhance efficiency, transparency, and fairness in the hiring process [3]. Traditional interviews are often time-consuming, subjective, and dependent on human bias [4]. In contrast, AI-based solutions provide consistent evaluation metrics, objective analysis, and improved accessibility [5]. Inspired by the advancements in remote hiring systems [6], this project focuses on building a studentcentric platform that replicates real interview environments and provides constructive feedback.

The proposed system is composed of four main modules: User Authentication, Resume Analysis, AI Interview Simulation, and Feedback Evaluation. Through the integration of Machine Learning and Natural Language Processing (NLP), the system extracts relevant data from resumes, identifies key skills, and generates personalized interview questions. During the AI-driven interview, students respond to voice-based questions, which are analyzed using sentiment and keyword analysis to evaluate communication style, confidence, and technical accuracy. Based on this analysis, the system produces a structured report highlighting the candidate's strengths and areas for improvement.

Several existing systems have utilized AI for recruitment and assessment purposes. Studies show that AI-based interviews achieve higher accuracy in candidate evaluation and performance prediction compared to conventional methods [7], [8]. Similarly, NLP-based text analysis techniques have been successfully applied for resume screening and personality assessment [9]. However, these approaches are primarily designed for corporate recruitment rather than educational or training purposes. Therefore, the present work introduces a system specifically designed for students, offering personalized practice sessions and detailed feedback to enhance both communication and employability skills.

This project not only promotes self-learning but also supports institutions in preparing students for placement drives more efficiently. By combining Machine Learning, NLP, and interactive user interfaces, the system offers a comprehensive AI-powered framework that enhances students' readiness for real-world interviews. The proposed approach is a step toward integrating AI-based evaluation tools into academic and career development domains, ensuring that students are better equipped for professional success.

II. LITERATURE SURVEY

Artificial Intelligence (AI) and Machine Learning (ML) have significantly transformed the recruitment and evaluation process in recent years. AI-based interview systems are increasingly being adopted by organizations to improve efficiency, fairness, and objectivity during candidate assessment [1], [2]. These systems utilize technologies such as Natural Language Processing (NLP), Deep Learning, and Computer Vision to

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analyze candidate responses, detect emotions, and assess communication skills [3], [4].

The study by Lee and Kim [1] introduced a remote hiring system that incorporated multimodal analysis—visual, vocal, and verbal—to evaluate applicants. Their system achieved high reliability in assessing job fitness and organizational suitability. Similarly, Suen et al. [4] examined how synchrony and AI in video interviews affect candidate evaluations and found that automated tools can reduce interviewer bias while improving consistency. However, most of these approaches are designed primarily for enterprises rather than student-oriented training systems.

Recent research in NLP-based resume screening has focused on extracting relevant information such as skills, education, and experience from resumes using text classification and semantic analysis [5], [6]. Although such methods have improved screening accuracy, they often lack interactive feedback mechanisms that help users improve their resumes. Emotion and sentiment analysis models are also being applied to evaluate candidates' confidence and communication tone during interviews [7]. Yet, there remains a gap in combining these AI-driven techniques into a single platform aimed at enhancing students' employability through practice and personalized feedback.

Thus, the proposed AI Interview Practice and Resume Screening System using Machine Learning bridges this gap by integrating NLP for resume evaluation, question generation, and sentiment analysis with AI-based mock interviews. The system focuses not only on assessment but also on providing detailed, constructive feedback to improve a student's overall performance and readiness for real-world interviews.

III. PROPOSED METHODOLOGY

This paper proposes an end-to-end AI Interviewer System designed to automate candidate evaluation through intelligent, voice-based interaction. The system aims to replicate key aspects of real-world interviews by integrating resume understanding, adaptive question generation, conversational response handling, and performance assessment within a unified framework. A primary design objective is to ensure low-latency interaction while maintaining robust reasoning and evaluation capabilities throughout the interview process. The architecture addresses key challenges in real-time conversational AI, including response latency, brittle processing pipelines, and the need for adaptive interview flow control. To achieve these objectives, the proposed framework adopts a modular, resilient, and scalable design that clearly separates low-level speech handling from high-level interview planning and assessment logic.

