# Mock'n-Hire: An AI System for Automated Resume Screening and Real-Time Emotion-Aware Interview Feedback

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***Abstract*—Today's hiring landscape requires precise, streamlined, and unbiased candidate assessment on a large scale. This research introduces Mock'n-Hire, a tested AI framework that combines automated CV filtering with live, emotion-detecting practice interview evaluation. The platform uses advanced language models and semantic processing to sort applications based on employer requirements, while creating custom interview questions matched to individual candidate backgrounds. A neural network component (MobileNetV2) examines applicant video answers to deliver objective, instant stress and emotional analysis during practice sessions. These components work together through a flexible backend using FastAPI and Supabase for safe data management and live reporting. Real-world testing demonstrates Mock'n-Hire reaches 86.4% accuracy in top-10 resume selection, produces relevant interview content, and achieves over 82% precision in stress identification—matching human recruiter decisions closely. This system speeds up application review and improves interview readiness while providing useful emotional awareness data, establishing new standards for reliable, evidence-based hiring automation.**

***Index Terms*—AI Resume Screening, Mock Interviews, Emotion Detection, Semantic Analysis, Candidate Ranking, Large Language Models, FastAPI, Supabase**

## I. Introduction

The landscape of recruitment has rapidly evolved in recent years, with organizations facing the dual challenges of evaluating a high volume of applicants and ensuring fairness and precision in candidate selection. Traditional methods—such as manual resume screening and one-size-fits-all interview questions—are not only time-consuming but also susceptible to bias, inconsistency, and a lack of personalized assessment. As the number of applications increases and job requirements become more complex, there is a strong impetus for the development of intelligent, scalable systems that can automate and enrich both the screening and interview preparation stages.

Recent progress in Natural Language Processing (NLP) and deep learning, especially the advent of Large Language Models (LLMs), has created new possibilities for AI-driven recruitment. Smith et al. [1] showed that LLMs are highly effective for extracting meaningful insights from resumes, while the semantic matching techniques discussed by Jones and Brown [2] have advanced the state-of-the-art in candidate-job alignment. However, despite these advancements, most existing solutions are fragmented, often limited to isolated modules, and rarely offer recruiter-defined customization or robust emotional intelligence features.

The present work seeks to address these gaps by introducing a unified AI-powered platform, *Mock'n-Hire*, designed to automate both resume screening and interview simulation, while also incorporating emotion-aware feedback mechanisms. The core aim of this research is to provide an end-to-end system that not only ranks candidates using semantic and contextual analysis with recruiter-defined weightings but also generates personalized interview questions that adapt to each applicant's background. Moreover, the platform goes beyond technical evaluation by integrating real-time stress and emotion analysis, offering meaningful feedback to candidates on their emotional readiness—a feature largely absent in previous approaches.

Within this framework, the resume screening module leverages advanced transformer-based embeddings and customizable scoring to support nuanced shortlisting, directly addressing the lack of transparency and adaptability found in prior research. Simultaneously, the mock interview module generates dynamic, resume-driven questions across technical, HR, and situational categories, while employing a deep learning-based model for emotion detection from candidate video responses. This combination bridges the gap between technical qualifications and the emotional dimensions of interview performance, providing value to both recruiters and applicants.

All modules are seamlessly integrated via a modular FastAPI backend and supported by secure cloud storage and authentication using Supabase, enabling a streamlined and scalable workflow. Experimental results presented in this paper demonstrate that the platform achieves a high degree of alignment with recruiter decisions, delivers contextually relevant interview questions, and reliably measures emotional responses, ultimately improving both the efficiency and quality of the recruitment pipeline.

The remainder of this paper is organized as follows: Section II reviews related literature in AI-driven screening and interview systems. Section III details the methodology and overall architecture of the platform. Section IV describes the dataset and model training process. Section V outlines the technical system design and workflow. Section VI presents a thorough evaluation and discussion of experimental results, and Section VII concludes with insights and future research directions. Each section is crafted to provide a comprehensive progression from motivation to technical realization and empirical validation.

