Vivekanand Education Society's Institute of Technology

Department of Computer Engineering

Group No.: 28
Date :- 23/10/2024

Project Report (2024-25) - Sem VII

EmoScan: Real-Time Facial Analysis for Online Interviews

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<u>CERTIFICATE of Approval</u>

This is to certify that ***<u>Raj Tandon(D17C/62)</u>*** of Fourth Year Computer Engineering studying under the University of Mumbai has satisfactorily presented the project on "***EmoScan: Real-Time Facial Analysis for Online Interviews***" as a part of the coursework of PROJECT-I for Semester-VII under the guidance of ***<u>Mrs. Indu Dokare</u>*** in the year 2024-2025.

Date

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ACKNOWLEDGEMENT

We are thankful to our college Vivekanand Education Society's Institute of Technology for considering our project and extending help at all stages needed during our work of collecting information regarding the project.

It gives us immense pleasure to express our deep and sincere gratitude to Assistant Professor **Mrs. Indu Dokare** (Project Guide) for her kind help and valuable advice during the development of project synopsis and for her guidance and suggestions.

We are deeply indebted to Head of the Computer Department **Dr.(Mrs.) Nupur Giri** and our Principal **Dr. (Mrs.) J.M. Nair ,** for giving us this valuable opportunity to do this project.

We express our hearty thanks to them for their assistance without which it would have been difficult in finishing this project synopsis and project review successfully.

We convey our deep sense of gratitude to all teaching and non-teaching staff for their constant encouragement, support and selfless help throughout the project work. It is a great pleasure to acknowledge the help and suggestion, which we received from the Department of Computer Engineering.

We wish to express our profound thanks to all those who helped us in gathering information about the project. Our families too have provided moral support and encouragement several times.

INDEX

1 INTRODUCTION

1.1. Introduction to the project

In today's digital landscape, remote communication and virtual interactions have become an integral part of professional and personal engagements, particularly in the context of online interviews. With the increasing reliance on remote platforms, traditional interviewing methods face limitations in providing a holistic view of the interviewee. Factors such as emotional state, identity verification, and demographic insights are often missed, leading to an incomplete understanding of the candidate. To address these challenges, this project proposes the development of a JavaScript-based system that integrates facial detection and recognition technologies using TensorFlow.js. By leveraging this advanced technology, we aim to offer a more insightful and dynamic approach to the virtual interview process.

The main objective of this project is to create a tool that enables comprehensive facial analysis in real time during online interviews. This system is designed to activate the camera, facilitating several crucial tasks to improve the interviewing experience. Face recognition technology ensures the accurate identification of the interviewee, while face landmark detection identifies key features such as eyes, nose, and mouth to track facial expressions and subtle movements. Furthermore, face expression recognition analyzes the emotional states of candidates, offering insights into their reactions and mood during the interview. In addition to these features, the system includes age and gender recognition, which provide demographic data to the interviewer, further enriching the understanding of the interviewee.

The use of TensorFlow.js offers a powerful advantage by allowing the system to run directly in the browser, ensuring real-time processing without relying on server-side computation. This client-side approach enhances both privacy and security, as sensitive data remains within the user's control, while also improving accessibility and usability. Users benefit from the convenience of instant feedback and analysis without the need for complex setups or backend infrastructure. The system's capability to function in both browser and Node.js environments further broadens its applicability, making it a versatile solution for a wide range of virtual interview scenarios.

By integrating these advanced facial analysis features into a single platform, this project aims to revolutionize the remote interview experience. The combination of real-time face detection, expression analysis, and demographic identification offers interviewers a more complete view of their candidates, enhancing the accuracy and efficiency of the selection process. Beyond its immediate use in interviews, this technology has the potential to be applied in various other domains, such as customer service, virtual meetings, and security, showcasing the transformative power of modern web technologies.

This project demonstrates the practical applications of facial recognition and analysis technologies in real-world scenarios, particularly within the framework of online interviews. By equipping interviewers with tools for in-depth analysis of candidates, it offers a significant improvement in the quality and effectiveness of remote interviews. Additionally, it paves the way for future innovations in facial recognition.

1.2. Motivation for the project

The rapid growth of remote communication, particularly in areas like online interviews, virtual meetings, and remote learning, has highlighted the need for effective and reliable tools to enhance human interaction. Traditional online interviews lack the ability to provide critical non-verbal cues, such as facial expressions, emotional states, and real-time identity verification, which are crucial in assessing candidates' demeanor and engagement. This gap in communication has motivated the development of a sophisticated face detection and recognition system that enhances the interview process by offering real-time analysis of participants' facial features.

Furthermore, advancements in JavaScript and TensorFlow.js have made it feasible to build browser-based applications capable of performing complex facial recognition tasks without compromising user privacy. Leveraging these technologies not only offers a seamless user experience but also ensures real-time performance, making the system more practical for professional use. The motivation for this project stems from the desire to create a tool that brings both technological innovation and practical value to the interview and remote communication process, improving decision-making and enhancing user interaction in online settings.

1.3. Drawback of the existing system

The existing systems for online interviews and remote communication, while effective in connecting individuals, suffer from several key limitations. One of the primary drawbacks is the lack of real-time facial analysis, which limits interviewers' ability to gauge non-verbal cues such as emotions, facial expressions, and attentiveness. This reduces the depth of interaction and makes it difficult to assess a candidate's demeanor and personality, which are often important factors in hiring decisions. Moreover, current systems lack integrated solutions for age and gender estimation, as well as automatic identity verification, leading to potential issues in verifying the authenticity of participants.

Another major limitation is the reliance on centralized, resource-heavy systems that require external servers for processing facial recognition tasks, which can compromise both efficiency and user privacy. These systems often suffer from latency, especially in real-time applications, and do not provide an optimal user experience. Additionally, most existing facial recognition technologies are either costly or lack flexibility, especially in browser-based environments. This creates a gap in accessibility for smaller organizations and individuals looking for a lightweight, real-time solution that operates efficiently within the browser.

1.4. Problem Definition

With the growing prevalence of online interviews and virtual communication, there is a clear need for more advanced tools that can provide deeper insights into candidates and participants beyond just their verbal responses. Current online platforms lack the capability to analyze and interpret critical non-verbal cues such as facial expressions, emotions, and attentiveness, which are vital for making informed decisions during interviews. Additionally, there is no built-in mechanism to verify the identity of participants in real-time or assess characteristics such as age and gender, which can lead to potential security and authenticity issues.

Moreover, existing facial recognition systems are often resource-intensive, relying on powerful servers and external processing units, making them unsuitable for real-time, browser-based applications. This lack of efficiency and privacy, coupled with limited accessibility to smaller organizations and individuals, poses a significant challenge. The problem is further compounded by the absence of an integrated solution that combines face detection, recognition, expression analysis, age estimation, and gender identification in a single, lightweight system. Thus, there is a strong need for a browser-based, real-time face detection and recognition system that addresses these gaps, ensuring privacy, efficiency, and a seamless user experience for online interviews.

1.5 Relevance of the Project

This project is highly relevant in today's digital age, where online communication and remote work have become increasingly common across various sectors, including recruitment, education, and professional meetings. The shift towards virtual environments has created a need for tools that can replicate in-person interactions, especially for activities like interviews, where assessing a candidate's non-verbal communication—such as facial expressions, attentiveness, and emotional state—plays a critical role in decision-making. By providing real-time facial analysis, this project adds significant value to the interview process, enabling interviewers to make more informed judgments.

Additionally, with advancements in machine learning and JavaScript technologies like TensorFlow.js, there is growing demand for lightweight, browser-based applications that can perform complex tasks like face recognition, emotion detection, and age estimation without relying on external servers. This makes the project relevant not only for its practical applications in interviews but also for its contribution to the evolving landscape of web-based machine learning solutions. The project aligns with the increasing focus on privacy and efficiency, as it operates directly in the browser, ensuring both real-time performance and user data security, making it highly relevant to modern technological needs.

1.6 Methodology used

The development of the face detection and recognition system will follow a comprehensive methodology encompassing several key stages. Initially, the project setup and environment configuration will involve installing necessary tools and libraries such as Node.js and TensorFlow.js, along with configuring version control. Data collection and preparation will follow, involving the acquisition of a diverse dataset of facial images that are preprocessed and annotated for identity, landmarks, expressions, age, and gender. Model development will then take place, focusing on face detection, landmark detection, recognition, expression analysis, age estimation, and gender recognition, either by training new models or integrating pre-trained ones using TensorFlow.js. Integration and real-time processing will ensure the models work cohesively to analyze live video input with minimal latency. The user interface will be designed to be intuitive, allowing interviewers easy access to the system's features, such as live video feed and real-time analysis display. Extensive testing and evaluation will be conducted to measure the accuracy and reliability of each model using metrics like accuracy, precision, recall, F1 score, and Mean Absolute Error (MAE), alongside usability testing for the interface. Optimization efforts will focus on enhancing performance across various devices and platforms, leading to the final deployment on a web server or cloud platform. The project will be thoroughly documented, detailing the development process, usage guidelines, and technical specifics, while also identifying future enhancements to improve model accuracy, expand functionality, and explore new applications.

