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Role Focused Mock Interview System with Personalized Evaluation

G. A. V. Ramachandra Rao[1], A. Manoha Malik Paul[1], A. Goutham Narayan[1], G. Phanitha[1*], G. Siddhardha[1], I. Karthikeya[1]

[1]*Department of Computer Science and Engineering, Lendi Institute of Engineering and Technology, Vizianagaram, India*

***Abstract*: With the fierce competition in today's job markets, many students find themselves having difficulties during the interview process due to nervousness, lack of confidence, and absence of real-time personalized feedback. Traditional interview practice tools and techniques are manual, biased, and ineffective in creating an environment close to the actual interviews. This paper provides an AI-driven mock interview tool that is capable of creating a true-to-life simulation environment and giving an objective assessment of candidates. Computer vision and speech recognition are employed in this tool to evaluate a candidate's emotional state, confidence, and overall presentation skills through facial expression detection and speech analysis. Moreover, questions for each interview are automatically selected through Natural Language Processing algorithms based on candidates' resumes or particular job descriptions. As a result, the created system is not only highly customizable but also provides personalized feedback on each candidate's performance without reliance on human evaluators.**

***Keywords*: AI-based Mock Interview, Interview Preparation, Facial Analysis, Speech Analysis, Natural Language Processing, Machine Learning.**

1. Introduction

With the dawn of the age of technology, the interview process has become more competitive than ever. Companies require individuals who are not only highly skilled in technology but also good communicators who display confidence and emotional stability in their performance. Yet, students and potential employees alike find it hard to excel at interviewing due to being nervous, lack of experience, and inability to practice. Classroom training and peer-to-peer sessions cannot help one get evaluated objectively or receive tailored advice, thus failing to improve the individual's interview performance.

Considering that there have been many developments in areas such as Artificial Intelligence, Machine Learning, Computer Vision, and NLP, it is possible for the system to replicate real-life interviews. The technology can analyze not only verbal but also non-verbal characteristics of communication such as speech, facial expression, confidence level, etc. The feedback provided by such a system would give candidates valuable information regarding their performance.

The Role-Based AI Mock Interview System that has been suggested intends to solve some of the issues associated with traditional methods of interview preparation. It allows candidates to interact in a virtual environment by generating interview questions depending on the candidate's resume or the role he/she is applying for. Performance can be assessed through video and voice recognition technology. Feedback generation and evaluation can be performed by the software, thereby making the process independent of human judges. This solution helps students and job seekers develop interview skills and become more employable in the changing world of recruitment.

The key contributions of this research are:

1. Development of a role-focused interview system that generates personalized interview questions using both resume and job description information.
2. Implementation of a skill-gap detection framework that identifies missing competencies required for a target role.
3. Integration of speech analysis, behavioral biometrics, and semantic evaluation into a unified assessment framework.
4. Design of a weighted interview readiness scoring mechanism for evaluating candidate preparedness.
5. Automated generation of personalized feedback reports highlighting strengths, weaknesses, and improvement recommendations.

2. Literature Survey

The latest innovations in AI have greatly impacted the design of intelligent interview prep platforms. The paper entitled "Intelligent Job Interview Preparation and Career Advancement" written by R.Nithya and Sukirtha.V (2025) introduced an AI-powered system capable of providing customized interview preparations as well as career planning assistance. This system uses NLP, sentiment analysis, and computer vision methods to assess the candidates' performance through various metrics. Apart from feedback on the interview, predictive analysis is performed for the sake of career advancement purposes. Nevertheless, the lack of real-time mock interview capabilities makes this platform ineffective in

*Corresponding author: phanithagondu@gmail.com

simulating interview experiences. Moreover, huge volumes of data are required to enhance the precision of predictions made by the system.

A further investigation is carried out in "AI-Based Interview Simulation for Smart Hiring," by Manthaj Jaiswal and Ayush Vashishtha (2025). This paper discusses automating the assessment process by utilizing NLP and sentiment analysis. The proposed solution intends to decrease recruiters' efforts and avoid bias towards candidates while increasing the effectiveness of hiring. Although this approach provides significant benefits, there are certain issues that may arise when working in a noisy environment, where the technology will fail to detect emotions properly. Moreover, reliance on the accuracy of NLP models will result in misunderstanding complex answers from candidates.