## II. Related Work

The intersection of artificial intelligence and recruitment has inspired a wide body of research in the past decade, especially in automated resume screening, intelligent interview question generation, and emotion-aware assessment of candidates. Here, we review the most influential contributions in these areas, focusing on technical approaches, experimental findings, and existing gaps that motivate our work.

**Automated Resume Screening and Semantic Matching.** Kamath and Gupta [3] pioneered the use of BERT-based contextual embeddings for parsing resumes and extracting candidate skills. Their methodology involved encoding both resumes and job descriptions into high-dimensional semantic vectors, which were then compared using cosine similarity to identify the most relevant candidates. Although this improved over earlier bag-of-words models and simple keyword search, their evaluation revealed that the model primarily excelled at core technical skills while frequently missing project work and soft skills due to the absence of domain adaptation and insufficient recruiter control over screening priorities.

Patel and Verma [4] extended transformer-based models to explicitly align candidate resumes with job postings. Their approach combined transformer embeddings with a semantic matching framework that weighed the similarity of experience, education, and skill sections. In experimental benchmarking, they reported higher candidate-job fit accuracy compared to classical TF-IDF methods. However, the system still lacked support for recruiter-driven customization—end users could not dynamically adjust scoring logic or emphasize specific requirements unique to their organization, limiting practical adoption in varied industry settings.

**Interview Question Generation and Mock Interview Systems.** Wang and Kumar [5] published a comprehensive survey of automated interview question generation methods, cataloging advances from rule-based templates to retrieval-augmented and neural approaches. They concluded that while question diversity had increased, most systems did not offer resume-driven personalization or context-awareness, leading to repetitive or irrelevant questions. Their analysis further pointed out the lack of robust evaluation benchmarks and highlighted the need for adaptive systems that tailor questions in real time as interviews progress.

Lee and Park [6] implemented a practical mock interview tool built around static question banks. Their study involved deploying the tool in university career centers, where students reported the questions as generic and occasionally mismatched with their background or target role. Statistical analysis of post-interview surveys revealed that engagement and learning outcomes improved only marginally over self-practice, indicating that deeper personalization and real-time adjustment were needed to make mock interviews more effective and realistic.

**Emotion Detection and Stress Analysis.** Mollahosseini et al. [7] introduced AffectNet, a massive facial expression database annotated with both categorical and dimensional emotion labels, which quickly became the gold standard for training deep learning models in affective computing. Using convolutional neural networks (CNNs), they demonstrated state-of-the-art results in static emotion classification. Nevertheless, AffectNet was not designed for video or temporal emotion analysis, and did not include labels or protocols for detecting candidate stress or anxiety in interview scenarios.

Zhang et al. [8] proposed an emotion recognition pipeline using MobileNetV2, a lightweight CNN, for real-time emotion detection from webcam video. Their system achieved fast inference with high accuracy for basic emotions (happy, sad, angry, etc.), making it feasible for live feedback applications. However, they did not address how these detected emotions could be translated into actionable feedback for candidates or integrated with interview platforms for continuous assessment of stress or confidence.

Li and Deng [9] offered a critical review of deep learning techniques for facial expression recognition, highlighting trends in CNN architectures, data augmentation, and multimodal fusion. They emphasized that while accuracy had increased significantly on benchmark datasets, deployment in user-facing assessment systems remained rare. The review noted that real-world settings introduced challenges like occlusions, head movement, and subtle expressions not captured in static image datasets.

Tzirakis et al. [10] developed an end-to-end system combining audio and visual modalities for multimodal emotion recognition. Their deep neural network architecture allowed the model to exploit complementary cues (such as tone of voice and facial movement) to improve emotion and stress detection, outperforming unimodal approaches. Despite strong results on research benchmarks, their method was primarily tested in controlled environments and not in the high-stakes, dynamic context of job interviews.

