

IntelliView: An AI Based Mock Interview Platform

Swati Uparkar¹, Saurabh Hundare², Varun Gazala³, Sarvesh Chaudhari⁴, Ankush Jain⁵

¹Artificial Intelligence and Data Science Department, Shah & Anchor Kutchhi Engineering College

²Artificial Intelligence and Data Science Department, Shah & Anchor Kutchhi Engineering College

³Artificial Intelligence and Data Science Department, Shah & Anchor Kutchhi Engineering College

⁴Artificial Intelligence and Data Science Department, Shah & Anchor Kutchhi Engineering College

⁵Artificial Intelligence and Data Science Department, Shah & Anchor Kutchhi Engineering College

Abstract - The IntelliView initiative represents a pioneering endeavor designed to empower novice job seekers through the integration of state-of-the-art Artificial Intelligence (AI) and Natural Language Processing (NLP) technologies. This platform employs a sophisticated blend of HTML, CSS, JavaScript, and the Deep Face method, introducing a comprehensive framework to redefine interview assessment and augment job application preparation. The primary module facilitates text-based analysis, enabling users to engage with real-time interview questions by entering responses directly into the web interface. Subsequently, advanced algorithms compare users' responses to expected answers, yielding a percentage similarity score and presenting the correct answer. Beyond affording essential interview practice, this feature furnishes constructive feedback, enhancing users' responses and ultimately refining their interview performance. In the second module, IntelliView introduces a dynamic interview environment with video-based analysis. Users respond to inquiries utilizing webcams, enabling the system to meticulously record both verbal responses and facial expressions. Leveraging the Deep Face method, the platform conducts real-time emotion and sentiment analysis, offering users insights into their emotional states throughout interviews. This feedback facilitates the refinement of non-verbal communication skills, empowering candidates to recognize emotional tendencies and adapt interview strategies accordingly. The third module functions as a comprehensive resume builder, employing HTML, CSS, and JavaScript to provide diverse templates tailored to individual needs. In summation, IntelliView heralds a transformative paradigm in job application preparation, seamlessly amalgamating technological advancements and human interaction to equip first-time job seekers with the requisite tools for navigating the competitive job market successfully.

Key Words: Interview Assessment, DeepFace, NLP, Text-based analysis, Video-based analysis, Resume Builder

1.INTRODUCTION

In the rapidly evolving landscape of contemporary employment, the convergence of Artificial Intelligence (AI) and Natural Language Processing (NLP) has yielded groundbreaking advancements in job application preparation and interview assessment. This research delves into the IntelliView project, an innovative initiative meticulously crafted to empower entry-level job seekers through the integration of cutting-edge technologies. The three integral modules within the IntelliView platform cater to distinct facets of the job-seeking process. The text-based analysis module immerses users in real-time interview scenarios, wherein their responses undergo meticulous evaluation against predetermined benchmarks. This not only provides users with a platform for practical interview practice but also offers constructive feedback aimed at refining and optimizing their overall interview performance.

Moving beyond traditional assessments, the introduction of the video-based analysis module marks a significant departure. Leveraging the Deep Face method, this module conducts real-time emotion and sentiment analysis, providing users with invaluable insights into their non-verbal communication dynamics during interviews. Such feedback proves instrumental in refining candidates' emotional intelligence, allowing them to adapt their communication strategies accordingly.

Lastly, the third module of IntelliView serves as a robust resume builder, meticulously designed using HTML, CSS, and JavaScript. Offering multiple templates tailored to individual needs, this component equips job seekers with a comprehensive toolkit for crafting bespoke resumes. Collectively, these modules signify a paradigm shift in the employment preparation domain, harmonizing technological sophistication with nuanced human interaction.

2. LITERATURE SURVEY

Here is a survey of pertinent literature techniques. It outlines the several methods that were employed. The brief information about the referred research papers is explained in this section.

In Paper[1], the researchers offer a computational framework that counts the interviewee's communication-related performance and provides performance feedback based on the analysis of multimodal data like voice and facial expressions.

In Paper[2], it explains how to utilize a software program that uses the Haar-Cascade Algorithm with a pre-trained model called DeepFace to identify various human emotions.

In Paper[3], the research's study objective is to gauge how semantically equivalent multi word sentences are for the guidelines and procedures found in railway safety documentation.

In Paper[4], the objective of this paper was to create an interview simulation using Deep learning and speech-to-text systems.