2 Literature Survey

2.1 Research Paper

1. Amara, K., Ramzan, N., Achour, N., Belhocine, M., Larbas, C. and Zenati, N., 2018, October. Emotion recognition via facial expressions. In *2018 IEEE/ACS 15th International Conference on Computer Systems and Applications (AICCSA)* (pp. 1-6). IEEE.

Abstract:

This paper explores the recognition of seven emotional states—neutral, joy, sadness, surprise, anger, fear, and disgust—based on facial expressions using 3D face models. The study involves six participants, and features are extracted using coefficients describing facial expression elements. These features, captured with Microsoft Kinect, are classified using the k-NN classifier and a Multi-Layer Perceptron (MLP) neural network. By applying the Facial Action Coding System (FACS), the research assesses the effectiveness of Action Units (AU) in distinguishing emotions. The experiments achieve high recognition accuracy, especially using the k-NN method, indicating the reliability of 3D face models for emotion recognition.

Inference:

The study confirms that 3D facial modeling provides a significant advantage in emotion recognition, overcoming the limitations of 2D methods in handling lighting conditions and head movements. The classification results demonstrate that the k-NN algorithm outperforms MLP in recognizing emotions, particularly in subject-independent tests. This suggests that simpler models like k-NN can effectively capture emotion-related features when dealing with smaller datasets. The research highlights the promise of using low-cost devices like Kinect for practical, real-time emotion detection applications, especially in human-computer interaction contexts.

2. Ozdemir, M.A., Elagoz, B., Alaybeyoglu, A., Sadighzadeh, R. and Akan, A., 2019, October. Real time emotion recognition from facial expressions using CNN architecture. In *2019 medical technologies congress (tiptekno)* (pp. 1-4). IEEE.

Abstract:

This paper introduces a Convolutional Neural Network (CNN) based on the LeNet architecture for real-time emotion recognition through facial expressions. The system combines datasets from JAFFE, KDEF, and a custom dataset to train the CNN model for seven emotion categories: happy, sad, surprised, angry, disgust, afraid, and neutral. With an achieved accuracy of 96.43% in training and 91.81% in validation, this method provides a low-cost solution for recognizing facial emotions in real-time. It utilizes the Haar Cascade for face detection and employs deep learning to ensure high classification accuracy in a variety of use cases.

Inference:

The study demonstrates the effectiveness of deep learning, particularly CNN architectures, in facial emotion recognition. The authors successfully merge multiple datasets and apply a CNN-based model to detect seven distinct emotional states with high accuracy. The real-time testing capability showcases the potential applications of this system in industries such as consumer behavior analysis, mental health diagnosis, and human-computer interaction. This work exemplifies how a well-optimized CNN can enhance facial emotion recognition accuracy, positioning it as a valuable tool for various real-time and practical applications.

3. **Zhou, S., Wu, X., Jiang, F., Huang, Q. and Huang, C., 2023. Emotion recognition from large-scale video clips with cross-attention and hybrid feature weighting neural networks. *International Journal of Environmental Research and Public Health*, *20*(2), p.1400.**

Abstract:

This paper introduces a novel approach to emotion recognition from large-scale video clips using a hybrid neural network model. It integrates face and context features via cross-attention mechanisms and hierarchical feature encoding to improve accuracy. The system captures complementary gains from both facial expressions and surrounding contexts, mitigating issues of emotion confusion. The model uses deep fusion to merge adaptive emotion features, significantly enhancing the classification of emotional states. Extensive experiments on the CAER-S dataset demonstrate the system's effectiveness in applications like mental health assessments and job stress analysis using video data.

Inference:

The research successfully addresses the challenge of emotion recognition by integrating face and context features, overcoming the limitations of existing models that rely solely on facial data. The cross-attention mechanism allows for better interaction between multiple data streams, leading to improved understanding of emotional states. The model's strong performance on large-scale datasets showcases its potential for real-world applications, such as assessing stress levels or tourist satisfaction from video clips. By focusing on hybrid feature weighting, the paper sets a precedent for further advancements in context-aware emotion recognition systems.

4. **Thushara, S. and Veni, S., 2016, March. A multimodal emotion recognition system from video. In *2016 International Conference on Circuit, Power and Computing Technologies (ICCPCT)* (pp. 1-5). IEEE.**

Abstract:

This paper presents a multimodal emotion recognition system that integrates facial and speech features to improve the recognition of human emotions. The system extracts geometric and appearance-based features from facial expressions and prosodic and spectral features from speech to detect six universal emotions: happy, sad, surprise, disgust, fear, and anger. Using a Support Vector Machine (SVM) classifier, the system processes facial and audio data separately and then fuses them for a more robust performance. This work demonstrates the potential of combining facial and acoustic modalities to enhance the accuracy of emotion recognition systems, achieving improved performance over unimodal approaches.

Inference:

This study highlights the advantages of combining facial and speech modalities for emotion recognition. While facial and speech features individually offer some level of accuracy, fusing them increases system performance and robustness. The authors' choice to use SVMs, due to their simplicity and flexibility, strengthens the classification process. Their results show that a multimodal approach can better recognize and classify emotions in real-time applications like healthcare, telecommunication, and robotics. This paper also emphasizes the potential of such systems in aiding humans with disabilities and contributing to fields like psychiatry and behavioral science.

5. **Zhou, S., Wu, X., Jiang, F., Huang, Q. and Huang, C., 2023. Emotion recognition from large-scale video clips with cross-attention and hybrid feature weighting neural networks. *International Journal of Environmental Research and Public Health*, *20*(2), p.1400.**

Abstract:

This paper presents an advanced method for emotion recognition from large-scale video clips by utilizing cross-attention and hybrid feature weighting neural networks (CAHFW-Net). The system integrates facial expressions with context information from video sequences to improve the accuracy of emotion detection. The approach employs dual-branch encoding to process facial and contextual features separately, followed by a cross-attention mechanism to capture their complementarity. Additionally, an adaptive-attention block assigns optimal fusion weights for deep feature integration, producing a more refined understanding of emotional states. Experimental validation on the CAER-S dataset demonstrates the model's superior performance in recognizing emotions for various applications, such as mental health assessments and stress level estimation.

Inference:

The study emphasizes the importance of contextual information in emotion recognition, showing that models relying solely on facial expressions may produce ambiguous results. By integrating face and context through a cross-attention mechanism, the model is able to rectify emotional misunderstandings and more accurately classify emotional states. The hierarchical structure of feature encoding and the use of adaptive weighting in feature fusion provide significant improvements in model performance. This approach has broad applications, particularly in fields like healthcare, where emotional insights can assist in mental health evaluation and stress monitoring through video-based analysis.

6. **Dagar, D., Hudait, A., Tripathy, H.K. and Das, M.N., 2016, May. Automatic emotion detection model from facial expression. In *2016 International Conference on Advanced Communication Control and Computing Technologies (ICACCCT)* (pp. 77-85). IEEE.**

Abstract:

This paper introduces an automatic framework for emotion recognition using facial expressions, emphasizing the challenge of subject-independent recognition in real-life scenarios. The system extracts facial attributes using Gabor feature extraction and principal component analysis (PCA) to determine expressions, employing a neural network for classification. Six fundamental emotions (happiness, sadness, anger, disgust, surprise, and fear) are recognized by analyzing facial muscles via the Facial Action Coding System (FACS). The model processes live-stream video frames, applies clustering for emotion detection, and classifies emotions through K-means clustering enhanced by PCA.

Inference:

The proposed model effectively captures and recognizes facial emotions using feature extraction and machine learning techniques. By utilizing Gabor filters for facial feature extraction and PCA for dimensionality reduction, the system achieves robust classification. However, the results indicate overlapping emotions for some expressions, suggesting that further refinement is needed to enhance accuracy. The model's reliance on clustering makes it suitable for real-time applications such as human-computer interaction, but improving the classifiers and expanding the training dataset could lead to better handling of complex emotional states.

