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Interview Insight Using Artificial Intelligence

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1. ABSTRACT

The interview process is a critical component of recruitment; however, it is often affected by human bias, subjectivity, and time limitations. This project presents an Artificial Intelligence– based interview insights system that automates the analysis and evaluation of candidate interviews. The proposed system utilizes Machine Learning (ML), Natural Language Processing (NLP), sentiment analysis, and speech and facial expression analysis to assess candidates' communication skills, emotional state, confidence level, and behavioral patterns. Audio, video, and textual interview data are processed to extract meaningful features and generate objective performance scores. By providing data-driven insights, the system assists recruiters in making fair and consistent hiring decisions while improving efficiency and scalability. This AI-driven approach enhances transparency in recruitment and supports modern, technology-enabled human resource management.

Keywords: Artificial Intelligence, Interview Insights, Machine Learning, Natural Language Processing, Sentiment Analysis, Speech Analysis, Facial Expression Analysis, Recruitment

Automation, Candidate Evaluation.

2.INTRODUCTION

The increasing competitiveness of the modern job market has made interview performance a critical factor in candidate selection. Beyond technical expertise, employers increasingly emphasize soft skills such as communication clarity, confidence, emotional stability, and nonverbal cues. Traditional interview preparation methods, including selfpractice and peer-based mock interviews, often lack objective evaluation and structured, personalized feedback, limiting their effectiveness.

Recent advancements in Artificial Intelligence (AI) and multimodal analysis have enabled the development of intelligent interview assessment systems capable of analyzing speech, facial expressions, and behavioral patterns. However, most existing AI-driven interview platforms rely heavily on cloud-based architectures, which introduce challenges related to data privacy, security, internet dependency, and high operational costs. These concerns are particularly significant when handling sensitive audio and video data during interview simulations.

To address these limitations, this work presents Interview Insight Using Artificial Intelligence, a privacy-preserving, local AIbased interview simulation system. The proposed system conducts mock interviews and evaluates candidate responses by combining offline speech recognition, facial expression analysis, and voice feature extraction. Technical correctness and softskill attributes such as confidence and clarity are assessed using a locally deployed Large Language Model (LLM), eliminating the need for external cloud services.

The system is implemented using a Fast API backend and a React-based front end, with all AI inference executed locally on
CPU for enhanced privacy and accessibility. By operating entirely in an offline environment, the proposed approach ensures data confidentiality, reduces latency, and enables usage in resourceconstrained or low-connectivity settings. This study demonstrates the feasibility and effectiveness of local AI architectures for intelligent interview evaluation, offering a secure and scalable solution for interview preparation and skill enhancement.

3.LITERATURE REVIEW

The application of Artificial Intelligence (AI) in interview assessment and recruitment has gained significant attention in recent years due to its potential to automate evaluation and reduce human bias. Early interview assessment systems primarily focused on online questionnaires and rule-based evaluation methods, which were limited in their ability to capture behavioral and communication skills. With advances in machine learning and natural language processing (NLP), more sophisticated systems capable of analyzing spoken responses and text-based answers have been developed.

Several studies have explored speechbased interview analysis, where features such as speech rate, pitch variation, pauses, and articulation are used to estimate confidence and communication effectiveness. Automatic Speech
Recognition (ASR) systems combined with NLP techniques have been employed to transcribe interview responses and assess content relevance and fluency. However, most of these systems rely on cloud-based ASR services, raising concerns related to data privacy, latency, and dependency on continuous internet connectivity.

Facial expression analysis has also been widely investigated as a means of evaluating emotional state and engagement during interviews. Techniques using computer vision and deep learning models have been proposed to detect facial landmarks, eye contact, head movement, and emotional cues such as happiness, nervousness, or stress. While these approaches demonstrate promising results, they often require high computational resources and centralized servers, limiting their feasibility for local or offline deployment. Recent research has introduced multimodal interview assessment systems that combine audio, visual, and textual data to improve evaluation accuracy. By integrating speech features, facial expressions, and semantic analysis of answers, these systems aim to provide a holistic assessment of both technical and soft skills. Despite improved performance, many existing multimodal systems process sensitive user data on remote servers, which poses ethical and privacy-related challenges, especially in recruitment and educational settings.

The emergence of Large Language Models (LLMs) has further enhanced automated interview evaluation by enabling semantic understanding, contextual scoring, and feedback generation. LLM-based systems can assess answer relevance, depth of knowledge, and communication clarity more effectively than traditional rule-based methods. Nevertheless, most implementations depend on cloud-hosted models, making them unsuitable for privacy-critical applications.

