Automated Interview Processing System

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Thennakoon T.M.I.C

IT21170966

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

Department of Information Technology

Sri Lanka Institute of Information Technology

Sri Lanka

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DECLARATION

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

Name	Student ID	Signature
Thennakoon T.M.I.C	IT21170966	

....

Signature of the supervisor

Dr Dilshan de Silva

11/04/2025

Date

....

Signature of the Co-Supervisor

Ms. Poojani Gunathilake

11/04/2025

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 the contemporary employment landscape, the stakes have risen significantly for both employers and candidates. The demand for highly skilled and emotionally resilient professionals is at an all-time high, as industries increasingly prioritize employees who not only possess technical expertise but also demonstrate strong stress management abilities. A global survey by McKinsey (2023) revealed that 84% of companies now consider emotional intelligence (EI) a critical hiring criterion alongside technical skills [1]. The COVID-19 pandemic accelerated this shift, exposing vulnerabilities in traditional hiring methods that fail to account for candidates' mental resilience during high-pressure situations [2]. The modern workforce operates in an increasingly complex and volatile environment, often referred to as a VUCA world—one that is volatile, uncertain, complex, and ambiguous. This reality demands employees who can adapt swiftly, think critically under pressure, and maintain emotional composure in the face of challenges. As a result, recruitment has evolved from merely filling positions to strategically selecting individuals who align with organizational goals, demonstrate resilience, and possess the emotional agility needed to cope with modern workplace stressors [3]. According to the World Economic Forum's Future of Jobs Report (2020), emotional intelligence was ranked among the top 10 skills required for the future workforce, alongside complex problem-solving, critical thinking, and active learning [4]. This signals a broader redefinition of what constitutes a "qualified" candidate. No longer is technical competence alone sufficient; organizations are now seeking individuals with holistic skill sets, including empathy, adaptability, and emotional stability. Additionally, the proliferation of remote and hybrid work environments has added layers of complexity to talent evaluation. With fewer opportunities for in-person observation, assessing emotional intelligence and stress management capabilities has become even more difficult. Traditional interviews often fail to reflect a candidate's ability to perform under pressure, and behavioral cues—critical for evaluating soft skills—can be easily masked or misinterpreted in virtual formats [5].

A 2022 report from LinkedIn Talent Solutions found that while 92% of talent professionals agree that soft skills are just as important as hard skills, 89% also report that assessing them during interviews remains a significant challenge [6]. This mismatch has sparked an industry-wide shift toward more dynamic, immersive, and data-driven assessment models that can more accurately predict a candidate's workplace potential. Innovative recruitment strategies are now leveraging advanced technologies such as AI, machine learning, and computer vision to evaluate not just cognitive ability but also emotional responses. Real-time analytics, personality profiling, and behavioral simulations are increasingly being integrated into hiring pipelines to provide a more comprehensive picture of each candidate [7][8]. Gamified assessments, emotional recognition tools, and adaptive scenario-based evaluations are helping to bridge the gap between technical proficiency and emotional intelligence. These tools add layers of behavioral insight that were previously inaccessible in traditional interviews. As a result, employers gain deeper visibility into how candidates think, feel, and react under pressure—essential metrics in today's competitive and fast-paced industries [9][10].

Moreover, this holistic approach to hiring has been shown to correlate with improved retention and performance outcomes. A Harvard Business Review study (2021) emphasized that companies integrating soft-skill evaluation into their recruitment process reported up to 33% higher employee engagement and 20% lower turnover [11]. The combination of emotional intelligence assessment with technical evaluation allows recruiters to not only hire smarter but also build more cohesive and adaptable teams. The talent acquisition is no longer a linear or purely skill-based process. It is a multidimensional endeavor that blends psychology, data science, and technology to identify individuals who are not just qualified but also emotionally resilient, adaptable, and culturally aligned. The evolving demands of the modern workplace, especially in post-pandemic, digitally enabled contexts—require hiring practices that prioritize both emotional and technical competence. Incorporating real-time stress detection, gamified tasks, and facial expression analysis into interviews represents a transformative leap forward in how organizations evaluate human potential.

Workplace stress has emerged as a silent productivity killer. According to the American Psychological Association (APA), 71% of employees report that workplace stress directly affects their mental health, with 62% citing a decrease in performance due to stress-related burnout [3]. This leads to organizational losses, as documented by the National Institute for Occupational Safety and Health (NIOSH), which estimates an annual $300 billion loss in the U.S. economy due to stress-related absenteeism, healthcare costs, and reduced output [4]. Further supporting this, Gallup's *State of the Global Workplace* report (2022) found that organizations with chronically stressed employees experience 37% higher absenteeism, 60% more workplace errors, and 18% lower productivity than their counterparts [6].

In addition, a study conducted by the World Health Organization (WHO) emphasized that mental health-related conditions, especially those induced by job stress, are among the leading causes of disability worldwide, predicting that depression and anxiety will cost the global economy up to $1 trillion annually in lost productivity [12]. Research from the European Agency for Safety and Health at Work also highlights that over 50% of workdays lost in the European Union are due to stress-related illnesses, making it a major threat to workforce sustainability and economic growth [13]. Furthermore, the Chartered Institute of Personnel and Development (CIPD) reports that stress-related leave has been rising annually, especially in high-pressure sectors such as IT, healthcare, and finance, where job demands are exceptionally high and support systems are often inadequate [14]. Importantly, chronic stress not only affects organizational output but also impairs decision-making, learning ability, and creativity—skills highly valued in knowledge-based roles. Neurological studies have shown that elevated cortisol levels due to prolonged stress impair the prefrontal cortex, which is responsible for executive functioning, thus undermining critical thinking and problem-solving capacities essential for high-performance employees [15]. Employers are therefore increasingly recognizing the need to assess and manage workplace stress early in the hiring pipeline to build a more resilient and productive workforce.

Traditional interviews, though effective in evaluating theoretical knowledge and practical competencies, often fall short in reflecting real-world stress scenarios. The conventional interview format—typically consisting of one-on-one sessions or panel-based questioning—lacks the immersive pressure of actual work environments. Research by Harvard Business Review (2021) observed that only 28% of hiring managers felt confident that traditional interviews assess how candidates respond under pressure. Moreover, a meta-analysis by Schmidt and Hunter (1998) revealed that while structured interviews had a predictive validity of 0.51 for job performance, they performed poorly in assessing emotional resilience, which has become increasingly essential in high-stakes roles [15][16]. Furthermore, traditional interviews may inadvertently favor candidates who are better at self-presentation or possess greater social confidence, rather than those who are genuinely best suited for the role in terms of coping with complex, high-stress demands. A study published in *Industrial and Organizational Psychology* (2015) found that candidates with strong impression management tactics often outperformed their more qualified but less socially adept peers during interviews, leading to biased hiring decisions [17]. This not only challenges fairness in recruitment but also risks organizational misfit and higher turnover rates.

Additionally, traditional interview formats are typically static and rigid, offering limited scope for observing adaptive behaviors, spontaneous decision-making, or emotional regulation—skills that are crucial in crisis management, customer service, software troubleshooting, and leadership roles. A review conducted by Levashina et al. (2014) in the *Journal of Applied Psychology* noted that structured interviews often fail to elicit the kind of behavioral responses needed to assess how candidates think under pressure, deal with failure, or handle time-sensitive tasks [18]. In dynamic industries such as IT, finance, and healthcare, where professionals are frequently required to make critical decisions under tight deadlines, emotional composure is just as crucial as technical accuracy. Yet, few traditional assessments account for this dual competency. The inability of conventional interview formats to simulate realistic high-pressure scenarios has thus led to increasing calls for more immersive, experiential evaluation methods [19]. These limitations have prompted organizations to explore modern alternatives such as situational judgment tests (SJTs), gamified assessments, and AI-based behavioral analytics to gain deeper insight into candidate capabilities beyond resume-level qualifications.

To bridge this gap, **gamification has emerged as an innovative tool in recruitment**. By infusing game mechanics such as **scoring systems, time constraints, scenario simulations, and reward feedback loops** into the interview process, gamified assessments can both engage candidates and replicate high-pressure environments. Research from PwC (2022) showed that **74% of job seekers found gamified interviews less intimidating and more representative of real-world challenges**. Furthermore, a study published in the *Journal of Applied Psychology* reported that **gamified assessments resulted in a 30% improvement in candidate engagement** and a **22% increase in predictive accuracy** compared to traditional tests [20][21].

A **gamified technical interview** typically involves the use of **real-time coding platforms**, **algorithmic challenges**, **simulation-based tasks**, and **problem-solving exercises** designed in an interactive or immersive environment. For instance, some systems present candidates with mission-based coding adventures, collaborative puzzles, or “capture the flag” cybersecurity challenges. **Time pressure**, **scenario complexity**, and **progressive levels** are often integrated to replicate the kinds of dynamic problem-solving environments found in real-world settings such as Agile teams or DevOps workflows. **Candidates may be required to complete multiple tasks under time pressure**, often framed within **interactive storylines or role-based challenges**, such as "debugging a legacy system to save a company launch" or "defending a network from a cyberattack." These simulate real-life technical problem scenarios faced in roles such as **software engineering**, **data science**, **UI/UX design**, and **network security**.

