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Ai-Driven Virtual Interview Coach Using Deep Learning

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KEYWORD

AI interview preparation, resume analysis, technical assessment, HR interview, voice-based inter-action

ABSTRACT

This article describes an interview preparation system that collects and evaluates candidates objectively. The system automates the interview process to enhance the recruitment using the AI assistance. This solution comprises three key technologies as: real time emotion detection based on Convolutional Neural Networks, natural language processing for a resume summary and speech recognition for evaluation of the response. The system is integrated with an ATS for the screening of resumes, An HR interview simulator for HR interviews on the area of effective communication and behavioral skills and a technical test for evaluating the knowledge in a particular field. Through extensive testing, the platform demonstrates significant improvements in both candidate preparation efficiency and performance quality compared to traditional methods. The system also helps the candidates to prepare for interviews since systems ability to automatically generate questions, instant feedback respondents and offer details of an individual performance. The research presents an unbiased and scalable answer that meets the intersection of the traditional interview hiring techniques with the modern technology capabilities for the AI aided recruitment.

I. Introduction

For a job seeker, demonstrating a particular degree of readiness is a vital aspect of the interview, given today's cut-throat competitive environment [17,18]. At times a traditional interview might be effective, but they are often time consuming and do not adequately prepare the candidates for the various questions and scenarios [19,20]. The proposed system bridges this gap by simulating real-world interview environments using AI. It prepares the candidates for different recruitment phases such as resume screening, HR interviews and tech evaluations.
The system evaluates the communication skills, technical knowledge, experience and qualification according to job description. System conducts human-like interviews and assessments through intelligent dialogue. It features AI-powered interactive interviews that generate questions based on previous answers, also generate feedback and performance scores to highlight strengths and improvement areas. Has a resume analysis, voice-based interviews for HR test, and rates candidate's performance.
Interview preparation is made more convenient through AI driven tools and seamless automation which enhances how the job competition looks now. This, in turn, aids in tailoring the process and enhances prowess, therefore

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raising the bar for the game - skills, success ratio and most importantly self-assurance. By providing a hybrid approach catering towards flexibility and personal engagement for recent graduates and eager candidates, skills are honed and developed further.

II. Need of Research

In the rapidly evolving job market, interview preparation presents significant challenges that traditional methods fail to address adequately. The growing complexity of recruitment processes demands innovative approaches that leverage advanced technological solutions to bridge critical gaps in candidate evaluation and preparation.

The research identifies four fundamental challenges:

1.Personalization Limitations: Tools that exist today that aim to assist in preparation lack the function to provide feedback against a candidate's profile or job role, ultimately undermining skill assessment tools [1].

2.Resource Inefficiency: There is an evident need for more efficient recruitment techniques, as the current ones used take up both time and effort from both candidates and their employers.

3.Comprehensive Skill Mapping: The modern recruitment approach is holistic since it addresses several skills deficiencies such as engineering skills, language skills, and flexible imagination skills.

4.Authentic Experience Simulation: Candidates can only develop realistic professional tactics through putting themselves in high pressure situations such as interviews, which traditional preparation practices do not do.

The goal of the proposed research is to design an AI: based platform for interview preparation that departs from traditional ones. It specifically targets the creation of a comprehensive, individualized preparation approach enabled through a more intelligent, dynamic and interactive model.

