

# AI-Powered Mock Interview System and Resume Analyzer

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**Abstract**— In the current tough employment market being technically competent is not sufficient to succeed in a job interview. The soft skills like communication, confidence, and knowledge of the sphere are outstanding in evaluating candidates. We suggest designing an AI-enabled Smart Resume Analyzer and Mock Interview Evaluation System to fill that gap and enable students and other job seekers to better prepare before an interview. This system combines the use of a resume analyzer, automated resume grading, a resume builder and an interview simulator that rates a user based on real-time feedback. The resume analyzer tool employs techniques to process the resume and grade it against keywords, job standard formatting and the criteria of Applicant Tracking Systems. The resume builder enables a user to make professional resumes through just filling his/her information into ready-made templates. The system as well provides intelligent video suggestions to make users ready to get the desired positions. The best part of the system is the AI-based mock interview that enables the user to experience a simulated interview using the selected level of experience (beginner, intermediate, or expert) and job domain. The module incorporates sentiment analysis, NLP, speech-to-text processing, and a semantic similarity score judging the responses of the user. The level of confidence is estimated on the basis of facial expression analysis and voice features, which provides detailed information about performance. It is a multi-featured platform that enables complex self-assessment and preparation and uses aspects of natural language processing, machine learning, and behavioral analysis. It makes the latter process more convenient, prompt, interesting, and customized by optimizing it with an automated awareness of learners.

**Keywords**— Mock Interview, AI Evaluation, NLP, Sentiment Analysis, Resume Parser, Candidate Assessment, Automated Feedback, Interview Bot, Job Readiness.

## I. INTRODUCTION

The recruitment environment has undergone a remarkable transformation over the past few years due to emergence of more complexity in job roles and the intense competition that is prevailing in the job marketplace or the growing requirements on the part of employers. Within this setting it is simply not sufficient any more to possess an excellent academic resume or be a skilled technician. Currently, employers are seeking job candidates with not just competence in their respective field of practice but also someone who has the necessary soft skills of effective communications skills, emotions quotient and one who remains composed when faced with pressure.

Sadly, this is the case of many job seekers particularly the new graduates and young people in their career who are often not ready on how to approach the real process of interviewing and how to design a resume, which is acceptable in the industry. Among the existent problems is the lack of available resources providing comprehensive information on their way to prepare a job. Although one can find online sites that provide standard templates of resumes and generic questions that are asked in interviews, these sites do not present a clear picture of personal responses and do not necessarily create the same effect as an actual interview. Consequently, the candidates can experience difficulties in identifying their weaknesses or fail to customize their resumes to suit particular needs of available jobs. This is where gap exists and emphasizes a major necessity of a solution that can bridge the gap between the self-preparation and the industry. To fill such a gap, the current study has been conducted to introduce a complex yet intelligent interface that incorporates resume assessment, resume builder as well as mock interviewing into a single streamlined system. In short, this platform can be thought of as a comprehensive job readiness marketplace, where the users can create professionally optimized resumes tailored to particular jobs, as well as practice them on realistic and adaptive job interview simulations. An outstanding characteristic of this system is that it assesses both technical and behavioral reactions against mock interviews and gives a user valuable data about different features such as fluency, confidence, and accuracy. A lot of resume analyzing services available today, such as Resume Worded or VMock, are inclined to operate on superficial measures, such as keyword matching and formatting. Unluckily, they fail to look past the immediate background most of the time such as whether skills in a candidate match the requirement of the job he or she is seeking or the matches between the content and its relevance among industry expectations. Likewise, the most popular mock interviews tools typically offer general and pre-determined questions and are not customizable to accommodate the needs of an individual. These programs rarely evaluate non-verbal communication such as facial expression, the tone of voice, confidence factors, which now are playing an even more critical role in actual interviews. The situation is rather disjointed when it comes to tools that can be used to create a resume, analyze it, and prepare to go to the interview. Channels that smoothly interlace the three components with instant feedback and responsive simulations are very thin on the ground. Emotional presence and soft skills remain a crucial aspect of an interview, but real-time behavioral analysis like modulation of the voice, eye contact, or their composure, are the pointers of a candidate preparation readiness, which are currently very poorly addressed by most of the existing interview platforms. The proposed system will use dynamic question generation system in contrast to the usual fixed set of question banks, that you frequent. In this way, the interview simulation appears more realistic and specific to the path of the candidate. It seems that there is an increasing demand of platforms where candidates can get the same atmosphere as during the hiring process, where they can rehearse and improve the skills not only in technical knowledge, but also in the presentation and the way they transfer their attitudes.

