INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT (IJSREM)
VOLUME: 09 ISSUE: 04 | APRIL - 2025 SJIF RATING: 8.586 ISSN: 2582-3930

MockMate: AI-Powered Online Mock Interview Assessment and Evaluation System

Dr. Harsha A. Bhute
Dept. of Information Technology
Pimpri Chinchwad College of Eng.
Pune, India
harsha.bhute@pccoepune.org

Aaradhana D. Patil
Dept. of Information Technology
Pimpri Chinchwad College of Eng.
Pune, India
aaradhana.patil21@pccoepune.org

Pooja N. Nemade
Dept. of Information Technology
Pimpri Chinchwad College of Eng.
Pune, India
pooja.nemade21@pccoepune.org

Siddhesh M. Narsingkar
Dept. of Information Technology
Pimpri Chinchwad College of Eng.
Pune, India
siddhesh.narsingkar21@pccoepune.org

Abstract:* In the current competitive job market, being well-prepared for interviews is essential to landing a job. Traditional mock interviews, however, are not scalable and can call for a large human resource commitment. By providing a tailored, automated, and interactive online platform driven by artificial intelligence, MockMate tackles this problem. The system mimics actual interview situations, assesses candidate responses in real time, and provides thorough, data-driven feedback by utilizing cutting-edge Natural Language Processing (NLP) and speech-to-text technologies. In addition to customizing their interviews and choosing career roles, candidates can also obtain performance ratings based on their ability to communicate, solve problems, and be technically proficient. The system analyzes the responses using NLP models like BERT, TF-IDF, and Cosine Similarity and records them using OpenAI Whisper. A thorough report that highlights areas for development and compares user responses with ideal answers is produced. Secure, effective, and high-availability service is guaranteed by MockMate, which is built with a scalable architecture utilizing Next.js, Node.js, and PostgreSQL and deployed using Docker and Kubernetes on cloud platforms like AWS/GCP. This platform enables users to increase their interview readiness, boost their confidence, and increase their chances of success by bridging the gap between traditional interview preparation and contemporary AI capabilities.

Keywords- BERT, TF-IDF, Cosine Similarity, OpenAI Whisper, Evaluation .

I. INTRODUCTION

In today's competitive job market, obtaining a job has become more difficult, and applicants must exhibit not only technical proficiency but also excellent communication and problem-solving abilities. Structured and efficient preparation is a crucial component of career development because a candidate who is well-prepared has a much higher chance of succeeding in interviews. Personalized, real-time feedback is often lacking from traditional interview preparation techniques like self-study, reading interview guides, taking part in peer mock interviews, or scheduling professional coaching sessions. Conventional mock interview formats are also time-consuming, expensive, and challenging to scale because they necessitate the presence of human interviewers. This calls for the creation of an automated system that can give job seekers personalized, data-driven, and interactive feedback.

Advances in natural language processing (NLP) and artificial intelligence (AI) have made it possible for AI-driven interview preparation platforms to assess candidate responses, replicate real-world interview situations, and provide helpful criticism. The goal of this project is to create an online mock interview platform driven by AI that lets applicants choose particular job roles, create job descriptions, and enter their experience levels to create customized interview questions. To measure coherence, relevance, and quality, the system will use OpenAI Whisper to transcribe spoken responses and then use natural language processing (NLP) techniques like spaCy, BERT, TF-IDF, and Cosine Similarity to analyze the responses in real-time. In order to pinpoint areas for improvement, candidates will receive thorough feedback that includes a graded assessment on a scale of 1 to 10 and a thorough comparison of their responses with ideal responses.

The suggested platform's architecture prioritizes security, scalability, and efficiency. For an interactive and responsive user experience, the frontend is created with Next.js, and for a polished and contemporary look, Bootstrap/Tailwind CSS is used. Node.js powers the backend, with Express.js managing application logic and Python (Flask) integrated for processing AI modules. Drizzle ORM optimizes database management and queries, while PostgreSQL ensures effective storage of structured job-related data at the database layer. Through the use of intelligent scoring algorithms, speech-to-text processing, and NLP-based answer evaluation, the AI & ML layer improves candidate assessment.

