Project Phase II Report On

Q&AI: AI Mock Interview Bot

Submitted in partial fulfillment of the requirements for the award of the degree of

Bachelor of Technology

in

Computer Science and Engineering

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CERTIFICATE

This is to certify that the project report entitled ***"Q&AI: AI Mock Interview Bot"*** *is a bonafide record of the work done by* ***Gokul Baburaj (U2003087), Joel Manuel C. J. (U2003106), Maria Sabi (U2003127), Merene Benson (U2003132)****, submitted to the Rajagiri School of Engineering & Technology (RSET) (Autonomous) in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology (B. Tech.) in Computer Science and Engineering during the academic year 2023-2024.*

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Abstract

The AI Mock Interview Bot is an application designed to enhance interview preparation for job seekers and aspiring professionals. This project aims to create an intelligent virtual interview platform that simulates real interview scenarios, offering users the opportunity to practice answering questions while receiving valuable feedback.

The AI Mock Interview Bot conducts mock interviews by asking a series of questions generated from the users' resume. Users can respond to interview questions in real-time, simulating a genuine interview setting. The bot then evaluates the users' responses and gauges their confidence level based on factors such as speech patterns, tone, and body language. It also analyses the language proficiency and factual accuracy of users' answers. The AI system employs sentiment analysis and emotion detection to assess the emotional tone of users' responses.

After each interview session, the bot generates a detailed scorecard, offering users feedback on their performance. This feedback is essential for users to identify their strengths and areas for improvement. Users can also view their progress over time.

The AI Mock Interview Bot empowers users to refine their interview skills, boost confidence, and receive constructive feedback, ultimately increasing their chances of success in real job interviews. This project represents a valuable tool for career development and interview preparation in an increasingly competitive job market.

Contents

List of Abbreviations

AI - Artificial Intelligence

ASCII - American Standard Code for Information Interchange

BERT - Bidirectional Encoding Representation for Transformers

CBOW - Continuous Bag of Words

CNN - Convolutional Neural Network

CTC - Connectionist Temporal Classification

HTML - Hypertext Markup Language

KNN - K-Nearest Neighbour

LSTM - Long Short-Term Memory

LLaMA - Large Language Model Meta AI

LLM - Large Language Model

NLP - Natural Language Processing

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Chapter 1

Introduction

1.1 Background

Traditional interview preparation methods have long relied on resources like books and guides. These materials, though they offer valuable insights into common interview questions, strategies, and general tips, are static. They lack the ability to provide interactive and personalized experiences.

Mock interviews with human partners are another approach. This helps in direct feedback and provides a realistic setting. However, the received feedback largely depends on the subjective nature of the evaluator which introduces biases and inconsistency.

A technological advancement in this space is offered by online platforms offering mock interviews. They often leverage recorded video interviews and automated assessments to provide feedback. But they may fall short in terms of dynamic question generation and personalized feedback.

Video interview platforms have gained popularity, especially in the remote hiring process. They facilitate virtual interviews but their focus is on the employer side than the candidate's preparation.

Chatbots and virtual also provide users with simulated conversational experiences. While these tools can offer a degree of interactivity, limitations may arise in terms of natural language understanding, making it a challenge to simulate realistic interview scenarios.

1.2 Problem Definition

The problem definition is to empower candidates to refine their interview skills by utilizing the AI Mock Interview Bot, providing an interactive and dynamic experience for the user.

It helps set one on the path to interview success, whether one is practicing for their dream job or aiming to enhance their professional presence,

1.3 Scope and Motivation

The AI Mock interview bot has the opportunity to revolutionize the way individuals, especially students, prepare for interviews and refine their skills. The interview bot simulates a realistic interview scenarios, enabling candidates to tackle the nerves and anxieties associated with job interviews. It also offers personalized feedback on one's performance, helping users identify and address their strengths and weaknesses. Further, the potential integration of the application with college placement cells expand its scope. The interview bot has the potential to cater to a wide and diverse audience of job seekers, empowering them to achieve their dreams and advance their careers.

Existing interview preparation methods share limitations like personalized feedback, dynamic question generation, and realistic interview simulation. An interview's success hinges on one's presentation, language proficiency, confidence, and even expressions. In today's competitive job market, one must recognize their strengths and weaknesses and work on improving their shortcomings in order to acquire their dream job. Therefore it is extremely important that mock interview platforms provide an analysis of these factors and personalized feedback. Such platforms must also be able to eliminate any bias towards the candidates to provide an unfiltered and just feedback.

1.4 Objectives

To develop an AI-powered mock interview bot that

- offers realistic interview simulations and asks questions based on resume
- grade answers to the simulated questions on
  - factual accuracy
  - grammatical accuracy
- analyze user responses based on confidence and sentiment
- provides detailed feedback and performance analytics for improvement

1.5 Challenges

1. Collecting and storing user interview data raises privacy and security concerns.
2. Mimicking human interaction, including body language and non-verbal cues pose as a challenge.
3. Analyzing extended video and audio recordings for interviews can strain computational resources.
4. There may be prejudice in how the bot makes decision if training data is biased.

1.6 Assumptions

1. Stable Network connection: Since all the signal response is done through the web, if there is no stable network, the response from the bot will be delayed.
2. Only One Face must be visible: Our bot is designed to analyze a single face, they can have difficulty providing accurate results if multiple faces are detected.
3. Clear Audio Output : The output must be clear and not muffled so that the bot can analyse the speech properly.
4. Language Requirement : The interview will be conducted exclusively in the English language.

1.7 Societal / Industrial Relevance

The AI Mock interview bot shows profound relevance in equipping the youth, among others, with the communication skills and confidence required to ace their job interviews.

As an interview's success hinges not only on the candidate's technical skills, but equally on their presentation, language proficiency, confidence and non-verbal cues, the interview bot serves as a valuable tool in interview preparation yielding better equipped, qualified candidates.

The application also addresses the need for accessible and effective interview preparation tools that give ample feedback highlighting the user's strengths as well as areas for improvement.

1.8 Organization of the Report

The report begins with an introduction that provides context, outlines the problem and the scope and motivation for the project. It also underscores the assumptions and challenges undertaken and the significance of the AI Mock Interview Bot. The second chapter then delves into a comprehensive review of existing literature and research in the field, providing a foundation for understanding the project's context within existing knowledge.

The third chapter then details the implementation prerequisites in hardware and software. Following this, the fourth chapter details the system design illustrating the architecture and modules involved in the project, as well as the project execution plan using Gantt chart and work schedules. Finally, the concluding chapter summarizes the key findings and outcomes of the project. The references and appendices are then provided to offer a comprehensive resource base for the report.

Chapter 2

Literature Survey

2.1 AI Mock Interview Bot: An emotion and confidence evaluator[1]

The paper 'AI-based mock interview evaluator: An emotion and confidence classifier model'[1] proposed an AI mock interview platform that bridges the gap between the actual interview and its preparation. The system assesses the user based on 3 factors: emotion, confidence, and knowledge base. Emotion is analysed based on facial expressions using a CNN algorithm which will classify the emotion among 7 categorical emotions. Confidence evaluation is performed based on speech recognition using NLP and Pydub audio python libraries. Knowledge assessment involves keyword mapping, semantic analysis, and web scraping for keyword extraction.

The system is divided into 5 phases: Face recognition, data separation, facial expression recognition, confidence recognition based on speech score, and knowledge base. The face recognition module involves image acquisition, image pre-processing and recognition. The candidate's photo is collected on registration. The image is then converted into grayscale in the shape of 50*50 pixels. The system uses a Har-cascade classifier to classify faces. The python library Face_Recognition is used for face recognition of the live photo of the candidate to the candidate's uploaded image. Live data is separated into audio-video format using OpenCV library.

The facial expression recognition module begins with training the deep learning model. The dataset is divided into training and testing folder containing 28821 images in training and 7066 in testing. The 7 categorical values are happy, sad, angry, disgust, anger, neutral and fear and image has a dimension of 48*48. For training, a CNN model has 6 layers. The first 4 are convolution layers and the other 2 are fully connected layers. Max pooling was also employed. 10 epochs were given for training which generated an accuracy of 80.75 for training and 76.34 for testing. The live video is then broken down into frames

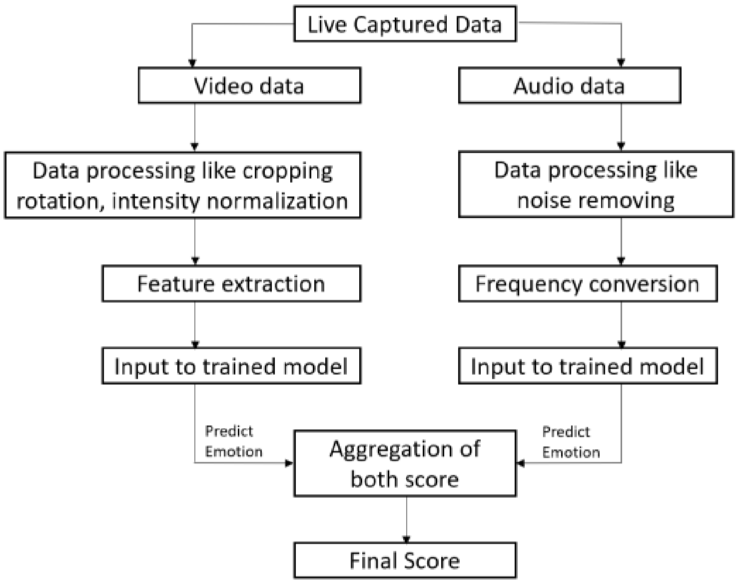

Figure 2.1: System Architecture of emotion and confidence evaluator[1]

and each frame is made into 48*48 pixels and then converted to grayscale. Facial features are extracted in the convolutional layers and the model will predict the output emotion which gets converted into a score.

Confidence recognition module focuses on speech recognition and categorization based on 7 emotions. Preprocessing steps are loading speech audio by 'Speech Segement' library, normalising each 'Audio Segment' object to +5.0dB, transforming the object to an array, removing silences at the beginning and end, length normalization and noise reduction. It also performs feature extraction like energy, zero crossed rate, and mel-frequency cepstral coefficient. Training is performed using an LSTM-based neural network.

For speech recognition, a deep learning algorithm trained with 8 emotions is used. Audio files of 7 different categorical emotions are given as input. The 'Audio Segment' object is normalized into Pydub which is then converted into an array by NumPy and Audio Segment. Silence is removed using Librosa and padded to equal length using NumPy. This is then fed into an LSTM network.

The user's knowledge base is evaluated by converting the audio to text using speech-to-text. Keyword extraction is done, followed by syntax and semantic correctness which is converted to a score. The correctness of the answer will be checked based on the keywords in the database and a score is generated. An average of these scores is generated. The scoring module is divided into facial emotion score, confidence score and knowledge base.

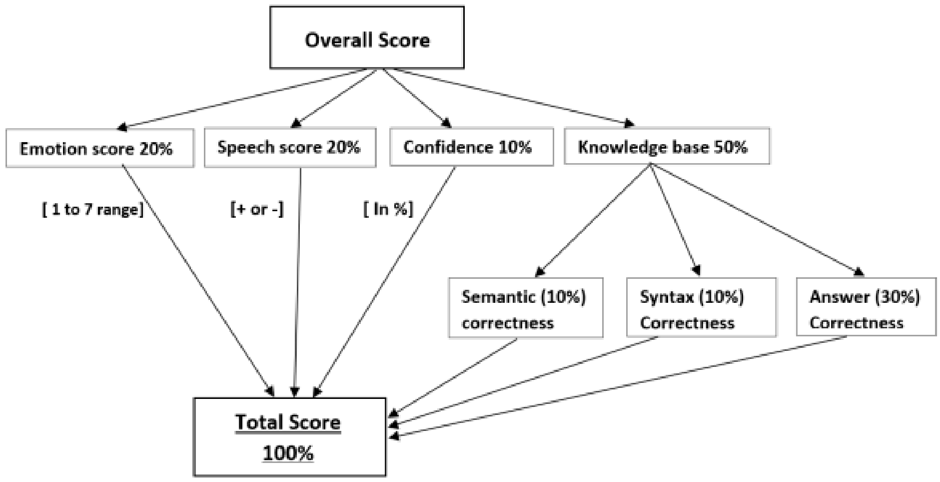

Figure 2.2: Scoring System of emotion and confidence evaluator[1]

1. Emotion score: weightage of 20% in the range of 1-7
2. Speech: weightage of 20% divided as positive or negative
3. Confidence: weightage of 10%
4. Knowledge base: weightage of 50% divided as
    - Semantic correctness: weightage of 10%
    - Syntax correctness: weightage of 10%
    - Answer correctness: weightage of 30%

The final score of the candidate is then generated.

2.2 Automated Question Generation in Interview Bot[3]

The research paper, 'Interview Bot with Automatic Question Generation and Answer Evaluation'[3], introduces a chatbot that can be used for conducting interviews with new applicants who are applying for a new position in the company. It explores the possibility of using BERT (Bidirectional Encoding Representation for Transformers) to generate questions for a particular domain using the resume uploaded by the candidate ahead of time. The paper further explores the possibility of using chatbots to conduct interviews for MNCs having a large number of applicants apply every time to filter out the weaker applicants.

	Generated Question	Retrieved Question	Answer
1	What is used to define a class template?	Explain the concept of class.	A class serves as a template from which unique objects can be built. A class may include fields and methods that characterize an object's behavior.
2	What is Python?	State whether there exists a compiler for python or not.	Yes, it has a compiler that works automatically because of which it remains unnoticed.
3	What is the name of the scikit-learn python library used for machine learn- ing?	Which library in python is used for ML (machine learning)?	Scikit-learn is the python library used for Machine learn- ing applications
4	What is hidden in data abstraction?	What is abstraction?	Abstraction is keeping the internal implementation hid- den and displaying only the information that is necessary.
5	What is the purpose of a message pass- ing?	Explain what system class is used for.	The System class's goal is to give users access to system resources.

Table 2.1: Result of dynamic question generation[3]

Question	Original Answer	Student Answer	Result
What will happen if the main method's signature is changed to remove the static modifier?	Program throws "No Such Method Error" error at runtime	There would be ambiguity for the entry point of the program	65.45
Object reference that has been declared as an instance variable its default value is?	Null, unless it is defined explicitly	Garbage	4.55
Can a top-level class be made pri- vate or protected?	A top-level class cannot be hidden or protected.	Either "public" or no modifier is permitted.	14.95

Table 2.2: Answer evaluation of dynamic question generation[3]

The paper divides the proposed method into five major components – Resume screening, Question generation, Answer evaluation, Proctoring, and Chatbot. The first is the

Resume screening module, this module deals with this module takes the resume of the interviewee as input and analyzing it to extract the major components of the resume like skills and job roles. The question generation module takes the major components analyzed by the resume screening module to generate questions for the required job role that matches the person's profile using BERT. The Answer evaluation module is used to evaluate the user's response to the generated question using cosine similarity to the expected answer. The proctoring module utilizes the camera of the laptop or computer to analyze if malpractices are done in the interview or not by reading the answer from a book or mobile. The chatbot is the interface module where all the other components are integrated to generate a fully functional application.

The result of testing the application provides promisingly high results for both question generation and answer evaluation. This shows that chatbots based on transformer models can be used for filtering candidates for the interview process.

2.3 CUTIE : Interview Bot[2]

The paper[2] presents a study on CIT University Tutoring Interviewer Environment (CUTIE), an interview bot developed to help university students improve communication skills and confidence needed to tackle job interviews. The bot carries out mock interviews by posing questions and then examining video and audio to analyze emotions and sentiments in real-time. The study involved analyzing 114 student videos, comparing manual expert scoring with CUTIE's scoring, and investigating factors influencing the bot's performance.

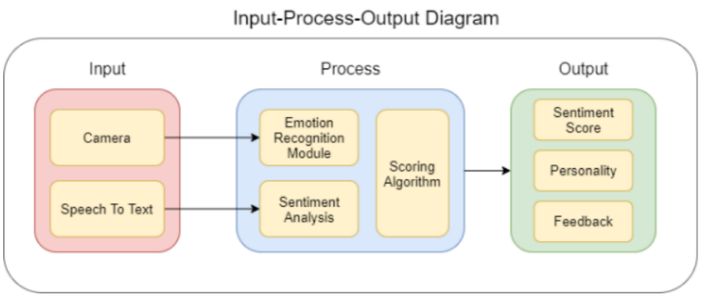

Figure 2.3: I/O Diagram of CUTIE[2]

The system takes as input video and audio of the mock interview. The video is then used for emotion recognition, and the audio - after being converted to text - is used for sentiment analysis. The gathered data is processed through a scoring algorithm that yields the sentiment score and the spectrum of emotions exhibited throughout the interview.

CUTIE employs Vue.js as the web client due to its adaptable nature and integration capabilities with various libraries and tools. For server-side development, the Python web framework, Django, is utilized, offering rapid development and robust security features. Additionally, to handle data queries efficiently, the system incorporates GraphQL, an open-source query language.

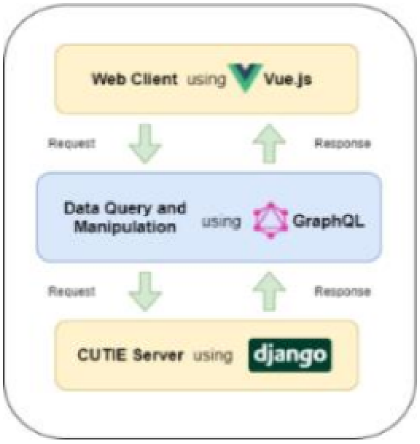

Figure 2.4: Architecture Diagram of CUTIE[2]

The bot conducts sentiment analysis through a two-step process. First, it converts the recorded audio into text. Next, the transcribed text is interpreted using AFINN list- a list of English words given valence scores from -5 to +5 for positive or negative sentiments. This involves splitting the transcribed text into a list of words, then matching them to the AFINN list. The sentiment score is finally computed by adding up the valence scores of positive and negative words said during the interview.

Facial emotion recognition is also performed in this paper through a two-step process. First, the JavaScript face recognition API is used to identify faces. This tool uses the Face Matcher function to find human faces, and makes predictions on facial landmarks using confidence scores. Following this, the extracted data is used to identify emotions through a Convolutional Neural Network (CNN) model that uses depth-wise separable convolutions and densely connected blocks.

The robot was tested through the evaluation of 114 student videos submitted as answers to an interview questionnaire. The scores given by the bot were compared to that given manually by an expert. However, the scores showed no correlation. An investigation then showed that the bot scored those students who used a computer or phone microphone higher scores than those who used earphones. It is speculated that the distance between the mouth and the earphone mic contributed to the low sentiment score. Additionally, the lighting setup during the interviews also influenced the results.

The paper further suggests several additions to the overall system design. This includes incorporating performance tracking analytics, identifying grammar and enunciation issues, and implementing body posture recognition. Additionally, the study suggested the expansion of the project to students at other universities in the future.

Thus, the paper offered a thorough examination of CUTIE: the interview bot's development and validation. The study emphasized the potential of interview bots in enhancing communication skills and confidence in job interviews.The paper also highlighted the limitations of the bot in giving accurate scores due to the influence of audio tools and lighting setups used during the interview. The paper finally suggested potential advancements in the system's design that could improve its functionality and use in the future.

2.4 LSTM–CNN–grid search-based deep neural network for sentiment analysis[7]

One novel LSTM-CNN-grid search-based deep neural network for sentiment analysis is presented in the study named 'A novel LSTM–CNN–grid search-based deep neural network for sentiment analysis'[7]. Understanding hidden thoughts, feelings, and emotions in user-generated web content is the study's main goal. The suggested model uses grid search to optimize hyperparameters, which improves its efficiency in producing ideal outcomes and reducing predetermined losses. Alternative techniques for sentiment analysis are also covered in the study, including neural networks, KNN, CNN, LSTM, CNN-LSTM, and LSTM-CNN.

The suggested model is a deep neural network that uses a complex grid-search LSTM-CNN architecture. One prominent hyperparameter tuning method used to find the best set of hyperparameters for a machine learning model is grid search. There is a methodical procedure involved in using grid search. A hyperparameter grid is first constructed by giving each hyperparameter a range of values. After that, a grid is made that includes every possible set of hyperparameters. Ultimately, every point in the grid is assessed for the model's performance, enabling the best set of hyperparameter combinations to be chosen. The number of neurons in the hidden layer, batch size, dropout percentage, number of epochs, optimization algorithm, and other crucial hyperparameters are particularly taken into account in this paper's grid search. The methodical grid search investigation of these hyperparameters enhances the LSTM-CNN model's overall resilience and performance optimization.

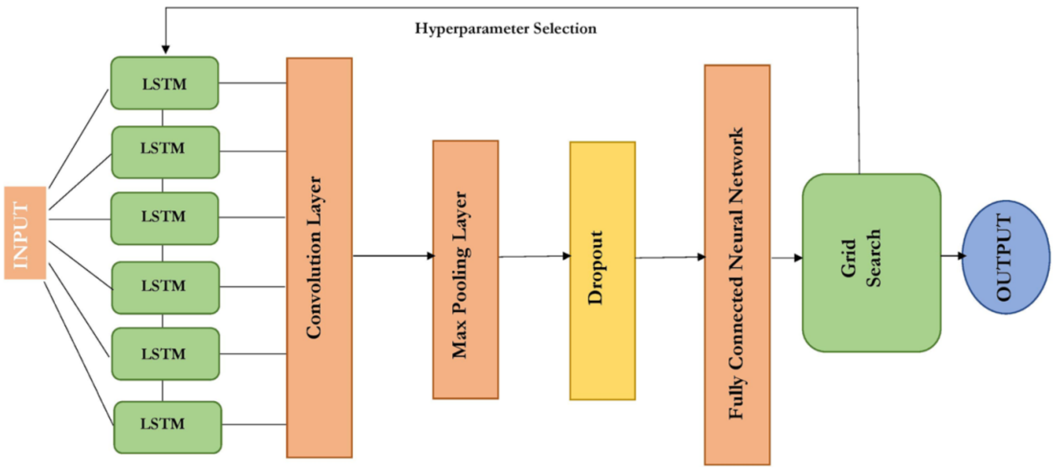

Figure 2.5: LSTM-CNN-GS architecture[7]

Three essential elements are included in the structured process of sentiment analysis methodology: data exploration, data cleaning/preparation, and data transformation.

The first investigation of the dataset using statistical and visual aids is called data exploration. The purpose of this stage is to describe the dataset's attributes, including size, quantity, and correctness. Finding connections between various data variables, comprehending the structure of the dataset, spotting anomalies, and evaluating the distribution of data values are all made easier during the exploration phase.

Making the text readable for analysis in the intended task is the main goal of data cleaning and preparation. This stage involves several preprocessing methods, including the removal of HTML and ASCII characters, lowercasing, punctuation, stopwords, tokenization (splitting text into discrete parts or tokens), stemming, and lemmatization. Lemmatization takes into account the word's true meaning, whereas stemming only takes into account the word's form. All of these procedures help to polish the data and get it ready for further examination.

Word vectorization, a popular term for the process of transforming text data into a numerical format, is one type of data transformation. A prominent technique for producing word embeddings in this context is the two-layer neural network known as Word2Vec. Word2Vec is based on two models: skip-gram and Continuous Bag of Words (CBOW). The CBOW model predicts the middle word by combining dispersed representations of context. On the other hand, the skip-gram model uses the input word's distributed representation to predict the context.

The machine learning algorithm—in this example, LSTM-CNN-GS—is then applied after the data has been transformed. A training set and a testing set are created from the data, with 80% of the data going toward training and 20% toward testing. The material is then divided into positive and negative sentences using machine learning methods. Important characteristics including accuracy, precision, sensitivity, specificity, and F-1 score are used to evaluate the model.

