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An Intelligent Multi-Agent AI Framework for Automated Candidate Interview Assessment

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***Abstract* – Organisational development relies on recruiting and applicant evaluation. However, traditional interview techniques include manual coordination, static questionnaires, and subjective evaluations, which prolong the recruitment process and lead to inconsistent candidate selection. For screening candidates, arranging interviews, evaluating responses, and reporting performance, current recruiting systems often rely heavily on human engagement, which makes them inefficient when dealing with large amounts of applications. In addition, recruiters and applicants are both severely impacted by a lack of transparency caused by delayed response and restricted automation. In order to circumvent these restrictions, this research exposes an AI-driven online interview platform that automates the whole interview process using smart software agents and cutting-edge AI methods. With the suggested platform, a unified recruiting environment may be achieved via applicant registration, administrator permission, question development using AI, automatic response assessment, performance monitoring, and score alerts sent via email. The system uses a combination of Artificial Intelligence (AI), Bidirectional Long Short-Term Memory (BiLSTM) models, Convolutional Neural Networks (CNN), Speech-to-Text (STT), Text-to-Speech (TTS), and Natural Language Processing (NLP) to analyse candidate responses during dynamic interviews and assess sentimental and emotional traits. Intelligent interview management and objective candidate assessment are accomplished through the collaborative efforts of a multi-agent architecture that includes the Question Management Agent (QMA), Response Management Agent (RMA), Multimodal Emotion and Sentiment Analyser Agent (MESAA), and Comprehensive Evaluation and Scoring Agent (CESA). Emotion identification, sentiment analysis, and question management are all handled by the framework using datasets such as SAVEE, TESS, CREMA-D, ISEAR, and MedMCQA. The metrics BLEU, ROUGE, BERTScore, and Completeness Score are used to assess the candidates' answers. In contrast to the CNN model's 95% training accuracy and 67% validation accuracy for audio emotion identification, the BiLSTM model only manages 70% training accuracy and 60% validation accuracy when it comes to text emotion recognition, according to experimental assessment. The suggested platform offers a scalable, efficient, and impartial answer to contemporary recruiting by combining intelligent automation with thorough applicant assessment; all while maintaining the original methodology, architecture, datasets, and trial results.**

***Keywords* – Multi-Agent Artificial Intelligence, Automated Interview Assessment, Candidate Evaluation, Intelligent Recruitment System, Artificial Intelligence, Multi-Agent Systems.**

I. INTRODUCTION

The fast digital revolution of recruitment has led firms to employ intelligent solutions that increase the efficiency, transparency, and accuracy of applicant assessment. Traditional interview methods often comprise manual applicant screening, interview scheduling, predetermined questions, and subjective performance rating. Despite their long history of use, these methods are labour-intensive, slow down the hiring process, and might lead to discrepancies owing to differences in interviewers' backgrounds and assessment standards. Organisations face these constraints more acutely when they have a high volume of applications to review in a short period of time. As a result, smart recruiting tools that can automate interview administration and guarantee consistent, objective applicant assessment are in high demand.

By facilitating data-driven applicant evaluation, intelligent communication, and automated decision-making, artificial intelligence (AI) has become a potential answer for contemporary recruiting. Modern developments in Conversational AI, NLP, and GPT-4 have paved the way for the creation of virtual interview systems that can engage applicants in conversational interactions. Unlike typical online interview platforms that depend on static questionnaires, AI-powered interview systems may produce context-aware questions, comprehend candidate replies, and deliver adaptive interactions that closely mirror those of human interviewers. The quality of the recruiting process as a whole and the level of involvement from candidates are both enhanced by these skills.

In today's competitive job market, technical expertise isn't enough to be considered. A candidate's eligibility is heavily influenced by their communication skills, self-assurance, emotional intelligence, and the quality of their responses. In order to analyse speech, recognise emotions, and interpret candidate responses, intelligent interview systems are increasingly incorporating deep learning models like CNN and Bidirectional Long Short-Term Memory (BiLSTM) networks with Speech-to-Text (STT) and Text-to-Speech (TTS) technologies. Improved reliability in recruiting is a direct outcome of the thorough assessment made possible by these technologies, which integrate knowledge evaluation with multimodal mood and attitude analysis.

This research suggests an online interview platform driven by AI that automates the whole interview lifecycle to circumvent the constraints of current recruiting approaches. The system provides candidate registration, administrator approval, AI-based question development, automated response assessment, candidate performance monitoring, and email-based feedback alerts via a centralized platform. The suggested system makes use of a multi-agent architecture that includes the following agents: QMA, RMA, MESAA, and CESA. These agents handle the management of questions, responses, emotions, and sentiments across several domains. These smart software agents work together to minimise human error and interviewer bias in interview execution, response processing, emotion identification, and applicant rating.