Docker and Kubernetes are used in the platform's deployment to guarantee security and scalability, allowing it to accommodate large user bases and numerous concurrent interview sessions. GitHub Actions is used to manage continuous integration and deployment (CI/CD), allowing for smooth updates and performance enhancements. Key management procedures to safeguard user data, SSL/TLS encryption for safe data transfer, and Clerk for authentication are examples of security features. Because the platform is hosted on AWS/GCP, it has high availability, processing power, and storage capacity to effectively manage AI-driven processing.

By introducing an AI-enhanced system that is accessible, scalable, and able to provide personalized interview feedback, this research is significant because it bridges the gap between traditional and modern interview preparation techniques. Through interactive AI-driven mock interviews, the suggested system will not only assist candidates in honing their interviewing techniques but also provide recruiters and institutions with a useful tool for efficiently evaluating and mentoring applicants. The goal of this research is to develop a dependable, flexible, and intelligent interview preparation tool that will enhance job readiness and candidate performance in actual interviews by utilizing the most recent developments in AI and NLP.

II. LITERATURE SURVEY

Mock interviews have gained significant attention as an effective method for enhancing candidate preparedness, confidence, and professional readiness. They offer opportunities to simulate real-world interview scenarios, enabling candidates to practice responses, receive feedback, and improve their performance.Harchar (2012) conducted an action research study to explore the impact of mock interviews on teacher and administrator candidates' self-efficacy and interview preparedness. The study found that participants experienced a significant boost in confidence and improved interview performance through iterative practice and constructive feedback. Additionally, it emphasized the importance of detailed evaluation reports that provide actionable insights for candidates to refine their skills [1].In a similar context, Huss et al. (2017) examined mock interviews as a workplace simulation for secondary education pre-service teachers. Their study highlighted that simulated high-stakes interviews, conducted by school administrators, provided candidates with valuable experience and constructive feedback. The results indicated that mock interviews enhanced candidates' verbal communication skills, reduced interview anxiety, and facilitated a better understanding of the hiring process [2].The role of mock interviews as a training tool was further explored by Harerimana et al. (2024) in a qualitative study focused on researcher development. The study utilized an online mock interview protocol to help novice researchers develop skills in conducting qualitative interviews. It concluded that pre-interview preparation, technical readiness, and self-evaluation are crucial factors for successful interviews, making mock interviews a suitable training approach for research students [3].Beyond traditional mock interviews, advancements in Speech-to-Text Recognition (STR) technology have significantly enhanced the effectiveness of interview simulations. Shadiev et al. (2014) reviewed the use of STR in educational settings and found that it improved student comprehension, particularly for non-native speakers and students with disabilities. STR provided real-time transcriptions that facilitated clearer communication and post-interview analysis, enhancing learning outcomes [4].For interview response analysis, Anusuya and Katti (2009) proposed the use of advanced speech recognition techniques, including Hidden Markov Models (HMM) and Mel Frequency Cepstral Coefficients (MFCC). These methods were shown to achieve high accuracy in speech-to-text conversion and linguistic analysis, making them ideal for evaluating candidate responses in mock interviews [5]. Similarly, Das et al. (2015) introduced a speech recognition system using Viterbi algorithms for efficient speech decoding, further contributing to the development of automated interview evaluation systems [6].The integration of artificial intelligence (AI) in mock interview platforms has also been a growing trend. Patil et al. (2021) proposed a real-time mock interview system using deep learning technologies. Their system used convolutional neural networks (CNN) for facial expression analysis and grammar specification language (GSL) for speech-to-text conversion. Candidates received immediate feedback on their facial expressions, head movements, and grammatical accuracy. The platform's graphical feedback and performance tracking further supported candidates in improving their interview skills through repeated practice [7].Moreover, Eftekhari (2021) explored the use of intelligent speech recognition for qualitative research. The study demonstrated the effectiveness of AI-powered transcription systems in generating accurate interview transcripts, reducing transcription time, and improving data analysis. These insights could be directly applied to mock interview platforms to provide automated performance evaluations and personalized feedback reports [8].Collectively, these studies underscore the transformative role of mock interviews, STR technology, and AI-driven evaluation in enhancing candidate readiness. A comprehensive online mock interview platform that incorporates AI-based facial analysis, speech recognition, grammar assessment, and real-time feedback would offer candidates a robust, scalable, and effective solution for interview preparation.[9]This paper presents a mock interview platform leveraging speech recognition, text-to-speech, and GPT-3.5 to simulate realistic interviews. It integrates pose detection using Mediapipe for feedback on body language. The simulator gives candidates personalized feedback on both verbal and non-verbal aspects of performance, enhancing real-world readiness.[10]InterviewX introduces a personalized AI interview system using Retrieval-Augmented Generation (RAG) for real-time, domain-specific question generation, and QLoRA for fine-tuning models efficiently. It integrates Google Speech APIs, Gemini models, and AWS-based compiler for coding rounds, with plans for facial detection.[11]This system supports collaborative interview preparation, especially in Data Structures and Algorithms (DSA), using WebRTC, WebSockets, and Docker. It offers live video interviews, a shared coding environment, and containerized code execution. Designed for accessibility, it enables scheduling, feedback, and interactive practice sessions. The suggested platform's architecture prioritizes security, scalability, and efficiency. For an interactive and responsive user experience, the frontend is created with Next.js, and for a polished and contemporary look, Bootstrap/Tailwind CSS is used. Node.js powers the backend, with Express.js managing application logic and Python (Flask) integrated for processing AI modules. Drizzle ORM optimizes database management and queries, while PostgreSQL ensures effective storage of structured job-related data at the database layer. Through the use of intelligent scoring algorithms, speech-to-text processing, and NLP-based answer evaluation, the AI & ML layer improves candidate assessment.