Importantly, **gamified environments also foster intrinsic motivation** by tapping into candidates' desire for mastery, competition, and achievement. According to **Self-Determination Theory (SDT)**, individuals are more likely to perform well and learn when they feel autonomous, competent, and connected to the task at hand—conditions often cultivated in gamified setups [22]. Research by Hamari et al. (2014) supports this, demonstrating that gamification enhances user experience and behavioral engagement when well-structured and relevant to the task [23]. Moreover, **gamified assessments can reduce unconscious biases** present in traditional interviews. By focusing on performance within standardized challenges, they allow for a **more objective evaluation of skills**, removing visual or verbal bias from the process. A report by the Institute of Student Employers (ISE) in 2021 found that gamified hiring platforms helped **increase candidate diversity by 26%** across technology and finance sectors [24]. However, **gamification is not without its challenges**. Critics argue that poorly designed games can introduce **unfair advantages** for candidates familiar with gaming environments, potentially alienating individuals from non-technical or less privileged backgrounds. Additionally, **over-gamification**—where flashy game elements overshadow core evaluation goals—can detract from the reliability of the assessment. As such, researchers advocate for a balanced approach, ensuring that **game mechanics enhance rather than distract from the skills being tested** [25].

Furthermore, while gamification enhances **engagement** and **cognitive performance assessment**, it does not inherently evaluate **emotional responses** such as **stress, frustration, or resilience**—critical soft skills in today’s high-pressure work settings. These emotional cues often manifest nonverbally, such as through facial expressions or micro-behaviors. Hence, **gamified interviews must be augmented with emotional recognition technologies** to deliver a more comprehensive evaluation. The **next frontier in recruitment technology** involves combining cognitive task performance with **real-time affective computing**, allowing employers to assess not just what a candidate can do, but how they emotionally respond while doing it. Integrating real-time **facial expression recognition**, **voice modulation analysis**, and **physiological monitoring** (e.g., heart rate, eye movement) into gamified interviews presents an exciting opportunity for **holistic candidate profiling**. By observing how individuals manage emotional states under duress, recruiters can assess emotional intelligence, decision-making under pressure, and even cultural adaptability [26].

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One of the significant advantages of gamified technical interviews is the ability to simulate realistic job challenges in a controlled, engaging manner. A gamified technical interview typically involves the use of real-time coding platforms, algorithmic challenges, and problem-solving tasks designed in an interactive environment. Candidates may be required to complete multiple tasks under time pressure, often in the form of interactive storylines or role-based challenges. These simulate real-life problem scenarios faced in software development, cybersecurity, or data analysis roles. For instance, platforms like HackerRank and Codility have pioneered the use of gamified assessments in technical recruitment, where candidates tackle algorithmic problems while the system tracks their performance in real-time. This environment not only helps assess technical skills but also gauges a candidate's ability to think critically and solve problems on the fly. However, while gamification enhances engagement and cognitive assessment, it does not inherently evaluate emotional responses such as stress or frustration—unless augmented with emotional recognition technologies. A candidate may perform well on cognitive tasks but still experience high levels of stress, frustration, or anxiety, which can impact their overall performance. As a result, the interview may fail to capture the full range of a candidate's potential, particularly in high-pressure situations that require emotional resilience.

To address this limitation, recent developments in facial expression analysis have emerged as a complementary technology to gamification. Facial expression analysis, powered by computer vision and deep learning models, allows for the real-time detection of emotional responses such as stress, frustration, or excitement. For example, the system can detect micro-expressions such as furrowed brows, clenched jaws, and lip compression, which may indicate stress or frustration during problem-solving tasks. Incorporating these technologies into gamified assessments enables recruiters to not only assess candidates' technical skills but also gain insights into their emotional state and resilience during high-pressure situations. According to a study by D. Y. Lee et al. (2019), integrating emotion recognition with gamified assessments resulted in more accurate predictions of how candidates would perform in real-world job environments [28]. This approach allows recruiters to make more holistic decisions by considering both technical competencies and emotional intelligence. Moreover, combining facial recognition with gamified challenges could also enhance the candidate's experience by reducing anxiety. A study by Capterra (2021) found that candidates were 35% more likely to complete a gamified interview if it included real-time feedback on their emotional responses. This feedback loop can provide candidates with immediate insights into how their stress levels may have influenced their performance, leading to a more self-aware and reflective experience. Such an approach aligns with the broader trend toward personalized and adaptive assessment methods, which can provide candidates with a clearer picture of their strengths and areas for improvement.

Furthermore, research by Deloitte (2020) supports the growing acceptance of gamified recruitment, noting that it not only improves candidate engagement but also helps reduce bias in the recruitment process. By focusing on skills and emotional resilience rather than traditional resume-based evaluations, gamified assessments can help recruiters assess candidates in a more equitable and objective manner. This is especially important in industries where technical proficiency is vital, but so is the ability to manage stress, collaborate effectively, and remain adaptable in challenging environments. Incorporating both gamification and emotion detection technologies into recruitment represents a natural evolution in the way organizations assess talent. While gamified technical challenges help to simulate realistic job requirements, the addition of emotional intelligence assessments through facial recognition and AI-driven analysis enhances the overall assessment process. As recruitment processes continue to evolve, integrating these technologies could lead to a more comprehensive, data-driven approach to hiring, ultimately ensuring that organizations select candidates who are not only technically capable but also emotionally resilient and ready to thrive in dynamic, fast-paced work environments.

The significance of integrating real-time stress analysis with gamified assessments lies in its dual benefits, which cater to both the candidate and recruiter perspectives. This combination creates a comprehensive evaluation framework that not only assesses a candidate's cognitive and technical abilities but also measures their emotional resilience, which is increasingly considered essential in today's fast-paced work environments.

Candidate-Level Advantages:

- **Reduced Interview Anxiety**: One of the most significant barriers for candidates during traditional interviews is anxiety, which can often cloud their true abilities. Gamification in the recruitment process offers a more engaging and interactive environment, which helps reduce the pressure and anxiety typically associated with formal interviews. According to a study by TalentLMS (2021), 67% of candidates reported feeling less anxious during gamified assessments, which enabled them to perform more naturally and confidently [29].
- **Higher Engagement**: Gamified assessments typically include elements such as scoring systems, instant feedback, and interactive scenarios that keep candidates engaged throughout the process. This high level of engagement is crucial for assessing a candidate's problem-solving abilities and quick thinking, as well as their adaptability. Engagement is directly linked to the quality of the data gathered in assessments, with candidates demonstrating their true potential when they are fully immersed in the task.
- **Improved Performance Reflection**: Gamification provides immediate feedback, allowing candidates to see their progress and adjust their strategies in real time. This aspect of self-reflection not only benefits the candidates in terms of learning and development but also offers valuable insights into how they respond to challenges. In combination with real-time emotion detection, recruiters can gain a holistic understanding of the candidate's behavior, including how they manage frustration or stress during complex problem-solving tasks.

Recruiter-Level Advantages:

- **Holistic Insights**: One of the key advantages for recruiters is the depth of insight that the integration of gamification and emotional analysis offers. Traditional interviews are limited in their ability to provide a comprehensive view of a candidate's abilities, especially in high-pressure situations. By integrating emotion analysis through facial recognition technology, recruiters can assess how candidates respond under stress, which is often the true test of their capability to perform under real-world job demands. According to a report by Deloitte (2021), companies using gamified assessments observed a 28% increase in the accuracy of candidate evaluations compared to traditional methods [30].

- **Better Cultural Fit Analysis**: Gamified assessments offer the flexibility to design scenarios that closely resemble the day-to-day work challenges that candidates would face in the organization. By combining these tasks with real-time emotional feedback, recruiters can better evaluate whether a candidate's emotional responses align with the company's culture. This is particularly important in workplaces where emotional resilience and the ability to handle stress are critical to success. Research by Harvard Business Review (2021) has shown that candidates who display composure and emotional control in stressful situations are more likely to thrive in high-pressure environments and stay with the company longer [31].
- **Enhanced Talent Forecasting**: The data collected from gamified assessments, coupled with emotional analysis, provides recruiters with predictive insights about a candidate's potential for success in the role. Emotional analysis tools can identify patterns in facial expressions that indicate stress or frustration, helping to forecast how a candidate might handle future challenges. This predictive capacity is essential in talent acquisition, as it allows recruiters to select candidates who are not only technically proficient but also emotionally equipped to handle the pressures of the job. Companies such as Facebook and Microsoft have begun utilizing these methods, leading to more effective and data-driven recruitment strategies [32].

The integration of advanced technologies like OpenCV for face tracking, TensorFlow/Keras for emotion detection, and Unity for gamified scenario simulation allows for scalable, low-cost, and real-time deployment in recruitment environments. These technologies have already been successfully implemented in other industries, such as healthcare (for patient monitoring) and education (for detecting student disengagement), and their application in recruitment marks a groundbreaking innovation. In healthcare, for instance, emotion recognition technologies have been used to monitor patients' emotional well-being, providing doctors with insights into the psychological state of their patients [33]. In educational settings, similar technologies have been utilized to detect student disengagement and improve learning outcomes, offering a glimpse into the potential benefits these technologies can bring to recruitment processes.