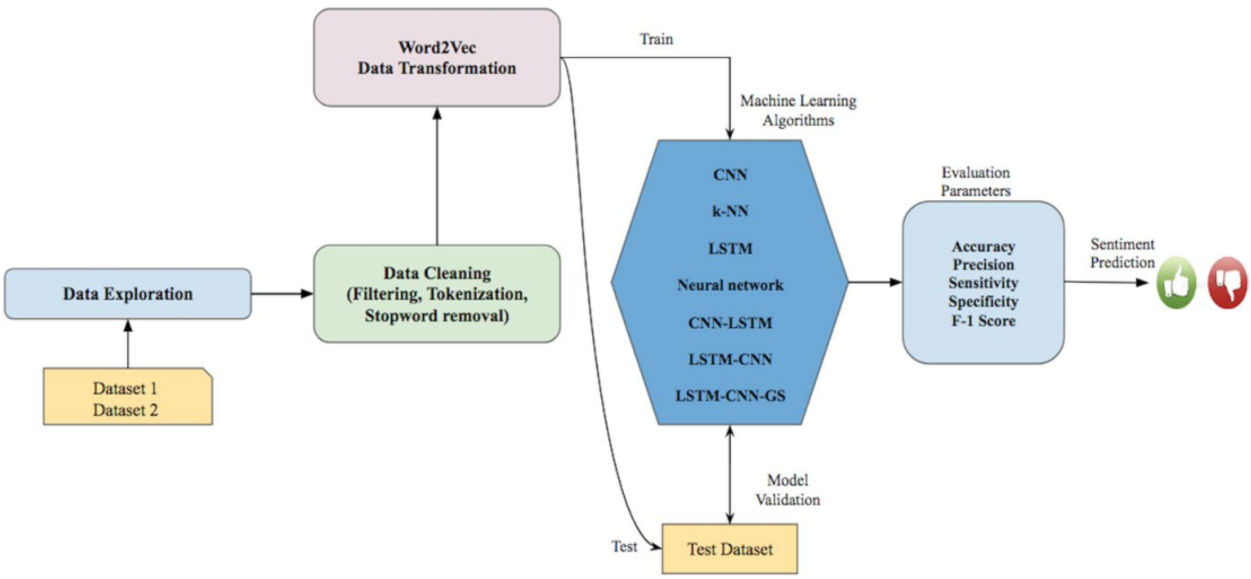

Figure 2.6: Methodology for sentiment analysis[7]

The IMDB Dataset of 50K Movie Reviews and Amazon reviews for sentiment analysis are the two datasets used in the study to show the superior performance of the LSTM-CNN-GS model, which achieves an accuracy rate of over 96%.

2.5 Decoder-only model for Speech-to-Text and Large Language Model Integration[8]

The paper[8] introduces Speech-LLaMA, a novel approach that effectively integrates acoustic information into text-based large language models (LLMs) for speech processing tasks. The authors propose an end-to-end integration technique that maps compressed acoustic data into the semantic space of the LLM using an audio encoder and Connectionist Temporal Classification (CTC). They go into elaborate detail on the model's practical characteristics, such as attention mask selection, duration compression, and fine-tuning techniques. The experimental results highlight the effectiveness of the proposed method, demonstrating Speech-LLaMA outperforming strong baselines in speech translation tasks. The study begins by highlighting large language models' (LLMs') high performance on a range of natural language processing tasks. The authors stress the potential benefits of enhancing human-machine interaction through the integration of voice signals into LLMs. Current methods such as deep integration and cascaded systems are addressed, noting the difficulties in balancing the two modalities and reducing integration costs without sacrificing functionality. In response to these challenges, the authors propose Speech-LLaMA as an efficient end-to-end integration method.

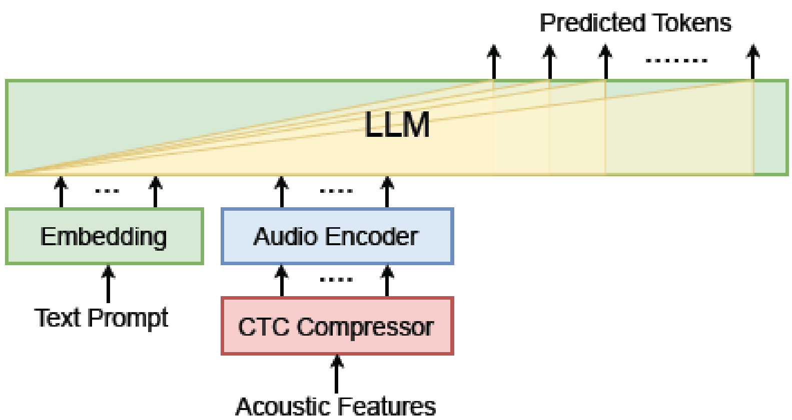

Figure 2.7: Architecture of Speech-LLaMA[8]

The proposed neural model comprises three key components: a pre-trained text neural language model (LLaMA-7B), an audio encoder, and a Connectionist Temporal Classification (CTC) compressor. The CTC compressor is pre-trained to align audio and text durations by selecting representative frames from the audio signal, employing two methods: blank-removing, where frames predicted as the blank symbol are discarded, and frame-averaging, where hidden states of consecutive frames with the same CTC predictions are averaged. The audio encoder bridges representations from the CTC compressor to the text embeddings, optimizing its integration with the LLaMA model during fine-tuning. For instructive learning, each training sample is prepended with a text prompt describing the task, such as "audio → English" or "transcribe the audio into English." LoRA fine-tuning is applied to four attention matrices in each layer of the LLaMA Transformer, enhancing training stability through a two-stage process where the audio encoder is initially trained with the CTC compressor and LLaMA frozen before introducing LoRA for further optimization.

Additionally, the model's versatility is explored through a "from-scratch" training approach, replacing pre-trained components with randomly initialized ones. This includes a decoder-only architecture with a convolutional 2D encoder and a smaller randomly initialized autoregressive network, conditioning text sequence generation purely on the audio signal. The overall architecture aims to provide a robust and flexible framework for speech modeling with effective integration of audio information and language semantics.

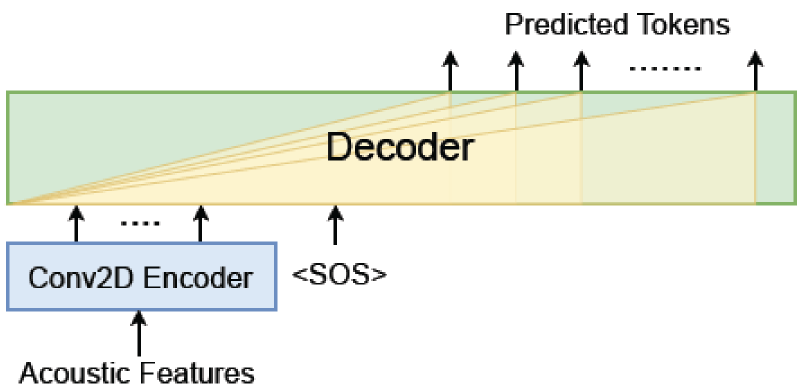

Figure 2.8: Decoder-Only Architecture of Speech-LLaMA[8]

This work presents a detailed analysis of the practical features of the proposed model, including how to choose the right duration compressor, attention mask, and fine-tuning techniques. The CoVoST 2 dataset and BLEU scores are among the measurements and data that the authors describe in detail. They also go over the model configuration, including the LoRA fine-tuning method and the CTC compressor's parameters.

The results from the speech translation experiments clearly showcase the powerful impact of Speech-LLaMA. Outperforming even the most robust baselines, this model exhibits remarkable advancements in translation performance. Additionally, the study investigates various audio length compressors and concludes that the CTC compressor continually outperforms the convolutional one. Beyond this, the authors delve into the benefits of a decoder-only architecture, demonstrating that such models can match the competitiveness of encoder-decoder models while utilizing fewer parameters.

In conclusion, the paper presents Speech-LLaMA, a novel approach that integrates acoustic information into text-based LLMs for speech processing tasks. When compared to strong baselines, the translation performance of the proposed approach shows significant improvements. The authors show the possible benefits of decoder-only models and conduct a thorough investigation of the model's effectiveness. This work enhances the field of speech processing by demonstrating how successfully speech signals may be integrated with large language models.

2.6 Transformers[9]

The paper, 'Transformers: State-of-the-Art Natural Language Processing[9]', describes Transformers, an open-source library from Hugging Face and one of the libraries most advanced in natural language processing based on Transformer architecture. This comprehensive toolkit comprises three key components: tokenizers, which convert raw text into index encodings; transformers, generating contextual embeddings from these encodings; and heads which are key to task-specific predictions using the generated embeddings.

An interesting aspect of the Hugging Face library is that it has expanded into a model hub, becoming in fact an exclusive platform for users to upload, download, and share pre-trained models. Naturally, this pre-trained model is finely tuned for a variety of NLP tasks, such as language understanding, generation, and translation. The design of the library is aimed at both research and production, stressing extensibility, simplicity, and speed. It's also compatible with different frameworks such as PyTorch and TensorFlow; an ideal tool for the whole of the NLP community.

Built around these core components, the Hugging Face library provides users with several choices for deployment (ONNX / CoreML; TorchScript), making it more flexible and allowing its use in a wider range of applications. In this way, the paper well demonstrates how flexible the library is by revealing its active involvement from all quarters of local society. Among them are model architects involved in the creation, task trainers who take advantage of its functions and application users applying it to practical examples. The paper accordingly depicts the multifaceted impact of the Hugging Face library on language processing, showing how this effect has encouraged both progress and collaboration in natural language processing (NLP).

Transformers
Masked $[x_{1:N \setminus n} \Rightarrow x_n]$
BERT RoBERTa
Autoregressive $[x_{1:n-1} \Rightarrow x_n]$
GPT / GPT-2 Trans-XL XLNet
Seq-to-Seq $[\sim x_{1:N} \Rightarrow x_{1:N}]$
BART T5 MarianMT
Specialty: Multimodal
MMBT
Specialty: Long-Distance
Reformer Longformer
Specialty: Efficient
ALBERT Electra DistilBERT
Specialty: Multilingual
XLM/RoBERTa

Figure 2.9: Types of transformers in hugging face[9]

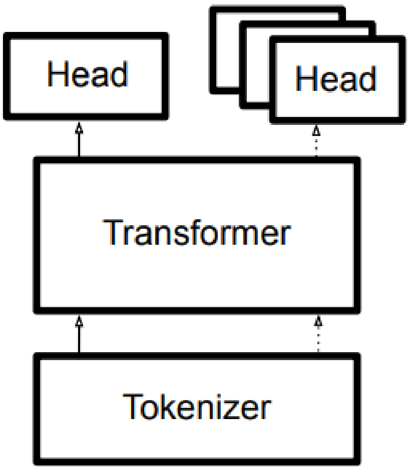

Figure 2.10: Hugging face model architecture[9]

2.7 Emotion Detection Using Facial Expression Involving Occlusions and Tilt[14]

The paper promises to deliver more reliable emotion detection systems even in real-world scenarios where emotions are expressed across various modalities. Advancements in real-time processing and edge computing have also made it possible for emotion detection systems to respond quickly. This has led to many practical applications in areas such as human-computer interaction systems, healthcare diagnostics, and driver monitoring in the automotive industry

2 datasets can be taken for example:

- AFFE (Japanese Female Facial Expression) : This dataset contains emotions of neutral, happy, angry, disgust, fear, sad, and Surprise of seven Japanese women. In total, there are 213 grayscale facial expression images in this database. Each image is of size 256×256.

- CK+ (Extended Cohn-Kanade Dataset): The Extended Cohn-Kanade Dataset (CK+) primarily focuses on the six basic emotions: anger, contempt, disgust, fear, happiness, and sadness. Each person in the dataset is typically associated with posed facial expressions representing these basic emotions.

The process is based on 6 layers of CNN, in which 5 convolution layers are used including the max-pooling layer and one dense layer with a dropout function. The first step is facial identification and then cropping the image in the second step. In the third step, the image is vertically flipped and 2 images from 7 angles from each image are formed producing a total of 14 images in the final step.

Later on, the first CNN layer uses a 5 × 5 filter. It takes a 32 × 32 sized image of grayscale which means the number of channels is 1.

Its output size is 32 feature maps. It breaks images into a small subsection of size 5 × 5. Then to reduce the data of the image, the max pool function is used which pools out the max value in the region. After applying max-pooling, the size becomes 11 × 11 but it keeps the output size the same as the convolutional layer.

In the second layer, the output size increases from 32 × 32 to 64 × 64 with the same filter size. The input size is 11 × 11. After that, the max pool volume becomes [4 × 4 × 64], while applying the third convolutional layer results in a size of [4 × 4 × 128]. The max-pooling produces a size of [2 × 2 × 128].

Now as reducing the output size of the convolutional layer begins, the output rate is reversed. In the fourth layer, after max-pooling, the CNN model makes only a 2 × 2 kernel size 64 feature map and gives [1 × 1 × 64].

In the fifth layer of convolution, the volume becomes [1 × 1 × 32] and produces 32 feature maps. The dense layer is applied with 1024 hidden neurons. A dense layer or fully connected layer changes the 2- or multi-dimensional data into flat data.

All these layers use the ReLU activation function, which is a SoftMax function. Machine-learning-based models have two phases training and testing/execution. The training phase runs and makes the suitable function, called f(x).

Initially, preprocessing is performed on the image, and features are extracted. Then CNN is applied to find the pattern and the trained model is saved.

In the next phase, the trained model and weights are loaded to predict the labels for the test samples.

The result gives us the format by analyzing the emotions of the user and checking within the 2 datasets ie. JAFFE and CK+ by applying the above-mentioned methodology and providing us with the most accurate emotion that is detected

2.8 Other Existing Methods

2.8.1 Google's Interview Warmup[10]

This platform was created by google themselves to help people prepare for their interview by making them choose a field from data analytics, digital marketing, E-commerce, IT support, project management, UX design, cybersecurity, and general. Once the field is chosen, the user will be asked a series of questions related to the field and they will be asked to record their audio response or type it in and submit it. At the end of the interview, the questions they answered and their responses will be displayed, and they will be able to view the fluency of their speech along with the accuracy. The user will also be able to see the most commonly used words in the response, the number of job-related terms used, and also see the various talking points of the responses.

2.8.2 InterviewBot[11]

This is a paid interview preparation bot and one of the best ones out there. It asks the user to enter the number of questions and a few other settings for the interview. The interview is performed by a human-like avatar model that asks questions and makes the mock environment feel real. Once the interview is done, the analysis is generated using ML algorithms it analyses problems like the duration of the answer, word count and speed, the number of hesitation words like 'um' and 'er' used, sentiment analysis, the number of times the user smiled, composure, the number of times the user looked away and how much eye contact was maintained. This helps get a very good understanding of what the user should focus on and what his/her shortcomings are. The avatar also helps users with fear of facing an interviewer overcome such problems.

2.8.3 InterviewSchool[12]

InterviewSchool is an online practice software that performs mock and live interviews. The mock interview is powered by AI and can help find what good and bad words are to be used in or to avoid in an interview. The live interviews are sessions conducted with actual coaches to get a real feel of an interview. This application also provides coaches to train along with and also provides counseling and job tracking.

Chapter 3

Requirements

3.1 Hardware requirements

- Camera
- Microphone
- Nvidia GPU

3.2 Software requirements

- Python 3.0+
- Hugging face transformers
- ChatGPT API

Chapter 4

System Architecture

4.1 System Overview

Users can sign up or log into the desktop application, Q&AI. From the home page, a resume can be uploaded and in doing so, questions will be generated by the bot based on the resume and the corresponding domain of the job application. A real-time environment is utilized to ask each question generated. The response is then stored in audio, video, and text format and sent for further processing. An analysis that includes fact check, sentiment, grammar, confidence levels, and emotion detection is performed on the response. Scores and feedback are generated based on this analysis. Users can also view past scores and track their progress.

4.2 Architectural Design

4.2.1 Architecture Diagram

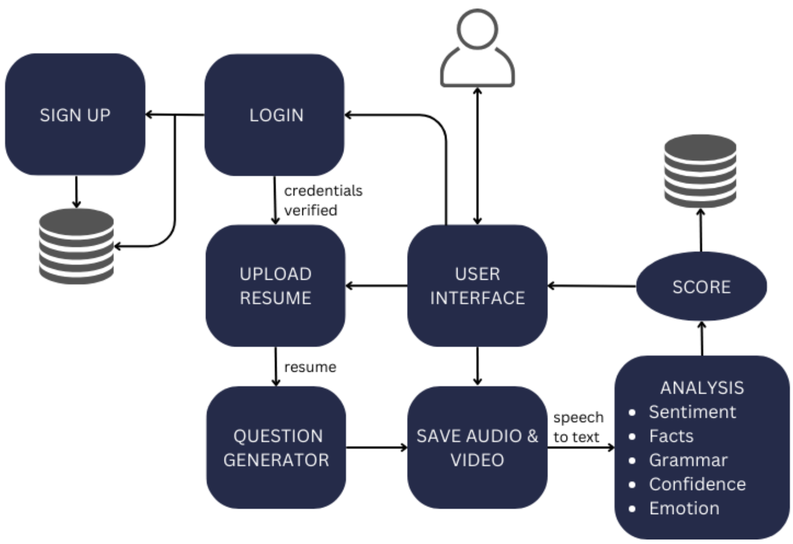

Figure 4.1: Architecture Diagram

4.2.2 Sequence Diagram

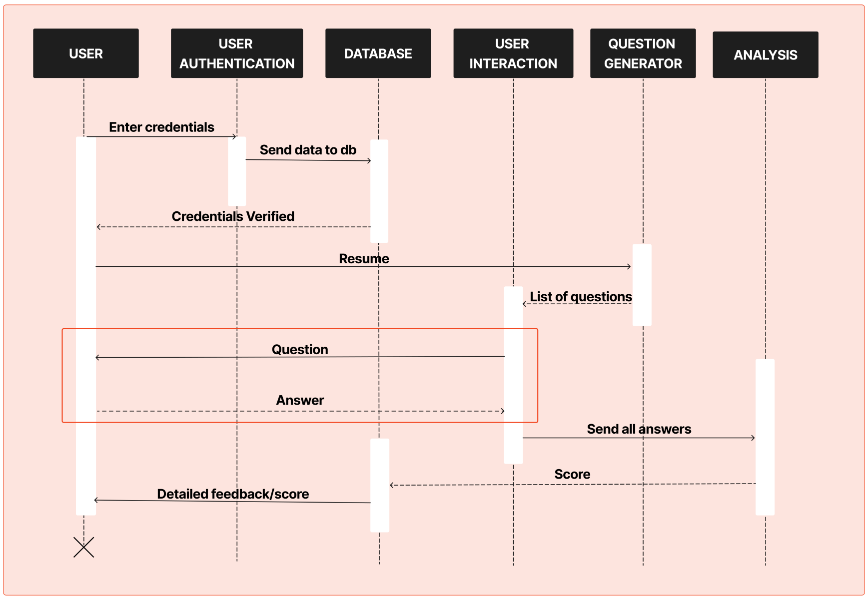

Figure 4.2: Sequence Diagram

4.2.3 Use Case Diagram

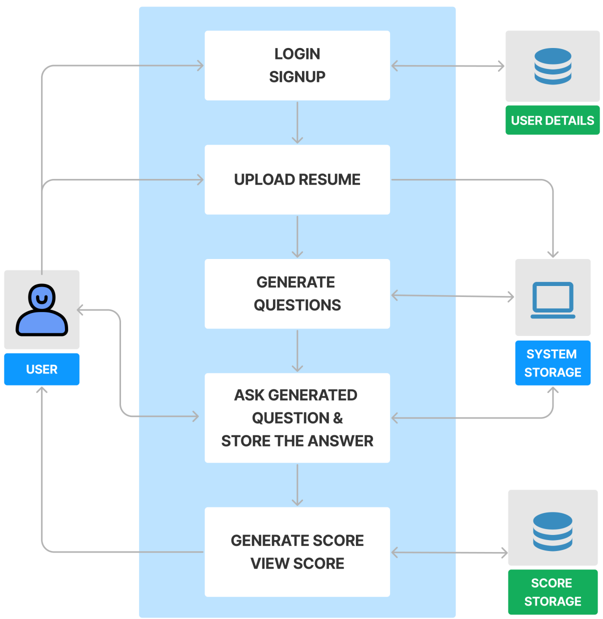

Figure 4.3: Use Case Diagram

4.3 Module Division

The system consists of four major modules:

- User authentication module
- Question generation module
- User Interaction module
- Analysis module

4.3.1 User Authentication Module

Registered users can log in using their username and password. The credentials will be validated against those stored in the database. New users can sign-up by entering their details which will be then stored in the database and then continue to log in. Once the credentials are verified, user will be directed to the home page of the application.

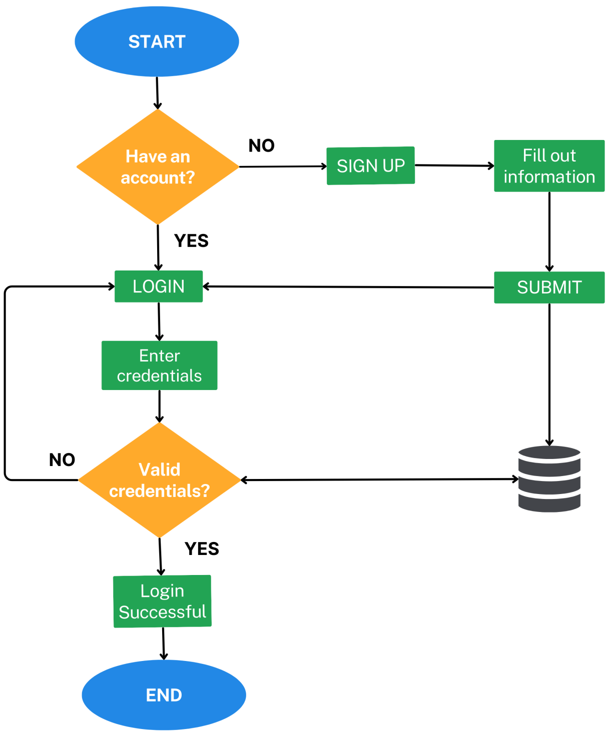

Figure 4.4: User Authentication Module

4.3.2 Question Generation module

The uploaded resume in PDF format is converted into text. Then key features are extracted and passed onto the question generation phase. Question generation is performed using a transformer model like BERT, RoBERTa or ChatGPT. The pre-trained model then takes the resume and generates questions based on it. The questions generated are then stored in the local storage.

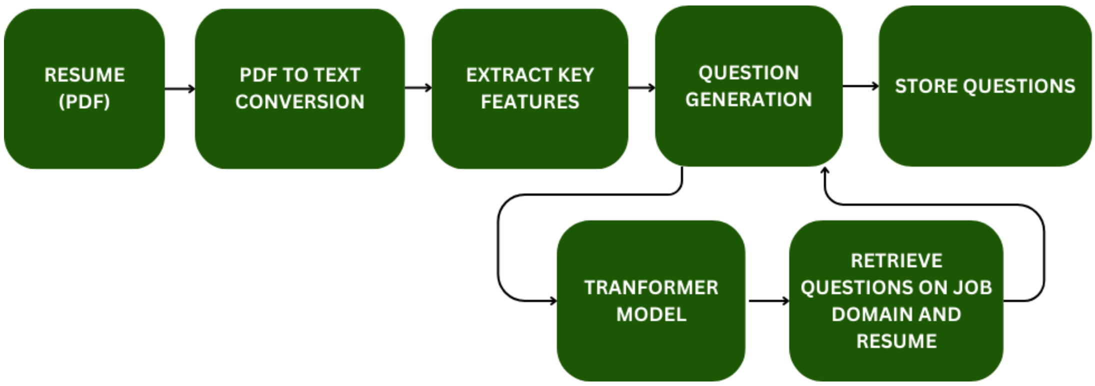

Figure 4.5: Question Generation Module

4.3.3 User Interaction module

The questions from the question generation module are asked to the user one by one. Response to each question is retrieved from the user through the camera and microphone. The audio is also converted to text format and the response is sent to the analysis module as audio, video, and text.

