Autonomous Interview Process System

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Project Proposal Report

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DECLARATION

I declare that this is my own work and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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ABSTRACT

In today's competitive IT sector, the recruitment process demands both efficiency and precision to identify the best candidates for technical roles. This proposal presents the development of an innovative automated interview process tool designed to streamline and enhance the candidate evaluation process in the IT sector. The tool integrates advanced technologies such as natural language processing, voice analysis, and machine learning to assess candidates' confidence, emotional states, and technical skills. The system focuses on four core functions: 1) Evaluating personality and confidence through analysis of tone, pitch, and frequency during interviews, 2) Using emotional analysis and gamified assessments to gauge technical skills and problem-solving abilities, 3) Assessing code complexity and maintainability through a front-end editor, and 4) Shortlisting candidates based on video-based mock exam to evaluate attire and clarity.

The proposed system is designed with flexibility and scalability in mind, employing open-source technologies and frameworks to ensure cost-effectiveness and ease of integration into existing HR systems. By reducing human biases and enhancing the overall candidate evaluation process, the Automated Interview Process Tool has the potential to significantly improve the quality of hires, contributing to the success and innovation within tech organizations. And also in today's competitive job market, organizations are increasingly seeking efficient and objective methods to assess potential candidates. Traditional interview processes often fall short in providing a comprehensive evaluation of a candidate's abilities, leading to the need for innovative solutions. A key function of this tool focuses on identifying the candidate's confidence level through voice frequency analysis. By examining various vocal features such as pitch, tone, and frequency, the tool is able to gauge confidence with a high degree of accuracy. This function not only enhances the overall assessment but also provides deeper insights into the candidate's interpersonal skills and readiness for the role. The integration of this confidence analysis into the automated interview process tool promises a more nuanced and reliable evaluation, enabling employers to make informed hiring decisions.

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LIST OF ABBREVIATIONS

Abbreviation	Definition
IT	Information Technology
HR	Human Resources
MFCC	Mel-Frequency Cepstral Coefficients
AI	Artificial Intelligence
DNN	Deep Neural Network
SMART	Specific, Measurable, Achievable, Realistic, Time-bound
API	Application Programming Interface
NLTK	Natural Language Toolkit
CNN	Convolutional Neural Network
UAT	User Acceptance Testing
IEEE	Institute of Electrical and Electronics Engineers
PLP	Perceptual Linear Prediction
EURASIP	European Association for Signal Processing
ORG,	Organization

Table 0-1 : List of Abbreviations

1. INTRODUCTION

1.1 Background

The evolution of technology in human resources has led to significant changes in how organizations approach the recruitment process. Traditional face-to-face interviews, while effective to an extent, often rely heavily on subjective judgments that can be influenced by unconscious biases. These biases may stem from various factors, including the interviewer’s perceptions, the candidate’s physical appearance, and even the social or cultural context in which the interview takes place. As a result, companies are increasingly seeking innovative and objective methods to assess candidates, ensuring that the hiring process is both fair and effective.

One area of innovation that has gained considerable attention is the use of automated tools for candidate evaluation. These tools leverage various forms of artificial intelligence (AI) to analyze different aspects of a candidate's performance. Among these tools, voice frequency analysis stands out for its ability to provide insights into a candidate's psychological state, particularly their level of confidence. This is crucial in roles that require strong communication skills, leadership, and the ability to remain composed under pressure.

Voice frequency analysis refers to the examination of a person's vocal characteristics, including pitch, tone, rhythm, and modulation. These characteristics can reveal a wealth of information about a person's emotional state, including their confidence level. By analyzing these vocal features, employers can gain a deeper understanding of how confident a candidate is during an interview. This analysis is particularly valuable in scenarios where confidence plays a key role in job performance, such as in sales, leadership, and customer service roles.

1.2 Literature Survey

The concept of using vocal analysis to gauge psychological traits is not new; it has been the subject of research for several decades. However, recent advancements in AI and machine learning have dramatically improved the accuracy and reliability of these analyses, making them a viable option for modern recruitment processes.

1.2.1 Historical Perspective on Voice Analysis

Early studies on voice analysis focused primarily on its role in communication and emotional expression. In the 1960s and 1970s, researchers like Murray and Arnott (1993) explored how different vocal cues could convey emotions such as happiness, anger, and sadness. This research laid the foundation for understanding how voice can be used to infer emotional states and psychological traits. Although these early studies were limited by the technology of the time, they provided valuable insights that continue to inform modern voice analysis techniques. [1].

1.2.2 Voice Frequency Analysis in Psychological Research

The relationship between vocal features and psychological states has been extensively studied in the field of psychology. For instance, research by Juslin and Scherer (2005) delved into how vocal expressions can reflect a person's emotional state. They discussed how variations in pitch, loudness, and tempo are often associated with specific emotions. This work highlighted the potential of using vocal features as indicators of underlying psychological traits such as confidence, anxiety, or stress. [2]

Scherer (2003) also emphasized the importance of understanding vocal expressions in social and professional settings. He noted that certain vocal characteristics, such as a steady tone and controlled pitch, are often perceived as indicators of confidence, which can influence the outcome of social interactions, including job interviews [3]

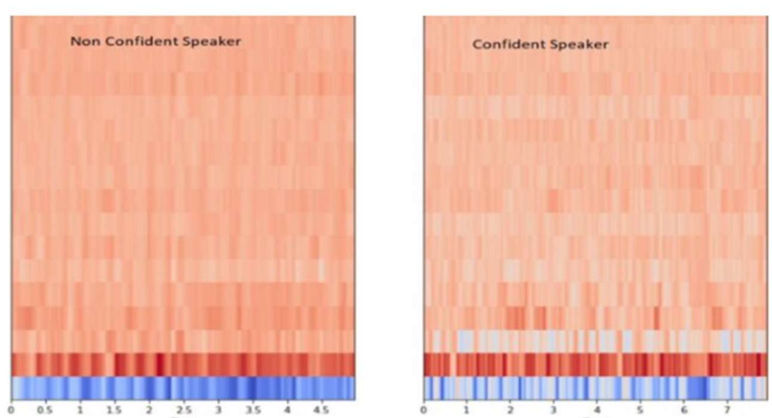

Figure 1.1: MFCC of a non-confident and confident speaker

1.2.3 Machine Learning and Automated Voice Analysis

The advent of machine learning has opened new avenues for the application of voice analysis in various domains, including recruitment. Luengo et al. (2016) conducted a comprehensive review of machine learning techniques used for emotion recognition in speech. Their research demonstrated that machine learning algorithms, when trained on large datasets, could accurately predict emotional states, including confidence, based on vocal features. This study provided a robust framework for the development of automated tools that can assess confidence levels in real-time during job interviews. [4]

Further advancements in deep learning have enabled even more precise analyses. For instance, Reiter and Schuller (2017) explored the use of deep neural networks (DNNs) for emotion recognition in speech. Their research indicated that DNNs could outperform traditional machine learning models in identifying subtle emotional cues in speech, including those associated with confidence. [5]

1.2.4 Applications in Human Resources

The practical application of voice frequency analysis in human resources has been explored in several recent studies. [6] Kim et al. (2018) examined the effectiveness of voice-based analysis tools in job interviews. Their research involved the use of voice analysis software to assess the confidence levels of candidates during mock interviews. The study found that candidates who exhibited higher confidence levels, as indicated by their vocal patterns, were more likely to be perceived positively by interviewers. This finding suggests that voice frequency analysis can be a valuable addition to the hiring process, providing objective data that complements subjective assessments.

Another study by Parekh and Panchal (2020) explored the use of AI-driven voice analysis in remote interviews. With the rise of remote work, organizations have increasingly relied on video conferencing tools for interviews. This study highlighted the potential of integrating voice analysis into these tools to assess confidence levels, even in a remote setting. The researchers found that voice frequency analysis could effectively distinguish between confident and anxious candidates, providing valuable insights for remote hiring. [7]

1.2.5 Voice Analysis in the Context of Gender and Culture

The application of voice frequency analysis must also consider the potential influence of gender and cultural factors. Research by Wu et al. (2019) explored how gender differences can affect vocal characteristics and the perception of confidence. Their study found that men and women often exhibit different vocal patterns, which can influence how their confidence is perceived. This research underscores the importance of developing voice analysis tools that are sensitive to these differences, ensuring that assessments are fair and accurate across diverse candidate pools.

Similarly, cultural factors can also play a role in vocal expression and perception. Matsumoto and Hwang (2016) investigated how cultural norms influence vocal behavior and emotional expression. They found that individuals from different cultural backgrounds may exhibit varying vocal characteristics, which can affect the interpretation of their confidence levels. This research highlights the need for culturally adaptive voice analysis tools that can accurately assess confidence in a global workforce. [8]

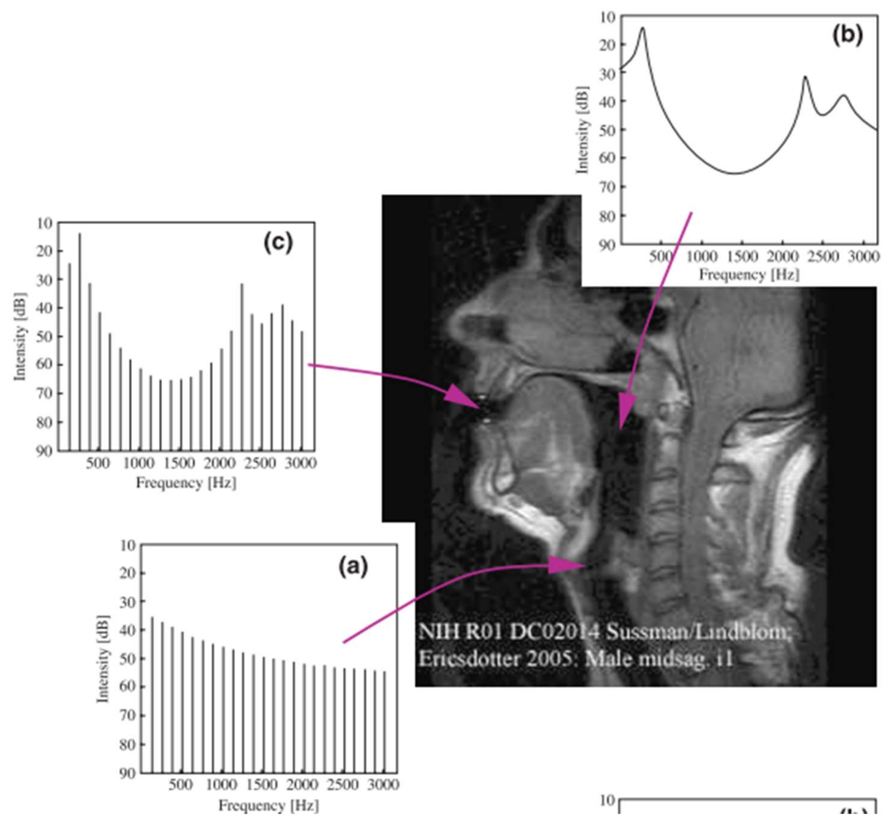

Figure 1.2: Phonetic differences in male speech, highlighting the variation in frequency and intensity.

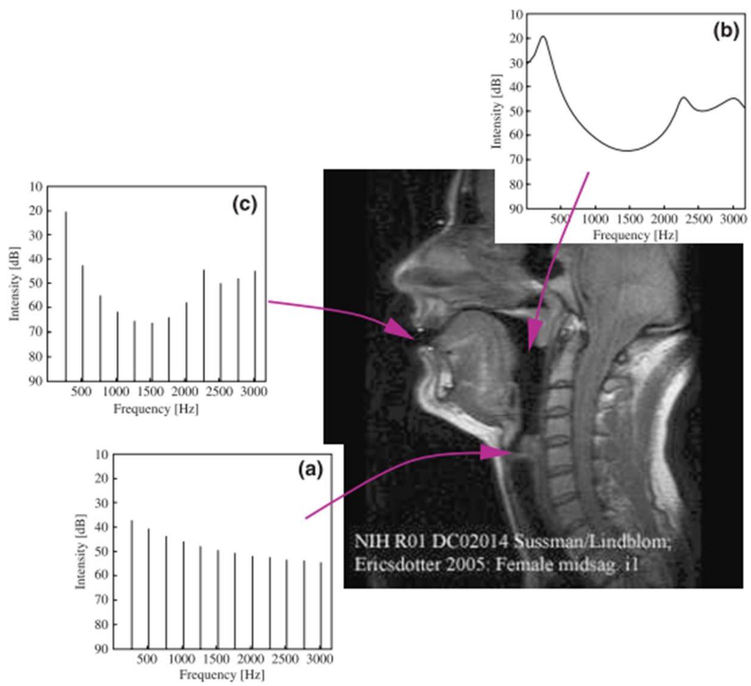

Figure 1.3: Phonetic differences in female speech, highlighting the variation in frequency and intensity.

1.2.6 Challenges and Considerations

While the potential benefits of voice frequency analysis in recruitment are substantial, several challenges must be addressed to ensure its effective implementation. One of the primary challenges is the need for large and diverse datasets to train machine learning models. These datasets must include a wide range of vocal characteristics, representing different genders, cultural backgrounds, and emotional states. Ensuring the diversity and representativeness of these datasets is crucial to developing voice analysis tools that are fair and accurate.

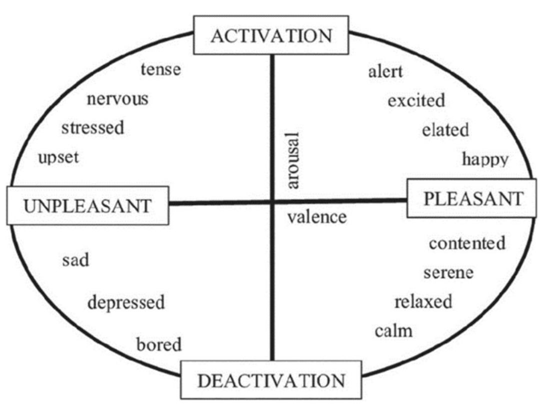

Figure 1.4: Emotion Detection

Another challenge is the ethical considerations associated with using AI-driven tools in recruitment. The use of voice analysis to assess confidence raises questions about privacy, consent, and the potential for algorithmic bias. It is essential that organizations implementing these tools do so with transparency and fairness, providing candidates with the necessary information about how their data will be used and ensuring that the tools are free from discriminatory biases.

Finally, the integration of voice analysis into the broader recruitment process requires careful planning and coordination. Voice analysis should be used as a complementary tool, providing additional insights that enhance, rather

1.3 Research Gap

Reference	Research Paper 1	Research Paper 2	Research Paper 3	Proposed Function
Analysis of Tone	✓	X	✓	✓
Analysis of Pitch	✓	X	X	✓
Analysis of Frequency	X	✓	X	✓
Correlation with Personality Traits	X	X	✓	✓
Confidence Level Indicators	X	X	X	✓

Table 1-1: Research Gap

Despite the considerable advancements in automated interview systems and AI-driven recruitment technologies, a significant research gap persists in accurately identifying and assessing candidate confidence levels using voice frequency. While numerous studies have explored the general application of voice analysis in various domains, including emotion detection, stress identification, and behavioral insights, the specific focus on confidence detection in professional interview contexts remains underdeveloped.

1.3.1 Existing Technologies and Their Limitations

The current body of research predominantly centers on emotion recognition from voice data, leveraging parameters such as tone, pitch, and rhythm to infer a speaker's emotional state. Notable studies have successfully employed machine learning algorithms to identify emotions like happiness, sadness, anger, and fear based on vocal cues [9]. However, confidence—a nuanced and context-specific attribute—differs fundamentally from these primary emotions. Confidence in a speech context is not merely an emotion but a complex interplay of certainty, assertiveness, and self-assurance, which are conveyed through subtle vocal modulations.

One of the critical limitations of existing emotion detection models is their tendency to generalize confidence as a byproduct of positive emotions like happiness or enthusiasm. These models often fail to distinguish between genuine confidence and other positive affective states, leading to inaccurate assessments in high-stakes scenarios like job interviews. For instance, a candidate might exhibit signs of nervousness, such as a slight tremor in their voice, but still be confident in their knowledge and responses. Current systems might misinterpret such nuances, categorizing the speech as uncertain or hesitant, thereby impacting the candidate's evaluation unfairly.

Moreover, the datasets used in most voice analysis research are often limited in scope, focusing on controlled environments where participants are prompted to express specific emotions. Such datasets do not adequately capture the spontaneous and context-dependent nature of confidence in real-world interviews, where candidates might experience a range of emotions simultaneously. This limitation points to a gap in both the methodology and the data used to train models for confidence detection.

1.3.2 The Complexity of Confidence as a Vocal Attribute

The complexity of confidence as a vocal attribute is another area where existing research falls short. Confidence is expressed through a combination of vocal characteristics, including pitch stability, speech rate, and vocal intensity. While these features are well-documented, the interaction between them in conveying confidence has not been thoroughly explored. For example, stable pitch may indicate confidence in some individuals but could be a sign of rehearsed or monotonous speech in others, lacking genuine assertiveness. Similarly, a fast speech rate might be associated with enthusiasm and confidence in certain cultures but could signal nervousness or lack of preparedness in others.

This complexity underscores the need for more sophisticated models that can account for cultural and individual differences in confidence expression. The current research gap, therefore, lies in developing algorithms that can accurately differentiate between these subtle variations and provide a more nuanced analysis of confidence levels in diverse populations.

1.3.3 The Need for Real-World Data

Another significant gap in the existing literature is the reliance on synthetic or laboratory-generated data rather than real-world interview scenarios. Most studies on voice frequency analysis are conducted in controlled settings where variables are carefully managed, and participants are aware they are being recorded for research purposes. This environment often fails to replicate the pressure and spontaneity of a real interview, where candidates might respond differently to questions or exhibit unanticipated vocal traits due to stress or uncertainty. To bridge this gap, there is a pressing need for research that incorporates real-world interview data, capturing the authentic vocal behaviors of candidates in actual interview settings. Such data would provide a richer, more representative foundation for training models that can accurately detect confidence levels. Furthermore, integrating this real-world data with advanced machine learning techniques, such as deep learning and neural networks, could enhance the precision and reliability of confidence detection systems.

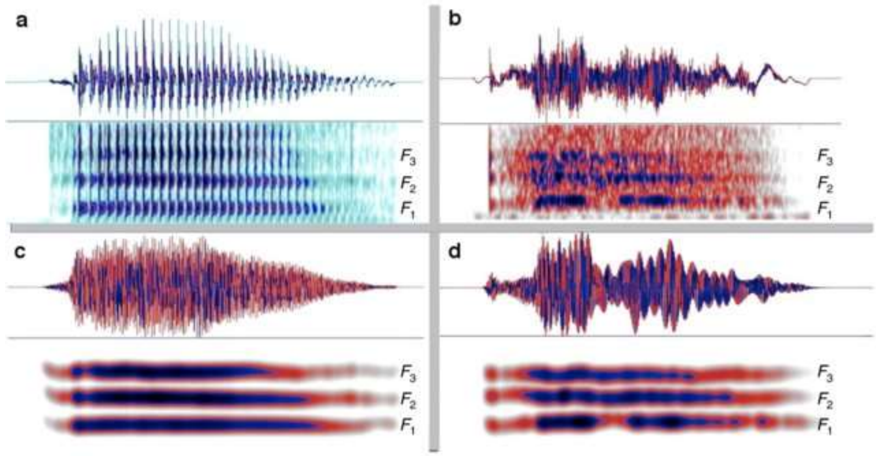

Figure 1.5: Four types of speech stimuli. Amplitude waveforms (top of each panel) and broadband spectrograms

1.3.4 The Overlooked Intersection of Confidence and Professional Competency

Another dimension of the research gap concerns the intersection of confidence and professional competency. While confidence is an essential trait for job performance, it must be considered alongside the candidate's technical skills, problem-solving abilities, and cultural fit within an organization. Current AI-driven interview tools often evaluate these aspects separately, without considering how they interact in the candidate's overall presentation.

For example, a candidate who exudes confidence but lacks technical knowledge may still be rated highly by systems that prioritize vocal traits over content. Conversely, a highly knowledgeable candidate who is less vocally assertive may be unfairly penalized. This highlights the need for a holistic approach that integrates confidence detection with other evaluative criteria, ensuring a more balanced and accurate assessment of a candidate's suitability for a role.

1.3.5 Future Directions for Research

Addressing the research gap in confidence detection through voice frequency requires a multi-faceted approach. Future research should focus on developing comprehensive datasets that reflect the diversity and complexity of real-world interview scenarios. Additionally, there is a need for more sophisticated algorithms that can accurately interpret the interplay of vocal features in conveying confidence, considering cultural and individual differences.

Furthermore, integrating confidence detection with other aspects of candidate evaluation, such as technical competency and cultural fit, could lead to more holistic and effective AI-driven interview systems. By addressing these gaps, future research can contribute to more equitable and accurate hiring processes, ultimately benefiting both employers and candidates.

1.4 Research Problem

Automated interview systems and AI-driven recruitment tools have seen significant advancements, yet accurately assessing candidate confidence remains a significant challenge. Confidence, a critical trait influencing interview outcomes, is complex to measure using voice data alone. Despite various studies focusing on emotion recognition through voice analysis, there is a noticeable gap in specifically addressing confidence in professional interview contexts.

1.4.1 Current Limitations

Existing voice analysis technologies primarily focus on general emotions such as happiness, sadness, and stress, often leveraging parameters like tone, pitch, and rhythm. These systems tend to generalize confidence as a positive emotional state, failing to distinguish it from other affective states. This results in inaccurate assessments, particularly in high-stakes interviews where genuine confidence can be misinterpreted due to factors like nervousness or stress.

- **Distinguishing Confidence from Positive Emotions:** Current models often misinterpret confidence as a byproduct of positive emotions, neglecting the nuanced nature of confidence, which involves assertiveness and self-assurance.

- **Limited Real-World Data:** Most studies use controlled environments or synthetic datasets, which do not adequately reflect the spontaneous and varied nature of real-world interviews. This limits the applicability of current models to actual interview settings.

- **Complexity of Vocal Attributes:** There is a lack of comprehensive understanding of how different vocal attributes (e.g., pitch stability, speech rate) interact to convey confidence. This complexity requires more sophisticated models that account for individual and cultural differences.

This research aims to address the limitations in current confidence detection systems by developing an advanced model that accurately measures confidence using voice frequency in real-world interview scenarios. The study will focus on:

- **Developing Models**: Creating models that differentiate confidence from other emotions and affective states
- **Utilizing Real-World Data**: Incorporating data from actual interviews to enhance the model's accuracy and reliability.
- **Understanding Vocal Attributes**: Investigating the interplay between various vocal features to better capture the nuanced expression of confidence.

Addressing these gaps will improve the fairness and accuracy of automated interview systems, leading to more effective and equitable hiring processes. By focusing on confidence detection, the research will enhance the ability of AI systems to assess candidates comprehensively, benefiting both employers and candidates.

2 OBJECTIVES

2.1 Main Objective

The primary objective of our function is to enhance the accuracy and efficiency of the interview process through the use of advanced technology. By leveraging AI and machine learning algorithms, we aim to provide a comprehensive assessment of a candidate's qualifications, skills, and potential fit for the role. This function is designed to streamline the recruitment process, reduce bias, and ensure that only the most qualified candidates are shortlisted for further evaluation.

The sub-objectives of the automated interview process tool are designed to be **SMART**: they are **Specific** in targeting key aspects of communication and personality assessment, **Measurable** through detailed analysis of voice attributes and feedback reports, **Achievable** with the integration of advanced technologies and algorithms, **Realistic** in their alignment with the tool's capabilities and goals, and **Time-bound** with clear milestones for implementation and evaluation.

2.2 Sub-Objectives

Objective 1: Assessment of Communication Skills

- The objective of assessing communication skills is to thoroughly evaluate how candidates articulate their thoughts during an interview. This includes analyzing their speech clarity, coherence, and overall communication effectiveness. By implementing sophisticated real-time analysis tools, we can capture and scrutinize audio recordings from interviews. These tools will measure various parameters such as speech clarity, pacing, volume, and the frequency of filler words. The goal is to create a comprehensive picture of how well a candidate can communicate under pressure. Additionally, the analysis will extend to generating detailed communication reports, which will highlight the strengths and weaknesses in a candidate's communication style. These reports will serve as a valuable resource for interviewers, helping them to identify areas where the candidate may need improvement or where they excel

Objective 2: Assessment of Personality through Voice Analysis

- This sub-objective aims to delve into the nuances of a candidate's personality by closely examining their voice during the interview process. The analysis focuses on identifying key personality traits such as confidence, assertiveness, and emotional stability by studying variations in tone, pitch, and speech patterns. The first step involves defining the specific personality traits that are most relevant to the job role and assessing how these can be measured through voice analysis. Once these traits are clearly identified, advanced algorithms will be developed to interpret the voice data accurately. These algorithms will correlate specific voice characteristics with the defined personality traits, enabling a deeper understanding of the candidate's overall demeanor. The results of this analysis will be compiled into comprehensive personality reports. These reports will provide insights into the candidate's confidence levels, stress responses, and overall emotional state, offering a valuable perspective that complements traditional interview assessments.

Objective 3: Integration with Interview Feedback

- The integration of voice analysis with traditional interview feedback forms the cornerstone of a comprehensive candidate evaluation process. This sub-objective focuses on combining the insights gained from voice analysis with other forms of feedback, such as interviewers' observations and video analysis. One critical task under this objective is the evaluation of the video feed from the interview. By performing sentiment analysis on the video, we can further identify non-verbal cues that signal a candidate's confidence or discomfort. The integration process involves developing algorithms that merge the results of the voice analysis with the sentiment analysis from the video feed. These combined results will then be incorporated into the overall interview feedback, creating a holistic view of the candidate's performance. This integrated approach ensures that the evaluation is not limited to a single aspect of the interview but considers multiple dimensions of the candidate's abilities and personality. Moreover, continuous refinement of these algorithms based on real-world data and feedback will enhance their accuracy and reliability over time, ensuring that the integrated feedback remains robust and insightful.