III. Literature Survey

Recently, artificial intelligence (AI) and machine learning (ML) concepts have changed the recruitment process at an accelerated pace in fields such as emotion detection for recruitment, resume analysis, and speech recognition. Singh et al. [1] worked on a machine learning emotion detection tool which involved support vector machines and random forest methods alongside CNN, which is a form of deep learning. Their findings earn high efficiency from experimentation in controlled environments but their problems including lighting interactions and the partiality of isolation are exposed in the practical environment. Similarly, Porcu et al. [2] sought to learn whether facial expression analysis can be used to estimate quality of experience (QoE) during a video call and further highlighted challenges such as reading an emotion requiring subtlety that has to be done between cultures. Within the domain of resume analysis Jagwani and Meghani [3] describe a model that uses Latent Dirichlet Allocation (LDA) and Named Entity Recognition (NER) based processes for increasing the efficiency of the resume reproduction process. Though successful in computing the ratings of resumes to a much more complex schematic than simply a key word search, there were reservations in term of the application of the concept across various resume layout styles and the precision of the domain specialties marking. Along the same lines Daryania et al. [4] build a NLP driven, resume screening technology that enabled substantial changes in the first perusal of resumes. Speech recognition, another critical component of modern recruitment systems, has seen advancements with the adoption of neural network-based techniques. Jain and Rastogi [5] reviewed the evolution of these technologies, noting substantial improvements in transcription accuracy through models such as OpenAI Whisper. However, challenges persist in scenarios with background noise, accented speech, and domain-specific jargon. Collectively, these studies underscore the potential of AI in automating and enhancing various aspects of recruitment while highlighting gaps such as the need for greater contextual understanding, robust emotion detection in dynamic environments, and scalable systems capable of adapting to diverse user profiles. These challenges form the foundation for our proposed AI-powered interview preparation system, which integrates emotion analysis, resume evaluation, and speech recognition into a unified, adaptive platform to address these limitations.

IV. System Overview

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The proposed platform is an advanced AI-powered tool designed to improve interview readiness by simulating realistic scenarios. It addresses various stages of the recruitment process, such as resume evaluation, HR discussions, and technical skill assessments. Using intelligent algorithms, the system adapts its questions in real time based on user responses, creating a tailored and interactive experience. After each session, candidates receive constructive feedback, including insights into strengths and areas requiring improvement, enabling them to enhance their skills and build confidence.

This system incorporates unique features like voice-enabled HR interviews, detailed CV analysis, and adaptive questioning to provide a comprehensive evaluation. By automating the preparation process, it minimizes time constraints while delivering a personalized approach to skill-building. Specifically designed for job seekers and recent graduates, the plat-form offers an engaging and efficient way to develop abilities, ultimately increasing their success in securing desired positions in the competitive job market. (see Fig. 1)

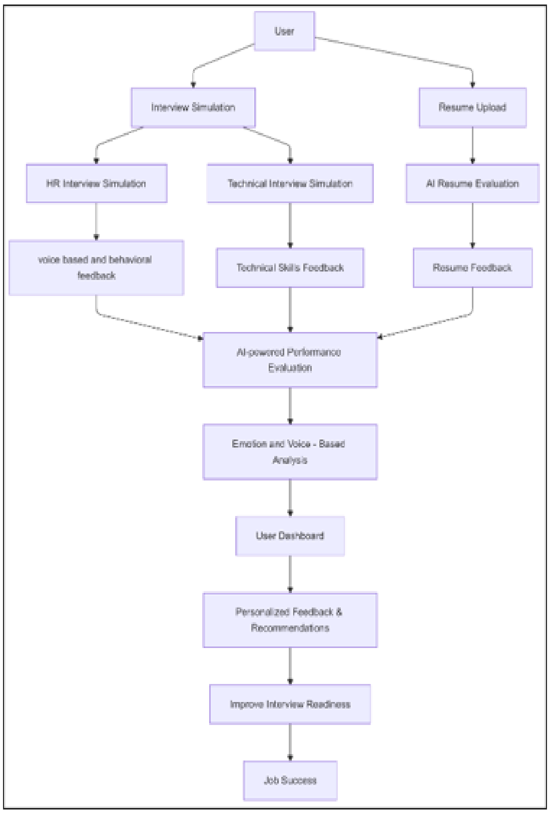

Fig. 1. System Overview

V. Methodology

The AI interview tool integrates multiple technologies into a single solution. It features a Flask backend that has three major components – resume screening, sentiment analysis, and voice analysis.

Resume screening employs linguistic programming to scrape the necessary information from the application documents, and create relevant questions for the interviews. The sentiment analysis module makes use of CNN to study live video feeds of people’s emotions by capturing one frame every second which is then encoded to base64 for analysis. Another react-based integration in the tool makes use of speech analysis to transform voices into text, therefore enabling the ma-chine to assess the responses more effectively.