Docker and Kubernetes are used in the platform's deployment to guarantee security and scalability, allowing it to accommodate large user bases and numerous concurrent interview sessions. GitHub Actions is used to manage continuous integration and deployment (CI/CD), allowing for smooth updates and performance enhancements. Key management procedures to safeguard user data, SSL/TLS encryption for safe data transfer, and Clerk for authentication are examples of security features. Because the platform is hosted on AWS/GCP, it has high availability, processing power, and storage capacity to effectively manage AI-driven processing. By introducing an AI-enhanced system that is accessible, scalable, and able to provide personalized interview feedback, this research is significant because it bridges the gap between traditional and modern interview preparation techniques. Through interactive AI-driven mock interviews, the suggested system will not only assist candidates in honing their interviewing techniques but also provide recruiters and institutions with a useful tool for efficiently evaluating and mentoring applicants. The goal of this research is to develop a dependable, flexible, and intelligent interview preparation tool that will enhance job readiness and candidate performance in actual interviews by utilizing the most recent developments in AI and NLP.

III. SUMMARY

Mock interviews are effective tools for enhancing candidate confidence and interview performance through iterative feedback and real-world simulations. They also serve as valuable training tools for researchers to develop interviewing skills. Integrating Speech-to-Text Recognition (STR) technology enhances learning experiences, particularly for non-native speakers and students with disabilities. Advanced speech recognition models like Hidden Markov Models (HMM) and Mel Frequency Cepstral Coefficients (MFCC) improve speech analysis accuracy. AI-powered systems further enhance mock interviews by providing real-time feedback on facial expressions, grammar, and performance tracking. Combining these approaches can create comprehensive platforms for effective interview preparation.