3 METHODOLOGY

3.1 Software Solution

In developing the automated interview process tool, we will adopt Agile methodology to ensure iterative progress and continuous improvement throughout the project lifecycle. Agile practices emphasize flexibility, collaboration, and customer feedback, which are crucial for creating a tool that meets the evolving needs of our users. We will implement Agile through Scrum, a popular Agile framework, which involves dividing the project into manageable sprints. Each sprint, typically lasting 2 to 4 weeks, will focus on delivering specific features and improvements. Regular sprint reviews and retrospectives will enable the team to gather feedback, assess progress, and adjust the project plan as needed, ensuring that the final product aligns with stakeholder expectations and project goals.

Additionally, Agile methodology will facilitate effective communication and collaboration within the development team and with stakeholders. By holding daily stand-up meetings and sprint planning sessions, the team can address any issues promptly, share updates, and coordinate efforts efficiently. This approach will not only enhance the transparency and adaptability of the development process but also allow for the integration of new insights and technologies. The iterative nature of Agile ensures that the project remains responsive to changes, resulting in a robust and user-centric solution that evolves based on real-time feedback and emerging requirements.

3.2 System Overview and Integration

The confidence level assessment function is a critical component of the broader automated interview process tool. This function operates within a multi-layered architecture that includes data collection, signal processing, feature extraction, and machine learning-based analysis. The voice data is captured during the interview process, where it is subjected to analysis to identify key attributes such as pitch, frequency and intensity.

The system is designed to be seamlessly integrated into the interview process, capturing audio data as candidates respond to questions. The voice analysis module is directly linked to the front-end interface, enabling fast processing and give feedback. The results are stored in a centralized database, where they can be accessed for further evaluation and comparison with other assessment metrics.

- Frontend (React): React is used to build the user interface of the interview tool. It provides a dynamic and responsive interface for candidates and interviewers, displaying feedback and analysis. React components manage the audio recording interface, display confidence scores, and present visualizations of voice attributes.

- Backend (Python): Python handles the back-end processing of audio data. It uses libraries such as librosa for audio analysis, and Django for creating the API endpoints. Python is well-suited for handling complex data processing tasks and integrating with machine learning models.

- Machine Learning Frameworks: Libraries such as TensorFlow and PyTorch are used to develop and train machine learning models for confidence assessment. These frameworks support the development of sophisticated algorithms for feature extraction and prediction.

A system diagram illustrates how this function fits into the overall architecture. It shows the flow of data from input (captured voice) through processing (feature extraction and analysis) to output (confidence level reports). The diagram also highlights the integration points with other system components, such as emotional analysis and interview feedback.

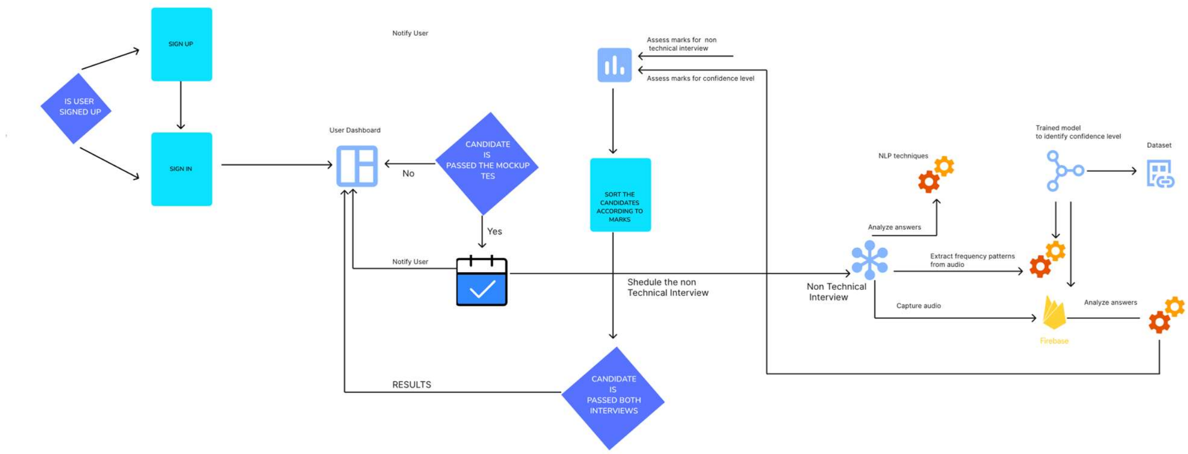

Figure 3.1: System Diagram

3.3 Detailed Process of Confidence Level Assessment

3.3.1 Data Collection and Preprocessing

The first step in the methodology is the collection of voice data from the candidate. During the interview, the system captures audio through a high-quality microphone, ensuring that the data is clear and free from background noise. This is crucial as the accuracy of the confidence assessment heavily depends on the quality of the input data. [10]

Once the audio is captured, it undergoes preprocessing to remove any unwanted noise and to standardize the signal. This involves applying filters to eliminate background sounds, normalizing the audio levels, and segmenting the audio into smaller chunks for detailed analysis. The preprocessing step ensures that the subsequent analysis is based on clean and consistent data.

After preprocessing, the system performs initial segmentation of the voice data, dividing it into meaningful units such as words or phrases. [11] This segmentation is important for analyzing pitch and frequency variations at a granular level, allowing the system to focus on specific parts of the speech that may reveal confidence or anxiety.

- ❖ Noise Reduction: Python’s librosa library applies noise reduction techniques to clean the audio data. [12]
- ❖ Normalization: The pydub library is used to normalize audio levels, ensuring consistent volume across different recordings.
- ❖ Segmentation: Audio data is segmented into smaller units using Python scripts to facilitate detailed analysis.

3.3.2 Feature Extraction

Feature extraction is the next critical step in assessing confidence levels. In this stage, the system analyzes the preprocessed audio data to extract key vocal features that are indicative of confidence. These features include pitch, frequency, amplitude, and tonal variation. [12]

- **Pitch Analysis:** [13]The system examines the pitch of the voice, looking for variations that might indicate a lack of confidence. For instance, a consistently high pitch may suggest nervousness, while a steady, moderate pitch is often associated with confidence [15]. Librosa is used to extract pitch information from the audio signal.

- **Frequency Analysis:** The system also analyzes the frequency spectrum of the voice [14]. High-frequency components may correlate with stress or anxiety, while a balanced frequency range typically indicates a more confident tone. The Fourier Transform, implemented using numpy, is applied to analyze the frequency spectrum of the voice.

- **Amplitude and Intensity:** The system measures the amplitude and intensity of the voice. A confident speaker usually has a steady and controlled amplitude, whereas fluctuations might indicate uncertainty. Amplitude measurements are taken to assess the intensity of the voice, using librosa to quantify variations.

These features are extracted using advanced signal processing techniques, including Fourier transforms for frequency analysis and pitch detection algorithms for identifying pitch variations. The extracted features form the basis for the machine learning models that will classify the confidence levels.

3.3.3 Machine Learning Model Training and Deployment

With the extracted features, the system moves to the analysis stage, where machine learning models are employed to assess confidence levels. The system uses a supervised learning approach, where models are trained on labeled datasets containing audio samples with known confidence levels. [13]

- **Training Phase:** The training phase involves feeding the supervised learning model a large dataset of labeled voice recordings using TensorFlow [12] or PyTorch. The model learns to identify patterns in the voice features that correspond to different confidence levels. This training process is iterative, with the model being refined over multiple cycles to improve its accuracy.

- **Validation and Testing:** After training, the model is validated using a separate dataset to ensure that it can accurately predict confidence levels in new, unseen data. The validation phase helps fine-tune the model, adjusting parameters to minimize errors and enhance predictive accuracy.

- **Deployment:** Once validated, the model is deployed within the system's architecture. During an actual interview, the model receives the extracted features in real-time and predicts the candidate's confidence level. The system is designed to handle these predictions swiftly, providing immediate feedback to interviewers or candidates.

The machine learning model is continuously updated as more data is collected, ensuring that it adapts to different accents, languages, and interview contexts. This adaptability is crucial for maintaining the system's relevance across diverse candidate pools.

3.3.4 Post-Interview Analysis and Report Generation

After the interview, the system compiles the results of the real-time analysis into a comprehensive report. This report provides detailed insights into the candidate's confidence levels, highlighting specific moments where confidence was high or low.

- **In-Depth Post-Processing:** After the interview, the audio recordings are processed using advanced signal processing techniques. The system applies the machine learning model to the entire duration of the interview, ensuring that each segment of the candidate's responses is carefully analyzed. This post-processing approach enables the system to detect subtle variations in pitch, frequency, and tone that might not be as evident in real-time analysis.

- **Detailed Reporting:** The report includes a graphical representation of the candidate's confidence throughout the interview, with annotations explaining the significance of certain voice attributes. For example, the report might note that a sudden drop in pitch was correlated with a difficult question, or that a consistent tone throughout the interview indicates steady confidence.

- **Comparative Analysis:** The system also supports comparative analysis, where the candidate's performance can be compared to a baseline or to other candidates. This feature is useful for interviewers who want to benchmark candidates' confidence levels against industry standards or job-specific requirements.

- **Feedback for Continuous Improvement**: For organizations that conduct multiple rounds of interviews or follow-up interviews, the system can track changes in a candidate's confidence over time. This longitudinal analysis provides valuable feedback for both the candidate and the organization, highlighting areas of improvement or persistent challenges.

3.3.5 Algorithm Refinement and Continuous Learning

The final step in the methodology involves the continuous refinement of the system's algorithms. As more data is collected from interviews, the system uses this data to retrain and improve its machine learning models. [18]

- **Data-Driven Refinement:** The system incorporates feedback from interview outcomes, comparing predicted confidence levels with actual performance metrics. This data-driven approach ensures that the system's predictions remain aligned with real-world outcomes, improving its reliability over time.

- **Feedback Loop:** The system includes a feedback loop where interviewers can manually adjust the confidence assessments based on their observations. These adjustments are fed back into the system, helping to calibrate the model for future interviews.

- **Adaptability to New Contexts:** As the system encounters new interview contexts or industries, it continuously updates its models to account for these variations. This adaptability ensures that the system remains effective across a wide range of scenarios, from technical interviews to executive assessments.

3.3.6 System Integration and Workflow

The confidence assessment function is integrated into the broader interview process workflow, ensuring that it works seamlessly with other components such as emotional analysis and interview feedback

- **Integration with Other Functions: The** confidence assessment function is designed to complement other aspects of the interview tool, such as emotional recognition and technical skill evaluation. By combining these functions, the system provides a comprehensive view of the candidate, highlighting both their technical abilities and personal attributes.

- **Data Flow and Reporting:** The system is designed to handle data flow efficiently, from initial audio capture to final report generation. The workflow includes stages for data preprocessing, real-time analysis, and post-interview reporting, ensuring that all relevant data is captured and analyzed thoroughly.

- **Customizable Workflow**: Organizations can customize the workflow to suit their specific needs, whether they require immediate feedback during the interview or prefer a more detailed post-interview report. The system's modular design allows for flexibility in how the confidence assessment function is deployed and used.

3.3.7 Summarizing the technologies

Category	**Details**
Technologies	Python, React, TensorFlow, Django, OpenCV, NLTK
Techniques	Feature Extraction, Signal Processing, Voice Analysis, Data Augmentation
Algorithms	Pitch Detection Algorithms, Mel-Frequency Cepstral Coefficients (MFCCs), Neural Networks for Voice Analysis
Architectures	Convolutional Neural Networks (CNNs)

Table 3-1: Summary of technologies

3.4 Testing Phase

The testing phase for the automated interview process tool, specifically focusing on the confidence level assessment through voice attributes, involves several critical steps to ensure the accuracy, reliability, and robustness of the system. This phase encompasses various types of testing, including unit testing, integration testing, and system testing, each addressing different aspects of the tool.

- ❖ Unit Testing: Unit testing will be conducted to validate individual components of the system. For the voice analysis models, unit tests will be implemented to ensure that each function responsible for processing and analyzing voice data performs as expected. This includes testing the algorithms for extracting voice features such as frequency and pitch variations, and verifying that they accurately produce the required output. Python's unittest framework will be used to automate these tests, allowing for frequent and consistent testing of code changes. [19]

- ❖ Integration Testing: Integration testing focuses on ensuring that different modules and components of the system work together seamlessly. For the automated interview tool, this involves testing the interaction between the frontend React application and the backend Flask server. Integration tests will validate that voice recordings are correctly sent from the user interface to the backend, where they are processed by the machine learning models. Additionally, tests will be conducted to ensure that the results are accurately returned to the frontend and displayed to the user. Tools like Postman for API testing and pytest for backend testing will be employed.

- ❖ System Testing: System testing will encompass end-to-end testing of the entire application to ensure that all features and functionalities work as intended in a real-world environment. This includes validating the complete workflow from recording and processing voice data to displaying the confidence level results. System tests will simulate real user interactions and evaluate the tool's performance under various conditions, such as different audio qualities and user scenarios. Testing will be conducted on different devices and browsers to ensure compatibility and responsiveness.

- ❖ Performance Testing: Performance testing will assess the tool's efficiency and scalability, particularly focusing on the machine learning models' processing times and the system's ability to handle multiple simultaneous users. This will involve load testing to simulate high traffic conditions and stress testing to identify any performance bottlenecks. Tools like JMeter for load testing and profiling tools for measuring model inference times will be used.

- ❖ User Acceptance Testing (UAT): User Acceptance Testing will be performed to ensure that the system meets the requirements and expectations of its end users. This testing phase will involve real users interacting with the application to validate that it provides accurate and useful feedback based on voice analysis. UAT will also collect feedback on usability, user experience, and any potential issues that need addressing before the final deployment.

- ❖ Regression Testing: As new features are added or existing features are modified, regression testing will be conducted to ensure that previously implemented functionalities remain unaffected. This involves running a suite of tests to verify that changes do not introduce new bugs or issues in the system.

3.5 Anticipated Conclusion: Results, Application, and Real-World Use

The implementation of the automated interview process tool, with its core function of assessing confidence levels through voice attributes such as frequency and pitch variations, is expected to yield several significant outcomes. By leveraging advanced voice analysis techniques and integrating them into a comprehensive interview platform, the tool will offer valuable insights into a candidate's confidence and communication skills.

3.5.1 Results:

- **Enhanced Assessment Accuracy:** The tool will enable more precise evaluation of a candidate's confidence levels by analyzing variations in voice frequency and pitch. The use of machine learning algorithms and deep learning models will enhance the accuracy of these assessments, leading to more reliable candidate evaluations.

- **Detailed Feedback Reports:** The system will generate comprehensive reports that highlight key attributes of the candidates' confidence, providing interviewers with actionable insights. These reports will include metrics on vocal attributes and confidence levels, supporting data-driven decision-making.
- **Improved Interview Process:** The automated analysis will streamline the interview process by providing objective measures of confidence, reducing bias, and ensuring that all candidates are evaluated consistently.

3.5.2 Applications:

- **Recruitment and Human Resources:** HR departments can use the tool to enhance their recruitment processes, making it easier to identify candidates who exhibit strong confidence and communication skills. This will lead to better hiring decisions and more effective talent acquisition strategies. [20]

- **Professional Development:** The insights gained from the tool can be used for employee development, helping individuals understand their communication strengths and areas for improvement. This feedback can be valuable for coaching and training programs aimed at enhancing professional skills.

- **Remote and Virtual Interviews:** With the increasing prevalence of remote and virtual interviews, the tool provides a standardized method for assessing candidates' vocal attributes, ensuring consistency in evaluations across different interview settings. [20]

4 Project Requirements

4.1 Functional Requirements

The system must be capable of analyzing audio recordings from interviews in real-time or near real-time to assess candidates' confidence levels.

I. System need to be capable to Integrate with audio capture tools to record and submit those files. And the system should support various audio formats and provide a user-friendly interface for recording and uploading.
II. System need to process and analyzing audio data to detect variations in frequency and pitch.
III. System should capable of generating feedback for the interviewers.
IV. System should consist of algorithms to analyze voice attributes and detect patterns indicative of confidence.
V. System should consist of reporting mechanisms to present confidence levels in an understandable format.
VI. System should able to linking voice analysis results with other interview feedback data.
VII. System should be able to providing a consolidated report that combines audio analysis with other evaluation criteria.

4.2 Non-functional requirements

I. Performance: The system must perform efficiently under expected workloads.

Requirements:

- Fast processing times for audio analysis.
- Minimal latency in feedback and reporting.

II. Scalability: The system should be able to handle an increasing number of users and data volumes without performance degradation.

Requirements:

- Scalable architecture to support growth.
- Efficient data management and processing.

III. Security: The system must ensure the confidentiality and integrity of sensitive data.

Requirements:

- Data encryption for audio recordings and analysis results.
- Secure user authentication and authorization mechanisms.

IV. Usability: The system should be easy to use and navigate for all user types.

Requirements:

- Intuitive user interface design.
- Comprehensive user guides and help documentation.

V. Reliability: The system must be reliable and available for use at all times.

Requirements:

- High availability and minimal downtime.
- Robust error handling and recovery mechanisms.

4.3 Technical Requirements

Technology Stack

- ❖ **Frontend**: React.js for user interface development.
- ❖ **Backend**: Python with Django for server-side processing.
- ❖ **Database**: Firebase
- ❖ **Audio Analysis**: Library Librosa for audio processing.
- ❖ **Voice Analysis Algorithms**: TensorFlow for implementing machine learning models.

4.4 User Requirements

I. Candidates: Candidates are individuals applying for positions and undergoing the interview process using the tool.

Key Needs:

- **User-Friendly Interface:** Candidates require a straightforward interface for recording responses, submitting answers and navigating through the system.

- **Voice and Video Recording**: They need the ability to record their responses.
- **Feedback Access:** Candidates should be able to access their feedback reports, which detail their confidence levels and other analysis results.
- **Guidance and Support:** Clear instructions and support are necessary for candidates to understand how to use the tool effectively and interpret the feedback they receive.

II. Interviewers: Interviewers are individuals responsible for evaluating candidates and making decisions based on the analysis provided by the tool.

Key Needs:

- **Candidate Management:** Interviewers need access to a dashboard where they can view and manage candidate profiles, recorded responses, and feedback reports.
- **Reporting**: Interviewers need the capability to generate and review comprehensive reports on candidates to aid in the decision-making process.

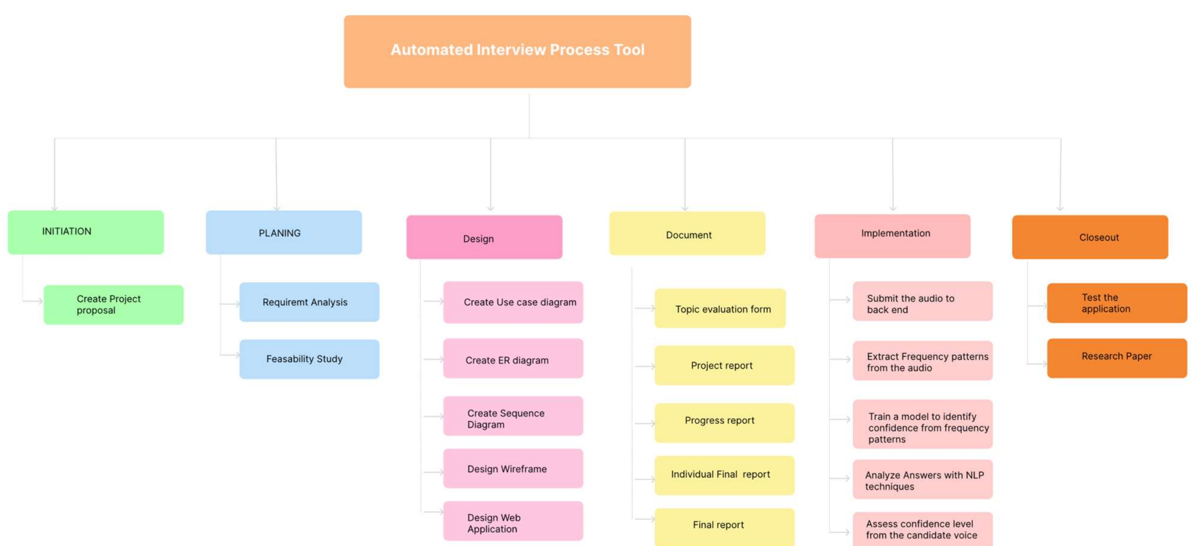

Figure 4.1 : Work Breakdown Chart

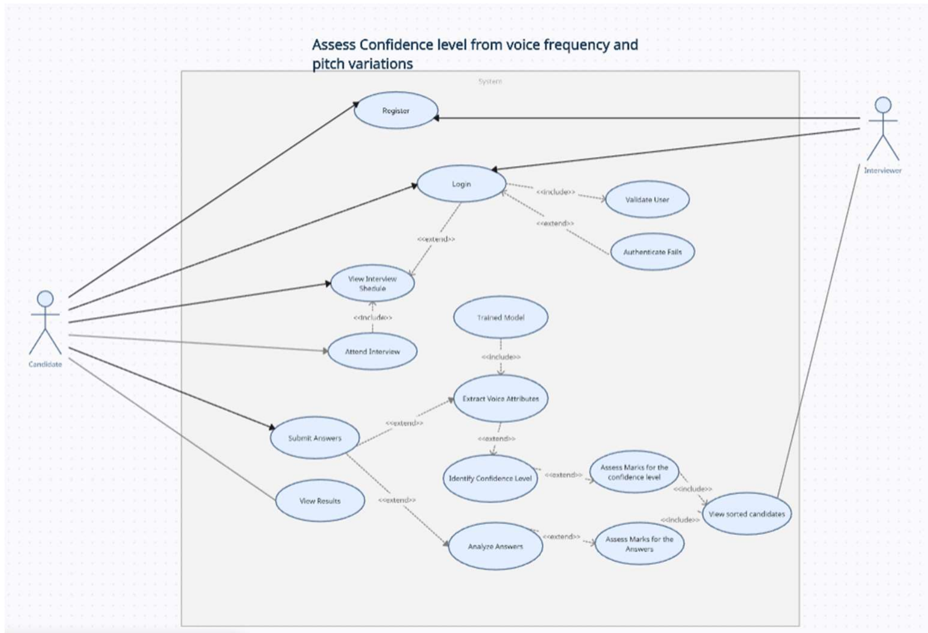

Figure 4.2: use case diagram

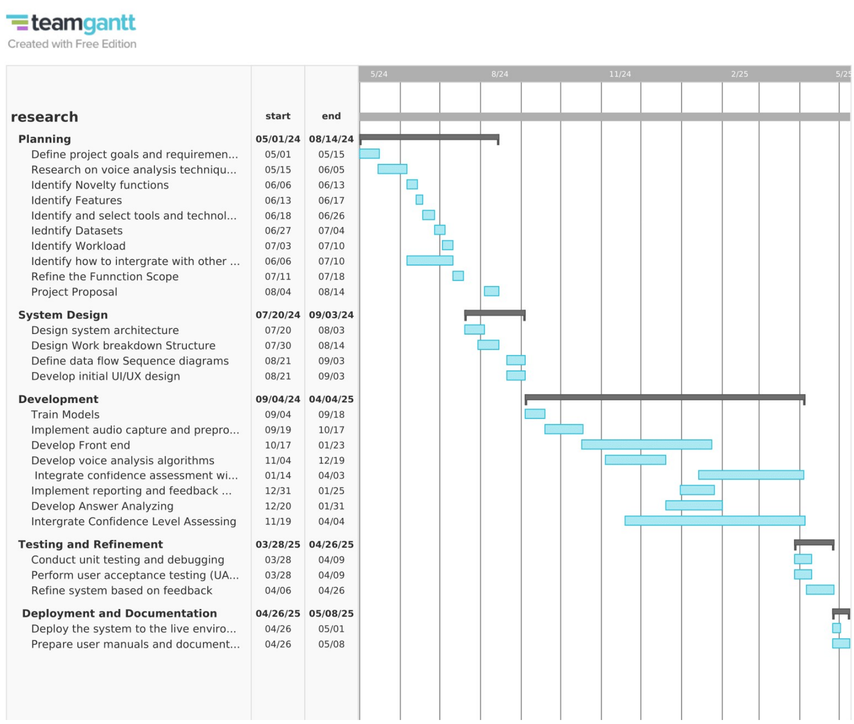

Figure 4.3: Gannt chart

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AUTONOMOUS INTERVIEW PROCESS SYSTEM

24-25J-047

Project Proposal Report

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August 2024

DECLARATION

I declare that this is my own work and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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23/08/2024
Date

ABSTRACT

In today's competitive IT sector, the recruitment process demands both efficiency and precision to identify the best candidates for technical roles. This proposal presents the development of an innovative automated interview process tool designed to streamline and enhance the candidate evaluation process in the IT sector. The tool integrates advanced technologies such as code analysis, complexity measurement, and maintainability evaluation to assess candidates' technical skills in software development. The system focuses on four core functions: 1) Evaluating personality and confidence through analysis of tone, pitch, and frequency during interviews, 2) Using emotional analysis and gamified assessments to gauge technical skills and problem-solving abilities, 3) Assessing code complexity and maintainability and 4) Shortlisting candidates based on video-based mock exams to evaluate attire and clarity.

One of the key functions of this tool is the evaluation of code complexity and maintainability using three primary metrics: Cyclomatic Complexity (CC), Weighted Complexity (WC), and Cognitive Complexity. These metrics are critical in determining the quality and robustness of the candidate's code, providing insight into their ability to write maintainable and efficient software. By automating the assessment of these metrics, the system ensures an objective and precise evaluation, reducing the potential for human error and bias. This function is designed to be integrated seamlessly with existing HR systems, offering flexibility, scalability, and cost-effectiveness. The automated code evaluation tool is poised to enhance the recruitment process by providing a comprehensive analysis of a candidate's technical proficiency, ultimately contributing to better hiring decisions and fostering innovation within tech organizations.

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1. INTRODUCTION

1.1 Background

The speed at which software is developed has completely changed how businesses create, manage, and expand their applications. Strong techniques to evaluate and guarantee code quality are becoming more and more necessary as software systems get more sophisticated. Conventional code reviews are crucial, but they frequently rely too much on the subjective judgment of reviewers, which can result in errors and inconsistencies. These difficulties have led to the creation of automated techniques that provide measurable, objective metrics of code quality, making assessments more consistent and trustworthy.