WebSocket connections enhance real-time communication between the frontend and the backend and minimize latency, ensuring that there is seamless data sharing. The backend enables the analysis of a combination of text questionnaires and video feeds taken simultaneously. The result is a system that is highly robust and provides an enjoyable interview experience due to its modular and flexible structure.

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A. Resume Analysis and Applicant Tracking System (ATS) Module

The Resume Analysis and Evaluation Module utilizes language processing, machine learning, and recruitment technologies for human resources evaluation, effectively making recruitment a seamless and automated task. In this section, the individual steps taken by the module are explained.

Resume Analysis in ATS Modules: The analysis of a resume is a means of evaluating a candidate for a position using their collected resumes, parsing them and comparing them against the job's requirements. This process also ensures assessment is impartial owing to the algorithms it employs alongside machine learning [1].

Data Extraction and Parsing: OCR in combination with NLP helps reformat resumes of various types, including PDFs, Word Documents and simple text, into easily analysable data [6].

- **Data Segmentation:** Name, date or job title recognition is one of the most essential tasks of NER[2].
- **File Compatibility:** Parsing accuracy was achieved through the use of standardised formats ensured accuracy [7].

Other important aspects of a resume were evaluated through TF-IDF before being compared against a job description through cosine similarity, LSA and custom weighting [8].

Content Quality Assessment: To assess grammatical or formatting issues BERT and other transformers based NLP models are utilized [6]. Grammar enhancing tools such as Grammarly [2], alongside Flesch-Kincaid scores [7] are used to ensure clarity for a reader. Resumes that are complex and difficult to understand are simplified so recruiters can better understand them.

Scoring Algorithms: Specific job descriptions are supplemented with key functions via TF-IDF, which assist ATS in evaluating resumes against them and experience weighting [9]. Resumes adhering to ATS standards are prioritized, while non-standard formats are penalized [10]. These algorithms objectively rank candidates for efficient review.

Feedback Reports: ATS-generated feedback highlights areas for improvement, missing skills, and structural adjustments. Recommendations include adding relevant keywords and reordering sections for clarity [11]. This personalized feedback optimizes resumes for ATS compatibility and recruiter attention. [12].

B. Emotion Recognition in Modern Interview Platforms

New automated interview platforms use artificial intelligence in emotion analysis and it has taken the world of interviews by storm. These platforms can be able to analyse candidate's emotional response in real time which can help the candidates gain insight on their behavioural tendencies.

The emotion recognition framework is grounded on the use of state-of-the-art machine learning and computer vision technology. While the older systems relied on these basic classification algorithms, such as support vector machines and random forest, modern systems employ convolutional neural networks (CNN) to improve accuracy [12]. According to the framework, the system identifies seven main categories of facial expressions: joy, sorrow, anger, fear, surprise, disgust and calm.

Main stages:

- **Face Detection:** Isolating facial regions in video frames.
- **Feature Extraction:** Analysing facial landmarks and muscle movements.
- **Emotion Classification**: Categorizing features into specific emotional states.
- **Real-Time Processing:** Delivering actionable insights based on analyses.

Although there are issues with the technology regarding lighting and facial occlusion, emotion detection is very useful in healthcare, education and even automated interviews where nonverbal behaviour is of utmost importance[1].

System Architecture and CNN Implementation

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The emotion detection module is central to the AI interview system, analysing video streams in real time to evaluate candidates' emotional responses. CNNs are pivotal in this module due to their robust image classification capabilities, achieving accuracy rates up to 90% in similar tasks[1].

CNN Processing Pipeline

1. Input Layer Processing

- **Video Frame Capture:** Using WebRTC, video streams are captured in real time, with frames extracted at a predefined rate to balance efficiency and performance [6].
- **Frame Preprocessing:** Frames undergo resizing and normalization for consistent CNN input, ensuring optimized detection of emotional features.
- **Face Detection:** Algorithms like Haar cascades or DNN models identify faces in each frame, extracting the region of interest (ROI) for further processing.