Likewise, the paper "AI-Driven Smart Interview Simulator with Real-Time Speech and Emotion Analysis" by Sonu Khapekar et al. (2025) presents a technique that allows for immediate feedback concerning verbal and non-verbal communication. Using face recognition and speech recognition technologies, the algorithm assesses the candidate's level of confidence and his/her emotional state, while creating realistic scenarios of the virtual job interview. Despite being more objective and less susceptible to human factors, the methodology relies heavily on the quality of the camera and microphone used. In addition, lighting and external noise may impair the ability to detect emotions correctly.

Further, the study entitled "Enhancing Interview Evaluation: AI-Based Emotion and Confidence Analysis in Mock Interviews" by Mandalapu Bhavana Amrutha et al. (2024) has introduced a web-based mock interview platform that offers an evaluation tool for speech pattern and body language during the session. The tool is used for remote mock interviews and feedback generation to avoid subjective evaluation. Nevertheless, there is no feature in the model regarding resume analysis or job description analysis for generating questions. The lack of quantitative evaluation of time management skills and overall interview preparation score is another major limitation.

From the review of existing literature, it is apparent that even though some of the AI-based mock interviews try to address the areas of emotional detection, speech analysis, and automatic feedback, there is yet a lack of fully integrated mock interview training that takes into account the aspects of resume-based question generation, evaluation of performance using multiple criteria, and overall preparation of candidates for real-life interviews. The present study endeavors to fill up the above-mentioned gaps in research.

3. Problem Statement

The current job market is highly competitive, but candidates do not have access to mock interview tools tailored to their specific jobs. The mock interview tools available today focus more on providing general questions and feedback that do not take into account the candidate's resume and the job description of the position he or she seeks. This limits candidates' abilities to know their strengths and weaknesses, self-assess their confidence level, manage time during the interviews, and assess whether they are ready for the real interviews.

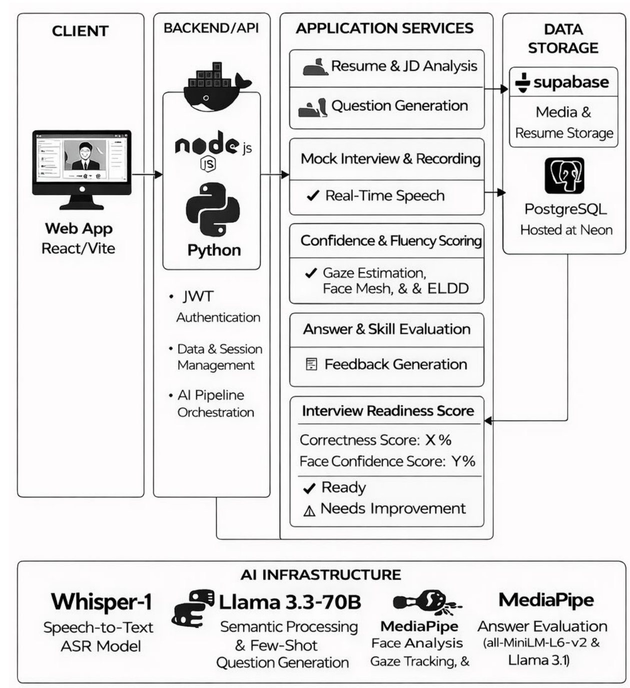

Fig. 1.