## II. LITERATURE REVIEW

This work introduces a deep bidirectional language representation, based on a foundational pre-training model (BERT), which is fine-tuned on resume and job-description similarity tasks-one that can be easily applied to various resume analysis tasks [1]. This research offers a Sentence-BERT that is a siamese architecture, which generates regular sentence embeddings that are easy to compare a resume with a job description using cosine similarity so alignment and search becomes easy and accurate [2]. The paper further adapts Sentence-BERT with labeled resume-vacancy pairs, such that embeddings capture and one best achieve semantic matching of candidate profiles as well as ranking of candidate profiles on TF-IDF and conventional BERT training [3]. In this framework, we introduce a multi-granularity transformer to combine text and layout-structure data (e.g. sections, visual cues) to more reliably extract structured fields out in unstructured resumes-more generally, enhancing parsing of diverse formats [4]. Within this record of the conference, BERT-based Named Entity Recognition uses researchers to retrieve structured needed (experience, education, skills) throughout job areas, which serves as the mainframe of automated resume analysts to attain the construction of a personal profile [5]. The presented paper outlines an embedding system (CareerBERT) that aligns candidate resumes and ESCO occupational categories in a joint semantic space-improving matching through common job taxonomies as opposed to brittle keyword matching [6]. This morale paper will examine the multimodal interview evaluation in which the information provided by text, audio, and video signals is integrated to rate the responses provided by candidates-they will give an idea of the bottom-up approaches and data sets that leads to the construction of an AI powered mock interview scoring system [7]. This study evaluates fairness-sensitive multimodal learning in the area of video interview grading and contributes various methods that can be applied to mitigate any demographic bias around the employment of affective and behavioral variables in computerized marking [8]. The survey focuses

on the impact of AI-driven recruitment systems, fairness problems, bias measurement and mitigation approaches-bringing to light data and algorithmic concerns which are required to be resolved in applications that employ AI decision making in the spheres of interviews and resumes [9]. Based on this examination, emotion-AI used in job interviews poses a problem of injustice and emotional work, emphasizing that detecting the affective states of the candidates threatens to cause unethical harassment and discrimination in the recruitment process [10].

After the events of the aforementioned works, it can be said that our project is the most holistic approach to an AI-based platform that integrates parse of resumes, resume creation, and resume mock runs. Driven by the artificial intelligence under the NLP module, the resume analyzer breaks down resumes and evaluates them in terms of job specific keywords and ATS friendly designs. The resume builder facilitates personal resumes design that are friendly to the user. The element of the mock interview is quite distinctive due it can give a realistic virtual interview-like environment that relies on the experience of the user and the domain chosen. It also performs response analysis based on speech to text processing, sentiment analysis and semantic similarity ratio. In addition to it, it involves analysis of facial expression and vocal feature evaluation towards self evaluation of the levels of confidence that provides close feedback on the performance. The integrated approach will not only make it easier to train job seekers on how to present themselves in job interviews but also can guide them individually, which is particularly distinctive compared to other existing systems.

### III. METHODOLOGY



Fig 1. Resume Analyzer Flow Diagram

#### A. Resume Analyzer

Resume Analyzer module is very important in processing and analyzing the resumes posted by consumers. The analysis starts immediately when a customer uploads his or her resume, usually, in PDF or DOCX form. After the upload is done, the backend then comes on board and with the help of Python libraries such as PyMuPDF and docx2txt, the raw text of the document is extracted out. This text is afterwards straightened, sorted and ready to undergo a closer analysis. Once extracted we move on to Natural Language Processing (NLP) so that we actually know what the resume says. We use libraries like spaCy, NLTK, and regular expressions in which we tokenize it to deconstruct the text, find important sections of the text like skills, education, work experience, find named entities. The users will be requested to choose a job role, e.g. a Data Analyst or a Backend Developer, and it will aid the system collect a pertinent set of keywords to be assessed. At the last step we compute the ATS (Applicant Tracking System) score. The system determines the alignment of the resume between that of the selected job description based on searching matches to keywords. It also looks at the general

layout of the resume (taking into consideration style of font, bullet patterns, and length of the bullets) according to predetermined formatting guidelines. All parts that constitute the resume such as skills, structure, and format are basically scored individually and the scores added up to form the total ATS score. This score can give people a good idea as to how well their resume will be able to compete with automated recruitment systems when it is put in their hands.