Using automated techniques to measure code complexity and maintainability is one of these ideas that has garnered a lot of popularity. These tools examine different parts of the code using a variety of metrics and algorithms, giving valuable insights that are essential for upholding strict software quality standards. It's critical to comprehend code complexity and maintainability to ensure software robustness, long-term sustainability, and ease of future expansions.

Code complexity refers to the intricacy of the code structure, which can impact the ease of understanding, testing, and modifying the software. High complexity often correlates with increased difficulty in maintaining the code, leading to higher costs and potential errors during updates. To address these challenges, metrics such as Cyclomatic Complexity (CC), Weighted Complexity (WC), and Cognitive Complexity have been developed to provide a more objective assessment of the code.

Developers and organizations can better understand the structural and cognitive demands of their codebases with the help of these measurements. It is feasible to find parts of the code that might need to be refactored or simplified by applying these metrics consistently, which improves the software's overall maintainability and quality. Large-scale projects benefit greatly from this strategy since reliable code quality is essential to the project's success

1.2 Literature Survey

Over time, the literature on maintainability and code complexity has changed dramatically, reflecting the growing significance of high-quality software in an increasingly digital society. The need for automated tools that can consistently evaluate and enhance code quality has been fueled by the emergence of large-scale, complex software systems. The important research and techniques that have influenced the state of knowledge and practice regarding code complexity measurement and maintainability are reviewed in this section.

1.2.1 Code Complexity and Its Impact on Software Maintainability

One of the earliest and most popular metrics for evaluating code complexity is cyclomatic complexity (CC). CC, first introduced by McCabe in 1976, is a quantitative method for evaluating the complexity of a particular codebase. It counts the number of linearly independent paths through a program's source code. The usefulness of CC in anticipating parts of the code that are likely to be error-prone or challenging to maintain has been confirmed by numerous researches. For instance, a study by [1] demonstrated that modules with high cyclomatic complexity were more prone to defects, underscoring the need for regular complexity analysis during the software development lifecycle.

The concepts of CC are expanded upon by Weighted Complexity (WC), which considers other variables including the depth of nested loops and the weight of various control structures. Because it takes into consideration the differing levels of difficulty linked to various coding structures, this statistic provides a more comprehensive understanding of complexity. Research by Kemerer (1995) [2] highlighted the limitations of using CC alone and proposed WC as a complementary measure that can better predict maintainability challenges in large and complex systems.

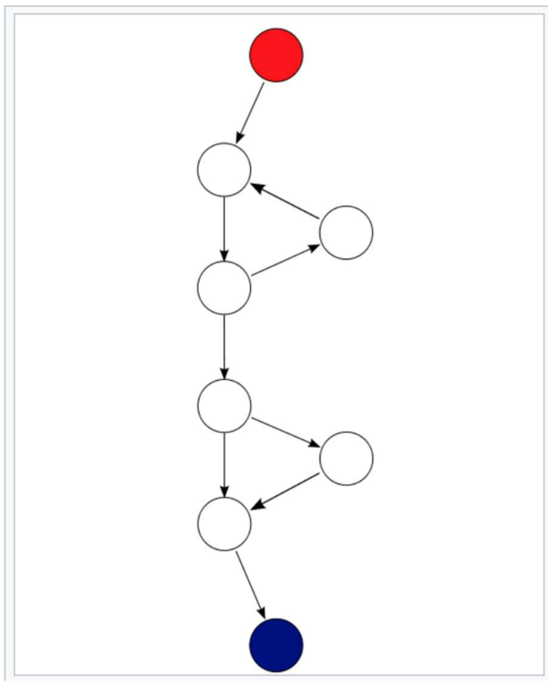

Figure 1.1 :A control-flow graph of a simple program.

A control-flow graph of a simple program. The program begins executing at the red node, then enters a loop (group of three nodes immediately below the red node). On exiting the loop, there is a conditional statement (group below the blue node), and finally the program exits at the blue node. This graph has 9 edges, 8 nodes, and 1 connected component, so the cyclomatic complexity of the program is 9 - 8 + 2^1 = 3.

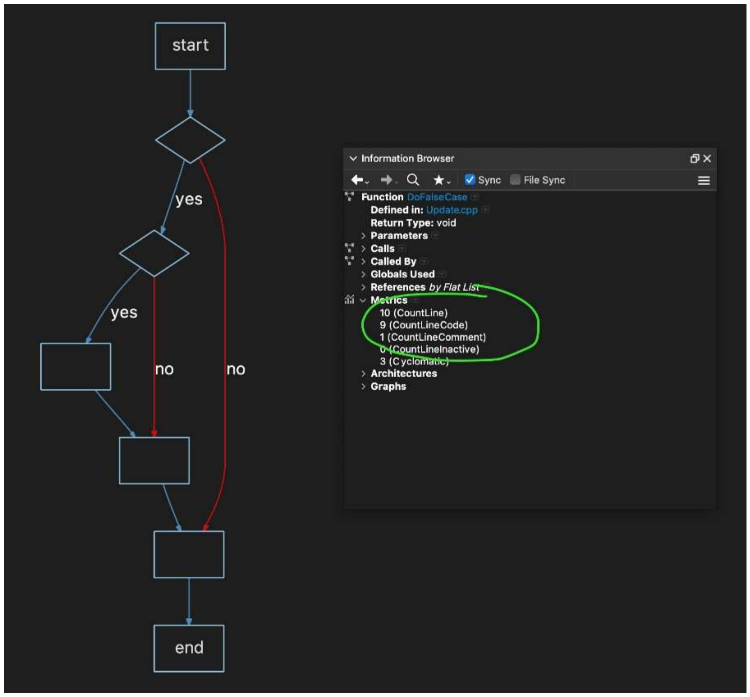

Figure 1.2: Function DoFalseCase – interesting name when there are 2 yes and 2 no cases

Complexity = 3

A relatively recent concept, Cognitive Complexity, concentrates on the human side of code comprehension. SonarSource established this metric in 2017 with the goal of quantifying the mental effort needed to comprehend a piece of code. In contrast to CC and WC, which are mostly concerned with the structural elements of code, Cognitive Complexity highlights the cognitive burden that developers must bear. Researches such as those by Curtis et al [3] have shown that Cognitive Complexity is a strong predictor of code maintainability, particularly in modern, agile development environments where quick comprehension of code is crucial.

1.2.2 Automated Tools and Techniques for Complexity Analysis

In order to guarantee consistent and impartial evaluations, the use of automated technologies for code complexity analysis has been a major advancement. Continuous integration/continuous deployment (CI/CD) pipelines now require tools like SonarQube, which includes metrics like Cognitive Complexity and CC. SonarQube's ability to provide real-time feedback on code quality has been validated by studies such as the work by Cao [4], which found that integrating such tools into the development process can significantly reduce the incidence of code defects and improve overall software quality.

Other tools like CodeMR and CodeScene have also been widely used in the industry, offering comprehensive dashboards that visualize complexity metrics alongside other quality indicators. Research by Kamei et al. [5]has demonstrated that these tools not only help in identifying complex code areas but also in planning refactoring efforts, making them invaluable for maintaining long-term code health in large projects.

1.2.3 Application of Complexity Metrics in Agile Environments

Complexity measurements play an even more crucial role in agile software development, where frequent iteration and continual improvement are essential. Agile approaches place a strong emphasis on quick feedback cycles, which necessitate quick comprehension and modification of code by engineers. In this context, metrics such as Cognitive Complexity have been very helpful because they support the agile principle of keeping code simple. Research has demonstrated that teams who use Cognitive Complexity measures into their code reviews are more adept at managing technical debt and sustaining good code quality over time [6]

Furthermore, recent research has investigated the incorporation of complexity measurements into agile project management tools. For instance, a Study [7] investigated how teams may incorporate complexity metrics into agile sprints to get real-time feedback on how maintainable their code is. Teams are able to prioritize refactoring activities according to complexity measurements, which has been demonstrated to enhance decision-making during the sprint planning process.

1.2.4 Comparative Analysis of Code Complexity Metrics

Numerous code complexity metrics have been established over time, each with advantages and disadvantages. The most often used measures to assess software quality are Cyclomatic Complexity (CC), Weighted Complexity (WC), and Cognitive Complexity. These metrics can be used to various software project types and software development lifecycle stages, according to a comparative study of them.

Because of its simplicity and ease of computation, cyclomatic complexity, or CC, is frequently preferred. It gives the complexity of the control flow of a program a clear, numerical number that is especially helpful for pointing out possible testing obstacles. Nevertheless, neither the cognitive burden on developers nor the differing levels of complexity associated with various control structures are taken into consideration by CC. On the other hand, Weighted Complexity (WC) offers a more sophisticated measure of complexity by attempting to overcome these drawbacks by giving weights to various control structures. In spite of this, WC might be more difficult to use and understand, especially in large-scale initiatives.

In contrast, cognitive complexity moves the emphasis from structural complexity to the human-readable nature of the code. In agile and fast-paced development contexts, where code readability and maintainability are critical, this statistic is very useful. Research has demonstrated that, particularly in projects with a high developer turnover rate, Cognitive Complexity can predict code maintainability more accurately than standard measures like CC [8]. The comparison of these measures shows that, although CC and WC are useful in evaluating structural complexity, Cognitive Complexity offers a more comprehensive understanding by considering the role of humans in software development.

1.2.5 Leveraging Python Libraries for Code Maintainability

Python libraries provide strong capabilities for controlling and assessing code complexity, which is useful in the process of improving code maintainability. Without the need for intricate machine learning models, developers may assess and enhance code quality using well-known metrics like Cyclomatic Complexity (CC), Weighted Complexity (WC), and Cognitive Complexity thanks to Python's robust ecosystem of tools.

The mccabe [9], lizard [9], and radon [9] libraries are very helpful for assessing code complexity. A range of tools, including basic measurements like lines of code and insights into measures like cyclomatic complexity, are available for analyzing Python code using Radon. With the help of this library, developers may create thorough reports that identify parts of the codebase that might need to be refactored. The mccabe library, on the other hand, is a more specialized tool that helps developers comprehend the complexity of specific functions or methods by calculating the Cyclomatic Complexity of Python code. This understanding is essential for writing code that is simple to test and debug.

Python's wily module expands on standard complexity analysis for weighted complexity by adding variables like code churn and the effects of modifications over time. Wily keeps track of all code updates made throughout the project's lifetime, enabling developers to evaluate the impact of changes on complexity and maintainability. In long-term projects where the maintainability of the software can change dramatically over time, this historical view is invaluable.

Another important measure that may be examined with Python libraries is Cognitive Complexity (flake8-cognitive-complexity, an extension of the well-known flake8 tool) [10]. This plugin provides an alternative to strictly structural metrics like Cyclomatic Complexity by measuring the cognitive burden necessary to comprehend a piece of code. Developers can use this tool to find code that may be structurally simple, but its logical complexity makes it hard to understand.

By leveraging these Python libraries, the project can implement a comprehensive strategy for analyzing and improving code maintainability. These tools provide actionable insights that can guide refactoring efforts, ensuring that the code remains clean, readable, and easy to maintain throughout the development lifecycle. This approach not only simplifies the complexity analysis process but also ensures that the software remains robust and scalable, ultimately leading to more sustainable software development practices.

1.2.6 Challenges and Future Directions

There continue to be issues in maintainability evaluation and complexity estimation despite advancements in these areas. One of the main problems is the possibility of misapplying or misinterpreting metrics, which can cause an excessive focus on simplifying code at the expense of other crucial features like readability or performance. [11]recommend that future research concentrate on creating more comprehensive strategies that strike a balance between complexity and other elements of software quality.

Furthermore, new opportunities for improving complexity measures are presented by the rise of machine learning in software engineering. Research on the application of AI to forecast code maintainability based on historical data has started, as seen by studies. [12]This could result in estimates of complexity that are more precise and dynamic.

1.3 Research Gap

Reference	Research Paper 1	Research Paper 2	Research Paper 3	Proposed Function
Code complexity Assessment	✓	✓	✓	✓
Code Maintainability Assessment	✓	✓	X	✓
Using CC, WCC, CFS	X	X	X	✓
Automated Tool for interview use	X	X	X	✓
Validation Against Industry Standards	X	✓	X	✓

Table 1-1: Research Gap

Although automated systems for assessing technical skills have made tremendous progress, there is still a crucial gap in the reliable and consistent evaluation of code complexity and maintainability. While there are many tools available for evaluating code quality, most of them concentrate on surface-level measures like lines of code or simple complexity calculations. The nuances of contemporary software development are difficult to fully analyze using these techniques, especially when it comes to striking a balance between variables like readability, maintainability, and scalability.

Beyond basic metrics, an extensive evaluation of code complexity needs to take into consideration other elements like Cyclomatic Complexity (CC), Weighted Complexity (WC), and Cognitive Complexity. Although these sophisticated metrics provide more profound understanding of the cognitive and structural components of code, current tools often cannot include these measurements into a comprehensive evaluation. This disparity emphasizes the need for more advanced methods that, in addition to measuring complexity, offer useful advice for raising code quality and, ultimately, improving software development processes as a whole.

1.3.1 Existing Technologies and Their Limitations

Most code quality evaluation techniques available today concentrate on surface-level measures like code coverage, cyclomatic complexity, and lines of code. These techniques work well for finding fundamental structural problems, but they frequently don't give a complete picture of the complexity and maintainability of the code [4]. For example, well-known tools such as SonarQube and PMD provide information about possible defects and code smells, but they usually evaluate individual code snippets instead of a project's overall maintainability. Furthermore, these instruments frequently depend on elementary heuristics that fail to consider the intricate interplay among many complexity measures, including Cyclomatic Complexity, Weighted Complexity, and Cognitive Complexity.

The incapacity of current tools to offer practical insights that consider the larger context of the codebase is a major drawback. Cyclomatic complexity, for instance, counts the number of independent pathways that may be taken through the source code of a program; nonetheless, it ignores readability and understandability, two important aspects of long-term maintainability. In a similar vein, Cognitive Complexity measures how hard a codebase is to grasp, but it ignores how hard this complexity interacts with other elements like code modularity and changeability

Another drawback is the ineffective integration of these complexity measurements into a coherent assessment framework by many of the tools now in use. The developer or code reviewer is typically left to evaluate the results as they typically provide distinct scores for each metric. Because various reviewers may prioritize different measures based on their own experiences or preferences, this might result in judgments that are biased or inconsistent. Consequently, a more integrated method that integrates these criteria into a single, thorough assessment of code complexity and maintainability is required.

1.3.2 The Complexity of Measuring Code Maintainability

Measuring code maintainability is a complex task that goes beyond basic measurements. Maintainability is a broad term that encompasses many different aspects, including the code's modularity, quality of documentation, conformance to coding standards, and ease of modification or extension. These features are not fully captured by traditional complexity measurements such as Weighted Complexity or Cyclomatic Complexity. For example, even though a piece of code has a low cyclomatic complexity, it may still be challenging to maintain if it is not well documented or is strongly integrated with other system components. [13]

In addition, there might be complicated and context-dependent interactions between various complexity measures. For instance, making a codebase more modular may result in a decrease in Weighted Complexity but an increase in Cognitive Complexity since developers will need to comprehend how several modules interact with one another. Similar to this, attempts to streamline a program's control flow may result in a reduction of Cyclomatic Complexity but an increase in Cognitive Complexity due to less comprehensible code. With traditional techniques, which frequently treat complexity measurements as independent variables, it is challenging to capture these choices.

This complexity underscores the need for more sophisticated tools that can account for the interactions between different complexity metrics and provide a more holistic assessment of code maintainability. Such tools should not only measure these metrics but also analyze how they impact the overall maintainability of the codebase, providing actionable insights that developers can use to improve the quality of their code.

1.3.3 Challenges in Evaluating Code Complexity in Real-World Applications

The current software and tools for evaluating code complexity have a significant flaw in that they mostly rely on theoretical models and synthetic benchmarks, which may not accurately represent the difficulties faced by developers in actual projects [14]. The diversity and complexity of code seen in real software projects are not captured by the limited, controlled codebases used for the validation of many existing technologies. This may result in instruments that function effectively in theory but give inaccurate or unhelpful insights in actual use.

Real-world codebases often contain legacy code, third-party libraries, and other complexities that are not present in synthetic benchmarks. Moreover, real-world projects are developed by teams of varying skill levels, following different coding standards and practices. These factors can significantly impact the maintainability of the code, but they are often overlooked by traditional complexity metrics.

To address this gap, there is a need for research that focuses on evaluating code complexity and maintainability in real-world projects. By studying how complexity metrics correlate with real-world outcomes, such as the frequency of bugs or the time required to implement changes, It can develop more accurate and useful tools for assessing code maintainability

1.3.4 The Overlooked Intersection of Confidence and Professional Competency

The connection between developer efficiency and code complexity is a further aspect of the research gap. Although it is often known that maintaining complicated code can be challenging, less is known about how different forms of complexity affect the productivity of developers. For instance, high cognitive complexity may slow down code reviews or raise the risk of introducing errors during maintenance, while high cyclomatic complexity may make it more difficult to test a piece of code.

The majority of current tools concentrate on finding and eliminating complexity, but they don't offer any information about how these efforts affect the productivity of developers. This is a crucial error because the main objective of simplifying code is to increase developer productivity by making it easier for them to comprehend, alter, and expand upon the code. But lowering one kind of complexity could unintentionally raise another, resulting in trade-offs that aren't always visible when looking at the raw data.

Tools that quantify code complexity and assess how these parameters affect developer productivity are required to fill this gap. Developers might use such tools to assist them prioritize their efforts by giving them insights into the trade-offs associated with lowering certain sorts of complexity. Through the integration of developer productivity statistics with complexity measures, these tools have the potential to offer a more comprehensive evaluation of code quality and maintainability.

1.3.5 Future Directions for Research

A multifaceted approach is needed to close the research gap in code complexity and maintainability. Creating extensive datasets that accurately capture the variety and intricacy of real-world software projects should be the main goal of future study. More advanced tools are also required, ones that may provide a more comprehensive evaluation of code maintainability by taking into consideration the interplay between various complexity indicators.

More useful tools for controlling code quality may result from the integration of complexity measures with other facets of software development, like developer productivity and project management. Future research can help provide more precise and practical tools for evaluating code complexity and maintainability by filling up these gaps, which will eventually help developers and organizations.

1.4 Research Problem

The effective evaluation of code complexity and maintainability is a critical challenge in software engineering, particularly as software systems grow in size and complexity. Despite the availability of various tools and metrics designed to analyze code quality, significant limitations persist in providing a comprehensive and accurate assessment.

1.4.1 What problems will the system answer?

- **Fragmented Metric Evaluation:** Current tools tend to evaluate metrics such as CC, WC, and Cognitive Complexity in isolation, failing to integrate these diverse metrics into a cohesive assessment framework. This fragmentation results in an incomplete understanding of code complexity and its impact on maintainability.

- **Surface-Level Analysis:** Many tools focus on basic complexity measures without considering the nuanced aspects of code quality, such as readability and maintainability. For example, CC may highlight complex decision points, but it does not account for how these points affect overall code readability or maintenance.

- **Lack of Real-World Context:** Most analysis tools rely on controlled environments or synthetic code examples, which may not accurately represent the complexities of real-world codebases. This limitation affects the applicability of these tools in practical development scenarios, where code quality and maintainability are influenced by various factors including team practices and project requirements.

This research aims to address the limitations in current code analysis systems by developing an integrated approach to measuring code complexity and maintainability. The study will focus on,

- **Developing Integrated Models:** Creating methodologies that combine multiple complexity metrics (CC, WC, Cognitive Complexity) to provide a comprehensive assessment of code quality and maintainability.

- **Enhancing Real-World Applicability:** Incorporating data from actual codebases and development environments to improve the relevance and accuracy of the analysis.
- **Understanding Code Quality Attributes:** Investigating how different metrics interact to affect code readability, maintainability, and scalability.

Addressing these will enhance the ability of automated tools to provide a detailed and actionable analysis of code quality. By focusing on an integrated approach to code complexity, this research aims to improve the effectiveness of software development practices, ultimately leading to more maintainable and scalable codebases.

2 OBJECTIVES

2.1 Main Objective

This function's major goal is to improve code complexity and maintainability assessments by utilizing cutting-edge metrics and techniques. Our goal is to offer a thorough evaluation of code quality by utilizing well-known code metrics including Cyclomatic Complexity (CC), Weighted Complexity (WC), and Cognitive Complexity. The purpose of this feature is to increase knowledge about the relationship between code complexity and readability, maintainability, and overall program quality. By providing a consistent, unbiased analysis, the aim is to help developers write more scalable and maintainable code, which will expedite the development process and enhance the long-term health of codebases. This function's sub-objectives are made to be **SMART**: They are Possible through the use of proven code metrics and tools, Measurable through extensive metric analysis and reports, and Specific in addressing important areas of code complexity and maintainability. Their application to real codebases is realistic, and they are time-bound with distinct implementation and assessment milestones.

2.2 Sub-Objectives

Objective 1: Comprehensive Evaluation of Code Complexity

- The primary purpose of this objective is to assess code complexity using metrics for cognitive complexity, weighted complexity, and cyclomatic complexity (CC, WC). Evaluating several aspects of code complexity and their effects on maintainability is the aim. Our goal is to find difficult places in real-world codebases that could make them harder to read and maintain by using these measures. We'll use sophisticated libraries and tools to compute these metrics and provide in-depth code complexity reports. These reports will identify places that need to be simplified or refactored, giving developers practical advice on how to improve the quality of their code. In addition, the thorough assessment will aid in the establishment of code complexity standards that can direct future development procedures and advancements.

Objective 2: Analysis of Maintainability Metrics

- This sub-objective looks at how well code follows readability and simplicity standards and best practices in order to determine how maintainable it is. The complexity analysis results will be used to generate maintainability metrics, which will emphasize features like readability, modularity, and comprehension. As part of the analysis, code will be examined to make sure it follows best practices and coding standards for maintainability. The outcomes will be combined into reports on maintainability, which will give developers advice on how to write better code. In order to assist long-term maintainability, these reports will also include recommendations for code structure improvement and restructuring.

Objective 3: Integration with Development Practices

- A comprehensive assessment requires integrating the findings of the maintainability and code complexity analyses with the current methods of development. To produce a holistic view of code quality, this sub-objective combines the feedback from code reviews and development practices with the metrics data. In order to make sure that complexity and maintainability metrics are considered in addition to other quality traits, the integration process will create procedures for integrating these metrics into the code review procedure. This objective seeks to improve the analysis's relevance and application by assessing how code complexity affects development processes and considering input from real-world settings. For as long as software development is ongoing, the analysis will be valuable and relevant thanks to constant improvement of the metrics and integration techniques.

3 METHODOLOGY

3.1 Software Solution

To ensure an iterative, flexible, and user-centric development process, the Agile methodology will be used in the creation of the function for analyzing code complexity and maintainability. Agile methodologies are a good fit for this project because they enable ongoing improvement based on input from stakeholders, which is crucial for producing a tool that efficiently satisfies the requirements of project managers and developers. We will use the Scrum Agile framework, which is renowned for its methodical approach to managing intricate software projects through incremental development and frequent feedback loops.

The project will be broken up into a number of sprints, each lasting two to four weeks, in order to apply Agile. Specific facets of the code complexity and maintainability function, such as the creation of metrics, integration with current tools, and report production, will be the emphasis of these sprints. In order to guarantee that the scope of work is both achievable and in line with the overall project goals, the team will participate in sprint planning at the beginning of each sprint to establish specific targets and deliverables.

Daily stand-up meetings will be held during the sprint to monitor progress, pinpoint any roadblocks, and make sure everyone on the team is working in unison. These brief, targeted sessions will improve communication and provide prompt problem-solving, which will keep the project moving forward. A sprint review will be held at the conclusion of each sprint to show stakeholders the functionality that was produced during the sprint. The input obtained from these reviews will be essential for improving the product and making sure it fulfills user requirements. Furthermore, the team will do sprint retrospectives to evaluate their performance and pinpoint opportunities for growth, thereby fostering ongoing improvements to the product and development methodology.

3.2 System Overview and Integration

One crucial component of the automated interview process tool is the code complexity and maintainability assessment function. This feature is integrated into a multi-layered architecture together with reporting, analysis, and code contribution. The code is uploaded via a front-end editor, after which it undergoes a variety of metrics analyses to assess its complexity and maintainability.

The system's seamless integration into the interview process enables candidates to submit code that is instantly examined for maintainability and complexity. The analysis's findings are kept in a centralized database that is accessible for additional review and comparison with additional assessment measures.

- Frontend (React): React is used to build the user interface of the code editor. It provides a responsive and interactive platform for candidates to submit code, receive feedback, and view complexity metrics. React components manage the code submission interface and display the results of the analysis.

- Backend (Python): Python handles the back-end processing of the submitted code. It uses libraries like Radon and PyComplexity to calculate various complexity metrics, and Django to create API endpoints. Python's versatility makes it ideal for integrating different complexity measurement tools and algorithms.

- Code Analysis Frameworks: Libraries such as Radon, PyLint, and Cognitive Complexity are used to measure code complexity and maintainability. These frameworks support the calculation of Cyclomatic Complexity, Weighted Complexity, and Cognitive Complexity.

How this function works into the larger architecture is shown in a system diagram. It illustrates how data moves from input (code that has been submitted) to processing (complexity analysis) to output (reports on complexity and maintainability). The figure also shows the points of integration with other parts of the system, including the modules for emotional analysis and confidence evaluation.

3.3 In depth clarification of the function's Process

3.3.1 Code Collection and Preprocessing

Radeon will be used to maximize performance for the implementation of the code complexity and maintainability function. Docker will be utilized to oversee code submission, verify compilation, and guarantee environment consistency throughout various deployment phases.