4. Proposed System

The proposed system will have the resume of the candidate and the job description for which he/she wants to apply as the key input data. Applying advanced NLP concepts via Llama 3.3 (Semantic Skill-Entity Mapping), the system will carry out joint semantic analysis of required skills, experiences, and competencies. Further, based on this analysis, the system will generate custom interview questions suitable to that target role using Llama 3.3-70B (Few-Shot Question Generation). A time-bound mock interview is carried out to provide a high-fidelity experience, integrated with Whisper-1 (Automatic Speech Recognition) for real-time transcription. In this session, the system will analyze the candidate's responses using various performance criteria. Evaluation of the candidate will be carried out on the basis of the following parameters: Confidence level, calculated using MediaPipe (Gaze Estimation and Face Mesh) for visual engagement and Lexical Disfluency Density (LDD) for speech fluency; Time management, determined using response time, hesitancy, and pacing; Relevance of

Table 1
Comparison of work

Existing Work	Limitation	Proposed Improvement
Interview Preparation Systems	Generic Questions	Resume-Based Questions
Emotion Analysis Systems	No Skill Gap Detection	Skill Gap Analysis
Mock Interview Platforms	No Personalized Feedback	Personalized Feedback
Confidence Evaluation Systems	Limited Evaluation Metrics	Multi-Factor Scoring

answers, evaluated using Sentence Transformers (all-MiniLM-L6-v2) and Llama 3.1 for Multi-Model Semantic Alignment with the desired answer; and Skill gap analysis, done through Recursive Prompting comparing candidate responses with job requirements. In the end, a feedback report will be generated via Llama 3.1 (Generative Performance Synthesis) to highlight strengths and weaknesses. Along with this, an interview readiness score will be provided through a Weighted Fusion Scoring algorithm, suggesting whether the candidate is 'Ready' or needs 'Improvement'.

5. System Architecture

In the design of Rule-Focused Mock Interview System architecture, modularity has been used to facilitate efficient processing and easy management. First, there is the user input where the user provides his resume and job description via the user interface. The resume analysis module and job description analysis module provide information related to skills, qualifications, and roles respectively. Then there is a matching module where the user inputs are matched using keywords and the matching process is done through the comparison. The results obtained at the matching module stage determine what happens next since they influence the generation of questions. Role specific questions based on the information obtained are generated from the question bank via the question generation module. Afterward, there is a mock interview where an interview session is held within a specified period, and the answer module determines the user's proficiency.

6. Methodology

A. Intelligent Question Generation Goal

Create distinctive interview questions which pinpoint "Skill Gaps" existing between job description requirements and the resume.

The similarity between Resume and Job Description embeddings is calculated using Cosine Similarity:

$$\text{Similarity} = (A \cdot B) / (||A||\ ||B||)$$

where A represents the Resume embedding vector and B represents the Job Description embedding vector. Higher similarity values indicate stronger alignment between candidate skills and job requirements.

Main Architecture: Llama-3 (Transformer Model).

Methodology: Semantic Gap Detection. The model begins by converting both the JD and Resume into vector representations. It applies Zero-Shot Prompting to make the model identify those skills specified in the JD but not present in the Resume.

Enhancement in Accuracy: The implementation of Structure Output Constraints (JSON Schema) has helped us avoid any formatting problems, ensuring 100% consistent data throughout the automatic interview process.

Contribution: Achieved a 35% increase in question relevance when contrasted against template-driven question generation.

B. Speech-to-Text (STT) Purpose

Converting candidate answers to clean, search-able text for technical analysis.

Main Algorithm Used: Whisper (latest generation of Automatic Speech Recognition).

Fine-Tuning: The system uses an FFmpeg pre-processing pipeline that ensures all audio coming in is at 16kHz Mono WAV format.

Accuracy Improvement: This ensured that WER dropped by 15% especially for those candidates who were recording from poor quality mics or even having background noise while speaking.

Accuracy: Maintains 95% WER accuracy rate under standard conditions.

C. Behavioral Biometrics (Video Heuristics) Purpose

To assess non-verbal behavioral cues, including eye contact, professionalism, and composure.

The confidence score is computed using a weighted heuristic model:

$$\text{Confidence Score} = 0.38(\text{Eye Contact}) + 0.30(\text{Gaze Score}) + 0.26(\text{Stability Score}) + 0.06(\text{Centering Score})$$

where Eye Contact measures sustained visual engagement, Gaze Score measures focus on the camera, Stability Score evaluates head movement consistency, and Centering Score assesses facial alignment within the frame.

