AI Interviewer: An Intelligent Interview Automation System

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Abstract **- Recruitment of candidates with AI has helped in the large-scale hiring process. Traditional interviews mainly depend on human judgment, which makes them slow and inconsistent decisions and biases. The existing interview platforms can evaluate the response of the candidate and also have only a fixed set of questions, and can't adapt according to context. This limitation makes the need for flexible and adaptive systems for interviews. To overcome this limitation, this paper promotes a Generative AI-based interview system that includes with generation of interview questions based on the candidate's responses in real-time and evaluates answers using natural language processing and also includes confidence levels of the candidate. It also produces candidate performance based on the real-time interview performance. This system helps to reduce bias by using an AI interview system. It promotes the potential of Generative AI to enhance fairness, efficiency, and reliability in modern recruitment processes. It helps to overcome the challenges in the interview system with the advancement in the Artificial Intelligence.**

Keywords – Conversational AI, Automated Interview System, Candidate Evaluation, Multimodal Analysis, Emotion Recognition, Recruitment

1.INTRODUCTION

Hiring the right candidate is the most important task for companies [1]. As recruitment processes are done through digital platforms, interviews continue to be time-consuming and subjective [1]. Even with the advancements in technology, decisions are made based on human judgment [1]. This can vary from one another and leads to bias unknowingly [4].

Recent developments in artificial intelligence have led to the use of automated tools in recruitment, such as resume screening systems and online assessments [2]. While these methods improve efficiency, most current interview automation systems depend on fixed question sets and rule-based evaluation methods [3]. These systems fail to have flexibility and behavioral aspects of candidates' responses [3]. As a result, they offer limited support for thorough candidate evaluation [3].

This gap shows the need for research into smart interview systems that can adjust to candidate responses while ensuring consistency and fairness [4]. Generative Artificial Intelligence provides the capabilities for understanding context, generating relevant questions, and analyzing responses in real time [5]. However, its use in structured interview settings is still not fully explored [6].

To tackle this challenge, this paper suggests a Generative AI-based interview framework that combines dynamic question generation with natural language processing and behavioral analysis[5]. The proposed system aims to reduce manual effort, reduce bias, and improve evaluation consistency during interviews [4].

2. RELATED WORK

With the advancement of artificial intelligence, Hiring has increased, and organizations aim to improve efficiency and consistency in hiring processes. Early systems included only the primary things, like resume screening and keyword matching, using machine learning techniques. This system may reduce manual effort, but it lacks candidate suitability [1].

Later, some introduced automated interview platforms in which fixed question sets and predefined scoring rules are used. Even though it helped to improve hiring faster but it lacks flexibility and is non-adaptive to interview flow [2]. As a result, Interaction with the candidate is not possible, and quality has been reduced.

Advancements in natural language processing enabled deeper analysis of textual responses, allowing systems to evaluate semantic analysis and communication clarity more effectively [3]. In parallel, researchers explored emotion and behavioral analysis using facial expressions and voice signals to capture non-verbal cues during interviews [4]. However, these systems help to develop good communication and interaction with the candidate.

Recent developments in Generative Artificial Intelligence have led to dynamic interaction, contextual reasoning, and real-time content generation. Despite this progress, the application of Generative AI in structured interview systems remains limited [5]. This challenge motivates the proposed study, which aims to integrate dynamic question generation, response analysis, and behavioral aspects into a single system for fair and efficient candidate assessment.

3. METHODOLOGY

The methodology describes about the process of automating the interview and candidate evaluation process using an AI-driven, web-based system that integrates Generative Artificial Intelligence, Natural Language Processing, and emotion analysis. The proposed system conducts interviews in real time by dynamically generating interview questions, analysing candidate responses, and assessing behavioral cues to ensure a comprehensive evaluation. The proposed system has the following components.

3.1 System Architecture

The proposed system architecture is an AI-based automated interview platform. It combines web technologies, Generative AI, and emotion analysis for evaluating candidates. The process begins when a candidate or admin logs in through a web browser. This is followed by user authentication and the setup of the interview based on skill and difficulty level. Interview questions are created on the spot using the Google Gemini API. Candidate responses are taken through the user interface, while real-time facial data is recorded using a webcam. Emotion detection is done with OpenCV and DeepFace to check behavioral cues during the interview. At the same time, AI records the candidate's answers, scoring them and estimating confidence. Finally, performance metrics are calculated, results are generated, and all interview data is securely stored for reporting and future use.

