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Smart Interview: AI-Driven Interview Automation with Candidate Performance Analysis

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Abstract— In many organizations, technical interviews can be quite different depending on the interviewer, and this can cause inconsistencies, biases, and scaling issues in the interview process. To address these issues, this paper presents an intelligent interview system that employs a Large Language Model (LLM) to automate the entire technical interview process. The system offers role-specific questions depending on the job description of the candidate and allows administrators to define parameters such as difficulty level, number of questions, and type of questions. The system allows different types of question formats, including descriptive, coding, and multiple-choice questions. For the purpose of validation in evaluation, the system employs structured validation for multiple-choice questions, without revealing the answers, and employys LLM scoring for descriptive answers. To maintain integrity in remote technical interviews, the system allows the use of lightweight proctoring features such as motion detection and tab switching. The system also allows automated scoring, summary, and email notification. The experimental results show that the system improves consistency in scoring, automates the process, and scales the interview process. The proposed system is a practical and flexible solution for AI recruitment.

The study concludes: Large Language Model (LLM), Intelligent Interview System, Technical Interview Automation, Role-Specific Question Generation, Structured Validation, LLM-Based Scoring, Remote Proctoring, Motion Detection, Tab-Switch Monitoring, Automated Scoring, AI-Based Recruitment.

I.INTRODUCTION

The adoption of technical interviews has been among the most sought-after trends in the evaluation of candidates in areas of expertise that require analytical skills and knowledge. However, the traditional approach in the evaluation of candidates through interviews has been known to be highly reliant on the perspectives of the interviewers, which may lead to inconsistencies in the evaluation criteria and subjective decision-making in the evaluation of candidates [1]. With the rising number of candidates in the evaluation process, it has become difficult to ensure that the evaluation criteria are standardized. Unlike traditional digital interview systems, which depend to a large extent on question banks, the use of LLMs enables the dynamic generation of interview questions based on job requirements. This is particularly useful in technical recruitment, where requirements are likely to be different. However, it is important to ensure that such tests are free from bias. Computer-based tests have been successful in incorporating structured validation systems to remove bias from scoring systems

[6], [7]. In addition to this, interview settings need to be provided with monitoring systems to ensure that there is no biased treatment, considering computational complexity [8]. This paper proposes a model for intelligent interviews that combine dynamic interview questions using LLMs with a hybrid validation system for responses and integrity monitoring. The questions are role-based and correspond to the job description provided by the candidate. The questions are role-based and correspond to the job description provided by the candidate. The questions can also be of varying difficulty levels. The questions can be of various types, such as descriptive questions, coding questions, and multiple choice questions. The objective type questions are compared internally without revealing the correct answer. The descriptive questions are evaluated by LLM. Moreover, motion detection and tab switching monitoring are also implemented to increase the reliability of the interview process without relying on any sophisticated surveillance system. The proposed framework for intelligent interviews is an attempt towards creating a consistent and dynamic solution for AI-based technical recruitment. The framework combines the use of generative intelligence along with a validation and monitoring system to increase the reliability and efficiency of the interview process.

II. RELATED WORK

The use of artificial intelligence in recruitment processes has been widely discussed in recent years. At first, the use of artificial intelligence in recruitment processes was largely focused on the assessment of resumes through keyword-based approaches. However, there has been an improvement in the use of artificial intelligence in recruitment processes in recent years. The recent approaches have started to use machine learning algorithms to assess candidate profiles to determine their suitability for the positions. The use of deep learning in the development of intelligent systems capable of understanding human language has improved in recent years. Large Language Models (LLMs) have demonstrated promising applications in conversational dialogue systems, question-answering systems, and text assessment systems. The intelligent systems have been used in the development of educational assessment systems to create questions and assess the responses of students. However, the use of artificial intelligence in designing intelligent recruitment systems has not been given much importance. With the development of machine learning, there has been a shift in the interest of many researchers towards supervised learning for the detection of speech pathology. Support Vector Machines and decision tree classifiers have been in fashion because of their ability to handle non-linear data. Research work on feature extraction due to the presence of complex interactions, and classification using Random Forests, has been quite promising. However, these classifiers have been found to be inefficient in high-dimensional spaces. Some studies on automated interview systems have also explored the application of video-based emotion analysis, speech sentiment analysis, and behavior-based evaluation frameworks. While the application of these approaches is beneficial in enhancing the fairness and objectivity of the evaluation process, they also demand high computational power for the integration of multiple modalities. Moreover, most of the existing online interview systems are based on predefined question sets, which makes these systems less flexible and adaptable to the needs of the interviewers.