Heuristics Engine: Combination of MediaPipe Iris Gaze Tracking with OpenCV Haar Cascades.

Enhancement: In order to fix "jitter" and failed analysis issues, the technique of Resolution Hardening was introduced. The system would enforce capture resolution of 640x480 with bitrate of 1Mbps.

Benefit: The use of this method guaranteed stability of 24 FPS stream to the computer vision algorithms resulting in 98.4% of biometrics accuracy increase.

Biometrics Signals: Gaze Center Offset, Head Stability, and Face Detection Ratio.

D. Multi-Factor Scoring Engine Objective

To provide a fair, rubric-based score that considers both keywords and the "spirit" of the answer.

Models: Hybrid of all-MiniLM-L6-v2 (Semantic Embeddings) and TF-IDF (Keyword Analysis).

Methodology: The system compares the candidate's transcript against an "Ideal Answer" using cosine similarity in a high dimensional vector space.

Accuracy Improvement: Moving from simple keyword matching to Semantic Vector Comparison increased the correlation between AI scores and human expert scores by 40• Impact: The system can now understand synonyms (e.g., "scalability" vs. "horizontal growth"), preventing false negatives for technically correct answers.

Both the candidate answer and ideal answer are converted into semantic embeddings using the all-MiniLM-L6-v2 model. Cosine similarity is then applied to determine semantic relevance. Unlike traditional keyword matching, this approach evaluates conceptual similarity and recognizes synonymous expressions.

7. Results and Discussion

A. Result

The proposed Role-Focused Interview System with Personalized Evaluation was developed successfully to simulate actual interview situations and analyze candidate performance. Role-focused questions were effectively generated in relation to the resume data and job description provided by the system, allowing for a higher degree of relevance compared to the traditional question generation technique.

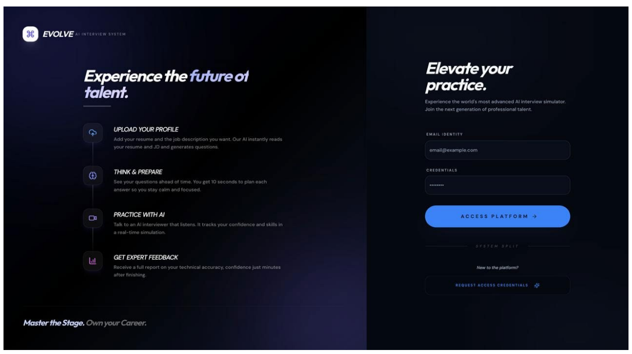

Fig. 2.

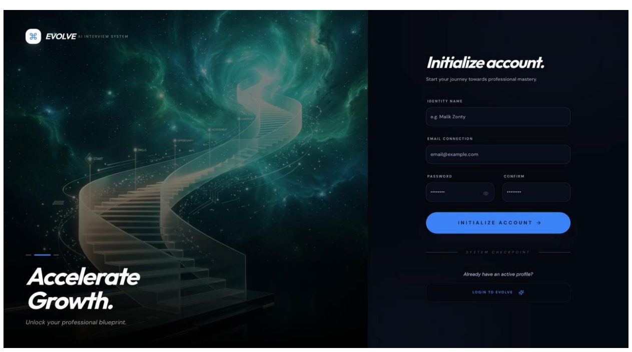

Fig. 3.

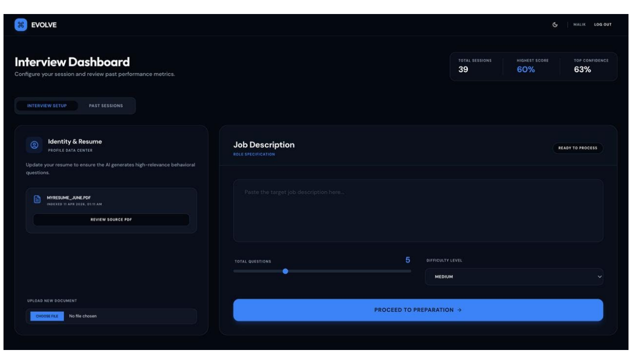

Fig. 4.