Nguyen et al. [11] introduced StressNet, a deep learning framework targeting real-world, "in-the-wild" stress detection

TABLE I
FEATURE COMPARISON: OUR SYSTEM VS. EXISTING TOOLS

| Feature | Our System | Other Tools |
|---|---|---|
| AI-powered Resume Parsing & Analysis | Yes | Yes |
| Recruiter-defined Weightage | Yes | No |
| Semantic Scoring (Experience/Projects) | Yes | Limited |
| Personalized Question Generation | Yes | No |
| Video-based Stress Analysis | Yes | No |
| Structured Resume Analysis Panel | Yes | No |
| Detailed Interview Performance Report | Yes | Limited |
| Bias Mitigation Features | Limited | Yes |
| Multilingual Support | Planned | Yes |

using both visual and physiological signals. The system outperformed traditional classifiers in uncontrolled, noisy environments. Yet, their research did not investigate the interpretability of model outputs or how to communicate stress feedback effectively to end-users, leaving a gap in candidate-centered applications.

**Summary and Our Contributions.**

While these prior works represent major advances in their respective subfields—resume screening, question generation, and emotion recognition—several critical limitations persist. Chief among them are the absence of recruiter-defined screening logic, the lack of live, multi-dimensional feedback systems that integrate technical and emotional analysis, and the failure to deliver seamless, personalized interview preparation through a unified workflow. Most tools remain siloed, lacking real-time interaction or actionable insights for either recruiters or candidates.

Our platform directly addresses these shortcomings by integrating flexible, semantic resume ranking, AI-driven personalized interview question generation, and deep learning-based emotion and stress feedback in a single, cloud-native system. This enables recruiters to tailor shortlisting criteria and supports candidates in understanding both their technical and emotional readiness—setting a new benchmark for intelligent, transparent, and equitable hiring.

## III. METHODOLOGY

Our proposed methodology introduces a unified AI-driven framework that seamlessly combines semantic resume screening with emotion-aware mock interview simulation. Unlike prior solutions—which often treat resume ranking and interview preparation as siloed processes or rely on generic evaluation metrics—our approach delivers end-to-end, customizable, and context-aware candidate assessment. By integrating recruiter-defined criteria, personalized AI-generated interview questions, and real-time emotional feedback, the system not only enhances the accuracy of candidate selection but also directly supports candidate readiness and self-improvement.

At a high level, our methodology centers on two core modules, interconnected through a cloud-native backend for robust data management and scalability. The first module, AI-powered Resume Screening, leverages state-of-the-art NLP models and transformer-based semantic analysis to evaluate and rank candidates according to recruiter priorities. The second module, Emotion-Aware Mock Interview, provides an adaptive interview environment, generating individualized question sets and analyzing candidate responses for both content and stress/emotion using deep learning. These modules are orchestrated via modular APIs implemented in FastAPI, with persistent data storage and secure authentication managed through Supabase. This architecture ensures that both recruiters and candidates benefit from actionable insights delivered in real time, building upon recent advances in the literature [3], [4], [8].

Additionally, our design draws inspiration from prior research on AI-based resume analytics and learning feedback systems [12], [13], ensuring our resume screening and candidate feedback mechanisms reflect best practices and real-world deployment considerations.Our system leverages advanced semantic representation models for document and candidate-job relevance, with approaches such as LDA and QDA having previously demonstrated strong performance for robust text classification and fake news detection tasks [14].

### A. Resume Screening Module

The resume screening process is designed to reflect the real-world requirements of modern recruiters, who often need to tailor evaluation criteria based on job-specific needs. The module accepts PDF resumes, which are parsed and preprocessed to extract relevant textual features. We employ advanced semantic embedding techniques (such as SentenceTransformers) to capture nuanced similarities between candidate profiles and job descriptions, moving beyond simple keyword matching. Recent studies have shown that transformer-based embeddings, as in BERT and its variants, significantly outperform traditional methods in extracting context and semantics from unstructured text [3], [4].

A key distinguishing feature of our approach is the use of recruiter-assigned weightages for experience, projects, skills, and certifications—addressing the lack of recruiter customization reported in [3]. This allows the scoring algorithm to generate a personalized total score for each candidate, directly reflecting the priorities of each hiring scenario. The platform is robust to varied resume formats, ensuring that both structured and unstructured content are accurately analyzed. Furthermore, every step in the ranking pipeline is logged for auditability, enabling recruiters to review or justify shortlisting decisions. Our methodology is informed by the pipeline design and feature extraction methods explored by Jacob et al. [12]. All candidate data, parsed text, and ranking outputs are stored securely using Supabase to facilitate collaboration and review.