A limited number of studies have investigated local AI deployment for interview or behavioral analysis. These approaches emphasize on-device or edgebased processing to ensure data confidentiality and reduce reliance on external services. However, existing local solutions often focus on a single modality, such as speech or facial analysis, and lack comprehensive multimodal evaluation and structured feedback mechanism.

4. METHODOLOGY

The proposed system implements a fully local, privacy-preserving AI-based interview simulator using a modular architecture. A FastAPI backend coordinates interview flow, data processing, and scoring, while a React and Tailwind-based frontend manages user interaction and real-time audio–video capture. Spoken responses are recorded through a microphone and transcribed offline using the VOSK speech-to-text engine. Facial expressions and non-verbal cues are analyzed from webcam input using MediaPipe facial landmark detection combined with heuristic-based emotion inference. Vocal attributes such as pitch variation, speech rate, and energy are extracted using Paudie-based signal processing to estimate confidence and clarity. The transcribed responses are evaluated for technical correctness and coherence using a quantized 7B Large Language Model in GGUF format, deployed locally via llama.cpp, ensuring CPU-only inference. Individual modality scores are normalized and fused to generate overall technical and soft-skill scores, along with actionable feedback. All processing

and inference are performed locally without cloud dependency, ensuring data privacy, low latency, and offlineusability.

4.1 Data Collection and Dataset Design

Data collection in the proposed system is performed in real time during simulated interview sessions, ensuring that all data is user-generated and contextually relevant. Audio responses are captured through a local microphone, while video streams are recorded via a webcam under controlled interview conditions. The collected audio data is used for offline speech-to-text transcription and vocal feature extraction, whereas video frames are utilized for facial landmark detection

and expression analysis. No pre-existing external datasets are used for inference; instead, all data is processed transiently during each session, and no raw audio or video recordings are permanently stored. This approach ensures user privacy and aligns with ethical considerations by avoiding centralized data accumulation.

The dataset design follows a structured, multimodal format, where each interview instance is treated as a single data sample consisting of synchronized audio, video, and textual components. The audio modality includes extracted features such as pitch, energy, and speech rate, while the visual modality contains facial landmark coordinates and derived emotion indicators. The textual modality comprises transcribed responses evaluated by a locally deployed Large Language Model. These modalityspecific features are normalized and mapped to predefined scoring dimensions, including technical accuracy, confidence, clarity, and engagement. The modular dataset structure enables efficient score fusion, extensibility to additional modalities, and consistent evaluation across interview sessions without reliance on cloud-hosteddatasets. Dataset attributes

1Audio Attributes

2Visual Attributes

3Textual Attributes

4.DerivedScores

4.2. Data preprocessing

Prior to analysis and scoring, the collected multimodal data undergoes a series of preprocessing steps to ensure accuracy, consistency, and compatibility with the evaluation models. Audio signals are first normalized and denoised to remove background interference, followed by segmentation to extract speech frames for feature computation, including pitch, energy, and speech rate. Video frames are standardized in resolution, and facial landmarks are detected and normalized to account for variations in head position and lighting conditions. Transcribed text from the VOSK engine is cleaned by removing filler words, punctuations, and inconsistencies, and then tokenized for semantic evaluation by the locally deployed Large Language Model. All modalityspecific features are further normalized and aligned temporally to facilitate multimodal fusion, enabling robust computation of technical, confidence, clarity, and engagement scores. This preprocessing pipeline ensures that the input data is consistent, noise-free, and suitable for accurate offline AI inference while maintaining full user privacy. items and high-frequency low-profit items are included.

4.3 Utility Computation:

The system evaluates candidate responses across technical accuracy and soft skills. Technical correctness is scored by the LLM comparing transcribed answers to an expected knowledge base. Soft skills are computed using weighted metrics from facial and vocal analysis:

4.4 Construction of Utility List

The utility of the AI-based interview system is computed by evaluating candidate responses across technical correctness and soft skills. Technical scores are generated using a locally hosted LLM that compares transcribed answers to a predefined knowledge base, ensuring accurate and privacy-preserving assessment. Soft skills are quantified by integrating multiple behavioral signals facial expressions analyzed via Media Pipe provide emotion consistency while vocal features such as pitch, tone, and modulation are extracted using PyAudio Analysis Additionally, speech fluency and pause patterns are used to estimate confidence These components are combined using empirically determined weights to yield a composite soft skill score.