7. **Siam, A.I., Soliman, N.F., Algarni, A.D., Abd El-Samie, F.E. and Sedik, A., 2022. Deploying machine learning techniques for human emotion detection. *Computational intelligence and neuroscience*, *2022*(1), p.8032673.**

Abstract:

This paper presents a real-time approach to human emotion detection using machine learning techniques. The methodology involves preprocessing images using MediaPipe for key point generation, followed by angular encoding of these key points to extract distinguishing features. A variety of machine learning models, including SVM, KNN, Naïve Bayes, Random Forest, and Multilayer Perceptron (MLP), are applied for emotion classification. The approach is evaluated on multiple datasets, such as CK+, JAFFE, and RAF-DB, achieving a high accuracy of 97%. The study is particularly useful for robotic vision applications, where real-time emotion recognition is crucial.

Inference:

This research showcases the effectiveness of combining facial landmarks and angular encoding for accurate emotion detection. The use of deep learning frameworks, such as MediaPipe for real-time landmark generation, and machine learning classifiers, like SVM and MLP, provides high recognition rates across diverse datasets. The system is versatile, handling different modalities in robotic vision applications. The successful integration of angular encoding with machine learning demonstrates the system's potential for applications requiring real-time emotional assessment, although further refinement could enhance performance in more varied and complex environments.

8. Joseph, A. and Geetha, P., 2020. Facial emotion detection using modified eyemap–mouthmap algorithm on an enhanced image and classification with tensorflow. *The Visual Computer*, *36*(3), pp.529-539.

Abstract:

This paper proposes a facial emotion detection system using a modified eyemap-mouthmap algorithm, enhanced with image preprocessing through discrete wavelet transform (DWT) and fuzzy logic. The system detects key facial features, such as eyes and mouth, and constructs facial geometry for emotion recognition. Classification is performed using TensorFlow's neural network framework, which evaluates emotions on multiple datasets, including KDEF, Oulu-CASIA, and CK+. The modified algorithm demonstrates improved detection accuracy compared to state-of-the-art methods, offering efficient identification of facial emotions.

Inference:

The research effectively integrates advanced image processing techniques, such as DWT and fuzzy logic, to enhance image quality and improve emotion detection accuracy. The modified eye map-mouthmap algorithm, combined with TensorFlow for classification, provides a significant improvement over traditional methods, particularly in identifying subtle emotions. The system's success across multiple datasets highlights its robustness and potential for real-world applications in fields like human-computer interaction. Further research could focus on optimizing processing times to make the system more suitable for real-time applications.

9. Jadhav, B., Sawant, A., Shah, A., Vemula, P., Waikar, A. and Yadav, S., 2024, March. A Comprehensive Study and Implementation of the Mock Interview Simulator with AI and Pose-Based Interaction. In *2024 1st International Conference on Cognitive, Green and Ubiquitous Computing (IC-CGU)* (pp. 01-05). IEEE.

Abstract:

The paper titled "A Comprehensive Study and Implementation of the Mock Interview Simulator with AI and Pose-Based Interaction" presents an innovative platform aimed at improving job seekers' interview skills. In an increasingly competitive job market, technical skills and soft skills are essential, and the ability to handle interviews effectively has become crucial. The Mock Interview Simulator developed in this project offers a transformative tool for job preparation. Utilizing AI-driven interviewers and real-time posture detection with the Mediapipe framework, it creates a dynamic and personalized interview environment. The simulator integrates speech recognition, text-to-speech, and OpenAI's GPT-3.5 Turbo API to deliver a realistic, interactive interview simulation. It provides valuable feedback on both verbal responses and body language, helping users improve their performance across multiple dimensions. This paper outlines the technical design and capabilities of the system, focusing on how AI and pose-based interaction contribute to an immersive interview preparation experience.

Inference:

The Mock Interview Simulator developed in this project represents a significant advancement in interview preparation technologies by incorporating both AI-driven feedback and posture analysis. This dual approach allows users to refine not only their verbal responses but also their non-verbal communication skills. By integrating real-time posture feedback, the simulator highlights the importance of physical presence during interviews, something often overlooked in traditional preparation methods. The system's use of GPT-3.5 Turbo for natural language processing and real-time feedback provides users with detailed insights into their performance, thereby enhancing their readiness for real-world interviews. The system's flexibility, modularity, and real-time interaction capabilities make it a valuable tool for individuals seeking to improve their interview skills, and it sets the stage for further enhancements such as the inclusion of virtual reality and personalized learning pathways.

10 Asha, P., Shabu, J., Refonaa, J. and Selvan, M.P., 2023, August. Automated Interview through Online Video Interface. In *2023 International Conference on Circuit Power and Computing Technologies (ICCPCT)* (pp. 1315-1321). IEEE.

Abstract:

This paper presents an Automated Video Interview Interface (AVII), a system leveraging AI, natural language processing, and machine learning to streamline the recruitment process. AVII automates candidate evaluation, using video conferencing to assess responses, facial expressions, and body language remotely. With features like pre-recorded questions, real-time scoring, and the ability to generate detailed performance reports, the system offers an efficient alternative to traditional interviews. The integration of facial recognition and natural language processing allows for a comprehensive evaluation of both technical and soft skills. This technology promises to enhance recruitment efficiency, reduce human bias, and provide personalized feedback for candidates.

Inference:

The AVII system addresses the growing need for efficient, unbiased, and scalable recruitment processes in today's job market. By automating the evaluation of candidates, it minimizes human involvement and potential bias, resulting in a fairer hiring process. The inclusion of real-time analysis of body language and facial expressions enhances the depth of candidate assessment. However, challenges such as technical issues and the loss of human interaction remain.

3.Requirement Of Proposed System

3.1 Functional Requirements

The proposed face detection and recognition system for online interviews includes several key functional requirements that ensure its effectiveness and usability in real-time scenarios. These requirements focus on the core functionalities necessary to provide accurate, efficient, and seamless facial analysis.

1. **Face Detection:**

○ The system must be able to detect multiple faces in real-time from the video input provided by the user's camera.

○ It should outline detected faces with bounding boxes and identify facial landmarks like eyes, nose, and mouth.

2. **Face Recognition:**

○ The system should accurately identify individuals by comparing their faces to a pre-registered database.

○ It must allow users (e.g., interviewers) to upload and maintain a database of known individuals for identity verification.

3. **Face Landmark Detection:**

○ The system must detect key facial landmarks to assist in facial expression analysis and to improve recognition accuracy.

○ These landmarks should be detected consistently even in varying lighting conditions and angles.

4. **Face Expression Recognition:**

○ The system must analyze facial expressions in real-time, classifying emotions such as happiness, sadness, anger, or neutrality.

○ Results should be displayed instantly, allowing interviewers to monitor emotional responses during interviews.

5. **Age Estimation and Gender Recognition:**

○ The system should estimate the age and determine the gender of the detected faces.

○ Age and gender labels should be displayed with the other analysis results in real-time.

6. **Real-time Processing:**

○ The system must process all tasks (face detection, recognition, landmark detection, expression recognition, age estimation, and gender recognition) in real-time with minimal latency.

○ It should work seamlessly in the browser, without the need for server-side processing, to ensure user privacy and responsiveness.

7. **User Interface:**

○ The system must provide an intuitive interface that displays the video feed, detected faces, and real-time analysis results such as identity, emotion, age, and gender.

○ The interface should allow interviewers to interact with the system easily, without requiring technical expertise.

8. **Database Management:**

○ The system must allow the interviewer to manage a database of known individuals, including adding new faces and updating existing entries for face recognition purposes.

3.2. Non-Functional Requirements

- **Performance:**

  The system should offer real-time processing with minimal latency and handle multiple faces without degrading performance. It must maintain accuracy across varying conditions.

- **Scalability:**

  The system must efficiently handle an increasing number of faces in the recognition database. It should work smoothly across devices, including desktops and mobile phones.

- **Usability:**

  The interface should be intuitive, allowing non-technical users to operate it easily. Results should be clear and easy to interpret.

- **Reliability:**

  The system must run without frequent crashes and continue processing even under poor network conditions. Reliability is key for uninterrupted online interviews.

- **Security and Privacy:**

  User data should be processed locally to ensure privacy, with encrypted databases for sensitive information. Compliance with data protection regulations is essential.

- **Portability:**

  The system should function across multiple platforms, browsers, and devices. It must be accessible on both desktop and mobile environments.

- **Maintainability:**

  A modular design ensures easy updates or bug fixes, with clear documentation for future maintenance. This keeps the system adaptable and flexible for improvements.

- **Extensibility:**
  The system should allow the addition of new features, such as improved algorithms or security updates. Scalability should not require major system changes.