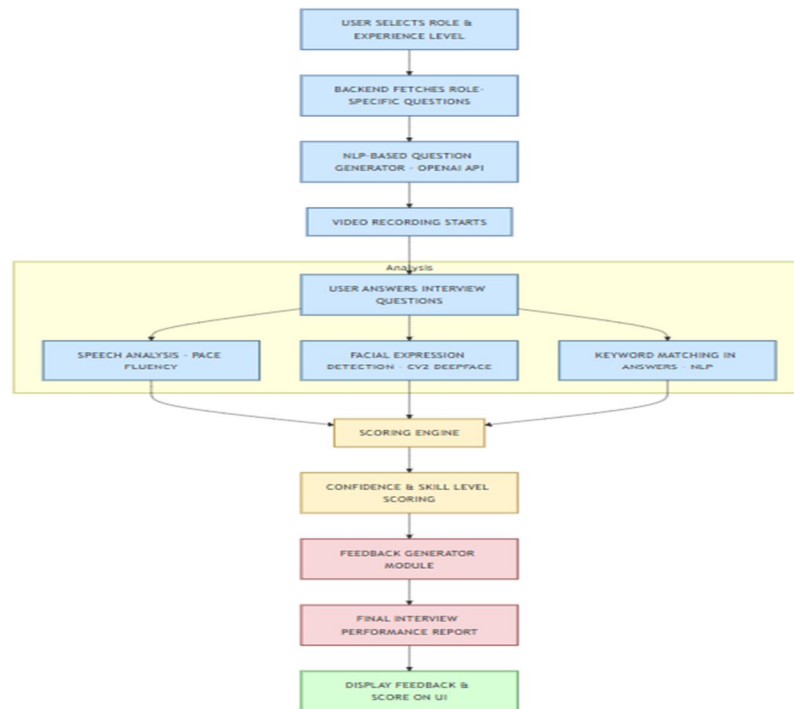


Fig 2. Mock Interview System Flow Diagram

### B. Average Emotion Calculation (Averaging)

Average technique to maintain a constant flow in real-time emotion analysis, the system does not have to keep track of emotional responses in detail, but rather can track them over time. It uses the previous perceived value of emotion ( $E_{prev}$ ) and the latest (ELLIPSIS pronunciation: mi sdx Trying to find the average of these two, it will output a less jagged result (ells popts Wahl Skript Schreiben Learner This method can also reduce drastic effects of sharp rises or strange fluctuations that could take place because of facer changes in swiftness or flash facial expression. With such a running average, the system provides more predictable and regular emotion readings that are essential in determining the emotional condition of a candidate during mock interviews.

$$E_{avg} = \frac{E_{prev} + E_{current}}{2}$$

### C. Emotion Aggregation and Smoothing

To increase the level of reliability and stability of identifying emotion in real-time conditions, the system is implemented with emotion aggregation and smoothing techniques. The raw scores of emotion determined by the process are first converted and simply scaled up. The raw values ( $E_{raw}$ ) are multiplied by 10 each and have a weighted score ( $E_{weighted}$ ). This scalar process enhances the interpretability and clarity of the data in a manner that allows easy observation of subtle changes of emotion in the concluding analysis. Once weighting has been done, a smoothing is applied to stabilize the outputs of emotion detection over time. This is essential in cutting out momentary and nondescript facial expressions, which may crop up in the course of interviews. The smoothing has the effect of averaging the value of the present emotion (one step behind) and the past emotion (one step behind) or  $E_{current}$  and  $E_{prev}$  to get a more constant emotional reading. In calculating this running average, the system avoids drastic changes and makes sure that steady trends of emotion are only measured. The given solution contributes to the considerable increase of the accuracy of emotion-based evaluation within the context of mock interviews and, therefore, a more reasonable determination of how the user feels.