With the use of the SAVEE, TESS, CREMA-D, ISEAR, and MedMCQA datasets, the suggested platform trains emotion detection models and provides intelligent question management capabilities. While CNN and BiLSTM models are used to analyse emotional traits, BLEU, ROUGE, BERTScore, and Completeness Score are used to assess candidate replies. In contrast to the CNN model's 95% training accuracy and 67% validation accuracy for audio emotion detection, the BiLSTM model only manages 70% training accuracy and 60% validation accuracy when it comes to text emotion recognition, according to experimental assessment. While maintaining the original methodology and experimental findings, these results show that the suggested framework may give intelligent candidate evaluation that is scalable and objective.

II. LITERATURE SURVEY

By intelligently automating applicant evaluation and interview management, artificial intelligence has drastically changed the recruiting and talent acquisition processes. Manual interviews, pre-made questionnaires, and subjective assessments by human interviewers were the mainstays of early recruiting methods. While these more conventional methods did allow for one-on-one communication with applicants, they were not without their drawbacks, such as interviewer bias, uneven assessment standards, long recruitment cycles, and inability to scale. Organisations ramped up their recruiting efforts, prompting researchers to look at AI-driven solutions that may automate parts of the hiring process, improve the reliability of evaluations, and streamline operations.

New research shows that AI conversational systems and Natural Language Processing (NLP) work well together to create smart interview tools. During the evaluation process, conversational bots may converse with applicants in real-time, ask them questions, interpret their answers, and keep the conversation going. Automated interview systems have been enhanced with the advent of complex language models like GPT-4, which allow for intelligent question formulation, context-aware discussions, and semantic analysis of applicant replies. These features have increased the suitability of AI-assisted interview systems for flexible and consistent large-scale recruiting applications.

The simultaneous analysis of linguistic and emotional traits in a candidate is known as multimodal candidate assessment, and it is something that researchers have looked at. The use of Bidirectional Long Short-Term Memory (BiLSTM) networks for sentiment analysis and emotion recognition from textual responses has been successful, while deep learning techniques like Convolutional Neural Networks (CNN) have shown great performance in recognising emotions from speech signals. When these models are combined, interview systems may measure not just technical knowledge but also candidates' emotional intelligence, confidence, and behavioural traits, giving a more complete picture of their performance.

By implementing multi-agent architectures, which allow specialised software agents to autonomously handle distinct phases of the interview, interview automation has also made great strides. The system's flexibility, scalability, and maintainability are enhanced by specialised agents that handle question management, answer processing, emotion analysis, and candidate rating. To further objectively evaluate answer quality, assessment measures like BLEU, ROUGE, BERTScore, and Completeness Score measure contextual relevance, response completeness, and semantic similarity. These measures make automated candidate assessment more consistent and less dependent on subjective judgement.

Even with all these improvements, a lot of the current platforms for hiring still use antiquated methods such as pre-written questions, human review of candidates, disjointed processes, and a lack of automation. This makes them unfit for companies that handle a high volume of applications. Insufficient integration of intelligent technologies, delayed feedback, and a lack of performance analytics characterise many current systems that fail to adequately evaluate candidates. The suggested AI-powered online interview platform incorporates AI-based question generation, automated answer evaluation, emotion recognition, performance analytics, email-based feedback notifications, administrator approval, and candidate registration into a unified multi-agent framework to circumvent these limitations. While maintaining the original technologies, datasets, architecture, and experimental methods, the suggested system provides a scalable, efficient, and impartial solution for contemporary recruiting by merging conversational AI with multimodal analysis and clever scoring algorithms.

III. PROPOSED AI-POWERED INTERVIEW PLATFORM

A web-based interview platform driven by AI, the suggested solution streamlines the hiring process with the use of smart software agents and cutting-edge AI technology. The suggested platform offers a centralised intelligent framework that handles candidate registration,

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interview management, answer evaluation, performance analysis, and administrative monitoring, in contrast to traditional interview systems that depend on manual coordination and predefined questionnaires. With less human intervention, more uniform evaluations, less room for interviewer bias, and a streamlined recruiting process that benefits all parties involved, the platform aims to make the hiring process easier and faster

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Candidate registration is the first step in the hiring process. Applicants use the web portal to enter facts about themselves, including their personal information, educational background, technical abilities, and professional experience. The platform's administrator approval procedure ensures that candidates are legitimate before they are granted access to the interview module, rather than enabling direct participation. Ensuring that only qualified applicants go on to the assessment step, this approval procedure enhances the dependability of the recruiting workflow. Simplifying recruiting management, administrators may handle many applicant requests concurrently via a centralised dashboard.