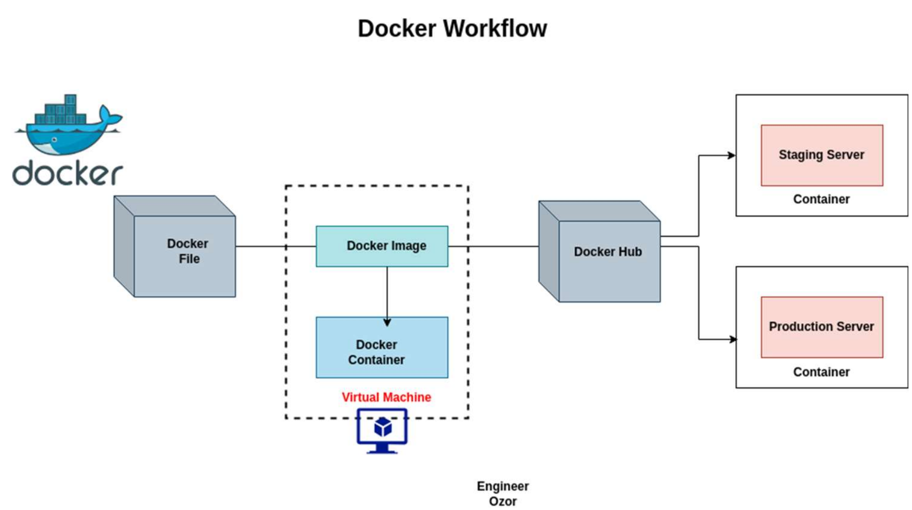

Figure 3.1: Docker Workflow Diagram

The candidate will first submit the code from the front end. Submitted code will then be forwarded to a different Docker-created environment on the back end. The purpose of the phase is to safeguard and secure the system's backend logic. The status of the compilation will then be examined in this isolated environment using Docker. The code will be used to determine the maintainability and complexity of the code later on in this procedure. The complexity will be determined by utilizing three metrics at the same time. The candidate will receive a mark based on the complexity system. These three metrics will be connected via a number of algorithms to function as a single system.

3.3.2 Identifying Metrics

This is a crucial step in assessing code complexity and maintainability. In this stage, the system analyzes the preprocessed code to extract key metrics that are indicative of its complexity and maintainability. These metrics include Cyclomatic Complexity (CC), Weighted Complexity (WC), and Cognitive Complexity.

- **Cyclomatic Complexity (CC):** The system calculates the Cyclomatic Complexity of the code using the Radon library. This metric indicates the number of linearly independent paths through the code, helping to assess its complexity.

- **Weighted Complexity (WC):** Weighted Complexity is calculated using custom Python scripts that assign weights to different code constructs (e.g., loops, conditionals) based on their complexity. This metric provides a more nuanced view of the code's complexity.

- **Cognitive Complexity:** The system uses the Cognitive Complexity metric to evaluate how difficult the code is to understand. This metric considers not only the code structure but also how it is perceived by a human reader.

These features are extracted using Python libraries and custom scripts, forming the basis for the final complexity and maintainability assessment.

3.3.3 Code Analysis and Reporting

The system proceeds to the analysis stage, where it assesses the complexity and maintainability of the code, after extracting the pertinent aspects. Instead of using machine learning, the system classifies the code using predetermined thresholds and patterns.

- **Cyclomatic Complexity Analysis:** The system compares the calculated CC against industry standards to determine whether the code is overly complex. High CC values may indicate that the code is difficult to maintain and understand.

- **Weighted Complexity Analysis:** The WC metric is analyzed to identify parts of the code that may be unnecessarily complicated or could be simplified. This analysis helps in pinpointing specific areas of the code that require attention.

- **Cognitive Complexity Analysis**: The Cognitive Complexity metric is used to assess how easy the code is to read and understand. The system flags code that exceeds acceptable cognitive complexity levels, suggesting that it may be difficult for others to maintain.

The results of the analysis are compiled into a comprehensive report that provides detailed insights into the code's complexity and maintainability. This report can be used by interviewers to assess the candidate's coding abilities and by candidates to improve their code quality.

3.3.4 Algorithm Refinement and Continuous Learning

The complexity analysis algorithms are continuously refined as the last step in the technique. The system uses this data to improve the criteria and rules utilized in the analysis as more code contributions are analyzed.

- Data-Driven Refinement: The complexity measurements and thresholds are updated by the system based on input from code reviews and interview results. This guarantees the system's long-term accuracy and applicability.

- Adaptability to New Languages: As the system encounters code written in different programming languages, it updates its algorithms to account for language-specific constructs and patterns. This adaptability ensures that the system remains effective across a wide range of coding scenarios.

3.3.5 System Integration and Workflow

The role of assessing code complexity and maintainability is incorporated into the larger interview process workflow, guaranteeing smooth communication with additional elements like emotional analysis and confidence evaluation.

- **Integration with Other Functions:** The purpose of the code complexity and maintainability assessment is to supplement the technical competence evaluation and personality assessment components of the interview instrument. Through the integration of these features, the system offers a full perspective of the candidate's coding skills and their fit with their personal qualities.

- **Data Flow and Reporting:** The system is designed to manage the data flow efficiently, from initial code submission to the final report generation. The workflow includes stages for code preprocessing, complexity analysis, and post-submission reporting, ensuring that all relevant metrics are captured and analyzed thoroughly.

- **Customizable Workflow:** Organizations can customize the workflow to meet their specific needs, whether they require immediate feedback during the interview or prefer a more detailed post-interview report. The system's modular design allows for flexibility in how the code complexity and maintainability assessment function is deployed and used.

3.3.6 Summarizing the technologies

Category	**Details**
Technologies	Python, React, Django, OpenCV, Docker, Radeon
Techniques	Cyclomatic Complexity, Cognitive Complexity, Weighted Complexity
Algorithms	Code Parsing Algorithms, Complexity Measurement Techniques
Architectures	Custom Python-based architectures for code analysis

Table 3-1: Summary of technologies

3.4 Testing Phase

The testing phase for the code complexity and maintainability assessment function involves several steps to ensure the accuracy, reliability, and robustness of the system.

- ❖ Unit Testing: The separate parts that compute code complexity metrics will be verified by unit testing. Testing the algorithms that determine weighted complexity, cognitive complexity, and cyclomatic complexity is part of this. We'll utilize the unit test framework in Python for this.

- ❖ Integration Testing: The main goal of integration testing is to make sure that the front-end editor to the back-end analysis process for code submission and analysis functions flawlessly. To ensure that code contributions are handled successfully and that the analysis findings are returned to the front end with accuracy, tools like as Postman and pytest will be used.
- ❖ System Testing: System testing will encompass end-to-end testing of the entire application, ensuring that all features and functionalities work as intended. This includes validating the complete workflow from code submission to report generation.

- ❖ Performance Testing: Performance testing will assess the efficiency and scalability of the complexity analysis function, particularly focusing on the system's ability to handle multiple simultaneous code submissions.

- ❖ User Acceptance Testing (UAT): UAT will involve real users interacting with the application to validate that it provides accurate and useful feedback based on code complexity analysis.

- ❖ Regression Testing: Regression testing will be conducted to ensure that any new features or changes do not introduce bugs or issues in the existing functionality.

3.5 Anticipated Conclusion: Results, Application, and Real-World Use

The implementation of the code complexity and maintainability assessment function is expected to yield significant outcomes:

3.5.1 Results:

- **Improved Code Quality Assessment:** By examining code complexity and maintainability, the tool will allow for a more accurate assessment of a candidate's coding abilities. This will produce candidate evaluations that are more trustworthy.
- **Detailed Feedback Reports:** Interviewers will receive actionable insights from the system's extensive reports, which highlight important facets of the code's complexity.
- **Better Coding Standards:** The tool will assist guarantee that all candidates' code is evaluated uniformly by offering objective measurements of code complexity, which will encourage better coding standards.

3.5.2 Applications:

- **Recruitment and Human Resources:** HR departments can use the tool to enhance their recruitment processes, making it easier to identify candidates who write maintainable and efficient code.
- **Code Reviews and Professional Development**: The insights gained from the tool can be used for code reviews and professional development, helping developers understand their strengths and areas for improvement.
- **Technical Interviews:** The tool provides a standardized method for assessing code quality, ensuring consistency in evaluations across different interview settings.

4 Project Requirements

4.1 Functional Requirements

The system must be capable of analyzing code submissions near real-time to assess candidates' code complexity and maintainability.

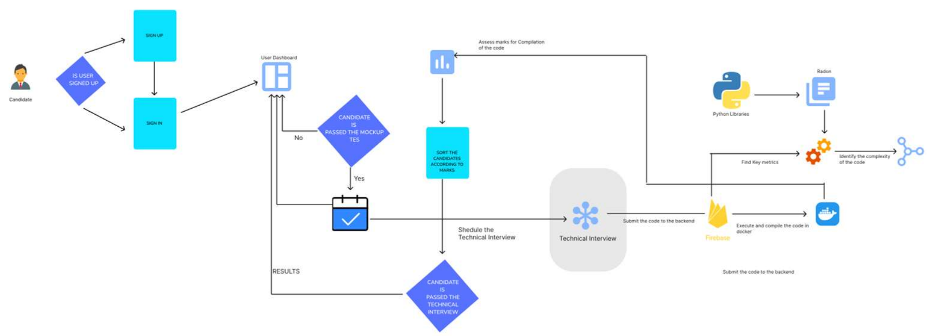

Figure 4.1: System Diagram

I. To enable applicants to submit their code files, the system must interface with tools for code submission. The system needs to accommodate many programming languages and offer an easy-to-use interface for uploading and modifying code.

II. In order to identify differences in complexity measures such as Cyclomatic Complexity, Cognitive Complexity, and Weighted Complexity, the system must process and evaluate code data.

III. After the provided code is analyzed, the system ought to be able to provide the interviewers with feedback.

IV. The system ought to include algorithms for examining the characteristics of the code and identifying trends that point to complexity and maintainability.

V. Reporting features that provide code complexity levels in an intelligible manner should be included of the system. The system should be able to link code analysis results with other interview feedback data.

VI. The system should be able to provide a consolidated report that combines code analysis with other evaluation criteria.

4.2 Non-functional requirements

I. Performance: The system must perform efficiently under expected workloads.

Requirements:

- Fast processing times for code analysis.
- Minimal latency in feedback and reporting.

II. Scalability: The system should be able to handle an increasing number of users and data volumes without performance degradation.

Requirements:

- Scalable architecture to support growth.
- Efficient data management and processing.

III. Security: The system must ensure the confidentiality and integrity of sensitive data.

Requirements:

- Data encryption for code submissions and analysis results.
- Secure user authentication and authorization mechanisms.

IV. Usability: The system should be easy to use and navigate for all user types.

Requirements:

- Intuitive user interface design.
- Comprehensive user guides and help documentation.

V. Reliability: The system must be reliable and available for use at all times.

Requirements:

- High availability and minimal downtime.
- Robust error handling and recovery mechanisms.

4.3 Technical Requirements

Technology Stack

- **Frontend**: React.js for user interface development.
- **Backend**: Python with Django for server-side processing.
- **Database**: Firebase
- **Code Analysis:** Radon and Pylint for analyzing code complexity..
- **Submission and Compilation:** Docker for managing code submission and checking compilation.

4.4 User Requirements

I. Candidates: Candidates are individuals applying for positions and undergoing the interview process using the tool.

Key Needs:

- **User-Friendly Interface:** Candidates require a straightforward interface for recording responses, submitting answers and navigating through the system.
- **Code Submission and Editing:** They need the ability to submit their code files and, if necessary, edit them.
- **Feedback Access:** Candidates should be able to access their feedback reports, which detail their confidence levels and other analysis results.
- **Guidance and Support:** Clear instructions and support are necessary for candidates to understand how to use the tool effectively and interpret the feedback they receive.

II. Interviewers: Interviewers are individuals responsible for evaluating candidates and making decisions based on the analysis provided by the tool.

Key Needs:

- **Candidate Management:** Interviewers need access to a dashboard where they can view and manage candidate profiles, recorded responses, and feedback reports.

- **Reporting**: Interviewers need the capability to generate and review comprehensive reports on candidates to aid in the decision-making process.

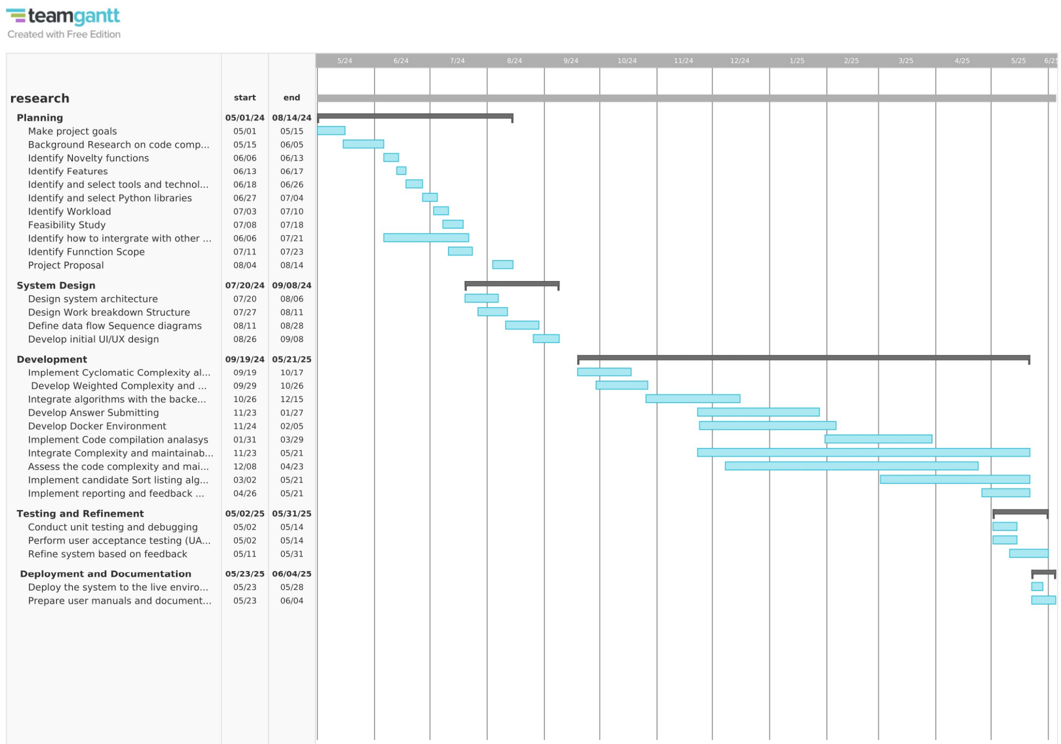

Figure 4.2: Gannt chart

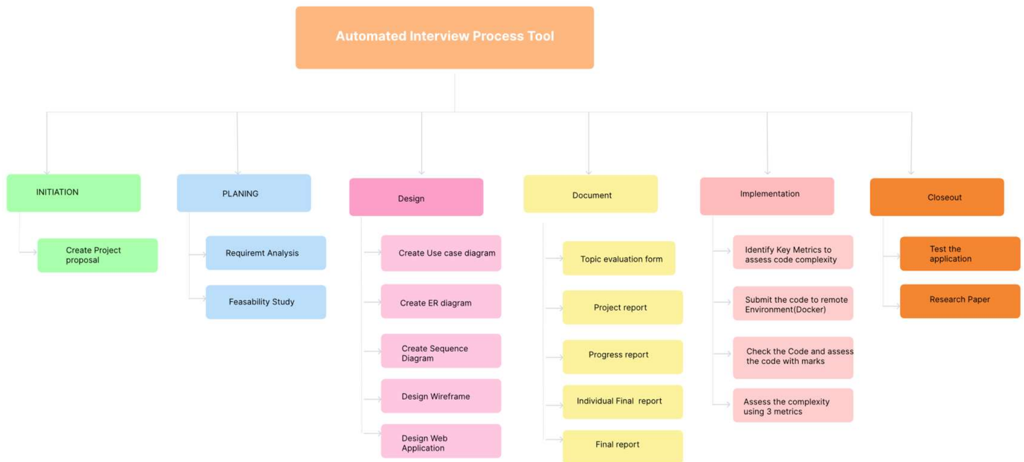

Figure 4.4 : Work Breakdown Chart

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Automated Interview Processing System

24-25J-047

Project Proposal Report

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B.Sc. (Hons) Degree in Information Technology Specialized in Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology

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August 2024

DECLARATION

I declare that this is my own work and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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-- ------------------23/08/2024------

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-- ------------23/08/2024------

Signature of the Co-Supervisor
(Ms. Poojani Gunathilake) Date

ABSTRACT

The increasing demand for effective candidate assessment methods in high-stress industry environments has led to the exploration of innovative approaches. This research focuses on developing a gamified environment designed to evaluate applicants' problem-solving skills while simultaneously measuring their stress levels through facial expression analysis. The integration of emotional analysis into technical skill assessment aims to provide a more accurate understanding of a candidate's ability to perform under pressure. Current solutions for facial recognition and stress measurement exist, but there is a gap in combining these elements within a gamified setting to assess problem-solving abilities.

The primary objective of this research is to develop a system that evaluates both technical skills and emotional resilience through gamification. Using OpenCV for real-time facial expression analysis and leveraging deep learning techniques, stress levels will be categorized into low, moderate, and high. This categorization will help recruiters determine whether candidates can thrive in stressful environments typical of industry settings. Unity will be used to create the gamified environment, providing a more engaging and less stressful alternative to traditional interviews. The system's effectiveness will be evaluated through rigorous model training and testing, utilizing available datasets for stress detection via facial expressions.

This research aims to bridge the gap in current assessment tools by offering a comprehensive solution that not only tests technical abilities but also gauges a candidate's emotional readiness for high-pressure work environments.

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1. INTRODUCTION

1.1 Background & Literature survey

In today's rapidly evolving job market, the demand for highly skilled professionals has intensified, making it increasingly important to assess not only technical expertise but also how candidates manage stress. Traditional interview methods, while effective in evaluating technical skills, often fall short in capturing a candidate's ability to handle high-pressure situations that are prevalent in many professional settings. Stress in the workplace can have profound impacts, including decreased productivity, increased employee turnover, and higher rates of absenteeism. These issues underscore the urgent need for more comprehensive assessment methods that not only evaluate technical competencies but also measure stress management capabilities [1][2].

The detrimental effects of stress on employee performance and organizational health are well-documented. For instance, a study by the American Psychological Association (APA) found that workplace stress is a leading cause of burnout, which can lead to significant declines in productivity and employee morale [3]. Research indicates that 61% of employees report feeling stressed at work, with 45% of them citing that stress negatively affects their job performance and overall satisfaction [4]. The impact of this stress can be seen in higher turnover rates and absenteeism. The National Institute for Occupational Safety and Health (NIOSH) reports that stress-related issues cost U.S. companies an estimated $300 billion annually due to lost productivity, increased healthcare costs, and higher employee turnover [5].

Furthermore, a survey conducted by Gallup found that organizations with highly stressed employees experience 37% higher absenteeism and 18% lower productivity compared to companies with lower stress levels [6]. These statistics highlight the significant financial and operational burdens that stress can impose on organizations. Addressing these issues through improved assessment methods that gauge not only technical skills but also stress management is crucial for enhancing overall organizational performance.

Research has long established that stress can significantly impair job performance, particularly in high-stress roles such as those in IT and other technical fields. The traditional interview process is often inadequate in simulating the genuine pressures of the workplace, focusing predominantly on technical knowledge and problem-solving skills within a controlled, low-pressure environment. This limitation highlights the necessity for evaluation methods that incorporate stress assessment as a fundamental component [7][8]. Effective stress management is crucial for maintaining high levels of productivity and job satisfaction, and for mitigating issues such as burnout and turnover.

Gamification, the application of game-design elements to non-game contexts, has emerged as an innovative tool in recruitment. By transforming the interview process into a game-like experience, gamification creates a more engaging and less intimidating environment for candidates. This approach not only alleviates some of the anxiety associated with traditional interviews but also provides deeper insights into a candidate's cognitive abilities, creativity, and problem-solving skills. Studies have demonstrated that gamified assessments can offer a more authentic evaluation of a candidate's abilities compared to conventional methods [9][10]. The game-like environment can help candidates perform at their best, revealing their true potential without the distortions of interview-induced stress.

Within this component, the technical interview process mainly focuses on evaluating a candidate's technical skills and problem-solving abilities through a series of structured assessments. Candidates are typically required to solve coding challenges, algorithmic problems, or system design scenarios that test their proficiency in relevant technical domains, such as programming languages, data structures, and software engineering principles. This process often involves whiteboard sessions, live coding exercises, and technical questions aimed at assessing both theoretical knowledge and practical problem-solving capabilities. While this approach is effective in determining a candidate's technical expertise, it primarily operates within a controlled environment, which may not accurately reflect the pressures and complexities of real-world situations. Consequently, while valuable for assessing technical competencies, the traditional technical interview process may benefit from integration with additional methods that evaluate

how candidates handle stress and perform under pressure, providing a more holistic view of their

potential [19][20].

The advent of facial expression analysis, leveraging computer vision and machine learning, has further advanced the capability to assess emotional states in real-time. This technology enables the interpretation of emotions based on facial cues, making it particularly useful for measuring stress. Research has identified specific facial expressions—such as furrowed brows, tightened lips, and widened eyes—that are strongly correlated with stress levels [11][12]. Integrating facial expression analysis into a gamified assessment could significantly enhance the accuracy of stress measurement, providing valuable insights into a candidate's emotional responses during the evaluation process.

Facial expression analysis, supported by advancements in computer vision and machine learning, has emerged as a powerful tool for enhancing the evaluation of candidates' emotional responses during assessments. Utilizing a dataset from Kaggle, which includes a comprehensive image set of 35,887 examples, we have divided the data into a training set (80%), validation set (10%), and test set (10%). This dataset allows for the application of Convolutional Neural Networks (CNN) to accurately classify facial expressions into one of seven categories: anger, disgust, fear, happiness, sadness, surprise, and neutral. The objectives of this approach are twofold: first, to apply CNNs for precise facial expression recognition, and second, to ensure that each facial image is classified correctly according to its emotional category. By integrating this technology into the assessment process, we aim to gain real-time insights into a candidate's stress levels and emotional states, which can complement traditional technical evaluations and provide a more nuanced understanding of how candidates manage stress in high-pressure situations [21][22].

Combining gamification with real-time stress measurement through facial expression analysis represents a novel and comprehensive approach to candidate assessment. This integration addresses the shortcomings of traditional interviews by reducing the inherent stress of the assessment process while simultaneously evaluating both technical skills and emotional resilience. The use of advanced technologies, such as OpenCV and TensorFlow, ensures that this approach is not only accurate but also scalable [13][14]. Such an innovative system offers a dual advantage: it mitigates the stress typically associated with interviews and provides a richer, more nuanced view of a candidate's capabilities.

The impacts of stress on employees and organizations are substantial. High levels of workplace stress lead to decreased job satisfaction, lower productivity, and increased absenteeism, affecting the overall performance and health of organizations. Companies may face higher costs related to employee turnover and recruitment, as well as potential damage to their reputation and work environment. By adopting a gamified environment for assessments, organizations can reduce the stress experienced by candidates, leading to more accurate evaluations and a better fit for the role. This approach not only enhances the recruitment process but also helps in identifying candidates who are likely to thrive in high-pressure environments, ultimately benefiting both the individual and the organization [15][16].

Despite advancements in facial recognition and stress measurement technologies, there remains a notable gap in their application within gamified recruitment settings. Existing solutions like RealEyes offer effective facial expression analysis for stress measurement but have not yet been integrated with gamified assessments of problem-solving skills. This research aims to bridge this gap by developing a system that combines emotional analysis with technical skill evaluation, providing recruiters with a more comprehensive and effective tool for candidate assessment [17][18]. This innovative approach holds the potential to transform recruitment practices, ensuring that organizations can better assess both the technical and emotional capabilities of candidates, leading to improved hiring outcomes and organizational performance.

1.2 Research Gap

The current body of research on emotional analysis and gamified assessments, while valuable in its respective domains, exhibits significant limitations due to its fragmented and siloed nature. Existing studies tend to focus on isolated aspects of either emotional analysis or gamified assessments, without considering the potential benefits of an integrated approach that combines these elements to offer a more comprehensive and nuanced evaluation system.

The following table (Table 1.1) provides a summary of the analysis of existing research studies concerning the integration of emotional analysis with performance data, gamified assessments, and the evaluation of technical skills and problem-solving abilities. It highlights the key aspects that have been covered in each of the referenced studies and identifies the gaps that the proposed function aims to address.

Reference	Research Paper 1	Research Paper 2	Research Paper 3	Proposed Function
Emotional Analysis	✓	X	✓	✓
Gamified Assessments	X	✓	X	✓
Integration of Emotional and Performance Data	X	X	✓	✓
Evaluation of Technical Skills	X	✓	X	✓
Evaluation of Problem-Solving Abilities	X	✓	X	✓

Table 1.1 : Research Gap

For instance, Research Paper 1 by Smith et al. [23] presents an in-depth exploration of real-time emotional analysis in online learning environments. This research emphasizes the importance of monitoring students' emotional states to enhance their learning experiences. Smith et al. [23] highlight that emotional analysis can be instrumental in identifying when a learner is experiencing frustration, confusion, or engagement, which can, in turn, inform adaptive learning interventions. However, despite the robust emotional analysis framework proposed, the study stops short of integrating these emotional insights with other performance-related data. The research does not explore how emotional analysis can be used in conjunction with performance metrics, such as the evaluation of technical skills or problem-solving abilities. This omission is critical because understanding the interplay between emotional states and performance can provide a more holistic view of a learner's capabilities and challenges. Furthermore, the study focuses primarily on emotional analysis in isolation, without considering how these emotional insights could be applied within a gamified assessment context, which is increasingly recognized as an effective tool for engaging learners and enhancing motivation.

In contrast, **Research Paper 2** by Johnson and Lee [24] investigates gamified assessment techniques aimed at evaluating technical skills in remote education settings. The study underscores the effectiveness of gamification in making assessments more engaging and interactive, particularly in environments where direct, in-person evaluation is not feasible. Johnson and Lee [24] argue that gamified assessments can simulate real-world challenges and provide a dynamic platform for students to demonstrate their technical skills. However, the study's scope is limited to the technical aspects of these assessments and does not account for the emotional factors that may influence a student's performance in such settings. For example, a student’s anxiety or overconfidence could significantly impact their performance during a gamified assessment, yet this emotional dimension is entirely overlooked in the research. Additionally, the study does not consider the potential benefits of integrating emotional analysis into the gamified assessment process to create a more adaptive and personalized evaluation system. This lack of integration represents a significant gap, as the inclusion of emotional data could lead to more accurate assessments by accounting for the affective factors that influence learning and performance.