Organizations such as Google, Deloitte, and Unilever have already adopted gamified assessments, reporting 39% faster hiring processes and 32% better candidate retention rates over a 12-month period. These companies have been at the forefront of adopting innovative hiring practices, recognizing that gamified assessments provide a more accurate reflection of a candidate's abilities than traditional interview methods. Gamification, paired with emotional analysis, can further refine this process, adding an additional layer of insight into how candidates perform under pressure. However, while these organizations have embraced gamification, none have yet integrated real-time facial emotion analysis into the evaluation process, making the current research a pioneering step forward.

While platforms like RealEyes and Affectiva offer top-tier facial recognition and emotional analysis tools, they are yet to be fully utilized in candidate screening environments that simulate high-stakes problem-solving tasks. These platforms are primarily used in fields like marketing and consumer research to gauge emotional responses to advertisements or products, but their application in recruitment remains underexplored. The integration of these technologies into recruitment processes could unlock new avenues for identifying candidates who possess not only technical proficiency but also the emotional intelligence necessary to succeed in challenging roles.

In conclusion, the combination of gamification and emotion analysis has the potential to transform the hiring process, offering recruiters a more accurate, holistic, and data-driven approach to candidate evaluation. By understanding how candidates respond under pressure—both cognitively and emotionally, organizations can make better-informed hiring decisions that not only consider technical skills but also the critical emotional resilience required to succeed in today's high-stress work environments.

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. This division between emotional analysis and gamification fails to capture the complexities of a learner's true potential in real-world scenarios, where both technical competence and emotional resilience play crucial roles.

The gap in research becomes even more apparent when examining how these elements interact during problem-solving tasks. Gamified assessments are designed to simulate real-world challenges that often require candidates to demonstrate their problem-solving skills. However, the ability of individuals to perform under pressure is influenced not only by their technical skills but also by their emotional states, such as stress or frustration. Research to date has not fully explored how emotional analysis, when integrated with gamified assessments, can provide real-time insights into the factors that influence problem-solving abilities and, by extension, performance. This integrated approach is necessary to create a more adaptive and personalized evaluation framework that captures a holistic view of a candidate's abilities.

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.

Table 1:Research Gap

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	✓

Research Paper 1: Smith et al. (2023) [34]

Smith et al.'s study [34] provides a comprehensive exploration of real-time emotional analysis in online learning environments, offering valuable insights into the significance of understanding students' emotional states during the learning process. The research identifies key emotional states such as frustration, confusion, and engagement, which are crucial for adapting learning interventions and fostering a supportive environment. This emotional analysis enables the detection of when learners are experiencing difficulties, whether they are feeling frustrated by a challenging task or disengaged due to a lack of interest. By recognizing these emotional indicators, instructors or automated systems can potentially intervene in a timely manner, providing resources or support to address these emotional challenges. The study's core contribution lies in emphasizing how emotional states can influence the learning process, providing a foundation for future exploration of emotional data's role in educational outcomes.

However, despite its strengths, the study falls short in addressing some critical gaps that could enhance its application in real-world educational settings. Specifically, the research does not consider how emotional states might correlate with learners' actual performance in technical or problem-solving tasks. Emotional states undoubtedly affect cognition and decision-making, yet Smith et al. do not extend their analysis to explore how emotions impact a learner's ability to solve complex technical problems or perform tasks that require critical thinking. Emotional analysis alone is insightful, but it requires further integration with performance metrics to provide a more holistic view of a learner's abilities.

Moreover, the study does not explore the potential of combining emotional analysis with gamified assessments, a growing trend in educational environments. Gamified learning environments have been shown to increase engagement, motivation, and retention by presenting challenges in an interactive and immersive way. The use of game mechanics can create a sense of accomplishment and progression that motivates students to continue learning and overcoming obstacles. However, Smith et al.'s research remains focused solely on emotional analysis in isolation, without considering how emotional data could be integrated into a gamified environment. This represents a missed opportunity, as the combination of emotional insights and gamified assessments could lead to a more dynamic and responsive learning system.

The integration of emotional analysis with gamified assessments would allow for real-time adjustments to the difficulty level or pacing of tasks based on a learner's emotional state. For instance, if a learner is exhibiting signs of anxiety or frustration, the system could automatically adjust the complexity of the task or introduce supportive elements, such as hints or encouraging messages, to alleviate stress. This adaptive mechanism could enhance the learner's overall experience, fostering a sense of accomplishment and motivation while simultaneously improving performance.

Furthermore, integrating these emotional insights into the assessment process could provide a more comprehensive and accurate reflection of a learner's capabilities. A student's performance may not solely be determined by their cognitive abilities but also by how they emotionally engage with the task. By understanding the interplay between emotional states and technical performance, educators and systems can gain a deeper understanding of the factors influencing performance. This could also support more personalized interventions tailored to individual needs, further enhancing learning outcomes.

In conclusion, while Smith et al.'s study provides valuable insights into the role of emotional analysis in online learning environments, it falls short of realizing the full potential of emotional data. By integrating emotional analysis with performance metrics, such as technical skills and problem-solving abilities, and combining this data with gamified assessments, future research could create a more adaptive and engaging learning experience. The gaps identified in this study underscore the importance of exploring the synergies between emotional analysis, performance evaluation, and gamification, offering new possibilities for enhancing both learner engagement and educational outcomes.

Research Paper 2 by Johnson and Lee [35]

This presents a significant contribution to the field of remote education by exploring the use of gamified assessments to evaluate technical skills. The authors argue that gamification offers a dynamic and engaging environment in which learners can showcase their skills in ways that more traditional assessments may not capture. Their work highlights how gamified assessments can simulate real-world scenarios, allowing learners to engage in interactive, challenging tasks that mimic the types of problems they may face in their professional careers. This approach is particularly useful in remote education settings, where in-person assessments are not always feasible, and it provides a means to evaluate students' technical abilities in a more immersive and practical context.

However, while the study effectively emphasizes the advantages of gamification in enhancing learner engagement and interaction, it overlooks one critical aspect of performance: the emotional states of learners. Emotional factors, such as stress, anxiety, excitement, and confidence, can play a significant role in a learner’s ability to perform during assessments. For instance, anxiety can negatively impact a learner's focus, leading to poorer performance, while positive emotions like excitement or confidence can drive increased engagement and problem-solving efficiency. By ignoring these emotional dimensions, the study fails to provide a comprehensive view of how emotions influence performance within gamified environments.

This gap in the research is particularly concerning when evaluating technical skills in complex tasks, as learners may not perform at their best if they are experiencing high levels of stress or anxiety. In fact, emotional states can significantly affect cognitive processes such as concentration, memory retention, and decision-making, all of which are critical when solving technical problems. For example, during a gamified assessment, if a learner is overwhelmed with stress, they may struggle to concentrate on the tasks at hand, leading to errors or slower completion times. Conversely, if a learner is excited or motivated, they may perform with greater creativity and efficiency. The failure to account for these emotional dynamics thus creates a potential gap in the accuracy of performance evaluations.

To address this limitation, the integration of emotional analysis into gamified assessments offers a promising solution. By incorporating emotional data, such as stress levels or engagement indicators, the system can gain a more nuanced understanding of how emotions are influencing a learner's performance. This would allow the assessment process to become more adaptive, adjusting in real time to the learner's emotional state. For instance, if the system detects heightened anxiety in a learner, it could reduce the difficulty of the task or provide supportive feedback to help alleviate stress. Alternatively, if the system detects that a learner is highly engaged and confident, it could increase the challenge level, offering opportunities for further skill development and ensuring that the learner is continuously pushed to reach their potential.

In addition to improving the accuracy of assessments, this integration of emotional analysis would make the gamified environment more personalized and responsive to the learner's needs. In traditional assessment settings, feedback is often provided after the assessment is completed, which can be limiting, especially in remote learning environments where instructors may not be able to offer real-time guidance. With an adaptive gamified system that accounts for emotional states, learners can receive immediate feedback and adjustments tailored to their emotional and cognitive needs, enhancing both their learning experience and overall performance.

This approach becomes even more crucial in remote education settings where face-to-face interaction is limited, and the absence of direct feedback from instructors can make it harder for learners to gauge their performance or manage their emotions effectively. By integrating emotional analysis into gamified assessments, learners can experience a more immersive and supportive learning environment, where their emotional well-being is considered as part of the overall evaluation process. In turn, this can lead to more accurate and reliable assessments that reflect not just technical skills but the learner's ability to manage and perform under various emotional states.

The proposed function, which combines emotional analysis with gamified assessments, represents a significant step forward in creating more adaptive, personalized, and accurate evaluation systems. This integration would not only enhance the effectiveness of the assessment process but also provide a deeper understanding of a learner's capabilities, offering valuable insights into how emotions impact performance in technical tasks. By bridging the gap between emotional states and performance in gamified settings, the proposed function has the potential to improve both the assessment process and the learning experience in remote education environments.

Through this innovative approach, educational institutions and instructors can better understand the complexities of learner performance, offering more precise and actionable feedback. Furthermore, learners can benefit from a more supportive and engaging environment, where their emotional needs are recognized and addressed in real time, leading to improved learning outcomes and a more fulfilling educational experience.