In Paper[5], it delves into the analysis of emotion detection and places a focus on blink count as well.

In Paper[6], it primarily centers on the utilization of NLP techniques, specifically NLTK and Ngrams, for assessing text similarity. It serves as a guide for conducting text similarity analysis on provided input.

In Paper[7], it introduces a real-time facial emotion detection system using OpenCV, Deep-Face, and TensorFlow. It aids narcotics officers in suspect identification and assists robots in recognizing emotions like happiness, nervousness, and neutrality.

In Paper[8], the paper presents a novel Face- Based Video Retrieval (FBVR) pipeline designed for unconstrained television-like videos. It introduces a new dataset for evaluation and achieves high retrieval accuracy (97.25% mean average precision) while maintaining real-time processing speed.

In Paper[9], the suggested algorithm in this study automatically evaluates and forecasts an interviewee's nonverbal cues and offers pertinent comments.

In Paper[10], the mock-interview platform that is suggested in this study assesses candidates' traits of personality and interview performance in addition to analyzing the textual, audio, and visual aspects of an interview.

3. PROPOSED WORK

This research paper explores a comprehensive approach that combines emotion detection, text analysis, and resume building to leverage textual data effectively. Text Analysis methods, including Natural Language Processing (NLP) and Machine Learning Algorithms, are used to analyze and compare similarities between the actual and expected solutions. Furthermore, the paper discusses the application of these techniques in resume building where HTML, CSS and JavaScript is used.

A. Video Analysis

For video analysis facial recognition is a really an important step, for which we have used Haar Cascade face detection. Haar cascade face detection is a method used for detecting faces in images or video. It is based on the Haar wavelet technique and is an effective and computationally efficient way to perform face detection. The Haar Cascade face detection is widely used due to its simplicity and efficiency.

a. DeepFace

Architecture: Max-pooling, fully linked, and convolutional layers are present in various layers of DeepFace. It utilizes a 3D face model to map faces into a 3D space, allowing for pose-invariant face recognition.

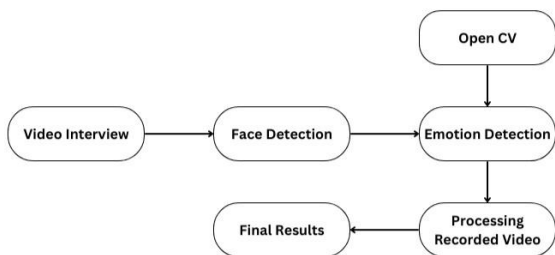
Face Alignment: DeepFace aligns faces to a canonical pose, reducing variations caused by pose and improving recognition accuracy.

Metric Learning: It uses a metric learning approach to learn a similarity function that compares faces in a continuous representation space.

b. CNN Overview

Basic Architecture: Convolutional, pooling, and fully linked layers are the components of CNNs. While pooling layers decrease the spatial dimensions of the features, convolutional layers extract features from input images.

Training: Backpropagation and gradient descent are commonly used in CNN training to minimize a loss function, including mean squared error or cross-entropy loss.



B. Text Analysis

For the project, the system takes input from the users and then processes it further to generate outcomes and similarities.

Text analysis encompasses a wide range of techniques aimed at understanding, interpreting, and extracting meaningful information from text. At its core, text analysis involves processing and analyzing textual data to uncover patterns, trends, and insights that can inform decision-making, drive innovation, and enhance understanding.

Here's a simple breakdown of how it works:

Preprocessing: Before calculating similarity, the input sentences are preprocessed. This involves:

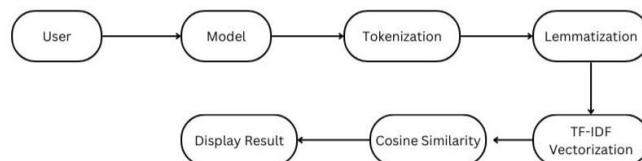
Tokenization: Breaking down each sentence into individual words or tokens.

