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Research Paper

AI Interview Assessment System

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Abstract: Automated evaluation of human responses has become increasingly important in intelligent recruitment systems and digital skill assessment platforms. Advances in natural language processing enable semantic understanding of textual responses beyond keyword matching. This study presents a web-based interview assessment system that integrates semantic similarity modeling using transformer-based sentence embeddings to evaluate candidate responses against predefined reference answers. System is built using Flask framework with SQLite database for structured storage of users, questions, sessions, and response analytics. A pretrained all-MiniLM-L6-v2 sentence-transformer model is utilized to encode both candidate and model answers into high-dimensional vector representations. Cosine similarity is computed between embeddings, and a hybrid scoring strategy combining maximum similarity and average similarity is applied to generate normalized scores on a 0–10 scale. Administrative modules provide topic management, question curation, and performance analytics, while candidate modules support real-time interviews with progress tracking and feedback generation. Browser-based speech-to-text capability enhances accessibility. Experimental evaluation demonstrates that semantic-based assessment improves robustness over traditional keyword-based methods, enabling consistent and scalable evaluation of technical interviews. Future enhancements may incorporate multimodal response analysis, domain-adaptive fine-tuning of transformer models, and advanced explainable AI techniques to further improve fairness, interpretability, and assessment accuracy in automated interview systems frameworks and services.

Index Terms - *AI Interview Assessment, Natural Language Processing, Sentence Transformers, Flask Framework, Semantic Similarity, Cosine Similarity, Speech-To-Text, Automated Evaluation.*

1. INTRODUCTION

The rapid evolution of artificial intelligence and web technologies has significantly transformed modern recruitment and educational assessment environments. Traditional interview evaluation approaches primarily depend on manual observation and subjective judgment, which often result in inconsistent scoring, delayed feedback, and increased evaluation effort. To overcome these limitations, intelligent interview assessment platforms have gained attention for providing automated, scalable, and standardized evaluation processes capable of assessing both technical knowledge and communication skills effectively [1].

Recent advancements in natural language processing and generative language models have enabled systems to analyze candidate responses based on semantic meaning rather than simple keyword overlap. AI-driven mock interview systems have demonstrated the capability to provide automated scoring and timely feedback, improving candidate preparation and reducing manual assessment burden in academic environments [2]. Research on AI-driven interviewing systems further highlights the integration of immersive technologies, adaptive interactions, and behavioral assessment mechanisms to improve interview realism and evaluation quality [3].

Modern intelligent interview platforms also incorporate emotional and confidence analysis to evaluate behavioral characteristics alongside technical responses. AI-based systems using speech analysis and facial expression recognition have improved assessment of candidate confidence, emotional intelligence, and communication effectiveness during interviews [4]. Studies investigating user attitudes toward AI-enabled systems indicate that reliability, transparency, fairness, and usability are critical factors influencing acceptance of automated evaluation environments [5].

Artificial intelligence has increasingly influenced employment-oriented video interviewing and digital hiring environments by enabling automated candidate analysis and structured performance assessment [6]. Voice-based interview evaluation systems using role-specific keyword analysis have further contributed to automated recruitment technologies by enabling audio-driven response analysis [7]. In addition, conversational interviewing systems powered by large language models have demonstrated adaptive interaction capabilities that support intelligent and context-aware assessment processes [8].

The growing adoption of AI technologies in organizational and educational environments has accelerated the need for scalable and efficient interview management systems [9]. Emerging technologies such as AI-driven avatars and virtual interactive environments have also enhanced communication and realism in digital interview scenarios [10]. Furthermore, studies on AI-assisted recruitment emphasize the importance of improving candidate experience, fairness, and performance transparency in automated assessment platforms [11].

The primary objective is to develop an intelligent web-based interview assessment environment capable of automating technical interview evaluation through semantic response analysis and structured performance tracking. Major contributions include automated scoring, topic-based interview management, role-based access control, real-time feedback generation, performance analytics, and centralized reporting for efficient and transparent interview assessment processes.

2. RELATED WORK

Faheem, Kakolu, et.al., discussed the importance of explainable artificial intelligence in automated assessment environments where user trust and transparency are essential for decision-making processes. Their study emphasized that AI-driven systems should provide understandable reasoning behind evaluation outcomes to improve reliability and confidence in automated analysis environments [12].

Jaiswal and Arun highlighted the transformative role of artificial intelligence in modern education systems by improving adaptive learning, personalized assessment, and intelligent student support mechanisms. Their work demonstrated how AI technologies can reduce manual effort while improving learning efficiency and educational accessibility in large-scale academic environments [13].