2. Convolutional Layers

- **Hierarchical Feature Extraction:** Early layers detect basic features (e.g., edges and corners). Deeper layers identify complex patterns (e.g., muscle movements).
- **Pooling Layers:** Max pooling reduces spatial dimensions while retaining key information. (see Fig. 1)

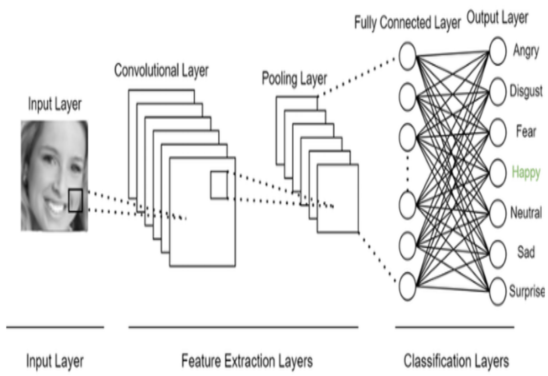

Fig. 2. CNN Model

3. Classification Layers

- **Fully Connected Layers:** Extracted features are flattened and passed to these layers for emotion classification.
- **Softmax Activation:** Produces a probability distribution across the seven emotions: happiness, sadness, anger, fear, surprise, disgust, and neutral [8].
- **Real-Time Predictions:** Results are visualized graphically, often with bounding boxes highlighting detected emotions.

Integration with the Interview System: The emotion detection module integrates seamlessly with the video processing pipeline. Video frames captured via WebRTC are transmitted to the backend using socket connections, where the Flask server processes them through the CNN pipeline. Detected emotions are then sent back to the frontend for live visualization, ensuring minimal latency and an interactive user experience [1]. This streamlined real-time feedback loop eliminates the need for manual frame uploads, enhancing system performance**.**

C. WebRTC

WebRTC (Web Real-Time Communication) is a free software and a built-in feature of web browsers and mobile applications that gives allows P2P (peer to peer) communication to take place in real time. It eliminates the requirement for any software components enabling the transmission of audio, video and data making it ideal for video conferencing and online broadcasting, collaborations among other tools [6]. Web Real-Time

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Communication technology is achieved in accordance with the standards set by the World Wide Web Consortium (W3C) and Internet Engineering Task Force (IETF) which guarantees cross-device compatibility[13].

Components of WebRTC

Media Capture: getUserMedia() API is an application that allows the recording of both video and audio by providing real-time access to the camera and microphones of the consumers.[9].

- **Signalling:** WebRTC connectivity is supported by external signalling such as Websocket which helps peers using the system to exchange connection details like offer SDP and ice candidates [16].
- **NAT Traversal:** The combined use of Interactive connectivity established order (ICE) and STUN server aids in getting around the use of public IP addresses for direct connections. If direct connections cannot be made, TURN servers take care of relaying the data ensuring a reliable connection even when behind firewalls or NATs [13].

Media Transmission:

- **RTP/RTCP:** those protocols control the actual-time transmission of media streams and offer remarks on quality.
- **SCTP:** Used for dependable transfer of non-media records, including messages or files [13].

Media Encoding/Decoding: WebRTC makes use of codecs like VP8, VP9 for video, and Opus for audio, permitting green compression and decompression of media streams [9].

Working of WebRTC

Media Capture: WebRTC gets media stream from users' devices via getUserMedia() API, which in turn provides direct access to the users' cameras and microphones, so the necessary video and audio is captured for further processing [15].

Peer Connection Establishment: WebRTC connects two or more users by using the session Description Protocol (SDP), which contain other details such as the ways in which these protocols will be packaged and sent. To send SDP offers, answers, and ICE candidates in one room, other applications such as WebSocket are required [14].