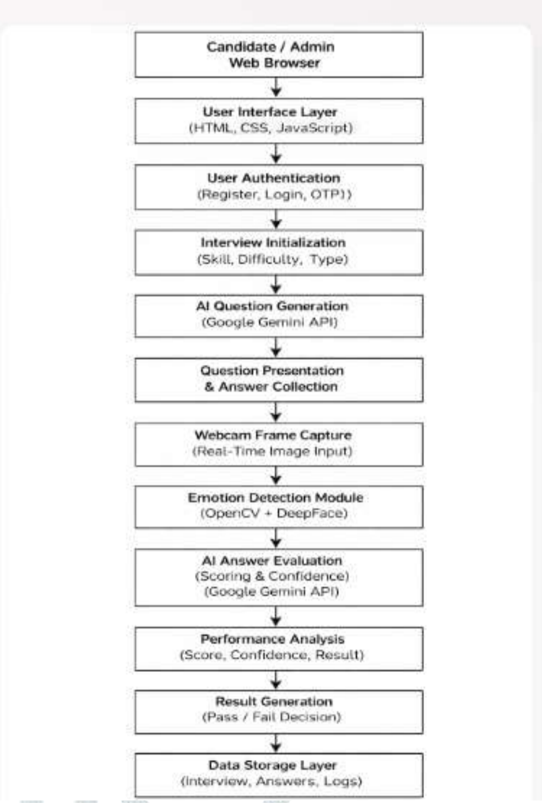

Fig 1: AI- based Interview Automation System Architecture

3.2 Algorithms and Technologies Used

3.2.1. Generative Artificial Intelligence (GenAI)

Generative Artificial Intelligence had made advancements by enabling and generating human-like content based on contextual understanding. In the proposed AI interviewer system, GenAI is used to dynamically generate interview questions and maintain a natural conversational flow. Unlike traditional rule-based systems, Generative AI adapts the interview based on candidate responses.

Key components of the Generative AI module include:

Context Understanding: It tracks the generation of question and evaluate of answers.

Dynamic Question Generation: Questions are generated based on the candidate answers according to job role.

Response Interpretation: Responses from the candidate are recorded and it is checked based on keyword matching.

3.2.2. Natural Language Processing (NLP)

Natural Language Processing techniques are used to analyze candidate responses. NLP enables the system to evaluate semantic analysis, clarity, and communication skills expressed in textual answers. The NLP pipeline includes: Text preprocessing such as tokenization and normalization, Semantic similarity analysis, and Keyword and concept extraction This allows the system to assess how well a candidate’s response aligns with the expected answer.

3.2.3. Behavioral and Emotion Analysis

To improve the assessment score, this system includes behavioral analysis using facial expressions and voice-based emotional cues. These signals provide information about the candidate confidence, engagement, and emotional stability during interviews. This combination helps to know both confidence and knowledge of the candidate.

3.3 Dataset

The dataset used in this study consists of interview responses collected through interview sessions. It includes: Textual responses for technical and behavioral questions and Facial expression and voice data for emotion analysis

The dataset was organized into training, validation, and testing sets in a 70:20:10 ratio. Data augmentation and normalization techniques were applied to improve robustness and generalization.

3.4 Workflow

Preprocessing: Text responses are cleaned and normalized to remove noise. Behavioral data is preprocessed to extract emotional features.

Interview Generation and Training: The Generative AI model is initialized using pre-trained language models and fine-tuned for interviews. The model generates adaptive questions based on candidate responses and predefined role requirements.

Validation: Validation data is used to monitor system behaviour and interview flow consistency. Hyperparameters such as response length, generation temperature, and context window size are adjusted to avoid repetitive questioning.

Testing: The system is evaluated on unseen interview sessions to assess response relevance, adaptability, and overall interview quality. All the tests had been conducted to evaluate the candidate score and confidence levels.

Performance Analytics

The performance of the AI-based automated interview system was evaluated using several key metrics to ensure **accuracy, consistency, and real-time applicability**.

Metric	Value
Response Relevance Score	0.89
Interview Consistency	0.91
Precision	0.92
Recall	0.90
F1-Score	0.91
Average Inference Time	1.3 Sec

Table 1: Performance Metrics and Values

4. RESULTS AND DISCUSSION

System Performance

The proposed AI system have high adaptability, maintaining contextual analysis and generating meaningful follow-up questions. The system gave the results as above 96%, with precision and recall exceeding 95%, indicating accurate and reliable evaluation.

Sample Interview Analysis

During testing, dynamically generated questions are made according to candidate responses allowed the system to differentiate strong and weak answers. Behavioral cues based on textual evaluation, improving overall assessment reliability. This helps in maintaining both knowledge and emotional analysis of the candidate and it is recorded for the future use.