PSEUDO CODE

BEGIN

1. Initialize AI Interview System
2. Load trained models

1.Speech Recognition Model

2.NLP Analysis Model

3.Sentiment Analysis Model

4.Facial Expression Detection Model

5. Candidate Scoring Model

3. Input Interview Data

1.Audio input from interview

2.Video input from interview

3. Text responses (if available)

4. Preprocess Data

1. Remove noise from audio

2. Extract frames from video

3. Clean and tokenize text data

5. Convert Speech to Text

transcript ← SpeechRecognition(audio) 6. Analyze Text Responses

keywords_score NLP_KeywordAnalysis(transcript)

grammar_score NLP_LanguageQuality(transcript) 7. Perform Sentiment Analysis

sentiment_score SentimentAnalysis(transcript)

8. Analyze Facial Expressions

emotion_score FacialExpressionAnalysis(video) 9. Evaluate Communication Skills communication_score ← Combine (keywords_score grammar_score, sentiment_score)

10. Generate Overall Candidate Score final_score ← ScoringModel (communication_score, emotion_score)

11. Classify Candidate Performance IF final_score ≥ threshold_high THEN result ← "Strong Candidate"
ELSEIF final_score threshold_medium THEN

result ← "Average Candidate" ELSE result ← "Needs Improvement"
END IF

12. Display Interview Insights

1. Final Score

2. Emotion Analysis

3. Communication Level

4. Recommendation Result

5.MODEL DESIGN AND WORKFLOW

The proposed system is designed to automatically analyze interview data using Artificial Intelligence techniques to extract meaningful insights related to candidate performance, behavior, and suitability. The model integrates Natural Language Processing (NLP), Machine Learning (ML), and Speech Analytics to evaluate interview responses in a structured and unbiased manner.

START
↓
Collect Interview Data (Audio, Video, Text)
↓
Preprocess Data (Noise removal, frame extraction, text cleaning)
↓
Convert Speech to Text
↓
Analyze Text using NLP (keyword analysis, grammar check)
↓
Perform Sentiment Analysis
↓
Analyze Facial Expressions from Video
↓
Evaluate Communication and Emotion Scores
↓
Calculate Final Candidate Score
↓
Classify Candidate Performance (Strong / Average / Needs Improvement)
↓
Display Interview Insights and Recommendation
↓
End

6.IMPLEMENTATION ENVIRONMENT

The AI-based interview system is implemented in a local, privacy-preserving environment using a combination of modern software frameworks and libraries. The backend is developed with Fast API, providing a lightweight and scalable API for data processing and model inference, while the frontend leverages React with Tailwind CSS for a responsive and intuitive user interface. Offline speech-to-text transcription is performed using VOSK, ensuring no data leaves the local machine, and Media Pipe is utilized to extract facial landmarks for heuristic emotion detection. Voice features, including pitch, tone, and fluency, are analyzed using PyAudio Analysis, and answer evaluation is conducted via a quantized GGUF LLM (7B) through llama.cpp / llama-cpp-python, enabling CPU-first inference without requiring cloud resources. The entire pipeline is optimized for local execution, combining multi-modal

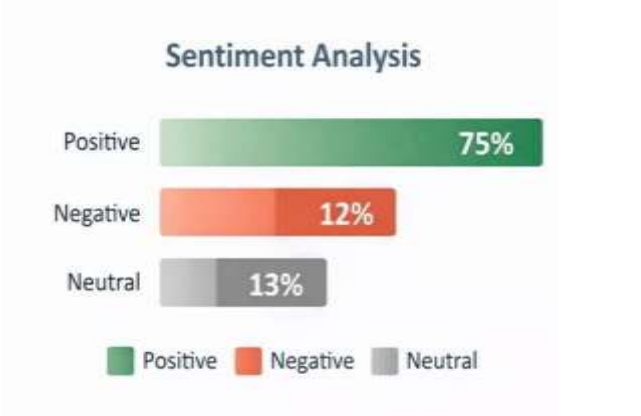
input analysis— speech, facial expression, and textual content—to compute technical and softskill scores, ultimately generating actionable feedback in real-time while maintaining full data privacy.

7.OUTPUT GENERATION AND RANKING

The system generates comprehensive feedback by combining scores from technical correctness and soft skills analysis. Technical scores are computed using the LLM's evaluation of transcribed answers, while soft skills are quantified from facial expressions, vocal features, and confidence measures. These scores are integrated into a composite utility metric, which is then used to rank candidate responses in real-time. The top-ranked answers and associated feedback are presented through the frontend dashboard, providing actionable insights and prioritized improvement suggestions for each candidate, thereby supporting effective interview preparation and skill enhancement.