3.3. Constraints

- **Real-time Processing:**
  The system must process face detection, recognition, and other tasks in real-time, which can be challenging on devices with limited computational power.
- **Browser Compatibility:**
  The system should be compatible with multiple browsers, but varying browser performance and support for machine learning libraries like TensorFlow.js may limit functionality.
- **Device Performance:**
  The system's performance may vary across devices, with older or less powerful devices potentially facing slower processing times or reduced accuracy.
- **Network Dependency:**
  While most processing happens in the browser, certain functionalities like face recognition database access might require stable internet connectivity.
- **Lighting and Environmental Conditions:**
  The accuracy of face detection and recognition could be affected by poor lighting, low-resolution cameras, or dynamic environments.
- **Privacy Regulations:**
  The system must comply with privacy laws, such as GDPR, which may restrict data usage, especially when storing and processing facial data.
- **Model Size and Optimization:**
  The use of lightweight models is necessary to ensure smooth operation in the browser, which may limit the complexity and accuracy of some tasks.

3.4. Hardware & Software Requirements

- **Hardware requirements**

○ **Development Machine**:

- **CPU**: A modern dual-core processor, such as Intel i3 or AMD Ryzen 3, to handle development tasks.
- **RAM**: At least 4 GB of RAM, with 8 GB recommended for smoother performance.
- **GPU**: Integrated graphics or a basic dedicated GPU (e.g., NVIDIA GTX 1050 or AMD equivalent) should suffice.
- **Storage**: Solid State Drive (SSD) with a minimum of 128 GB of storage space, 256 GB recommended for accommodating development tools and libraries.

- ○ **Webcam**:
  - A high-quality webcam is necessary if you intend to test and deploy real-time face detection and recognition applications.
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- **Software Requirements :**
- ○ **Operating System**:
  - Compatible with Windows 10/11, macOS, or a modern Linux distribution such as Ubuntu or Fedora.
- ○ **Node.js**:
  - Node.js version 10 or higher for server-side development and running JavaScript code outside the browser.
- ○ **Package Manager**:
  - npm (comes bundled with Node.js) or yarn for managing project dependencies.
- ○ **Code Editor/Integrated Development Environment (IDE)**:
  - Modern code editors like Visual Studio Code or WebStorm, which offer extensive support for JavaScript and TypeScript development.

3.5. Techniques utilized till date for the proposed system

- **K-Nearest Neighbor (K-NN)**: For face recognition using RGB-D data.
- **Image Preprocessing**: Resizing, normalization for dataset preparation.
- **Convolutional Neural Networks (CNN)**: For feature extraction and real-time testing.
- **Multi-Layer Perceptron (MLP)**: Paired with random and natural data division strategies.
- **Fuzzy C-Means (FCM) Clustering**: For facial classification.
- **Attention Mechanisms**: Cross-Attention (CA), Element Recalibration (ER), Adaptive-Attention (AA) Blocks.
- **Viola-Jones Algorithm**: Paired with Cascade Classifiers for face detection.
- **Support Vector Machines (SVM)**: Nonlinear SVM with Polynomial/RBF kernels for classification.
- **Support Vector Regression (SVR)**: Used for age estimation.

3.6. Tools utilized till date for the proposed system

- **TensorFlow.js**: For real-time deep learning in the browser.
- **Node.js**: Server-side handling of camera input and processing.
- **TensorFlow/Keras**: For training CNNs, MLPs, and SVM models.
- **OpenCV**: For implementing traditional methods like Viola-Jones and Gabor Filters.
- **Python Libraries**: NumPy, Pandas for data preprocessing, and scikit-learn for machine learning models.

3.7. Project Proposal

This project aims to develop a real-time face detection and recognition system tailored for use in online interviews. Utilizing **TensorFlow.js** and **Node.js**, the system will process live video feeds from the user's camera to analyze and interpret facial features in real time. The core functionalities include **face recognition**, which compares the detected face with stored data, **facial landmark detection** to pinpoint key features (e.g., eyes, mouth), **facial expression recognition** to gauge emotions, and **age estimation** and **gender recognition** to provide additional context.

The proposed system will be designed for scalability, ensuring compatibility across different devices and browsers, and optimized for low-latency performance, making it ideal for professional interview environments. This project will address common challenges like accuracy, speed, and resource efficiency by leveraging advanced machine learning models, with potential applications extending beyond interviews into areas such as security and remote monitoring. The system will also include an intuitive user interface for ease of use by interviewers, offering real-time insights into candidate profiles.

4.Proposed Design

4.1 Block diagram representation of the proposed system

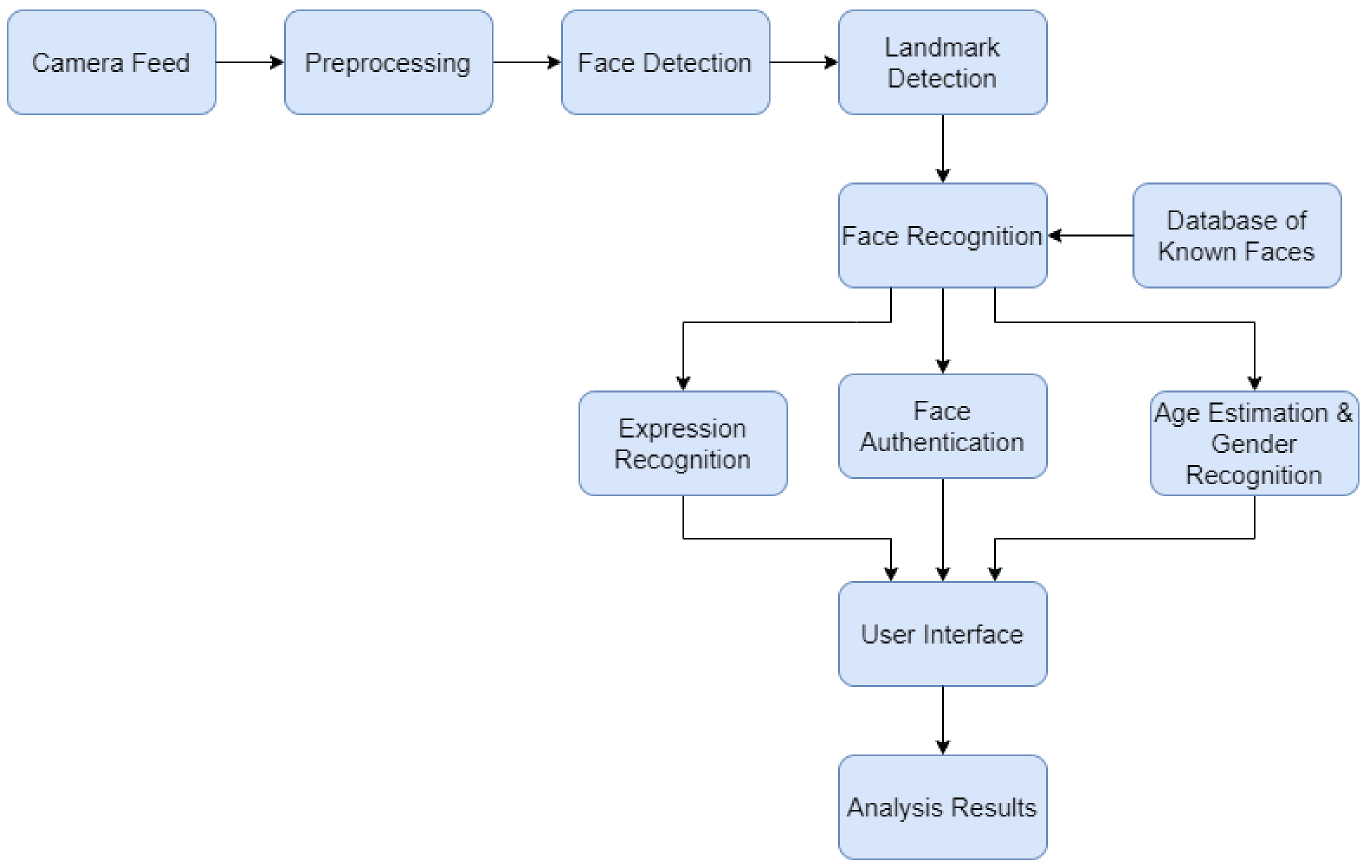

Fig 4.1 Block diagram

Explanation for the block diagram :

The block diagram represents a facial analysis system that processes a live camera feed to extract various information from faces, including facial recognition, expression analysis, and demographic estimation. Here's a detailed breakdown of each component:

1. Camera Feed

- This is the system's input, where a camera captures live video or images of people's faces. The captured data is then passed to the preprocessing stage for further analysis.