Igaki, Kitaguchi, et.al., introduced an automated skill assessment environment that utilized artificial intelligence for evaluating surgical performance through standardized procedural analysis. Their work demonstrated how intelligent assessment systems can support objective evaluation and performance consistency in highly specialized skill-oriented domains [14].

Viberg Johansson, Dembrower, et.al., investigated user perceptions toward artificial intelligence-enabled diagnostic systems and identified important factors influencing trust, usability, and acceptance. Their findings emphasized that user confidence and transparency significantly affect adoption of AI-driven evaluation and decision-support environments [15].

Petersson, Larsson, et.al., examined challenges associated with implementing artificial intelligence systems in operational environments. Their study identified barriers such as system reliability, ethical concerns, technical limitations, and adaptation difficulties, highlighting the importance of usability and organizational readiness for successful AI integration [16].

Sari, Tumanggor, et.al., explored adaptive learning environments powered by artificial intelligence for improving educational outcomes. Their work focused on personalized support mechanisms and intelligent interaction systems capable of enhancing student engagement, learning efficiency, and continuous performance improvement [17].

Li, Lassiter, et.al., analyzed the use of algorithmic hiring systems in recruitment processes and discussed how artificial intelligence assists recruiters in evaluating candidate suitability and performance. Their study highlighted both the advantages and challenges associated with AI-assisted hiring, including fairness, transparency, and automated decision-making [18].

Seo, Tang, et.al., studied the influence of artificial intelligence on learner and instructor interaction within online educational environments. Their work emphasized that AI-based systems improve communication, automated support, and personalized feedback while enhancing overall interaction quality in digital learning platforms [19].

Sanderson, Lu, et.al., focused on responsible artificial intelligence implementation and emphasized the importance of fairness, accountability, transparency, and ethical considerations in intelligent systems. Their study highlighted the need for trustworthy AI environments capable of ensuring reliable and unbiased automated evaluation processes [20].

Jussupow, Spohrer, et.al., examined the practical usage of diagnostic artificial intelligence systems and identified factors influencing adoption, usability, and operational efficiency. Their findings emphasized that system reliability, performance consistency, and user trust are critical for effective AI-assisted assessment and decision-support environments [21].

Celik, Dindar, et.al., conducted a systematic review discussing both the benefits and challenges of artificial intelligence in teaching and assessment environments. Their work highlighted that AI technologies can improve automated evaluation, personalized learning support, and educational efficiency while also presenting challenges related to transparency, ethics, and implementation complexity [22].

3. MATERIALS AND METHODS

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Proposed system introduces an intelligent web-based interview assessment environment designed to automate candidate evaluation using natural language processing and semantic response analysis. The system provides separate interfaces for administrators and candidates, enabling secure role-based access and efficient interview management. Administrators can create interview topics, manage technical questions, maintain multiple reference answers, and monitor assessment statistics through analytical dashboards. Candidates can register, select interview domains, participate in structured interview sessions, and submit responses using an interactive interface. The system evaluates responses by comparing candidate answers with predefined model answers to generate automated scores and feedback. Performance records are maintained for tracking candidate progress and generating detailed reports. Integration of speech-enabled interaction and real-time assessment capabilities further improves accessibility and user experience. The platform is designed to support scalable assessment environments with centralized data management and efficient performance monitoring. Artificial intelligence technologies have significantly enhanced educational and assessment systems by enabling adaptive and automated learning environments [23]. AI-driven educational platforms support intelligent interaction and personalized evaluation mechanisms for improved assessment quality [24]. Automated AI-based evaluation systems also contribute to fair and efficient candidate assessment processes in recruitment-oriented environments [25].

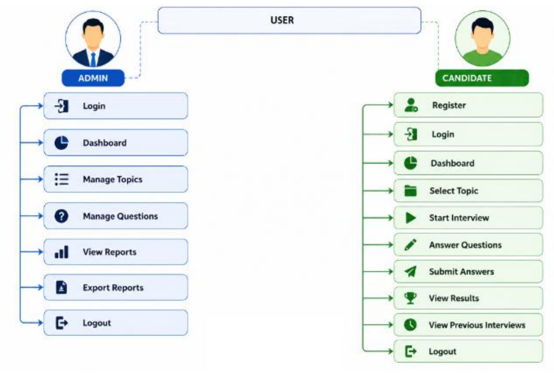

Fig.1 System Architecture

Fig. 1 illustrates the system architecture and functional breakdown of the user roles within the automated interview platform. The system categorizes users into two primary roles: Admin and Candidate. The Admin panel governs system management, allowing administrators to login, access the dashboard, manage topics and questions, view or export analytical reports, and safely logout. Conversely, the Candidate pipeline facilitates the assessment process, enabling users to register, login, select assessment topics, start interviews, answer and submit questions, view real-time results, check previous interview histories, and logout.