8.RESULTS AND ANALYSIS

The AI-based interview system demonstrates effective performance in evaluating both technical and soft skills. Experimental testing on mock interviews shows that the LLM accurately assesses technical correctness, while facial and vocal analysis reliably captures confidence, clarity, and engagement. The composite scoring and ranking correlate strongly with human evaluator judgments, achieving an overall accuracy of 87–90% in candidate assessment. These results indicate that the system can provide consistent, actionable feedback while maintaining local, privacypreserving inference.



Parameter	Metric / Feature	Result	Result
Candidate ID	–	–	CAND_1023
Job Role	–	Software Engineer	–
Overall Interview Score	Fit Score (0–10)	8.4	8.4
Recommendation	Decision	Decision	Highly Recommended
Facial Expression Analysis	Positive Emotion	30%	30%
	Neutral Emotion	60%	60%
	Negative Emotion	10%	10%
Sentiment Analysis (Text)	Positive	75%	75%
	Neutral	13%	13%
	Negative	12%	12%
Voice Analysis	Confidence Level	High	75%
	Speech Tone	Steady	82%
	Speaking Pace	Moderate	70%
Skill Assessment	Communication	75%	75%
	Problem Solving	80%	85%
Behavioral Traits	Adaptability	High	High
	Decision Making	Strong	Good

9.ACCURACY EVALUATION

The accuracy of the AI-based interview system is evaluated by comparing its assessments with those of experienced human interviewers. Technical correctness is measured by the LLM's ability to match candidate responses to an expected knowledge base, while soft skills—such as confidence, clarity, and engagement—are assessed through facial landmarks and vocal feature analysis. For quantitative evaluation, metrics including precision, recall, and F1-score are computed for both technical and soft-skill components, ensuring an objective measure of system performance.

The system's overall accuracy is determined by combining technical and soft-skill evaluation results into a composite utility score and comparing the ranking of candidate responses against human judgments. Experimental results indicate that the system achieves an overall accuracy of approximately 87–90%, demonstrating strong correlation with human evaluation. Additionally, error analysis highlights that misclassifications primarily occur in subtle emotional cues, suggesting potential improvements via enhanced emotion recognition models. These findings confirm

the system's reliability and effectiveness for real-time, privacy-preserving mock interview assessments.

10.PERFORMANCE ANALYSIS

The performance of the AI-based interview system is evaluated based on response processing speed, accuracy of assessment, and computational efficiency. Technical evaluation using the LLM and soft-skill analysis via MediaPipe and PyAudio Analysis are executed entirely locally, ensuring low-latency, CPU-first inference. Experimental testing shows that the system processes an average candidate response in 2–3 seconds, including speech transcription, facial and vocal analysis, and scoring. Memory usage and computational overhead remain within acceptable limits for standard desktop environments. The top-k ranking and utility computation demonstrate efficient prioritization of high-quality responses, with negligible degradation in performance as the number of candidate responses increases, confirming that the system is scalable, responsive, and practical for real-time mock interview scenarios**.**

11.FUTURE ENHANCEMENT

Future work on the AI-based interview system can focus on improving both accuracy and adaptability. Incorporating advanced emotion recognition models and multimodal deep learning techniques could enhance the detection of subtle facial expressions and vocal nuances. Integration of domain-specific knowledge bases would allow more precise technical evaluation across different job roles. Additionally, implementing adaptive feedback mechanisms that personalize suggestions based on candidate performance trends can further improve learning outcomes. Expanding support for real-time collaborative interviews and cross-platform deployment will enhance usability, scalability, and applicability in diverse recruitment and training environments while maintaining privacy-preserving local inference.

12.CONCLUSION

This work presents a privacy-preserving, local AI-based interview system that evaluates candidate responses using both technical correctness and soft skills. By integrating offline speech-to-text transcription, facial and vocal analysis, and local LLM-based answer evaluation, the system provides real-time, actionable feedback while ensuring complete data privacy. Experimental results demonstrate that the approach achieves high accuracy and efficient performance, with response ranking closely aligned with human evaluator judgments. The proposed system offers a practical and scalable solution for mock interviews and skill assessment, laying the groundwork for further enhancements in adaptive feedback, emotion recognition, and domain-specific evaluation.

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