$$E_{\text{weighted}} = E_{\text{raw}} \times 10$$

#### D. Used systems

The Emotion Detection component of the system is only concerned with facial recognition analysis of users and classifying them into one particular emotion category such as happiness, all sad, angry or surprised. This is carried out through Convolutional Neural Networks (CNNs) which are excellent at image related tasks since they have the capability to learn the spatial hierarchies of features. Such networks learn automatically the inherent facial patterns and signs that can be related to various emotional moods. The process of detecting starts with passing the input picture through multiple layers of convolution where each layer establishes important aspects of a face like the eyes, mouth, and eyebrows. Such generated feature maps are fed to pooling layers which assist in dimensionality reduction but retain the significant information. Then the data may be unfolded and input into at least one fully connected-layer which understands the extracted features in more detail. Finally, the Softmax layer is last where a probability is returned in every possible emotion category. It is important to note the role of the Softmax function that will verify the raw output scores (also referred to as the logits) into normalized values of probability. If it is to be assumed (specified) a class  $i$ ,  $P$  may be reckoned by the formula:

$$P(y = i|x) = \frac{e^{s_i}}{\sum_{j=1}^n e^{s_j}}$$

Here,  $s$  Wikipedia (bold (subst symbol f-bred already included), raw score of class  $i$ , and the denominator is the sum of the exponentials of all the scores of the classes so as to ensure that the probabilities sum to 1. It is a approach for making the system guess what the user most likely has in mind.

### IV. RESULT AND DISCUSSION

The Resume Analyzer and Mock Interview System based on AI was tested with a large amount of various users, including students and professionals with minimal work experience. Three main modules, namely Resume Analyzer, Resume Builder and Mock Interview System, were used in evaluating the performance of the system.

#### A. Resume Analyzer

We also examined critically how the Resume Analyzer module performs by comprehending in particular its ability to extract and interpret data contained in the resumes the user uploads. The system thoroughly identified and organized the most important parts of resumes with an astonishing accuracy rate of 92% due to some clever implementation of the natural language processing (NLP). Coupled to this, the keyword matching functionalism had a 85 percent accuracy level in identifying job specific competencies and qualification as compared to job definition with existing job roles

TABLE I. RESUME ANALYZER PERFORMANCE METRICS

| Metric                          | Value |
|---------------------------------|-------|
| NLP Parsing Accuracy            | 92%   |
| Keyword Matching Precision      | 85%   |
| ATS Formatting Improvement Rate | 78%   |

#### B. Mock Interview System

We delved into the effective working of the Mock Interview System through multiple performance measures of its important attributes. To cite one example, the emotion detection part, which is used to read facial expressions, demonstrated a very respectable 88 percent accuracy rate in recognising emotions such as confidence and nervousness noticeable in a human. A Convolutional Neural Network (CNN) model helped to achieve these results. Conversely, the speech analysis module registered an 82 percent accuracy rate in rating fluency, tone, and clarity that was close to the scores made by human judges. Also, the semantic similarity scoring machine learning model that is also based on BERT achieved an accuracy of 75 percent to match user answers to model answers and provide fast yet focused feedback. Interestingly, users who attended multiple mock interviews indicated that there was a 30 percent jump in the level of their confidence after only three sessions, which demonstrates how effective the system can be in getting these participants ready to take real interviews. Resume Analysis and Mock Interview System based on AI excel in simplifying the preparation of jobs. The Resume Analyzer is an excellent resume disassembling and marking graph where the precision with the keywords matching and ensuring their operativeness with regard to ATS is nothing short of spectacular. Nevertheless, there