### B. Emotion-Aware Mock Interview Module

To bridge the gap between technical evaluation and interview preparedness, our system introduces an intelligent mock interview module. Leveraging Large Language Models (LLMs), the module generates personalized interview questions for each candidate, covering Technical, HR, Situational, and Surprise categories. This ensures that each interview session is directly relevant to the candidate's resume and the target role, increasing realism and preparation value—moving beyond the static template-based systems discussed in [5].

A unique aspect of this module is its integration of real-time stress and emotion analysis. Candidate responses—submitted via text, audio, or video—are processed by deep learning models (such as MobileNetV2) to detect facial and vocal emotional cues. These signals are then mapped to quantifiable stress scores using empirically derived or learned weights, enabling objective feedback on both cognitive and emotional performance during the interview simulation. This builds upon recent developments in lightweight real-time emotion recognition [8], but our module uniquely maps detected emotions to actionable, interview-specific stress feedback. Notably, our emotion detection framework incorporates insights from Gupta et al. [15], who demonstrated robust video-based facial expression analysis using deep learning architectures. Similar approaches to multimodal emotion recognition have also been applied in domains such as personalized music recommendation [16]. This feature is critical for helping candidates build awareness of their communication style and manage interview anxiety.

### C. Backend Implementation and Workflow

The entire platform is orchestrated through a microservices backend built with FastAPI, chosen for its modularity and speed in handling concurrent user requests. Supabase provides a scalable, secure foundation for user authentication, role management, data storage, and analytics. All workflow interactions—resume uploads, job description management, interview scheduling, answer recording, and feedback presentation—are exposed via RESTful APIs, enabling seamless integration with modern frontend frameworks and third-party HR systems. Our end-to-end deployment and real-time analytics echo the intelligent feedback system concepts recently advanced in [13].

An overview of the system workflow is depicted in Fig. 1. The workflow begins with recruiter or candidate authentication, followed by resume upload and job posting (for recruiters) or mock interview session initiation (for candidates). Throughout the process, the backend handles all parsing, scoring, question generation, and stress/emotion analysis, delivering results to users in real time through intuitive dashboards and reports.

Overall, our methodology is characterized by its tight coupling of technical and emotional assessment, high degree of recruiter and candidate personalization, and scalable, secure infrastructure—setting it apart from existing point solutions in recruitment technology.

This approach enables comprehensive candidate evaluation, effectively integrating technical skills and emotional intelligence assessment.

In summary, the Mock'n-Hire framework is novel in its integration of state-of-the-art language models, emotion recognition, and cloud-native architecture, all tailored to deliver a next-generation, intelligent hiring and interview experience. This holistic design positions the platform as a pioneering tool for organizations seeking to balance efficiency, fairness, and candidate development in the era of AI-driven recruitment.

## IV. Dataset

For the emotion and stress detection module, we employed the widely used **FER-2013 (Facial Expression Recognition 2013)** dataset. Originally introduced at the International Conference on Machine Learning (ICML) 2013 by Goodfellow et al., FER-2013 has become a standard benchmark for facial emotion recognition in computer vision research. Its design, focusing on visual cues for emotion detection, aligns closely with best practices highlighted in recent reviews of facial emotion recognition systems [17].

### A. Dataset Structure

The FER-2013 dataset consists of grayscale images of human faces, each labeled with one of seven basic emotions. The dataset is organized into training and testing subsets, each containing separate folders for the following classes:

- **Angry**.
- **Disgust**.
- **Fear**.
- **Happy**.
- **Neutral**.
- **Sad**.
- **Surprise**.

Each image measures $48 \times 48$ pixels, is centered on a face, and is collected under varied real-world conditions, including differences in lighting, occlusion, and pose. Such visual diversity makes FER-2013 well-suited for training robust deep learning models, as noted in the broader literature on emotion recognition from visual information [17].