- Lowercasing:** To maintain uniformity, all tokens will be converted to lowercase.
- Removing stopwords:** Words that are too common to be valuable for similarity comparison, like 'and', 'the', etc., are removed.
- Stemming:** word reduction to its root (e.g., "walking" becomes "walk").
- TF-IDF Vectorization:** Once the preprocessing is done, the preprocessed sentences are transformed into numerical vectors using the TF-IDF vectorizer. The TF-IDF measures a word's significance within a sentence in relation to a corpus, or group of sentences.
- Cosine Similarity Calculation:** The cosine similarity between the two texts is derived post vectorization. No matter how big or small the angle between two vectors is, cosine similarity calculates the cosine of that angle to show how similar they are. Higher cosine similarity indicates higher similarity between the sentences.

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \|\mathbf{B}\|} = \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}}$$

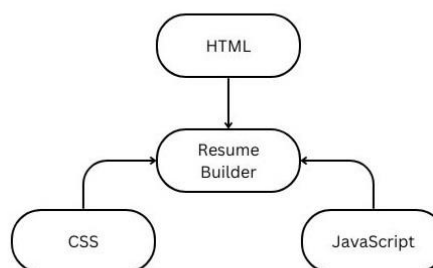
Return: The similarity score, which goes from 0 to 1—0 denoting no resemblance and 1 denoting sentence similarity—is returned by the function.

So, in simple terms, this function takes two sentences, converts them into numerical representations using TF-IDF, then calculates the cosine similarity between these representations to measure how similar the sentences are.



C. Resume Builder

The digital age has transformed the job application process, with online resumes becoming a standard requirement. To meet this demand, individuals can now create dynamic and visually appealing resumes using web technologies such as HTML, CSS, and JavaScript. This research paper presents a comprehensive guide to building an interactive resume builder application using these technologies. The paper covers key aspects of resume building, including form design, data validation, dynamic preview, and PDF generation. This research paper provides a practical guide for building an interactive resume builder application using HTML, CSS, and JavaScript.



4. METHODOLOGY

To effectively leverage textual data in employment preparation, the proposed work takes a multifaceted approach integrating resume building, text analysis, and emotion detection. In order to put this all-encompassing strategy into practice, a methodical methodology is developed that consists of discrete steps that are specific to each project component.

First, the methodology starts with gathering and preparing textual data from multiple sources, such as external datasets and user inputs. The textual data is preprocessed using natural language processing (NLP) techniques, which include tokenization, lowercasing, stopwords removal, and stemming. By ensuring the textual data is consistent and tidy, this pretreatment phase makes reliable analysis and comparison possible.

The methodology goes into the construction of text analysis and emotion detection modules after data initial treatment. In order to identify emotions in video analysis, faces in video streams are recognized using the Haar cascade face detection technique. Next, facial expressions and feelings are analyzed using DeepFace architecture, which aligns faces to a canonical pose and uses metric learning to compare faces in a continuous representation space. Text analysis methods are used in parallel to examine and contrast user-provided textual inputs. Preprocessed sentences are vectorized using the TF-IDF method, and the similarity between sentences is then calculated using the cosine similarity approach.

In parallel, the methodology proceeds with the development of the resume builder module, leveraging web technologies such as HTML, CSS, and JavaScript. The resume builder application is designed to offer users a dynamic and visually appealing platform for crafting personalized resumes. Key aspects of resume building, including form design, data validation, dynamic preview, and PDF generation, are meticulously implemented to enhance user experience and functionality.

Iterative testing and validation are carried out during the implementation phase to guarantee the reliability and efficiency of every module. In order to determine areas that require improvement and refinement, user feedback and performance metrics are gathered and examined. The process is based on constant iteration and optimization, guaranteeing that IntelliView, the finished product, is an excellent example of technology used wisely for job preparation.