Aspect	Key Insight	Technology	Outcome
Mock Interviews	Effective for enhancing confidence and performance through practice and feedback	Real-world simulations and iterative feedback	Improved self-efficacy and interview skills
Researcher Training	Useful for developing qualitative interviewing skills	Mock interview protocols	Enhanced research interview competence
Speech-to-Text Recognition (STR)	Improves learning experiences for non-native speakers and those with disabilities	STR technology	Better comprehension and accessibility
Speech Analysis	Enhances speech recognition accuracy	Hidden Markov Models (HMM), Mel Frequency Cepstral Coefficients (MFCC)	Accurate speech-to-text conversion and analysis
AI-Powered Systems	Provides real-time feedback on various aspects of performance	AI-based facial expression analysis, grammar assessment, performance tracking	Improved candidate self-awareness and skill refinement

Table 1: Analysis of existing work

VI. METHODOLOGY

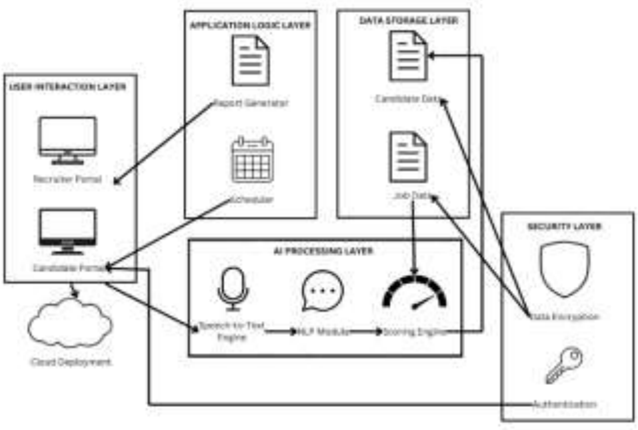

Fig1.System Architecture Diagram

System Overview:

AI-driven assessment, secure data management, and smooth interaction are all made possible by the online mock interview platform's structured, multi-layered architecture. User Interaction Layer, Application Logic Layer, Data Storage Layer, AI Processing Layer, and Security Layer are the five main layers that make up the system.

Layer of User Interaction:

Candidates can register, choose job roles, add a description of the skills they need, and take part in mock interviews on the candidate portal, which was created with Next.js to provide a responsive and interactive user experience.

- Recruiter Portal: Gives mentors and recruiters access to performance reports and candidate progress tracking.
- Cloud Deployment: To guarantee high availability, scalability, and dependability, it is hosted on AWS or GCP.

Fig 2. UI of Homepage

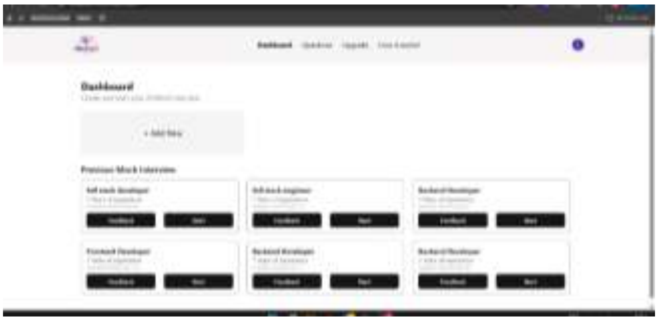

Fig 3. UI of Dashboard

Fig 4. UI of Interview page

Application Logic Layer Report Generator:

- Produces an extensive report on the candidate's evaluation that includes comments, ratings, and contrasts between the information supplied and ideal answers.
- Scheduler: Ensures a seamless user experience by effectively managing and scheduling practice interviews.

Layer of Data Storage:

- PostgreSQL: Holds organized information about jobs, such as interview questions, ideal answers, and job descriptions.
- Drizzle ORM: A database management tool that guarantees efficient data handling and queries.

AI Processing Layer:

To quantitatively evaluate the semantic similarity between a candidate's response and the ideal answer, our system utilizes Cosine Similarity, a widely adopted metric in Natural Language Processing (NLP).