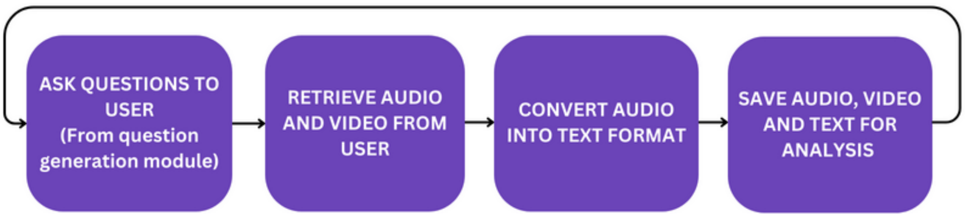

Figure 4.6: User Interaction module

4.3.4 Analysis Module

Language Proficiency

The language check module functions by breaking down the user's answer into individual words (tokens) and analyzing their grammatical properties through Part-of-Speech (POS) tagging and dependency parsing. This process helps identify the syntactic structure and relationships between words in the text. The module then applies predefined grammar rules to detect common errors such as subject-verb agreement, pronoun usage, verb tense consistency and misplaced modifiers. Score, from a scale of 1-5, is calculated by applying weights to the errors identified. The algorithm for the same is given below.

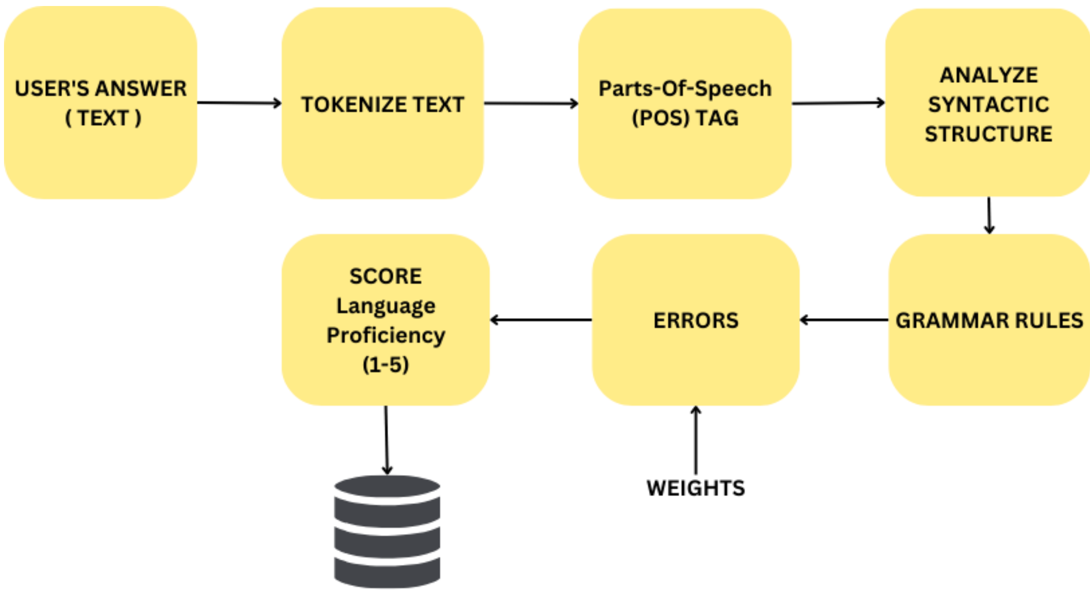

Figure 4.7: Language Proficiency

Algorithm 1 Grammar Check Algorithm

1: Tokenize the paragraph into individual words or tokens.
2: Perform Part-of-Speech (POS) tagging on each token to determine its grammatical category (noun, verb, adjective, etc.).
3: Perform dependency parsing to analyze the syntactic structure of the sentences and identify relationships between words.
4: Implement grammar rules to check for common errors such as subject-verb agreement, pronoun-antecedent agreement, verb tense usage, articles, sentence fragments, run-on sentences, and misplaced modifiers.
5: Flag tokens or phrases that violate grammar rules as potential errors.
6: Count flagged errors.
7: **return** Error count

Factual Accuracy

The user's answer in text format is summarized and given to a transformer model to generate accurate answers for the corresponding question. The cosine similarity of the user's answer and their respective accurate answers are taken and a cosine similarity score is generated. The generated score is then converted to a score in the range 1-5.

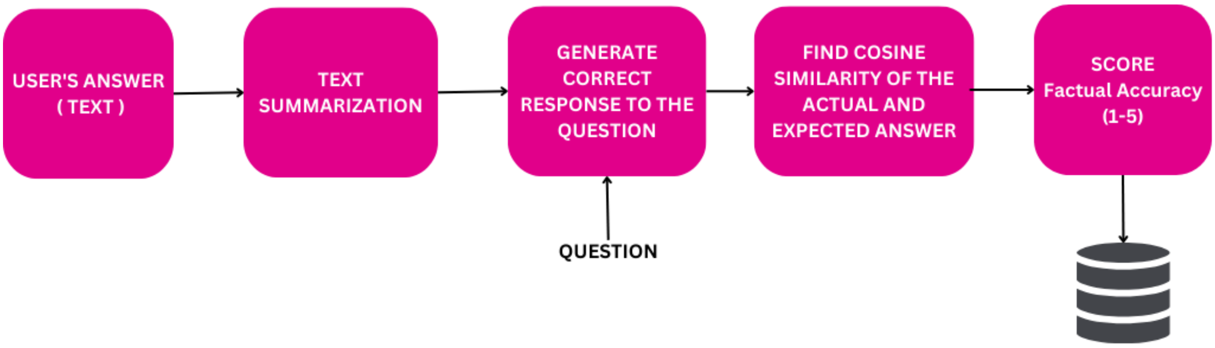

Figure 4.8: Factual Accuracy

Algorithm 2 Factual Accuracy Algorithm

Take the answer provided by the user and store it in variable X.
Take the accepted answer for the question and store it in variabvle Y.
Find cosine similarity between X and Y and store it in variable out.
Convert the similarity into rating from 1-5.
return rating

Emotion Detection

The video received as input is first converted into frames and stored in temporary storage. The extracted frames are then sent to a CNN model that identifies the emotions shown in each frame. The most probable emotion is then identified from the frame and stored. The system then finds the emotion that lasted the highest duration and stores it as a percentage.

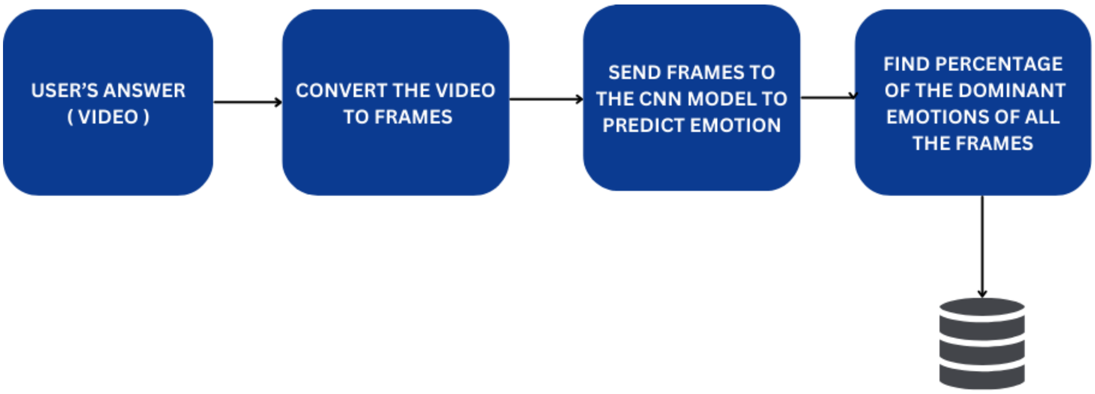

Figure 4.9: Emotion Detection

Sentiment Analysis

The user response in text is the input. Data pre-processing is performed on the dataset (Eg: lowercasing, stopword removal, etc.). The resultant data is transformed into a numerical vector. A sentiment classification model like a transformer model is used to predict whether the text has a positive, neutral, or negative sentiment.

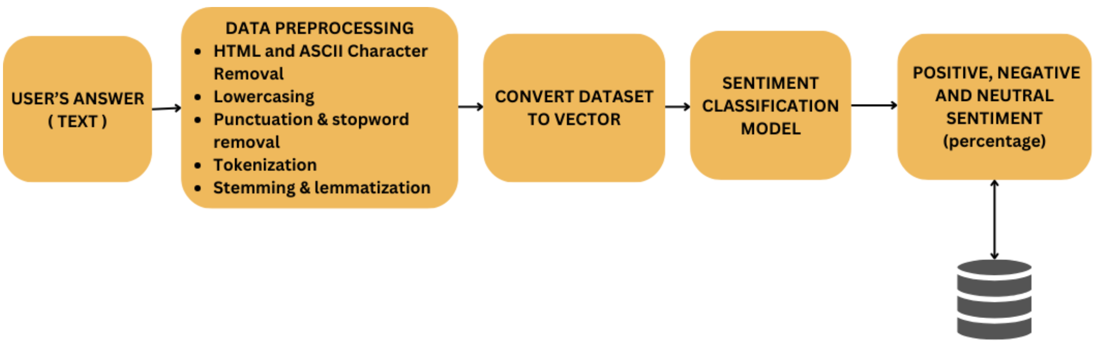

Figure 4.10: Sentiment Analysis

Confidence Analysis

Audio and video are fed as input to this module. From audio, key features like original duration, speaking duration, and speech rate are extracted. Confidence from audio is rated based on pause duration and speech rate and an overall score from 1-5 is generated. Video is first converted to frames. The eye positions in frames are noted and the total frames in which the user looks straight is used to generate a score from 1-5. A weighted average score from the text and audio component is the confidence score.

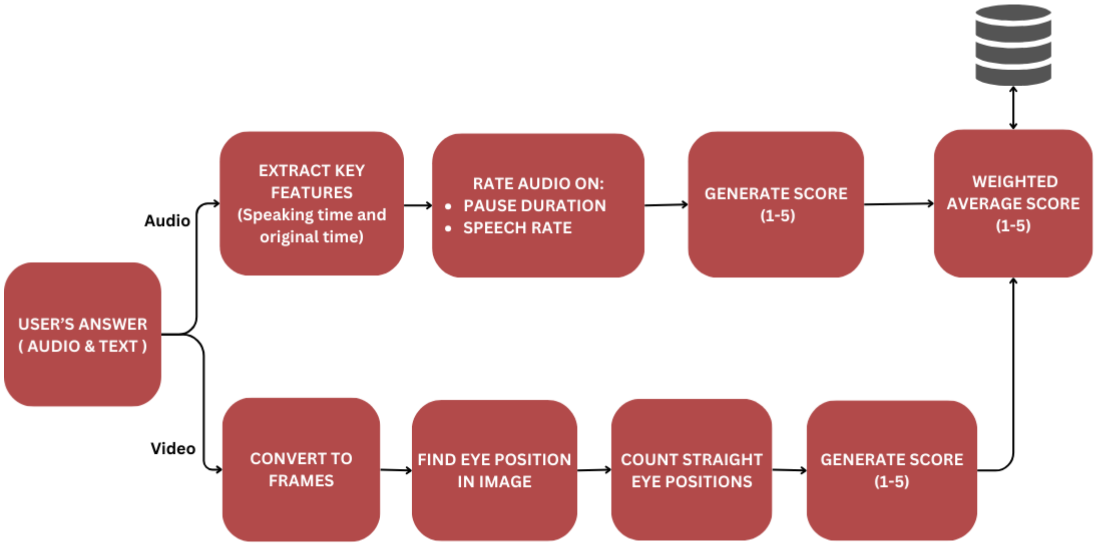

Figure 4.11: Confidence Analysis

4.4 Work Breakdown and Responsibilities

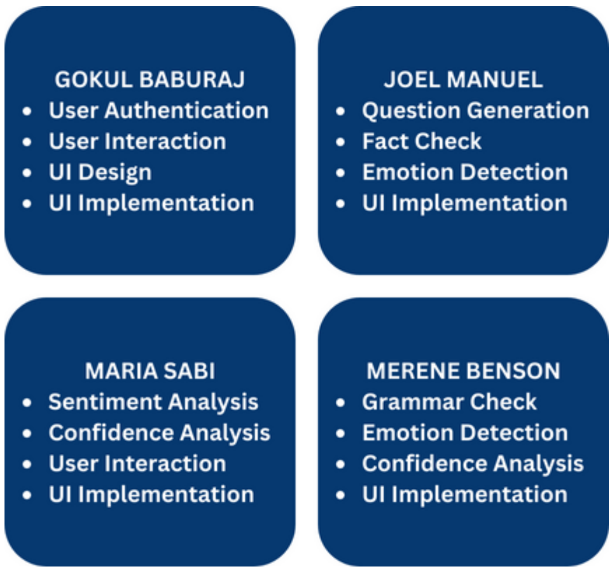

Figure 4.12: Work Breakdown

4.5 Work Schedule - Gantt Chart

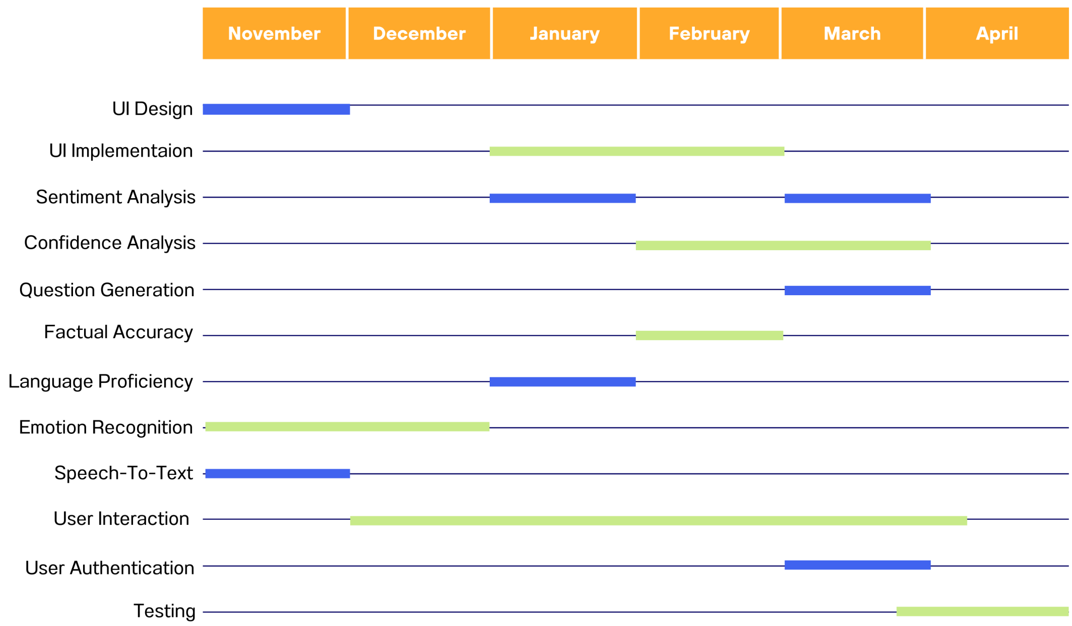

Figure 4.13: Gantt Chart

Chapter 5

System Implementation

5.1 Datasets Identified

5.1.1 FER 2013[21]

This dataset is a dataset consisting of various facial emotions anger, neutral, sad, disgust, surprise, and fear.

Table 5.1: Anger emotion from the FER 2013 dataset[21]

5.2 Proposed Methodology/Algorithms

Users can register or log in to Q&AI. Users can submit a resume from the homepage, which instructs the bot to create questions relevant to a particular job depending on the resume's content. There is also an option to choose the number of questions for the interview from 5-12. The real-time presentation of these questions is accompanied by the recording of user responses in text, audio, and video formats for later processing. The responses are thoroughly analyzed by the system, which also performs fact-checking, sentiment analysis, grammatical evaluation, confidence levels, and emotion recognition. This analysis is used to create scores and feedback. Users can also monitor their progress over time and view their previous scores. The user can also view tips as to how to make their interview better.

The methodology we use consists of four major components:

- User authentication module
- Question generation module
- User Interaction module
- Analysis module

5.2.1 User authentication module

This module consists of the user login and sign-up to the application. A username and password are fetched from the user. For sign-up, these are saved into a MySQL database. For login, these parameters are validated against the existing database.

5.2.2 Question generation module

This module consists of resume uploading and the generation of questions based on it. The user once signed in, is asked to upload their resume as PDF in ATS format and specify the desired number of questions from 5 to 12. The PDF will then be converted into text using PyPDF2. This text is then sent to the ChatGPT API to generate the questions to be asked in the interview. The generated questions are then stored in the local system. This module helps to generate questions that are personalized to the user's job description and experiences and gives the application a more personalized touch.

5.2.3 User Interaction module

This module mainly deals with the interaction with the user during the interview process. It is implemented using the Tkinter Python library. It consists of asking the user questions from the question generation module in the form of text. It also records the audio and video of the user using OpenCV, converts the audio to text using the pydub and speech-recognition modules, and stores the data in the local system for analysis.

5.2.4 Analysis module

Language Proficiency

This module checks the grammatical accuracy of the response and evaluates it using a transformer model Gramformer. The user's answer in text format is given to the transformer, sentence by sentence. The model then outputs the number of errors per sentence, and using this information the language score is calculated as follows.

```
def calc_score(num,len):
  len=len/5
  score= 1-(num/(len))
  # print("score",score)
  if 0.9 < score <= 1:
    return 5
  elif 0.7 < score <= 0.9:
    return 4
  elif 0.4 < score <= 0.7:
    return 3
  elif 0.2 < score <= 0.4:
    return 2
  else:
    return 1
```

Here variable num is the total number of grammatical errors identified in the user's answer and variable len denotes the number of words in the input text. The language proficiency is evaluated and represented on a scale between 1 and 5.

Factual Accuracy

This module helps check the accuracy of the given responses for the questions generated. The response is sent to the CharGPT API along with the question. ChatGPT is prompted to rate the response in a score of 1-5 and the score is returned and stored.

Emotion Recognition

This module analyzes the overall emotion from the video using the Deepface Python library. The analyzed emotions are anger, disgust, fear, happiness, sadness, surprise, and neutral. These emotions are identified for the entire video and the overall percentage of how long each emotion was present is stored as analysis.

Sentiment analysis

This module takes the user's response text to analyze if it has a positive or negative sentiment. The text is preprocessed and tokenized using AutoTokenizer. A transformer model called cardiffnlp is used to predict the sentiment output as analysis.

Confidence analysis

This module tries to understand the overall confidence of the user when giving the interview. It uses the user's audio and video for analysis. The confidence score from audio is found using my-voice-analysis library from python. The speaking duration and original duration of the audio are found to calculate the pause duration as given below.

```
if(original/speaking>=2):
    score+=1
elif(original/speaking>=1.75):
    score+=2
elif(original/speaking>=1.5):
    score+=3
elif(original/speaking>=1.25):
    score+=4
elif(original/speaking>=1):
    score+=5
```

Speech rate is also analyzed from the audio. Normal speech rate is 3 or 4 syllables per sec. This knowledge is leveraged to calculate the score as given below.

```
if rate<=2:
    score+=1
elif rate<3:
    score+=2
elif rate==3:
    score+=3
elif rate<=4:
    score+=4
else:
    score+=5
```

The confidence score from a video is determined by analyzing the user's eye contact during an interview. The video is processed frame by frame using a Python module called eyegame, which classifies the direction of the person's eyes in each frame (left, right, center, up, or down). The score is calculated based on the proportion of frames where the user maintains eye contact by looking towards the center. This score is then normalized to a range of 1 to 5. The final score is calculated by taking a weighted average by rounding the sum of 0.7*audio_confidence and 0.3*video_confidence.

5.3 User Interface Design

The user interface design is highlighted in this section.