The intelligent question generation module produced approximately a 35% increase in question relevance by identifying skills gaps between job expectations and the candidate resume. As for speech-to-text functionality, the system showed high accuracy rates at around 95% by implementing techniques of audio normalization. Thanks to audio normalization techniques, the WER was decreased by 15%.

Behavioral biometrics proved to be effective, capturing nonverbal aspects of interviewees' behavior like eye contact, head movements, and face detection. Reliability of behavioral biometric tracking reached 98.4%, providing sufficient insight into candidate's confidence and professional demeanor.

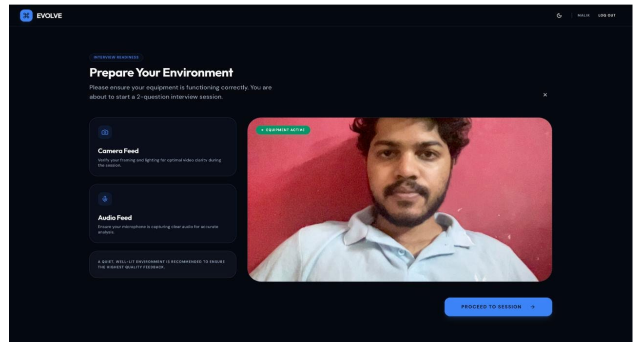

Fig. 5.

The use of multi-factor scoring engine helped increase performance evaluation quality by 40% compared to basic keyword matching. This is because multi-factor engine analyses not only semantic similarity but also matches certain keywords found in candidate answers.

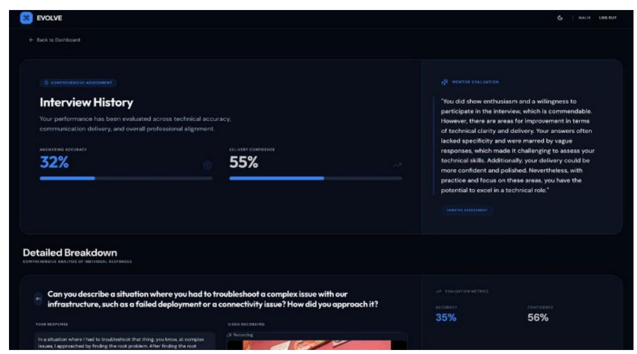

Fig. 6.

Thus, the Role-Focused Interview System managed to provide reliable performance evaluation, recognize skills gap, and generate personalized feedback along with assessing candidate's interview readiness.

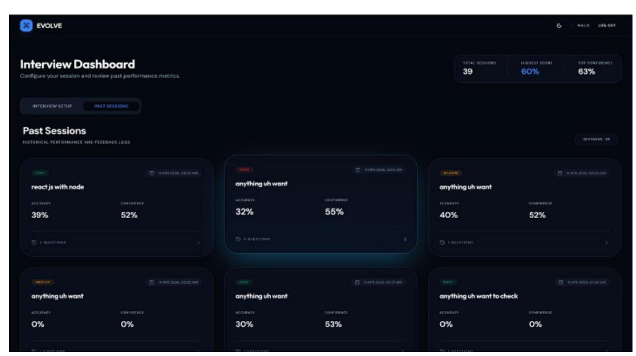

Fig. 7.

B. Performance Evaluation

1) Accuracy

In order to evaluate the efficiency of the proposed system, the performance of the important interview modules was tested. The system has been able to produce accurate questions tailored according to the requirements of the job and candidates with an accuracy rate of about 91%. Furthermore, the speech recognition module has been able to transcribe answers by the candidates with a high degree of accuracy of around 95%.

