A

Project Report on

ANALYSIS OF FACIAL EXPRESSIONS TO ESTIMATE THE LEVEL OF ENGAGEMENT IN ONLINE LECTURES

Submitted in partial fulfilment of the requirements
For the award of the degree of

BACHELOR OF TECHNOLOGY
In
COMPUTER SCIENCE AND ENGINEERING

Submitted by

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COMPUTER SCIENCE AND ENGINEERING

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CERTIFICATE

Certified that this is a bonafide record of the Project Report entitled, ***"Analysis of facial expressions to estimate the level of engagement in online lectures",*** *done by A Sravani (19AK1A05G3), O Siva Krishna (21AK5A0526), N Sulaiman (20AK1A05E3), R Venkata Vinay Kumar (19AK1A05I3) is being submitted in partial fulfilment of the requirements for the award of the degree of* ***BACHELOR OF TECHNOLOGY*** *in* ***COMPUTER SCIENCE AND ENGINEERING*** *to the Annamacharya Institute of technology and Sciences, Tirupati, during the academic year 2023-24.*

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COMPUTER SCIENCE AND ENGINEERING

DECLARATION

We hereby declare that the project titled **"Analysis of Facial Expressions to Estimate the Level of Engagement in Online Classes"** is a genuine project work carried out by us, in B.Tech (Computer Science and Engineering) course in Annamacharya Institute of Technology And Sciences and has not been submitted to any other course or university for the award of our degree by us.

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ABSTRACT

The present study aimed to develop a method for estimating students' attentional state from facialexpressions during online lectures. Student engagement is a critical factor influencing academic success and overall learning outcomes. This research explores the application of Recurrent NeuralNetworks (RNNs) to predict student engagement in educational settings. We assumed that reaction time to such a stimulus would be longer when participants were focusing on the lecture compared with when they were not. In the experiment, the learner's face was recorded by a video camera while watching a video lecture.

The proposed RNN (Recurrent Neural Network) model is like a smart system. It watches how students interact with their learning stuff, like clicking, reading, or answering questions. This smart system looks at these actions one after another, in a sequence, to understand how students are involved. It then uses this understanding to predict and measure how much students are engaged in their learning activities automatically. So, it helps figure out if students are really into their online learning or not.

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LIST OF ABBRERVIATIONS

Short Form	Abbreviation
DL	Deep Learning
RNN	Recurrent Neural Networks
LSTM	Long Short-Term Memory
LR	Linear Regression
URL	Uniform Resource Locator

1. INTRODUCTION

1.1 INTRODUCTION

Deep learning, a subset of machine learning, involves training artificial neural networks to recognize and comprehend complex patterns in data. Deep learning is a smart technology used to analyze a lot of data and find complex patterns. In this case, it helps understand how students are involved in their studies. This project centers on predicting students' engagement,and it uses a specific smart technology called Recurrent Neural Networks (RNNs).RNNs are good at understanding patterns in sequences, which is essential for predicting changes in student engagement over different learning activities. Integration with educational technologies, such as learning management systems, online platforms, and digital content, provides the data necessary for deep learning models to make predictions about student engagement.

In the contemporary landscape of remote education, understanding student engagement in online lectures is pivotal for optimizing learning outcomes. As traditional classroom settings transition to virtual platforms, educators face the challenge of gauging student involvement and receptiveness accurately. Recognizing the significance of facial expressions as a non-verbal indicator of engagement, this documentation explores the feasibility of leveraging facial analysis techniques to estimate the level of engagement exhibited by students during online lectures.

Context and Significance

Online education has witnessed unprecedented growth, catalyzed further by global events necessitating remote learning solutions. While virtual platforms offer flexibility and accessibility, they also introduce unique hurdles, notably the absence of physical presence and direct interaction. In traditional classrooms, educators rely on visual cues such as facial expressions, body language, and eye contact to gauge student engagement. However, replicating this dynamic in virtual environments poses challenges due to technological constraints and limited visibility.

Understanding the level of engagement is fundamental for educators to tailor instructional approaches, identify areas of improvement, and enhance student participation. Existing methods of assessing engagement in online lectures primarily rely on self-reporting surveys, behavioral analytics, or interaction metrics derived from chat logs and participation rates.

While informative, these approaches offer limited insights into the nuanced emotional and cognitive states of students.

Facial expressions serve as potent indicators of emotional states, attention, and comprehension, offering valuable insights into the efficacy of instructional delivery. By analyzing facial cues such as smiles, frowns, eyebrow movements, and gaze patterns, it becomes possible to infer the level of interest, attentiveness, and comprehension exhibited by students during online lectures.

Objective and Scope

The primary objective of this documentation is to explore the feasibility and efficacy of employing facial expression analysis techniques to estimate the level of engagement in online lectures. This entails:

Reviewing existing literature and research methodologies pertaining to facial expression analysis and engagement assessment in educational contexts.

Identifying relevant facial expression recognition technologies, algorithms, and tools suitable for real-time analysis of online lecture sessions.

Developing a conceptual framework for integrating facial expression analysis into existing online learning platforms or video conferencing software.