Research Paper 3 by Patel et al. [25] attempts to address some of these issues by integrating emotional analysis with performance metrics within e-learning systems. The study acknowledges that both emotional states and performance data are critical to understanding a learner's overall experience and outcomes in online education. Patel et al. [25] explore how emotional data, such as indicators of stress or engagement, can be correlated with performance metrics to provide insights into how these factors interact. This integration represents a step forward in recognizing the complexity of the learning process, where emotions and performance are interlinked. However, despite this progress, the study still falls short in several key areas. Notably, the integration of emotional and performance data is not extended to the evaluation of technical skills or problem-solving abilities, which are critical components of a learner's overall competence. Moreover, the study does not explore how these integrated insights could be operationalized within a gamified assessment framework, which would enhance the relevance and applicability of the findings in real-world educational settings. The study also lacks a detailed examination of how the integration of emotional and performance data could be used to tailor the learning experience to individual needs, thereby enhancing the efficacy of the educational interventions.

The limitations of these studies highlight the need for a more comprehensive approach that integrates emotional analysis with performance data within a gamified assessment framework. The proposed function aims to fill these gaps by offering a multi-dimensional evaluation tool that considers not only the emotional states of learners but also their technical skills and problem-solving abilities in a gamified context. This approach is innovative in several ways. Firstly, by integrating emotional analysis with performance data, the proposed function will provide a more holistic view of a learner's capabilities, allowing educators to better understand the factors influencing performance and to tailor interventions accordingly. For instance, if a learner is identified as being highly anxious during a gamified assessment, the system could adjust the difficulty level of the tasks or provide additional support to help the learner manage their anxiety, thereby improving their performance.

Secondly, the proposed function will incorporate these insights into a gamified assessment framework, which has been shown to increase engagement and motivation among learners. By embedding emotional analysis within a gamified context, the proposed function will enable real-time adjustments to the assessment process based on the learner’s emotional state, making the evaluation more adaptive and personalized. This is particularly important in remote or online education settings, where direct, real-time feedback from instructors may not be available. The integration of emotional analysis into gamified assessments will also allow for the creation of more nuanced and multi-faceted assessments that can better capture the complexities of learning and performance.

Furthermore, the proposed function will address the need for evaluating technical skills and problem-solving abilities, which have been largely neglected in the existing research. By incorporating these elements into the assessment process, the proposed function will provide a more comprehensive evaluation of a learner's overall competence, going beyond the limited focus of current studies. This will be particularly beneficial in fields where technical skills and problem-solving abilities are critical, as it will allow for a more accurate and complete assessment of a learner’s readiness for real-world challenges.

The proposed function represents a significant advancement over existing research by addressing the gaps identified in previous studies [23][24][25]. It offers a novel, integrated approach that combines emotional analysis, performance data, and gamified assessments to provide a more comprehensive and nuanced evaluation tool. This approach not only fills the gaps in the current research but also provides a practical solution that can be applied in real-world educational environments, particularly in remote and online settings where traditional assessment methods may fall short. By offering a more holistic and adaptive assessment framework, the proposed function has the potential to significantly enhance the effectiveness of educational interventions and improve learning outcomes for students across a wide range of disciplines.

1.2.1 Identification of Key Gaps

In the evolving technical interview process system there has been a growing interest in the integration of emotional analysis, gamified assessments, and the evaluation of cognitive and technical skills to enhance learning outcomes. While significant advancements have been made in each of these areas individually, the existing research often addresses these components in isolation, failing to explore their interconnectedness. This fragmented approach overlooks the potential benefits of a more holistic assessment system that integrates emotional and performance data with gamified elements to provide a more comprehensive evaluation of learners' abilities. The following sections identify and elaborate on the key gaps in the current literature that the proposed function aims to address.

1. Gamified Assessments

Research on gamified assessments, as explored by Johnson and Lee [2], has shown that gamification can be an effective tool for evaluating technical skills, particularly in remote or online education settings. Gamified assessments are recognized for their ability to engage learners and provide a dynamic platform for demonstrating competencies in a simulated environment. However, Johnson and Lee's study [2] does not consider the emotional dimensions that can significantly influence a learner's performance in such assessments. The impact of emotions, such as anxiety or overconfidence, on the effectiveness of gamified assessments has not been adequately addressed, which is a crucial oversight given the role that emotions play in learning and performance. Additionally, there is a lack of research on integrating emotional analysis with gamified assessments, which could provide a more personalized and adaptive evaluation framework.

2. Integration of Emotional and Performance Data

The integration of emotional analysis with performance data is a critical area where existing research has shown some promise but remains underdeveloped. Patel et al. [3] have made progress by correlating emotional states with performance outcomes in e-learning environments, recognizing that emotions can have a significant impact on a learner's overall experience and success. However, this integration is not extended to include specific assessments of technical skills or problem-solving abilities, which are essential components of many educational programs. Moreover, the potential of using integrated emotional and performance data to create more adaptive learning environments, particularly through gamification, has not been fully explored. This gap highlights the need for a more comprehensive approach that considers both emotional and performance data in a unified framework, particularly in gamified learning contexts where real-time adaptation based on emotional states could enhance learning outcomes.

3. Evaluation of Technical Skills

The evaluation of technical skills is an area where current research, particularly that of Johnson and Lee [2], has focused on using gamified assessments to simulate real-world challenges and assess learners' competencies. While this approach has been effective in certain contexts, it lacks the integration of emotional analysis, which could provide a more complete understanding of a learner's abilities. For example, a learner's technical performance could be influenced by their emotional state, such as stress or confidence levels, yet this interaction is not considered in existing gamified assessment frameworks. Furthermore, the lack of research on how technical skills can be assessed in conjunction with emotional and performance data leaves a significant gap in understanding the full range of factors that contribute to technical proficiency.

4. Evaluation of Problem-Solving Abilities

Problem-solving abilities are another critical area that has not been adequately addressed in the current research landscape. Johnson and Lee [2] include problem-solving as part of their gamified assessments, but like the evaluation of technical skills, this is done without considering the role of emotional states in influencing problem-solving performance. Emotions can significantly impact a learner's approach to problem-solving, affecting their creativity, persistence, and decision-making processes. However, existing research does not integrate emotional analysis into the assessment of problem-solving abilities, nor does it explore how such integration could be used to tailor problem-solving challenges to the learner's emotional state. This represents a significant gap, as the ability to accurately assess and adapt to a learner's emotional state during problem-solving tasks could lead to more effective and personalized learning experiences.

While existing research has provided valuable insights into emotional analysis, gamified assessments, and the evaluation of technical skills and problem-solving abilities, there are significant gaps that need to be addressed. The lack of integration between emotional analysis and other critical aspects of the learning process, particularly within gamified assessment frameworks, limits the effectiveness of current educational interventions. The proposed function aims to address these gaps by offering a comprehensive, integrated approach that combines emotional analysis, performance data, and gamified assessments to provide a more holistic and adaptive evaluation framework. This approach has the potential to significantly enhance the accuracy and relevance of assessments, leading to better learning outcomes for students across a wide range of educational settings.

1.3 Research Problem

The research problem at hand investigates the effectiveness of integrating emotional analysis and gamified assessments to evaluate candidates' technical skills and problem-solving abilities, addressing a significant gap in current assessment methodologies. Traditionally, candidate evaluation has primarily focused on assessing technical competencies and problem-solving skills through standardized tests and interviews conducted in controlled environments. These conventional methods, while effective in measuring specific technical abilities, often fail to account for the emotional and psychological aspects that are critical in high-pressure work environments. As industries increasingly demand professionals who can perform effectively under stress, there is a pressing need to develop assessment tools that capture not only technical skills but also candidates' emotional resilience and stress management capabilities [26].

Current assessment practices frequently employ static tests or interviews that may not accurately reflect the real-world pressures encountered in demanding roles. These traditional methods often neglect the influence of stress on performance, providing an incomplete picture of a candidate’s true capabilities [27]. This limitation underscores the necessity for more comprehensive evaluation systems that can measure both technical proficiency and emotional readiness, particularly for roles where high stress and pressure are inherent components of the job.

To address this critical gap, this research proposes the development of an innovative assessment system that integrates gamification with real-time emotional analysis through facial expression recognition. By leveraging OpenCV and advanced deep learning techniques, the proposed system will analyze candidates' facial expressions to categorize their stress levels into low, moderate, and high [28]. This approach aims to provide valuable insights into how candidates’ emotional states impact their problem-solving abilities and technical performance during the assessment process. The integration of emotional analysis into the evaluation framework is expected to offer a more nuanced understanding of a candidate’s ability to handle stress while solving complex problems, thereby providing a more accurate assessment of their suitability for high-pressure roles.

The gamified environment, designed using Unity, is intended to create a more engaging and less intimidating assessment experience compared to traditional interview settings. Gamification has been shown to enhance candidate engagement and reduce anxiety, potentially leading to more authentic assessments of both technical skills and emotional resilience [29]. By simulating real-world challenges in a game-like context, the system aims to replicate the pressures and complexities candidates may face in their actual roles, offering a more realistic measure of their problem-solving abilities and stress management skills [30]. This approach contrasts with traditional methods that often fail to account for the dynamic and high-pressure nature of the work environment, thereby providing a more comprehensive evaluation.

The proposed research will involve rigorous model training and testing to validate the effectiveness of the integrated system. This process includes evaluating the accuracy and reliability of stress detection through facial expressions, as well as assessing the impact of gamified scenarios on performance evaluations. By analyzing performance data from a diverse pool of candidates, the research seeks to determine whether the combination of emotional analysis and gamification offers a more reliable and holistic assessment compared to conventional evaluation methods [31]. The effectiveness of this integrated approach will be measured in terms of its ability to accurately reflect candidates' technical skills, problem-solving capabilities, and emotional resilience under stress.

The ultimate goal of this research is to enhance the recruitment and selection process by offering a dual-faceted evaluation system that not only tests technical proficiency but also gauges emotional readiness for high-pressure work environments. By bridging the gap between traditional assessment methods and the realities of modern industries, the proposed system aims to provide a more accurate and comprehensive measure of a candidate's overall suitability for demanding roles [32]. This research has the potential to significantly improve recruitment outcomes, ensuring that candidates are better prepared for the challenges they will face in their professional roles.

The integration of emotional analysis and gamified assessments represents a significant advancement in candidate evaluation methodologies. By addressing the limitations of traditional assessment practices and incorporating a more holistic approach, this research aims to develop a system that offers a deeper and more accurate understanding of candidates' abilities. The proposed system's focus on both technical skills and emotional resilience aligns with the evolving demands of high-pressure work environments, ultimately contributing to more effective recruitment and selection processes [33]. The findings from this research could pave the way for new standards in candidate assessment, ensuring that professionals are well-equipped to excel in the complex and demanding roles they undertake.

2. OBJECTIVES

2.1 Main Objectives

The main objective of developing a system that evaluates technical skills and problem-solving abilities while incorporating emotional analysis within a gamified environment is to create a comprehensive and nuanced assessment tool that captures both cognitive and emotional aspects of a candidate's performance. This innovative approach aims to address several key challenges in traditional candidate evaluations.

The system seeks to enhance the accuracy of assessing technical skills by embedding these assessments within a gamified framework. Traditional technical evaluations often involve static tests or interviews conducted in controlled settings, which may not fully reflect a candidate's performance under real-world conditions. By integrating technical assessments into engaging, game-like scenarios, the system aims to simulate the dynamic and challenging environments that candidates are likely to encounter in their actual roles. This approach not only makes the evaluation process more interactive and less intimidating but also provides a more realistic measure of a candidate's problem-solving abilities and technical proficiency [26][27].

The system incorporates real-time emotional analysis to evaluate how candidates handle stress and pressure during the assessment. Emotional resilience is a critical factor in many high-pressure job environments, and traditional methods often fail to account for how stress impacts performance. By using facial expression analysis and other emotional indicators to monitor stress levels throughout the assessment, the system aims to provide insights into how candidates manage their emotions while solving complex problems. This dual focus on technical and emotional performance helps to create a more holistic view of a candidate's suitability for roles that require both high technical competence and the ability to thrive under stress [28][29].

The integration of emotional analysis within a gamified environment also addresses the issue of candidate engagement and anxiety. Gamification has been shown to enhance engagement and reduce stress, potentially leading to more authentic assessments of both technical skills and emotional resilience [30]. By creating a more engaging and less intimidating assessment experience, the system aims to capture a more accurate representation of a candidate's true abilities and potential.

The main objective of this system is to bridge the gap between traditional assessment methods and the real-world demands of high-pressure work environments. By combining technical skill evaluations with emotional analysis in a gamified context, the system aims to offer a more comprehensive and accurate assessment tool that reflects both the cognitive and emotional dimensions of performance. This approach is expected to improve recruitment outcomes by providing a deeper understanding of candidates' abilities, ultimately helping organizations to select individuals who are not only technically skilled but also capable of thriving in challenging and high-stress roles [31][32].

2.2 Specific Objectives

There are three specific objectives that must be reached in order to achieve the overall objective described above.

1. Enhance Candidate Experience

The first objective is to significantly enhance the candidate's experience throughout the assessment process. Traditional assessment methods, such as static tests and interviews, can often be stressful and impersonal, potentially affecting candidates' performance and engagement. By integrating gamification into the assessment process, the goal is to create a more engaging, interactive, and enjoyable experience for candidates. Gamified assessments aim to reduce anxiety and intimidation, providing a more relaxed environment that encourages candidates to perform at their best. This involves designing user-friendly interfaces, incorporating game-like elements that motivate and engage candidates, and ensuring that the overall experience is both enjoyable and informative. The enhanced experience is expected to lead to more authentic and accurate reflections of candidates' abilities and reduce performance anxiety that could skew results [26][29].

2. Design Gamified Assessments that Accurately Evaluate Technical Skills

The second objective is to design and implement gamified assessments that accurately measure technical skills and problem-solving abilities. Traditional methods of assessing technical skills often involve straightforward tests or problem-solving scenarios that may not fully capture a candidate's capabilities in real-world settings. By embedding these assessments within a gamified environment, the system aims to create scenarios that simulate real-world challenges and complexities. This involves developing game-like simulations that accurately reflect the technical requirements of the job and integrating these simulations with robust scoring mechanisms to objectively evaluate candidates' technical skills. The goal is to ensure that the gamified assessments are both challenging, and representative of the actual tasks candidates will face in their roles, thereby providing a more comprehensive evaluation of their technical competencies [27][30].

3. Measure Stress Levels During Problem-Solving Tasks

The third objective is to effectively measure stress levels during problem-solving tasks. Emotional resilience and the ability to handle stress are critical components of performance in high-pressure roles, yet traditional assessments often fail to account for these factors. The proposed system will incorporate real-time emotional analysis using facial expression recognition and other stress indicators to monitor and evaluate candidates' stress levels throughout the assessment. This involves developing algorithms and models to accurately detect and categorize stress responses based on facial expressions and physiological signals. By measuring stress levels during problem-solving tasks, the system aims to provide insights into how well candidates manage pressure and how their emotional state impacts their problem-solving abilities. This information will be crucial for assessing candidates' suitability for roles that involve high levels of stress [28][31].

Achieving these specific objectives enhancing the candidate experience, designing accurate gamified assessments, and measuring stress levels will contribute to the overall goal of developing a comprehensive system that evaluates both technical skills and emotional resilience. This integrated approach aims to provide a more accurate and nuanced assessment of candidates, better reflecting their abilities and readiness for high-pressure roles.

3. METHODOLOGY

The proposed system is designed to evaluate candidates' technical skills and problem-solving abilities while incorporating emotional analysis within a gamified environment. This system aims to provide a comprehensive assessment by combining three critical components: enhancing the candidate experience, accurately evaluating technical skills through gamified assessments, and measuring stress levels during problem-solving tasks. The methodology for achieving these objectives involves several key processes.

The system enhances the candidate experience by creating an engaging and interactive gamified environment. This involves designing user-friendly interfaces and integrating game-like elements that reduce candidate anxiety and make the assessment process more enjoyable. The goal is to foster a positive and less intimidating environment, thereby encouraging candidates to perform at their best and provide a more accurate reflection of their abilities.

The system incorporates gamified assessments to evaluate technical skills. These assessments are designed to simulate real-world challenges and complexities relevant to the candidates' prospective roles. By embedding technical evaluations within engaging game scenarios, the system aims to accurately measure candidates' problem-solving abilities and technical proficiency. The assessments are constructed to reflect the actual tasks and conditions candidates will encounter in their roles, ensuring that the evaluation is both challenging and relevant.

The system integrates real-time emotional analysis to measure stress levels during the problem-solving tasks. Using advanced facial expression recognition and other stress detection techniques, the system monitors and evaluates candidates' emotional states throughout the assessment. Stress levels are categorized into low, moderate, and high, providing insights into how well candidates manage pressure and how their emotional state influences their performance. This information is crucial for assessing candidates' suitability for roles that involve high levels of stress.

The methodology involves a multi-faceted approach that combines enhanced candidate experience, accurate technical skill evaluation through gamification, and real-time stress measurement. By integrating these components, the system aims to provide a more comprehensive and accurate assessment of candidates, reflecting both their technical abilities and emotional resilience in high-pressure environments.

3.1 System Architecture

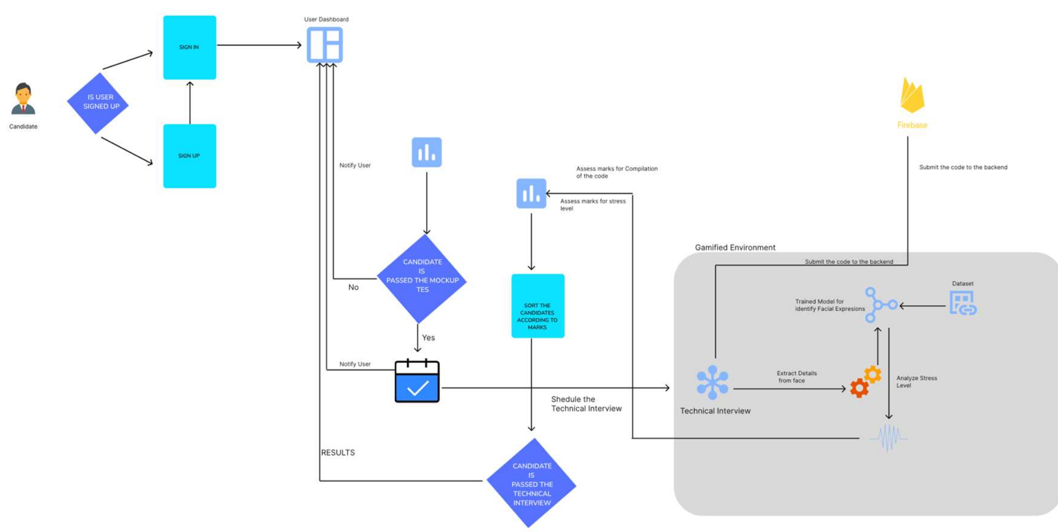

Figure 1 : System Diagram

The process depicted in the diagram begins with the candidate, who is represented by a simple icon on the left side of the diagram. This candidate is at the very start of their journey in what appears to be a recruitment or assessment process. The first action the candidate takes is to create a profile within the system. This profile is likely a digital record that includes a wide array of information about the candidate. At a minimum, it might contain personal details such as the candidate’s name, contact information, educational background, and work experience. However, depending on the complexity of the system, this profile could also store initial test results, uploaded documents like resumes or certifications, and perhaps even initial self-assessments or personality tests.

Once the profile is created, the data is stored in a central **Candidate Database**. This database acts as the repository for all candidate-related information throughout the entire process. It ensures that all relevant data is securely stored and easily accessible whenever it's needed during the various stages of evaluation. From here, the **Data Distribution** component takes over. This component plays a crucial role in the system as it ensures that the candidate's data is appropriately routed to the various modules that will be involved in assessing the candidate. The effectiveness of this step is paramount, as it allows for seamless transitions between different parts of the system, ensuring that no data is lost or misplaced as the candidate progresses through the evaluation process.

The Data Distribution component likely operates automatically, using predefined logic to determine which data is sent where. For example, basic information such as the candidate's educational background and work experience might be sent to a module that assesses qualifications, while specific test results might be sent to another module that handles technical assessments. The integrity and accuracy of data distribution are essential, as any errors at this stage could lead to miscommunication or misinterpretation of the candidate's abilities, potentially affecting the outcome of the evaluation.

After the candidate's data has been distributed appropriately, the system enters a critical phase where the candidate's technical skills are evaluated. This phase is represented in the diagram by a diamond-shaped decision point labeled "Candidate passes the technical test?" Here, the system must determine whether the candidate possesses the necessary technical expertise to proceed further in the process. The nature of this technical test could vary significantly depending on the role for which the candidate is being assessed. For example, it might involve coding challenges, problem-solving exercises, or practical tasks that mimic the types of work the candidate would be expected to perform on the job.

The decision-making process at this stage is binary and straightforward: if the candidate fails the technical test, the system immediately generates a "FAILED" status, which is then recorded in the **Candidate Database**. This outcome indicates that the candidate has not met the minimum technical requirements necessary for the role, and as a result, they are no longer considered for further stages of the assessment. This immediate termination of the process for unqualified candidates ensures that only those who have the requisite skills continue, streamlining the process for both the candidates and the evaluators.

On the other hand, if the candidate successfully passes the technical test, the system proceeds to the next phase of evaluation. This positive outcome is also recorded in the database, ensuring that the candidate's progress is meticulously tracked. The transition from technical assessment to the next stage is crucial, as it reflects the candidate's ability to meet the core technical demands of the role. Passing this test indicates that the candidate has a solid foundation in the technical skills required and is ready to be evaluated on other important factors, such as their ability to handle stress and their emotional resilience.

The decision point here is a fundamental component of the system, as it acts as a filter that separates those candidates who have the necessary technical skills from those who do not. This filtering mechanism helps maintain a high standard within the recruitment process, ensuring that only the most capable candidates are considered for the position. Furthermore, by automating this decision-making process, the system can quickly and efficiently handle a large number of candidates, making it scalable and adaptable to different recruitment needs.

Once the candidate has passed the technical assessment, they enter a more nuanced phase of the evaluation process, where the focus shifts to analyzing their emotional and psychological responses under stress. This phase is represented in the diagram by a section labeled as a **Gamified Environment**. In this context, "gamified" refers to the use of game-like elements and mechanics to create an engaging and immersive environment where candidates can be assessed in a more dynamic and interactive manner. This approach is particularly effective in evaluating how candidates perform under pressure, as it simulates real-world scenarios that require quick thinking, problem-solving, and emotional resilience.

Within this gamified environment, the candidate is likely subjected to a series of tasks or challenges that are designed to test their ability to manage stress while still performing effectively. These tasks might involve time-sensitive puzzles, problem-solving exercises, or decision-making scenarios where the candidate must balance multiple competing priorities. The goal here is not just to assess the candidate’s technical abilities but also to observe how they handle the stress and pressure that often accompany challenging situations.

The system uses advanced technologies to monitor the candidate's emotional state throughout these tasks. For example, OpenCV, an open-source computer vision and machine learning software library, might be used to track and analyze the candidate’s facial expressions in real-time. By doing so, the system can detect subtle changes in the candidate’s emotional state, such as signs of anxiety, frustration, or confidence. This data is invaluable in assessing the candidate’s emotional intelligence, which is a key factor in determining how well they might perform in a high-pressure work environment.

The system categorizes the candidate's stress levels into three distinct levels: low, moderate, and high. This categorization allows for a more granular analysis of the candidate’s emotional responses, providing deeper insights into how they might react in different situations. For instance, a candidate who consistently shows low stress levels might be seen as calm and composed, while one who frequently exhibits high stress might be perceived as less capable of handling pressure. The use of a gamified environment, combined with real-time emotional analysis, represents a sophisticated approach to candidate evaluation that goes beyond traditional testing methods.

The diagram indicates the use of Firebase, a platform developed by Google for creating mobile and web applications, which is likely used to handle the backend processes, such as storing real-time data from the gamified environment. This integration ensures that all the data collected during the emotional analysis is securely stored and can be accessed later for review or comparison with other candidates.

After the candidate has completed the gamified assessment, the system moves into the final stage of the evaluation process. Here, the candidate’s overall performance, which includes both their technical skills and their ability to manage stress and emotions, is thoroughly evaluated. The system aggregates all the data collected during the previous stages, including technical test results, stress level analysis, and emotional responses, to make a final determination about the candidate’s suitability for the role.

This stage is represented in the diagram by another decision point, which determines whether the candidate has passed or failed the overall assessment. If the candidate meets all the required benchmarks, they are marked as "PASSED." This outcome indicates that the candidate not only possesses the necessary technical skills but also demonstrates the emotional resilience and stress management capabilities that are essential for success in the role. The "PASSED" status is then recorded in the Candidate Database, and the candidate may be considered for further steps in the recruitment process, such as interviews or job offers.

If the candidate does not meet the necessary criteria, they are marked as "FAILED." This outcome suggests that the candidate, while perhaps technically competent, may not have demonstrated the emotional stability or stress management required for the position. The "FAILED" status is also recorded in the database, and the process concludes for that candidate. This final evaluation ensures that only those candidates who are well-rounded in both technical and emotional aspects are selected, which helps in building a strong and capable workforce.

The result generation step is critical as it encapsulates the entire evaluation process into a single, actionable outcome. By automating this process, the system can quickly and efficiently determine the best candidates from a pool of applicants, making the recruitment process more effective and reducing the time required to identify top talent.

This figure 1 diagram represents a highly sophisticated candidate evaluation system that leverages both traditional technical assessments and modern, gamified methods for stress and emotional analysis. By integrating these diverse evaluation techniques, the system provides a comprehensive understanding of each candidate's capabilities, ensuring that only the most qualified and well-rounded individuals are selected. This approach not only improves the quality of hires but also enhances the overall efficiency of the recruitment process, making it more scalable and adaptable to different organizational needs.

3.1.1 Software Solution

In the ever-evolving landscape of recruitment, the demand for effective candidate assessment methods, especially in high-stress industry environments, is paramount. Traditional interviews and technical assessments often fail to capture a candidate's ability to perform under pressure, which is crucial in many roles. This necessitates a novel approach, one that not only evaluates technical skills but also measures emotional resilience. The software solution proposed in this section aims to bridge this gap by developing a gamified environment that assesses both problem-solving abilities and stress levels through real-time facial expression analysis. This approach leverages the principles of the Software Development Life Cycle (SDLC) while embracing agile methodologies to ensure adaptability and responsiveness to changing requirements.