TF-IDF Vectorization-Initially, both the candidate's response and the ideal response are converted into numerical vectors using Term Frequency-Inverse Document Frequency (TF-IDF). This transformation reflects the importance of words in the context of the response.

Similarity Computation:

Once vectorized, the **Cosine Similarity** is calculated between the two vectors. The formula is:

$$\text{Cosine Similarity} = \frac{A.B}{|A||B|}$$

Where:

- A and B are TF-IDF vectors of the candidate's answer and ideal answer respectively.
- $A \cdot B$ is the dot product.
- $|A|$ and $|B|$ are the magnitudes of the vectors.

Interpretation of Results:

- **Score = 1:** The candidate's answer is identical in meaning to the ideal answer.
- **Score close to 1 (e.g., 0.99):** High semantic similarity.
- **Score ~ 0.5 or lower:** Moderate to low relevance.
- **Score = 0:** No similarity.

For instance, a candidate answer scored 0.99 when matched with an ideal answer discussing logistic regression and bag-of-words, indicating a near-perfect semantic match. Such numerical similarity scores allow for objective grading and pinpointing of improvement areas.

Security Layer Authentication:

Clerk is in charge of overseeing safe user login and identity confirmation.

- Data encryption: Uses SSL/TLS protocols to guarantee safe data storage and transfer.
- Secure access control and the safe handling of cryptographic keys are guaranteed by key management.

DevOps and Deployment:

- Docker & Kubernetes: Used for containerized deployment and efficient scaling of services.
- CI/CD Pipeline: Implemented using GitHub Actions to automate testing, building, and deployment processes.

Workflow Process:

1. User Registration and Login: Candidates authenticate via Clerk and securely access the platform.
2. Job Role Selection: Candidates choose a job role and input a description to customize their interview experience.
3. Interview Simulation: AI generates contextually relevant interview questions.
4. Speech-to-Text Processing: OpenAI Whisper transcribes spoken responses in real-time.
5. AI-Driven Analysis and Scoring: The NLP engine processes responses, compares them to ideal answers, and assigns scores.
6. Report Generation: The system generates a detailed feedback report, including AI-suggested improvements.
7. Progress Tracking: Candidates can review past performance and refine their skills through iterative learning.

This layered methodology ensures a structured and effective approach to interview simulation, evaluation, and feedback generation, providing candidates with an insightful learning experience.

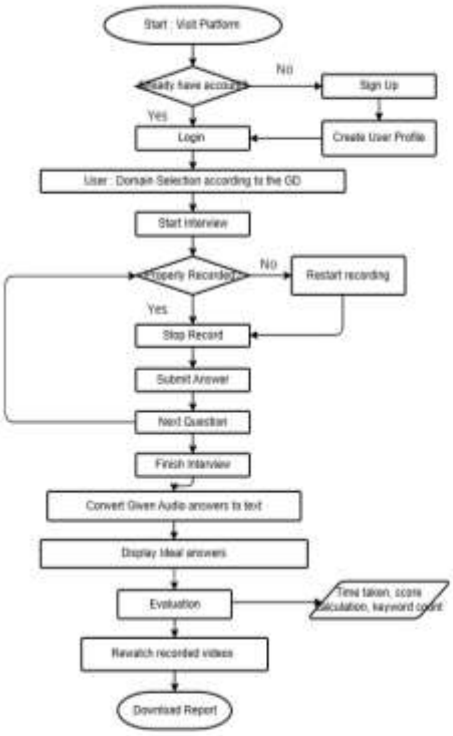

Fig5.Flowchart of the system

V. RESULTS

1. Scoring and Evaluation

The system evaluates candidates across predefined dimensions, assigning weighted scores to each category:

- **Problem-Solving Skills (40%)**
- **Communication Skills (20%)**
- **Technical Expertise (40%)**

The weighted scores are combined to produce a comprehensive assessment, ensuring a balanced evaluation.