2. Preprocessing

- Before face analysis, raw images from the camera need to be cleaned and prepared. Preprocessing involves steps like image scaling, noise reduction, color normalization, and adjusting lighting conditions. This ensures the image is in the best possible form for accurate detection.

3. Face Detection

- After preprocessing, the system identifies the regions in the image that contain faces. Various algorithms, such as Haar cascades, HOG (Histogram of Oriented Gradients), or deep learning methods, can be used to detect faces in real-time.

4. Landmark Detection

- Once a face is detected, the system detects specific facial landmarks like the eyes, nose, and mouth. These key points are used to align the face properly and serve as input for the next stages. This step ensures the system can handle different face orientations and expressions.

5. Face Recognition

- In this stage, the system compares the detected face with a **Database of Known Faces** to recognize and identify individuals. Face recognition involves extracting unique features of the face and matching them against stored face templates in the database. This helps in identifying known individuals.

6. Expression Recognition

- Here, the system analyzes facial features to detect emotions or expressions such as happiness, sadness, anger, or surprise. By interpreting the position and movement of facial muscles, the system can infer a person's emotional state.

7. Face Authentication

- Face authentication verifies whether the detected face matches a specific person’s stored template in the database (if available). This can be used for security and access control purposes. The system confirms if the individual is who they claim to be.

8. Age Estimation & Gender Recognition

- This component estimates the approximate **age** of the person and determines their **gender**. Age and gender recognition algorithms analyze facial features like skin texture, facial structure, and other demographic indicators to provide these insights.

9. User Interface

- The **User Interface (UI)** is where the results are displayed. This interface allows users to interact with the system and view the analyzed data, such as recognized faces, detected emotions, estimated age, and gender. It also serves as the control point for managing and viewing the system's functionality.

10. Analysis Results

- The final output includes all the gathered information, such as facial recognition results, emotion detection, age and gender, and authentication outcomes. This data can be used for various applications like security, marketing, behavioral analysis, or access control.

Overall Flow:

- The system starts by capturing a live video feed from a camera, preprocesses the image, and detects faces.
- Detected faces go through various stages, such as landmark detection, face recognition, and emotion analysis.
- If required, face authentication and demographic analysis (age and gender) are also performed.
- The user interface displays all the results to the end-user in real-time for further decision-making or action.

4.2. Modular diagram representation of the proposed system

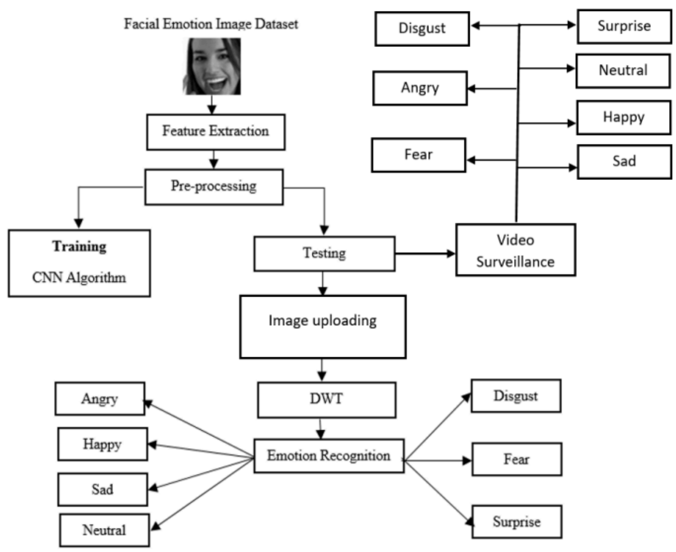

Fig 4.2 Modular Diagram

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Explanation for the modular block diagram:

This diagram represents a facial emotion recognition system workflow, which can be broken down as follows:

1. Input: Facial Emotion Image Dataset

- The system begins with a dataset that contains images of faces expressing various emotions.

2. Feature Extraction

- Important features from the facial images (like edges, corners, or specific facial characteristics) are extracted to represent the data in a way the system can understand.

3. Pre-processing

- The extracted features are pre-processed, possibly involving normalization, resizing, or data augmentation, to prepare them for further analysis.

4. Training (CNN Algorithm)

- A Convolutional Neural Network (CNN) algorithm is used to train the system on the pre-processed features to classify emotions. CNNs are widely used in image classification tasks as they are effective at recognizing patterns in visual data.

5. Testing

- After training, the system is tested with new images to evaluate its performance. This includes:
  - Image Uploading: A new image is uploaded for testing.
  - DWT (Discrete Wavelet Transform): DWT is applied to further analyze the image by transforming it into different frequency components, which can enhance recognition of patterns.
  - Emotion Recognition: The system recognizes the emotions in the uploaded image.

6. Emotion Categories

- Emotions recognized by the system include:
  - Angry
  - Happy
  - Sad
  - Neutral
  - Disgust
  - Fear
  - Surprise

7. Video Surveillance

- The system also has a video surveillance component, where real-time video feeds are processed for emotion recognition. Emotions like disgust, angry, fear, surprise, neutral, happy, and sad can be detected during surveillance.

Output: Emotion Recognition

- The system outputs the recognized emotion from the image or video input, identifying one or more of the listed emotions.

The diagram represents the overall flow from data preparation to emotion detection and recognition using CNN and DWT in a facial analysis system.

4.3 Design of the proposed system with proper explanation of each

a. Data Flow Diagrams

DFD(Level 2)

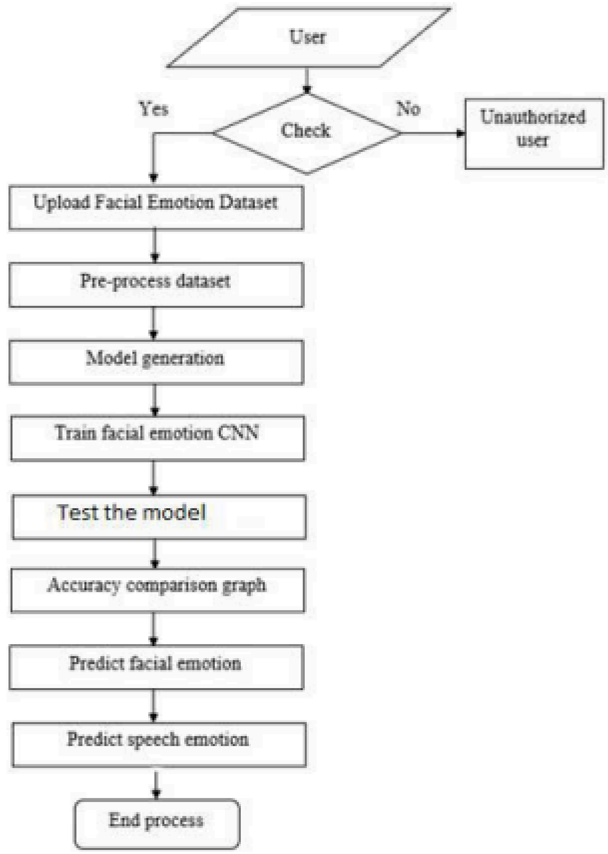

Fig 4.3.i Data Flow Diagram

The given Data Flow Diagram (DFD) illustrates the process of facial and speech emotion recognition. It begins with user authentication, where the system checks if the user is authorized. If not, access is denied. For authorized users, the process involves uploading a facial emotion dataset, pre-processing it, generating a model, training a Convolutional Neural Network (CNN) on the dataset, testing the model's accuracy, and comparing it graphically. The system then predicts facial emotions and speech emotions using the trained model. Finally, the process concludes with the end of the prediction phase.