1. Requirement Gathering

The first phase of the SDLC in this agile-based approach involves **requirement gathering**, where the primary goal is to understand the specific needs of the system. For this project, the requirements focus on two key aspects: the technical skills to be assessed and the emotional responses to be measured. Information was collected through a series of meetings with industry experts and stakeholders, including HR professionals and psychologists, to determine the types of technical problems that would be most effective in a gamified setting and the emotional cues that need to be recognized for stress analysis. These discussions highlighted the necessity of integrating a facial expression analysis tool like OpenCV to measure real-time stress levels, as well as using

Unity to create an immersive gamified environment. This phase ensures that the project's objectives are clearly defined and aligned with the stakeholders' expectations [34].

2. Feasibility Study (Planning)

Once the requirements are gathered, the next step in the agile SDLC is to conduct a feasibility study, which includes planning for various aspects of the project. This phase evaluates whether the proposed solution is viable from economic, technical, and scheduling perspectives.

- Economic Feasibility: The economic feasibility of this project focuses on the cost-benefit analysis of developing a gamified assessment tool. The system is designed to be cost-effective by utilizing open-source technologies like OpenCV for facial recognition and stress analysis, and Unity for the development of the gamified environment. The use of these technologies ensures that the development costs are kept low while providing a high return on investment in terms of the quality of candidate assessment [35].

- Technical Feasibility: This aspect evaluates whether the technical requirements for developing the system can be met with the available resources. The project necessitates expertise in software development, particularly in game development with Unity and facial recognition using OpenCV. Additionally, knowledge in deep learning techniques is crucial for categorizing stress levels based on facial expressions. The technical feasibility study concluded that the project could proceed, as the necessary skills and technologies are available within the development team [36].

- Scheduled Feasibility: The schedule feasibility involves determining whether the project can be completed within the allotted time frame. Given the agile approach, the project is divided into sprints, each focusing on different aspects of the system, such as integrating facial recognition, developing the gamified environment, and testing the system. This iterative approach ensures that any issues or changes in requirements can be addressed promptly, keeping the project on track for timely completion [37].

3. Design (System and Software Design Documents)

Following the planning phase, the design phase begins, where both system and software design documents are created. These documents outline the architecture of the proposed system and detail how each component will interact within the overall framework.

- System Design: The system design focuses on the high-level architecture, including the integration of Unity for the gamified environment and OpenCV for real-time facial expression analysis. The design document specifies how data flows through the system, from the candidate's interaction with the gamified environment to the analysis of their facial expressions and the categorization of their stress levels [38].

- Software Design: The software design document provides a more detailed view, including the algorithms used for facial recognition and stress analysis, the structure of the game environment, and the user interface design. This phase also involves creating mockups and prototypes to visualize the final product and ensure that it meets the user requirements outlined in the initial phase [39].

- Sequence Diagram

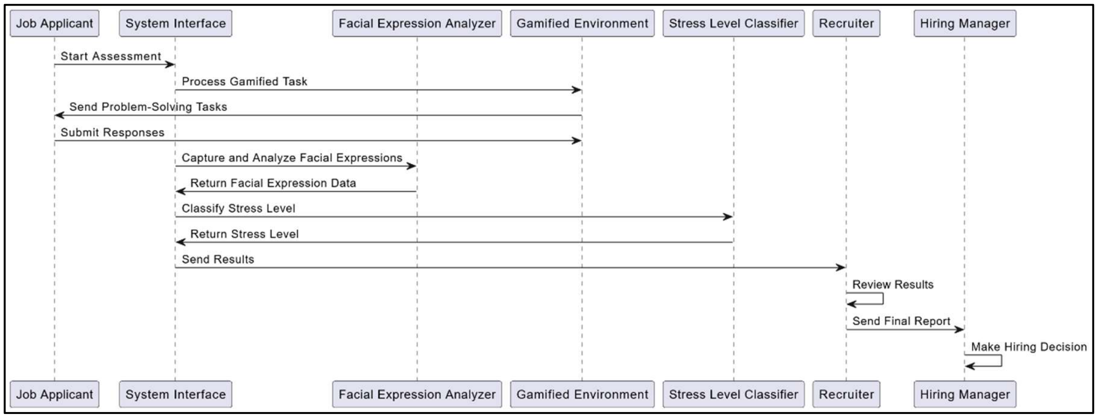

Figure 2 : Sequence Diagram

- Use Case Diagram

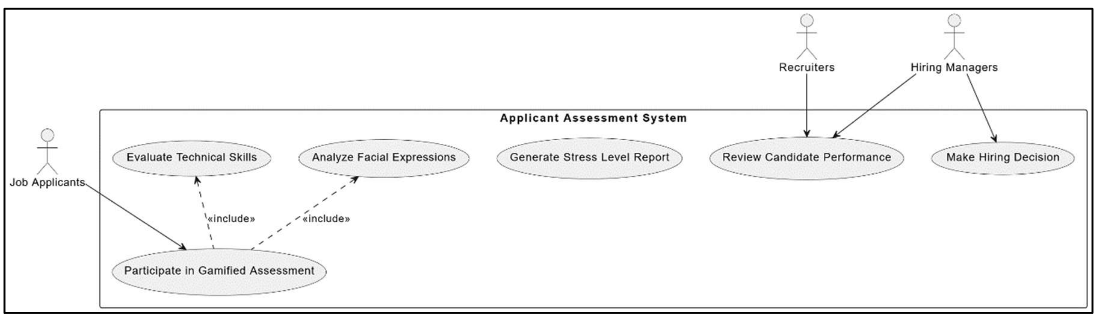

Figure 3 : Use case diagram

4. Development and Testing

Once the design is finalized, the development phase begins, where the actual coding and integration of various components take place. The agile methodology emphasizes continuous integration and testing throughout this phase to ensure that each sprint produces a functional and testable product.

- Development: The development process follows an agile framework, specifically Scrum, where the project is divided into several sprints. Each sprint focuses on different functionalities, such as integrating OpenCV for facial expression analysis, developing the game scenarios in Unity, and implementing the algorithms for stress categorization. Regular stand-up meetings are held to track progress, address any blockers, and ensure that the development stays aligned with the project goals [40].

- Testing: Testing is conducted in parallel with development, with each sprint producing testable outputs. Unit tests are written to verify the functionality of individual components, while integration tests ensure that the various parts of the system work seamlessly together. The final product undergoes rigorous stress testing using real-world scenarios to validate the accuracy of stress level categorization and the effectiveness of the gamified environment in evaluating technical skills under pressure [41].

5. Deployment and Maintenance

After successful development and testing, the system is deployed in a controlled environment, typically within a beta phase, to gather feedback from real users. This phase is crucial in identifying any final adjustments needed before a full-scale rollout.

- Deployment: The deployment phase involves releasing the system to a select group of users, such as HR professionals or recruitment agencies, who can provide valuable feedback. This feedback is used to make any necessary adjustments or improvements to the system, ensuring that it performs optimally in a real-world setting [42].

- Maintenance: Once deployed, the system enters the maintenance phase, where it is monitored for any issues or bugs that may arise. The agile methodology allows for continuous updates and improvements, ensuring that the system remains effective and up-to-date with the latest technologies and requirements. Regular maintenance cycles are scheduled to address any issues and to implement new features as needed [43].

The proposed software solution leverages the agile methodology within the SDLC framework to develop a comprehensive system that evaluates both technical skills and emotional resilience through gamification. By combining the strengths of OpenCV for real-time facial expression analysis with Unity's immersive environment, this system provides a more holistic approach to candidate assessment, addressing the shortcomings of traditional methods and offering a more accurate measure of a candidate's ability to perform under pressure.

3.1.2 Technologies , Algorithms and Techniques

3.1.2.1 Technologies

- ReactJS: For developing the front-end of the system where candidates interact with the gamified environment.

- Python: The primary language for backend development, including the implementation of deep learning models and real-time facial expression analysis.

- TensorFlow: A deep learning framework used to build and train neural networks for stress detection and emotion recognition.

- Firebase: A backend-as-a-service (BaaS) platform to handle real-time data storage and retrieval, particularly for managing candidate data and results.

- Unity: A game development platform to create the gamified environment that candidates will interact with.

- OpenCV: A computer vision library used for real-time facial expression analysis to assess candidates' stress levels.

3.1.2.1 Algorithms

- **Convolutional Neural Network (CNN): A deep learning architecture used for image recognition and classification, particularly in analyzing facial expressions to detect stress levels.

3.1.2.2 Techniques

- Transfer Learning: Leveraging pre-trained models to enhance the accuracy of the stress detection model, especially when dealing with limited data.

- Data Augmentation: Enhancing the training dataset by creating variations of the existing data to improve the robustness of the deep learning models.

This structure aligns well with the goal of creating an integrated system for technical skill and emotional resilience assessment in a gamified setting.

3.1.3 Commercialization

The proposed software solution is designed to address a critical need in the recruitment industry by providing a more comprehensive and accurate assessment of candidates' technical skills and emotional resilience under stress. This innovative approach leverages gamification, real-time facial expression analysis, and deep learning techniques to evaluate problem-solving abilities and categorize stress levels. As the system development progresses, it opens up several avenues for commercialization, targeting various sectors that prioritize both technical expertise and the ability to perform under pressure.

The commercialization strategy involves two main versions of the software:

1. Basic Version: The basic version of the system will be made available to companies and recruitment agencies looking for a more engaging and effective way to assess candidates. This version will offer the core features, including problem-solving assessments within a gamified environment and basic stress level detection using facial expression analysis. This version provides organizations with a cost-effective solution to enhance their recruitment processes and gain deeper insights into candidates' capabilities.
2. Premium Version: The premium version of the system will include advanced features, such as detailed stress level analytics, personalized reports, and customizable game scenarios tailored to specific industries or job roles. This version will appeal to organizations that require a higher level of detail and customization in their recruitment assessments. The premium version will be offered as a subscription-based service, with additional modules and features available as add-ons, allowing organizations to scale the system according to their needs.

The software's commercialization will be driven by partnerships with HR consulting firms, recruitment platforms, and large enterprises that regularly hire for high-stress roles. Additionally, the system can be marketed to educational institutions for use in mock assessments and career counseling sessions. The scalability of the system allows for its application across various industries, including technology, finance, healthcare, and more, making it a versatile tool for both recruiters and educators.

3.1.3.1 Future Scope

The system has significant potential for expansion and enhancement. The future scope of this project includes the following developments:

1. Integration with Biometrics: Beyond facial expression analysis, future versions of the system could integrate biometric data, such as heart rate and skin conductivity, to provide

a more comprehensive assessment of a candidate's stress levels. This multi-modal approach would enhance the accuracy of stress detection and offer deeper insights into a candidate's emotional resilience.

2. Expansion to Other Cognitive and Emotional Metrics: The system could be expanded to assess additional cognitive and emotional metrics, such as decision-making speed, adaptability to change, and emotional intelligence. This would further enrich the assessment process and provide a more holistic view of a candidate's capabilities.
3. AI-Powered Adaptive Learning: Future iterations of the system could incorporate AI-powered adaptive learning, where the game scenarios dynamically adjust based on the candidate's performance and stress levels. This would create a more personalized and challenging assessment experience, allowing recruiters to observe how candidates handle progressively difficult tasks under varying levels of stress.
4. Industry-Specific Customization: As the system gains traction, there is potential to develop industry-specific modules tailored to the unique requirements of sectors like finance, healthcare, or defense. These modules would include specialized game scenarios and stress metrics relevant to the demands of each industry, making the system even more valuable to targeted markets.
5. Global Market Expansion: With localization and language support, the system can be expanded to global markets, allowing organizations worldwide to benefit from this innovative recruitment tool. Partnerships with international recruitment agencies and HR platforms would facilitate the system's adoption across different regions and industries.
6. Research and Development Collaborations: Ongoing collaboration with academic institutions and research organizations could lead to the continuous improvement of the system's algorithms and assessment techniques. This would ensure that the system remains at the forefront of recruitment technology, incorporating the latest advancements in AI, machine learning, and behavioral science.

By strategically commercializing the current system and planning for future enhancements, this project has the potential to become a leading tool in the recruitment industry, offering unparalleled insights into candidates' abilities to perform under pressure and adapt to challenging environments.

4. PROJECT REQUIREMENTS

4.1 Functional Requirements

1. Real-Time Facial Expression Analysis

The system should capture and analyze candidates' facial expressions in real-time during their interaction with the gamified problem-solving tasks.

2. Stress Level Categorization

The system should accurately categorize detected stress levels into predefined categories (low, moderate, high) based on the facial expression data.

3. Gamified Problem-Solving Environment

The system should present and manage engaging problem-solving activities within a gamified environment developed using Unity, ensuring tasks are relevant to assessing technical skills.

4. Comprehensive Performance Evaluation

The system should record and evaluate candidates' technical problem-solving performance alongside their emotional resilience data, integrating both metrics to provide a comprehensive assessment report to recruiters.

4.2 Non-Functional Requirements

1. User-Friendliness

The system should offer an intuitive and engaging interface for both candidates and recruiters. It should ensure ease of navigation, clear instructions, and an immersive experience within the gamified environment and assessment dashboards.

2. Reliability

The system should consistently perform accurate real-time facial expression analysis and maintain seamless operation of the gamified environment without crashes or errors. It should ensure dependable performance throughout the assessment process.

3. Performance

The system should process real-time facial data and render the gamified environment efficiently, ensuring quick responsiveness and minimal latency. This is crucial to maintain user engagement and provide timely feedback during assessments.

4. Security

The system should protect all sensitive candidate information, including facial images and assessment results, through robust encryption and secure data storage practices. It must comply with relevant privacy regulations to ensure data integrity and user trust.

This structured approach ensures that the system not only meets its core functional objectives but also adheres to essential non-functional standards, providing a reliable, efficient, and user-centric solution for candidate assessment in high-stress industry environments.

4.3 System Requirements

The purpose of software requirements is to define the necessary software resources that must be implemented on a system to ensure that the proposed candidate assessment system functions properly.

1. ReactJS and Expo: To create a responsive and cross-platform front-end interface for both web and mobile users, allowing candidates to interact with the gamified assessment environment.
2. Keras and TensorFlow : To develop, train, and deploy deep learning models used for facial expression analysis and stress level categorization.
3. Visual Studio Code (VS Code): To implement and manage the development of the front-end, back-end, and machine learning models using Python and JavaScript.
4. OpenCV: To perform real-time facial expression analysis, capturing and processing candidate facial data during their interaction with the gamified tasks.
5. Flask: To serve as the back-end framework for running and managing the facial expression analysis models, processing data, and handling requests between the front-end and the server.
6. Firebase: To manage real-time data storage and retrieval, ensuring that candidate data and assessment results are securely stored and easily accessible for analysis.
7. Unity: To create and manage the gamified problem-solving environment, providing an engaging platform for candidates to demonstrate their technical skills under simulated stress conditions.
8. Node.js Server: To facilitate communication between the ReactJS front-end, Flask back-end, and Unity environment, ensuring a seamless integration of the different system components and real-time data synchronization.

This combination of tools and technologies will ensure that the system is robust, efficient, and capable of providing accurate and comprehensive assessments of candidates' technical and emotional skills in high-pressure situations.

4.4 User Requirements

This candidate assessment system will be developed for three types of users:

1. Job Applicants

Job applicants will use the system to participate in a gamified assessment environment where they can demonstrate their problem-solving skills. While engaging in the tasks, the system will also analyze their facial expressions in real-time to assess their stress levels. Applicants will receive feedback on both their technical performance and emotional resilience, helping them understand their strengths and areas for improvement.

2. Recruiters

Recruiters will use the system to evaluate candidates' performance in both technical skills and emotional resilience. The system will provide detailed reports, including categorized stress levels and problem-solving scores, enabling recruiters to make informed decisions about candidates' suitability for high-pressure roles. Recruiters can also compare candidates' performance metrics to identify the best fit for their organizational needs.

3. Hiring Managers

Hiring managers will use the system to review summarized data and insights provided by recruiters on candidate assessments. They will be able to view overall candidate rankings, specific stress responses during problem-solving tasks, and how each candidate's emotional resilience correlates with their technical performance. This information will assist in making final hiring decisions and in understanding how candidates might perform under real-world pressures in the workplace.

This multi-user system ensures that the needs of all stakeholders in the hiring process are met, from initial candidate assessment to final decision-making, by integrating both technical and emotional performance metrics into the evaluation process.

5. GANTT CHART

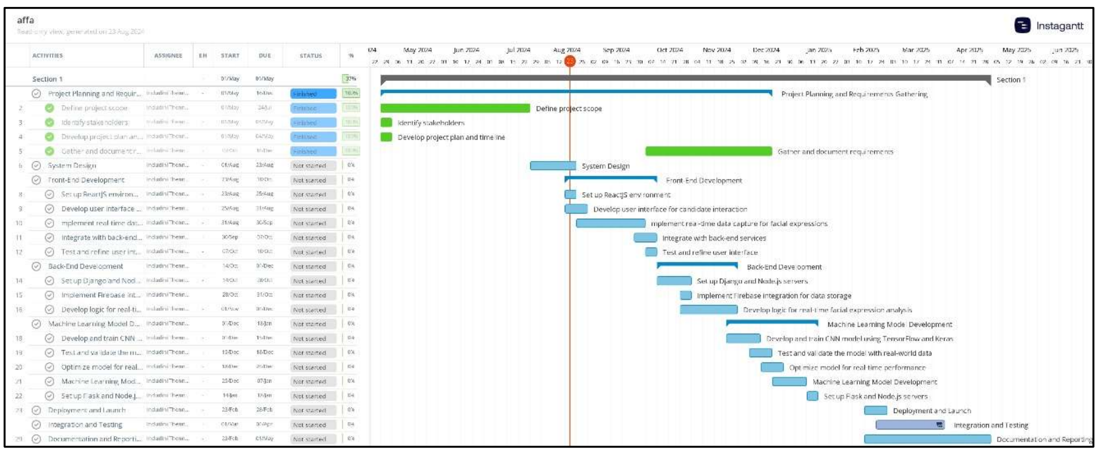

Figure 4: Gantt Chart

[Gantt Chat]

6. Work Breakdown Chart

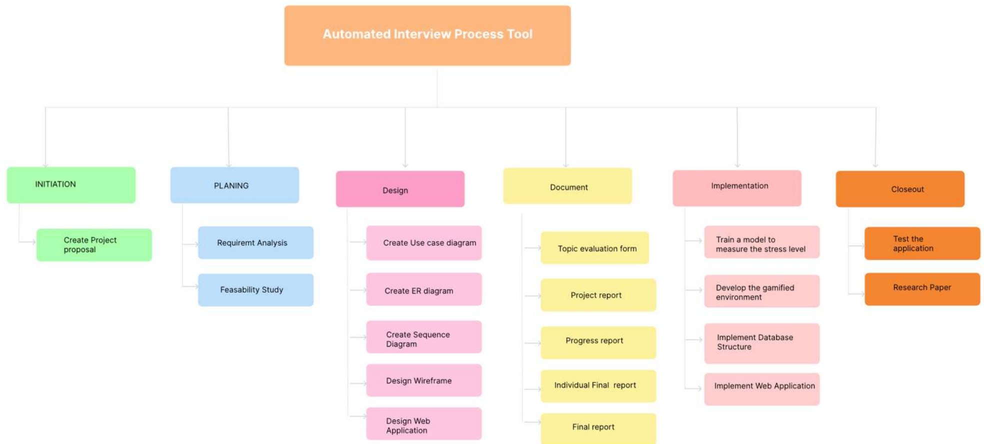

Figure 5: Work breakdown chart

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Automated Interview Processing System

24-25J-047

Project Proposal Report

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B.Sc. (Hons) Degree in Information Technology Specialized in Information Technology

Department of Information Technology

Sri Lanka Institute of Information Technology

Sri Lanka

July 2024

DECLARATION

I declare that this is my own work and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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Signature of the Supervisor
(Dr.Dilshan De Silva)

23/08/2024
Date

Signature of the Co-Supervisor
(Ms. Poojani Gunathilake)

23/08/2024
Date

ABSTRACT

In this respect, the rapidly changing labor market brings new and quite unforeseen challenges to the recruiting process, particularly in remote work and digital transformation. The more so that it will be incumbent to develop more sophisticated and comprehensive assessment tools, while video-based assessments are replacing face-to-face interviews. Fragmented techniques describe today's state of art for video interview evaluation: discrete instruments are in use to analyze separately contextual elements, verbal replies, or non-verbal clues. The effect of this lack of integration on hiring choices can be huge and result in incomplete, maybe biased, assessment of prospects.

The present project is set out to design a fully comprehensive video-based examination system for testing the performance of individuals in all-inclusive face-to-face mode. This system works towards filling up the missing links in hiring by using state-of-the-art machine learning and artificial intelligence technology to present a comprehensive assessment framework. The proposed system will incorporate Natural Language Processing to check the sentiment, coherence, and substance of the applicants' replies. This would prove very useful in gaining insight into the cognitive and verbal communication abilities of the candidates.

The suggested system will utilize speech analysis along with NLP to determine voice tone, fluency, and stress levels. This section of the assessment is of critical importance in evaluating how the candidate projects himself under distress, an indicator of his suitability for an interaction-intensive role. The system shall further infer through computer vision algorithms its body language, gestures, and facial expressions. One of the most powerful aspects of human interaction is non-verbal communication—most often carrying even more meaning than spoken words themselves. All these indicators will be gathered and examined so as to give a better insight into the technology regarding the candidate's emotional state, level of confidence, and involvement throughout the interview.

This methodology is unique as it focuses on the environment factors that often are ignored in many assessment tools. The environment of a video interview makes a lot of difference in how well a candidate can perform and how accurate the assessment is. Some factors that may introduce biases and obscure results include background noise, lighting, and internet connectivity. To address such problems, and thereby reduce the number of biased appraisals, the proposed method will include environmental assessments. Another critical element is the system's ability to appraise professionalism.

Professionalism is an elementary attribute required in most employment and more so in those that one works directly with clients or in a leadership capacity. This holistic approach will provide a more realistic and fuller picture of the candidate's fit for a position. The proposed approach will also be easy to use and scale for organizations that need to process a large number of candidates

within a short period. In the case of traditional methods of assessment, if issues of scalability prevail, that entails inconsistent results and higher administrative workloads. Powered by the power of cloud computing and parallel processing techniques, this system is capable of processing large amounts of data without affecting the reliability and correctness of the evaluations. Thus, it is with this in mind that this project has the goal of developing a video-based mock-up exam system that would significantly revolutionize the hiring process with a more comprehensive, objective, and scalable way of measuring the applicants.

Given the promise of such a merged range, this system provides ways of assessment that are holistic—ways in which a wide range of performances are exhibited by applicants during interviews. This is through the combination of NLP, computer vision, voice analysis, and environmental evaluations in one platform.

This, in the long term, would help companies to make better recruiting decisions and would be beneficial for both candidates and employers.

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LIST OF ABBREVIATIONS

ERP	Enterprise Resource Planning
NLP	Natural Language Processing
API	Application Programming Interface
GDPR	General Data Protection Regulation
SSL/TLS	Secure Sockets Layer/ Transport Layer Security
UI/UX	User Interface/ User Experience

1. INTRODUCTION

1.1 Background Literature

The recruitment landscape has undergone a sea change, all the more recently with this huge surge in remote work. Video interviews provide unique opportunities to bring in variation in supplementing or even replacing the traditional face-to-face interview. For instance, video interviews increase expediency and widen the search, but inherently have limits in the comprehensiveness of the candidate evaluation.

The literature has bossed a few ways to improve the interview process using AI and machine learning. The content coherence, relevance, and sentiment of what the respondents describe in those responses are analyzed using NLP techniques. It has developed speech analysis tools that can measure verbal fluency, tone, and stress levels of candidates, thereby demonstrating their communication skills. Additionally, it has implemented computer vision techniques to identify facial expressions, gestures, and postures—all of which are very important parts of a candidate's non-verbal communication.

Despite all these developments, existing systems typically have one major flaw: integration missing across these varied dimensions of assessment. Most of these tools are built to work for an aspect of the interview, be it speech or facial expressions, in which these things don't end up interacting to present an all-rounded view of the candidate. Moreover, rarely is the effect of the interview environment taken into account in the assessment process itself: light conditions, background noise, and internet connectivity. It is a wide gap, since the factors of the environment can affect the appearance of the candidate and do impact the perception by the assessor.

Previous Studies and Their Limitations

While some research has provided the basic foundation of automated interview assessment, it usually lacks elements that capture holistic evaluation. For instance, Zhang et al. (2022) proposed a framework that utilized natural language processing and deep learning techniques to score candidate responses based on content; however, non-verbal cues and environmental factors were not reflected. The system developed by Kim and Park focused on facial expression analysis for emotion detection during an interview, but this was not integrated with other assessment dimensions like speech and content analyses.

These studies again have their own limitations, thereby making a holistic approach imperative in this regard. This paper proposes an integrated system in which the powers of NLP, speech analysis, computer vision, and environmental assessments are harnessed together in order to better judge a candidate during a video interview.