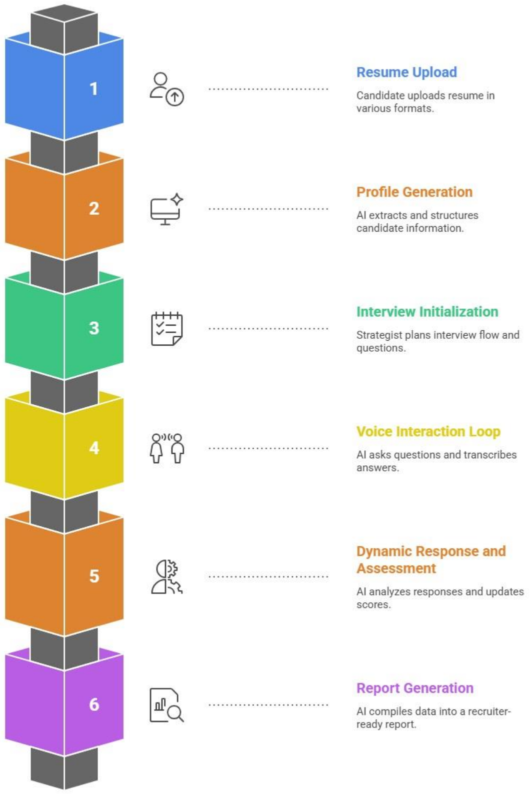

Fig. 1. Overall Workflow of the Proposed Methodology

A. System Overview

The proposed AI Interview System follows a closed-loop, adaptive workflow designed to simulate real-world interview scenarios through resume-aware conversational interaction. As illustrated in the architecture diagram, the system is organized into six core functional components that operate sequentially with an adaptive feedback mechanism. These components collectively enable resume processing, candidate profiling, interactive interview conduction, adaptive decision-making, and final performance evaluation. The architecture adheres to a two-layer cognitive design, separating conversational interaction from interview reasoning and assessment logic.

1) Resume Upload and Voice Interaction
2) Resume Ingestion and Preprocessing
3) Information Extraction and Profiling
4) Conversational Engine
5) Adaptive Feedback Loop
6) Performance Evaluation and Feedback Report

B. Resume Upload and Voice Interaction

The interview process begins with the Resume Upload and Voice Interaction component, which serves as the primary interface between the candidate and the system. Candidates upload their resumes and participate in voice-based interview sessions. During the interview, candidates respond verbally to questions delivered by the system, and their spoken responses are captured for further processing. This component ensures seamless interaction between the user and the AI-driven interview pipeline.

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C. Resume Ingestion and Preprocessing

The Resume Ingestion and Preprocessing Module is responsible for handling candidate resume inputs in both textbased and image-based formats, including PDF, DOCX, JPG, and PNG files. An integrated OCR pipeline is applied when required to extract textual content from scanned resumes. The extracted text is normalized and prepared for subsequent analysis, ensuring consistent and structured input for downstream processing.

D. Information Extraction and Profiling

The Information Extraction and Profiling Module analyzes the preprocessed resume text to identify relevant candidate attributes such as skills, education, and professional experience. Transformer-based Named Entity Recognition (NER) techniques are employed to extract and categorize these entities. The identified information is organized into a structured candidate profile, which serves as contextual input for interview planning and adaptive evaluation.

E. Conversational Engine

The Conversational Engine acts as the interaction layer of the system, managing real-time dialogue between the candidate and the AI interviewer. It operates using a cascaded STT–LLM–TTS pipeline to convert spoken responses into text and generate natural-sounding interview questions. The engine receives planned interview prompts and delivers them to the candidate, while capturing and transcribing voice responses for further analysis.