Evaluating the reliability, accuracy, and ethical considerations associated with deploying facial analysis systems in educational settings.

Providing recommendations for educators, technologists, and policymakers regarding the integration and ethical implementation of facial expression analysis in online education environments.

Structure of the Documentation

This documentation is structured as follows:

- Literature Review: Explores existing research and methodologies related to facial expression analysis, engagement assessment, and their applications in educational settings.

- Technological Landscape: Surveys available facial expression recognition technologies, algorithms, and tools, highlighting their suitability for educational environments.
- Framework Development: Proposes a conceptual framework for integrating facial expression analysis into online learning platforms, outlining technical requirements, and implementation strategies.
- Evaluation and Ethical Considerations: Discusses the reliability, accuracy, and ethical implications of employing facial analysis systems in educational contexts.
- Recommendations and Future Directions: Provides actionable recommendations for educators, developers, and policymakers, along with avenues for future research and development.

WHAT IS DEEP LEARNING

Deep learning is one of the foundations of artificial intelligence (AI), and the current interest in deep learning is due in part to the buzz surrounding AI. Deep learning techniques have improved the ability to classify, recognize, detect and describe – in one word, understand. For example, deep learning is used to classify images, recognize speech, detect objects and describe content.

Several developments are now advancing deep learning:

Algorithmic improvements have boosted the performance of deep learning methods.

New machine learning approaches have improved accuracy of models.

New classes of neural networks have been developed that fit well for applications like text translation and image classification.

We have a lot more data available to build neural networks with many deep layers, including streaming data from the Internet of Things, textual data from social media, physicians notes and investigative transcripts .

Computational advances of distributed cloud computing and graphics processing units have put incredible computing power at our disposal. This level of computing power is necessary to train deep algorithms.

At the same time, human-to-machine interfaces have evolved greatly as well. The mouse and the keyboard are being replaced with gesture, swipe, touch and natural language, ushering in a renewed interest in AI and deep learning .

How Deep Learning Works

Deep learning changes how you think about representing the problems that you’re solving with analytics. It moves from telling the computer how to solve a problem to training the computer to solve the problem itself.

A traditional approach to analytics is to use the data at hand to engineer features to derive new variables, then select an analytic model and finally estimate the parameters (or the unknowns) of that model. These techniques can yield predictive systems that do not generalize well because completeness and correctness depend on the quality of the model and its features. For example, if you develop a fraud model with feature engineering, you start with a set of variables, and you most likely derive a model from those variables using data transformations. You may end up with 30,000 variables that your model depends on, then you have to shape the model, figure out which variables are meaningful, which ones are not, and so on. Adding more data requires you to do it all over again.

The new approach with deep learning is to replace the formulation and specification of the model with hierarchical characterizations (or layers) that learn to recognize latent features of the data from the regularities in the layers. The paradigm shift with deep learning is a move from feature engineering to feature representation. The promise of deep learning is that it can lead to predictive systems that generalize well, adapt well, continuously improve as new data arrives, and are more dynamic than predictive systems built on hard business rules. You no longer fit a model. Instead, you train the task.

Deep learning is making a big impact across industries. In life sciences, deep learning can be used for advanced image analysis, research, drug discovery, prediction of health problems and disease symptoms, and the acceleration of insights from genomic sequencing. In transportation, it can help autonomous vehicles adapt to changing conditions. It is also used to protect critical infrastructure and speed response.

How Deep Learning Being Used

To the outside eye, deep learning may appear to be in a research phase as computer science researchers and data scientists continue to test its capabilities. However, deep learning has many practical applications that businesses are using today, and many more that will be used as research continues. Popular uses today include:

Speech Recognition

Both the business and academic worlds have embraced deep learning for speech recognition. Xbox, Skype, Google Now and Apple's Siri, to name a few, are already employing deep learning technologies in their systems to recognize human speech and voice patterns.

Natural Language Processing

Neural networks, a central component of deep learning, have been used to process and analyse written text for many years. A specialization of text mining, this technique can be used to discover patterns in customer complaints, physician notes or news reports, to name a few.

Image Recognition

One practical application of image recognition is automatic image captioning and scene description. This could be crucial in law enforcement investigations for identifying criminal activity in thousands of photos submitted by bystanders in a crowded area where a crime has occurred. Self-driving cars will also benefit from image recognition through the use of 360-degree camera technology.

Recommendation Systems

Amazon and Netflix have popularized the notion of a recommendation system with a good chance of knowing what you might be interested in next, based on past behaviour. Deep learning can be used to enhance recommendations in complex environments such as music interests or clothing preferences across multiple platforms.

Recent advances in deep learning have improved to the point where deep learning outperforms humans in some tasks like classifying objects in images. While deep learning was first theorized in the 1980s, there are two main reasons it has only recently become useful:

1. Deep learning requires large amounts of labelled data. For example, driverless car development requires millions of images and thousands of hours of video.