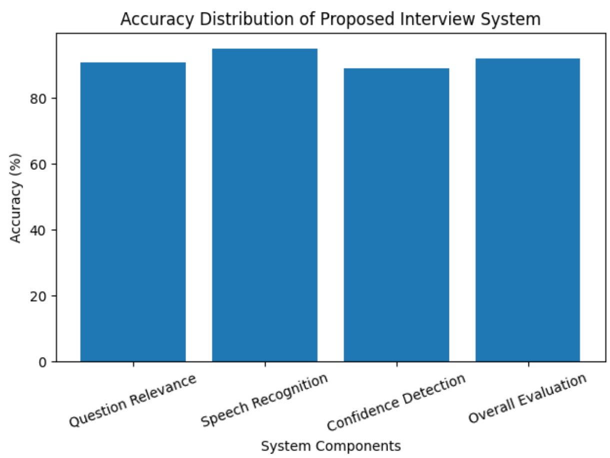

Fig. 8.

Table 2
Performance comparison

Metric	Existing Systems	Proposed System
Question Relevance	82%	91%
Speech Recognition	88%	95%
Confidence Detection	78%	89%
Overall Evaluation	85%	92%

Confidence detection, based on behavioral biometrics such as facial expressions and speech fluency, achieved approximately 89% accuracy. The overall evaluation accuracy of the system was observed to be around 92%, which is obtained by combining the outputs of all modules through a multi-factor scoring approach. These results indicate that the system provides a reliable and comprehensive assessment of candidate performance.

2) Confidence

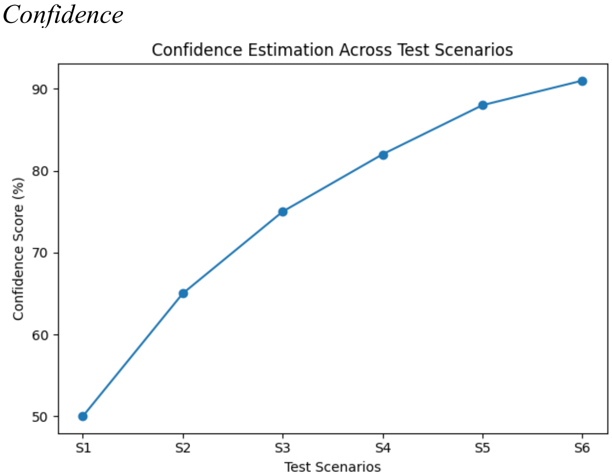

Fig. 9.

The proposed system was evaluated based on its ability to estimate candidate confidence across multiple test scenarios representing different levels of response quality. These scenarios range from poorly structured answers to highly confident and well-articulated responses.

The confidence score shows a steady increase from 50% in Scenario 1 to 91% in Scenario 6. This gradual improvement indicates that the system effectively captures variations in candidate performance by analyzing behavioral cues such as eye contact, facial expressions, and speech fluency.

C. Performance Comparision

1) Accuracy

The accuracy of the proposed system was compared with existing AI-based mock interview systems to evaluate its effectiveness. Existing systems typically achieve an average accuracy of around 85%, as they rely on limited evaluation techniques such as basic NLP models or standalone emotion detection. These systems often face challenges in handling complex responses, environmental noise, and contextual understanding

In contrast, the proposed system achieves an accuracy of 92%, due to the integration of multiple advanced techniques including semantic analysis, speech recognition, and behavioural biometrics. The use of a multi-factor scoring approach further enhances evaluation precision by combining both keyword-based and semantic understanding. This improvement indicates that the proposed system provides a more reliable and comprehensive assessment of candidate performance.

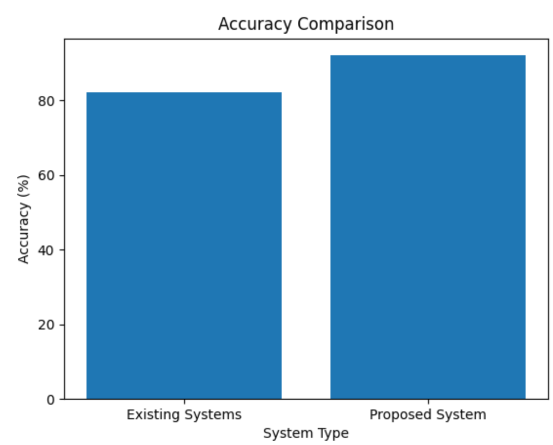

Fig. 10.