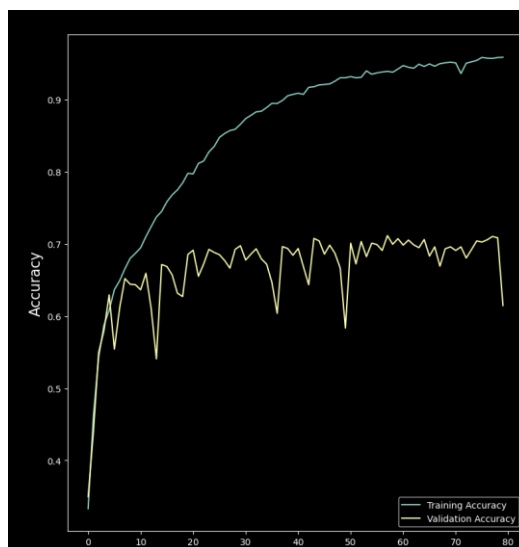
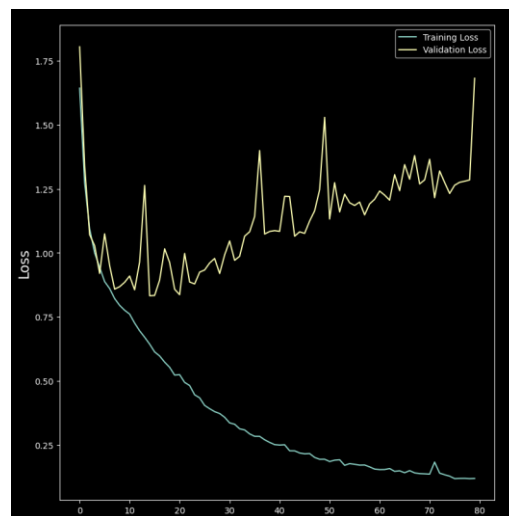
5. PERFORMANCE EVALUATION

We compared the performance of two models in the first stage of the video interview project: the pre-trained DeepFace model and our personally designed CNN model. These tests were carried out in the Jupyter Notebook environment.

The Metrics used for the proprietary trained CNN model are loss:- ‘Categorical CrossEntropy’, Learning Rate:- 0.0005, Epochs:- 80.

- Custom Trained Model (CNN):
 - Loss:- 0.1197
 - Accuracy:- 0.94

- Validation_Accuracy:- 0.62
- Validation_Loss:- 1.6816



As of in this graph we can see the accuracy vs the loss graph which concludes upto the assumption that model has slightly overfitted due to large number of epochs.

We tried to reduce the number of epochs but could not match the accuracy of the Deepface model as its accuracy was 97% and as a result used the Deepface model as our final model for the Video Based Interview process.

The testing of the both models are depicted in the further section of the performance evaluation.

Testing of Both the models are done using the same video recording of a candidate answering to the questions that are presented on the screen.

1. Result of the Custom Trained CNN model:

In this the model is fed with a Video of the candidate giving answers to particular questions and as we can see that the model divides each frame of the video in order to capture the Emotion from each frame for the final result.

As we can see that model is not displaying satisfactory results though it has been overfitted.



2. Result of the DeepFace model:

On the other hand DeepFace model also operates on the same principle of dividing each frame of the video and processing it and the results are also satisfactory with the system needs.



With an incredible precision score of 97.2%, the Deepface Model is the obvious choice for our application.

In summary, the key performance evaluation parameters for our model are model selection (Deepface Model), an accuracy rate of 97.2%, and our application preference for the Deepface Model due to its higher accuracy and graphical representation capabilities. This choice ensures that our application will provide users with the most accurate and visually appealing results.

The Second part of the project focuses on the Text Based Interview model that depicts the testing of the candidate based on the textual Question-Answering process.

For this we have tried two models that are the pre-trained model of spacy 'en_core_web_sm' and a custom nlp model that particularly uses cosine similarity.

1. Pre-trained en_core_web_sm model:

In this we just imported the model using the spacy library. The model is a starter kit for the text processing although giving a satisfactory accuracy for the given task.

2. Custom NLP model:

Particularly in this we have manually performed the pipeline of natural language processing which includes tokenization followed by stemming which is employed by PorterStemmer.

For calculating the similarity of the user text and the actual answer the similarity method used are Jaccard Similarity and Cosine Similarity.

1. Jaccard Similarity:

While employing this method gave promising results but lacked in giving more accurate results.

2. Cosine Similarity:

This method has given us the highest accuracy due to its ability to compare word vectors or embeddings, which represent the multi-dimensional meanings of words.

The key benefit of cosine similarity is that it works well for text document comparisons and can handle big documents.

As a result, the Custom NLP model which uses cosine similarity has been employed as it gives good accuracy for the text similarity task.

6. CONCLUSION

To sum up, the IntelliView project is revolutionizing the process of preparing job applications by utilizing cutting edge technologies to enable job seekers at the entry level. Through a comprehensive framework integrating AI, NLP, and the innovative Deep Face method, IntelliView redefines interview analysis with real-time assessments, constructive feedback, and dynamic insights into non-verbal communication. The multifaceted modules collectively signify a paradigm shift, providing a nuanced approach to the competitive job market. As technology and human interaction converge, IntelliView equips individuals with essential competencies, offering a glimpse into the future of job application preparation. This research underscores the project's technological underpinnings, methodological rigor, and its broader implications for reshaping the landscape of employment preparation.