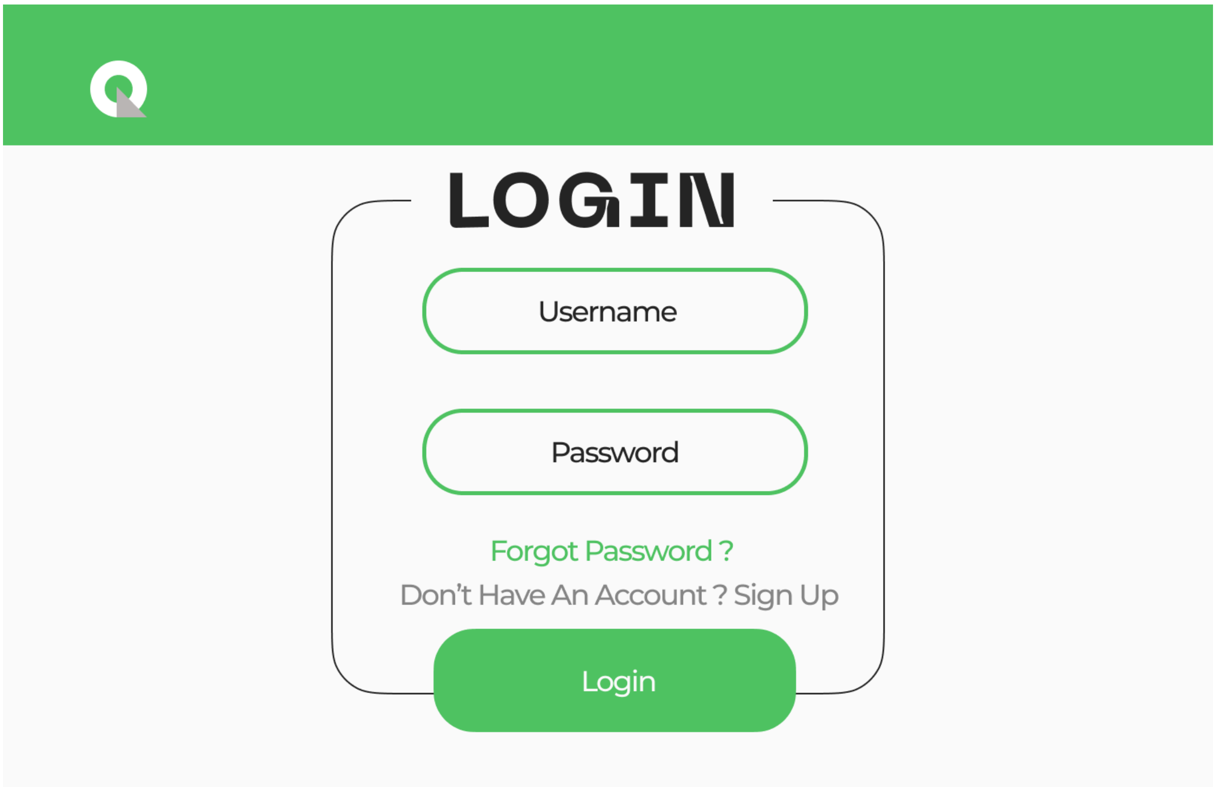

Figure 5.1: Login page

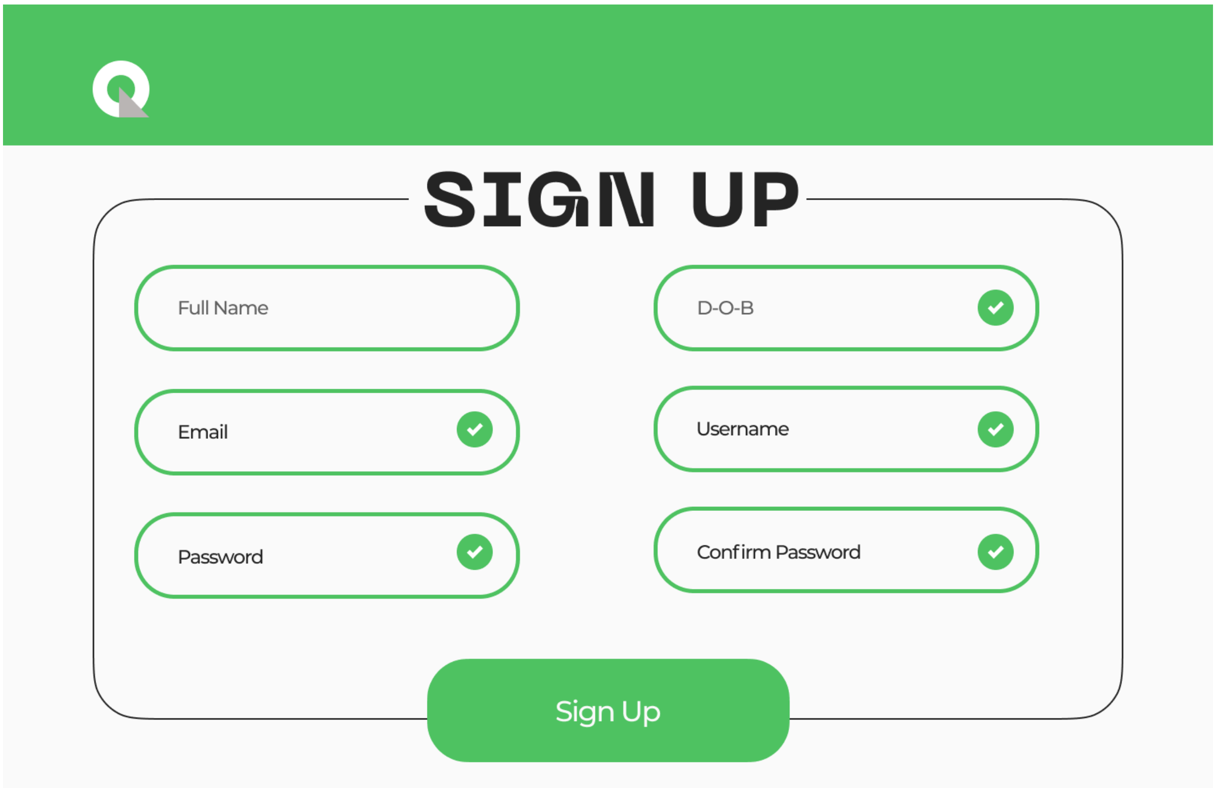

Figure 5.2: Sign-up page

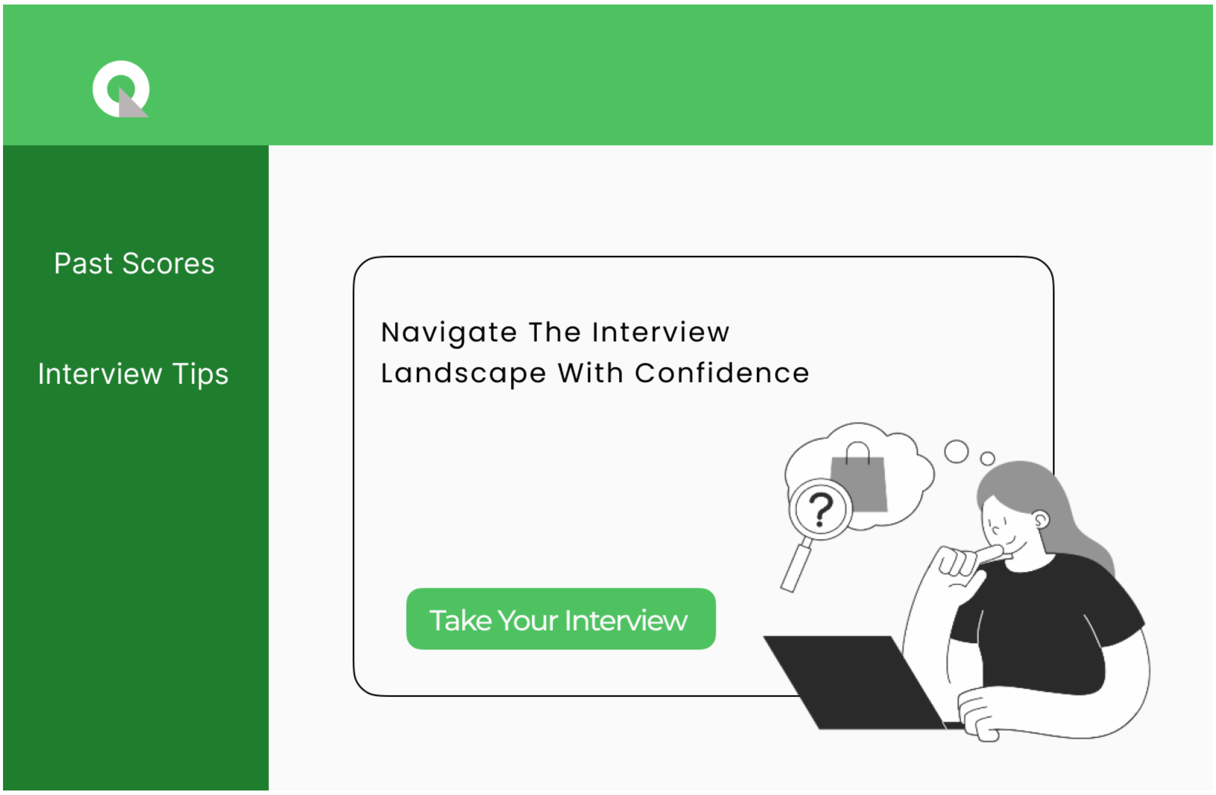

Figure 5.3: Landing page

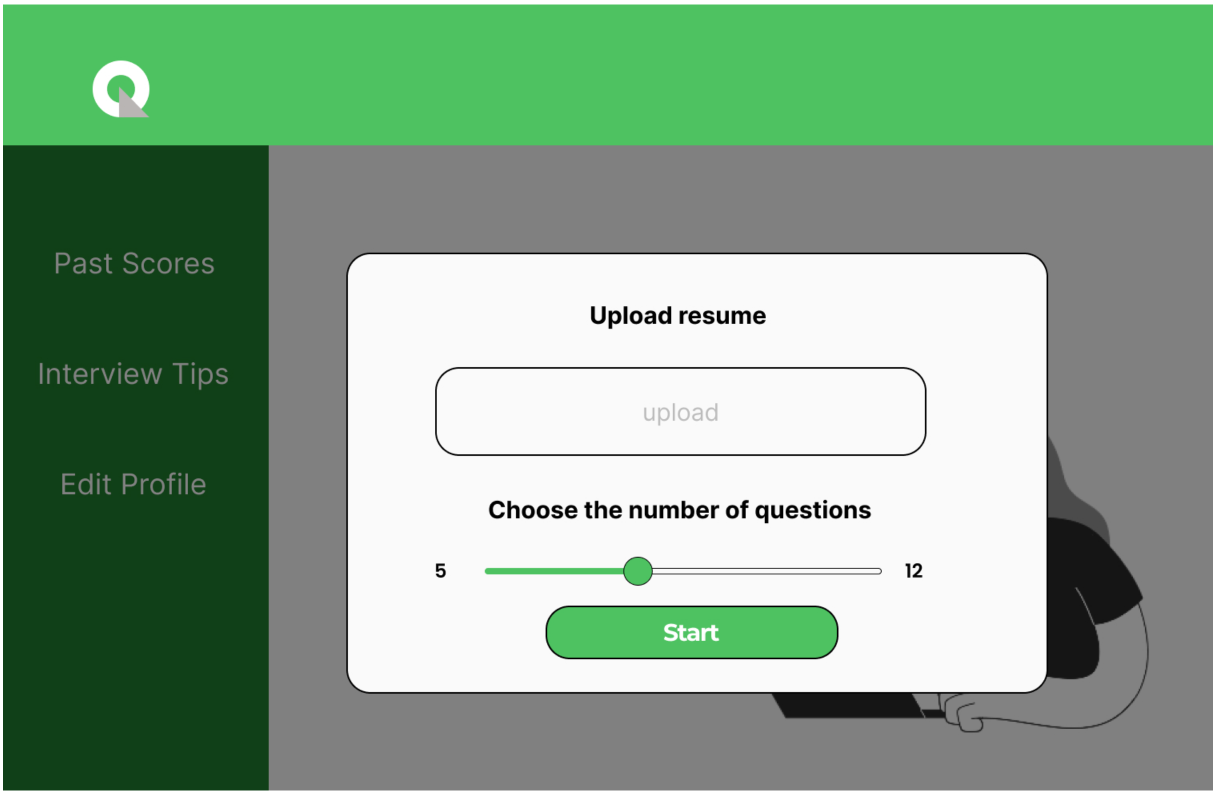

Figure 5.4: Upload resume

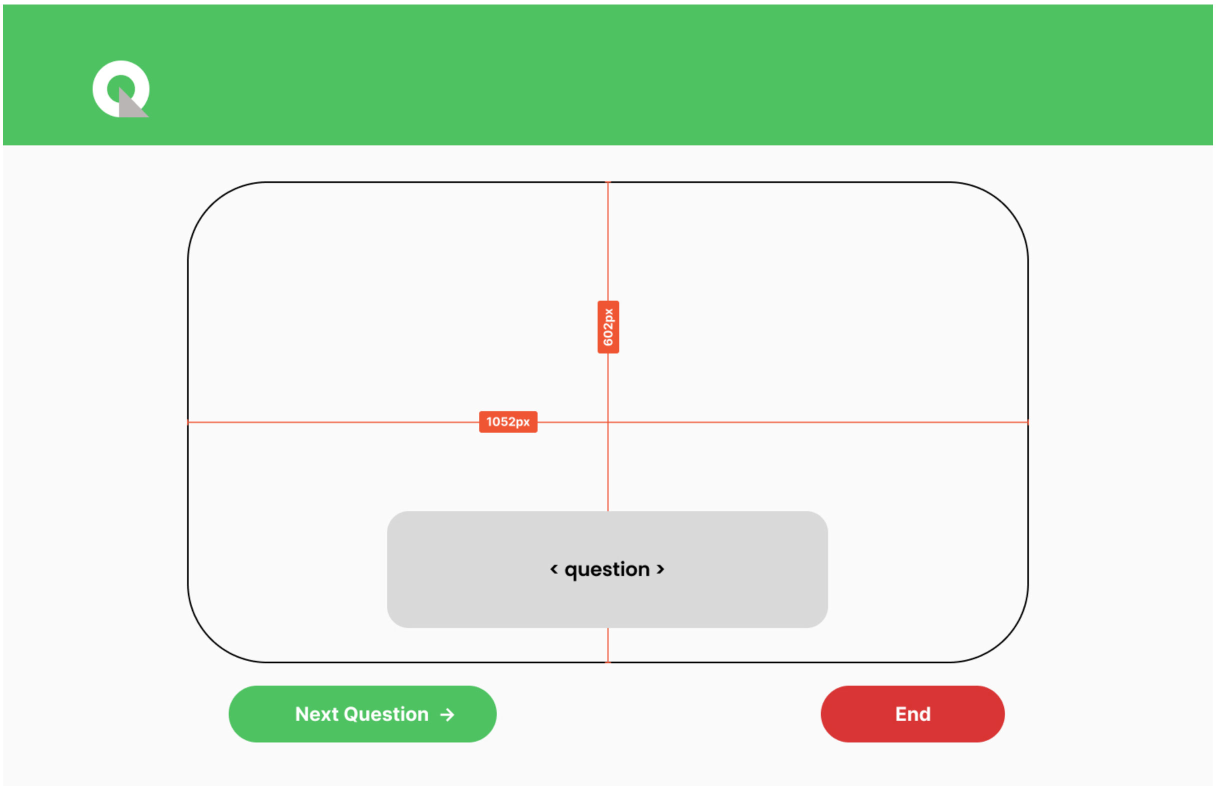

Figure 5.5: Interview setting

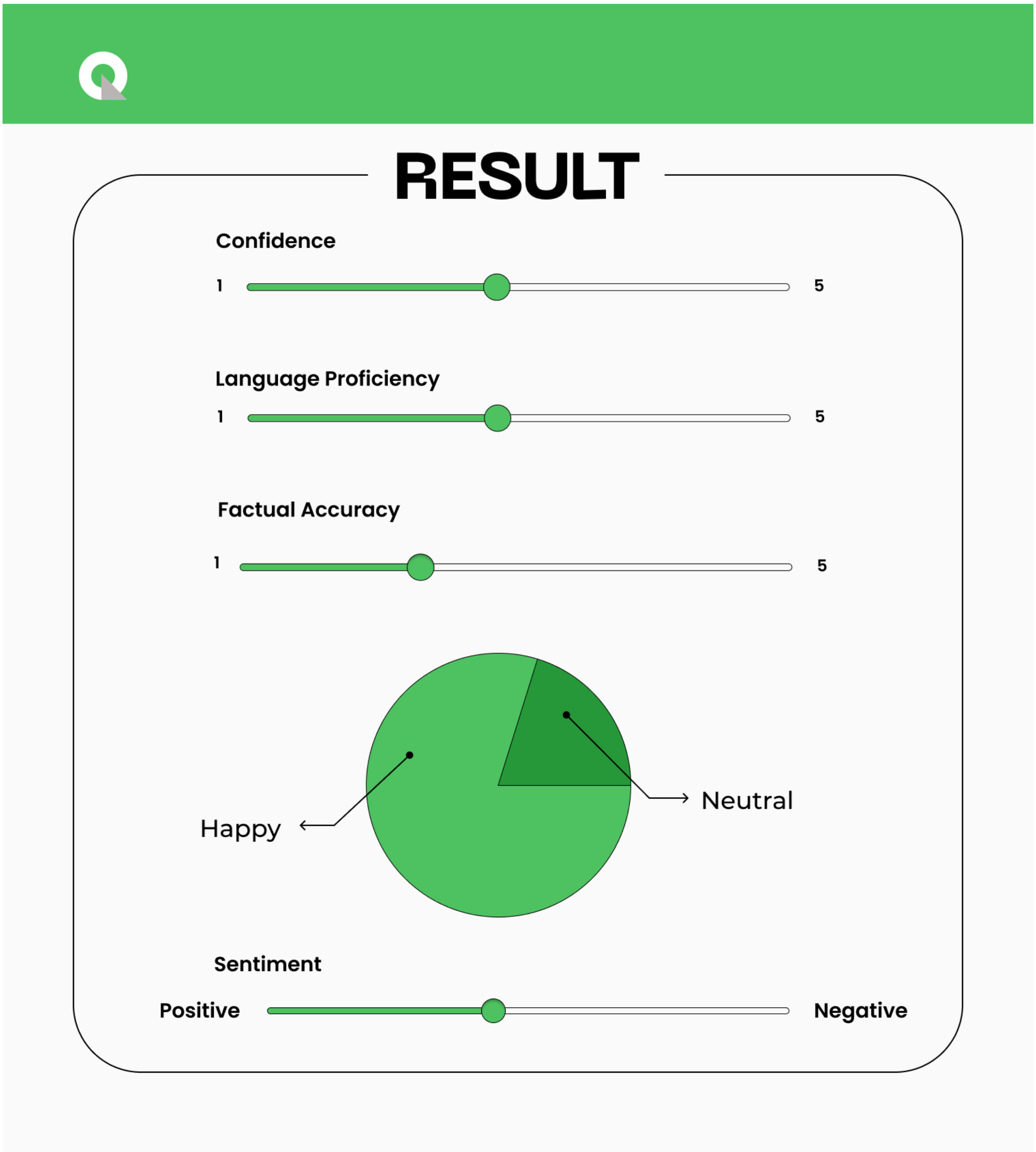

Figure 5.6: Result

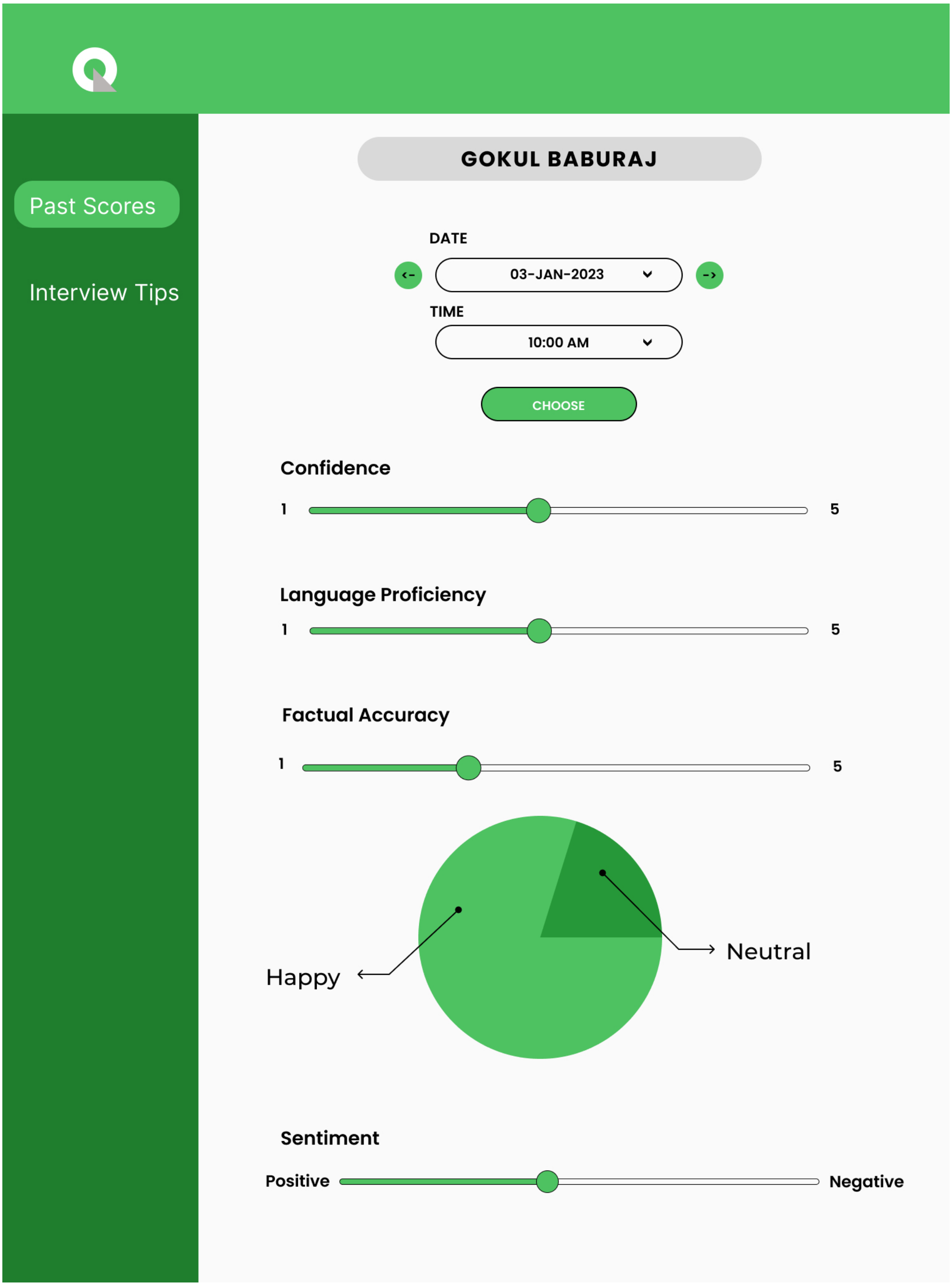

Figure 5.7: Past scores

Figure 5.8: Interview tips

5.4 Database Design

Q&AI makes use of two databases for its functioning. These databases are implemented using MySQL. MySQL is a popular relational database management system known for its reliability, performance, and ease of use. As an open-source database, MySQL offers cost-effective solutions for developers and businesses. MySQL's optimized query execution and indexing techniques ensure fast performance and efficient data retrieval. Its cross-platform support and compatibility with popular programming languages make it a versatile choice for application development.

The first database is used to store user information including username and password. The schema for the same is showed in Figure 5.9. The system refers to this database whenever a user tries to log in to the application. The entered credentials are matched against those stored in the database. If a match is found, user is allowed to access the application. A new entry is added to the database whenever a new user signs up to the application.

```
+----------+-------------+------+-----+---------+-------+
| Field    | Type        | Null | Key | Default | Extra |
+----------+-------------+------+-----+---------+-------+
| username | varchar(30) | YES  |     | NULL    |       |
| password | varchar(30) | YES  |     | NULL    |       |
+----------+-------------+------+-----+---------+-------+
2 rows in set (0.00 sec)
```

Figure 5.9: User Information Database

The second database is used to store user interview results along with its corresponding date and time. This data is retrieved whenever the user chooses to see past scores, specifying the date and time of the interview. The schema of the results database is shown in Figure 5.10.

Field	Type	Null	Key	Default	Extra
date	varchar(30)	YES		NULL	
time	varchar(30)	YES		NULL	
emotion	varchar(100)	YES		NULL	
fact	varchar(5)	YES		NULL	
confidence	varchar(50)	YES		NULL	
sentiment	varchar(5)	YES		NULL	
grammar	varchar(5)	YES		NULL	
username	varchar(30)	YES		NULL	

8 rows in set (0.01 sec)

Figure 5.10: Interview Results Database

5.5 Description of Implementation Strategies

Q&AI uses a variety of techniques and tools to ensure smooth functionality and strong performance across its modules.

The system captures audio and video during interviews using OpenCV, recording audio concurrently with video using its VideoCapture and VideoWriter functionalities. It then converts the recorded audio to text using the pydub and speech_recognition Python modules.

Q&AI leverages the ChatGPT API for generating interview questions based on uploaded resumes. The system sends resume text to the API and retrieves personalized interview questions.

The analysis module leveraged various transformer models and libraries to obtain high efficiencies. Language proficiency makes use of the transformer model, gramformer. Confidence analysis from audio is implemented using my-voice-analysis library from Python. From video, user's eye contact is analyzed using Python module, eyegame to contribute to confidence score. Factual accuracy of user responses are rated using ChatGPT API. Python DeepFace library is employed to identify users' emotion based on their facial expressions. The transformer model cardiffnlp is leveraged to perform sentiment analysis on the user responses.

5.6 Conclusion

The chapter on "System Implementation" outlines the development of Q&AI, a platform designed to assist users in improving their interview skills. The chapter discusses the datasets used, such as FER 2013 for facial emotion recognition. It also details the proposed methodology, encompassing modules for user authentication, question generation, user interaction, and response analysis. Key algorithms and techniques, including language proficiency evaluation, fact-checking with ChatGPT, and emotion recognition with Deepface, are highlighted.

Furthermore, the chapter explores the user interface design, showcasing wireframe designs for login, sign-up, resume upload, interview settings, result display, and progress tracking. Database design is explained, emphasizing the use of MySQL for storing user information and interview results. Implementation strategies using Python libraries like PyPDF2 for resume parsing and OpenCV for audio-video capture are discussed, emphasizing the system's comprehensive approach to interview preparation. Overall, the chapter provides insights into the technical aspects of Q&AI's development.