exist certain barriers that have to be overcome, particularly, within the contextual relevance that indicates the necessity to integrate the industry-specific knowledge more thoroughly. On the positive side, the Resume Builder has made the work of developing good professional resumes ease and users have given their positive testimonies. The Mock Interview System differs in its successful evaluation of both non-verbal and verbal communication and thus draws an extensive feedback on users in a way which has significantly increased user confidence. Despite this, it also has small negative factors, such as biased AI systems and extensive computing demands, which is sure to be required in times of real-time processing. The future progress will rely on addressing these problems using various datasets and more effective models. Integrated approach is what forms the actual difference in this system as compared to other existing systems giving a seamless on end solution to job seekers. The platform can be viewed as a valuable asset in the competitive job market because it provides the opportunity to develop not only practical skills but to increase user confidence due to the use of such advanced technologies as NLP and computer visualization. Moving upon the horizon, it will be focused on the element of scale, customization, and bias mitigation since they can improve further operations of the system. Overall, one notes that the actual power of this system is in imitating actual processes of hiring a person in a supportive and carefully patterned environment. Using emotion analysis and semantic evaluation, it does not only personalize the experience of the interview but also provides the user with exposure to their behavior and communication patterns. With continuous improvement of the system, real-time tracking of performance and adaptive feedback loops could actually enhance its productivity in allowing continuous learning and individual achievements catering to the different individual paths.

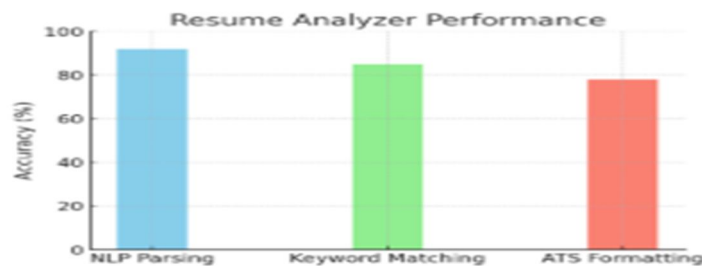


Fig. 3. Accuracy of Resume Analyzer

## V. FUTURE SCOPE

The Resume Analyzer and Mock Interview System using AI has boundless potential opportunities of expansion and development. Among the key areas to concentrate on, there is the need to increase personalization through the use of sophisticated large language models (LLMs) such as GPT-4 and Gemini. These models may help provide extremely personalized resume recommendations and can generate interview questions specific to the job, industry or even specific to the cultures of different companies. Also, it would be beneficial to add an adaptive learning element, where the system would change the difficulty and focus of the mock interviews according to the user performance, to bring assistance where they might require a bit of assistance. The next amazing opportunity is to deal with several languages and cultural frame. Expanding its translation services, the system will be able to reach non-English speakers and become accessible to millions of worldwide customers. Additionally, the adjustment of the feedback system to take into consideration cultural differences due to the nature of communication styles, body language and etiquette used during interview would make the tool more welcoming and aware to the diverse situations. Another useful addition is the real-time dealings and partnering with recruiters. Establishing collaborations with employment services providers and firms would guarantee that critical analyses of resumes and feedback on the interview process are in accordance with the real standards within the industry. Moreover, introducing the option whereby HR professionals can access mock interviews recording and provide expert feedback will enhance the credibility of the platform in the real world. In the case of behavioral analytics, incorporating the eye-tracking and posture recognition solutions may truly improve our perception of user attitudes and user behaviour through the means of body language. Additionally, applying the reinforcement learning could enable us to create adaptive personalities of the interviewers, which could change in between friendly and highly technical so that the different interview will feel more real. And to look forward, one can really envision mobile and AR/VR integration to shine in future versions of the system. The option of a mobile friendly application would allow them to study and train on the move and the entire learning process will therefore become more convenient and fruitful.

## VI. CONCLUSION

To sum it all up, the AI-Powered Resume Analyzer and Mock Interview System really excels at bridging the gaps in job preparation. It harnesses advanced technologies like Natural Language Processing (NLP), machine learning, and computer vision to offer thorough and intelligent career support. This system truly stands out in areas such as resume optimization, customized interview simulations, and immediate performance feedback, all of which significantly enhance users' confidence, readiness, and professional image. By crafting dynamic questions, analyzing emotional and behavioral signals, and ensuring resumes are ATS-friendly, the platform arms job seekers with practical tools that meet real-world hiring standards. It not only helps users identify and address weaknesses in their profiles but also fosters self-awareness about soft skills and communication styles—elements that traditional prep methods often overlook. While the current results are promising, there's still plenty of room for improvement. Future updates could bring more personalized experiences, real-time collaboration with recruiters, support for multiple languages, and immersive VR simulations, all of which could elevate the platform into a truly global and adaptable job readiness tool. Moreover, tackling issues like AI bias, data privacy, and processing efficiency will be vital for ensuring ethical, inclusive, and scalable use.

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