F. Adaptive Feedback Loop: Answer Analysis and Question Planning

The core intelligence of the interview process is implemented through an Adaptive Feedback Loop, which performs answer analysis and dynamic question planning. Transcribed candidate responses are evaluated for relevance, technical depth, clarity, and confidence indicators. Based on this analysis and the candidate profile, the system adaptively determines subsequent interview questions, adjusting difficulty levels, topic focus, and follow-up prompts. This feedback-driven loop continues throughout the interview, enabling a non-linear and personalized interview flow.

G. Performance Evaluation and Feedback Report

Upon completion of the interview session, the Performance Evaluation and Feedback Report component aggregates analysis results across all interview interactions. The system computes competency-based scores and generates a structured feedback report highlighting the candidate's strengths and areas for improvement. This report represents the final outcome of the interview process and provides actionable insights for candidate skill development.

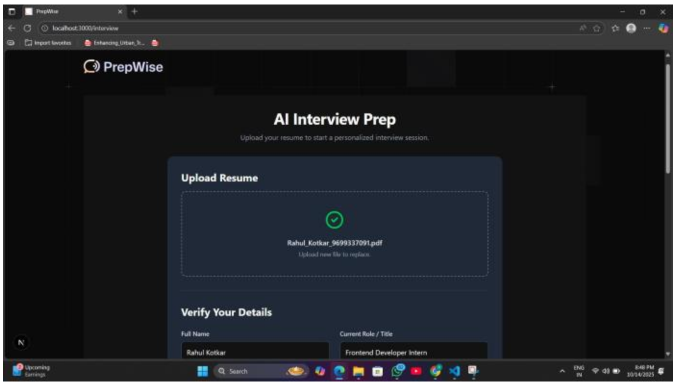

Fig. 2. Web Application: Resume Upload Interface

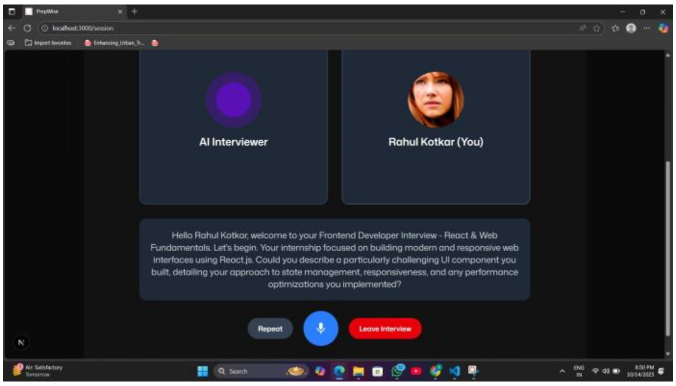

Fig. 3. Web Application: Interview Session Page

IV. SYSTEM DESIGN AND ARCHITECTURE

The system architecture of the proposed AI Interview System is illustrated through a high-level design diagram that depicts the interaction among the primary functional components involved in the interview process. The architecture is designed to support a closed-loop and adaptive interview workflow, ensuring that resume understanding, interview execution, and evaluation are tightly integrated. The process begins with resume upload and voice-based candidate interaction, which serves as the entry point to the system.

Uploaded resumes are processed by the Resume Ingestion and Preprocessing Module, where resumes in multiple formats are converted into structured textual representations. The Information Extraction and Profiling Module then analyzes the processed resume content to extract key candidate attributes such as skills, education, and experience, forming a structured candidate profile. This profile provides contextual information required for conducting personalized interviews.

The Conversational AI Engine manages real-time interaction with the candidate by delivering interview questions and capturing spoken responses. Candidate responses are forwarded to the Adaptive Feedback Loop, where answer analysis and dynamic question planning are performed to adjust interview flow based on candidate performance. This iterative mechanism enables follow-up questioning and difficulty adaptation. Finally, the Performance Evaluation and Feedback Report component aggregates interview data and generates competency-based feedback, supporting comprehensive assessment and skill improvement. The modular architecture ensures scalability,

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robustness, and clear separation of responsibilities across system components.