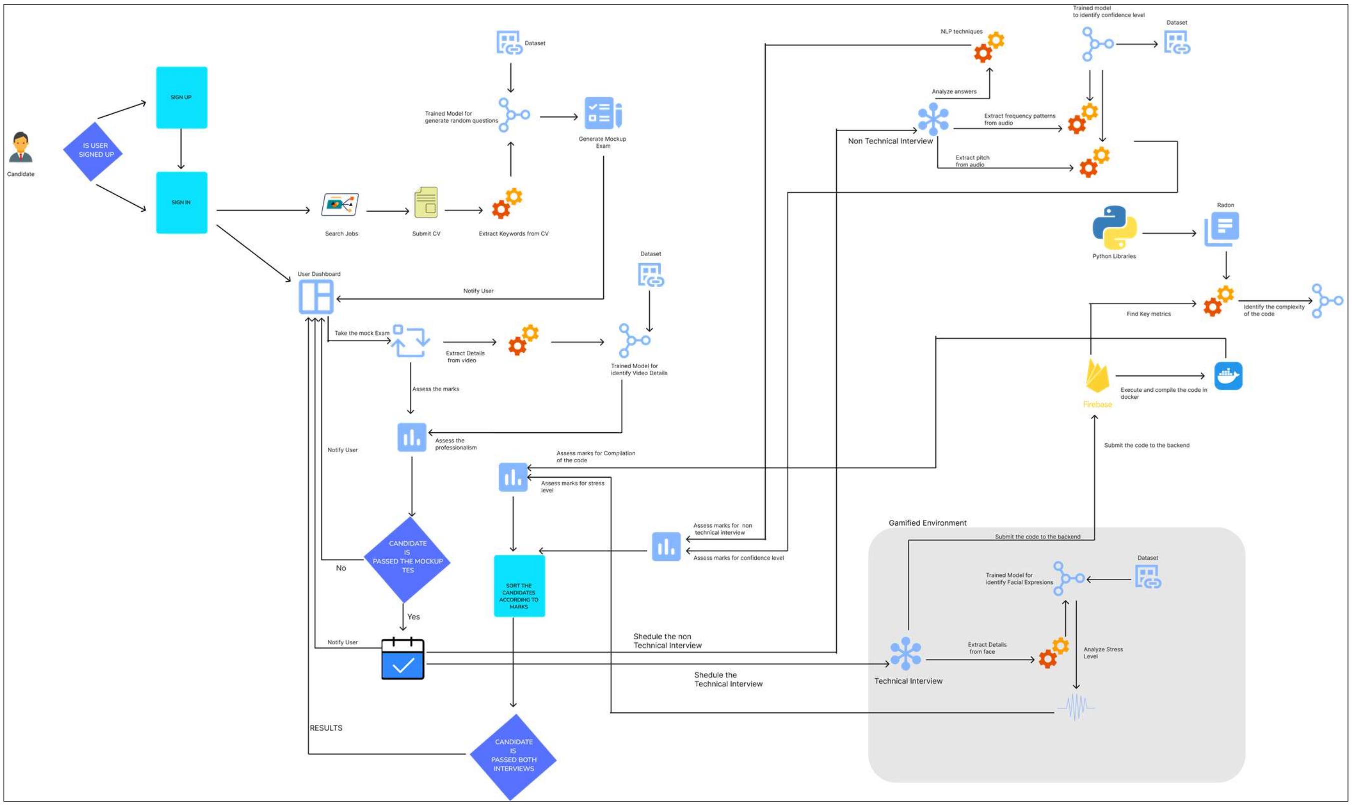

Figure 1: Key components of the system

https://www.figma.com/design/IbZwmLPfCOaIXyGP8RwexP/RESEARCH?node-id=5-30&t=2STU5AWbzWwoIjG5-1

1.2 Research Gap

While some parts of the automated interview assessment, such as Natural Language Processing, speech analysis, and computer vision, have made huge headway in highly circumscribed domains all on their own, stitching them all together into one system and making sure it can evaluate a candidate inside and out is quite another. Current systems almost without exception focus on a single element of the interviewing process, be it in the verbal response or nonverbal cue, without regard for how these interact to create a composite picture of the suitability of a candidate to any given position.

Furthermore, the environmental context in which a video interview is conducted has rarely been taken into consideration. This ranges from background noise to lighting conditions and finally, the strength and stability of the internet connection, all of which may affect both the candidate's performance and the quality of assessment. An example is poor lighting, which can lower the accuracy of facial expression analysis, or the influence of background noise on speech recognition algorithms.

The following table contrasts the proposed function of this study with previous research efforts, indicating the identified research gaps.

Reference	**Research Paper 1**	**Research Paper 2**	**Research Paper 3**	**Proposed Function**
Skills Extraction from CV.	✓	✓	X	✓
Generate questions related to extracted skills.	✓	X	X	✓
Use of video based mock-up tests.	X	✓	X	✓
Evaluation of professionalism and working environment using Machine learning.	X	✓	X	✓
Rating skills of candidate automatically.	X	X	✓	✓

Table 1: Comparison of previous researches

1.3 Identification of Key Gaps:

Most of the automated interview processing systems today operate independently on very granular aspects of speech analysis, natural language processing, or computer vision, without integrating these dimensions for arriving at an overall assessment. This fragmented approach misses the key interplay between verbal and non-verbal cues that's necessary for the holistic appraisal of a candidate. For instance, speech patterns that are taken out of context - the corresponding facial expressions or gestures that give complete meaning - are bound to result in partial or even wholly inaccurate interpretations of a candidate's response. A more robust system would need to tie these various components together in order to present a fully contextualized assessment.

What most of the existing tools often forget, however, is the environment in which the video interview takes place - and this may affect not just the performance of the candidate but also the accuracy of the assessment. Background noise, light, and other general setting conditions may introduce a number of biases that will distort the assessment. Most of the current systems, however, tend to forget such environmental variables and hence end up assessing candidates in ways that may not show their real potential. These are the factors to be taken care of so that candidates are judged based on their qualifications and ability and not by some external conditions that lie beyond their control.

The other critical factor in candidate evaluation is behavioural analysis, to which most of the respondent tools seem to respond inadequately. Although some of the tools consider facial expressions and gestures, most of them do not capture wider behavioural patterns that may arise during a job interview. This narrow focus limits its ability to yield nuanced insight into how such a candidate might perform in a real-world job setting. In effect, behavioural analysis must involve multi-faceted indicators, such as body language, eye contact, and overall demeanour, so that a more complete view concerning a candidate's suitability for a role can be built.

Not least important is the significant concern with regard to scalability and usability for most of the existing systems. Most of these systems either do not have processing capability for vast numbers of candidates or are unwieldy integrations into the present workflow of HR, hence reducing their usability for practical recruitment scenarios. More specifically, especially in larger organizations, scalability and ease of use stand out as a definite need. It will enhance not only the efficiency of the hiring process, but also accuracy and relevance in assessments.

1.4 Research Problem

The traditional recruitment process has so many problems in trying to gauge the ability of a candidate, especially in a remote setting. The convenience by video interviews is effective, but most of these times, it does not bear fruits due to lacunae or discrepancies with the available assessment tools. Usually, such tools focus on one aspect of the interview process, such as the content of speech or facial impressions, without providing the overall evaluation, including nonverbal communication, environmental factors, and general professionalism.

Key Issues:

Facial expressions, gestures, and body language—major constituents of nonverbal communication - are individual components of every conversation. Most automated assessment systems take little account of them. Therefore, if their evaluation goes wrong with these non-verbal elements, an incomplete perception of the candidate will result in biased hiring decisions. Not considering these subtle yet telling facets of communication may mean that candidates get screened out because their fit for the role is not realized - essentially, it compromises fairness and accuracy in hiring.

One can also find major determinants of video interview results within environmental factors, yet they often remain uncontrolled for in most existing systems. Poor lighting, a noisy background, or an unstable Wi-Fi connection can all skew the assessment for an unfair evaluation. These factors can affect the performance of a candidate, thereby creating biases that alter the results. Considering such environmental factors is quite important in ensuring that each candidate is evaluated based on a fair and consistent setting.

The second area in which current tools are deficient is in their inability to evaluate the professionalism of a candidate, which is quite important when relating to clients or even leadership roles. Most systems focus narrowly on technical skills or the content of interview responses and forget that how a candidate presents himself actually matters. Professionalism is about how, not what; it is not what a candidate says, but how they say it with regards to demeanor and confidence, having the ability to engage effectively. What would be more of a complete and holistic profiling system for candidate role suitability would be a system that allows assessment of not just what he responds with but also how it is delivered.

The other major challenge that most recruitment tools face is in regard to scalability, which is quite relevant when dealing with a huge pool of candidates. For any company to be competitive, especially in those industries where the best talent is in high demand, the ability to efficiently screen through hundreds or even thousands of applicants is important. Too many of the myriad systems in use today fall short on delivering the consistency and quality needed in their evaluations over such a large pool of applicants. What is needed in modern recruitment is a solution that is scalable enough to manage such volumes without having to compromise on the quality of the evaluation process.

2. OBJECTIVES

2.1 Main objective

Design a comprehensive system that will allow video-based mock-up tests to be used in evaluating the acumen of candidates in an objective way, apart from their grooming, professionalism, and working environment—thereby giving a holistic evaluation of their suitability for a particular role.

2.2 Sub objective

The key components of developing a comprehensive candidate evaluation system are the identification of relevant skills and generation of personalized test questions. These important skills may be extracted from the résumé or CV of the candidate using techniques from NLP, guaranteeing that what is constructed will be relevant and specific to the profile of a qualification the candidate has. It will then generate mock-up test questions based on the identified key skills, thereby personalizing the test to ensure that relevant areas are covered. This not only makes the mode of evaluation more accurate but also ensures that the candidates are tested over competencies most relevant to them vis-à-vis the applied role.

Machine learning and video analysis are another important modules of this system. It assesses the candidates with a video response to questions that utilize machine learning algorithms in picking areas on grooming, professionalism, and working environment. Computer vision techniques have been applied in the analysis of frames from a video so as to give insight into the candidate's presentation and the environment in which they are situated. Advanced analysis, such as this, will allow for the capturing of both verbal and non-verbal elements—usually not observable through traditional assessment methods—to provide a more holistic overview of the candidate's performance.

In order to achieve effectiveness, there needs to be a comprehensive process of validation for the system. The integrated assessment system will generate some outcomes that will be compared with those generated by traditional interview processes, which can act as a benchmark for accuracy and reliability. Through feedback from users and some performance metrics, the continuous refinement of the system in terms of accuracy and dealing with problems that occur while under test is processed. This way, the system maintains its reliability and effectiveness.

System design also considers user experience and scalability. The interface shall be user-friendly, providing smooth interaction between the candidates and the evaluation system. Optimal user experience is central to quickening adoption and ensuring ease of passage through the evaluation process by candidates. Moreover, the system should be such that it scales effortlessly to Enlarge the candidate count without loss of performance. In the growth of a system, high levels of accuracy and efficiency need to be maintained in order to meet larger organizations' demands, together with their more extensive candidate pools.

3. METHODOLOGY

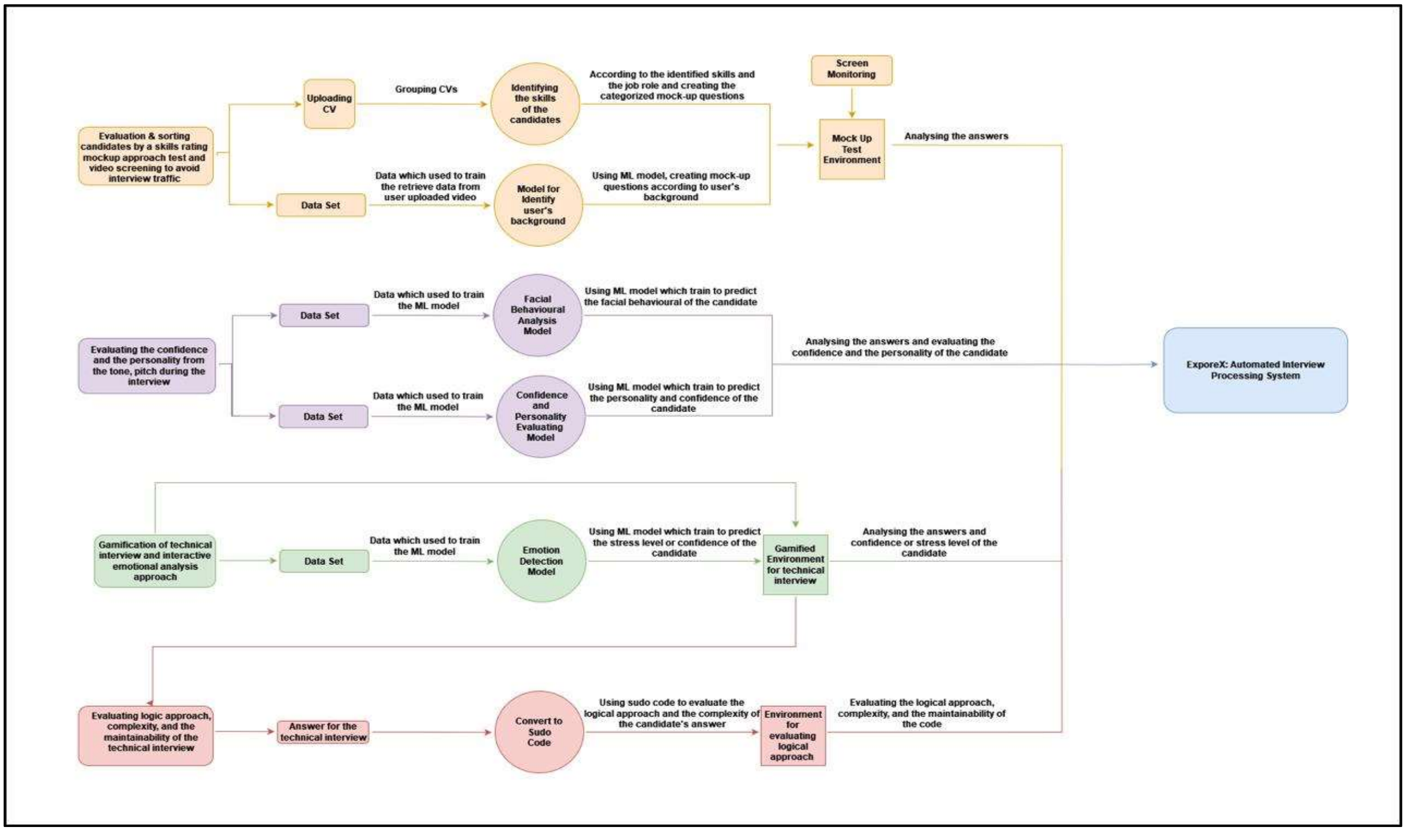

Figure 2: System Diagram for Automated Interview Processing System

The overall process flow of ExproeX is manifested in the system diagram above: Automated Interview Processing System. It will automate processes concerning candidate evaluation and selection through structured and data-driven methods. This methodology, being multi-staged, shall comprise machine learning models and real-time data analysis to prove effectiveness and accuracy in candidate assessment.

It all starts with the uploading of a CV and identification of the skill set for the candidate evaluation process. Candidates upload their respective résumés into the system, which undergo filtration on different aspects, such as qualification and experience, to consider only relevant profiles. The system, equipped with a machine learning model, maps the uploaded CVs against the job requirements and extracts important skills. This extracted information then forms the basis for further profiling, as the same will be trained into models that are capable of logging additional information from videos the candidates upload, therefore enriching the candidate profile with fuller insights.

The system then enters the mock-up test environment. Within this environment, candidates are tracked for authenticity as the system generates personalized mock-up questions that cater specifically to the candidate's identified skills and job role. The responses are instantaneously analyzed for the candidate's technical knowledge and proficiency, and feedback on performance is instant. This dynamic, personalized way of testing allows the system to measure the ability of the candidate in a very work-related manner.

Facial behavioral analysis and confidence evaluation further deepen the system. A career specialist model, trained on a comprehensive dataset, predicts the facial behavior of the candidate during an interview, looking for attributes such as attention and engagement. Around the same time, another model gives details about the personality and confidence of the candidate based on facial expressions, tone, and pitch of voice expressed during the interview. These assessments give critical insight into how this candidate might perform in real situations, especially for jobs that require great interpersonal skills and confidence.

Gamification of technical interviews and emotion analysis: The system will undergo interactive, gamified technical interviews designed to track problem-solving skills and technical knowledge of the candidate in a more engaging way. This also has an emotion detection model running parallel, predicting the stress levels and confidence of the candidate based on his performance in such tasks. The interactive approach does more than just test technical ability; it produces a large amount of very valuable data regarding how candidates work under pressure and therefore gives a much more rounded assessment of suitability for the role.

The evaluation process also comprises sudo code conversion and logical evaluation, wherein responses by candidates in technical interviews are changed into sudo code. This provides a single standard measure to enable the system to evaluate every candidate's answer for its logicality, complexity, and maintainability. With the evaluation of these aspects, the system will ensure that the candidates meet all the required standards in relation to problem-solving and quality of codes with respect to the technical roles.

Finally, all such analyses are integrated into the system in an automated decision-making and candidate prioritization phase. The automatic identification of candidates from any such system would be based on a candidate's relative standing with respect to others, based on performance in mock-up tests, behavioral analysis, emotional stability, and technical expertise. Bringing together these diverse elements into the comprehensive profile assessment will allow and support making informed decisions about whom to hire and who should make up the shortlist for any particular role.

This comprehensive methodology ensures that ExproeX: Automated Interview Processing System efficiently and accurately evaluates candidates to provide reliable solutions to organizations in streamlining their recruitment process.

Software solution

This video-based mockup test component will test candidate skills through its interactive and user-friendly nature. It consists of facilities such as a CV upload and parsing module, extraction of skills, generation of mock-up questions, video-based testing, and finally, an overall assessment module. Added to this, all these components shall be successfully integrated for smooth functioning and better user experience.

3.1.1 Development process

The development of the video-based mockup test system is iterative and agile to have flexibility and continuous improvement throughout. It comprises the following steps:

The first stage is requirement analysis, which is the gathering of needs and expectations from stakeholders to define the functionalities of the system. It involves detailed discussions with the stakeholders to clearly define the user roles, the essential features, and the performance expectations. These requirements, when thoroughly understood, ensure that a foundation for developing a system is laid that meets user needs and business objectives.

System design is the high-level architecture development phase, defining how all these different parts are going to interact with each other. It includes database schema design for data organization, user interface mockups for knowing what the end-user experience may look like, and flowcharts for the processes to be run within the system. All these elements of the design become blueprints for the implementation phase, making sure that everything in the system is well thought out before its development.

This is where the real work lies: bringing the system into being. It is at this point in the development process that the back-end will be developed with Python Flask, which entails building an API empowered by various libraries such as PyPDF2 for parsing the CVs, spaCy for extracting skills, and TensorFlow for scoring video responses. Afterwards, React on the frontend is used to design a responsive, dynamic user interface that can interact with the system in a very easy way by candidates. Database management is channeled through Firebase, which stores all the information related to a user, test results, and other vital information safely. The system architecture is monolithic, thus assuring that each component works harmoniously together.

Testing is the stage wherein various tests are run to make sure everything goes well. Unit tests are for small parts of the system; integration tests allow one to see whether all components can fit properly together. User acceptance testing ensures that the system provides all that is wanted by stakeholders under the requirements. This extensive testing process helps isolate any issues and fix them before deployment.

The deployment phase involves the launching of the system into a cloud platform, which ensures its scalability and reliability. It can serve variable loads with uniform performance due to this deployment on the cloud. Coupled with that is extensive user and administrator documentation for the operation and administration of the system in the best possible manner.

The final phase is the maintenance phase, which includes ongoing support and updating. The system is subject to continuous refinement in accordance with user feedback and evolving requirements to keep the system effective and current. In this way, as challenges evolve, the system remains relevant to the changing needs of both users and the organization.

3.1.2 Feasibility Study

The feasibility study assesses the practicality and viability of developing the video-based mockup test system from multiple perspectives:

Technical Feasibility

The technical feasibility of the project examines the available technologies and resources necessary for implementation. Key considerations include:

- **Technology Stack:** The use of Python Flask for backend development, React for frontend, and Firebase for database management is technically viable, given the team's expertise and available libraries.
- **Integration of Libraries:** The integration of libraries such as PyPDF2, spaCy, and TensorFlow has been assessed, and preliminary tests indicate compatibility and reliability for the intended functionalities.
- **Infrastructure Requirements:** The system can be hosted on cloud platforms, which provides the necessary infrastructure for scalability and performance.

Scheduling Feasibility

Scheduling feasibility evaluates the timeline for project completion. Key points include:

- **Project Timeline:** The project is divided into distinct phases, each with specific timelines. The expected completion of the system is projected to be within 4-6 months, allowing adequate time for development, testing, and deployment.
- **Resource Allocation:** The team has been allocated based on skills and availability, ensuring that tasks can be completed efficiently within the scheduled timeframe.
- **Milestones:** Key milestones, such as completion of requirement analysis, design, implementation, and testing phases, have been established to track progress and ensure timely delivery.

3.1.3 Requirement Gathering and Analysis

The requirement gathering and analysis phase is crucial for understanding the needs of stakeholders and defining the necessary features for the video-based mockup test system. This phase involved collaboration with candidates, evaluators, and project sponsors to ensure the system meets their expectations. The following methods were utilized to gather requirements effectively:

The development process of the video-based mockup test system began with interviews from stakeholders. This meant interviewing potential users of the system to understand exactly their expectations and challenges in the interview process. Those interviews revealed major insights on the main functionalities, which are User Authentication, CV Parsing, and types of questions keenly practiced by candidates. This direct interaction with the user was to ensure that the system designed would be for their needs and deal with common painful spots in the interviewing process.

This information-gathering process was supplemented by interviews, questionnaires, and surveys within a wider circle to collect quantitative data on the preferred features and user preference when it came to the preparation of interviews. Responses to these were carefully analyzed and ranked for priority against the most frequent requests from users. In this way, development would be focused on features with maximum impact on user experience, while at the same time aligning the system's capabilities with user expectations.

A competitive analysis was done over existing platforms that offer mock-up interview and question bank features. This provided insight into the strengths and weaknesses of current solutions, thereby enabling the development team to find best practices and user feedback from competing systems. Such lessons were put into this video-based mockup test system design, thereby gaining it unique advantages over other tools while correcting some of their weaknesses.

The project had a dataset improvement initiative in it, understanding that a robust dataset of interview questions is important. The starting point identification was planned to be sourced from Kaggle as a dataset, with enhancement to add categories, difficulty levels, and context to the questions, with example answers. Collaboration with users gave valuable feedback on the dataset, helping in finding lacuna and opportunities for its expansion. This could be achieved only because the dataset was continuously enriched, and therefore the system is able to provide a multitude of questions to answer the different needs of the candidates in preparation for a wide variety in roles.

3.1.4 Data Set

The dataset is integral to the video-based mockup test system, particularly for enhancing the candidate evaluation process. The following aspects outline the dataset's structure and improvements:

> The candidate evaluation system permits the acceptation of varied types of data, each important in ensuring that the whole process of assessment is broadly and efficiently conducted. The types of data taken include diversified coverage of interview questions from Kaggle categorized under job roles to ensure their relevance. Besides the data being collected through interview questions, data in the form of CVs are collected from candidates at the file upload point presenting personal information, education, work experience, and skills summary. Moreover, video replies by candidates for mockup tests provide another rich source of data for analysis related to verbal and non-verbal cues.

Mostly, this will mingle all types of data into the compilation, and that provides a balanced view in evaluating the qualifications of a candidate and his display of presentation skills.

The selection of data sources for the system is based on some strategic measures to further improve the quality and relevance of information assessed. A dataset from Kaggle is the major source of the interview questions and is thus taken as a starting point into which further improvements are to be applied. The CV data of the candidates used for making the data sets used for the mock-up tests are gathered directly; hence, the system will have fresh and pertinent information about a candidate. The dataset has been enhanced in several ways to make the updated dataset useful for candidates and evaluators alike. The skills are tagged to relevant topics in interview questions to make it easier to search and filter. The easiness level classifies the question under easy, middle, or difficult to allow a candidate to select problems according to his skill and ability. Context and sample answers have also been added to the question to make the candidate be guided on the kind of approach to use on answering the question. These are further improvements to make the dataset be of more value to the candidate and the evaluator.

Owing to the sensitive nature of this kind of information, the main concerns would be on data privacy and security. The type of data collected is in strict ore with regulations on data protection, such as the GDPR, which is meant to cover the privacy and confidentiality of users. Based on that, a security measure implemented through data anonymization and encryption, amongst others, intends to prevent sensitive information from reaching any unauthorized hands. These precautions ensure that users can trust the system to handle their information responsibility and securely.

It is a data structure that has been so designed that it can easily be analyzed and integrated into the system. The way the dataset is formatted through formats like CSV ensures an easy form of manipulation that will enable it to get analyzed. Metadata is also attached, capturing information about the data source, date created, and revision, which ensures traceability. All of that makes data management clean and beefs up the functionality of the system.

Data validation mechanisms have been developed to ensure the quality of data. Another mechanism for validation of data quality in this research was cross-checking the interview questions with good sources of information and expert opinion for further accuracy and relevance. Moreover, pilot testing among small groups of candidates was conducted to assure relevance and effectiveness in eliciting valuable performance insights from the candidates. This serves as validation of the fact that the system leads to reliable and meaningful evaluations.

By improving the dataset of interview questions and gathering comprehensive requirements, the video-based mockup test system is positioned to deliver an effective and engaging evaluation tool for candidates and evaluators alike.