Chapter 6

Results and Discussions

6.1 Overview

The application provides highly accurate results for all the aspects of the interview analyzed. The question generation module made using ChatGPT API can generate highly accurate questions on all fields the user has mentioned in their resume, it also generates questions on the user's past experiences and projects. Results generated from user responses are:

- Sentiment: Positive or negative sentiment
- Emotion: Emotions recognized in frames as a pie chart
- Confidence, language proficiency, factual accuracy: Score from 1-5

6.2 Testing

The login and sign-up page as shown in Figure 6.1, allows users to either log in with existing accounts or sign up as new users. User information, such as usernames and passwords, is stored securely in an SQL database. When a user tries to log in, the system checks the entered username and password against the stored records in the database. If the credentials match those of an existing user, the user is granted access and redirected to the landing page.

The landing page, as shown in Figure 6.2, provides users with options to take interviews or access a dashboard containing past scores and interview tips.

On clicking the "Take Your Interview" button, users are prompted to upload their resume from their local system and select the desired number of questions (ranging from 5 to 12) for the interview. This is shown in Figure 6.3.

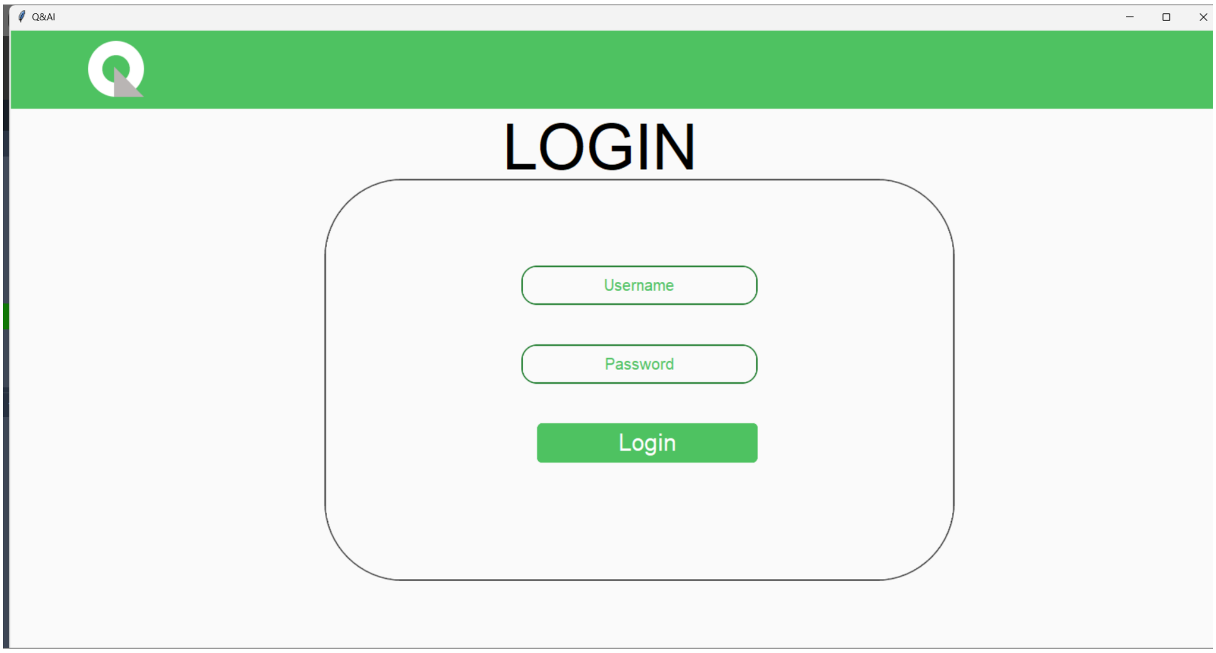

Figure 6.1: Login page

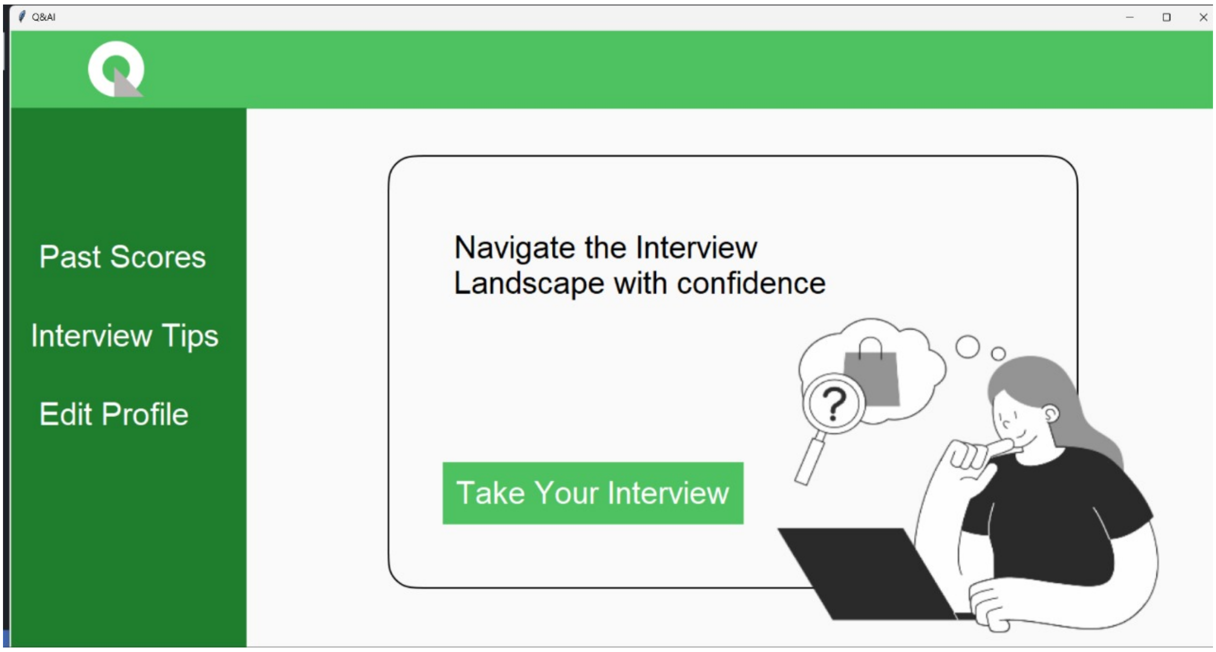

Figure 6.2: Landing page

Figure 6.4 depicts an active interview session where users are prompted to answer displayed questions. The "Next Question" button signals completion of the current question and prompts the system to display the next question. The "End" button concludes the interview, leading the system to progress to the results page.

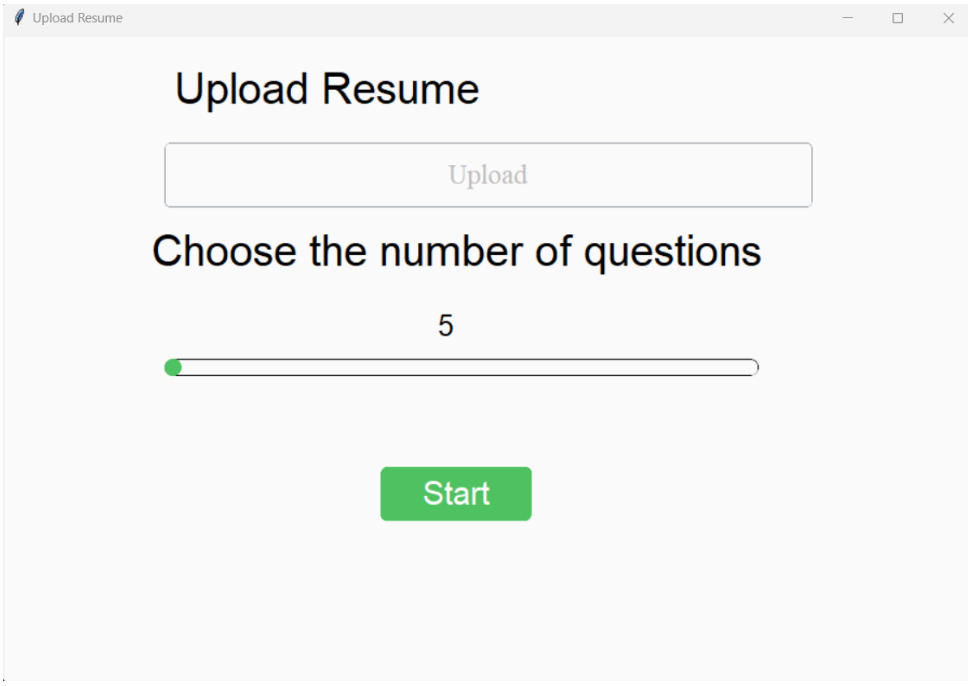

Figure 6.3: Upload Resume

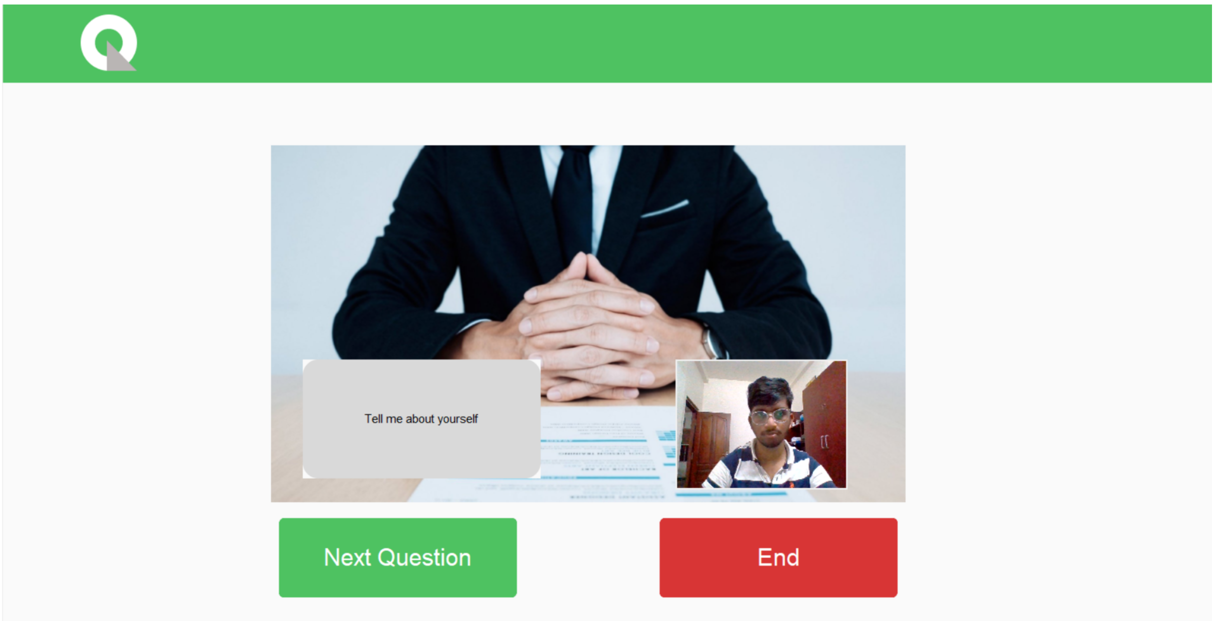

Figure 6.4: Ongoing interview

The results of the interview are displayed in Figure 6.5. Confidence, language proficiency, and factual accuracy are scored on a scale of 1-5. Emotions detected throughout the interview are displayed by means of a pie chart. Additionally, the sentiment analysis results are displayed as a measure of positivity or negativity.

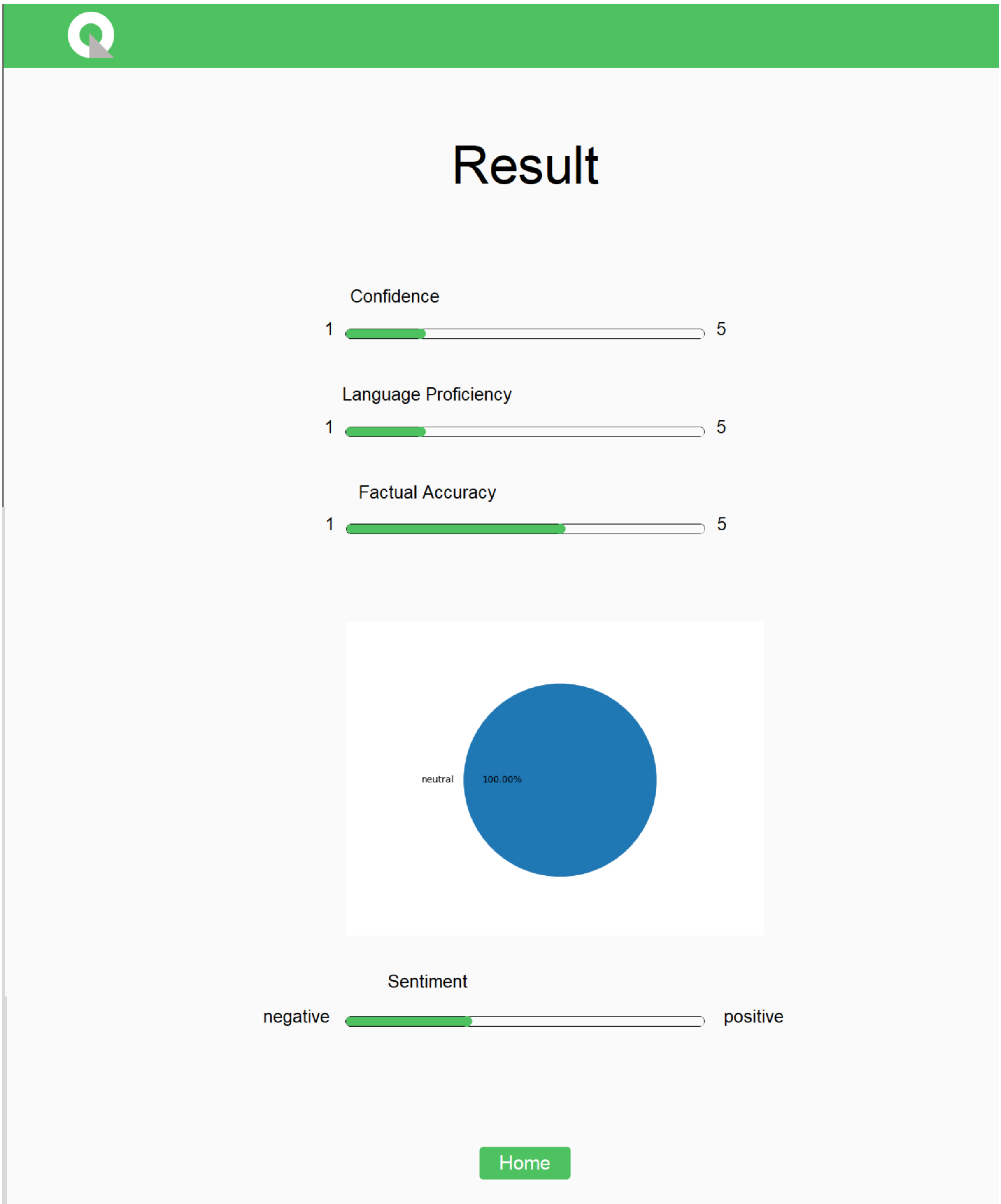

Figure 6.5: Result

Q&AI also provides users with interview tips that provide guidance on how to perform well in interviews. Figure 6.6 illustrates the ”Interview Tips” page employed by the system.

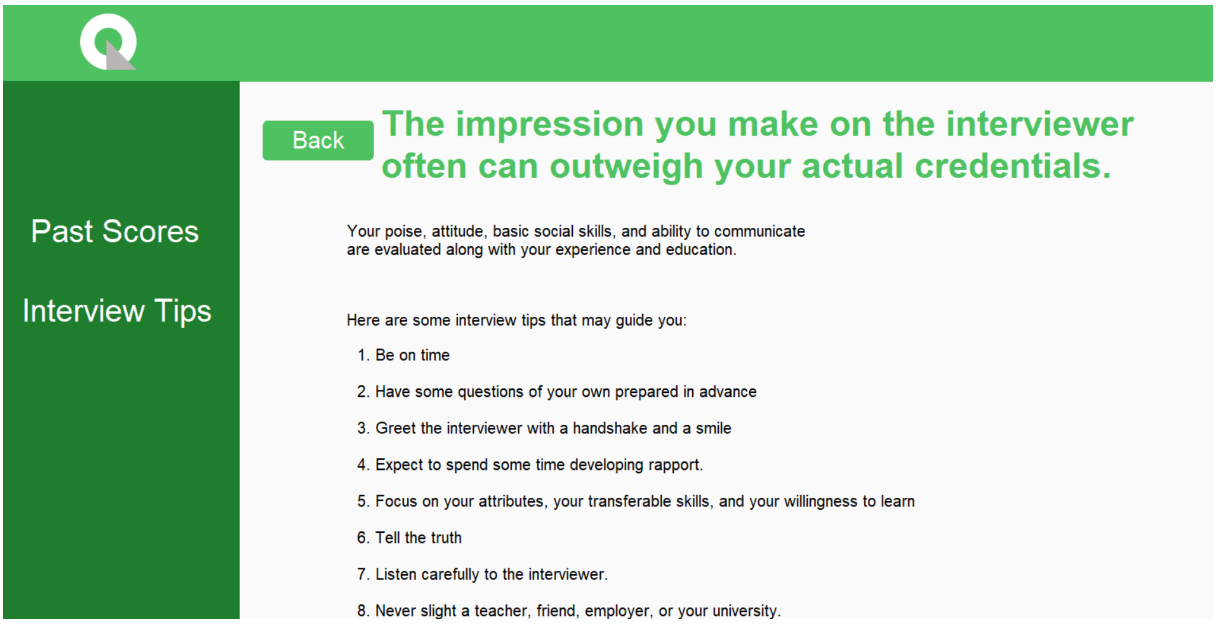

Figure 6.6: Interview tips

The system also enables users to monitor their scores through the "Past Scores" page shown in Figure 6.7. Users can select the date and time of their previous interviews to view the associated results. This allows users to track their progress over time.

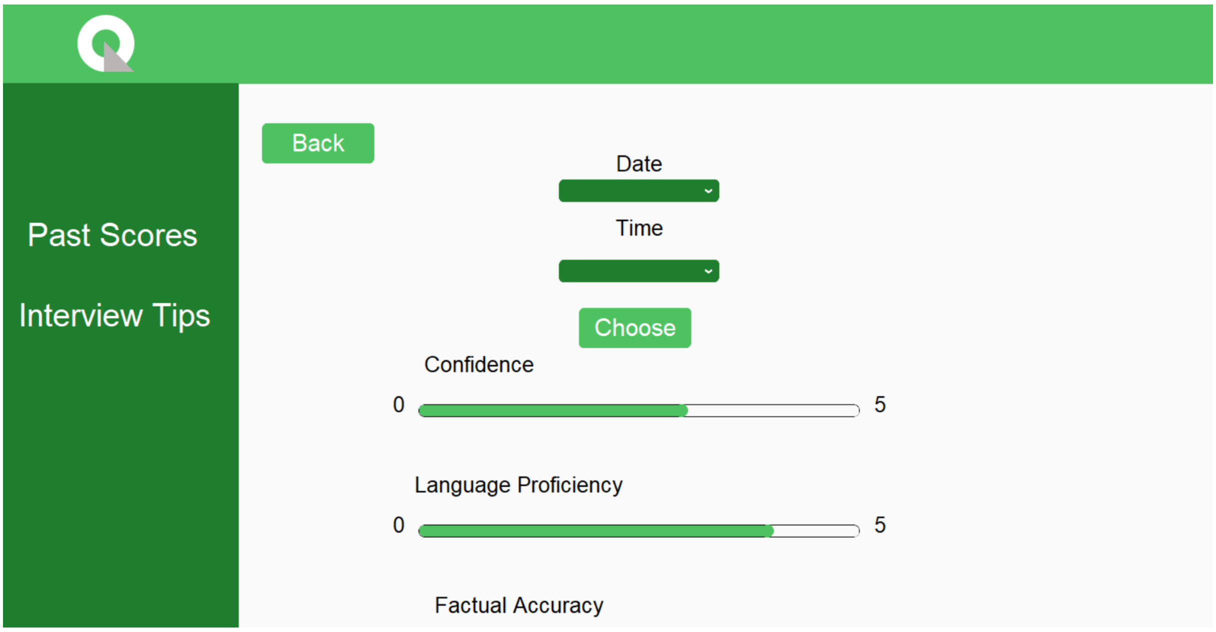

Figure 6.7: Past scores

6.3 Quantitative Results

The different phases of Q&AI Mock Interview Bot are evaluated and the results obtained from different modules are summarized here.

6.3.1 Question Generation Model

In this innovative resume analysis system of Q&AI Mock Interview Bot, a PDF resume is converted into text, and key features are extracted. Leveraging advanced transformer models like BERT, RoBERTa, or ChatGPT enhances question generation accuracy. Through API requests the model analyzes resume components, generating insightful questions. The utilization of sophisticated models such as ChatGPT elevates the credibility of the questions, ensuring a comprehensive understanding of the candidate's profile. This integrated approach streamlines the resume evaluation process, providing employers with precise and relevant information for effective candidate assessment. A sample example of questions generated for uploaded resumes from different is given in Table 6.1. The questions generated by the question generation module are highly accurate to the actual needed result.

SI. no	Question generated
Resume 1	Tell me about your experience with Python, TensorFlow, and Scikit-learn in ML development.
	Can you describe a recent ML project you worked on, including the problem, approach, and tools used?
	Can you discuss a project where you collaborated effectively with teams? How did you ensure good communication?
	What's your approach to solving complex ML problems? Can you share an example and your process?
Resume 2	Can you describe a significant project you've worked on and your role in overcoming challenges?
	Discuss your experience with CAD software like SolidWorks.
	How have you contributed to design and innovation in mechanical engineering projects?
	Can you share an example of a design innovation you introduced to improve mechanical system performance?

Table 6.1: Questions generated based on resumes of various domains

6.3.2 Language Proficiency

The language proficiency is examined with the aid of natural language processing, wherein the grammar is checked. The sentence is verified for grammar rules like noun-phrase construction, subject-verb agreement, use of articles, and the errors are counted. Examples where the language proficiency is found out for sample sentences are listed in Table 6.2. Based on the number of grammatical errors identified, the final language proficiency is arrived with.

Sentence	Number of errors
I is enjoy football	2
They teached me many thing	2
The main objective in my project is to finding the facial emotion	1

Table 6.2: Sentences and the number of grammatical errors found

6.3.3 Factual Accuracy

The factual accuracy can be checked by finding the cosine similarity between the actual and expected answers provided for the asked question. This can be done with accuracy checking using a transformer model. The transformer models are trained on a diverse dataset and the factual accuracy can hence be verified. Sample examples with factual accuracy score is listed in Table 6.3.

6.3.4 Emotion Detection

Upon receiving a video input, the system initiates the process by utilizing OpenCV to convert it into individual frames. These frames are subsequently fed into the DeepFace module, a robust facial emotion recognition tool. The module identifies emotions depicted in each frame, extracting the most probable emotion. The system then computes the emotion that persisted for the longest duration, storing it as a percentage representation. This streamlined approach ensures accurate and efficient emotion analysis, offering valuable insights into the dominant emotional expression throughout the video, enhancing the system's capability for nuanced emotion tracking and interpretation. Experiments

Question	Answer	Score
How do you evaluate an ML model?	I evaluate ML models using accuracy, recall, and F1 score by making use of their corresponding functions in sklearn.	4
What frontend technologies are you proficient in?	I am proficient in technologies like MySQL, MongoDB, etc.	1
Discuss your experience with CAD software like SolidWorks.	I have used CAD to develop a new kind of plating for a car I was designing	3
How have you used data analysis tools like Excel and SQL to drive business insights?	I've leveraged Excel's advanced formulas and pivot tables to analyze sales data, leading to a 15% revenue increase in my previous role. Additionally, I've used SQL queries to segment customer data, resulting in a 20% improvement in customer engagement and retention rates through targeted marketing campaigns.	5
What is a distributed ledger?	A distributed ledger is a type of database that is spread across multiple locations or participants.	2

Table 6.3: Factual accuracy score generated from answers

have been performed to evaluate the efficacy of DeepFace in comparison with other models and the results are presented in Table 6.4.