Some recent studies have also explored the application of AI-based evaluation mechanisms to minimize the subjectivity of the scoring process. While the application of a combination of rule-based evaluation and machine learning-based classification enhances the consistency of objective evaluation, the existing studies have not explored the prevention of answer leakage during multiple-choice-based validations and the reliability of the automated scoring process.Moreover, the application of lightweight proctoring techniques for remote interviews is still an area of research. Contrary to the current automated interview systems, the proposed system comprises the application of dynamic question generation based on the LLM approach, validation techniques based on multiple choices with structured assessment without answer disclosure, and the application of the LLM approach for scoring descriptive-type questions. Moreover, the application of lightweight motion detection and tab-switch monitoring is an effective technique for ensuring the authenticity of the interview process for remote interviews. The application of the integrated platform with the above characteristics also ensures a clear differentiation of the proposed system from the current AI-based recruitment systems.

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III. METHODOLOGY

The intelligent interview system to be developed will be modular in design with a common framework for question generation, evaluation, administrative control, and proctoring. The intelligent interview system will be of the client-server type. The interface for conducting the interview will be web-based, while all the processing will occur on the server side.

The system will consist of five major modules: the Candidate Interface Module, the LLM-Based Question Generation Engine, the Evaluation Engine, the Administrative Control Module, and the Integrity Monitoring Module.

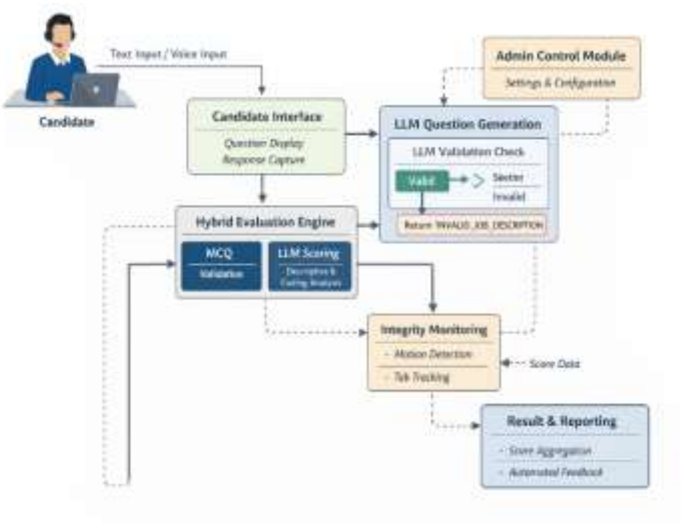

Fig 1: System Work Flow

A. Candidate Interface Module

The Candidate Interface Module is the interface for the interaction between the user and the system. The interface will provide the facility for the candidate to enter his or her details and the job description of the post for which the candidate is applying. On the basis of the details entered by the candidate, the system will display the questions in a structured format. The candidate will have the facility to answer the questions either by typing the answer or by giving the answer through voice input. If the answer is given through voice input, the system will convert the speech into text using the speech-to-text technology. The answer will then be sent to the evaluation engine.

B.LLM-Based Question Generation Engine

The Question Generation Engine is developed using the Large Language Model (LLM) to produce dynamic questions based on the job description. The questions produced by the engine are dynamic, depending on the inputs provided to the engine. The dynamic questions produced are organized depending on the inputs provided to the engine. The proposed system is novel compared to other interview systems, where the questions are predefined. The proposed system produces dynamic questions, which are context-dependent. Different types of questions are produced, such as descriptive, coding, and multiple-choice questions. In the case of multiple-choice questions, the engine is designed to produce questions that are organized without revealing the answer to the candidate.

C. Hybrid Evaluation Engine

The Evaluation Engine is used for the evaluation of the answers provided by the candidate and the generation of the corresponding scores. To make sure that the answers are evaluated in a fair manner, the proposed system uses the hybrid method. For multiple-choice questions, the proposed system automatically identifies the correct answer to the questions. The proposed system compares the correct answer to the question with the answer provided by the candidate. The proposed system does not reveal the correct answer to the candidate. For descriptive questions, the proposed system uses the LLM-based scoring method, wherein the answer is evaluated based on the relevance, completeness, clarity, and correctness of the answer. A normalized score is generated for the answer provided by the candidate.