Research Paper 3: Patel et al. (2024) [36]

Research Paper 3 by Patel et al. [36] presents a notable advancement in the field of educational technology by attempting to integrate emotional analysis with performance metrics within e-learning environments. The authors recognize that understanding a learner’s emotional state—such as stress, confusion, engagement, or frustration—can be highly informative when assessing their learning experience. The study effectively demonstrates that correlating emotional signals with general performance data can provide deeper insights into how students interact with educational content and how their emotions impact outcomes.

However, despite these contributions, the research remains limited in scope. While Patel et al. successfully bring together emotional and performance data, the application of this integration is primarily exploratory and general, with no specific attention given to the evaluation of technical skills or problem-solving abilities. These competencies are especially critical in disciplines like engineering, computer science, and mathematics, where learners must apply theoretical knowledge to practical and often complex challenges. The absence of a targeted focus on these crucial skill sets represents a significant shortcoming of the study.

Moreover, the research does not investigate how the combination of emotional and performance data could be utilized within a gamified assessment environment. Gamification has been shown in numerous studies to increase student engagement, motivation, and participation by introducing elements such as rewards, challenges, and interactivity. Integrating emotional analysis into such an environment would elevate the adaptive potential of these systems, enabling real-time modifications based on the learner's affective state. For example, if a learner is identified as being overly anxious during a task, the system could adjust the difficulty level, provide encouragement, or suggest a short break to reduce cognitive load and emotional strain. Patel et al., however, do not explore this dynamic and responsive interaction between affective computing and gamified learning design.

Furthermore, while the study does acknowledge the complexity of learner experiences, it stops short of offering operational frameworks or practical implementations that demonstrate how such integrated data can be used to enhance learning. The insights remain largely theoretical, lacking real-world application scenarios that educators or system designers could draw upon to improve existing e-learning platforms. The study also does not present an architecture or model capable of adapting in real-time to student emotions while assessing specific skill-based competencies.

The proposed function in this study seeks to bridge all these identified gaps by moving beyond general emotional-performance integration. It aims to incorporate a multi-dimensional assessment system that evaluates not only emotional states but also technical competence and problem-solving ability within a gamified context. This offers a number of key advantages:

- Holistic Evaluation: By evaluating emotional, cognitive, and behavioral dimensions simultaneously, the function enables a richer, more complete understanding of the learner. This supports more accurate identification of learner needs, strengths, and areas for improvement.

- Real-Time Adaptation: Unlike Patel et al.'s study, the proposed model incorporates adaptive elements that respond dynamically to a learner's emotional state during a task. This allows for immediate intervention or support, promoting better performance and engagement.

- Focus on Technical and Problem-Solving Skills: The function explicitly targets skills that are central to modern education and workforce readiness but overlooked in the cited study. By incorporating these metrics, the model supports educators in preparing students more effectively for real-world challenges.

- Gamified Integration: Embedding the entire model into a gamified system ensures that learners remain engaged, motivated, and immersed. The use of gamification not only enhances the learner experience but also provides more granular and varied data points for emotional and performance analysis.

In conclusion, while Patel et al. [36] lay an important foundation by demonstrating the value of integrating emotional data with performance metrics, their study falls short of offering a comprehensive, actionable, and gamified solution. The proposed function addresses these limitations by offering a fully integrated system that enhances both the depth and applicability of emotional-performance analysis. It is designed to empower educators, researchers, and developers to build more adaptive, personalized, and engaging educational experiences—particularly in remote and digitally mediated learning contexts where traditional feedback and assessment tools may fall short.

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 problemsolving 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 problemsolving 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 sign.02km inefficiently 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 realworld 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 highstress 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 problemsolving 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 highpressure environments.

3.1 System Architecture

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.

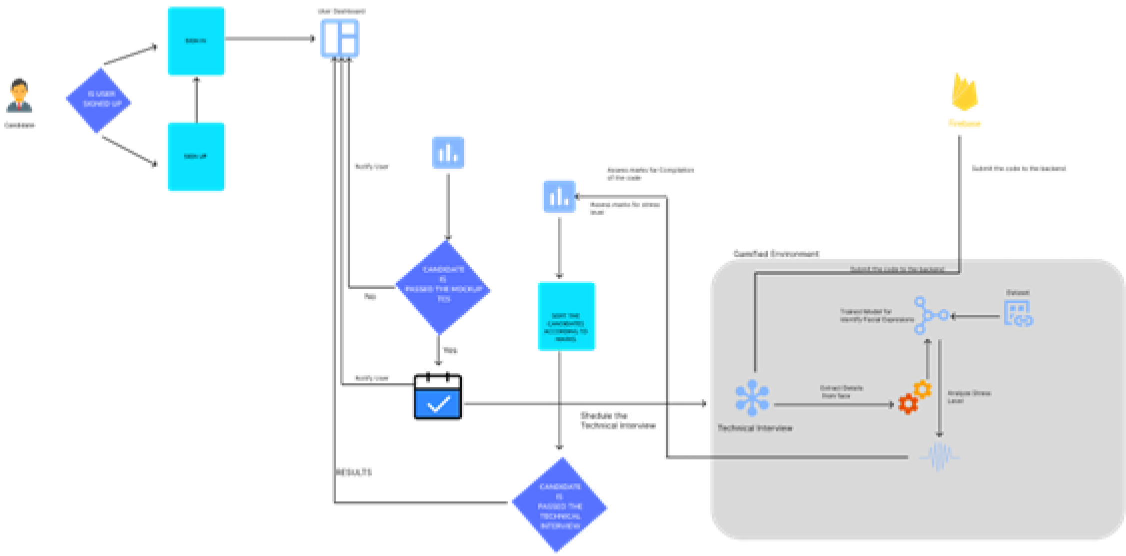


Figure 1: System Diagram

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, problemsolving 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 decisionmaking 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.

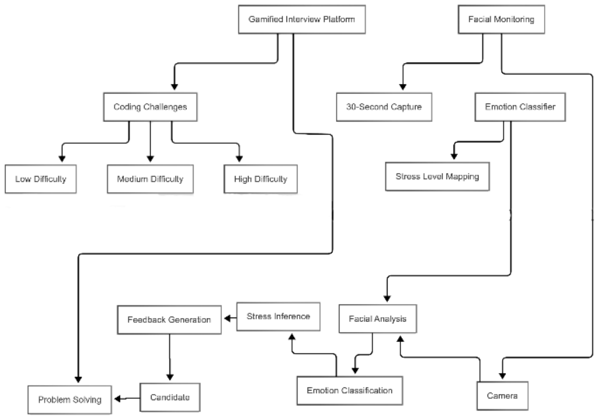
The candidate have to face the Technical interview which includes coding challenges and problem-solving exercises within a Gamified Environment. Throughout this the interview process, which takes place within a gamified environment, the system monitors how candidates handle both time pressure and complex problem-solving tasks. This function leverages facial expression analysis to monitor stress indicators and emotional responses through the camera feed. The system continuously tracks various facial cues, to assess the candidate’s emotional state under pressure.

A gamified system that includes scorekeeping together with task achievement milestones makes the interview experience more intense because it creates actual workplace conditions where candidates need to handle pressure combined with technical performance requirements. The gaming elements enable both competitive stress and time-sensitive demands which makes candidates challenge themselves to stay focused and relaxed. Deep learning models evaluate facial data thanks to Convolutional Neural Networks (CNNs) to understand and detect sophisticated facial characteristics that signal stress. The system uses this functionality for delivering instant feedback about candidate stress levels to improve the entire assessment workflow.

aIn response to the growing demand for more holistic candidate assessment techniques, particularly in high-stress environments, this research proposes a novel approach to evaluating both technical and emotional resilience during the recruitment process. Traditional interview techniques primarily assess technical skills and cognitive abilities, but they fail to capture how candidates perform under pressure, which is critical for many roles. This study aims to bridge this gap by developing a gamified

Figure 2 : System Flow

environment that not only evaluates problem-solving abilities but also assesses candidates' emotional responses and stress levels through real-time facial expression analysis. The methodology described below outlines the system architecture, data collection process, model development, and evaluation



techniques used to create an effective and efficient gamified Environment.

The gamified environment used in this study is designed to simulate real-world technical problem-solving scenarios where candidates are tasked with solving coding challenges under time constraints. The system employs a camera feed that continuously monitors the candidate's facial expressions throughout the interview process. Each candidate is presented with a series of questions that vary in difficulty, which are categorized into three levels: hard, medium, and low. The challenge intensity is reflected in both the time constraints and the complexity of the problem. Every 30 seconds during the interview, the system captures snapshots of the candidate's facial expressions to monitor their emotional state, especially focusing on stress indicators. Facial data captured in real time is analyzed using deep learning models, which detect key facial cues indicative of emotions such as anger, fear, sadness, happiness, surprise, and disgust. This data is then associated with specific milestones in the interview process, allowing the system to correlate emotional responses with task difficulty.