2. Report Generation

The systems can also generate a detailed, data-driven report for each candidate and they can download it. Reports include:

Quantitative Scores: The evaluation metrics are calculated based on weighted scores for predefined dimensions. The final score is computed as:

$S_{final} = w1.S_{problem\text{-}solving} + w2.S_{communication} + w3.\ S_{technical}$

Where:

w1, w2, w3 are the weights assigned to each metric

VOLUME: 09 ISSUE: 04 | APRIL - 2025 SJIF RATING: 8.586 ISSN: 2582-3930

$S_{\text{problem-solving}}$, $S_{\text{communication}}$, $S_{\text{technical}}$ are the individual scores for each dimension.

The scores are derived as follows:

- **Problem-Solving Skills:** Assessed using structured logic and analytical flow in responses.
- **Communication Skills:** Evaluated based on clarity, coherence, and engagement during responses.
- **Technical Expertise:** Measured by the use of domain-specific terms and the relevance of answers.

Fig6. Evaluation of Answer-1

Fig 7. Evaluation of Answer-2

The system was tested with technical interview questions to evaluate a candidate's knowledge and provide meaningful feedback. For instance, in a question related to Jenkins and CI/CD pipelines, the candidate gave a brief and somewhat generic response. The system rated this answer **2 out of 10**, indicating that it lacked technical details and depth.
To help the candidate understand what was missing, the system generated a complete and well-explained ideal answer. This included specific tools like Maven, Docker, and Kubernetes, and clearly described the stages of a typical CI/CD pipeline.
Additionally, the system provided feedback that pointed out areas for improvement—like the need to mention build tools, deployment targets, and how to handle failures. It also suggested how to structure a stronger response.
This kind of detailed analysis not only highlights where a candidate is struggling but also gives clear direction on how to improve. The final output, including all answers, ratings, and feedback, is compiled into a PDF report that the candidate can download and review later. This makes the evaluation more transparent, personalized, and useful for self-improvement.

Feedback Generation:
The GPT-4/Gemini model is prompted with:

1. The question
2. The candidate's answer
3. The ideal answer

It then generates a detailed analysis, suggestions for improvement, and motivational in-sights.

Posture Detection Algorithm:
The posture detection system uses MediaPipe's 33-point pose estimation to classify:

- Proper Eye Contact
- Hand and Leg Position (e.g., Crossed Arms)
- Head Movement and Slouching

Custom logic maps detected postures to feedback statements.

Adaptive Feedback Loop:
With each interview session, the system tracks progress and adapts the next set of questions and difficulty using:

Next Difficulty Level = Previous Level + δ (Performance Score)

Where δ is a function of consistency and recent feedback.

Proposed Algorithm to Find All Solutions:
The MockMate system proposes a structured and modular approach to evaluate candidates' mock interview performance using a combination of Large Language Models (LLMs), structured scoring techniques, and behavioral analytics. The algorithm consists of multiple phases:

1.Input Phase:

- Candidate Metadata: Job role, experience level, domain expertise.
- User Responses: Audio (converted to text), or directly typed textual answers.
- Session ID: Unique identifier for traceability and report generation.

2.Pre-processing Phase:
Speech-to-Text Conversion: Using Google Speech-to-Text API or Whisper model for voice inputs.
Noise Reduction: Optional module for cleaning transcription.
Punctuation Restoration: LLM-assisted grammar-aware reconstruction of raw transcripts.

3.Scoring Phase:(as mentioned above)
The scoring algorithm assigns a final evaluation score ($S_{f\ inal}$) based on weighted parameters.

$$S_{final} = w1 \cdot S_{problem} + w2 \cdot S_{communication} + w3 \cdot S_{technical}$$

Feedback Generation
Using OpenAI GPT-4-turbo or Gemini models, generate:

- Answer correction
- Improvement suggestions
- Highlighted strengths
- Behavioral cues (if facial/voice data available)

Report Generation:
The final output is a downloadable PDF report with:

- Session overview
- Question-wise scores
- LLM feedback
- Final rating and recommendations

Optional - Strength/Weakness Matrix:
Using clustering and normalized scoring:
Strength Category = arg max S_i,
Weakness Category = arg min S_i
Where Si refers to scores in categorized topics (e.g., OOPs, DSA, DBMS).