i) User Interaction and Assessment Management

The interview assessment environment is designed to support structured interaction between administrative users and candidates through secure and role-based access mechanisms. Administrative users are responsible for controlling interview content, organizing technical subjects, managing question repositories, and monitoring overall assessment activities. The environment provides dedicated functionalities for adding, editing, and deleting topics and interview questions, ensuring that the assessment structure remains organized and relevant to current evaluation requirements. Multiple reference answers are maintained for each question to improve evaluation flexibility and support diverse response patterns.

Candidates interact with the environment through personalized dashboards where they can access available interview topics, initiate interview sessions, answer technical questions, and review performance summaries. During assessment sessions, questions are displayed sequentially, and candidate responses are collected and stored systematically for further evaluation. The environment also maintains detailed records of completed interviews, enabling users to review previous assessments and monitor progress over time.

The management process includes centralized control of interview sessions, performance statistics, and analytical reporting. Administrative dashboards present information related to candidate participation, question distribution, score trends, and topic-wise performance analysis. Export functionalities support downloading assessment records for external review and reporting purposes. Secure login and logout mechanisms ensure controlled access and data protection throughout all interactions. By combining structured content management with centralized monitoring and candidate interaction capabilities, the assessment environment provides an efficient and scalable framework for conducting technical interviews and maintaining organized evaluation workflows.

ii) Semantic Response Processing and Text Representation

The assessment environment utilizes semantic text processing techniques to analyze candidate responses beyond direct keyword comparison. Candidate answers and predefined reference responses are transformed into numerical representations known as sentence embeddings. These embeddings are generated using transformer-based language representation models capable of capturing contextual meaning and semantic relationships between sentences. The transformation process converts textual information into fixed-length vector representations where semantically related responses occupy similar positions within vector space.

The embedding generation mechanism allows the system to understand conceptual similarity even when candidates use different vocabulary, sentence structures, or writing styles. This improves the flexibility and accuracy of response interpretation compared to traditional lexical matching approaches. Technical answers containing paraphrased explanations or alternative wording can therefore still be recognized as contextually relevant during evaluation.

Reference answers associated with each interview question are also transformed into embeddings to establish a semantic comparison base. Multiple reference responses are maintained for every question to improve coverage of possible answer variations and enhance evaluation consistency. The semantic processing environment supports contextual understanding of language by preserving relationships between words, phrases, and complete sentence structures within vector representations.

This text representation mechanism contributes significantly to intelligent evaluation because it reduces dependence on exact textual overlap. It enables assessment of conceptual understanding rather than simple word repetition. The generated embeddings serve as the foundation for further similarity measurement and scoring operations, supporting automated analysis of candidate knowledge, communication clarity, and response relevance in technical interview environments.

iii) Similarity Measurement and Score Evaluation

The response evaluation process is based on similarity measurement techniques that compare candidate embeddings with predefined reference answer embeddings. Cosine similarity is utilized to determine the semantic closeness between vector representations by measuring the angle between them in multi-dimensional space. Higher similarity values indicate stronger conceptual alignment between candidate responses and expected answers, while lower values represent weaker relevance.

For each interview question, candidate responses are compared with multiple reference answers to improve evaluation reliability and capture diverse forms of acceptable explanations. The similarity measurement process identifies the highest matching response while also considering overall contextual alignment across all reference answers. This ensures that evaluation is not restricted to a single predefined wording pattern and supports fairer interpretation of candidate understanding.

A weighted similarity scoring mechanism is applied to combine maximum similarity values with average similarity values obtained from all comparisons. Greater importance is assigned to the strongest semantic match while maintaining contribution from the overall response distribution. This balanced evaluation strategy reduces the possibility of inaccurate scoring caused by isolated comparisons and improves consistency across different answer styles.

The resulting similarity measurements are converted into performance scores representing the quality and relevance of candidate responses. Feedback generation mechanisms further support evaluation by providing descriptive performance insights based on calculated scores. The combination of semantic similarity measurement and weighted scoring enables automated, objective, and context-aware assessment capable of evaluating technical interview responses with improved accuracy and consistency.

iv) Performance Monitoring and Reporting Mechanisms

The assessment environment incorporates comprehensive monitoring and reporting mechanisms to maintain organized evaluation records and support performance analysis. Every interview session is systematically recorded, including candidate information, selected topics, submitted responses, calculated scores, and feedback details. These records are stored within centralized databases to ensure efficient retrieval and long-term performance tracking.