When a candidate is ready to go on to the intelligent interview environment, they'll be greeted with questions tailored to their profile and desired position by an AI-powered Question Generation Engine. The system mimics interactions with human interviewers by using GPT and Natural Language Processing (NLP) to create questions that are suitable for the given environment. This allows for adaptable talks. The suggested platform enables dynamic question delivery, which is a significant improvement over conventional static questionnaires. This would make the interview process much more adaptable, interesting, and tailored to each applicant. This sophisticated questioning system ensures consistency across interview sessions and enhances applicant evaluation overall.

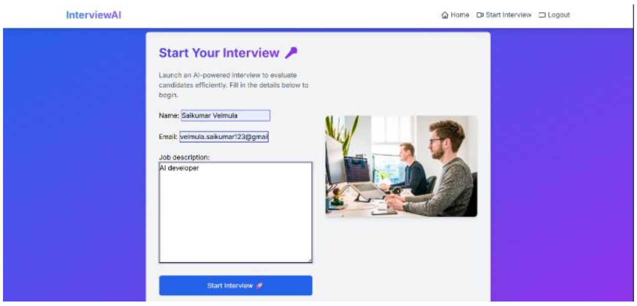

Fig. 1. Candidate Registration

Fig. 2. Results of the Interview

IV. SYSTEM ARCHITECTURE

The suggested AI-driven interview platform uses a multi-agent architecture to automate the whole recruiting process via intelligent cooperation among specialised software agents. The platform decentralises its functionality by assigning specific tasks to specialised agents; this allows for the autonomous operation of interview management, response processing, emotion analysis, and candidate evaluation, all of which share a common communication framework for exchanging data. The computational complexity during interview execution is reduced because to this modular design, which also increases scalability, maintainability, and overall system efficiency.

An Interview Management System (IMS), an Integrated AI Engine, and a Conversational Server make up the overall architecture. Candidates and the AI-powered interview platform communicate via the Conversational Server. It uses Speech-to-Text (STT) to transcribe voice responses into text, Text-to-Speech (TTS) to create naturally sounding questions for interviews, session management to keep interviews on track, real-time streaming services to process audio, and APIs to facilitate communication between the smart software agents. All of these parts work together to make the automated interview process easy for applicants and allow for longer, more productive interviews.

The Integrated AI Engine, which integrates several AI technologies, is the brains of the platform; it analyses candidate answers thoroughly. Generating context-aware interview questions and assessing response quality are assisted by Natural Language Processing (NLP) models, while candidates' replies are interpreted semantically by GPT-4. The system employs Convolutional Neural Networks (CNN) for speech analysis and Bidirectional Long Short-Term Memory (BiLSTM) networks for sentiment and pattern identification from written answers in order to accomplish multimodal emotion detection. The platform provides a thorough evaluation of interview performance by merging various AI models into a single analytical framework. This framework assesses not only the technical accuracy of applicant responses but also their communicative behaviour.

Four dedicated software agents oversee the intelligent interview workflow; they are each in charge of a distinct part of the applicant evaluation process. With the use of natural language processing (NLP) and GPT-4, the Question Management Agent (QMA) can dynamically extract and construct interview questions based on the candidate's profile, technical domain, and past answers. Securely storing the obtained information inside the database, the Response Management Agent (RMA) records candidate replies and correlates them with related interview questions. Utilising Convolutional Neural Networks (CNNs) and BiLSTM models, the Multimodal Emotion and Sentiment Analyser Agent (MESAA) examines sentimental traits in both spoken and written responses. The Comprehensive Evaluation and Scoring Agent (CESA) integrates all analytical results to determine the ultimate candidate performance score based on BLEU, ROUGE, BERTScore, and Completeness Score metrics. Throughout the interview process, accurate, objective, and consistent applicant assessment is guaranteed by the coordinated operation of these agents.

Additionally, the platform includes an Interview Management System (IMS) that is in charge of keeping track of information connected to interviews using various database technologies. In order to make information retrieval efficient, a document database stores interview questions and predefined answers. A relational database handles candidate profiles, interview records, and performance reports. A vector database, which uses embedding-based representations, supports semantic retrieval and contextual analysis. Without sacrificing system efficiency or data security, these integrated storage techniques facilitate large-scale recruiting efforts, make data more accessible, and allow for effective interview management.