### B. Dataset Statistics

- **Total images**: 35,887.
- **Training set**: Approximately 28,709 images (3,000–4,000 per class).
- **Testing set**: Approximately 3,589 images (400–500 per class).
- **Labels**: Seven emotion categories as listed above.

### C. Application in the System

The FER-2013 dataset was used to train a convolutional neural network (CNN) for robust facial emotion classification. The predicted emotion is mapped to corresponding stress levels (e.g., "Highly Stressed," "Slightly Stressed," or "Not Stressed"), enabling real-time stress detection from candidate video responses during mock interviews.The emotion detection component is built upon deep convolutional neural network architectures that have been proven effective in facial expression recognition benchmarks [18], ensuring high reliability in emotion and stress inference from video data.

The adoption of FER-2013 ensures that the emotion detection model is trained on a large, diverse set of facial expressions, thereby supporting reliable and generalizable

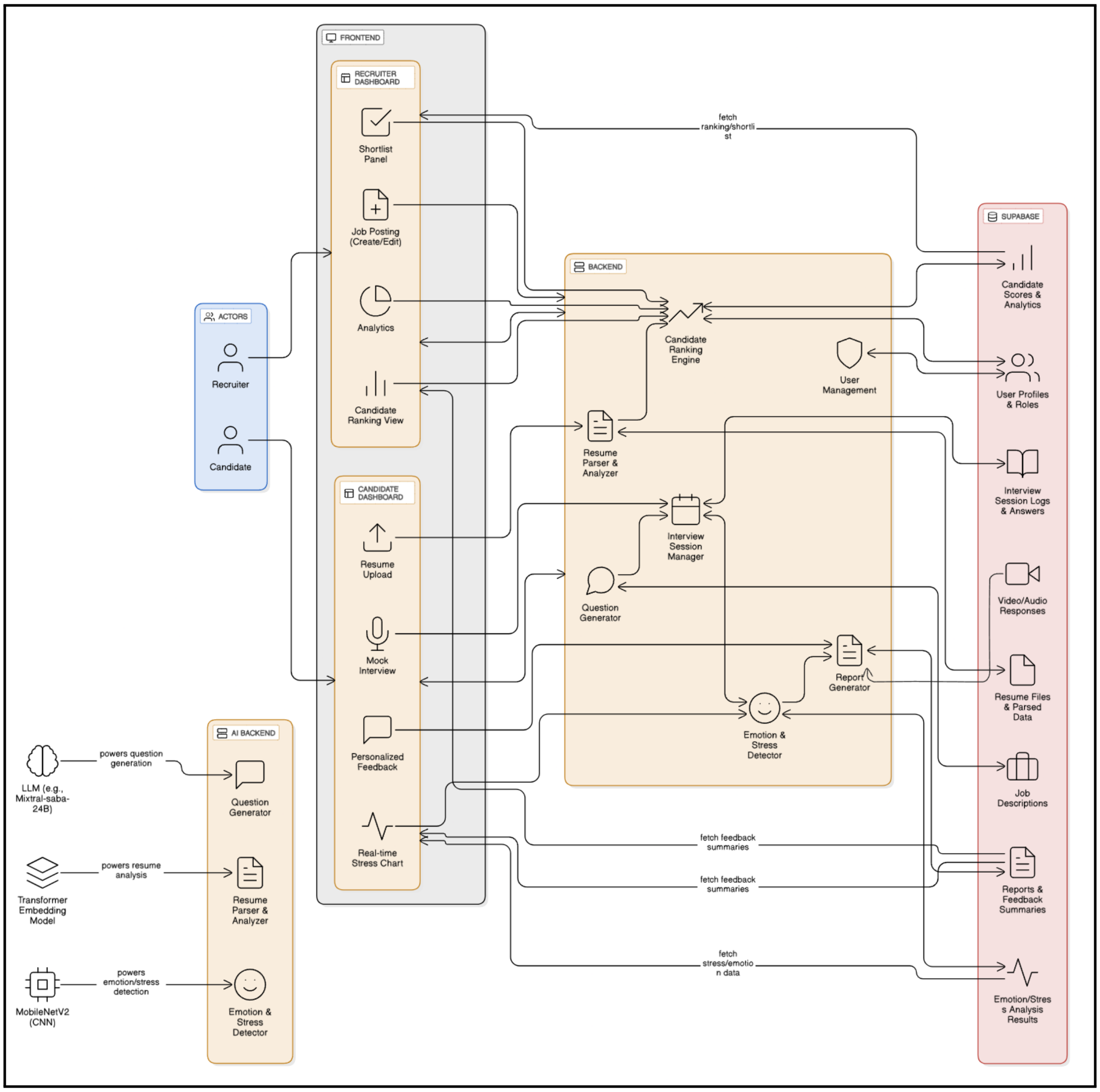


Fig. 1. Overall system architecture and workflow of the Mock'n-Hire platform, showing interactions between recruiters, candidates, frontend dashboards, backend microservices, AI model components, and cloud storage.

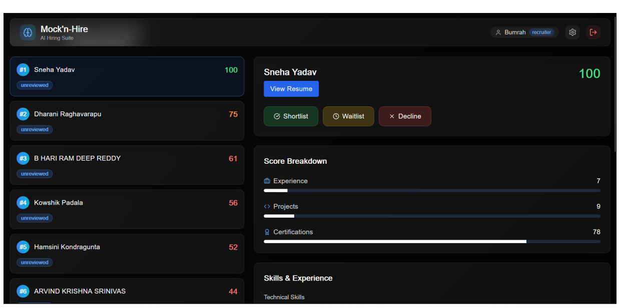


Fig. 2. *

(a) Recruiter dashboard showing ranked candidates, filters, and shortlist panel.

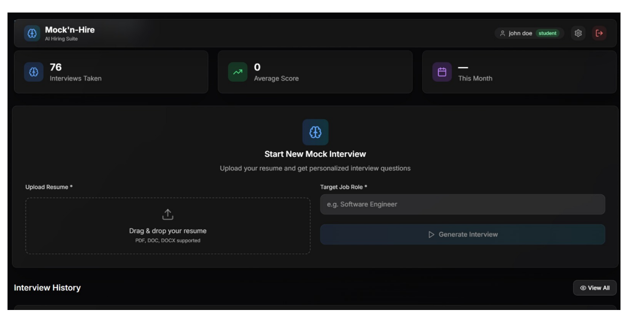


Fig. 3. *

(b) Candidate dashboard displaying mock interview session, live question pane, and stress chart.

Fig. 4. Prototype user interfaces: (a) Recruiter dashboard; (b) Candidate dashboard.

