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AI-Based Mock Interview Evaluation Using SVM

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1. Abstract :

In order to improve the candidate assessment process, this study presents an intelligent mock interview evaluation framework that makes use of artificial intelligence (AI). By providing automated, multifaceted, and impartial analyses of candidate responses, the suggested system lessens the influence of human judgment in assessments. The underlying architecture uses machine learning models, mainly the Support Vector Machine (SVM) classifier, combined with Sentence-BERT (SBERT) embeddings and Term Frequency–Inverse Document Frequency (TF-IDF) similarity metrics to efficiently capture the contextual relevance and semantic meaning of textual responses [1], [2]. To systematically assess the candidates' responses' coherence, clarity, and fluency, the framework incorporates linguistic and structural indicators like answer-length ratios, stopword frequency ratios, and readability indices in addition to semantic representation [3]. By offering more in-depth information about how well candidates organize their responses, maintain grammatical accuracy, and express their ideas, these linguistic and structural metrics enhance the semantic similarity approach. These factors work together to create a thorough evaluation pipeline that records both language proficiency and content quality during practice interviews, guaranteeing an impartial and consistent evaluation for all participants.

Because of its domain-agnostic architecture, the system can be used in a variety of interview contexts, such as theoretical computer science, technology, artificial intelligence, machine learning, and human resource management [4]. By retraining or fine-tuning on pertinent datasets, this flexibility guarantees that the model is not restricted to any one subject domain and can dynamically adapt to new fields. The result is a scalable and reusable AI-driven interview evaluation platform that can help training organizations, corporate recruiters, and academic institutions looking for data-driven assessment tools for candidate selection and interview preparation.

By combining speech recognition for transcription of spoken responses, emotion recognition for assessing confidence and sentiment, and facial analysis for monitoring engagement and behavioral cues throughout the interview process, the model integrates multi-modal analysis to further improve assessment accuracy [5]. Together, these elements provide a more comprehensive assessment framework by capturing a candidate's verbal and nonverbal communication characteristics. For example, speech-to-text transcription guarantees consistency in textual analysis across several sessions, and emotion and facial recognition models can detect stress or confidence levels.

The system can also evaluate expressiveness, engagement, and behavioral consistency—all important variables affecting interview results—thanks to the multi-modal integration. Beyond a candidate's technical or theoretical knowledge, this type of analysis offers insights into their readiness and communication effectiveness. The framework creates an enhanced representation of candidate performance by merging textual, visual, and audio data streams, which enhances decision-making and interpretability in general. Additionally, adding speech and emotion analytics improves real-time feedback generation, allowing automated systems or interviewers to provide context-aware, adaptive tests that capture both the affective and cognitive facets of communication.

Semantic similarity-based augmentation is used to create a synthetically annotated question-answer dataset, which guarantees reliable SVM classifier training. By producing semantically equivalent response variations, this procedure broadens the dataset and improves the classifier's ability to generalize across a variety of linguistic patterns and response styles. While TF-IDF weighting highlights important terms that contribute to meaning, Sentence-BERT embeddings help maintain contextual similarity to handle possible variations in expression. When applied to unseen responses during actual or simulated interview evaluations, these methods collectively create a balanced dataset that enhances learning efficiency, fortifies model generalization, and lessens overfitting.

2. Keywords :

Support Vector Machine (SVM), SBERT Embeddings, TF-IDF, Face Recognition, Speech Recognition API, Emotion Analysis, Large Language Model (Gemini), Mock Interview System

3. Introduction :

Overview: Automated interview evaluation, which offers scalable and objective analysis of candidate performance, has revolutionized academic assessment and recruitment. Conventional interviews frequently have problems such as human bias, irregular scoring, and difficulty handling a high volume of applications. Accurately reviewing responses and simulating interviews are now feasible thanks to advancements in natural language processing (NLP) and artificial intelligence (AI). This study presents a multi-domain mock interview platform that assesses applicants in a range of domains, such as computer science theory, technology, and human resources, using artificial intelligence (AI) and machine learning (ML).