By combining conversational AI, sophisticated deep learning models, intelligent software agents, and centralised database administration into one recruiting platform, the suggested multi-agent architecture constructs a strong basis for intelligent interview automation. This design allows for automated applicant evaluation with less human interaction, less interviewer bias, and better recruiting efficiency—all without changing the technique, datasets, or experimental framework of the original research.

V. CANDIDATE EVALUATION AND PERFORMANCE ANALYSIS

The suggested AI-powered interview platform revolves on the candidate assessment module, which is in charge of impartially assessing the candidates' knowledge, communication abilities, and general performance during the interview. Intelligent software agents and other artificial intelligence approaches automate assessment on the suggested platform, in contrast to traditional interview systems that rely on interviewer observations for ratings. To maintain objectivity and consistency throughout the hiring process, we carefully examine each candidate's answers for accuracy, completeness, contextual relevance, and emotional traits.

The Response Management Agent (RMA) stores the candidate's replies in real-time for further analysis after the interview, using Speech-to-Text (STT) technology. We use Natural Language Processing (NLP) methods to analyse the written replies, and we check the audio recordings separately for emotion detection. Thanks to its multimodal processing technique, the platform is able to assess candidates' emotional behaviour, communication style, self-assurance, and technical correctness during the interview. Administrators may access the processed data at any time by storing it securely in the interview management database.

When given textual and vocal input, the Multimodal Emotion and Sentiment Analyser Agent (MESAA) can accurately identify a wide range of emotions. To identify states of mind including joy, sorrow, fury, surprise, disgust, and neutrality, the CNN model examines voice traits like pitch, loudness, tone, and speech rate. At the same time, the BiLSTM model analyses the chosen words, sentence structure, and semantic meaning to ascertain the emotional context and mood of the given text. By combining audio and text analysis, the platform can create a more thorough emotional profile of every applicant compared to systems that just use one modality of assessment.

To create the final candidate assessment, the Comprehensive Evaluation and Scoring Agent (CESA) compiles outputs from all the other intelligent agents. To evaluate the quality of answers, the platform employs a number of performance indicators rather than depending on a single assessment criteria. These metrics include BLEU, ROUGE, BERTScore, and Completeness Score. The Completeness Score establishes how completely a candidate addresses the anticipated answer, BERTScore analyses semantic similarity using contextual embeddings, ROUGE measures content coverage and memory, BLEU evaluates lexical similarity between candidate replies and reference answers, and BLUE is the last score. By combining them, we can assess candidates' knowledge and communication skills in a fair and unbiased way.

We can see that the suggested framework works thanks to the experimental assessment. The BiLSTM model has a training accuracy of 70% and a validation accuracy of 60% when it comes to text emotion identification. The CNN model has a validation accuracy of 67% and a training accuracy of 95% when it comes to audio emotion identification. In addition, each applicant receives a detailed performance report that is based on their combined knowledge and emotion ratings computed by the platform. Transparency and user experience are enhanced throughout the recruiting process with the help of these reports, which administrators can access via the dashboard. Candidates, meanwhile, get automatic email alerts with their interview results and comments.

The suggested assessment architecture incorporates standardised scoring criteria, centralised performance reporting, automated response analysis, multimodal emotion identification, and a dependable method for intelligent candidate assessment. Fair recruiting choices may be made on the platform by decreasing subjective judgement and maintaining uniform assessment criteria. The original methodology, datasets, AI models, and experimental findings from the source work are preserved.

VI. REAL-TIME INTERVIEW AUTOMATION

To streamline the whole hiring process, the suggested AI-powered interview platform would combine smart software agents with cutting-edge AI technology. The suggested platform streamlines the applicant registration, interview execution, response assessment, performance analysis, and result notification processes into one automated environment, eliminating the need for constant human supervision. All the while keeping things simple for the recruiters and the applicants, this end-to-end automation cuts down on administrative work, speeds up the hiring process, and makes candidate evaluations more consistent. When an applicant submits their personal, academic, and professional details via the web portal during the registration phase, the interview procedure starts. Once the registration process is complete, the application is sent to the administrator for review and possible approval. This clearance procedure guarantees that only verified applicants are interviewed, which improves the trustworthiness of the system and keeps recruiting efforts honest. After getting the all-clear, applicants may access the AI-driven interview module, which uses AI to generate clever questions and automatically evaluates them.