Adaptive Learning and Continuous Feedback with repeated usage:

- Store session history.
- Personalize next interview difficulty.
- Provide visual charts for tracking streak and progress.

VI. CONCLUSION

This study introduces an AI-powered online mock interview platform that offers data-driven, automated, and customized interview simulations to improve job seekers' readiness. Candidates can practice job-specific interviews on the platform, get AI-driven feedback in real time, and enhance their performance with organized evaluation reports. A scalable and effective substitute for conventional mock interviews, which frequently call for human intervention, the system combines speech-to-text processing, natural language processing (NLP), and machine learning-based scoring mechanisms. According to the study, intelligent feedback can help candidates fill in the gaps in their responses, enhance their communication abilities, and increase their confidence for in-person job interviews. This underscores the importance of AI-driven assessment in career development. Furthermore, a wide audience can be assured of seamless accessibility and usability thanks to the platform's scalable and secure architecture.

VI. REFERENCES

[1] Harchar, R. (2012). Mock Interview Strategy: An Action Research Study of Administrator and Teacher Candidates' Preparation for Interview Field Experience.

[2] Huss, R., Jhileek, T., & Butler, J. (2017). Mock Interviews in the Workplace: Giving Interns the Skills They Need for Success. The Journal of Effective Teaching.

[3] Harerimana, A., Wicking, K., Biedermann, N., & Yates, K. (2024). Preparing for Data Collection: The Mock Interview as a Researcher's Training Tool. Taylor & Francis Online.

[4] Shadiev, R., Hwang, W.-Y., Chen, N.-S., & Huang, Y.-M. (2014). Review of Speech-to-Text Recognition Technology for Enhancing Learning. Educational Technology & Society.

[5] Anusuya, M. A., & Katti, S. K. (2009). Speech Recognition by Machine: A Review. International Journal of Computer Science and Information Security.

[6] Das, P., Acharjee, K., Das, P., & Prasad, V. (2015). Voice Recognition System: Speech-to-Text. Journal of Applied and Fundamental Sciences.

[7] Patil, R., Butte, A., Temgire, S., Nanekar, V., & Gavhane, S. (2021). Real Time Mock Interview Using Deep Learning. International Journal of Engineering Research & Technology (IJERT).

[8] Eftekhari, H. (2021). Transcribing in the Digital Age: Qualitative Research Practice Utilizing Intelligent Speech Recognition Technology. European Journal of Cardiovascular Nursing.

[9] Y. -C. Chou, F. R. Wongso, C. -Y. Chao and H. -Y. Yu, "An AI Mock-interview Platform for Interview Performance Analysis," 2022 10th International Conference on Information and Education Technology (ICIET), Matsue, Japan, 2022, pp. 37-41, doi: 10.1109/ICIET55102.2022.9778999.

[10] S. Diwate, “A Survey of AI-Driven Mock Interviews Using GenAI and Machine Learning (InterviewX),” 2024 4th International Conference on Ubiquitous Computing and Intelligent Information Systems (ICUIS), Dec. 2024. DOI: 10.1109/ICUIS64676.2024.10866631.

[11] M. M. Ahmad, P. Srivastava, V. Bharti, M. F. Shamsi, A. Jain and A. Vishnoi, "Collaborative Mock Interview Platform," 2024 OPJU International Technology Conference (OTCON) on Smart Computing for Innovation and Advancement in Industry 4.0, Raigarh, India, 2024, pp. 1-5, doi: 10.1109/OTCON60325.2024.10687866.