3.1.5 Implementation

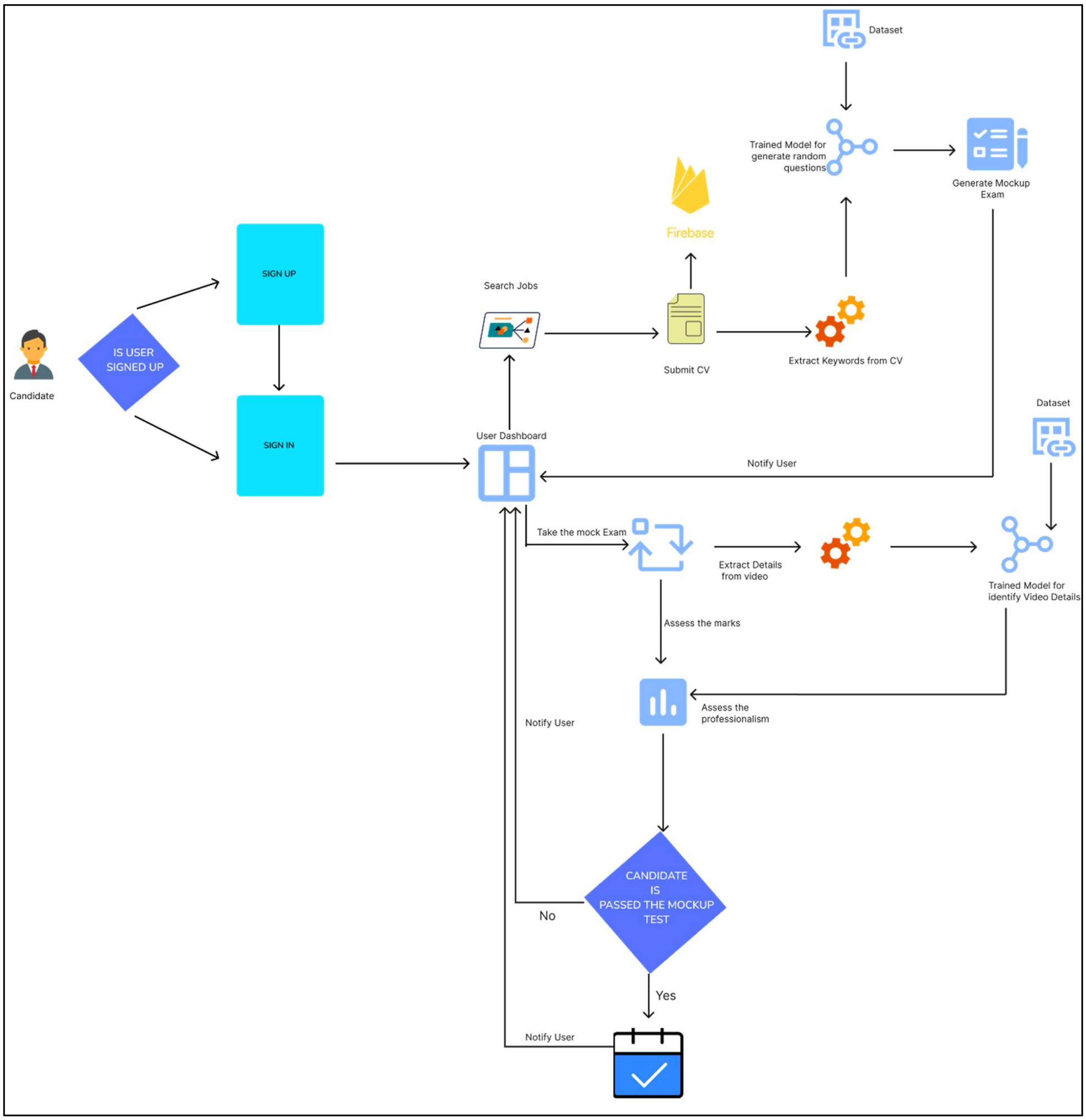

Figure 3: System diagram for the component

The implementation of the video-based mockup test system begins with a crucial step of user authentication. The system is designed to first verify whether a user has already registered. If the user is new, they are required to sign up, creating an account with the platform. This initial step ensures that all users accessing the system are authenticated, providing a secure environment for subsequent interactions. Once the user is signed in, they can seamlessly navigate through the platform's features, with the primary focus being on job search and application functionalities.

Upon successful authentication, users are directed to the job search feature, where they can explore various job opportunities listed on the platform. The system allows users to submit their CVs, which marks the beginning of an in-depth analysis process. The submitted CVs are stored securely in the Firebase database, ensuring that user data is handled with care and in compliance with data privacy standards. The core functionality of the system comes into play as the CV undergoes processing through advanced Natural Language Processing (NLP) techniques. These techniques are employed to meticulously extract relevant keywords that encapsulate the user's skills, qualifications, and work experiences. This keyword extraction is essential as it lays the foundation for generating a tailored mockup test that aligns with the candidate's unique profile.

Following the CV analysis, the system leverages a pre-trained machine learning model to generate a set of interview questions. These questions are carefully curated based on the keywords extracted from the candidate's CV, ensuring that the mockup test is personalized and relevant to the candidate’s skill set and experience. This dynamic question generation process is a key feature of the system, as it allows the mockup test to be highly specific to each candidate, thereby providing a more accurate assessment of their abilities in relation to the job they are applying for.

Once the mockup test is ready, the system notifies the user, who can then access the test through their personalized dashboard. The user dashboard acts as a central hub, offering users a comprehensive view of their application status, test results, and other relevant information. The dashboard's intuitive design ensures that users can easily navigate through the platform, making it simple to manage their job applications and access the mockup test.

The core component of the implementation is the video-based mockup test. During the test, the candidate is required to respond to the generated questions in a video format. This video is then subjected to a detailed analysis where the system extracts key details such as speech patterns, facial expressions, and other non-verbal cues. The extraction process is powered by machine learning algorithms that analyze the video in real-time, evaluating the candidate's communication skills, confidence, and ability to respond accurately under pressure. Additionally, the system considers the environmental context of the video, such as background settings, lighting conditions, and sound quality, to assess the professionalism and suitability of the candidate’s environment.

After the video is processed, the system uses trained machine learning models to evaluate the extracted data. The evaluation process is multifaceted, focusing on various metrics like the clarity of speech, body language, and the relevance of responses. This comprehensive analysis allows the system to provide a holistic assessment of the candidate, taking into account both the verbal content of their answers and the non-verbal cues that are often critical in an interview setting. The system's ability to integrate these different assessment dimensions ensures that the evaluation is both thorough and objective.

Finally, once the analysis is complete, the system determines whether the candidate has passed the mockup test. The results are promptly communicated to the user through the dashboard. If the candidate passes the test, they are notified of their success and can proceed with the next steps in their job application process. If the candidate does not pass, the system may offer feedback, allowing the candidate to understand areas for improvement and potentially retake the test. This iterative process ensures that candidates are given ample opportunities to refine their skills and enhance their chances of success in actual job interviews.

3.1.6 Use Case Diagram

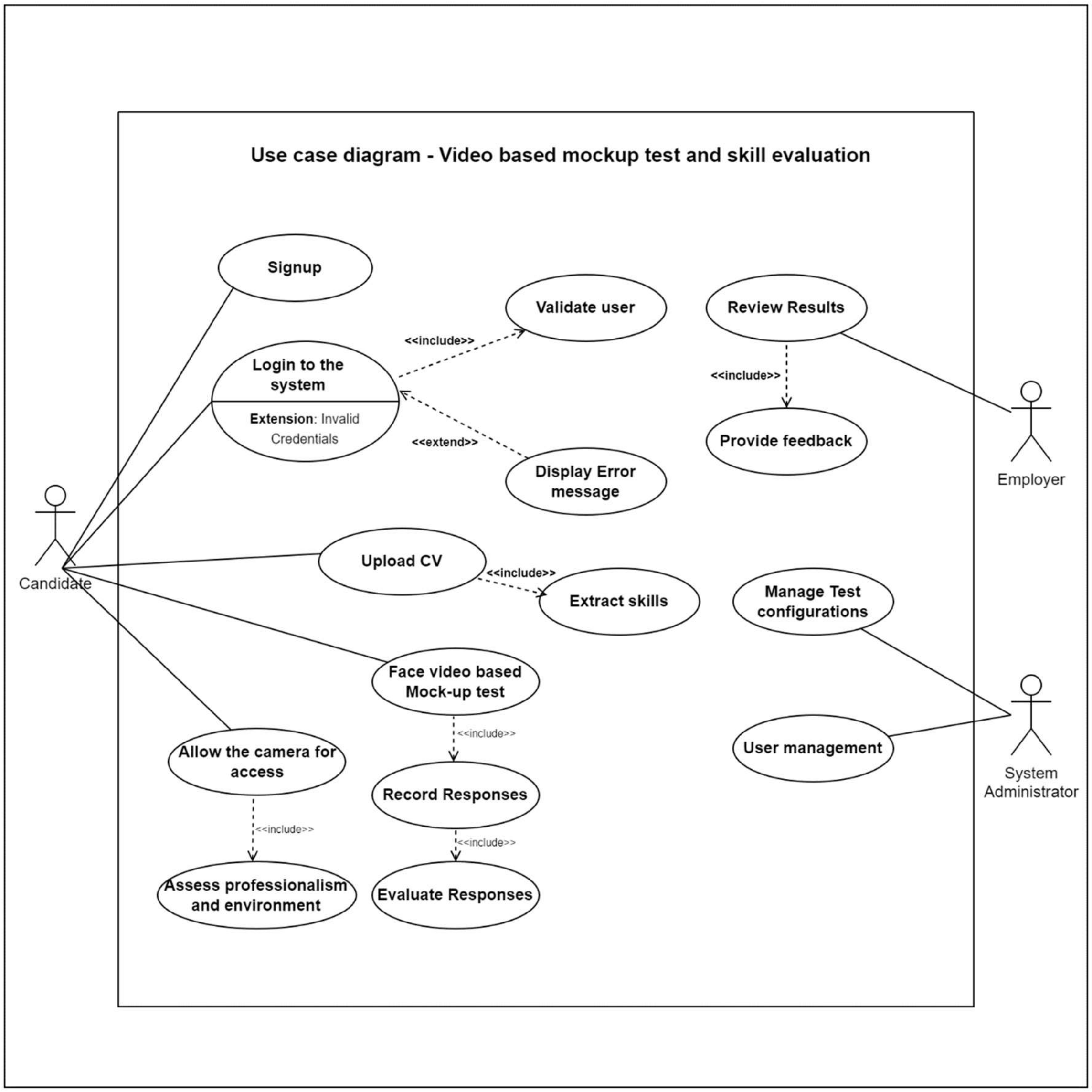

Figure 4: Use-case diagram

3.1.7 Sequence Diagram

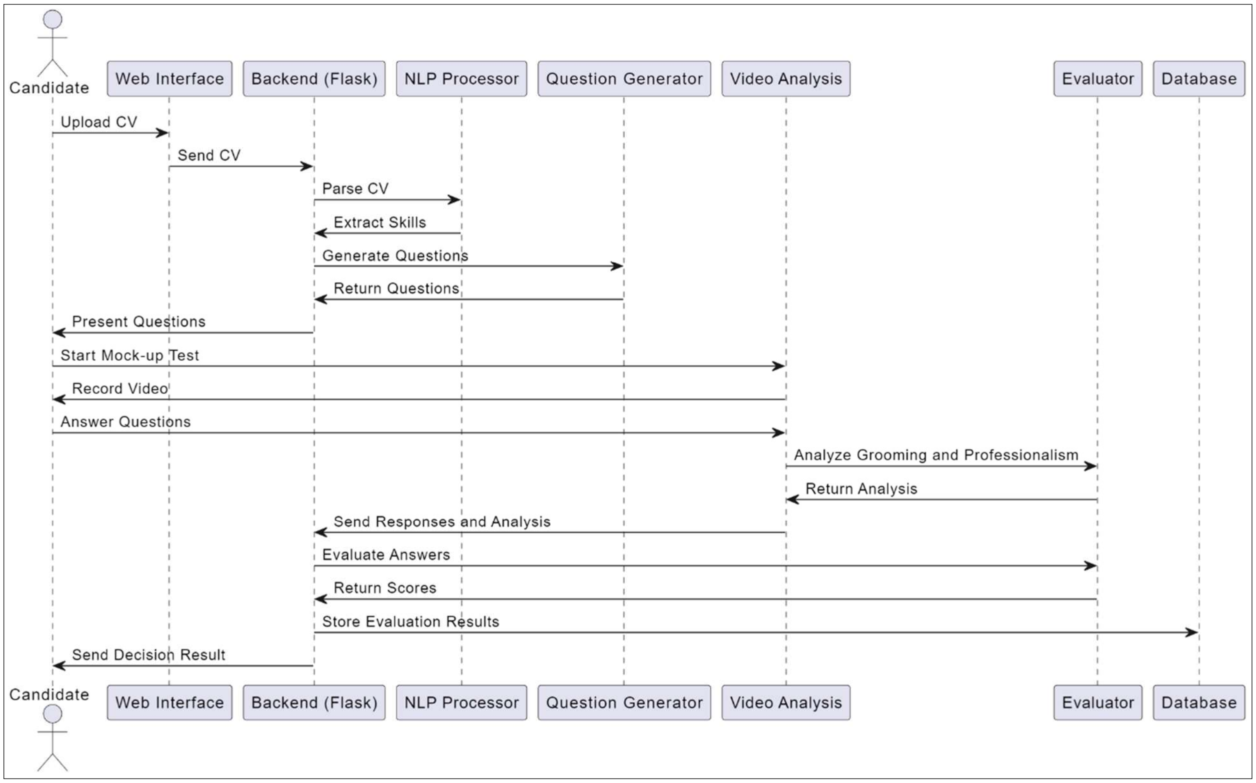

Figure 5: Sequence diagram

3.1.8 Testing

This phase essentially confirms to the stakeholders that all the functions of this application are free from any possible errors. It is planned that do that unit testing, integration testing, system testing, and user acceptance testing will be done. Moreover, in this phase will that made and developed to improve the quality of the software.

Testing of the candidate evaluation system takes place in phases to ensure that the application works properly and as users would expect it to. Unit testing would be the first stage of testing, whereby each function in the system is checked independently. The focus of this phase is the identification and fixing of faults in the source code; it verifies that each function performs the operation it is supposed to do. Unit testing is a kind of white-box testing that deals with the analysis of code at an internal or modular level to prove its correctness.

Following unit testing, there comes integration testing. During this phase, all the modules or sub-modules of the system are brought together and integrated, and the interactions between these components are tested. This step is imperative in finding out the problems that may arise from the integration of parts of the system with each other; failures or unexpected behaviors can be revealed, which were not observed during unit testing. The aim at this stage is to fine-tune the system for any integration problems and to get everything working harmoniously together.

After the system has undergone integration testing, it proceeds to system testing. At this stage, the fully integrated application is subjected to an extensive collection of various tests. System testing takes place immediately after the entire application has been assembled ready for evaluation. The testing will aim at testing the application as a whole by simulating real-life situations that the application is expected to operate under when fully complete and operational.

The final phase of testing is the user acceptance testing (UAT). During UAT, the developed application is tested against its initial requirements to ensure it meets the expectations and needs of the end users. This phase is conducted by customers and staff members; in this case, Sri Lanka Water Board members. Their feedback is important since it will confirm whether the application is ready to be rolled out into a live environment. UAT is the final checkpoint before releasing the system for production and distribution to end-users, ensuring that all requirements of the stakeholders are met and working as per conceptualization in real practice.

PROJECT REQUIREMENTS

3.2 User requirements

- **Job Applicants**: User-friendly interface, video recording, CV submission, real-time feedback.

- **Recruiters**: Dashboard access, customizable mockup tests, detailed candidate performance reports.

- **Administrators**: User account management, system monitoring, security and privacy tools.

3.3 Software requirements

- **Frontend: React.js**

- **Backend: Python Flask**

- **Database: Firebase**

- **Machine Learning: TensorFlow, OpenCV**

- **Video Handling: OpenCV**

3.4 Functional requirements

- **Authentication**: OAuth, JWT

- **CV Parsing**: NLP libraries, PyPDF2, docx2txt

- **Mockup Test Generation**: Custom algorithms, ML models

- **Video Recording**: Integrated video capture, OpenCV

- **Video Analysis**: Machine learning models, TensorFlow

- **Feedback and Reporting**: Automated reporting, data visualization tools

3.5 Non-functional requirements

- **Performance**: Optimized algorithms, caching
- **Scalability**: Horizontal scaling, cloud services (AWS, Google Cloud)
- **Security**: SSL/TLS encryption, data encryption
- **Usability**: UI/UX best practices, accessibility standards
- **Reliability**: High availability, error handling, logging
- **Compliance**: GDPR compliance, data protection regulations

4. GANTT CHART

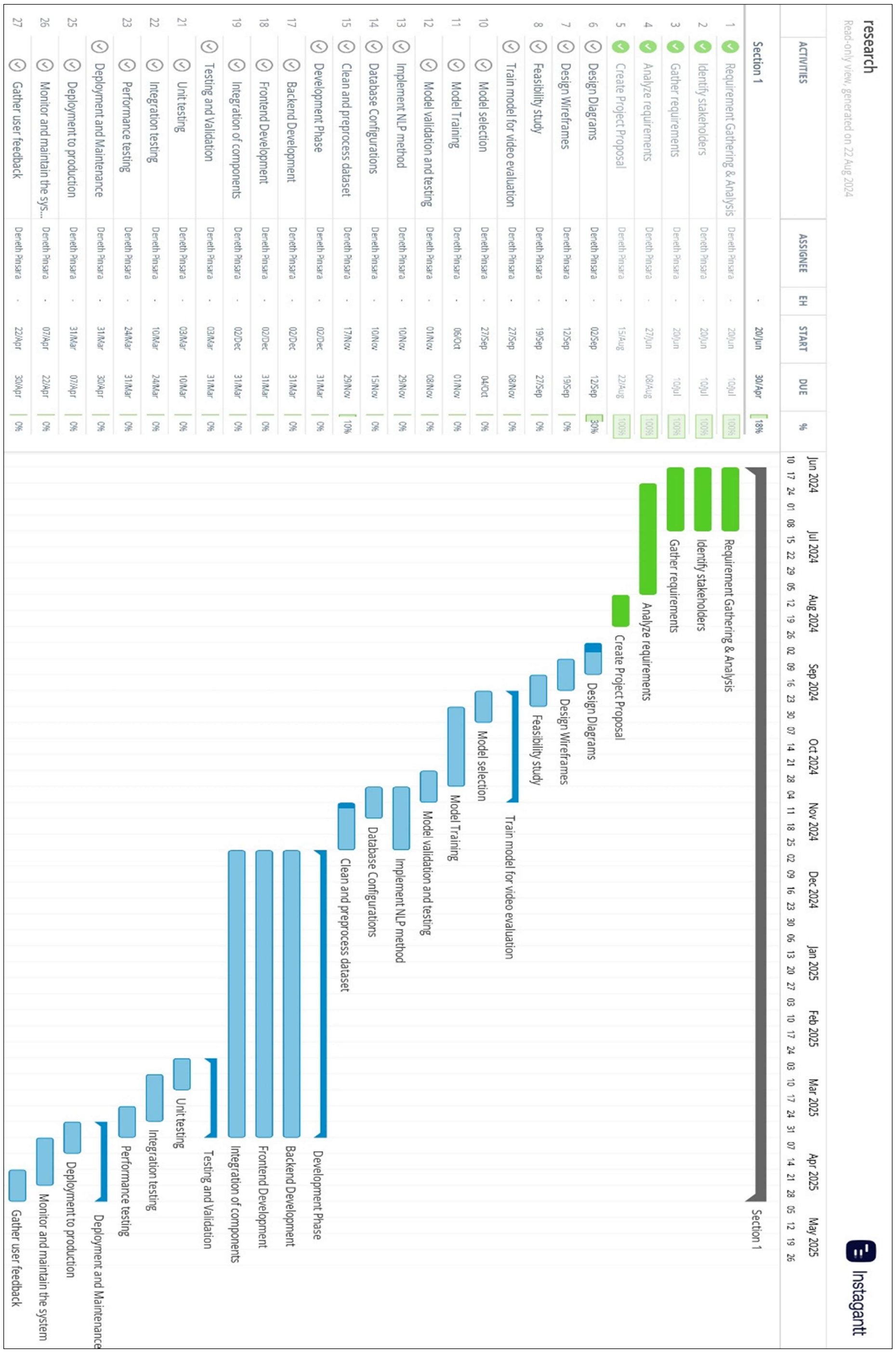

Figure 6: Gantt chart

https://drive.google.com/file/d/1m1C4nghpBSv7D3rZBfCP_IfbDsGh9csD/view?usp=sharing

4.1 Work breakdown Structure

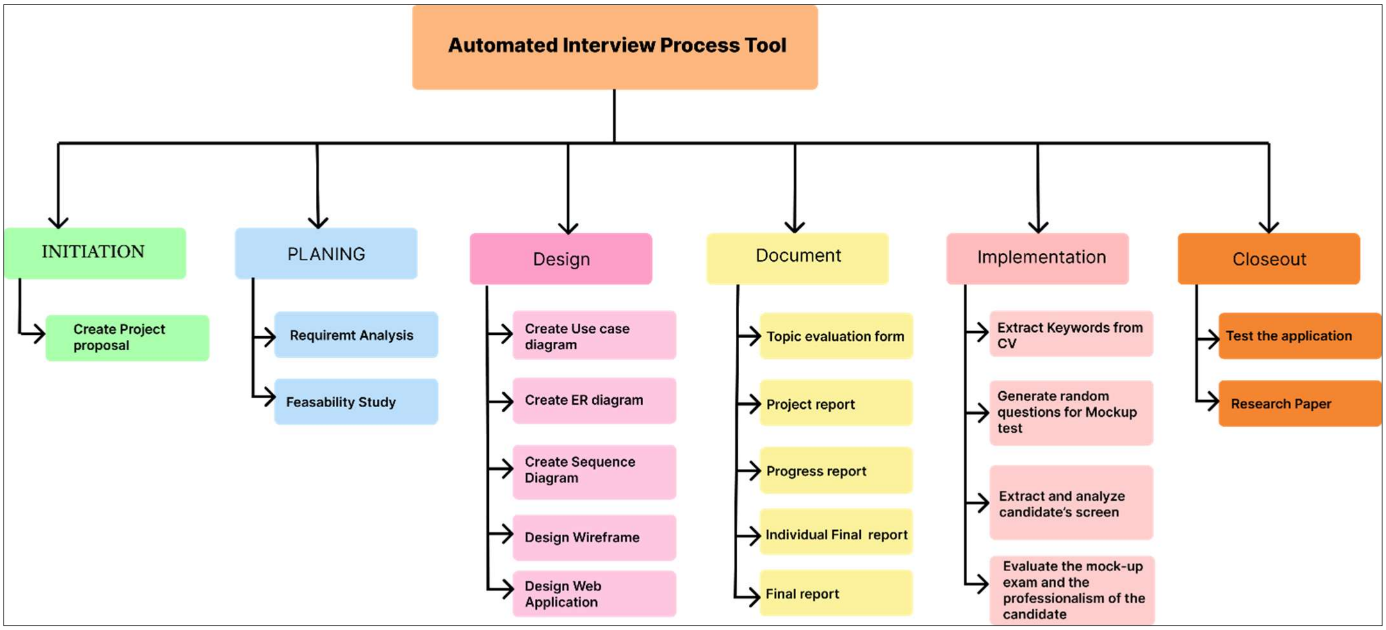

Figure 7: Work Breakdown Chart of the component

5. DESCRIPTION OF PERSONAL AND FACILITIES

- **Facilitators:**
  - Dr. Dilshan De Silva – Sri Lanka Institute of Information Technology (SLIIT)
  - Ms. Poojani Gunathilake – Sri Lanka Institute of Information Technology (SLIIT)

- **Facilities:**
  - https://scholar.google.com/
  - https://www.kaggle.com/

6. BUDGET AND BUDGET JUSTIFICATION

1. **Domain Registration (GoDaddy)**

   - **Domain (.com+.net+.xyz):**
     Estimated Cost: LKR. 5,000 annually for a combination of domains, depending on specific TLD prices.

2. **Web Hosting (Hostinger) – [if hosted]**

   Shared Hosting Plan:

   - Plan: Premium Shared Hosting
   - Features:
     - Supports multiple domains and email accounts.
     - Sufficient resources (100 GB SSD, unmetered traffic, 100 websites).
     - Free SSL, daily backups, and a free domain.

   Annual Cost: LKR. 20,000 (approximately)

3. **Database (Firebase)**

   - **Database Plan:** Firebase Blaze Plan (Pay-as-you-go)
   - **Annual Cost:** Estimated cost depends on usage, but for initial development, around LKR. 10,000 annually.

Feature	**Item Cost (LKR)**
Domain Registration	LKR. 5,000
Web Hosting (Hostinger)	LKR. 20,000
Database (Firebase)	LKR. 10,000

Table 2: Budget of the component

7. COMERCIALIZATION

7.1 Target Audience and Market Space

- **Target Audience:**
  - **Job seekers:** People who are actively looking for work, especially recent graduates and mid-level employees.
  - **Recruiters:** Hiring managers and HR specialists from small to large businesses seeking effective recruitment solutions.
  - **Educational Institutions:** Colleges and universities that want to include practice exams in their career services offerings.

- **Market Space**
  - **Industry:** Hiring and Human Resource Information Technology (HR Tech)
  - **Geographical Reach:** Initially focusing on Sri Lanka, with intentions to grow into other developing markets in Southeast Asia.
    Competitors include new AI-driven assessment tools, conventional employment companies, and online interview platforms.
  - **Unique Value Proposition:** All-encompassing evaluation that combines video-based mock exams, skill-based question creation, and CV parsing. Emphasize the candidate's abilities as well as environmental professionalism, providing a more comprehensive assessment instrument.

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APPENDICES

- **Plagiarism Report:**

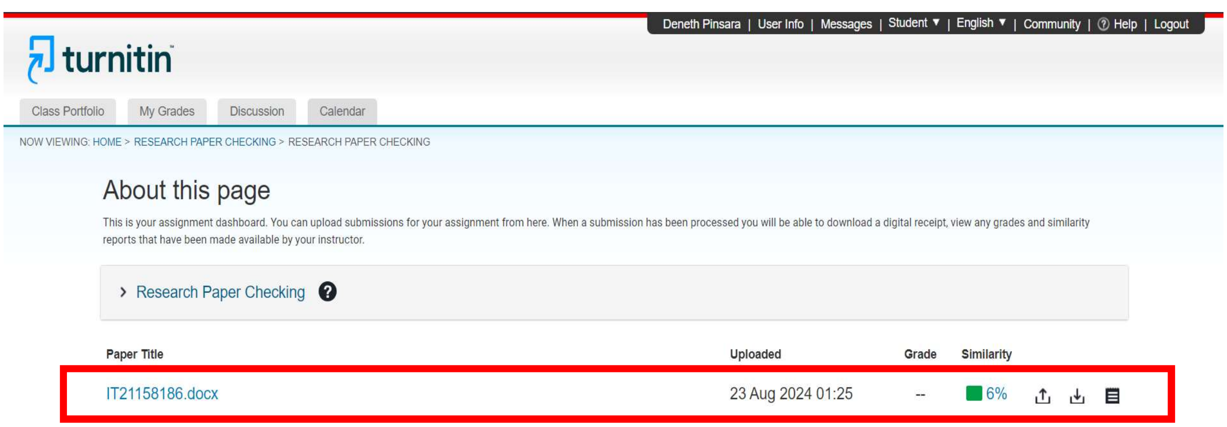

Figure 8: Plagiarism report

- **Survey link: https://forms.gle/YcRoRBzJSWc74X6d9**

(This is only for identify user experience with automated interview processes – Not for data collection)