This DFD provides a clear visual representation of the system's workflow, highlighting the key steps involved in facial and speech emotion recognition. It helps in understanding the sequence of operations, the data flow, and the overall functionality of the system.

b. Flowchart for the proposed system

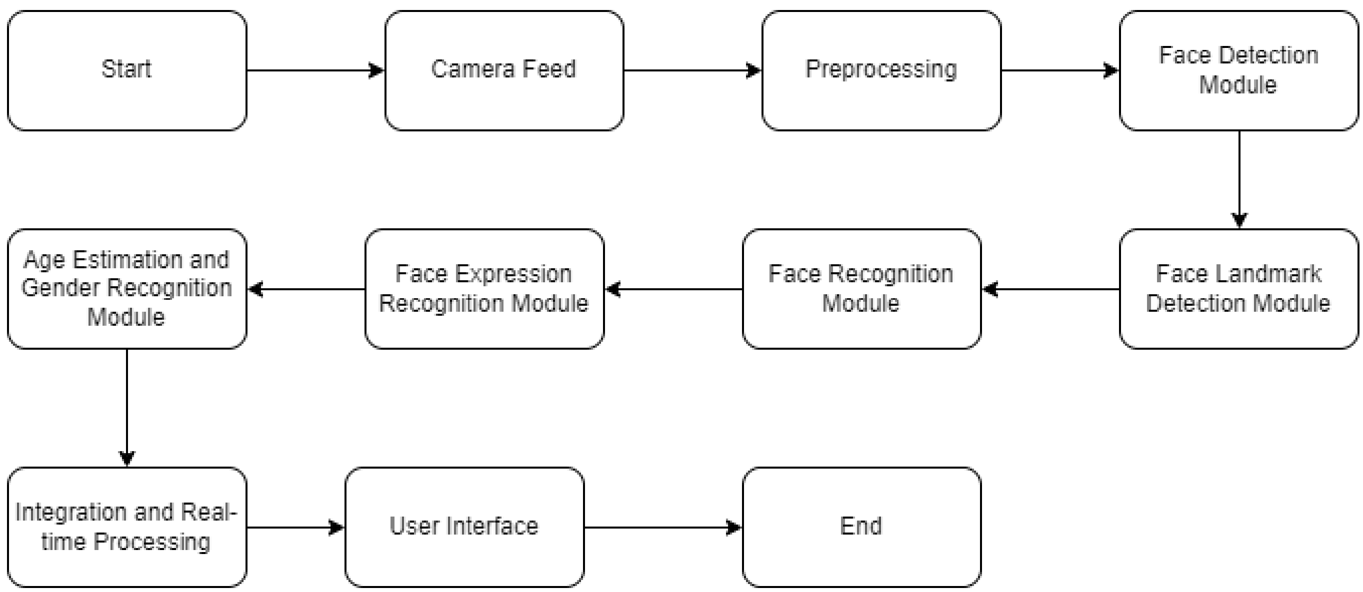

Fig 4.3.ii Flowchart

This flowchart outlines the step-by-step process of a face detection and recognition system designed for real-time online interviews. It begins with live video input from the camera (Step 2), which undergoes preprocessing (Step 3) to extract and normalize frames. The system then detects faces (Step 4) and identifies facial landmarks like eyes and nose (Step 5). Detected faces are compared with a known face database for recognition (Step 6). The system analyzes facial expressions (Step 7) and estimates age and gender (Step 8). All results are integrated in real-time (Step 9) and displayed via a user-friendly interface (Step 10), providing immediate feedback on identity, expressions, age, and gender. Finally, the system outputs the complete analysis (Step 11).

c.Activity Diagram

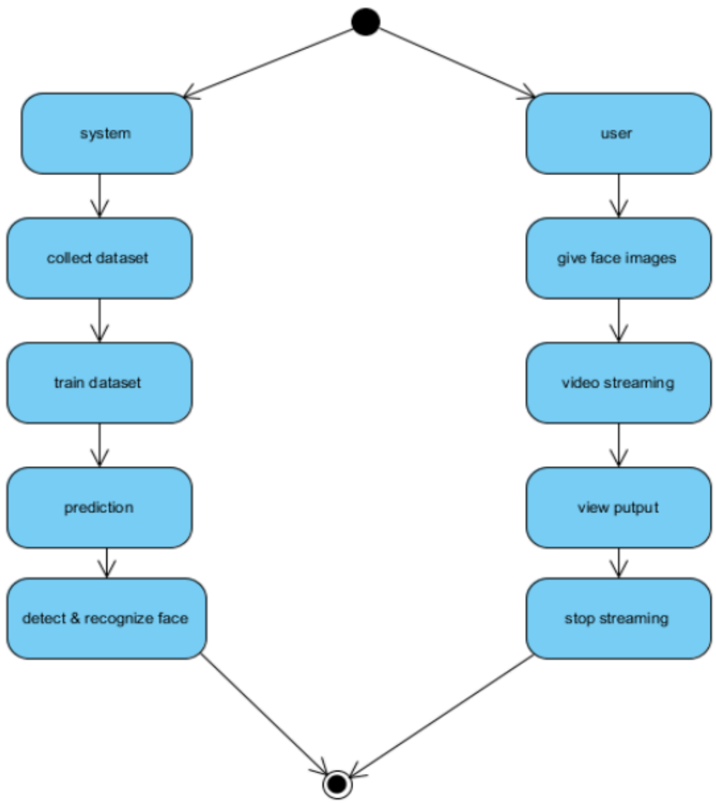

Fig 4.3.iii Activity Diagram

This diagram represents the interaction between the system and the user in a face detection and recognition process. On the system side, it begins by collecting a dataset, which is then used to train a machine learning model for face detection and recognition. Once the model is trained, it makes predictions by detecting and recognizing faces from new input data, such as images or video streams.

From the user's perspective, the process starts with providing face images to the system. The user initiates video streaming, allowing the system to analyze the video feed in real-time. The user then views the output, such as the identified or recognized faces, and can stop streaming once the process is complete. The diagram effectively illustrates the back-and-forth interaction needed for successful face detection and recognition in real-time applications.