NAT Traversal with ICE: Connecting users who are behind NAT and firewalls is not an easy task. This problem has been resolved by the WebRTC through its ICE structure which finds the best route of sending. Public IPs can be found with STUN servers while TURN servers are intermediates in case when there are direct connections that is not feasible [13]. (see Fig. 3)

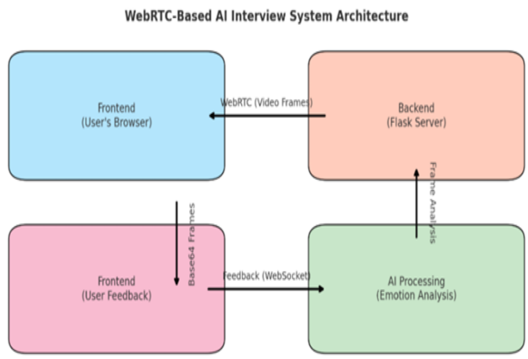

Fig. 3. WebRTC working

Data Transmission: After establishing a connection, WebRTC transmits audio and video using the real-Time Protocol (RTP) and manages the process using RTCP. Secure communication is ensured through SRTP and DTLS. For sending non-media data, WebRTC uses SCTP [14].

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Rendering: Decoded media streams are presented to users via HTML5 like components and enabling smooth playback in real-time communication situations [4].

D. Speech Recognition

Overview

The system incorporates React Speech Recognition on the front-end for the conversion of audio to text, and Text analysis is performed using flask on the back end. Audio to text data is transferred to the backend using WebSocket which guarantees real time interaction. This configuration allows conducting interactive interviews, and resume or technical review [9].

Components of Speech Recognition System

- **React Speech Recognition Library:** The presented library integrates the speech to text feature that facilitates transcription services in real time which is vital for processing input voice commands [4].
- **Flask Backend:** The backend is created using flask application which accepts the processed text and completed tasks like emotion detection or technical review and broadcasts it through WebSocket [9].
- **WebSocket:** It provides a standard method for bidirectional real time interaction between the frontend and the backend, allowing persistent communication and data transfer without needing to reload the page [5].
- **Text Analysis**: The backend deploying NLP and machine learning methods examine text by identifying user emotions or assessing sentiment and technical features [16].

Working of the System

- **Speech Capture:** Users talk unto a microphone and the audio is first transformed to enable the react speech recognition library to receive the text in real time which guarantees zero delay transcription [14] .
- **Text Transmission:** Transcribed text is transmitted to the Flask backend through WebSocket which monitors a continuous, real-time link for uninterrupted data transfer [16].
- **Text Analysis:** The backend analyses text for emotions, sentiments, or technical accuracy, leveraging NLP [16] and machine learning models to extract insights [9] [14].
- **Analysis Feedback:** After analysis, results are sent back to the frontend via WebSocket. Feedback includes emotional states, sentiment analysis, or technical evaluations, displayed in real-time [9].
- **Continuous Interaction:** The process repeats seamlessly as users continue speaking, supporting dynamic, ongoing interaction with real-time insights [4].

E. Technical Implementation Considerations

1. Real-time Processing:

For ensuring maximum outgoing smoothness in the interview setting where everything is in real time, optimizing the frame rate ensures that key frames are processed at a minimum amount of delay without affecting the accuracy of the video being streamed. The consumption of resources during the transmission of video frames is reduced due to the use of base64 encoding. Socket. IO enables low latency bi directional communication which allows real time video frame emotion prediction and analysis [4].

2. Performance Optimization:

By implementing model compression techniques such as quantization and pruning the overhead computations required for the CNN model is reduced which would enable faster inference times. Having a greater Throughput through batch pro-cessing and minimalizing delays across the video frames improves performance. Solitary interference during long inter-view sessions is ensures with effective performance of memory management [1].

HR Module Overview

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The process of conducting HR interviews is automated with the help of AI integration and enhancement to further evaluate the interviewee using speech recognition while interpreting the emotions and analysing the language used by the interview. This guarantees a robust yet objective evaluation that is highly scalable [6].