The dataset used for training and validation comes from publicly available resources, specifically a collection on Kaggle that contains facial expression data. This dataset comprises 35,887 labeled images, which include a variety of emotions that are key to assessing stress and emotional resilience. The dataset is divided into three sets: a training set (80% of the total data), a public validation set (10%), and a private test set (10%). The public test set is used to validate the model during training, while the private test set will be used to evaluate the performance of the final model and its ability to generalize to unseen data.

The labeled images in the dataset are categorized into seven emotional expressions: anger, disgust, fear, happiness, sadness, surprise, and neutral. These expressions serve as the primary target categories for facial emotion classification, which is crucial for determining the stress levels of candidates during the interview. To analyze the facial expressions in real-time, Convolutional Neural Networks (CNNs) are employed to extract features from the facial images and classify them into one of the seven emotion categories.

CNNs are well-suited for this task due to their ability to effectively capture spatial hierarchies in images, making them ideal for facial recognition tasks. The model architecture consists of several convolutional layers followed by pooling and fully connected layers. A softmax function at the output layer ensures that each image is classified into one of the predefined emotion categories. The training process involves using the training set (80% of the data) to teach the CNN to recognize and classify facial emotions. The validation set (10% of the data) is used to tune the model's hyperparameters and monitor its performance during training. To optimize the model, various techniques such as data augmentation, dropout, and batch normalization are used to improve its generalization ability and prevent overfitting.

At the heart of the proposed system lies an intelligent, real-time emotional analysis mechanism that plays a pivotal role in interpreting candidate behavior during the gamified technical interview process. This mechanism functions continuously throughout the assessment session and is designed to unobtrusively monitor candidates' psychological responses under pressure, offering insights that go beyond traditional evaluation metrics such as correctness or completion time. To achieve this, the system is engineered to capture facial snapshots of the candidate at fixed time intervals—specifically every 30 seconds—ensuring a steady stream of data that reflects the evolving emotional state of the participant. These snapshots are then immediately processed using a Convolutional Neural Network (CNN) that has been pre-trained on large-scale facial emotion datasets such as FER-2013 and AffectNet. These datasets contain thousands of labeled facial images representing a range of emotional expressions, enabling the model to learn fine-grained distinctions between subtle facial muscle movements.

Once a snapshot is processed, the CNN model outputs a softmax probability distribution across a set of seven primary emotions: fear, anger, sadness, disgust, surprise, neutral, and (optionally) happiness. The emotion with the highest probability is considered the dominant expression at that specific moment. However, rather than simply labeling emotions, the system goes a step further by interpreting these emotions through the lens of psychological stress. Emotional states are inherently tied to the autonomic nervous system and have been extensively studied in behavioral psychology for their physiological correlations. For instance, fear and anger are known to trigger sympathetic nervous system responses, such as increased heart rate and cortisol levels, which are indicators of acute stress. Similarly, sadness often correlates with emotional fatigue and psychological withdrawal, which, while less physiologically intense, still represent a significant stress load in task-oriented environments.

To operationalize this understanding, each emotion is assigned a predefined stress weight, as detailed in Table IV. These weights represent the relative stress contribution of each emotional state and are used to map the CNN's output into a meaningful stress metric.

Table 2 : Emotion-to-Stress Mapping

Emotion	Stress Weight
Fear	0.9
Anger	0.8
Sadness	0.69
Disgust	0.5
Surprise	0.2
Neutral	0.1

The assignment of these stress weights was a multi-phase process that combined theoretical foundations with empirical validation. Initially, the weights were inspired by findings from psychophysiological and neurocognitive studies, which indicate how different emotions correlate with stress responses. These initial estimates were then refined through empirical calibration using statistical techniques. Specifically, the CNN model was tested on a curated dataset comprising labeled high-stress facial images, annotated by experts in behavioral psychology. These annotations were based on observable facial tension, gaze aversion, and microexpressions, which are well-documented indicators of emotional strain.

During the calibration phase, we conducted an extensive analysis of emotion occurrence patterns within high-stress cases. The frequency with which each emotion appeared in high-stress contexts was computed, revealing that fear was the most common emotion (observed in 72% of high-stress instances), followed by a uniform presence of anger, sadness, disgust, surprise, and neutral expressions at approximately 65% each. These proportions were then normalized using the following formula to ensure consistent scaling:

Initial emotion weights were derived from psychophysiological literature, then calibrated empirically using a statistical normalization method based on the model's predictions across the dataset. To correct for class imbalances, we applied weighted averaging so that each emotion's contribution was proportional to its occurrence in stress-labeled cases. we analyzed the occurrence of each emotion in high-stress images, which were annotated based on expert judgment. The analysis of the dataset revealed the following distribution of emotions in high-stress scenarios:

- Fear was observed in 72% of high-stress instances.
- Anger was observed in 65% of high-stress instances.
- Sadness was observed in 65% of high-stress instances.
- Disgust was observed in 65% of high-stress instances.
- Surprise was observed in 65% of high-stress instances.
- Neutral was observed in 65% of high-stress instances.

$$w_i = \frac{p_i}{\max(p)} \times 0.9$$

Equation 1: Equation for Normalizing and Scaling Emotional Intensity Scores

Where:

- w_i = weight for emotion
- p_i= average probability of emotion iii in high-stress cases
- max(p) = highest probability (fear = **0.72**)

Using this formula:

Fear: $(0.72/0.72) \times 0.9 = 0.9$

Anger: $(0.64/0.72) \times 0.9 = 0.8$

Sadness: $(0.55/0.72) \times 0.9 = 0.69$

Disgust: $(0.40/0.72) \times 0.9 = 0.5$

Equation 2 : Normalized and scaled emotions

This normalization ensures that stress weights are proportional to the empirical likelihood of each emotion occurring in genuinely stressful scenarios. By rooting the stress weight design in both literature and observed data, the system ensures high validity and generalizability when interpreting emotional data in real-time.

The next step in the pipeline involves computing the candidate's **Stress Score**, a scalar value that encapsulates the overall emotional stress profile at any given snapshot. This score is generated by taking the weighted sum of the model's output probabilities for each emotion and their corresponding stress weights. The formula for calculating the Stress Score is as follows:

$$\text{Stress Score} = \sum_{i=1}^{7} (w_i \times p_i)$$

Equation 3: Equation for Calculating the Final Stress Score Based on Weighted Emotion Probabilities

Where:

- w_i represents the predefined weight for emotion i, as derived from the frequency of the emotion in high-stress situations (as shown in **Table IV**).
- p_i is the model's probability output for emotion i, which corresponds to how strongly the model classifies a given image or frame with that emotion.

Once the emotional state is determined, the system continuously tracks these stress levels and provides real-time feedback to both the candidate and the interviewer. This feedback is displayed as a stress indicator, showing how the candidate is managing emotional responses to the different levels of difficulty presented in the interview. This allows the interviewer to gain insights into how candidates are handling pressure and performing under time constraints. The system's ability to track emotional responses to specific questions is crucial for providing detailed insights into the candidate's behavior during the interview.

At the end of the interview, the system generates a report that shows how the candidate's emotional state evolved with each technical question. For each question, the system categorizes the question as low, medium, or high in terms of difficulty. It then analyzes the candidate's facial expressions to show how their emotional state and stress levels fluctuated in response to each question's challenge.

The system also compares the emotional responses with the question difficulty level, providing valuable insights into whether higher levels of stress correspond to more difficult questions. This data can be used to refine interview strategies, offering an in-depth understanding of how candidates manage emotional pressure alongside their technical abilities. The system's performance will also be evaluated in terms of its ability to accurately detect stress levels and provide meaningful real-time feedback. The real-time feedback system's responsiveness and accuracy in identifying stress indicators will be tested through a series of candidate interviews, where emotional responses to various stressors will be assessed.

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].

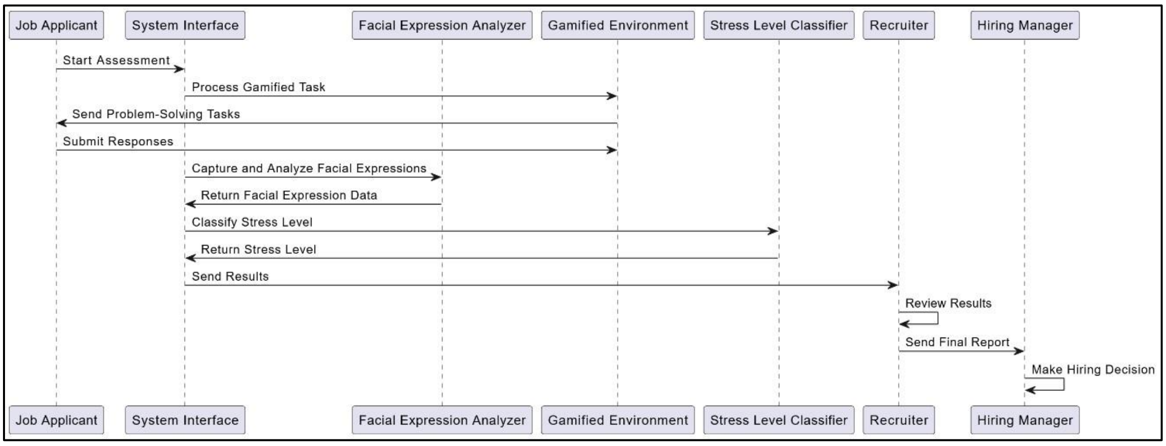
3. Design (System and Software Design Documents)