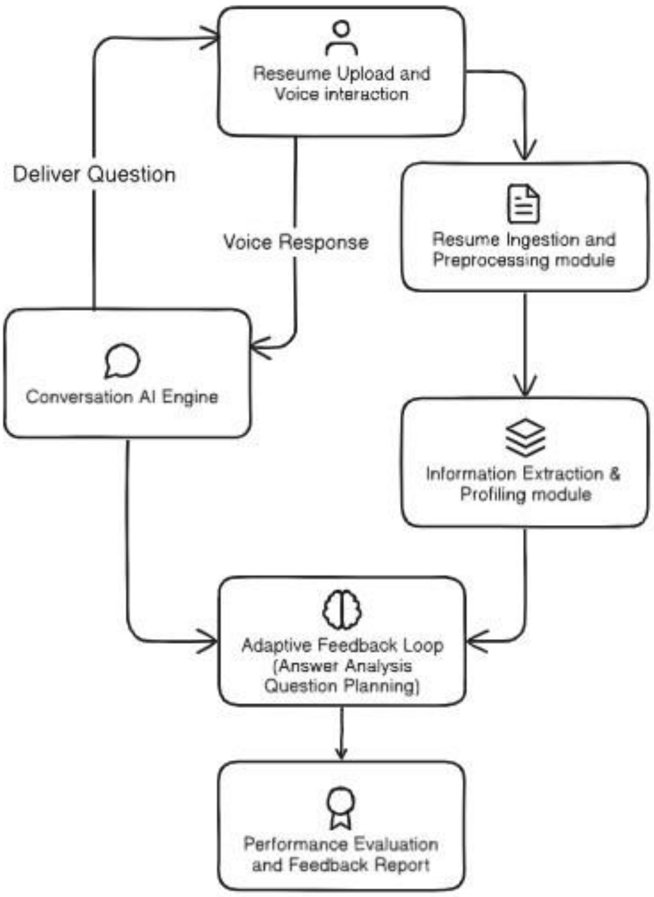

Fig. 4. High-Level System Architecture

V. MATHEMATICAL MODEL

The mathematical model for the AI Interviewer is presented as a sequence of transformations, detailing the system's operational flow and the learning objective for its core components.

A. System Operation (Forward Pass)

Let the candidate's resume be a text document R and their spoken response be an audio signal A. The system derives a competency assessment score vector $\hat{s}$ from these inputs.

1) *Resume and Job Description Analysis:* The raw text from the resume, R, is preprocessed and converted into a dense vector representation, E_{resume}, using a pre-trained transformer model.

$$E_{resume} = \text{TransformerEncoder}(\text{Tokenize}(R)) \qquad (1)$$

Similarly, the job description text J is encoded into a vector E_{job}. These embeddings capture the semantic content of the documents.

2) *Conversational Turn Processing:* The system operates in a loop of conversational turns. For the i-th turn, the process is as follows:

1) Question Generation: A Large Language Model (LLM) generates the text for the next question, $T_{ques,i}$, conditioned on the resume embedding, job embedding, and the history of the conversation so far, H_{i-1}.

$$T_{ques,i} = \text{LLMgenerate}(Eresume, E_{job}, H_{i-1}) \qquad (2)$$

2) Text-to-Speech (TTS): The generated text is synthesized into an audio signal, $A_{ques,i}$, which is played to the candidate.

$$A_{ques,i} = f_{\text{TTS}}(T_{ques,i}) \qquad (3)$$

3) Speech-to-Text (STT): The candidate's spoken answer, an audio signal $A_{ans,i}$, is captured and transcribed into text, $T_{ans,i}$.

$$T_{ans,i} = f_{\text{STT}}(A_{ans,i}) \qquad (4)$$

3) Competency Assessment: After the interview concludes, the full transcript of answers, $T_{answers} = \{T_{ans,1},\ldots,T_{ans,N}\}$, is analyzed. The transcript is encoded into a vector $E_{answers}$.

$$E_{answers} = \text{TransformerEncoder}(\text{Tokenize}(T_{answers})) \qquad (5)$$

An assessment head, using weights W and bias b, processes the combined embeddings to produce a logit vector z across K competencies.