Speech Recognition and Processing: The audio is recorded by the HR module through a microphone, then converted to a text file through the WebSocket and is later processed with speech to text recognition models such as google speech to text API or OpenAI's Whisper [2]. The content, structure and emotions of the words are further analysed with the help of real time transcription. Speech characteristics like pitch and tempo help detect emotions such as confidence or anxiety, ensuring nuanced candidate evaluation [7].

Emotion Detection through Facial Expression Analysis: A webcam captures video footage that a CNN processes to identify emotions that are expressed through the facial features of a person and through some micro-expressions like smiling or frowning. The memory image video frames are up-loaded in base64 format and the backend processes it to align verbal and non-verbal signals for better candidate evaluation reporting. [10].

Linguistic Analysis for Behavioural Insights: The system utilizes NLP methods to examine the essential understanding of the transcription together with the structural arrangement of the words. Moderating models that are built on transformer frameworks are utilized for tasks such as sentiment determination, topical relevance determination, and complexity determination. Further, this system goes through the answers given against the standard and gaps and key themes and sentiments and relevance of the given answers so that communication can be improved [12].

Integrated Flow of the HR Module: The module starts with the speech-generating software posing HR questions to the candidate. During the interview, as candidates answer the questions, their speech and facial expressions are analysed, and a single profile is built over the participating candidates. All the points are taken on set standards like a person’s communicational abilities and the level of emotional reasoning. It minimizes the risk of bias, increases opportunities for multilayered candidates, and gives justifiable assessment [5].

Output

Emotion recognition, speech detection, video analysis, and natural language processing are some of the automated features that are found in the new AI integrated interview HR module and which greatly improves candidate assessment. It enhances neutrality thus ensuring scalability., and granular insights previously unattainable in traditional HR interviews. By combining advanced AI techniques with practical HR requirements, the system redefines modern recruitment standards [16].

Technical Module: Comprehensive Description

The technical module evaluates a candidate's technical proficiency by analysing their resume to generate and assess questions. Using NLP techniques, technical skills are extracted from resumes and mapped to a database of predefined technical questions. During interviews, the system delivers these questions, evaluates responses, and provides feedback [1].

Workflow and Methodology

The workflow starts with resume analysis, where resumes in formats like PDF and Word are processed. OCR is used for scanned documents, while NLP parsers extract and structure data. Named Entity Recognition (NER) identifies skills, pro-jects, and qualifications, which are matched against a repository of questions. Questions are delivered via Text-to-Speech (TTS), and spoken responses are captured, transcribed using a Speech Recognition engine, and evaluated using NLP algorithms for correctness and depth [6].

Evaluation uses rule-based scoring or a deep learning model like a Transformer-based classifier. Emotion detection with CNN models and real-time speech analysis gauge confidence and clarity. Insights are consolidated into a dashboard with a comprehensive evaluation report [2].

Technical Insights and Algorithmic Reference

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BERT or GPT models are employed to examine the semantic structure of the responses and compare the answers to correct ones [9]. Skill matching is achieved via cosine similarity and semantic embeddings to fine-tune the questions being asked. A classifier trained against a technical dataset is used to evaluate responses while emotion recognition is done with CNN models as a complementary performance measure [10].

Dashboard and Feedback System: The dashboard integrates useful information and displays results that include a composite score based on the skill metrics, a composite score based on semantic accuracy, and metrics based on emotions. It also shows the overall score and at the same time offers improvement suggestions which enable reviewers to easily discover the strengths and weaknesses of the persons reviewed [11].

Feedback Module: Detailed Description: Comprehensive Description Despite a number of different inputs, the feedback module merges all the results from the ATS, HR and Technical modules for practical purposes. It helps ensure that all modules provide precise information as well as correct finding by bringing together the ATS results, HR assessment and specialist evaluation and consolidation for providing feedback [6].

Feedback Generation Process: The feedback under the ATS module focuses on the business areas and issues that need amelioration, in particular it concentrates on the quality of resume presented. Feedback from HR side provides assessment on the level of emotional intelligence possessed, communication efficiency, and performance in an interview. The scope of Technical feedback covers the score allocated to the responses for the technical questions and the score given to the baseline self-service skills [8].