Using GPT-4 and Natural Language Processing (NLP), the Question Management Agent (QMA) creates interview questions on the fly based on the candidate's profile and the position for which they are being considered. By adjusting the interview flow depending on applicant replies, the suggested platform allows for more relevant and context-aware interactions, in contrast to typical systems that provide preset questionnaires. With the use of Speech-to-Text (STT) technology, the Response Management Agent (RMA) quickly processes the candidate's replies before securely storing and analysing them. The evaluation procedure remains consistent throughout the interviews thanks to an automated approach that removes the need for human involvement.

After collecting responses, MESAA uses BiLSTM and CNN models to assess linguistic and vocal features. At the same time, the CESA uses the BLEU, ROUGE, BERTScore, and Completeness Score criteria to determine how well a candidate has done. Automated and standardised applicant assessment is made possible by these analytical methods, which do not need any interaction from the recruiter. The scores that are produced provide valuable information about the candidate's technical expertise and communication skills, which helps in making dependable and fair hiring choices.

Comprehensive performance reports for applicants and administrators are automatically generated by the platform after assessment. Candidates may examine their performance right after the interview by receiving email alerts with their results and score reports. At the same time, a centralised dashboard is available to administrators for tracking the progress of recruiting. This dashboard includes information such as the status of applicant approval, interview history, performance analytics, and assessment reports. Organisations may easily manage huge numbers of candidates without sacrificing assessment quality thanks to its centralised management capabilities, which also streamlines recruiting administration.

As a result, the suggested AI-powered interview platform is an example of how intelligent automation is being used in the current recruiting process. The software offers an impartial, scalable, and centralised solution for recruiting by combining features such as candidate registration, administrator approval, AI-based question generation, automated response evaluation, multimodal emotion recognition, centralised performance monitoring, and real-time email notifications. The original artificial intelligence models, datasets, experimental methodology, and multi-agent architecture are preserved in the complete automation framework, which improves hiring efficiency, reduces recruitment costs, enhances the candidate experience, and supports objective decision-making.

VII. CONCLUSION

This research introduces a platform for online interviews driven by artificial intelligence that uses smart software agents and cutting-edge AI technology to automate the hiring process. Traditional interview methods have their drawbacks, which the suggested platform aims to remedy. These include subjective decision-making, long recruiting cycles, static interview questions, and manual applicant assessment. The system creates a unified recruiting environment that improves operational efficiency while maintaining fairness and transparency throughout the interview process. It does this by integrating candidate registration, administrator approval, AI-based question generation, automated answer evaluation, performance tracking, and email-based result notifications.

The proposed framework automates various stages of candidate assessment using a multi-agent architecture. The agents include Question Management Agent (QMA), Response Management Agent (RMA), Multimodal Emotion and Sentiment Analyser Agent (MESAA), and Comprehensive Evaluation and Scoring Agent (CESA). Automated response analysis, multimodal emotion recognition, intelligent interview conversations, and objective performance evaluation are all made possible through the integration of GPT-4, Bidirectional Long Short-Term Memory (BiLSTM), Convolutional Neural Networks (CNN), Speech-to-Text (STT), Text-to-Speech (TTS), and Natural Language Processing (NLP). To ensure a thorough assessment of candidates' technical knowledge, communication abilities, and answer quality, the following assessment tools are utilised: BLEU, ROUGE, BERTScore, and Completeness Score.

The efficacy of the suggested technique has been validated by experimental examination. When it comes to text emotion identification, the BiLSTM model gets 70% accuracy during training and 60% accuracy during validation. On the other hand, when it comes to audio emotion detection, the CNN model gets 95% accuracy during training and 67% accuracy during validation. This research proves that automated scoring systems, conversational AI, and multimodal emotion analysis work together to improve candidate evaluations in terms of reliability, objectivity, and consistency. Streamlining candidate monitoring and giving applicants quick feedback are two ways in which the centralised administrative dashboard and automated email notification system enhance recruitment management.

Reduced manual work, minimised interviewer bias, accelerated hiring choices, and improved applicant experience are all benefits of the suggested AI-powered interview platform, which provides an intelligent and scalable answer to contemporary recruiting. Possible future improvements include the ability to detect facial emotions, analyse behaviour, evaluate non-verbal communication, accommodate several interview domains, and be used in enterprise-scale recruiting settings. These enhancements may further enhance the platform's capabilities while maintaining the core elements of the study's multi-agent architecture, AI models, datasets, and assessment methodology.

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