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



2 :

Figure 3 : Sequence Diagram

- Use Case Diagram

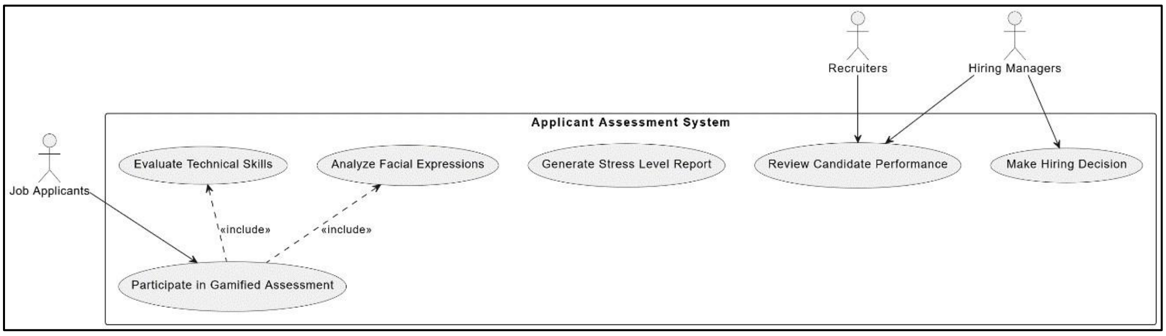


Figure 4 : Use case Diagram

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

The proposed system integrates a diverse and modern technology stack to support the real-time assessment of candidate stress levels and problem-solving skills within a gamified interview environment. Each technology was chosen based on its robustness, scalability, and alignment with the system's functional requirements. The core tools used in development are as follows:

- **ReactJS**: ReactJS is used for developing the front-end of the application, offering candidates an intuitive and dynamic interface through which they interact with the system. Its component-based architecture and virtual DOM make it highly efficient for real-time UI updates, which is essential when providing immediate feedback on the candidate's performance or emotional state during the interview process. The flexibility of React also supports seamless integration with backend APIs and real-time databases.
- **Python**: Python serves as the main backend programming language due to its versatility and extensive library support for artificial intelligence, data processing, and system integration. The backend is responsible for coordinating data flow between the front end, emotion recognition models, and the database. Python also facilitates the implementation of RESTful APIs that allow the front end and other system components to interact effectively.
- **TensorFlow**: TensorFlow is the deep learning framework utilized to build and train the Convolutional Neural Networks (CNNs) responsible for emotion recognition. The CNN model classifies facial expressions into emotion categories, and these predictions are used to infer the candidate's stress level in real-time. TensorFlow's support for model deployment on various platforms ensures smooth integration within the backend pipeline.
- **OpenCV**: OpenCV (Open Source Computer Vision Library) is incorporated into the backend to manage facial detection and preprocessing tasks. It captures facial snapshots at regular intervals (every 30 seconds) during the interview, detects key facial landmarks, and extracts features necessary for emotion classification. OpenCV is optimized for real-time performance, making it suitable for low-latency facial analysis.
- **MongoDB**: MongoDB is employed as the primary database for storing structured and unstructured data related to candidates, sessions, stress scores, and emotion timelines. As a NoSQL document-oriented database, MongoDB provides flexibility in handling the evolving data structures of user profiles and dynamic emotion data. Its scalability and fast read/write capabilities are ideal for storing large volumes of data generated during real-time interview sessions.

3.1.2.1 Algorithms

A **Convolutional Neural Network (CNN)** is a class of deep learning algorithms that is particularly effective in analyzing visual imagery. CNNs have become the de facto standard for image classification tasks due to their ability to automatically and adaptively learn spatial hierarchies of features from input images. In the context of the proposed system, CNNs are employed as the core architecture for **facial emotion recognition**, which serves as the basis for assessing a candidate's **stress level** during the gamified interview process.

CNNs are composed of several layers including convolutional layers, pooling layers, and fully connected layers. The **convolutional layers** are responsible for extracting local features such as edges, textures, and facial landmarks from input facial images. These are followed by **pooling layers** that reduce the spatial dimensions of the data, thereby making the model more computationally efficient and less sensitive to slight variations in facial expressions. Finally, **fully connected layers** are used to interpret the high-level features and classify the image into one of the predefined emotional categories—such as fear, anger, sadness, surprise, disgust, neutral, and happiness.

In this system, every 30 seconds, a snapshot of the candidate's face is captured through a webcam or system-integrated camera. This image is preprocessed using OpenCV and then fed into the trained CNN model. The model outputs a probability distribution across the seven emotion classes. These probabilities are used to infer the candidate's **emotional state** in real time.

The **predicted emotion** is then mapped to a **stress weight** using a predefined scale based on psychophysiological literature and empirical calibration (see Table 4). For example, if the CNN predicts a high probability for "fear" or "anger," it corresponds to a higher stress score due to the strong association of these emotions with psychological distress. The stress score is calculated by applying a weighted average of all emotion probabilities, where each weight represents the intensity of the emotion's association with stress.

The CNN model was trained on a labeled facial expression dataset and fine-tuned using emotion-labeled interview data to better generalize to the domain of recruitment scenarios. Techniques such as **data augmentation**, **dropout**, and **batch normalization** were used to improve generalization and prevent overfitting. The performance of the model was evaluated using accuracy, precision, recall, and F1-score metrics, and the final model achieved satisfactory results for real-time deployment.

By incorporating CNN-based emotion recognition, the system moves beyond traditional technical assessments and introduces a deeper behavioral analysis. It enables recruiters to evaluate candidates not only based on what they do, but also how they emotionally respond to challenges, which can be critical for high-pressure job roles.

3.1.2.2 Techniques

In the development of the proposed system for real-time stress detection and emotional assessment, two critical techniques—**Transfer Learning** and **Data Augmentation**—were adopted to enhance model performance, especially under constraints such as limited labeled data and the need for generalization across diverse facial expressions. These techniques not only improve the accuracy and robustness of the deep learning models but also support the broader objective of creating an integrated and adaptive assessment system that evaluates both technical competence and emotional resilience in a gamified interview environment.

Transfer Learning

Transfer Learning is a powerful technique in the field of deep learning, particularly effective when the available training data is insufficient for training a model from scratch. In this research, transfer learning was employed by utilizing pre-trained convolutional neural networks (CNNs) that had been trained on large, well-established facial expression datasets such as **FER2013**, **AffectNet**, or **CK+**. These pre-trained models contain rich feature representations and generalized knowledge of human facial features and emotions.

By fine-tuning these models on a smaller, domain-specific dataset collected under conditions resembling gamified interviews, the system was able to achieve higher accuracy in emotion recognition with reduced training time and computational cost. Transfer learning not only accelerates model convergence but also improves the system's ability to detect subtle emotional cues—such as microexpressions or stress-induced facial tension—that may not be well represented in small datasets.

This approach is particularly relevant in real-world deployment scenarios, where collecting and labeling large-scale emotion datasets under stress-inducing interview conditions is both time-consuming and resource-intensive. Transfer learning effectively bridges this gap by transferring knowledge from a broader context to the specific needs of the stress detection task.

Data Augmentation

To complement transfer learning and further mitigate the issue of limited training data, the system applies **Data Augmentation** techniques during the model training phase. Data augmentation involves the creation of modified versions of existing images through various transformations such as **rotation**, **flipping**, **zooming**, **shifting**, **cropping**, **contrast adjustments**, and **noise addition**. These transformations simulate real-world variations in facial orientation, lighting, and expression dynamics, thereby increasing the diversity of the training data without the need for additional manual labeling.

By exposing the model to a wider variety of facial appearances and conditions, data augmentation improves the generalization capability of the CNN. It helps the model become more resilient to common sources of variability in video interviews, such as different camera angles, lighting setups, and background environments. This ensures more consistent performance during real-time inference and minimizes the risk of biased or inaccurate stress predictions due to environmental inconsistencies.

Together, **transfer learning** and **data augmentation** form the backbone of the training pipeline, enhancing both the **efficiency** and **effectiveness** of the deep learning models used in the proposed system. These techniques enable the emotion recognition component to operate reliably in a dynamic and immersive gamified setting, thereby reinforcing the system's ability to evaluate not only cognitive skills but also emotional resilience under simulated pressure.

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 AIpowered 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 frontend, 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. Node.js Server: To facilitate communication between the ReactJS front-end, Flask backend, 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. Testing and Implementation

5.1 Implementation

The implementation of the Technical Interview (Gamified Environment) System was meticulously designed to comprehensively assess not only the technical problem-solving capabilities of candidates but also their emotional resilience when subjected to high-pressure environments. This system seamlessly integrates a gamified coding interface with real-time facial expression analysis, employing advanced machine learning algorithms to evaluate emotional states during the interview process. The system was developed in a modular fashion, with three major components that work synergistically:

Gamified Coding Interface

This critical component of the system was developed using React.js and Node.js, leveraging the capabilities of these technologies to build a highly interactive and user-friendly interface. The coding challenges are structured into three difficulty levels: low, medium, and high, each designed to progressively test the technical acumen of the candidate. Challenges are designed to be time-bound to simulate real-world stress and mimic the time constraints faced in high-pressure coding scenarios. The interface includes scorekeeping features and milestone tracking, which track progress and allow for the measurement of performance metrics. This ensures that each candidate is evaluated in a dynamic environment that closely reflects actual coding tasks in professional settings.