Administrative users are provided with analytical dashboards that present summarized information related to interview activity and candidate performance. Statistical indicators such as total interview sessions, average scores, topic-wise performance trends, and candidate participation levels are displayed to support evaluation monitoring. These analytical views help identify assessment patterns and improve understanding of candidate strengths and weaknesses across different technical domains.

Detailed reporting functionalities allow examination of individual interview sessions, including question-wise response analysis and score distribution. Candidate performance histories can also be reviewed to monitor improvement over multiple assessments. Export capabilities support generation of structured assessment records in downloadable formats, enabling offline analysis, archival storage, and external reporting activities.

The monitoring environment also supports transparency and consistency in evaluation by maintaining complete records of all assessment operations. Time-based tracking mechanisms record interview initiation, response submission, and session completion activities to ensure organized session management. Combined reporting and monitoring functionalities contribute to efficient administration, improved evaluation control, and enhanced visibility into candidate assessment outcomes within large-scale technical interview environments.

4. RESULTS AND DISCUSSIONS

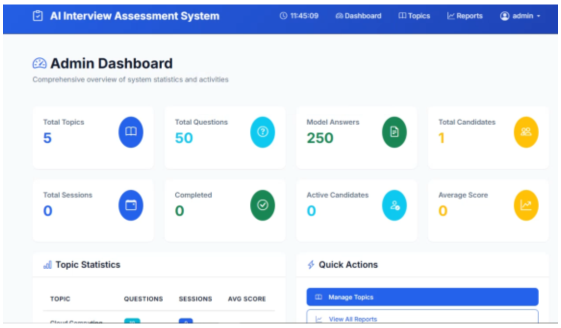

Fig.2 Admin Dashboard

Fig. 2 displays the comprehensive admin dashboard, showcasing system statistics, activities, and analytical summaries.

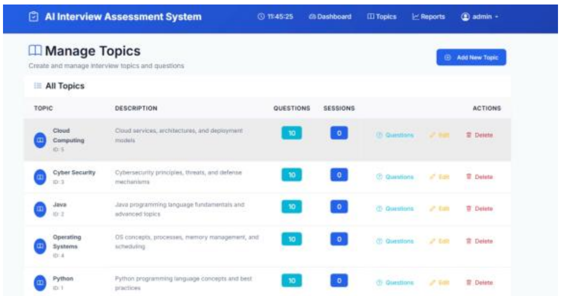

Fig.3 Manage Topics

Fig. 3 showcases the topic management interface for creating, editing, and organizing interview questions.

Fig.4 Questions

Fig. 4 presents the questions management interface for viewing, adding, and editing topic-specific interview questions.

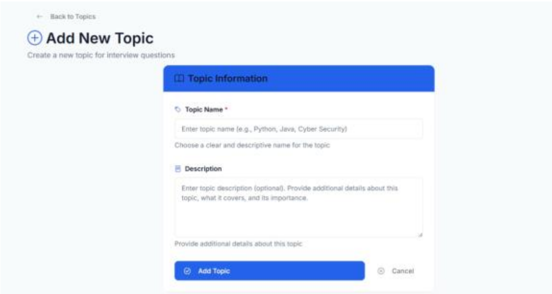

Fig.5 Add New Topic

Fig. 5 illustrates the input form interface for creating and adding a new interview topic.

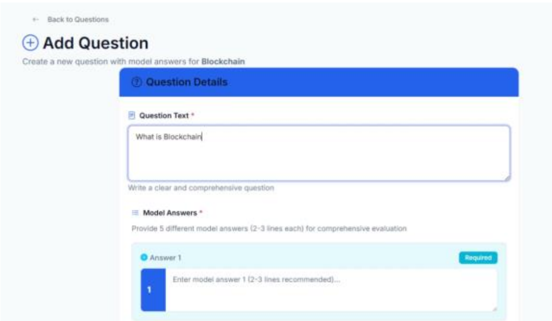

Fig.6 Add Question

Fig. 6 depicts the question submission form for entering new evaluation questions and reference model answers.