Method	Accuracy
DeepFace [16]	**0.9735**
TL Joint Bayesian [17]	0.9633
Combined Joint Bayesian [18]	0.9242
Tom-vs-Pete [19]	0.9310
POOF-HOG [20]	0.9280

Table 6.4: Comparison of accuracy of different deep learning models for emotion recognition

6.4 Sentiment Analysis

The sentiment of the user's input can be checked by passing the input text to a transformer model. In our case, it is done using the cardiffnlp transformer model. Transformer models compared to normal NLP models are more accurate as they can have a better understanding of the context than normal NLP models. This makes it more effective for NLP tasks like sentiment analysis over other conventional methods. From the context learned by the transformer model, it can easily understand if the overall sentiment of the user is positive, negative, or neutral. Table 6.5 shows some examples of text and its corresponding sentiment.

Text	Sentiment
I'm excited to work on this project.	Positive
I'm afraid I won't be able to take on much load during the weekends.	Negative
I have done courses in the field of AI & ML to have a better understanding before I dived into projects.	Neutral

Table 6.5: Text examples and sentiment found

6.5 Confidence Analysis

Confidence is extracted from audio and video. my-voice-analysis is used to extract pause duration ratio and speech rate to calculate audio confidence score. It is a Python library for the analysis of voice (simultaneous speech, high entropy) without the need of transcription. It breaks utterances and detects syllable boundaries, fundamental frequency contours, and formats. Librosa and SpeechRecognition are used more for general-purpose applications. Hence my-voice-analysis is chosen for extracting pause duration and speech rate from audio files. Table 6.6 shows the speech rate and pause ratio extracted from audio samples and its corresponding audio confidence score calculated.

The confidence level extracted from the video is determined by the user's eye contact maintained during the interview. A Python module called "eyegame" is employed to track the gaze direction in each frame of the video. When provided with an image containing a human face, the module outputs the direction of gaze, which is then used to assess the user's eye contact throughout the interview.

6.6 Discussion

Q&AI is hence an innovative approach for interview preparation. The resume upload feature by integrating transformer models help derive personalized questions for the user.

Audio S.No.	Speech rate (syllables per sec)	Pause ratio (Original_duration/Speech_duration)	Audio confidence score
1	2	1.7	2
2	3	1.3	4
3	5	1.2	5

Table 6.6: Audio examples and audio confidence scores

Language proficiency is found through grammatical error checking and the factual accuracy of the answers leverages transformer models. Emotion detection is used through advanced CNN models and sentiment analysis uses a transformer model. Confidence analysis extracts pause duration and speech rate from audio and eyeball position from video for generating the score.

In conclusion, the Q&AI Mock Interview Bot demonstrates effective functionality in generating tailored interview questions based on candidate resumes, assessing language proficiency, verifying factual accuracy, and detecting emotions. The system's integration of advanced technologies like transformer models and deep learning ensures accurate evaluation of candidates, offering valuable insights.

Chapter 7

Conclusions & Future Scope

In today's competitive job market, effective interview preparation is crucial for individuals seeking career opportunities. Q&AI: AI Mock Interview Bot emerges as an innovative solution to address the limitations of traditional interview preparation methods. This application revolutionizes the way individuals hone their interview skills by combining advanced artificial intelligence techniques with a user-friendly interface.

The core objective of the AI Mock Interview Bot is to provide users with a realistic and comprehensive interview experience. Traditional methods often fall short in offering personalized feedback and real-time performance analysis. This application bridges these gaps by simulating authentic interview scenarios, allowing users to practice and refine their communication, problem-solving, and presentation skills.

The overall design can further be improved by incorporating interviewer avatars to simulate a more realistic interview environment. The application can also be integrated with the placement cell website to make it accessible to students. Additionally, MAC and Linux-compatible versions may be developed.

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Appendix A: Presentation

Q&AI: An AI powered Mock Interview Bot
Final Presentation

Joel Manuel C J
Maria Sabi
Merene Benson
Gokul Baburaj

RSET

May 1, 2024

Guide: Dr.Saritha S.

Contents

Problem Definition

To empower candidates to refine their interview skills by utilizing AI Mock Interview Bot.

Project Objective

To develop an AI-powered mock interview bot that

- offers realistic interview simulations and asks questions based on resume
- grade answers to the simulated questions
- analyze user responses based on confidence and sentiment
- provides detailed feedback and performance analytics for improvement

Novelty of Idea and Scope of Implementation

- The AI Mock interview bot has the opportunity to revolutionize the way individuals prepare for interviews and refine their skills.
- Existing interview preparation methods share limitations like personalized feedback, adequate question generation, and realistic interview simulation.
- The bot simulates realistic interview scenarios, enabling candidates to tackle the nerves associated with job interviews. It offers personalized feedback on one's performance, helping users identify and address their strengths and weaknesses.
- It may also be integrated with college placement cells to expand its scope.

Literature Survey

AI-Based mock interview evaluator: An emotion and confidence classifier model

- The paper[1] proposed an AI-based interview platform that assesses users based on emotion, confidence, and knowledge base.
- Audio and video are both analyzed.
- Questions are taken from a database.
- **Emotion**: CNN algorithm
- **Confidence**: Speech recognition using Pydub, Librosa, and NumPy. LSTM is used as the classifier.
- **Knowledge**: Keyword mapping, semantic analysis.

Literature Survey

CIT University Tutoring Interviewer Environment

- CUTIE[2] is an interview bot developed using Vue.js and Django that performs real-time sentiment and emotional analysis.
- Audio and video are both analyzed.
- Questions are taken from a set of questions provided by Society of Human Resource Management.
- **Sentiment Analysis**: Compare input string to AFINN list and assign valence scores to positive and negative words used.
- **Emotion Recognition**: Javascript face recognition API.

Literature Survey

Interview Bot with Automatic Question Generation and Answer Evaluation

- In this paper[3], the interview bot scans resumes for keywords required for the job role.
- Initial screening with multiple-choice questions and in-depth evaluation with text-based short answer questions.
- Proctored interviews via camera to prevent cheating.
- Final score based on job match and interview performance.

Existing Methods

Google's Interview Warmup[10]

- Questions asked based on chosen domain-data analytics, digital marketing, E-commerce, IT support, project management, UX design, cybersecurity, and general.
- User may answer using text or audio.
- It analyses the most commonly used words, the number of job-related terms used, and also see the various talking points of the responses.

Existing Methods

InterviewBot[11]

- Questions are based on chosen domain
- Uses a human-like avatar model that asks questions and makes the interview environment feel real.
- It analyses problems like the duration of the answer, word count and speed, the number of hesitation words like 'um' and 'er' used, sentiment analysis
- Feedback depends on chosen subscription plan

Existing Methods

InterviewSchool[12]

- InterviewSchool is a suite of tools for interview preparation - mock interviews, live coaching, job tracking
- Questions are based on the chosen job role - from real questions that are reported from previous candidates
- Mock interviews powered by AI give feedback on what good and bad words are to be used or avoided

Existing Methods

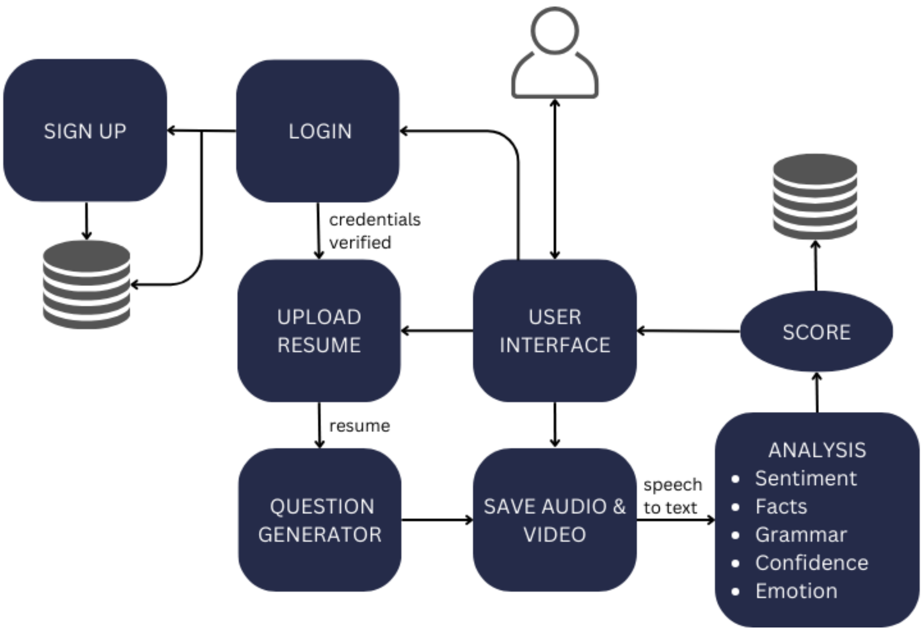
Chatbots

- Chatbots on transformer models like ChatGPT, BERT, etc. provide exceptional user interaction in text
- It can ask questions based on the user's response
- But audio and video of the user cannot be analyzed
- The score and feedback of the interview will always depend on how the user gives the prompt to the model
- Questions cannot be generated directly from a resume

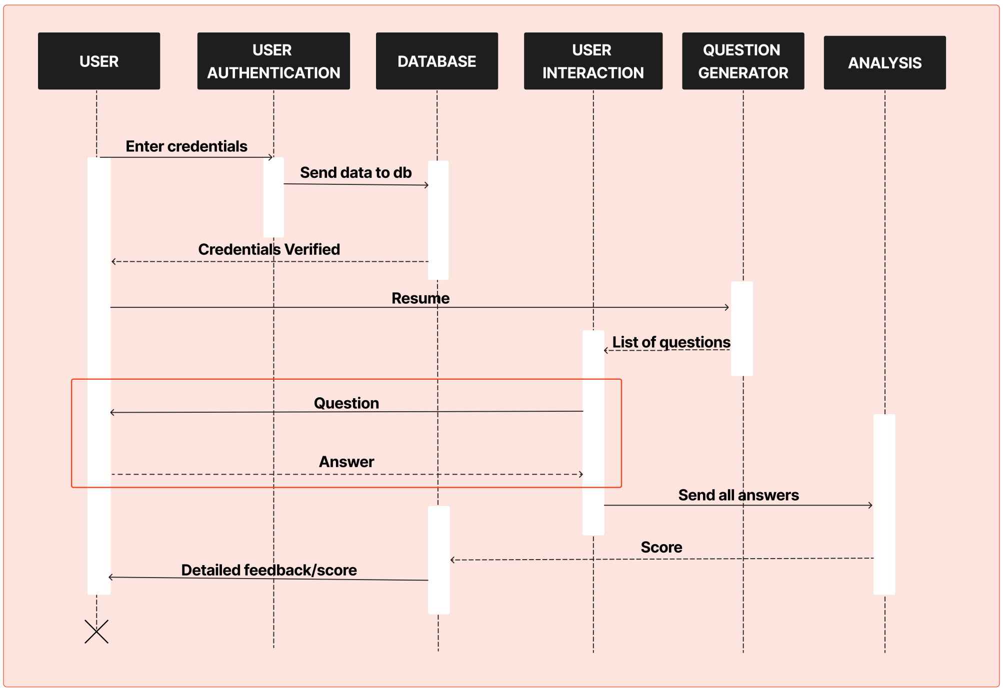
Proposed Method

- A user can sign up or log into the desktop application, Q&AI.
- From the home page, a resume can be uploaded.
- In doing so, questions will be generated by the bot based on the resume and the corresponding domain of the job application.
- A real-time environment is utilized to ask each question generated. The response is stored in audio, video, and text format and sent for further processing.
- An analysis that includes fact check, sentiment, grammar, confidence levels, and emotion detection is performed on the response.
- Scores and feedback are generated based on this analysis.
- Users can also view past scores and track progress.

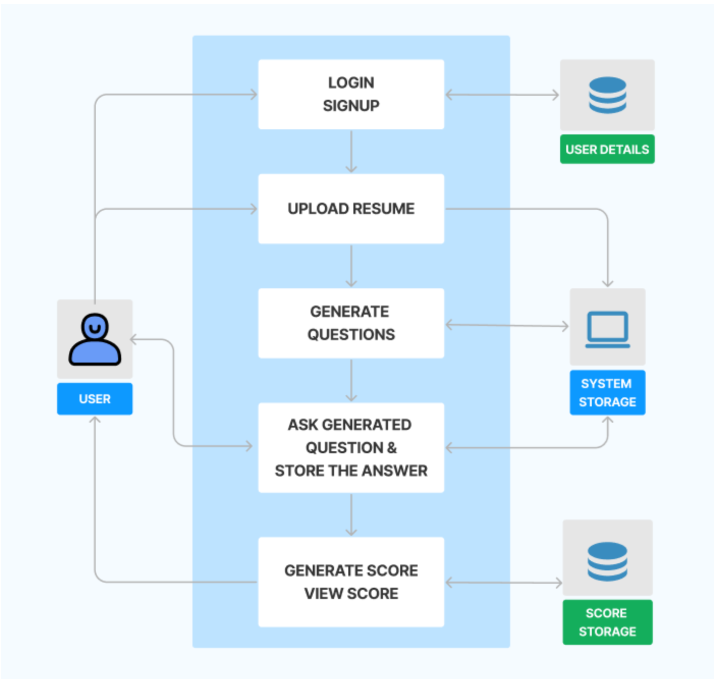
Architecture Diagram



Sequence Diagram



Use Case Diagram



Modules

1. User Authentication
2. Question Generator
3. User Interaction
4. Analysis
   - Language Proficiency
   - Factual Accuracy
   - Emotion Detection
   - Sentiment Analysis
   - Confidence Analysis

User Authentication Module

- Registered users can log in using their username and password.
- The credentials will be validated against those stored in the database.
- New users can sign-up by entering their details which will be stored in the database and then continue to log in.
- Once the credentials are verified, user will be directed to the home page of the application.

User Authentication Module

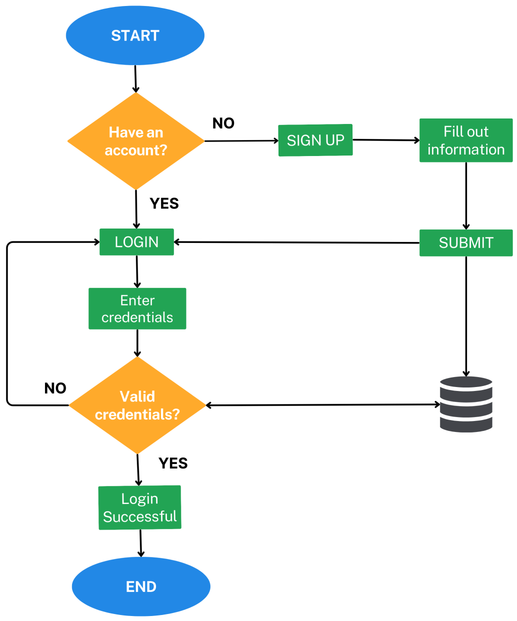


Figure: User Authentication Module

User Interaction Module

- The questions from the question generation module are asked to the user one by one
- Response to each question is retrieved from the user through the camera and microphone
- The audio is also converted to text format and the response is sent to the analysis module as audio, video, and text

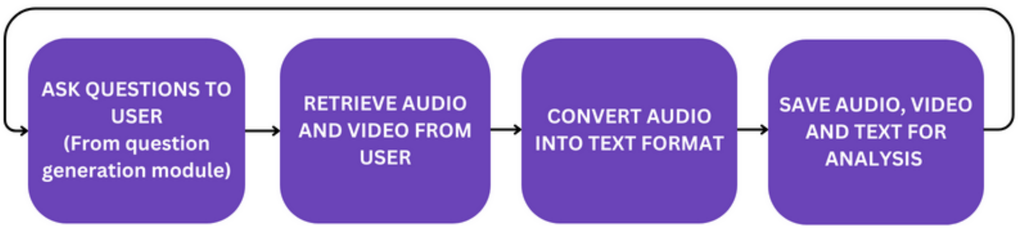


Figure: User Interaction

Question Generation Module

- The uploaded resume in PDF format is converted into text.
- Then key features are extracted and passed onto the question generation phase.
- Question generation is performed using a transformer model like BERT, RoBERTa or ChatGPT. The pre-trained model then takes the resume and generates questions based on it.
- The questions generated are then stored in the local storage.

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Question Generation Module

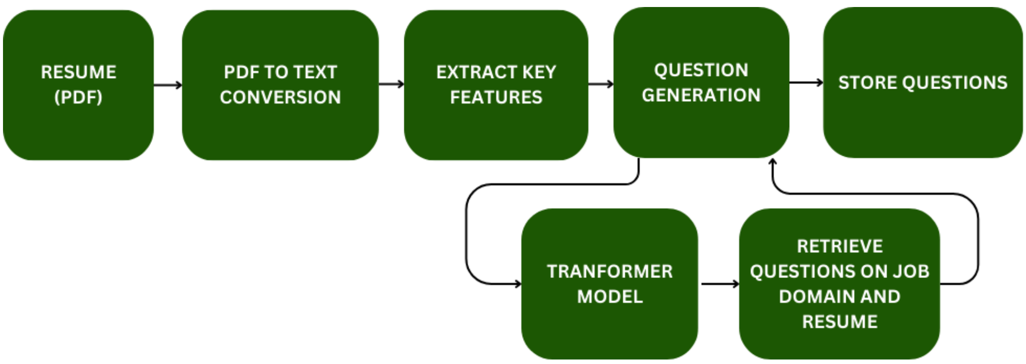


Figure: Question Generation

Analysis Module

Language Proficiency

- The module breaks down the user's answer into individual words (tokens) and analyzing their grammatical properties through Part-of-Speech (POS) tagging and dependency parsing.
- This process helps identify the syntactic structure and relationships between words in the text.
- The module then applies predefined grammar rules to detect errors such as subject-verb agreement, pronoun usage, article usage.
- Score, from a scale of 1-5, is calculated based on errors found and stored.

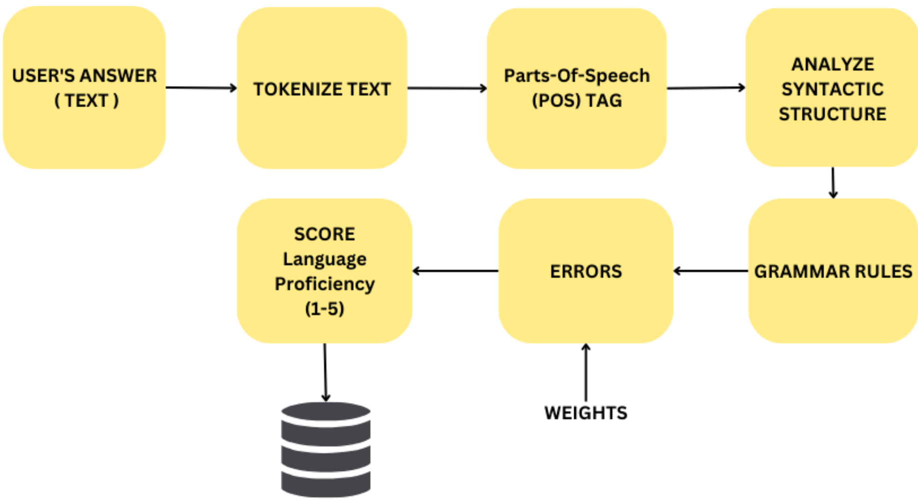


Figure: Language Proficiency

Algorithm 1 Grammar Check Algorithm

```
Tokenize the paragraph into individual words or tokens.
Perform Part-of-Speech (POS) tagging on each token to determine its grammatical category (noun, verb, adjective, etc.).
Perform dependency parsing to analyze the syntactic structure of the sentences and identify relationships between words.
Implement grammar rules to check for common errors such as subject-verb agreement, pronoun-antecedent agreement, verb tense usage, articles, sentence fragments, run-on sentences, and misplaced modifiers.
Flag tokens or phrases that violate grammar rules as potential errors.
Count flagged errors.
return Error count
```


Analysis Module

Factual Accuracy

- The user's answer in text format is summarized and given to a transformer model to generate accurate answers for the corresponding question.
- The cosine similarity of the user's answer and their respective accurate answers are taken and a cosine similarity score is generated.
- The generated score is then converted to a score in the range 1-5.

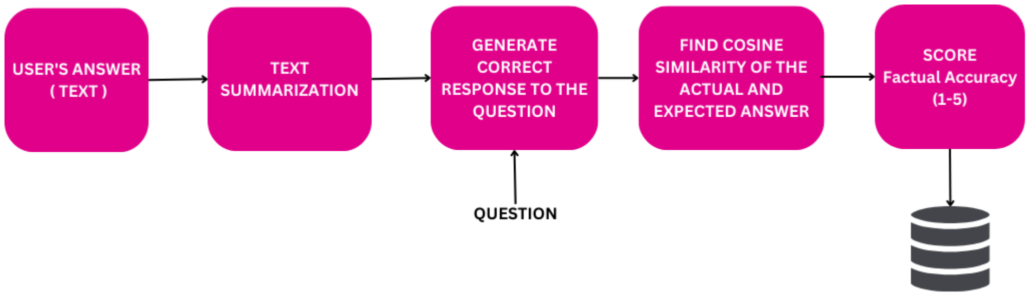


Figure: Factual accuracy

Factual Accuracy

Algorithm 2 Factual Accuracy Algorithm

1: Take the answer provided by the user and store it in variable X.
2: Take the accepted answer for the question and store it in variabvle Y.
3: Find cosine similarity between X and Y and store it in variable out.
4: Convert the similarity into rating from 1-5.
5: **return** rating

Analysis Module

Emotion Detection

- The video received as input is first converted into frames and stored in temporary storage.
- The extracted frames are then sent to a CNN model that identifies the emotions shown in each frame.
- The most probable emotion is then identified from the frame and stored.
- The system then finds the emotion that lasted the highest duration and stores it as a percentage.

Analysis Module

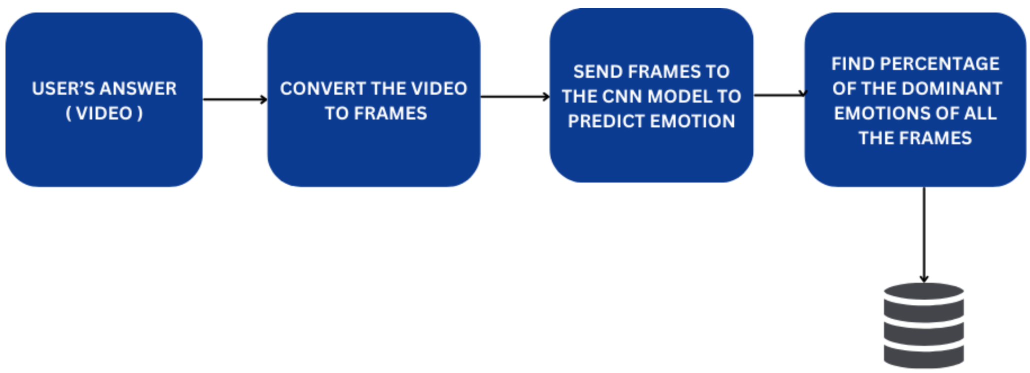


Figure: Emotion Detection

Analysis Module

Sentiment Analysis

- The user response in text format is the input. Data pre-processing is performed on the dataset (Eg: lowercasing, stopword removal, etc.).
- The resultant data is transformed into a numerical vector.
- A sentiment classification model like a transformer model is used to predict whether the text has a positive, neutral, or negative sentiment.