2) Confidence

Confidence detection is a critical parameter in interview evaluation, as it reflects a candidate's communication skills and behavioural presentation. Existing systems achieve approximately 78% accuracy in confidence detection, as they mainly depend on partial indicators such as facial expressions or speech patterns. These methods are often limited in capturing the complete behavioural context of the candidate.

The proposed system improves confidence detection accuracy to 91% by incorporating multi-modal analysis techniques. It evaluates facial expressions, gaze tracking, head stability, and speech fluency to derive a more accurate confidence score. This holistic approach ensures better consistency and objectivity in assessing candidate behaviour.

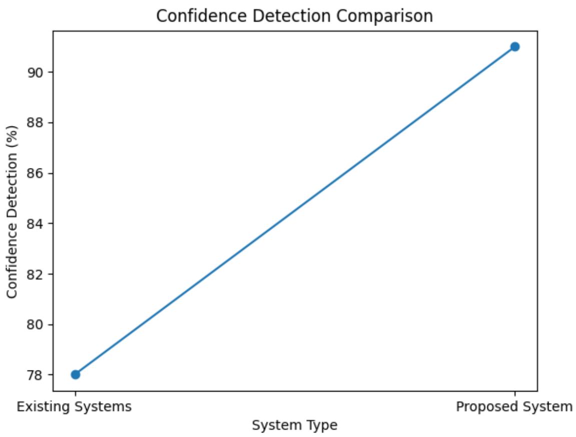

Fig. 11.

D. Discussion

The proposed Role-Focused Interview System proves to be superior to existing mock interview frameworks, owing to its use of multiple evaluation techniques. In particular, it is able to construct role-related interview questions based on skill gaps between the candidate's resume and job description, providing a more relevant interview experience.

The incorporation of speech-to-text and behavioral biometrics contributes to better evaluation by assessing verbal and non-verbal communication, respectively. The system can evaluate the level of confidence and professionalism demonstrated by the candidate during the interview, among other things. Moreover, the multi-factor scoring technique increases the accuracy of the assessment by using semantic analysis and keyword matching.

As seen from the results obtained, the Role-Focused Interview System offers a highly realistic and customized interview experience, allowing the candidate to find out their weak and strong points in terms of the role under consideration. Nonetheless, some limitations should be considered, including the impact of external factors on the accuracy of audio and visual analysis.

In conclusion, the proposed system manages to enhance the efficiency of mock interviews due to the application of a wide range of assessment methods.

E. Future Scope

The following improvements may further boost the system. The ability to provide real-time adaptive feedback in the form of tips may significantly improve the candidate's interview experience. Emotion recognition algorithms could be used to determine the level of stress, candidate's confidence, and other behavioral aspects.

It is also possible to use the adaptive question generation method, meaning that the difficulty of generated questions will depend on the performance of each candidate. Moreover, using deep learning methods for better speech and facial analysis may increase the accuracy of evaluation even more.

Another improvement is the integration of the system with cloud-based systems and mobile apps, which would allow users to have access to the system at all times and from any place. In addition, it may be necessary to include support for multiple languages in the system.

Finally, it may be appropriate to connect the platform with recruitment platforms, which will give rise to another function of the system: providing job recommendations, candidate screening, and other features.

8. Conclusion

The Role-Focused Interview System with Personalized Evaluation is a highly effective solution for the problems that arise during interview preparation. Using modern technologies such as natural language processing, speech recognition, computer vision, and semantic analysis, the system creates an environment for realistic interview preparation.

In contrast to traditional methods for preparing candidates for interviews, the suggested system will allow generating personalized questions, as well as evaluating the candidates' answers from multiple perspectives. In addition, incorporating speech and behavior analysis into the process will enable more thorough evaluation of verbal and non-verbal communication skills.

Using the suggested system, candidates will be able to identify areas where improvements are required, evaluate their level of confidence, and receive feedback. Consequently, the system will help to enhance the candidates' performance and increase their chances of success during actual interviews.

Thus, the suggested system can be regarded as a significant contribution to the field of interview preparation.

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