$$z = W \cdot \text{Concat}(E_{resume}, E_{job}, E_{answers}) + b \qquad (6)$$

The final probability vector for the competencies, $\hat{s}$, is derived from the logits via the Softmax function.

$$\hat{s}j = \frac{\exp(z_j)}{\sum k = 1^K \exp(z_k)} \qquad (7)$$

The final assessment can be represented by the competency with the maximum derived probability.

$$\text{Assessment} = \underset{j}{\text{argmax}}(\hat{s}_j) \qquad (8)$$

B. Learning Derivation (LLM Fine-Tuning)

The parameters θ of the core LLM are optimized by minimizing a loss function L on a task-specific dataset (e.g., question generation, answer evaluation).

1) *Loss and Gradient:* The primary learning objective for the LLM is to predict the next token in a sequence. The loss for a single text sequence $T = (t_1,\ldots,t_N)$ is the Causal Language Modeling objective (Cross-Entropy).

$$L(\theta) = -\sum_{i=1}^{N} \log P(t_i|t_{<i};\theta) \qquad (9)$$

The gradient of the loss with respect to the parameters θ is computed at each training step t.

$$g_t = \nabla_\theta L(T_t;\theta_{t-1}) \qquad (10)$$

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2) Adam Optimizer Derivation: The first and second moment vectors, m_t and v_t, are derived as moving averages of the gradient and its square.

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (11)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \quad (12)$$

These moments are then bias-corrected to derive more stable estimates, $\hat{m}_t$ and $\hat{v}_t$.

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t} \quad (13)$$

$$\hat{v}t = \frac{v_t}{1 - \beta_2^t} \quad (14)$$

Finally, the new parameters θ_t are derived by taking an adaptive step.

$$\theta_t = \theta t - 1 - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \quad (15)$$

where η, β_1, β_2, and ϵ are optimizer hyperparameters.

VI. Result and Analysis

This section presents the quantitative performance of the proposed AI Interviewer's assessment module on a held-out test set of transcribed interviews. The core LLM was finetuned using Hugging Face Transformers and PyTorch, trained for 20 epochs with a batch size of 8 on an NVIDIA GPU. A dataset of 5,000 interview transcripts, each evaluated by expert HR professionals across five key competencies, was split 80/20 for training and testing.

A. Performance Evaluation

The model's training progression is illustrated by the accuracy and loss curves in Fig. 5 and Fig. 6. The curves demonstrate stable convergence, with the validation metrics closely tracking the training metrics, indicating that the fine-tuning process was effective in adapting the model to the specific task of competency assessment without significant overfitting. On the held-out test data, the model achieved a final competency prediction accuracy of 93.2