Analysis Module

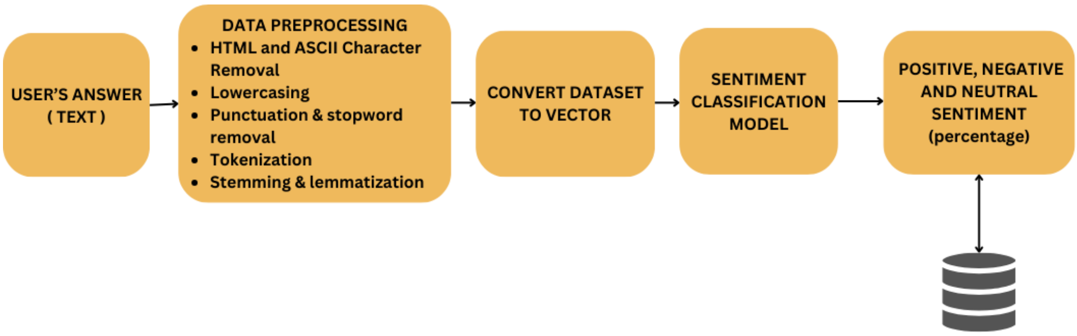


Figure: Sentiment Analysis

Analysis Module

Confidence Analysis

- Audio and video are fed as input to this module
- From audio, key features like original duration, speaking duration, and speech rate are extracted.
- Confidence from audio is rated based on pause duration and speech rate and a score from 1-5 is generated.
- Video is first converted to frames.
- The eye positions in frames are noted and the total frames in which the user looks straight is used to generate a score from 1-5.
- A weighted average score from the text and audio component is the confidence score.

Analysis Module

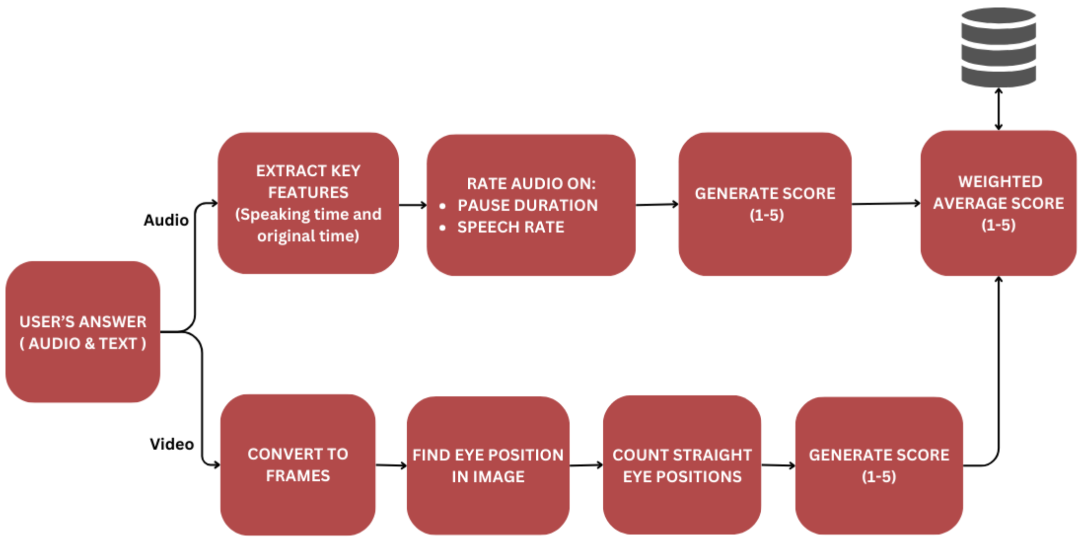


Figure: Confidence Analysis

Results

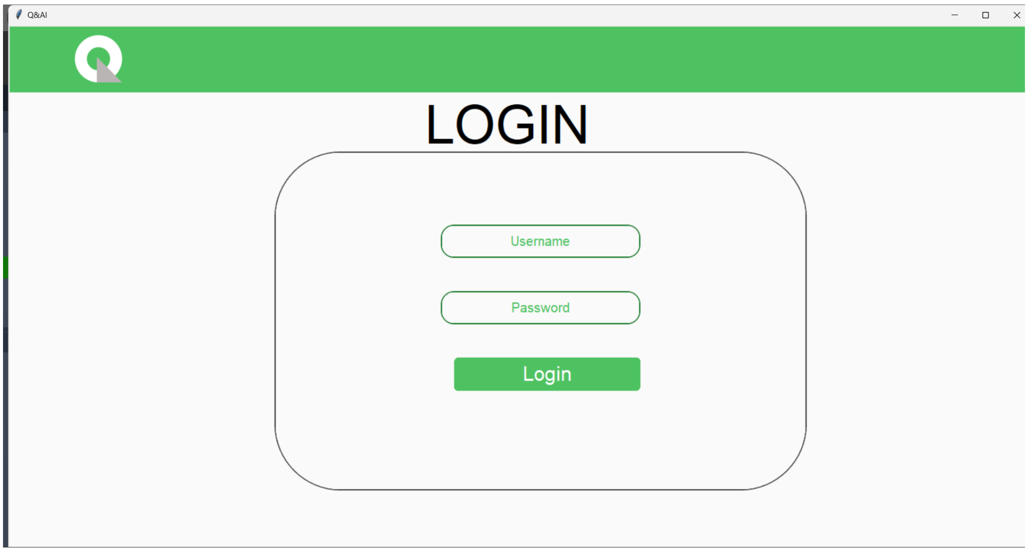


Figure: Login page

Results

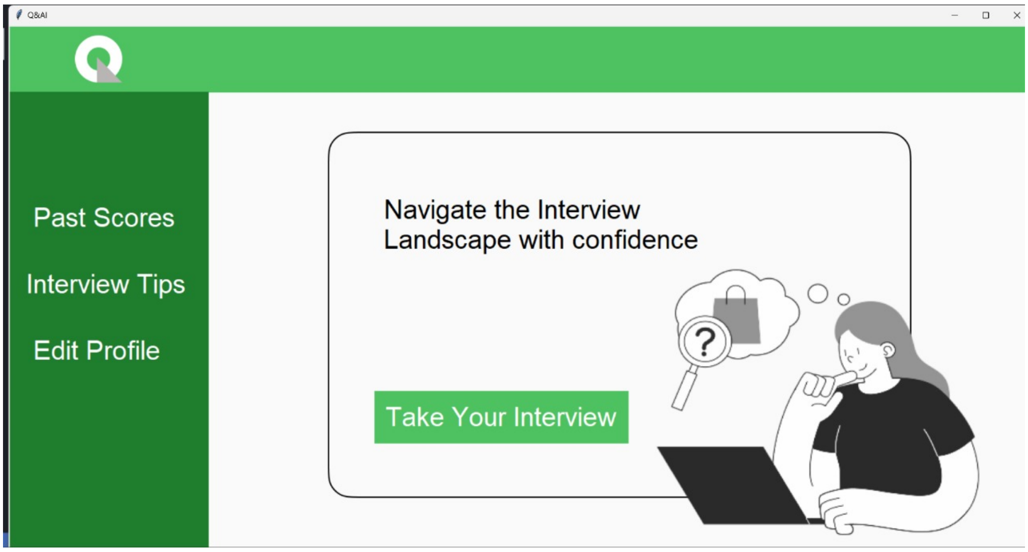
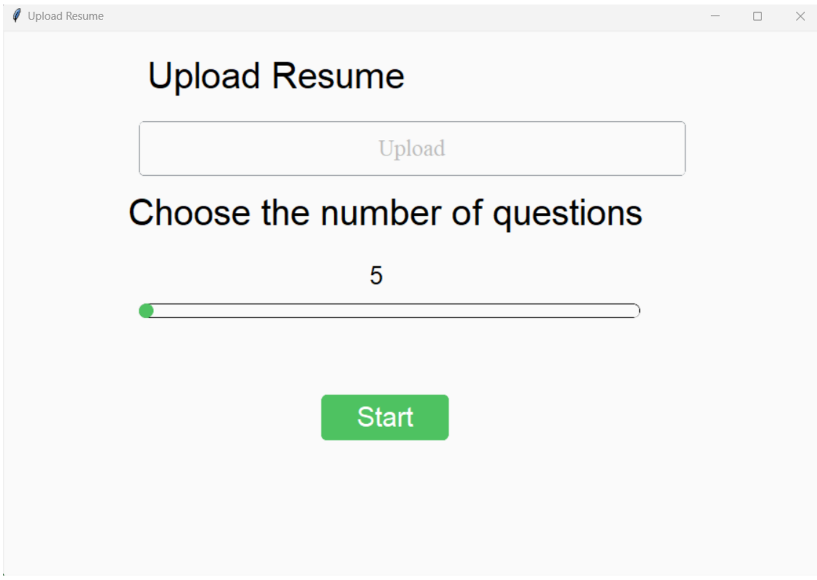


Figure: Landing page

Results



Results

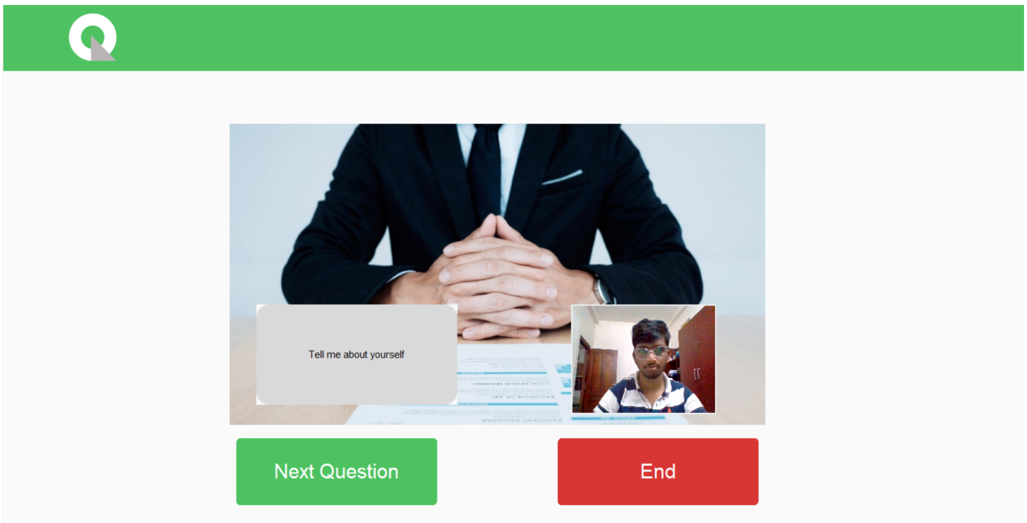
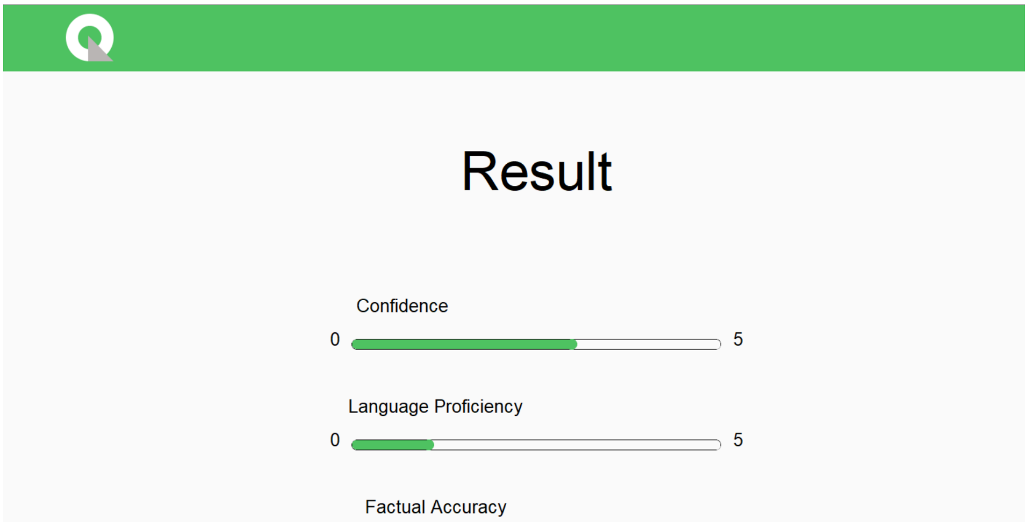
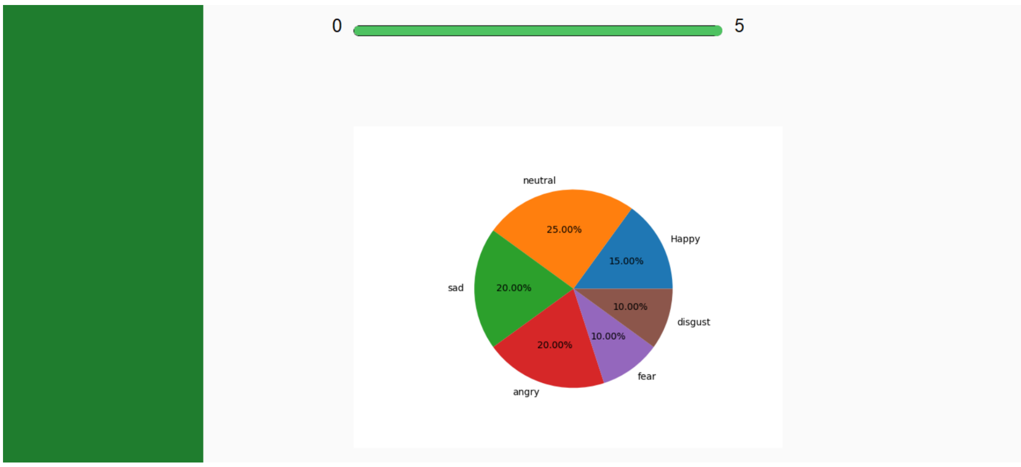


Figure: Ongoing interview

Results



Results



Results

Figure: Interview result

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Results

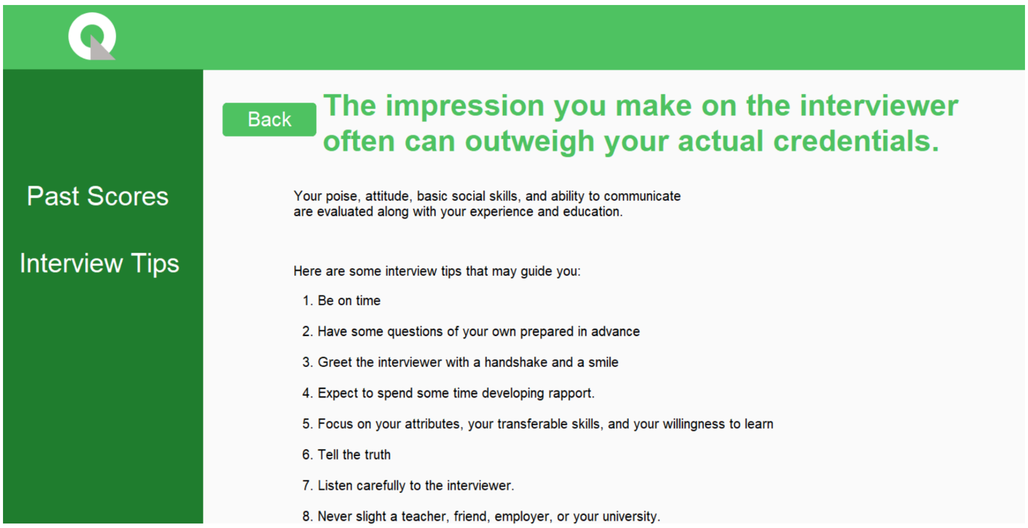

Figure: Interview tips

Results

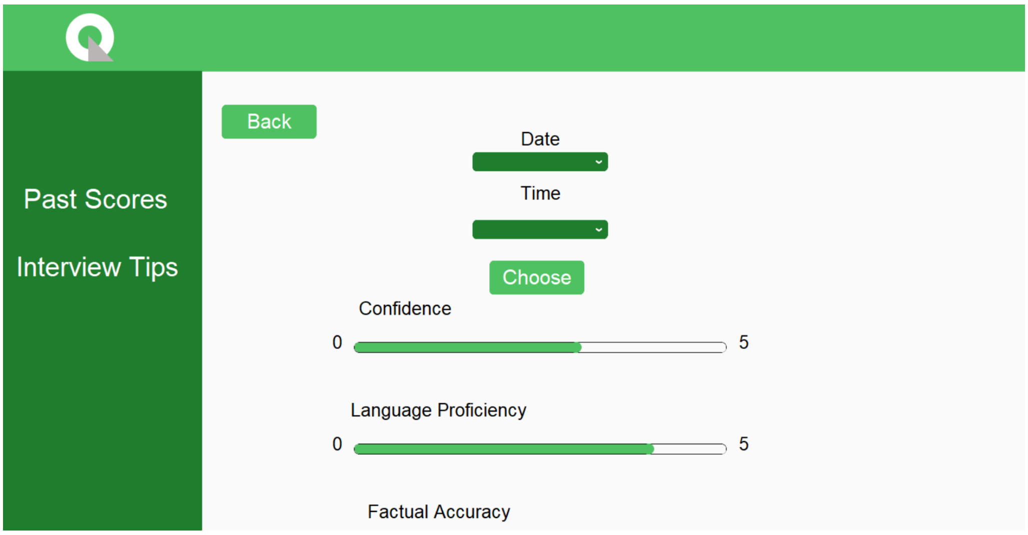

Figure: Past scores

Work Breakdown and Responsibilities

GOKUL BABURAJ
- User Authentication
- User Interaction
- UI Design
- UI Implementation

JOEL MANUEL
- Question Generation
- Fact Check
- Emotion Detection
- UI Implementation

MARIA SABI
- Sentiment Analysis
- Confidence Analysis
- User Interaction
- UI Implementation

MERENE BENSON
- Grammar Check
- Emotion Detection
- Confidence Analysis
- UI Implementation

Conclusion

Q&AI represents a powerful tool for individuals seeking to excel in their careers. It provides realistic interview simulations, valuable feedback, and insights into confidence, sentiment, emotions, language proficiency, and factual accuracy. This application equips users with the skills and confidence they need to succeed in the competitive job market.

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THANK YOU

CO-PO AND CO-PSO MAPPING

	PO 1	PO 2	PO 3	PO 4	PO 5	PO 6	PO 7	PO 8	PO 9	PO 10	PO 11	PO 12	PSO 1	PSO 2	PSO 3
CS451.1		1		2						2					
CS451 .2		2			2								2		
CS451		1.5		2	2					2			2		

JUSTIFICATIONS FOR CO-PO MAPPING

Mapping	LOW/MEDIUM/HIGH	Justification
CS451.1 -PO2	L	Students do a literature survey while preparing for the seminar and project
CS451.1 -PO4	M	They reach valid conclusions after the literature survey
CS451.1- PO10	M	Seminar presentations help them to develop public speaking skills
CS451.2-PO4	H	They do detailed research in their area of interest which help them to analyze and synthesis data.
CS451.2-PO5	M	They understand the limitations of the existing techniques and can use the engineering techniques to arrive at valid conclusions
CS451.2-PO10	H	Writing seminar report help them to develop technical report writing skills.
CS451.2-PSO1	M	By comparing different techniques, they can identify, analyze and design complex engineering problems.

Appendix B: Research Paper

Q&AI: An AI powered Mock Interview Bot for Enhancing the Performance of Aspiring Professionals

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***Abstract*— The Q&AI Mock Interview Bot is an application designed to enhance interview preparation for job seekers and aspiring professionals. This work aims to create an intelligent virtual interview platform that simulates real interview scenarios, offering users the opportunity to practice answering questions while receiving valuable feedback. The rationale of the Q&AI bot is its' innovativeness in generating questions. The questions generated for each user are exclusively from the user's resume uploaded to the bot. Henceforth, the questions will be very much relevant to a user. Users can respond to interview questions in real-time. The system evaluates the users' responses and gauges their confidence level, performs sentiment analysis and emotion detection. It also analyses the language proficiency and factual accuracy of users' answers. After each interview session, the bot generates a detailed scorecard. The Q&AI Mock Interview Bot empowers users to refine their interview skills, boost confidence, and receive constructive feedback. This paper presents the design and implementation of the tool for career development and interview preparation in an increasingly competitive job market.**

Keywords— Artificial Intelligence, Interview, Bot, Machine Learning

I. INTRODUCTION

Traditional interview preparation methods have long relied on resources like books and guides. These materials, though they offer valuable insights into common interview questions, strategies, and general tips, are static. They lack the ability to provide interactive and personalized experiences. A technological advancement in this space is offered by online platforms offering mock interviews. They often leverage recorded video interviews and automated assessments to provide feedback. But they may fall short in terms of dynamic question generation and personalized feedback. Video interview platforms have gained popularity, especially in the remote hiring process. They facilitate virtual interviews but their focus is on the employer side than the candidate's preparation. Chatbots and virtual environments also provide users with simulated conversational experiences. While these tools can offer a degree of interactivity, limitations may arise in terms of natural language understanding, making it a challenge to simulate realistic interview scenarios.

To address this, our proposed work, Q&AI Mock Interview Bot, emerges as an innovative solution that revolutionizes interview preparation. Q&AI bot provides a platform for job seekers to enhance their interview skills through virtual mock interviews. By simulating real interview scenarios and analyzing key aspects of the user's performance, including confidence, emotion, factual accuracy, and language proficiency, Q&AI empowers individuals to refine their presentation and communication skills. The application goes beyond traditional interview bots in two ways (i) by generating questions from the resume of a user and (ii) by generating performance feedback in the form of a detailed scorecard at the end of each session.

The paper is organized as follows. Section II describes the related work in the domain. The proposed Q&AI Mock Interview Bot is described in detail in Section III. The results and analysis of the proposed work is briefed in Section IV. The paper is concluded in Section V.z

II. RELATED WORK

An AI mock interview platform that bridges the gap between the actual interview and its preparation is outlined in [1]. The system assesses the user based on three factors: emotion, confidence, and knowledge base. Emotion is analyzed based on facial expressions using a CNN algorithm which will classify the emotion among seven categorical emotions, namely, happy, sad, angry, disgust, anger, neutral, and fear. Confidence evaluation is performed based on speech recognition using NLP. Knowledge assessment involved keyword mapping, semantic analysis, and web scraping is done for keyword extraction. [2] introduces a chatbot that can be used for conducting interviews with candidates applying for a position in the company. It explores the possibility of using BERT (Bidirectional Encoding Representation for Transformers) to generate questions for a particular domain using the resume uploaded by the candidate ahead of time. The work further explores the possibility of using chatbots to conduct interviews for MNCs having a large number of applicants. The result of testing the application provides promising high results for both question generation and answer evaluation. This shows that chatbots based on transformer models can be used for filtering candidates for the interview process. The CUTIE Interview Bot [3] is developed to help university students improve communication skills and confidence needed to tackle job interviews. The bot carries out mock interviews by posing questions and then examining video and audio to analyze emotions and sentiments in real-time. The study involved analyzing around 114 student videos, comparing manual expert scoring with CUTIE's scoring, and investigating factors influencing the bot's performance. The system takes as input video and audio of the mock interview. The video is then used for emotion recognition, and the audio, after being converted to text, is used for sentiment analysis. The gathered data is processed through a scoring algorithm that yields the sentiment score and the spectrum of emotions exhibited throughout the interview.