D. Administrative Control Module

The Administrative Control Module provides the administrators with easy and centralized control over the interview process. In this module, the parameters can be adjusted according to the level of difficulty, type of questions, number of questions, time duration of the interview, area of questioning, and the weighted value of the components. This point configuration enables the system to adjust to the different needs of the organization with ease by simply adjusting the parameters without changing the structure.

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E. Integrity Monitoring Module

The Lightweight Integrity Monitoring Module is used to ensure the integrity of the remote interview. The module monitors the movement and tab switching of the candidate during the interview. Once the thresholds are satisfied, the interview will be marked. The module does not use a heavy monitoring system to ensure the integrity of the interview.

F. Result and Reporting Module

Once the interview is completed, the system will then calculate the total scores acquired by the candidate in all the questions. It will then produce a summary of the performance of the candidate. The results will then be sent to the candidate via email. This module will therefore complete the automation of the interview process, making the system more efficient.

Fig 2: Flowchart of the Automated Interview Process

IV. PERFORMANCE ANALYSIS

The performance analysis of the intelligent interview system was done by carrying out controlled demonstrations in various technical fields. The analysis was intended to test the stability of the system, system responsiveness, and the reliability of automated scoring.

A. Evaluation

Mock interviews were carried out based on various job descriptions and levels of difficulty. Multiple choice and descriptive types of questions are used to test the stability of the system. The analysis was done by testing:

- The stability of automated scoring
- System responsiveness
- The effectiveness of integrity monitoring
- The reliability of system functionality

The analysis was done in a web-based environment.

B. Objective Question Validation

In the case of multiple choice questions, the system employs rule-based internal validation based on the comparison of user choices with a pre-defined answer. In our analysis, it was observed that the system performs well in identifying both correct and incorrect choices by maintaining the secrecy of the answer keys. This ensures stability.

C. Descriptive Evaluation Stability

In the case of descriptive types of questions, LLM is employed to validate user answers. The stability of the system was analyzed by performing repeated scoring tasks for the same answer. The result was found to be stable with negligible fluctuations.

D. Computational Performance

System responsiveness was validated by simulating system interaction during question generation and user response validation. The system was found to be efficient in question generation by utilizing LLMs. The formal objective validation process was found to consume negligible computational resources. The system was found to be stable during a series of interviews. This shows that the system is efficient in a normal environment.

E. Integrity Monitoring

To validate system stability, tab switch, and motion events are simulated during a series of interviews. The system was found to be efficient in threshold violations. The system was found to be stable without any delay.

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V. RESULTS AND DISCUSSION

The intelligent interview framework was tested for validation through a series of controlled mock interview sessions for various technical positions at different levels of complexity. The experimental results validate the effectiveness of the proposed intelligent interview framework for supporting reliable automated scoring, efficient processing performance, and lightweight integrity monitoring. The hybrid assessment mechanism was found to perform well during the testing procedure. For the scenario of multiple-choice answers, the rule-based internal validation was found to support

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deterministic scoring. The correct or incorrect answers were identified without exposing the answer keys. For the scenario of descriptive answers, the LLM-based scoring was performed. The system was re-assessed for the same input, which showed a minimum level of variations.

Fig 3: Final Candidate Performance Result Dashboard

The final output of the candidate performance, which has been produced after the completion of the interview session, is presented in the form of a dashboard. In this context, the aggregated average score of the candidate and the final status of the qualification, as per the evaluation criteria, is presented. The confidence level indicates the behavioral assessment, which has been calculated from the interview session that has been conducted. On the other hand, the accuracy value indicates the performance in the objective-type questions. In addition to this, the strengths and weaknesses are presented in the form of a qualitative assessment.

The candidate performance is presented in the form of a radar chart, which presents the performance of the candidate on different evaluation criteria, such as overall performance, technical knowledge, and behavioral confidence levels.

Fig 4: Aggregated Interview Results Dashboard (Admin View).