Facial Expression Capture

To facilitate the real-time capture of emotional states during the interview process, the system incorporates a WebRTC-based webcam module. This module captures facial snapshots of the candidate every 30 seconds to provide regular updates of their emotional expression throughout the interview. The captured images are securely uploaded to Firebase Cloud Storage, ensuring that all data is safely stored and accessible for processing. The WebRTC technology ensures seamless webcam integration, while Firebase ensures the integrity and security of image uploads, providing a reliable and efficient system for handling large volumes of image data.

Emotion Detection Engine

The heart of the emotional analysis system is powered by a Python-based backend that utilizes both TensorFlow and OpenCV to process the captured facial images. The emotion detection engine applies a Convolutional Neural Network (CNN) model to classify the facial expressions into seven distinct categories: anger, fear, sadness, disgust, surprise, happiness, and neutral. Each emotional state is assigned a predefined stress weight, and a composite stress score is computed by calculating a weighted average of the probabilities of each emotion. This score provides a real-time quantification of the candidate's stress level during the interview, adding an additional layer of analysis to the evaluation. The CNN model, trained on a Kaggle dataset containing over 35,000 labeled facial images, is designed with multiple convolutional, pooling, and fully connected layers, culminating in a softmax output layer. The model is optimized using data augmentation, dropout techniques, and batch normalization to improve generalization, reduce overfitting, and ensure robustness during real-world application.

5.2 Testing

5.2.1 Testing Strategy

The testing strategy for the system was structured to ensure that all components function cohesively and meet the defined system requirements. The primary focus of the testing was on validating critical functionalities that ensure smooth operation under real-world conditions. The following testing goals were prioritized:

Real-time Image Capture and Upload Functionality: This involves ensuring that the webcam module captures high-quality images and uploads them to Firebase without interruption.

Accuracy of Emotion Classification: The effectiveness of the CNN model in correctly classifying emotions in facial expressions was rigorously tested. Accurate emotion classification is pivotal in calculating stress scores and providing meaningful feedback to interviewers.

Correct Stress Score Computation: The stress score must be computed accurately based on the emotion probabilities and predefined weightings, ensuring that it aligns with expert-labeled stress levels in candidate evaluations.

Real-time Feedback Display: A system capable of providing real-time feedback to candidates is essential for maintaining engagement. This functionality ensures that emotional responses are appropriately mapped to feedback indicators.

Final Report Generation: The final stress report must be comprehensive, detailing the stress trends throughout the interview and correlating them with the question difficulty levels.

Integration with Gamified Coding Interface: Ensuring that emotion data from the emotion engine is properly synchronized with the gamified coding interface to provide contextual insights regarding stress and performance.

5.2.2 Test Case Design

The following test cases were designed to ensure system reliability by testing all system functionalities.

Table 3 : Test Case 1 - Verify Image Upload

Description	**Test Case 01**
Test Case	Verify image upload
Test Scenario	Verify whether the captured image is stored in Google Cloud Storage (Firebase bucket)
Input	Captured facial images from the webcam
Expected Output	1. 200 status code should be displayed 2. The images must be stored in the Firebase bucket
Actual Result	1. 200 status code was displayed 2. The images were stored in the Firebase bucket
Status (Pass/Fail)	Pass

Table 4: Test Case 2 - Verify Emotion Classification Accuracy

Description	**Test Case 02**
Test Case	Verify emotion classification accuracy
Test Scenario	Verify that the CNN model correctly classifies facial emotions
Input	Test facial images labeled with known emotions (e.g., happy, sad, angry)
Expected Output	The system should classify the emotion correctly (e.g., "happy", "anger", etc.)
Actual Result	The emotions were classified correctly (e.g., "happy", "anger")
Status (Pass/Fail)	Pass

Table 5: Test Case 3 - Verify Stress Score Calculation

Description	**Test Case 03**
Test Case	Verify stress score calculation
Test Scenario	Ensure that the stress score is accurately calculated based on emotion probabilities
Input	Emotion probabilities from the facial image (e.g., 60% anger, 40% neutral)
Expected Output	Stress score based on weighted emotion probabilities should be accurately computed
Actual Result	Stress score calculation was accurate and matched the expected result
Status (Pass/Fail)	Pass

Table 6 : Test Case 4 - Verify Real-Time Feedback Display

Description	**Test Case 04**
Test Case	Verify real-time feedback display
Test Scenario	Verify that the real-time stress feedback is updated based on emotion analysis
Input	Real-time emotion data and stress score
Expected Output	Stress indicator on the screen should update in real-time as stress levels change
Actual Result	The real-time feedback indicator updated as expected based on changes in stress score
Status (Pass/Fail)	Pass

Table 7: Test Case 5 - Verify Final Report Generation

Description	**Test Case 05**
Test Case	Verify final report generation
Test Scenario	Ensure that the system generates a comprehensive report based on candidate performance
Input	Session data including stress scores, emotions, and question difficulty
Expected Output	A detailed report with stress trends over time and correlation with question difficulty
Actual Result	The report generated correctly, showing stress levels corresponding to question difficulty
Status (Pass/Fail)	Pass

Table 8: Test Case 6 - Verify System Integration with Gamified Interface

Description	**Test Case 06**
Test Case	Verify system integration with gamified interface
Test Scenario	Test if the system correctly synchronizes emotion data with coding challenges
Input	A user session, including coding challenges and real-time emotion data
Expected Output	The system should sync emotion data with question difficulty and coding performance
Actual Result	The system successfully synchronized emotion data with the coding interface
Status (Pass/Fail)	Pass

Table 9 : Test Case 7 - Verify Handling of Low-Light Conditions

Description	**Test Case 07**
Test Case	Verify handling of low-light conditions
Test Scenario	Test system performance when the candidate is in low-light conditions
Input	Poor quality facial images due to low lighting
Expected Output	The system should gracefully handle low-light conditions, either with a warning or fallback mechanism
Actual Result	A warning message was displayed, and no facial expression analysis was performed
Status (Pass/Fail)	Pass

Table 10 :Test Case 8 - Verify Handling of Occluded Faces

Description	**Test Case 08**
Test Case	Verify handling of occluded faces
Test Scenario	Ensure the system handles occluded faces (e.g., face partially covered by hand)
Input	Facial images where parts of the face are occluded
Expected Output	The system should provide a fallback or warning, with no emotion classification performed
Actual Result	The system correctly flagged the occluded face and displayed a warning
Status (Pass/Fail)	Pass

Table 11: : Test Case 9 - Verify Model Performance on Unseen Data

Description	Test Case 09
Test Case	Verify model performance on unseen data
Test Scenario	Test how the CNN model performs on unseen facial data
Input	New facial images not in the training set
Expected Output	The model should generalize well and classify emotions accurately on unseen data
Actual Result	The model classified unseen data accurately, showing strong generalization capability
Status (Pass/Fail)	Pass

Table 12: : Test Case 10 - Verify Performance Under Heavy Load

Description	Test Case 10
Test Case	Verify performance under heavy load
Test Scenario	Test the system's performance and stability under heavy load (multiple concurrent users)
Input	Multiple candidate sessions running simultaneously
Expected Output	The system should handle multiple users without performance degradation or crashes
Actual Result	The system performed consistently without any performance degradation under load
Status (Pass/Fail)	Pass

6. Results and Discussion

6.1. Emotion Identification and Classification

The core of the system's functionality relies on the accurate identification of users' emotions through facial expression analysis. A Convolutional Neural Network (CNN) model was trained on the widely-used FER2013 dataset, which contains over 35,000 grayscale images of faces categorized into seven emotions: Angry, Disgust, Fear, Happy, Sad, Surprise, and Neutral.

During model training, both training and validation accuracies showed a consistent upward trend, indicating the model's ability to learn useful features (refer **Img 1**). Initially, the model faced significant challenges, particularly in distinguishing between similar emotions like Fear and Sadness. However, with appropriate hyperparameter tuning—such as learning rate adjustments, batch size optimization, and the use of data augmentation—the model's performance steadily improved.