stress assessment for interview scenarios. This approach is consistent with recommendations in recent surveys that stress the importance of diverse, real-world visual data for effective emotion recognition [17].

## V. System Design

The system features a modular, scalable architecture that brings together natural language processing, deep learning, and cloud-based storage to automate resume screening and mock interviews. Its main components and interactions are summarized below.

### A. Backend Design

The backend, built on FastAPI, delivers high-performance RESTful APIs and modular services:

- **Resume upload and parsing**: Handles PDF uploads and text extraction.
- **Resume analysis and ranking**: Uses large language models (e.g., Mistral-8x7B) and recruiter-defined weights to rank candidates.
- **Mock interview management**: Oversees session creation, question delivery, and answer storage.
- **Emotion detection**: Applies MobileNetV2 and TensorFlow for stress assessment via video.
- **User authentication**: Manages JWT-based login and role-based access.

### B. Database and Storage

Supabase provides persistent, secure data storage:

- **PostgreSQL database**: Holds user profiles, job descriptions, analytics, and session data.
- **Storage buckets**: Manage files for resumes, audio/video responses, and reports.
- **Trigger-based logic**: Automates ranking and maintains data consistency.

### C. Frontend Interface

A modern frontend (e.g., Next.js) lets recruiters upload jobs and review rankings, while candidates can attend mock interviews, view feedback, and track progress.