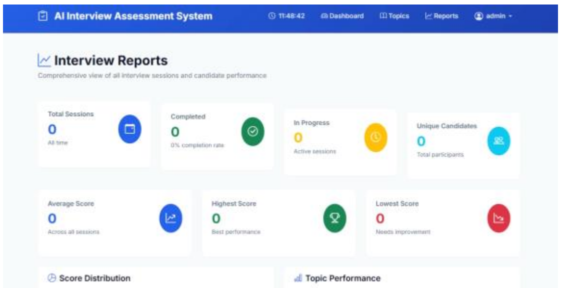

Fig.7 Interview Reports

Fig. 7 demonstrates the interview reports panel, tracking assessment metrics, session statuses, and candidate score trends.

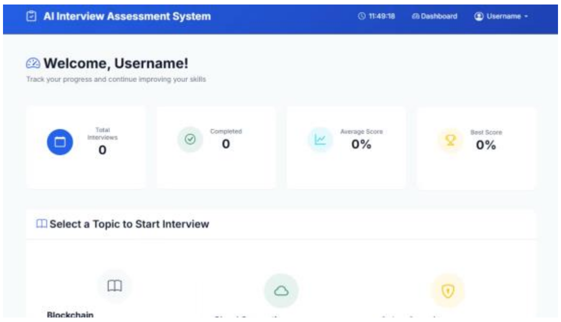

Fig.8 Username Dashboard

Fig. 8 displays the candidate welcome dashboard, highlighting progress metrics and interview topic selection options.

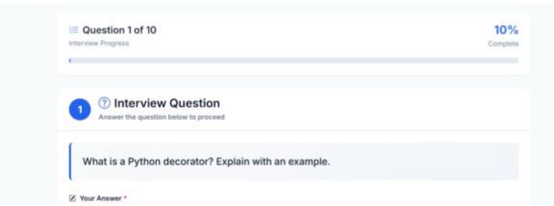

Fig.9 Interview

Fig. 9 presents the live candidate interview interface, featuring a question prompt and a progress tracker.

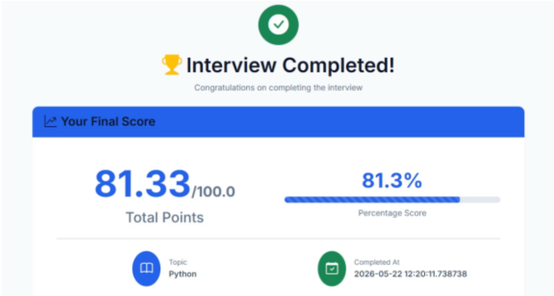

Fig.10 Results

Fig. 10 illustrates the final interview completion screen, detailing the candidate's total and percentage scores.

5. CONCLUSION

The developed system demonstrates effective automation of technical interview assessment by leveraging semantic understanding of candidate responses rather than relying on rigid keyword matching. Integration of transformer-based sentence embeddings enables meaningful comparison between user-generated answers and multiple reference responses, resulting in consistent and context-aware scoring. The hybrid evaluation strategy combining maximum and average similarity ensures balanced assessment of both partial and complete understanding of concepts. Operational outcomes indicate improved efficiency in interview management, where administrative users can easily create topics, manage questions, and analyze candidate performance through structured dashboards and visual reports. Candidate-side interaction supports a smooth interview experience with real-time question navigation, progress tracking, and immediate feedback generation. The inclusion of speech-to-text functionality enhances accessibility and usability for diverse users. Database-driven architecture ensures organized storage of sessions, responses, and analytics, enabling scalable handling of multiple interview records without performance degradation. The system also provides detailed performance insights at both individual and aggregate levels, supporting data-driven decision-making in evaluation processes. Overall, the approach establishes a reliable framework for automated assessment, reducing manual effort while maintaining evaluation consistency and fairness across varied technical domains and user inputs, making it suitable for deployment in academic evaluation environments, recruitment workflows, and skill validation platforms.

Future development can extend this system by incorporating multimodal assessment capabilities, enabling evaluation of spoken responses, facial expressions, and behavioral cues alongside textual answers for a more holistic interview analysis. Domain-adaptive fine-tuning of transformer models can be introduced to improve semantic accuracy for specialized technical fields. Integration of large language models may enhance dynamic question generation and adaptive difficulty adjustment based on candidate performance. Explainable AI techniques can be embedded to provide transparent justification for scoring decisions, improving trust in automated evaluation. Additionally, real-time proctoring mechanisms and fraud detection modules can strengthen assessment integrity. Deployment as a cloud-native microservices architecture with scalable APIs would improve system performance under high user loads. Incorporating multilingual support and personalization features can further expand accessibility and global usability across diverse candidate populations and recruitment environments.

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