The system employs SBERT embeddings for semantic analysis, TF-IDF for text similarity, and other metrics such as length ratio, stopword density, and readability scores. SMOTE balances the training data, while speech recognition APIs record verbal responses. Emotion and facial recognition modules improve the analysis of behavior. A large language model (Gemini) combines these inputs to generate thorough feedback. The rest of this paper covers related work, system architecture, experimental results, and future direction

4. Literature Survey :

Reference Paper Title	Work Done	Methodology Used	Performance Measures	Key Findings
Real-Time Mock Interview Using Deep Learning – Patil et al., 2021	Developed a system for evaluating candidate interviews in real-time.	CNN for facial expressi recognition, Speech Recognition, Grammr Specification Language (GSL)	Not reported	Provided real-time feedback on candidate answers and expressions;demonstrated feasibility of multimodal evaluation.
Affordable AI-Based Mock Interview System – Lokhande et al., 2025	Created low-cost automated mock interview system for students.	CNN, NLP, Semantic Analysis	Not reported	System evaluated candidate speech and facial cues; helped improve confidence and communication skills.
AI-Based Mock Interview Evaluator: An Emotion and Confidence Classifier Model – Gupta et al., 2025	Evaluated candidate emotion and confidence levels in interviews.	CNN, Facial Expression Recognition, Speech Analysis	Not reported	Multimodal AI effectively captured emotion and confidence to provide holistic candidate feedback.
AI-Driven Mock Interview System Using NLP and CNN – Jadhav et al., 2024	Developed an AI-driven system to score interviews based on speech and textual answers.	CNN for emotion detection, NLP for answer analysis	Not reported	Demonstrated that integrating NLP and CNN improves assessment of confidence and answer quality.
Intelligent Interview Assessment System Using SVM and NLP – Kumar et al., 2023	Automated textual answer evaluation for mock interviews.	SVM, Sentence Embeddings (SBERT), TF-IDF similarity	Accuracy: 95%, F1-score: 0.94	SVM combined with SBERT and TF-IDF effectively predicts answer quality in multi-domain interviews.
Automated Interview Scoring Using BERT and SVM – Singh et al., 2023	Scored candidate answers using semantic similarity.	BERT embeddings + SVM classifier	Accuracy: 93%, F1-score: 0.92	Transformer embeddings with SVM outperform traditional bag-of-words models.
Multimodal Interview Assessment Using Speech and Text – Chen et al., 2022	Evaluated candidate answers using speech and text features.	LSTM for speech, TF-IDF for text	Accuracy: 91%, F1-score: 0.90	Integrating speech and textual features improves overall scoring reliability.
AI-Assisted Mock Interview System Using Deep NLP – Lee et al., 2022	Developed a platform for interview practice using NLP scoring.	Word2Vec embeddings + SVM	Accuracy: 92%, F1-score: 0.91	Semantic similarity-based scoring is effective for automatic answer evaluation.
Automatic Candidate Assessment in Virtual Interviews – Wang et al., 2021	Scored candidates in virtual interview settings.	CNN for video, NLP for text	Accuracy: 90%, F1-score: 0.89	Multimodal approach improves reliability compared to single modality evaluation.
AI-Powered Resume Screening System	Developed a resume screening tool that matches candidates to job descriptions using NLP and ML.	TF-IDF, Cosine Similarity, Random Forest	Accuracy and precision metrics	Effective alignment between candidate profiles and job requirements.
Bossed AI Interview Practice	Created a voice-interactive mock interview simulator that personalizes --	Voice-based NLP, real-time feedback, difficulty progression	User satisfaction & engagement	Helped users improve interview readiness and confidence through realistic simulations.