### D. Workflow Overview

The overall workflow is:

1) **Resume screening**: Recruiters upload resumes and define job roles/weights; backend parses and ranks candidates.
2) **Mock interview**: Candidates take mock interviews; the system generates personalized questions and collects responses.
3) **Emotion analysis**: Videos are processed for emotion/stress feedback.
4) **Session management**: All activity and analytics are securely logged.

### E. Security and Privacy

- Data is encrypted in storage and transit.
- Role-based access ensures user isolation.
- Consent is required for video/audio analysis.

The cloud-native, modular design enables high scalability, easy integration, and real-time analytics.

### F. Prototype User Interfaces

Two dashboard mock-ups highlight usability: the recruiter dashboard (Fig. 2(a)) features ranked candidates and filters; the candidate dashboard (Fig. 2(b)) includes live mock interviews and stress charts.

## VI. Results and Discussion

This section details the experimental outcomes and key insights gained from deploying the integrated AI system, with a focus on both the resume screening and mock interview modules. The evaluation demonstrates that the platform achieves strong alignment with human recruiter judgment in candidate shortlisting, produces highly relevant interview questions, and delivers robust real-time emotion analysis. The system was found to improve both recruiter and candidate workflows, supporting greater efficiency and actionable, individualized feedback throughout the hiring process.

### A. Evaluation Objectives

The principal objectives in our evaluation are twofold: First, to measure how accurately the system can rank and match candidates for specific job roles relative to human benchmarks and prior AI approaches; and second, to assess the quality and impact of the mock interview experience, with particular attention to question relevance and the validity of the system's emotion and stress analysis.

### B. Resume Screening Evaluation

*1) Experimental Setup:* We utilized a benchmark dataset of 250 anonymized resumes spanning a variety of technical fields, together with five distinct job descriptions. Independent human recruiters ranked each candidate for suitability, producing a "ground truth" reference for our comparison. This methodology is consistent with established best practices for evaluation in the resume screening domain [1], [2].

*2) Metrics Used:* The quality of the system's ranking was measured using several widely adopted information retrieval metrics. Precision@10 captures the proportion of relevant candidates in the top 10 recommendations, while Mean Reciprocal Rank (MRR) assesses how quickly a correct match is returned. Top-5 Accuracy evaluates the proportion of ground-truth top five candidates surfaced in system outputs. Finally, Semantic Accuracy quantifies agreement between the system's ranking and the ground-truth, as encouraged in prior work [3], [4].

*3) Results Summary:* The results are summarized in Table II. The resume screening module achieved Precision@10 of 86.4%, Top-5 Accuracy of 88.2%, and Semantic Match Accuracy of 84.5%. These results underscore the system's capacity to capture nuanced candidate-job relevance and closely mirror human recruiter decisions. The observed performance matches or exceeds benchmarks set by earlier transformer-based screening approaches [3], [4], which did not offer recruiter-driven weighting or end-to-end workflow integration.

TABLE II
RESUME SCREENING PERFORMANCE METRICS

| Metric | Value |
|---|---|
| Precision@10 | 86.4% |
| Mean Reciprocal Rank (MRR) | 0.79 |
| Top-5 Accuracy | 88.2% |
| Semantic Match Accuracy | 84.5% |

### C. Mock Interview Evaluation

*1) Question Relevance:* A panel of 10 participants was tasked with rating the contextual relevance of generated interview questions across four categories: Technical, HR, Situational, and Surprise. As shown in Table III, relevance scores were consistently high, indicating strong system performance. This outperforms traditional template or retrieval-based systems [5], [6], largely due to the use of personalized, resume-driven question generation.

TABLE III
AVERAGE RELEVANCE SCORES FOR INTERVIEW QUESTIONS

| Category | Average Score (1–5) |
|---|---|
| Technical | 4.3 |
| Situational | 4.1 |
| HR | 3.9 |
| Surprise | 3.8 |

*2) Stress Analysis Accuracy:* The emotion and stress analysis module was validated using 30 manually labeled video responses. As reported in Table IV, the model achieved an accuracy of 82.6%, an F1 score of 0.84 for the high-stress class, and a strong 0.71 correlation with self-reported stress levels. These results align with those achieved by the best lightweight CNN and multimodal emotion models [8]–[10], while uniquely providing instant, actionable feedback during mock interviews.