Individual feedback reports are combined into a comprehensive report with detailed strengths, weaknesses, and overall performance ratings. This unified report guides HR professionals in making informed decisions and provides candidates with actionable improvement insights [10].

Feedback Display and Actionable Insights: The feedback is presented in a user-friendly interface. HR professionals gain data-driven insights for candidate selection, while candidates receive constructive guidance for improving resumes, communication skills, or technical knowledge. Personalized suggestions empower candidates to refine skillsets and approach interviews with confidence [12].

V. AI Interview System Results

1. Resume Analysis/ATS Module Results

Table 1: Resume Analysis

Metric	Value	Description
Resume Relevance Score	85%	Percentage alignment of resume content with the job description.
Grammatical Accuracy	95%	The grammar and readability score based on NLP models.
Keywords Identified	Java, React, MongoDB	Key skills and terms extracted from the resume.
Improvement Suggestions	Add project details in React.	Recommendations for enhancing resume alignment with job requirements.

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The ATS module showed in Table 1 demonstrates robust performance in document handling and information extraction. Notable achievements include faster-than-target processing times and high accuracy in skills matching.

2. Emotion Recognition Module Results

The emotion recognition system showed in Table 2 demonstrates strong performance across all emotional states, with particularly high accuracy for neutral and happy expressions.

Table 2: Emotion Recognition

Emotion Type	**Detection Accuracy**	**False Positive Rate**	**Processing Time**
Happiness	94.5%	3.2%	45ms
Sadness	91.2%	4.1%	43ms
Anger	89.8%	5.3%	44ms
Neutral	96.3%	2.1%	42ms
Anxiety	88.5%	5.8%	46ms
Confidence	92.1%	3.9%	44ms

3. Speech Recognition Module Results

The speech recognition module demonstrated in Table 3 shows robust performance across various conditions, maintaining high accuracy even with moderate background noise.

Table 3: Speech Recognition

Metric	**Clear Audio**	**With Background Noise**	**With Accent**
Word Error Rate	3.2%	8.5%	12.3%
Response Time	0.8s	1.2s	1.1s
Accuracy	96.8%	91.5%	87.7%
Confidence Score	0.92	0.85	0.81

4. HR Interview Module Results

The HR module demonstrated in Table 4 shows consistent performance in evaluating candidates across multiple criteria.

Table 4: HR Interview

Parameter	**Score**	**Description**
Communication Clarity	4.5/5	Evaluated on coherence and structure of responses.
Emotional Stability	4.0/5	Based on consistency in emotional responses throughout the interview.
Suggested Improvement Areas	Improve verbal examples.	Specific advice on enhancing verbal communication.

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5. Technical Assessment Results

Table 5: Technical Assesment

Assessment Area	**Success Rate**	**Average Time**	**Completion Rate**
Programming Questions	82.5%	15.3 min	94.2%
System Design	78.9%	22.1 min	91.8%
Algorithm Analysis	80.3%	18.7 min	93.5%
Database Concepts	85.1%	12.4 min	95.7%
Problem-Solving	83.2%	20.2 min	92.9%

The technical assessment module showed in Table 5 demonstrates strong performance in evaluating candidates' technical skills across different domains. Database concepts and programming questions showed the highest success rates, while system design questions proved more challenging for candidates. The completion rates remained consistently high across all assessment areas.

Conclusion

Finally, the Feedback Module is an important part for both the applicants and the HR team as it helps to evaluate the overall performance of the candidate. By integrating various outcomes from different modules and providing constructive feedback, the system guarantees that candidates will be skilled further, whereas HR experts will have an objective and reasonable approach to hiring. This module installed within AI interviewing system increases the efficiency and the equity of the hiring procedure.

Competing Interests Disclaimer:

Authors have declared that they have no known competing financial interests OR non-financial interests OR personal relationships that could have appeared to influence the work reported in this paper.

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