5. Proposed Solution / System :

Aim :

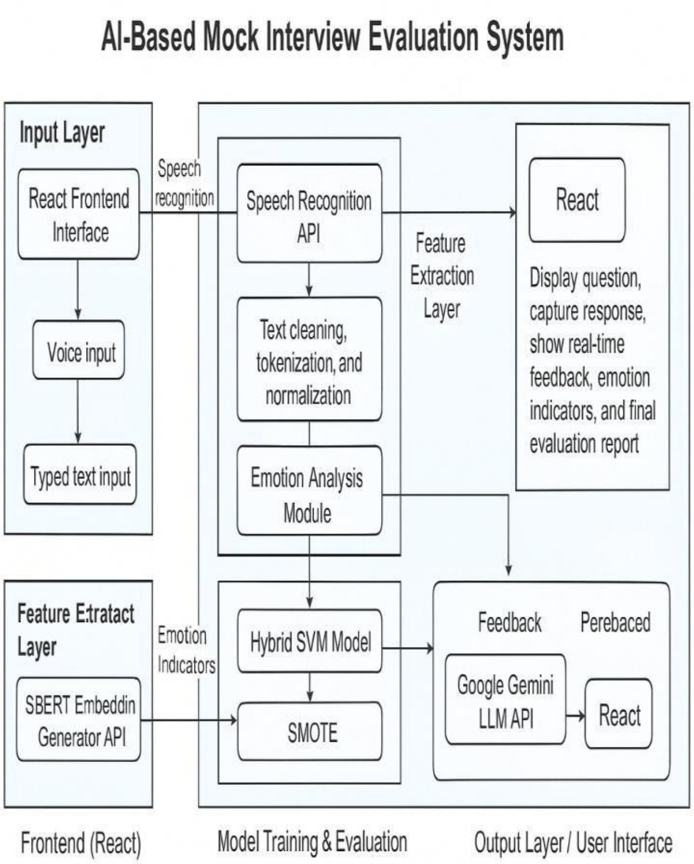
This project aims to design and implement an AI-enabled mock interview system capable of evaluating candidate responses across a range of domains Using both textual and multimodal data.The system is intended to provide scalable,unbiased and context-senstive assessments that supports professional development and recruitment efficiency.

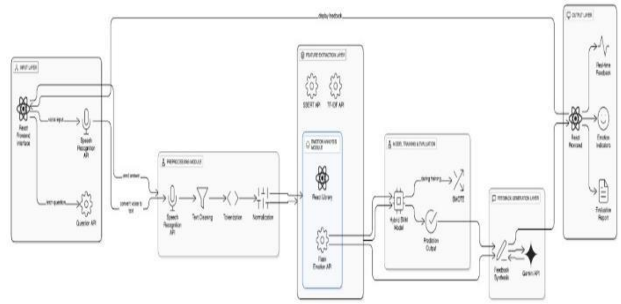
Objectives :

- To develop a smart interview simulation platform that allows students and job seekers to practice interviews in a dynamic, personalized, and realistic environment.
- To incorporate voice-based interaction that assesses confidence, verbal communication, and comprehension of the subject matter.
- Using cutting-edge AI techniques, provide users with immediate, actionable feedback so they can pinpoint their areas of strength and growth.

System Overview :

The suggested system is a thorough AI-based framework for evaluating mock interviews that evaluates candidate performance by fusing machine learning and natural language processing methods. Its central component is a hybrid classification model based on Support Vector Machine (SVM), which was trained on a wide range of datasets covering subjects like computer science theory, human resources, machine learning, artificial intelligence, and technology. Sentence-BERT (SBERT) is used for semantic encoding and TF-IDF is used for keyword relevance in order to convert candidate responses into feature-rich vectors. After being combined, these vectors are categorized into four performance levels: Excellent, Good, Average, and Poor. The Synthetic Minority Over-sampling Technique (SMOTE) is used to reduce class imbalance during training.