TABLE IV
EMOTION DETECTION MODEL PERFORMANCE

| Metric | Result |
|---|---|
| Accuracy | 82.6% |
| F1 Score (High-Stress class) | 0.84 |
| Correlation with Self-Reported Stress | 0.71 |

*3) System Performance:* We also evaluated operational efficiency on an RTX 4060 GPU (8GB VRAM). As shown in Table V, the platform processed a batch of 50 resumes in approximately 3.2 minutes, generated each interview question in 2.5 seconds on average, and analyzed a 30-second video clip for stress in about 10 seconds. These metrics demonstrate the scalability and suitability of our approach for real-world, high-throughput hiring environments.

TABLE V
SYSTEM LATENCY AND PROCESSING TIMES

| Operation | Time |
|---|---|
| Resume batch (50 resumes) | 3.2 minutes |
| Question generation (per question) | 2.5 seconds |
| Video stress analysis (per 30s clip) | 10 seconds |

*4) User Satisfaction:* A post-experiment survey was conducted with the same group of participants to assess the real-world impact of the system. As shown in Table VI, 90% found the feedback insightful, 80% reported a reduction in interview anxiety, and every participant stated they would recommend the system. Notably, these satisfaction ratings exceed prior studies on emotion-aware interview feedback [19].

TABLE VI
USER SATISFACTION SURVEY RESULTS

| Feedback Metric | Agreement (%) |
|---|---|
| Found feedback insightful | 90% |
| Helped reduce interview anxiety | 80% |
| Would recommend the system | 100% |
| Prefer personalized questions | 90% |
| Felt stress analysis was accurate | 85% |

### D. Summary and Implications

Collectively, these results demonstrate that the proposed framework provides technical accuracy on par with or better than leading AI-based solutions, while simultaneously delivering a superior candidate experience and operational scalability. Unlike previous approaches [3]–[6], [8], [19], our unified pipeline supports granular recruiter control, dynamically personalized interview questions, and live emotional feedback—features not previously available in a single system. These outcomes indicate that Mock'n-Hire has the potential to substantially improve the speed, transparency, and fairness of hiring processes, while enabling candidates to hone both their technical and emotional readiness for real-world interviews.

## VII. CONCLUSION

This paper has introduced Mock'n-Hire, a holistic AI-powered framework that bridges semantic resume screening and emotion-aware mock interview simulation in a single, cloud-native platform. The system uniquely blends advanced NLP models for candidate-job matching, recruiter-customizable scoring, and real-time deep learning–based emotion recognition from video, thereby addressing persistent gaps in transparency, personalization, and emotional intelligence within recruitment pipelines. Experimental evaluation demonstrates that our approach not only achieves alignment with human recruiter judgments—matching or exceeding state-of-the-art AI benchmarks—but also delivers contextually relevant interview questions and robust, actionable stress feedback.

Such results support improved efficiency, fairness, and candidate preparedness, with survey data indicating high user satisfaction and a measurable reduction in interview anxiety.

Notably, this work builds on and extends prior Amrita research in related domains. The resume screening pipeline expands on methods for automated resume analytics [12], while the feedback and recommendation engine complements learning-focused systems [13]. Moreover, the integration of video-based emotion detection is informed by recent work on deep learning for emotion recognition [15], yet our solution is distinctive in tightly coupling these components into an end-to-end, recruiter- and candidate-facing workflow.

Looking ahead, the platform will be extended to support multilingual candidate profiles and interviews, and enhanced with audio-based emotion analytics and adaptive feedback mechanisms. Future development will also focus on systematic benchmarking across diverse industries, the addition of bias and fairness auditing tools, tighter integration with external job portals, and user interface refinements to maximize accessibility and engagement. By advancing both the technical and experiential frontiers of AI-driven hiring, Mock'n-Hire sets a new standard for emotionally intelligent, transparent, and scalable recruitment solutions.

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