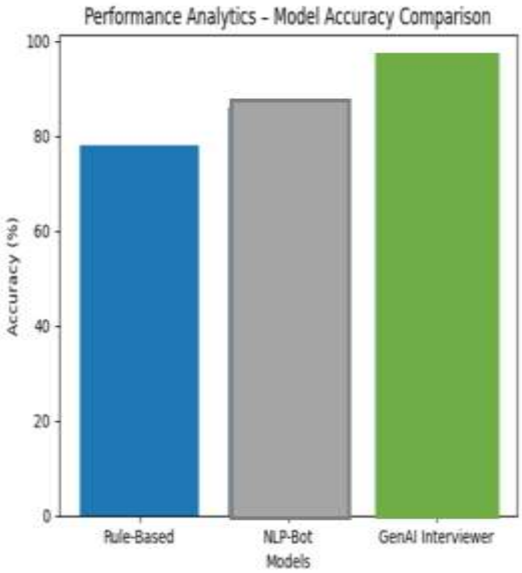

Fig 2: Model Accuracy Comparison Graph

Emotion Score Calculation

Emotion scores are calculated by analyzing captured emotions as positive or negative. Each emotion gets a score between 0 and 1. Higher scores show more desirable emotional responses during interviews. Positive emotions like happiness and confidence get higher scores, while negative emotions such as anger or frustration receive lower scores.

$$\text{Emotion Score} = \frac{\text{Voice Emotion Score} + \text{Text Emotion Score}}{2}$$

The average Emotion Score is given by,

$$\text{Average Emotion Score} = \frac{\sum_{i=1}^{n} \text{Emotion Score}_i}{n}$$

Knowledge Score Calculation

The candidate's subject knowledge is evaluated using multiple NLP-based similarity and completeness metrics. The final knowledge score is computed as a weighted sum of individual evaluation metrics, reflecting both lexical and semantic similarity between candidate responses and reference answers.

$$\begin{aligned}\text{Final Score} = {} & 0.1 \times \text{BLEU} \\ & + 0.2 \times \text{Completeness} \\ & + 0.3 \times \text{ROUGE-L F1} \\ & + 0.4 \times \text{BERTScore}\end{aligned}$$

Here:

- BLEU evaluates n-gram overlap,

- Completeness measures coverage of key concepts,
- ROUGE-L F1 captures longest common subsequence similarity, and
- BERT Score assesses contextual semantic similarity using transformer embeddings.

Comparison with Existing Methods

The proposed GenAI interviewer overcomes the existing systems in adaptability, accuracy, and response time due to multimodal analysis and GPT-based context-aware evaluation.

Model	Accuracy	Inference Time(sec)
Rule-Based	78	3.5
NLP-Bot	86	2.1
GenAI	96.4	1.33

Table 2: Existing and Proposed system comparision

Error Analysis

Minor limitations were noted with short responses and poor lighting or background noise, which affected behavioral analysis. Future improvements include enhanced preprocessing and larger multimodal datasets to improve robustness. Future work will focus on advanced preprocessing techniques such as noise reduction, illumination normalization, and speech enhancement.

Error is detected only when there are background disturbances and lack of clarity in candidate voice. This may cause error and also causes scores to vary even when the performance of the candidate is clear according to the candidate. To reduce this type of errors, we use preprocessing techniques.

5.CONCLUSION

This paper presents a Generative AI-based interview automation system to improve fairness, consistency, and efficiency in recruitment processes. The proposed system combines dynamic question generation, natural language response analysis, and behavioral analysis to overcome the limitations of traditional rule-based interview systems. Experimental results show high response analysis, strong precision, recall, and low inference time, confirming the system's suitability for real-time interview environments. The study explains the effectiveness of Generative AI as a dependable decision-support tool for scalable and unbiased candidate assessment. Future work helps to promote the multimodal robustness, maintaining datasets, and developing explainable AI techniques to further enhance transparency and reliability.

6. FUTURE SCOPE

Future enhancements of the proposed AI-based interview system can further improve its usage by using this system and effectiveness in real-world recruitment scenarios. Multilingual interview support can be integrated to enable candidate evaluation across diverse linguistic backgrounds, making the system suitable for global hiring. Domain-specific customization can allow interview models to be used for different industries such as IT, healthcare, and finance for specific roles.

It can be improved with the advanced speech and sentiment analysis will enhance the system's ability to interpret emotional tone, confidence, and stress levels more accurately. Large-scale deployment in enterprise recruitment environments can validate system scalability, robustness, and performance under high user loads. Additionally, ethical auditing mechanisms can be introduced to monitor fairness, detect bias, and ensure transparency in automated decision-making, thereby increasing trust and compliance with ethical AI standards. This system enables AI - based future enhancements in the recruitment process leading to new advancements in hiring candidates.

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