d. Screenshot of implementation

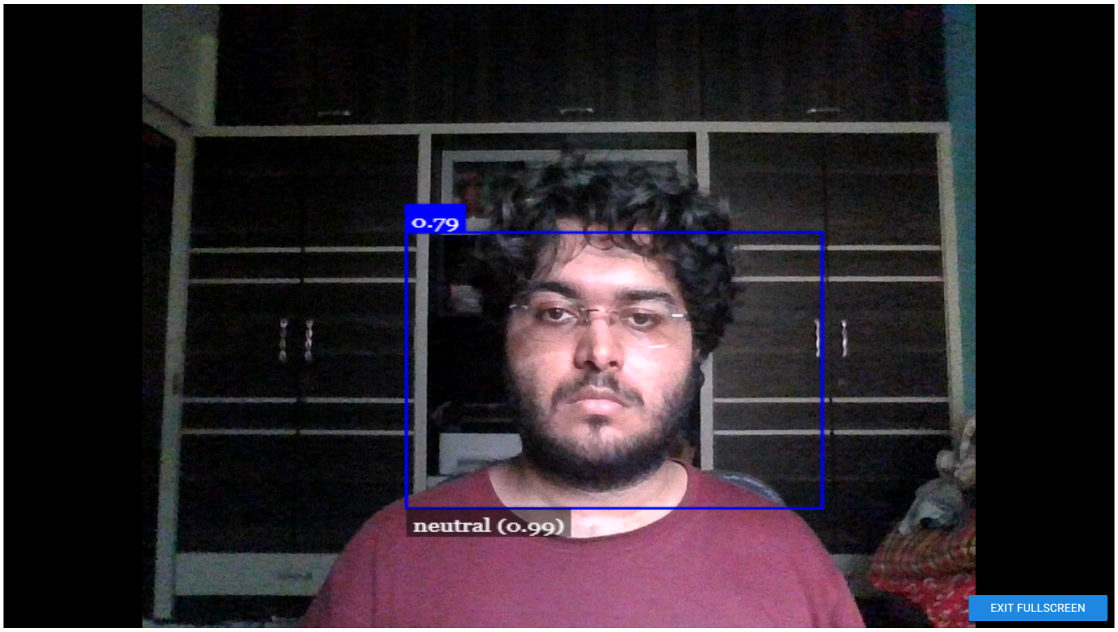

Fig 4.3.iv.a Face Emotion Recognition Fullscreen

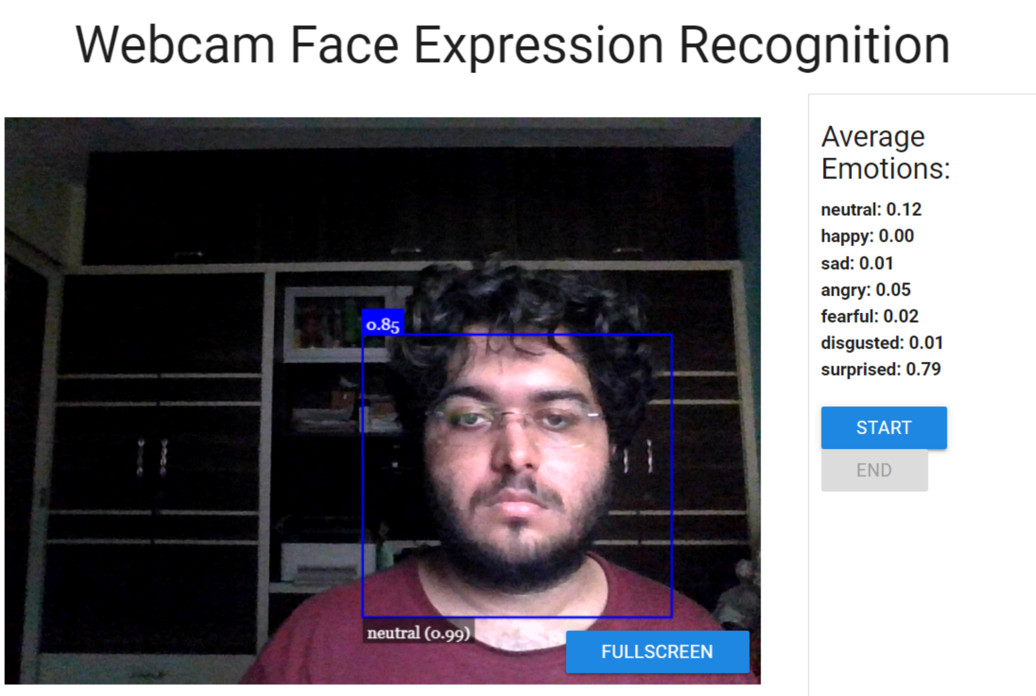

Fig 4.3.iv.b Face Emotion Recognition with average emotions

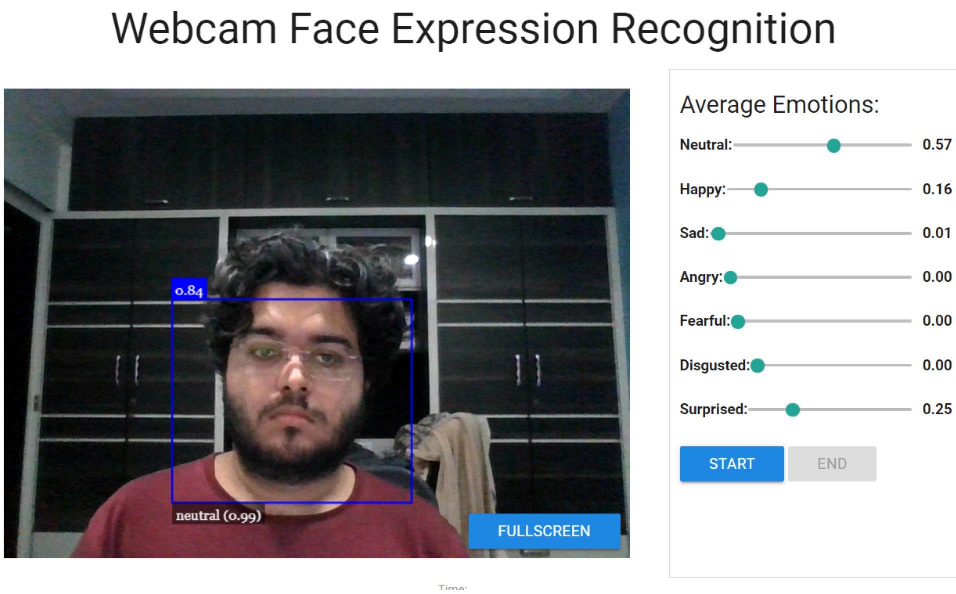

Fig 4.3.iv.c Face Emotion Recognition with average emotion sliders

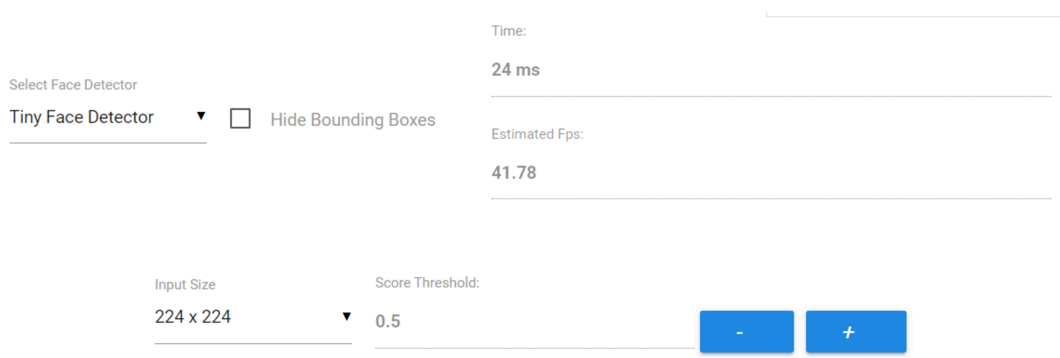

Fig 4.3.iv.d Display Output Information

4.3 Algorithms utilized in the existing systems

For your facial emotion recognition project, here are some algorithms that could be utilized based on common approaches in existing systems for facial analysis and recognition:

1. Convolutional Neural Networks (CNNs):

- CNNs are widely used for image-based tasks due to their ability to capture spatial hierarchies in data. For facial emotion recognition, CNNs can automatically extract relevant features such as expressions, facial movements, and landmarks from input images.
- **Usage in Emotion Recognition**: CNNs can be trained on facial emotion datasets (e.g., FER2013) to classify emotions like happiness, sadness, anger, and surprise by learning from facial images.

2. Transfer Learning:

- Transfer learning involves using pre-trained models like **VGGFace** or **ResNet**, which have been trained on large image datasets, and fine-tuning them for facial emotion recognition.
- **Usage in Emotion Recognition**: By leveraging pre-trained models, you can reduce the training time and improve performance for emotion detection tasks, especially when limited labeled data is available.

3. Support Vector Machines (SVM):

- SVMs are effective for classification tasks, particularly in high-dimensional spaces. They can be used in combination with facial feature extraction techniques (e.g., using CNN features).
- **Usage in Emotion Recognition**: After extracting features from facial images using CNNs, an SVM can be applied to classify emotions based on these features.

4. Long Short-Term Memory (LSTM) Networks:

- LSTM networks are a type of recurrent neural network (RNN) designed to model sequences and time-dependent data.
- **Usage in Emotion Recognition**: LSTMs can be used in scenarios where emotions evolve over time, such as video-based facial emotion recognition. By analyzing sequential frames from a video, LSTMs can capture the temporal dynamics of facial expressions.

5. Random Forest:

- Random Forest, an ensemble learning method, can also be used for emotion recognition by classifying extracted facial features into different emotion categories.
- **Usage in Emotion Recognition**: Random Forest is effective in handling datasets with multiple features (like facial landmarks and pixel intensities), offering high accuracy and interpretability.

6. K-Nearest Neighbors (KNN):

- KNN is a simple yet effective algorithm that classifies based on the closest feature vectors in the feature space.
- **Usage in Emotion Recognition**: KNN can be used for emotion classification by comparing extracted facial features from test images with the features of training images.

4.4 Project Scheduling & Tracking using Timeline / Gantt Chart

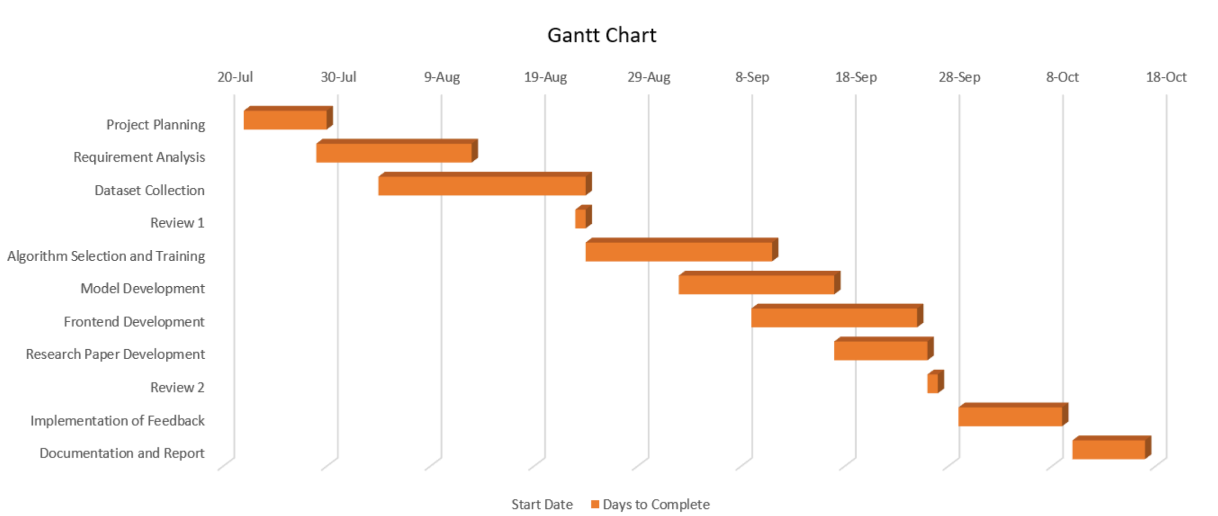

Fig 4.4 Gantt Chart

This chart outlines the timeline and key milestones of the project, illustrating task durations and dependencies for effective project management.