ACKNOWLEDGEMENT

The future scope of the IntelliView project is promising, poised to witness continued evolution and expansion in response to the dynamic landscape of job application preparation. Potential avenues for enhancement include the incorporation of additional AI algorithms to diversify the range of interview scenarios and augment the accuracy of feedback mechanisms. Further exploration into personalized learning algorithms could tailor the platform to individual user needs, ensuring a more adaptive and user-centric experience. Additionally, ongoing developments in natural language understanding and emotion recognition technologies could refine the project's capabilities in assessing both verbal and non-verbal communication. Collaborations with industry stakeholders and academia may facilitate the integration of real-world job market insights, fostering a more comprehensive and relevant tool for job seekers. The continual integration of emerging technologies and iterative refinement will be pivotal in sustaining the IntelliView project's efficacy and relevance in the ever-evolving landscape of employment preparation.

REFERENCES

- [1] Jadhav, Aaditya & Ghodake, Rushikesh & Muralidharan, Karthik & Varma, G & Jagan, Vijaya Bharathi. (2023). INTERNATIONAL JOURNAL OF SCIENTIFIC RESEARCH IN ENGINEERING AND MANAGEMENT (IJSREM) AI Based Multimodal Emotion and Behavior Analysis of Interviewee. 10.55041/IJSREM19049.
- [2] J. Kaur, J. Saxena, J. Shah, Fahad and S. P. Yadav, "Facial Emotion Recognition," 2022 International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES), Greater Noida, India, 2022, pp. 528-533, doi: 10.1109/CISES54857.2022.9844366.
- [3] A. W. Qurashi, V. Holmes and A. P. Johnson, "Document Processing: Methods for Semantic Text Similarity Analysis," 2020 International Conference on Innovations in Intelligent Systems and Applications (INISTA), Novi Sad, Serbia, 2020, pp. 1-6, doi: 10.1109/INISTA49547.2020.9194665.
- [4] Sahil Temgire , Akash Butte , Rohan Patil , Varun Nanekar, Shivganga Gavhane, 2021, Real Time Mock Interview using Deep Learning, INTERNATIONAL JOURNAL OF ENGINEERING RESEARCH & TECHNOLOGY (IJERT) Volume 10, Issue 05 (May 2021), doi : 10.17577/IJERTV10IS050213
- [5] A. K. A, A. H, N. P. Nair, V. A and A. T, "Interview Performance Analysis using Emotion Detection," 2022 4th International Conference on Inventive Research in Computing Applications (ICIRCA), Coimbatore, India, 2022, pp. 1424-1427, doi: 10.1109/ICIRCA54612.2022.9985667.
- [6] S. K. Sinha, S. Yadav and B. Verma, "NLP-based Automatic Answer Evaluation," 2022 6th International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2022, pp. 807-811, doi: 10.1109/ICCMC53470.2022.9754052.
- [7] N. C. Brintha, J. A. Narayana, G. L. V. S. Jaswanth, G. J. Chandrapal and D. Venkat, "Realtime Facial Emotion Detection Using Machine Learning," 2022 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES), Chennai, India, 2022, pp. 1-5, doi: 10.1109/ICSES55317.2022.9914318.
- [8] Ciaparrone, G., Chiariglione, L. & Tagliaferri, R. A comparison of deep learning models for end-to-end face-based video retrieval in unconstrained videos. *Neural Comput & Applic* **34**,7489–7506 (2022) <https://doi.org/10.1007/s00521-021-06875-x>
- [9] M. S. P, D. Hepsri Priya, P. Malavika and L. A, "Automated Analysis and Behavioural Prediction of Interview Performance using Computer Vision," 2022 IEEE 19th India Council International Conference (INDICON), Kochi, India, 2022, pp. 1-6, doi: 10.1109/INDICON56171.2022.10039785.
- [10] Y. -C. Chou, F. R. Wongso, C. -Y. Chao and H. -Y. Yu, "An AI Mock-interview Platform for Interview Performance Analysis," 2022 10th International Conference on Information and Education Technology (ICIET), Matsue, Japan, 2022, pp. 37-41, doi:10.1109/ICIET55102.2022.9778999.