The results of the interview are aggregated and presented through the administrative dashboard as shown in the image above. The image shows the overall results of the interview attempts conducted by the candidates. The bar chart shows the number of attempts conducted by the candidates, while the line graph shows the highest score achieved by the candidates. The image shows the overall results of the interview attempts conducted by the candidates.

Regarding the performance of the system, it was observed that the system was able to deliver acceptable latency levels for the question generation task. The objective validation process was observed to take negligible time. The LLM-based scoring process was observed to work within the acceptable time limit. There was no performance degradation observed during the execution of a series of interview tasks. The lightweight integrity monitoring process was observed to work efficiently regarding tab-switch events and motion threshold violations. The system was able to mark the sessions correctly without causing performance degradation. This verifies the efficacy of the lightweight integrity monitoring system for ensuring fairness in remote interview sessions. The experimental results verify the efficacy of the proposed intelligent interview system for providing a reliable system for AI-assisted technical recruitment. The system was observed to work efficiently regarding the provision of deterministic automated scoring, efficient processing performance, and lightweight integrity monitoring. The system can be extended for handling large-scale recruitment tasks in the future. The system can provide a reliable platform for the recruitment of qualified resources.

VII. CONCLUSION

In this paper, an intelligent interview system framework has been proposed, which includes adaptive question generation using a large language model (LLM), a hybrid response evaluation system, administrative configurability, and a lightweight integrity monitoring system. The intelligent interview system mitigates some of the conventional drawbacks of interviews, like their subjective nature and scalability.

The system is developed to dynamically generate role-based questions based on job descriptions and configurable parameters. This makes a flexible system for conducting technical interviews for a broad range of domains. The hybrid system employs deterministic approaches for multiple-choice question evaluation and a large language model for descriptive-type question evaluation. Apart from these functionalities, motion detection and tab switch monitoring have been added to make a practical solution for ensuring fair play in a virtual interview system. The experimental results demonstrate stable automated scoring, acceptable real-time response times, and efficient integrity monitoring. The system is also scalable for handling large-scale recruitment processes.

The intelligent interview system is a practical approach to utilize generative AI to make sure that the technical interviews are structured, scalable, and consistent. In the future, large-scale benchmarks can be created to enhance the adaptability of the system by using advanced analytics.

REFERENCES

[1] J. Joseph and M. V. Judy, "Developing an intelligent integrated software agent for streamlined interview automation and enhanced candidate insights," in *Proc. 2nd DMIHER Int. Conf. Artificial Intelligence in Healthcare, Education and Industry(IDICAIEI)*,2024,doi:10.1109/IDICAIEI61867.2024.10842712.

[2] P. Senarathne, M. Silva, A. Methmini, D. Kavinda, and S. Thelijjagoda, "Automate traditional interviewing process using natural language processing and machine learning," in *Proc. 6th Int. Conf. Convergence in Technology (I2CT)*, 2021, pp. 1–6.

[3] T. Young, D. Hazarika, S. Poria, and E. Cambria, "Recent trends in deep learning based natural language processing," *IEEE Computational Intelligence Magazine*, vol. 13, no. 3, pp. 55–75, Aug. 2018.

[4] O. Abdel-Hamid, A.-R. Mohamed, H. Jiang, L. Deng, G. Penn, and D. Yu, "Convolutional neural networks for speech recognition," *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 22, no. 10, pp. 1533–1545, Oct. 2014.

[5] T. Wu et al., "A brief overview of ChatGPT: The history, status quo and potential future development," *IEEE/CAA Journal of Automatica Sinica*, vol. 10, no. 5, pp. 1122–1136, May 2023.

[6] I. Naim, M. I. Tanveer, D. Gildea, and M. E. Hoque, "Automated analysis and prediction of job interview performance," *IEEE Transactions on Affective Computing*, vol. 9, no. 2, pp. 191–204, Apr.–Jun. 2018.

[7] R. Pandey, D. Chaudhari, S. Bhawani, O. Pawar, and S. Barve, "Interview bot with automatic question generation and answer evaluation," in *Proc. 9th Int. Conf. Advanced Computing and Communication Systems (ICACCS)*, 2023, pp. 1279–1286.

[8] C. Kim, J. Choi, J. Yoon, D. Yoo, and W. Lee, "Fairness-aware multimodal learning in automatic video interview assessment," *IEEE Access*.