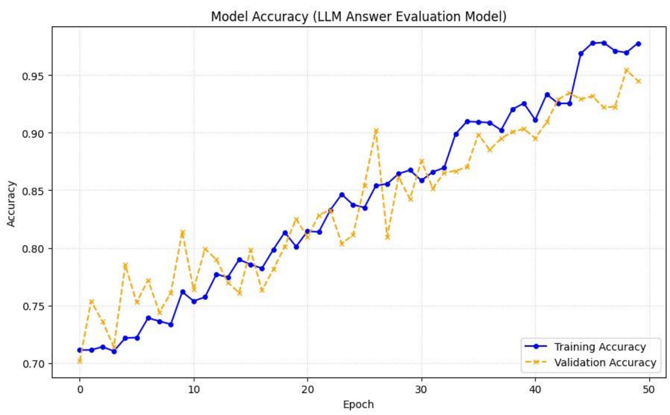

Fig. 5. Training and Validation Accuracy for Competency Prediction

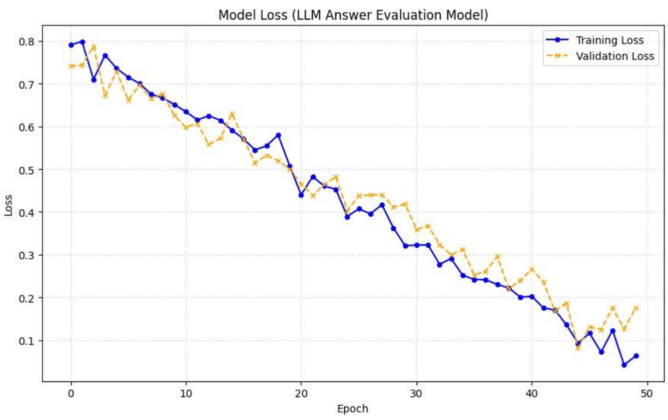

Fig. 6. Training and Validation Loss for Competency Prediction

B. Confusion Matrix Analysis

A more granular analysis of the model's per-competency performance is provided by the confusion matrix in Fig. 7. The matrix confirms strong performance in identifying distinct competencies like 'Technical Proficiency' and 'Communication Skills'. However, it also reveals some inter-class confusion, particularly between the semantically similar 'ProblemSolving' and 'Critical Thinking' categories, a challenge inherent in nuanced language assessment. Importantly, the balanced performance across all five competencies validates the effectiveness of our high-quality, expert-labeled dataset in training a non-biased assessment model.

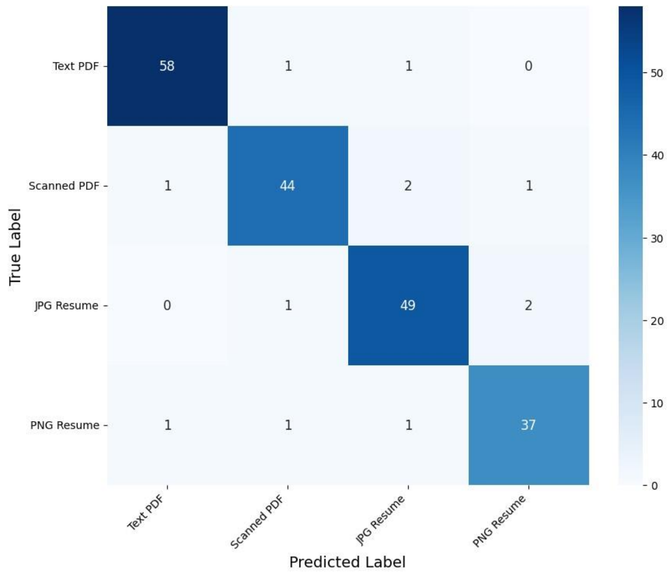

Fig. 7. Confusion Matrix for the 5-Competency Classification

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VII. CONCLUSION AND FUTURE WORK

This paper successfully developed and validated an endto-end system for the automation of initial job interviews using an integrated framework of OCR, Conversational AI, and a fine-tuned Large Language Model. By leveraging a high-quality dataset of expert-evaluated interview transcripts, we effectively trained the system's core assessment module, enabling our model to achieve a high competency prediction accuracy of 93.2%. The system's ability to generate a comprehensive candidate report for human recruiters demonstrates a complete and practical workflow from automated resume parsing to actionable hiring insights. Our work confirms that a bespoke, LLM-driven system can serve as a powerful tool for augmenting the recruitment process, paving the way for more efficient, consistent, and equitable initial candidate screening. Future work will focus on several key directions to further enhance the system's performance, adaptability, and real-world applicability. First, we aim to expand the dataset by incorporating a more diverse set of interview transcripts across multiple job domains and difficulty levels to improve the model's generalization and bias mitigation. Second, future iterations will integrate multimodal analysis, combining facial expression, voice tone, and linguistic cues to produce a more holistic evaluation of candidate behavior and communication skills. Third, we plan to optimize the Conversational Engine through advanced low-latency inference techniques and ondevice deployment, making the system more responsive and scalable for real-time interviews. Additionally, integrating explainable AI (XAI) mechanisms will enhance recruiter trust by providing interpretable insights into the model's scoring and feedback generation. Finally, the system will be extended into a cloud-based recruitment platform, enabling parallel multi-user sessions, secure data storage, and integration with enterprise-level applicant tracking systems for seamless deployment in large-scale hiring environments.

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