5 Proposed Results and Discussions

Determination of Efficiency

The efficiency of the Emotion Recognition system will be evaluated based on its processing speed and resource utilization. We will measure the time taken to analyze user-reported emotions from video input and generate predictions, aiming for results within a few seconds to ensure an optimal user experience. The system's ability to handle multiple concurrent users will also be assessed to ensure scalability and responsiveness.

Determination of Accuracy

To evaluate the accuracy of the emotion recognition model, we will analyze the performance metrics outlined in the evaluation measures. The accuracy will be calculated using the formula:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

where: **TP** = True Positives **TN** = True Negatives **FP** = False Positives **FN** = False Negatives

To evaluate the accuracy of the facial expression recognition model, we will analyze the performance metrics outlined in the evaluation measures. The accuracy of the facial expression recognition model is expected to range between **70-90%**, depending on the conditions of the input data. The face detection models, including the **Tiny Face Detector** and **SSD Mobilenet V1**, typically achieve a Mean Average Precision (mAP) of around **70-90%** on standard benchmarks. Regular updates and refinements of the machine learning model, using user feedback and the latest emotional recognition data, will further enhance accuracy.

Reports on Sensitivity Analysis

Sensitivity analysis will be conducted to understand how changes in user inputs (e.g., facial expressions, emotional context, and environmental factors) affect the model's predictions. This analysis will help identify which emotions and contextual factors have the most significant impact on the model's outputs. The results will guide further refinements to the model, ensuring that it remains robust and reliable in various scenarios.

6.Plan Of Action For the Next Semester

6.1 Work Done till Date

So far, significant progress has been made on the EmoScan project. We have successfully applied different machine learning models to detect face emotion based on user face input. After evaluating the accuracy of each model, we selected the one with the highest performance for our predictions. Additionally, we conducted a correlation matrix visualization to better understand the relationships between various features in our dataset.

Training of the selected model has been completed, furthermore, the frontend of the application has been developed, allowing for an intuitive user experience. The next steps involve integrating this frontend with the backend systems to create a cohesive platform. We are also in the process of building a comprehensive model for the mock interview process.

6.2 Plan of Action for Project II

Plan of Action for the Upcoming Semester

Integration of Audio Data:

Integrate audio data processing capabilities to enhance emotion recognition accuracy and provide a more comprehensive analysis of user responses during mock interviews. This will include implementing speech recognition to capture vocal tone and sentiment.

Video Calling Feature:

Develop and integrate a video calling functionality to allow users to conduct mock interviews in real-time. This feature will facilitate a more interactive experience, enabling users to practice interviews in a simulated environment.

Expansion of Recognition Models:

Explore additional machine learning models and techniques to improve the accuracy of both visual and audio emotion recognition. This may involve implementing deep learning architectures and ensemble methods that leverage both video and audio data for better predictive performance.

User Testing and Feedback:

Conduct user testing sessions to gather feedback on the application's usability and effectiveness, specifically focusing on the audio and video features. This will help identify areas for improvement and enhance user satisfaction.

Performance Optimization:

Focus on optimizing the overall system performance, including reducing response times for audio and video processing. Ensure that the application can handle multiple users simultaneously without issues during live mock interviews.

Documentation and Reporting:

Maintain comprehensive documentation of the project's development process and prepare reports detailing findings, challenges, and solutions, particularly regarding the integration of audio data and video calling features.

7.Conclusion

In conclusion, this project aims to address the limitations of traditional online interview methods by developing a sophisticated face detection and recognition system using JavaScript and TensorFlow.js. By integrating advanced features such as face recognition, landmark detection, expression analysis, age estimation, and gender recognition, the system aspires to enhance the effectiveness, security, and depth of remote interviews. Real-time processing within the browser ensures efficiency and privacy, while a user-friendly interface facilitates ease of use for interviewers. The proposed solution represents a significant advancement in web-based facial analysis technologies, offering a comprehensive tool to improve the accuracy and reliability of virtual interviews. Through rigorous evaluation measures, the project will ensure that the system meets high standards of performance and user satisfaction. Ultimately, this project aims to contribute to the evolving field of facial recognition technology, demonstrating its potential applications in various domains and setting the stage for future innovations in remote interaction and analysis.

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9.Appendix

9.1 List of Figures

9.2 Review Sheet

Industry / Inhouse:
Research / Innovation: **Project Evaluation Sheet 2024-25** **Class: D17A/B/C** D17

(28)

Title of Project (Group no): Group no: 28 EmoScan: Facial Real-Time Facial Analysis for Online Interviews

Mentor Name & Group Members: Bhavika Valecha, (D17C,69) Kunal Khubchandani (D17C,37), Dipti Hemnani (D17C,23), Raj Tandon (D17C,62)

	Engineering Concepts & Knowledge	Interpretation of Problem & Analysis	Design / Prototype	Interpretation of Data & Dataset	Modern Tool Usage	Societal Benefit, Safety Consideration	Environment Friendly	Ethics	Team work	Presentation Skills	Applied Engg & Mgmt principles	Life - long learning	Professional Skills	Innovative Approach	Total Marks
	(5)	(5)	(5)	(3)	(5)	(2)	(2)	(2)	(2)	(3)	(3)	(3)	(5)	(5)	(50)
Review of Project Stage 1	4	3	4	3	4	2	2	2	2	2	2	3	3	3	39

Comments: Define proper objectives.

Name & Signature Reviewer1

	Engineering Concepts & Knowledge	Interpretation of Problem & Analysis	Design / Prototype	Interpretation of Data & Dataset	Modern Tool Usage	Societal Benefit, Safety Consideration	Environment Friendly	Ethics	Team work	Presentation Skills	Applied Engg & Mgmt principles	Life - long learning	Professional Skills	Innovative Approach	Total Marks
	(5)	(5)	(5)	(3)	(5)	(2)	(2)	(2)	(2)	(3)	(3)	(3)	(5)	(5)	(50)
Review of Project Stage 1	04	03	03	03	04	02	02	02	02	02	02	03	03	03	38

Comments: Objective can be refined.

Date: 23/08/2024

Name & Signature Reviewer2
Pallavi Saindane

(28)

Industry/Inhouse: **Project Evaluation Sheet 2024-25** **Class: D17 C**

Title of Project(Group no): EmoScan: Real Time facial Analysis for Online Interviews (Group No. 28)

Group Members: Bhavika Valecha (D17C, 69), Dipti Hemanani (D17C, 23), Kunal Khubchandani (D17C, 37), Raj Tandon (D17C, 62)

	Engineering Concepts & Knowledge	Interpretation of Problem & Analysis	Design / Prototype	Interpretation of Data & Dataset	Modern Tool Usage	Societal Benefit, Safety Consideration	Environment Friendly	Ethics	Team work	Presentation Skills	Applied Engg &Mgmt principles	Life - long learning	Professional Skills	Innovative Approach	Total Marks
	(5)	(5)	(5)	(3)	(5)	(2)	(2)	(2)	(2)	(3)	(3)	(3)	(5)	(5)	(50)
Review of Project Stage 1	4	4	3	2	3	2	2	2	2	2	2	2	4	4	38

Comments: 1. Use diverse dataset.

Name & Signature Reviewer1
Pallavi S.

	Engineering Concepts & Knowledge	Interpretation of Problem & Analysis	Design / Prototype	Interpretation of Data & Dataset	Modern Tool Usage	Societal Benefit, Safety Consideration	Environment Friendly	Ethics	Team work	Presentation Skills	Applied Engg &Mgmt principles	Life - long learning	Professional Skills	Innovative Approach	Total Marks
	(5)	(5)	(5)	(3)	(5)	(2)	(2)	(2)	(2)	(3)	(3)	(3)	(5)	(5)	(50)
Review of Project Stage 1	4	4	3	2	3	2	2	2	2	2	2	2	4	4	38

Comments: Work on two more different dataset for image based model.

Date: 26th September, 2024

Name & Signature Reviewer2