Google's Interview Warmup [4] platform was created by Google themselves to help people prepare for their interview by making them choose a domain from data analytics, digital marketing, E-commerce, IT support, project management, UX design, cybersecurity, and general. Once the domain is chosen, the user will be asked a series of questions related to the domain and they will be asked to record their audio response or type it in and submit it. At the end of the interview, the questions they answered and their responses will be displayed, and they will be able to view the fluency of their speech along with the accuracy. The user will also be able to see the most commonly used words in the response, the number of job-related terms used, and also see the various talking points of the responses. In yet another bot [5] the interview is conducted by a human-like avatar model that asks questions and makes the mock environment feel real. Once the interview is done, the analysis is generated using machine learning algorithms. It analyses problems like the duration of the answer, word count and speed, the number of hesitation words like 'um' and 'er' used, sentiment analysis, the number of times the user smiled, composure, the number of times the user looked away and how much eye contact was maintained. This helps get a very good understanding of what the user should focus on and what his/her shortcomings are. The avatar also helps users with fear of facing an interviewer overcome such problems. However, this is a high cost model.

III. Proposed Methodology

The users of Q&AI Mock Interview Bot can sign up or log into the desktop application. From the home page, a resume can be uploaded and in doing so, questions will be generated by the bot based on the resume and the corresponding domain of the job application. A real-time environment is utilized to ask each question generated. The response is then stored in audio, video, and text format and sent for further processing. An analysis that includes fact check, sentiment, grammar, confidence levels, and emotion detection is performed on the response. Scores and feedback are generated based on this analysis. Users can also view past scores and track their progress. The system consists of four major modules, namely, user authentication module, question generation module, user Interaction module and analysis module. The architecture of the proposed methodology is given in Figure 1.

A. *User Authentication Module*

Registered users can log in using their username and password. The credentials will be validated against those stored in the database. New users can sign-up by entering their details like name, date of birth, email, username and password, which will be stored in the database. They can then continue to log in. Once the credentials are verified, users will be directed to the home page of the application.

B. *Question Generation Module*

The uploaded resume in PDF format is converted into text. Then key features are extracted and passed onto the question generation phase. Question generation is performed using a transformer model like BERT, RoBERTa, or ChatGPT. An API request is sent to such a model or a Hugging Face transformer is used. The model then analysis the major components of the resume and sends questions based on the resume back to the system. The generated questions are then stored to ask the user. Usage of highly complex and well trained models like ChatGPT can help increase the credibility of the questions generated. The workflow of question generation module is given in Fig 2.

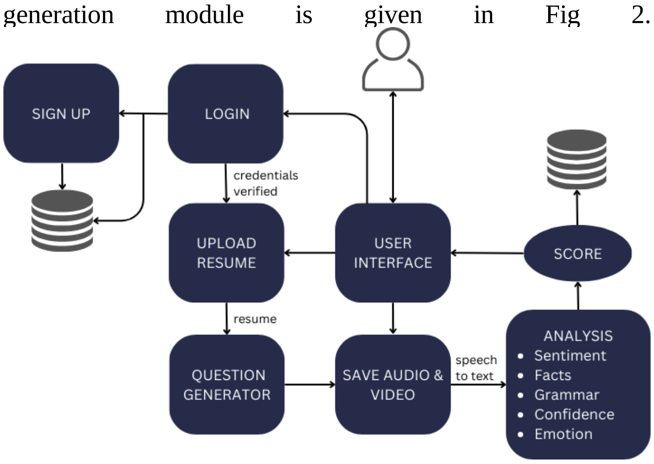

Fig. 1. Architecture of the Proposed Methodology

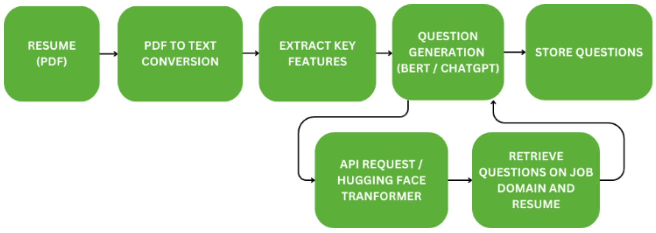

Fig. 2. Question Generation Module Diagram

C. User Interaction Module

The questions from the question generation module are asked to the user one by one. Response to each question is retrieved from the user through the camera and microphone. The audio is also converted to text format and the response is sent to the analysis module as audio, video, and text. This interaction is responsible for providing a realistic interview setting. After the question is displayed on the screen, within a few seconds the microphone turns on. The user will only have an option to submit the answer after speaking or quit from the interview. This interaction is repeated until the responses to all the questions are collected.

D. Analysis Module

1) Language Proficiency: Python's language tool library specifies the grammatical mistakes in the user's answers. The input text is parsed into its constituent elements, such as words, phrases, and sentences. Linguistic rules are then applied iteratively to each element, checking for violations of grammar rules or stylistic conventions. The detected errors are categorized based on their nature as grammar correctness, sentence structure, and clarity of expression with weights assigned based on severity. The proficiency score is then calculated by aggregating the weighted errors and then normalizing the score to a range of 1-5.

2) Factual Accuracy: The user's answer in text format is summarized and given to the ChatGPT API along with its corresponding question. Text summarization is done using Hugging Face transformers. A prompt instructs the GPT to score the factual accuracy of the answer on a scale of 1-5. The use of ChatGPT instead of other models is very useful as it is more accurate, better suited and easier to use than most other large language models.

3) Emotion Detection: The video received as input is first converted into frames. The frames are then sent to an ML model that uses CNN to detect the region where the face is present and the model then classifies the face detected to various emotions. This process can be simplified by using the Python DeepFace library. The extracted frames are sent to the DeepFace module that identifies the shown emotion. The most probable emotion is then identified from the frame and stored. The system then finds the emotion that lasted the highest duration and stores it as a percentage.

4) Sentiment Analysis: The user response in text is the input. Data pre-processing is performed on the dataset which includes HTML and ASCII character removal, lowercasing, punctuation and stopword removal, tokenization, stemming and lemmatization. A pre-trained word embedding from a Gensim model leveraging Word2vec is imported. This bot uses a 300 dimension word embedding. The resultant data is transformed into a numerical vector using these embeddings. A classifier like SVM is used to predict whether the text has a positive or negative sentiment. A metric like accuracy is used for evaluation. The percentage of positive to negative sentiment during the interview is the output to the user.

5) Confidence Analysis: Audio and video are fed as input to this module. A band pass filter is implemented to cut out the excess noises from the audio by mentioning low pass and high pass threshold values. From the audio, key features like pause duration, mel-frequency spectral coefficient, chroma-based features, short term fourier transform, spectral contrast and tonnetz are extracted. The direct extraction of these features are implemented using the Python package, librosa. Based on these features, clarity, modulation, pace, and volume are rated of each audio recording. 3 different people can perform this rating and an average rating is procured. A Bi-LSTM neural network is then used to train the audio and a confidence score from 1-5 is generated. Video is first converted to frames using OpenCV. Features like eye contact, blinks using EAR parameter, and frequent body movement in consecutive frames are noted. The videos are rated as high, medium or low confidence. 3 different people can also perform this rating.A classifier like Bi-LSTM is used to predict a score from 1-5. A weighted average score from the text and audio component is the confidence score. The confidence analysis module diagram is given in Fig 3.

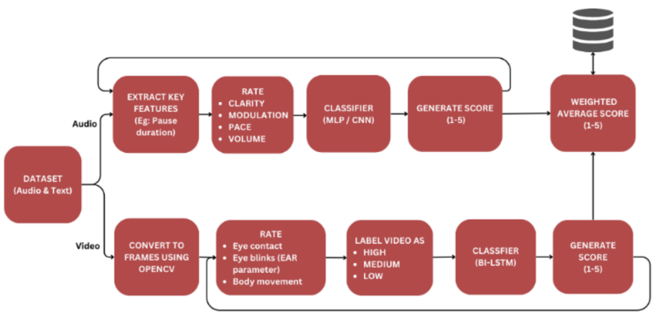

Fig. 3. Confidence Analysis Module Diagram

IV. Results and Discussions

The different phases of Q&AI Mock Interview Bot are evaluated in the section 3. The results obtained from different modules are summarized.

A. Question Generation Module

In this innovative resume analysis system of Q&AI Mock Interview Bot, a PDF resume is converted into text, and key features are extracted. Leveraging advanced transformer models like BERT, RoBERTa, or ChatGPT enhances question generation accuracy. Through API requests the model analyzes resume components, generating insightful questions. The utilization of sophisticated models such as ChatGPT elevates the credibility of the questions, ensuring a comprehensive understanding of the candidate's profile. This integrated approach streamlines the resume evaluation process, providing employers with precise and relevant information for effective candidate assessment. A sample example of questions generated for uploaded resumes from different is given in Table I. The questions generated by the question generation module are highly accurate to the actual needed result.

TABLE I. QUESTIONS GENERATED BASED ON RESUMES OF VARIOUS DOMAINS

SI. no	Question generated
Resume 1	Tell me about your experience with Python, TensorFlow, and Scikit-learn in ML development.
	Can you describe a recent ML project you worked on, including the problem, approach, and tools used?
	Can you discuss a project where you collaborated effectively with teams? How did you ensure good communication?
	What's your approach to solving complex ML problems? Can you share an example and your process?
Resume 2	Can you describe a significant project you've worked on and your role in overcoming challenges?
	Discuss your experience with CAD software like SolidWorks.
	How have you contributed to design and innovation in mechanical engineering projects?
	Can you share an example of a design innovation you introduced to improve mechanical system performance?

B. *Language Proficiency*

The language proficiency is examined with the aid of natural language processing, wherein the grammars and spellings are checked. The sentence is verified for the noun-phrase construction and the errors are counted. Examples where the language proficiency is found out for sample sentences are listed in Table II. The number of errors for each of the sentence is weighted and the final language proficiency is arrived with.

C. *Factual Accuracy*

The factual accuracy can be checked by finding the cosine similarity between the actual and expected answers provided for the asked question. This can be done with accuracy checking using a transformer model. The transformer models are trained on a diverse dataset and the factual accuracy can hence be verified. Sample examples with factual accuracy score is listed in Table III.

D. *Emotion Detection*

Upon receiving a video input, the system initiates the process by utilizing OpenCV to convert it into individual frames. These frames are subsequently fed into the DeepFace module, a robust facial emotion recognition tool. The module identifies emotions depicted in each frame,

TABLE II. SENTENCES AND THEIR NUMBER OF GRAMMATICAL ERRORS FOUND

Sentence	Number of errors
I is enjoy football	2
They teached me many thing	2
The main objective in my project is to finding the facial emotion	1

TABLE III. FACTUAL ACCURACY SCORE GENERATED FROM ANSWERS DOMAINS

Question	Answer	Score
How do you evaluate an ML model?	I evaluate ML models using accuracy, recall, and F1 score by making use of their corresponding functions in sklearn.	4
What frontend technologies are you proficient in?	I am proficient in technologies like MySQL, MongoDB, etc.	1
Discuss your experience with CAD software like SolidWorks.	I have used CAD to develop a new kind of plating for a car I was designing	3
How have you used data analysis tools like Excel and SQL to drive business insights?	I've leveraged Excel's advanced formulas and pivot tables to analyze sales data, leading to a 15% revenue increase in my previous role. Additionally, I've used SQL queries to segment customer data, resulting in a 20% improvement in customer engagement and retention rates through targeted marketing campaigns.	5
What is a distributed ledger?	A distributed ledger is a type of database that is spread across multiple locations or participants.	2

extracting the most probable emotion. The system then computes the emotion that persisted for the longest duration, storing it as a percentage representation. This streamlined approach ensures accurate and efficient emotion analysis, offering valuable insights into the dominant emotional expression throughout the video, enhancing the system's capability for nuanced emotion tracking and interpretation. Experiments have been performed to evaluate the efficacy of DeepFace in comparison with other models and the results are presented in Table IV.

E. *Sentiment Analysis*

The system begins by processing user text responses through a comprehensive data pre-processing pipeline. This involves removing HTML and ASCII characters, converting text to lowercase, eliminating punctuation and stopwords, and applying tokenization, stemming, and lemmatization. Subsequently, a pre-trained 300-dimensional word embedding model from Gensim, based on Word2Vec, is incorporated to capture semantic relationships within the text. The transformed data is then converted into numerical vectors using these embeddings. For sentiment analysis, machine learning classifiers are employed to predict whether the text expresses positive or negative sentiment. Evaluation is performed using metrics such as precision, recall and f1-score. The system calculates the percentage of positive to negative sentiment throughout the interview, providing users with a quantitative measure of the overall sentiment conveyed in their responses. This robust approach ensures a nuanced understanding of sentiment dynamics in textual interactions. Experiments are performed to evaluated for different

TABLE IV. COMPARİSON OF ACCURACY OF DİFFERENT DEEP LEARNİNG MODELS FOR EMOTİON RECOGNİTİON

Method	Accuracy
DeepFace [6]	**0.9735**
TL Joint Bayesian [7]	0.9633
Combined Joint Bayesian [8]	0.9242

Tom-vs-Pete [9]	0.9310
POOF-HOG [10]	0.9280

machine learning classifiers like SVM [11], Logistic Regression [12] , Decision Tree [13] and Naïve Bayes' [14] classifier. It is observed that SVM outperforms other types of classifiers in terms of metrics. The results are presented in Table V.

TABLE V. COMPARISON OF MACHINE LEARNING MODELS FOR SENTIMENT ANALYSIS

Model	Precision	Recall	F1 score
SVM [11]	0.8181	0.8642	0.8405
Logistic Regression[12]	0.8181	0.7748	0.7959
Decision Tree [13]	0.6700	0.6523	0.6610
Naive Bayes [14]	0.8108	0.7947	0.8026

V. CONCLUSION

In today's competitive job market, effective interview preparation is crucial for individuals seeking career opportunities. Q&AI, the Mock Interview Bot emerges as an innovative solution to address the limitations of traditional interview preparation methods. This application revolutionizes the way individuals hone their interview skills by combining advanced artificial intelligence techniques with a user-friendly interface. The core objective of the Q&AI Mock Interview Bot is to provide users with a realistic and comprehensive interview experience. The rationale of the work's innovativeness lies in the fact that questions generated for a user are completely, dependent on the resume provided by him/her. This application thus bridges gaps in interview bots by simulating authentic interview scenarios, allowing users to practice and refine their communication, problem-solving, and presentation skills. The overall design can further be improved by incorporating interviewer avatars to simulate a more realistic interview environment. The application can also be integrated with the placement cell websites of universities and academic institutions to make it accessible to students.

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Appendix C: Vision, Mission, Programme Outcomes and Course Outcomes

Vision, Mission, Programme Outcomes and Course Outcomes

Institute Vision

To evolve into a premier technological institution, moulding eminent professionals with creative minds, innovative ideas and sound practical skill, and to shape a future where technology works for the enrichment of mankind.

Institute Mission

To impart state-of-the-art knowledge to individuals in various technological disciplines and to inculcate in them a high degree of social consciousness and human values, thereby enabling them to face the challenges of life with courage and conviction.

Department Vision

To become a centre of excellence in Computer Science and Engineering, moulding professionals catering to the research and professional needs of national and international organizations.

Department Mission

To inspire and nurture students, with up-to-date knowledge in Computer Science and Engineering, ethics, team spirit, leadership abilities, innovation and creativity to come out with solutions meeting societal needs.

Programme Outcomes (PO)

Engineering Graduates will be able to:

1. Engineering Knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern Tool Usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal, and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and Team work: Function effectively as an individual, and as a member or leader in teams, and in multidisciplinary settings.

10. Communication: Communicate effectively with the engineering community and with society at large. Be able to comprehend and write effective reports documentation. Make effective presentations, and give and receive clear instructions.

11. Project management and finance: Demonstrate knowledge and understanding of engineering and management principles and apply these to one's own work, as a member and leader in a team. Manage projects in multidisciplinary environments.

12. Life-long learning: Recognize the need for, and have the preparation and ability to engage in independent and lifelong learning in the broadest context of technological change.

Programme Specific Outcomes (PSO)

A graduate of the Computer Science and Engineering Program will demonstrate:

PSO1: Computer Science Specific Skills
The ability to identify, analyze and design solutions for complex engineering problems in multidisciplinary areas by understanding the core principles and concepts of computer science and thereby engage in national grand challenges.

PSO2: Programming and Software Development Skills
The ability to acquire programming efficiency by designing algorithms and applying standard practices in software project development to deliver quality software products meeting the demands of the industry.

PSO3: Professional Skills
The ability to apply the fundamentals of computer science in competitive research and to develop innovative products to meet the societal needs thereby evolving as an eminent researcher and entrepreneur.

Course Outcomes (CO)

Course Outcome 1: Model and solve real world problems by applying knowledge across domains (Cognitive knowledge level: Apply).

Course Outcome 2: Develop products, processes or technologies for sustainable and socially relevant applications (Cognitive knowledge level: Apply).

Course Outcome 3: Function effectively as an individual and as a leader in diverse teams and to comprehend and execute designated tasks (Cognitive knowledge level: Apply).

Course Outcome 4: Plan and execute tasks utilizing available resources within timelines, following ethical and professional norms (Cognitive knowledge level: Apply).

Course Outcome 5: Identify technology/research gaps and propose innovative/creative solutions (Cognitive knowledge level: Analyze).

Course Outcome 6: Organize and communicate technical and scientific findings effectively in written and oral forms (Cognitive knowledge level: Apply).

Appendix D: CO-PO-PSO Mapping

CO-PO AND CO-PSO MAPPING

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
CO1	2	2	2	1	2	2	2	1	1	1	1	2	3		
CO2	2	2	2		1	3	3	1	1		1	1		2	
CO3									3	2	2	1			3
CO4					2			3	2	2	3	2			3
CO5	2	3	3	1	2							1	3		
CO6					2			2	2	3	1	1			3

3/2/1: high/medium/low

JUSTIFICATIONS FOR CO-PO MAPPING & CO-PSO MAPPING

MAPPING	LOW/MEDIUM/ HIGH	JUSTIFICATION
100003/ CS722U.1-PO1	M	Knowledge in the area of technology for project development using various tools results in better modeling.
100003/ CS722U.1-PO2	M	Knowledge acquired in the selected area of project development can be used to identify, formulate, review

		research literature, and analyze complex engineering problems reaching substantiated conclusions.
100003/ CS722U.1-PO3	M	Can use the acquired knowledge in designing solutions to complex problems.
100003/ CS722U.1-PO4	M	Can use the acquired knowledge in designing solutions to complex problems.
100003/ CS722U.1-PO5	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
100003/ CS722U.1-PO6	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
100003/ CS722U.1-PO7	M	Project development based on societal and environmental context solution identification is the need for sustainable development.
100003/ CS722U.1-PO8	L	Project development should be based on professional ethics and responsibilities.
100003/ CS722U.1-PO9	L	Project development using a systematic approach based on well defined principles will result in teamwork.

100003/ CS722U.1-PO10	M	Project brings technological changes in society.
100003/ CS722U.1-PO11	H	Acquiring knowledge for project development gathers skills in design, analysis, development and implementation of algorithms.
100003/ CS722U.1-PO12	H	Knowledge for project development contributes engineering skills in computing & information gatherings.
100003/ CS722U.2-PO1	H	Knowledge acquired for project development will also include systematic planning, developing, testing and implementation in computer science solutions in various domains.
100003/ CS722U.2-PO2	H	Project design and development using a systematic approach brings knowledge in mathematics and engineering fundamentals.
100003/ CS722U.2-PO3	H	Identifying, formulating and analyzing the project results in a systematic approach.
100003/ CS722U.2-PO5	H	Systematic approach is the tip for solving complex problems in various domains.
100003/ CS722U.2-PO6	H	Systematic approach in the technical and design aspects provide valid conclusions.

100003/ CS722U.2-PO7	H	Systematic approach in the technical and design aspects demonstrate the knowledge of sustainable development.
100003/ CS722U.2-PO8	M	Identification and justification of technical aspects of project development demonstrates the need for sustainable development.
100003/ CS722U.2-PO9	H	Apply professional ethics and responsibilities in engineering practice of development.
100003/ CS722U.2-PO11	H	Systematic approach also includes effective reporting and documentation which gives clear instructions.
100003/ CS722U.2-PO12	M	Project development using a systematic approach based on well defined principles will result in better teamwork.
100003/ CS722U.3-PO9	H	Project development as a team brings the ability to engage in independent and lifelong learning.
100003/ CS722U.3-PO10	H	Identification, formulation and justification in technical aspects will be based on acquiring skills in design and development of algorithms.
100003/ CS722U.3-PO11	H	Identification, formulation and justification in technical aspects provides the betterment of life in various domains.
100003/ CS722U.3-PO12	H	Students are able to interpret, improve and redefine technical aspects with mathematics, science and

		engineering fundamentals for the solutions of complex problems.
100003/ CS722U.4-PO5	H	Students are able to interpret, improve and redefine technical aspects with identification formulation and analysis of complex problems.
100003/ CS722U.4-PO8	H	Students are able to interpret, improve and redefine technical aspects to meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
100003/ CS722U.4-PO9	H	Students are able to interpret, improve and redefine technical aspects for design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
100003/ CS722U.4-PO10	H	Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools for better products.
100003/ CS722U.4-PO11	M	Students are able to interpret, improve and redefine technical aspects by applying contextual knowledge to assess societal, health and consequential responsibilities relevant to professional engineering practices.
100003/ CS722U.4-PO12	H	Students are able to interpret, improve and redefine technical aspects for demonstrating the knowledge of, and need for sustainable development.

100003/ CS722U.5-PO1	H	Students are able to interpret, improve and redefine technical aspects, apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
100003/ CS722U.5-PO2	M	Students are able to interpret, improve and redefine technical aspects, communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
100003/ CS722U.5-PO3	H	Students are able to interpret, improve and redefine technical aspects to demonstrate knowledge and understanding of the engineering and management principle in multidisciplinary environments.
100003/ CS722U.5-PO4	H	Students are able to interpret, improve and redefine technical aspects, recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.
100003/ CS722U.5-PO5	M	Students are able to interpret, improve and redefine technical aspects in acquiring skills to design, analyze and develop algorithms and implement those using high-level programming languages.
100003/ CS722U.5-PO12	M	Students are able to interpret, improve and redefine technical aspects and contribute their engineering skills in

		computing and information engineering domains like network design and administration, database design and knowledge engineering.
100003/ CS722U.6-PO5	M	Students are able to interpret, improve and redefine technical aspects and develop strong skills in systematic planning, developing, testing, implementing and providing IT solutions for different domains which helps in the betterment of life.
100003/ CS722U.6-PO8	H	Students will be able to associate with a team as an effective team player for the development of technical projects by applying the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.
100003/ CS722U.6-PO9	H	Students will be able to associate with a team as an effective team player to Identify, formulate, review research literature, and analyze complex engineering problems
100003/ CS722U.6-PO10	M	Students will be able to associate with a team as an effective team player for designing solutions to complex engineering problems and design system components.
100003/ CS722U.6-PO11	M	Students will be able to associate with a team as an effective team player, use research-based knowledge and research methods including design of experiments, analysis and interpretation of data.

100003/ CS722U.6-PO12	H	Students will be able to associate with a team as an effective team player, applying ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
100003/ CS722U.1-PSO1	H	Students are able to develop Computer Science Specific Skills by modeling and solving problems.
100003/ CS722U.2-PSO2	M	Developing products, processes or technologies for sustainable and socially relevant applications can promote Programming and Software Development Skills.
100003/ CS722U.3-PSO3	H	Working in a team can result in the effective development of Professional Skills.
100003/ CS722U.4-PSO3	H	Planning and scheduling can result in the effective development of Professional Skills.
100003/ CS722U.5-PSO1	H	Students are able to develop Computer Science Specific Skills by creating innovative solutions to problems.
100003/ CS722U.6-PSO3	H	Organizing and communicating technical and scientific findings can help in the effective development of Professional Skills.