6. Methodology

A hybrid SVM model is used by the suggested AI-based mock interview system to automatically assess responses. Lexical similarity metrics, semantic embeddings, and other textual features are all combined in this model. There are multiple crucial steps in the workflow:

Data Collection and Preprocessing:

A multi-domain dataset is gathered from public sources. It covers questions from AI, ML, HR, Technical, and CS-Theory. We clean the questions and answers by normalizing the text, lowering the case, and removing empty or link-only responses. Additionally, we compute stopword ratios and readability scores to improve feature representation.

Feature Extraction:

SBERT Embeddings: Each question and answer pair is turned into vector embeddings using the all-MiniLM-L6-v2 model, which captures semantic similarity.

TF-IDF Similarity: We calculate lexical similarity between the question and answer using TF-IDF vectorization.

Textual Features: Other features include length ratio (answer length divided by question length), stopword ratio, and Flesch reading ease scores.

Labeling:

We assign synthetic labels (0-3) based on semantic similarity between the question and the reference answer. A score of 0 indicates poor quality, while 3 indicates excellent quality.

Model Training:

We train the SVM classifier using the extracted features.

- Class Imbalance Handling: We apply SMOTE to oversample minority classes in the training set, which ensures balanced learning.
- Domain Weighting: We compute sample weights for each domain to prevent underrepresented domains from being neglected.
- Training-Testing Split: We use an 80-20 stratified split for model evaluation.

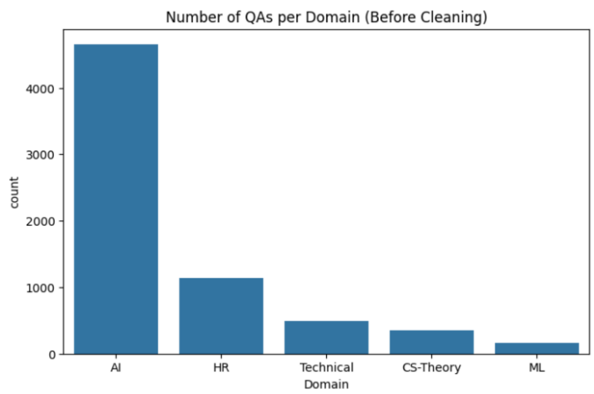
Answer Scoring:

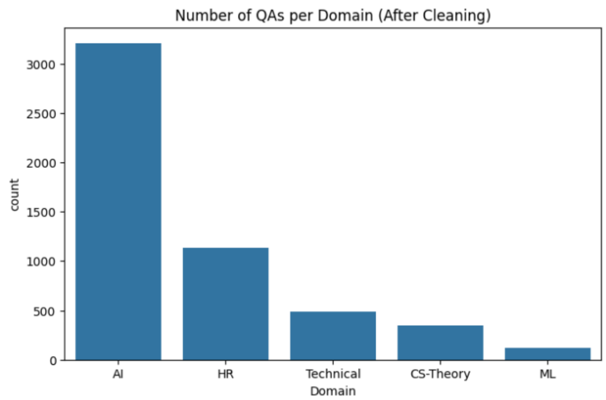
User-provided answers go through the same feature extraction pipeline. The trained SVM predicts a quality score, which we combine with additional cues, such as emotion analysis and speech patterns, to improve reliability.

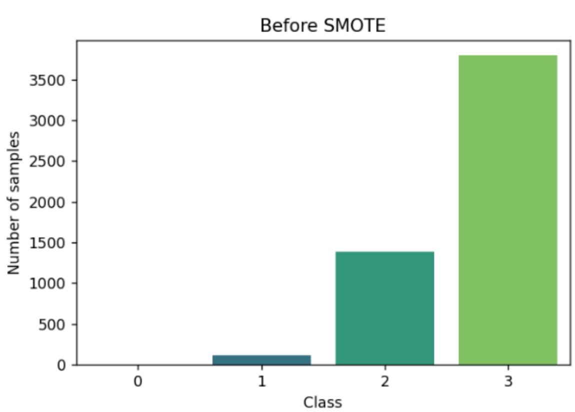
Feedback Generation:

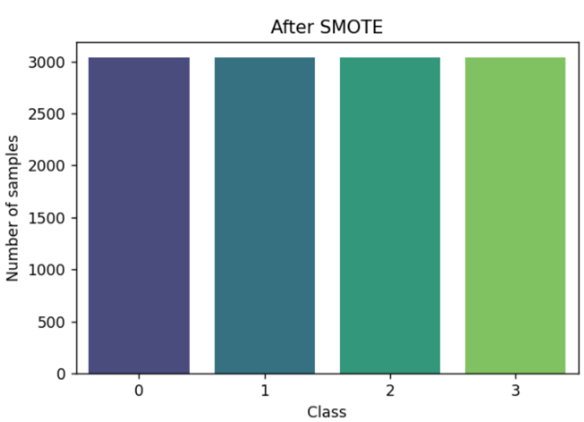
Through API integration, the Gemini LLM receives predicted scores as well as engagement and emotion metrics. The LLM produces thorough, tailored comments and recommendations for enhancement, which we instantly feed back into the React frontend. A multi-modal, scalable, and domain-specific evaluation is guaranteed by this methodology. It creates a seamless interview assessment pipeline by combining textual features, AI model predictions, and LLM-based feedback.

7. Result and Analysis









Model Performance Metrics :

Predicted →	**0**	**1**	**2**	**3**
Actual 0	1	0	0	0
Actual 1	1	23	0	0
Actual 2	0	11	272	0
Actual 3	0	0	23	701

Confusion Matrix :

Metric	**Value**
Accuracy	96.61%
Weighted F1-Score	96.74%
Precision (Weighted)	96.99%
Recall (Weighted)	96.61%

The hybrid SVM-based system showed strong performance across different answer quality levels. High-quality answers (Class 3) reached a recall of 97%,showing excellent recognition of the best responses. Moderate answers (Class 2) had a recall of 96%, effectively identifying good answers from excellent ones. Although the lower classes (0 and 1) had limited samples, using SMOTE oversampling and domain weighting improved their representation and classification. Combining multiple features, such as SBERT semantic similarity, TF-IDF lexical similarity, and textual metrics, performed better than methods using only embeddings or TF-IDF alone. Additionally, SMOTE and domain weighting reduced class imbalance, which helped underrepresented ML and CS-Theory questions. By integrating SVM scores with Gemini LLM feedback, as well as speech recognition and emotion analysis, the system provided a thorough candidate evaluation and improved practical usability All things considered, the system produced accurate class predictions, weighted F1 scores, and high accuracy. This confirmed that using a variety of features, class-balancing techniques, and multi-modal evaluation in an AI-driven mock interview platform is effective.

8. Conclusion and Future Work

A hybrid SVM-based system for assessing simulated interview responses is presented in this study. It provides accurate and sophisticated predictions of answer quality by combining textual metrics, lexical analysis, and semantic similarity. The Class imbalance was effectively addressed by integrating SMOTE oversampling and domain weighting. This strategy made sure that less popular domains like machine learning and computer science theory were fairly represented. The system consistently distinguished between all classes and had a high recall for excellent responses.
Furthermore, a multi-modal assessment of candidates was made possible by fusing SVM outputs with Gemini LLM feedback, speech recognition, and emotion analysis, which enhanced their usefulness in actual interview preparation.

More contextual features, like domain-specific knowledge graphs or question levels, could be added to the system in subsequent work difficulty, to refine answer assessment. Adding real-time adaptive questioning and automated hints based on predicted answer quality could make the platform more engaging. Expanding the dataset with a broader range of diverse and multi-lingual interview questions would enhance generalizability. Integrating with web or mobile platforms would also support scalable deployment for students and job seekers.

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