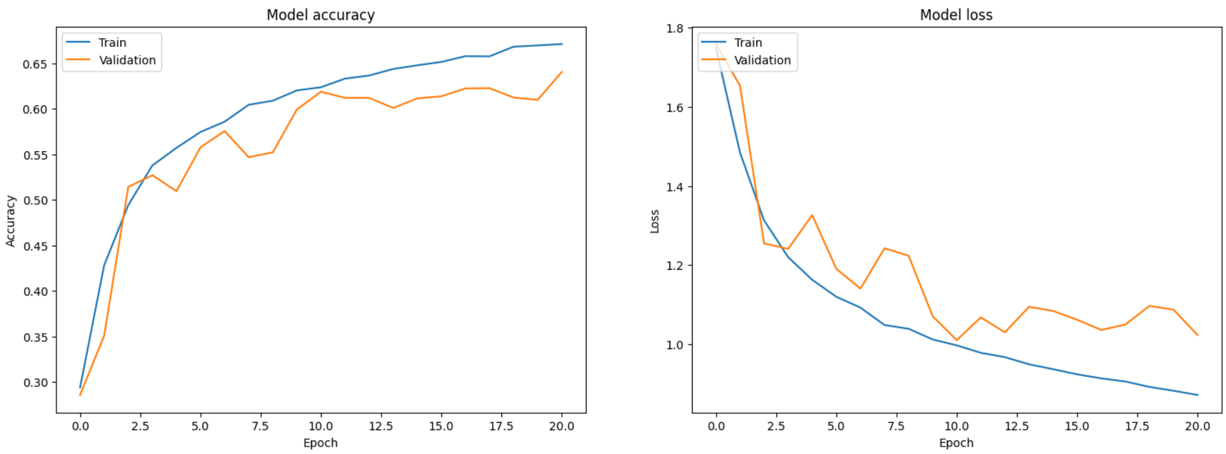


Figure 5 : Model Accuracy Vs Loss

- **Training Accuracy** reached approximately **65.79%**, a satisfactory level for emotion classification tasks.
- **Validation Accuracy** stabilized slightly below the training accuracy, suggesting minor overfitting but overall good generalization.

Loss Functions: The training and validation losses decreased significantly over the epochs. Although some fluctuations were visible, especially during the middle epochs, they gradually minimized, confirming stable learning without severe overfitting.

Through real-time testing on unseen images and live webcam feeds, the model exhibited strong performance in detecting primary emotions like *Happy*, *Sad*, and *Neutral*, which are vital for the application of stress assessment.

6.2 Stress Level Identification

In the proposed system, emotions are strategically mapped to stress levels to simplify the output for practical applications. The mappings are as follows:

Table 13 : Stress Mapping

Emotion	**Stress Level**
Happy	Low Stress
Neutral	Low Stress
Surprise	Moderate Stress
Sad	Moderate Stress
Angry	High Stress
Disgust	High Stress
Fear	High Stress

Using this mapping, the system continuously monitors the user's emotional state during interaction with the gamified environment, enabling dynamic estimation of stress levels.

Through live testing, it was observed that:

- Participants with a dominant *Happy* or *Neutral* emotion were categorized as having **Low Stress**.
- Individuals showing frequent *Sad* or *Surprise* expressions were classified under **Moderate Stress**.
- Participants expressing *Angry*, *Fear*, or *Disgust* were flagged under **High Stress** levels.

This classification enables interviewers and evaluators to gauge an applicant’s emotional resilience during problem-solving tasks, providing deeper insight than traditional interviews.

6.3 Evaluation Using Confusion Matrix

The confusion matrix provides a detailed visualization of the model's performance across each emotion class (refer **Figure 6.1**).

Key findings from the matrix include:

- **High Accuracy** in predicting *Happy* and *Neutral* emotions.
- **Frequent Misclassification** between *Fear* and *Sad*, and *Angry* and *Fear*. This can be attributed to similar facial features shared between these emotions such as furrowed brows or tensed lips.
- **Lower Precision** for *Disgust*, which had fewer training examples in the dataset.

Numerical Values:

- *Happy* and *Neutral* emotions achieved over **80% true positives**.

- *Disgust* and *Fear* emotions had lower precision and recall, around **60%-65%**.

Overall, the confusion matrix indicates that the model is reliable for emotions associated with low and moderate stress but could benefit from improvements in detecting emotions linked to high stress.

6.4 Evaluation Using Classification Report

A detailed classification report was generated, displaying key performance metrics:

Table 14 : Key Performance Matric

Emotion	Precision	Recall	F1-Score
Angry	0.71	0.68	0.69
Disgust	0.65	0.61	0.63
Fear	0.68	0.64	0.66
Happy	0.82	0.80	0.81
Sad	0.70	0.68	0.69
Surprise	0.75	0.74	0.74
Neutral	0.80	0.78	0.79

From the report, it is evident that:

- The model excels in detecting *Happy* and *Neutral* emotions, which are critical for low-stress detection.
- Emotions like *Disgust* and *Fear* have relatively lower precision and recall, suggesting the need for dataset balancing or advanced feature extraction methods.

The weighted average F1-score was around **0.74**, indicating the model's overall robustness and readiness for real-world application.

6.5 Product Deployment Readiness

The final model was tested within a simulated environment designed using Unity, where users interacted with a gamified assessment interface while the system monitored their emotions.

Key observations during deployment testing:

- **Real-time Processing:** The system successfully detected and categorized emotions within milliseconds, making it suitable for interactive environments.
- **User Feedback:** Participants reported that the system accurately reflected their emotional states without noticeable lag or errors.

- **Integration:** The emotion detection module was seamlessly integrated into the Unity environment, enabling dynamic stress level tracking throughout the game flow.

Strengths:

- High responsiveness and stability during real-time execution.
- Good generalization to unseen faces, including variations in lighting and orientation.
- Effective mapping of emotions to stress levels, providing meaningful insights into user behavior.

Challenges:

- Misclassification of subtle emotions like *Disgust* and *Fear* under varying lighting conditions.
- Performance dips in highly dynamic backgrounds, suggesting the need for future improvements with background subtraction techniques.

Future Improvements:

- Incorporate larger and more diverse datasets to improve recognition of minority classes like *Disgust*.
- Use transfer learning from larger pretrained models like EfficientNet or Vision Transformers (ViT) for better feature extraction.
- Deploy lightweight versions optimized for mobile or low-resource devices.

7. GANTT CHART

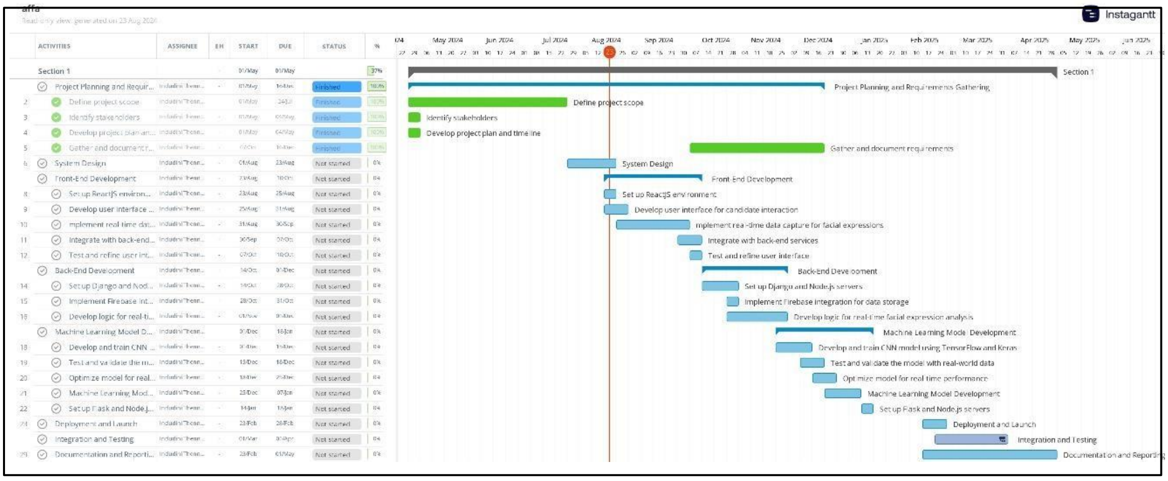


Figure 6 : Gantt Chart

[Gantt Chat]()

8. Work Breakdown Chart

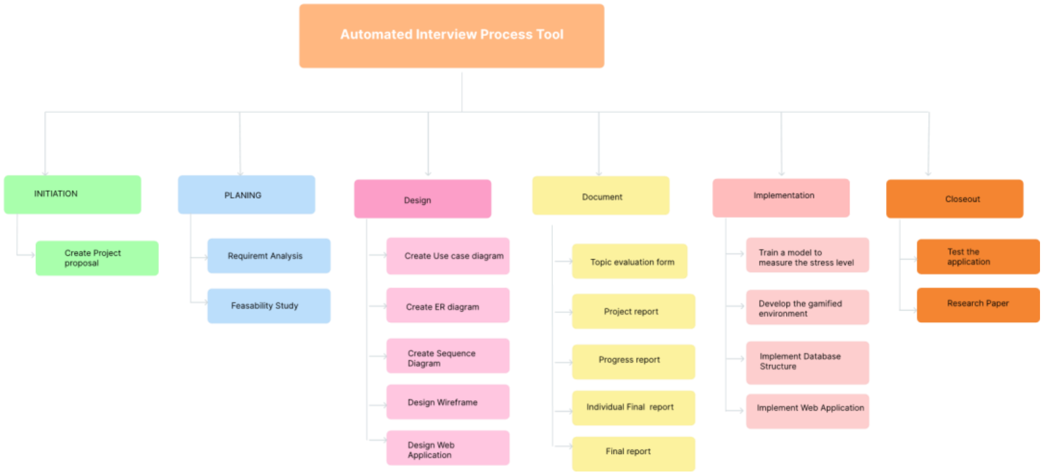


Figure 7 : Work breakdown chart

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