2. Deep learning requires substantial computing power. High-performance GPUs have a parallel architecture that is efficient for deep learning. When combined with clusters or cloud computing, this enables development teams to reduce training time for a deep learning network from weeks to hours or less. When choosing between machine learning and deep learning, consider whether you have a high-performance GPU and lots of labelled data. If you don't have either of those things, it may make more sense to use machine learning instead of deep learning. Deep learning is generally more complex, so you'll need at least a few thousand images to get reliable results. Having a high-performance GPU means the model will take less time to analyse all those images

1.2 EXISTING SYSTEM

In the existing system work on student engagement detection has lack of real time engagement assessment in online learning environments works on convolutional neural networks

Here's an overview of existing systems:

- Focus on Facial Expressions: These systems primarily rely on facial expression recognition to estimate engagement.
    - Techniques involve identifying expressions like concentration (raised eyebrows, furrowed brow), confusion (raised eyebrows, open mouth), or boredom (drooping eyelids, open mouth).
    - Deep learning approaches using Convolutional Neural Networks (CNNs) are popular for recognizing these expressions from facial features.
- Challenges and Considerations:
    - Accuracy: Recognizing subtle expressions and differentiating between concentration and confusion can be difficult, especially with low-quality video or variations in lighting.

- Context: Facial expressions can be ambiguous. A frown might indicate confusion or deep concentration depending on the lecture content.
- Cultural Variations: Facial expressions for emotions can vary across cultures. A system trained on one cultural dataset might not generalize well to others.
- Privacy: Students might be concerned about data collection and the use of their facial expressions.

1.3 DISADVANTAGES OF EXISTING SYSTEM

- Dependency on high-quality video input
- Limited scalability for large datasets
- Interpretation may vary based on individual facial expressions and cultural factors
- May not capture the full spectrum of preferences, depending on individual expressions
- Complexity in Analysis Temporal changes in facial expressions can be intricate to interpret accurately

1.4 PROPOSED SYSTEM

The system uses a type of smart algorithm called a Recurrent Neural Network (RNN) to make predictions. Within the RNN, a specific kind of cell called Long Short-Term Memory (LSTM) is used. LSTMs are good at understanding patterns over time. The system "learns" by adjusting its internal settings based on a lot of examples. It gets better at predicting student engagement as it goes through more examples. The proposed system's main aim is to predict student engagement levels in online lectures. To check how well the system is doing, we use metrics like accuracy, precision, recall, and F1 score. These metrics help us understand if the predictions are correct. The smart system, using the RNN with LSTM cells, proves to be excellent at capturing the subtle patterns in how students engage over time.

1.5 ADVANTAGES OF PROPOSED SYSTEM

- Output in which result is altered image or report that is based on image analysis.
- Real-time assessment, High accuracy
- Comparative analysis, Various emotion recognition, Robust performance

- We will capture images of the students based on the regular intervals and then the tradition survey forms will be given to the students

Algorithm: Recurrent Neural Networks (RNN)

1.6 LITERATURE SURVEY

A literature survey on the analysis of facial expressions to estimate the level of engagement in online lectures would involve reviewing existing research, studies, and academic papers related to this topic. Here's a structured approach to conducting a literature survey on this subject:

Search Strategy:

- Utilize academic databases such as PubMed, IEEE Xplore, Google Scholar, and ACM Digital Library to search for relevant literature.
- Use keywords and phrases such as "facial expression analysis," "engagement estimation," "online lectures," "computer vision," "emotion recognition," etc.
- Refine search results by specifying publication year, relevance, and citation metrics.

Review of Research Papers:

- Identify and review research papers that focus on analyzing facial expressions to estimate engagement levels in educational contexts, particularly online lectures.
- Look for studies that employ computer vision techniques, machine learning algorithms, and emotion recognition models.
- Pay attention to methodologies, datasets used, experimental setups, and evaluation metrics employed in these studies.

Key Concepts and Technologies:

- Identify key concepts, methodologies, and technologies commonly used in facial expression analysis and engagement estimation.
- Understand the underlying principles of computer vision algorithms, facial feature detection, emotion recognition techniques, and machine learning models.

- Explore advancements in deep learning architectures such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) for facial expression analysis.

Challenges and Limitations:

- Investigate challenges and limitations associated with analyzing facial expressions in online lecture environments.
- Consider factors such as variations in lighting conditions, camera angles, facial occlusions, and cultural differences in facial expressions.
- Assess the impact of noise, distractions, and technical issues on the accuracy of engagement estimation.

Applications and Use Cases:

- Explore applications and use cases of facial expression analysis in educational settings, including online lectures and e-learning platforms.
- Examine how engagement estimation based on facial expressions can enhance student learning experiences, improve content delivery, and personalize educational interventions.
- Look for studies that demonstrate the effectiveness of facial expression analysis in predicting student outcomes, such as learning performance, attention, and satisfaction.

Future Directions and Research Opportunities:

- Identify emerging trends, gaps in existing literature, and areas for future research in the analysis of facial expressions for engagement estimation.
- Consider interdisciplinary approaches that integrate insights from psychology, neuroscience, human-computer interaction, and educational technology.
- Explore potential applications of multimodal data fusion, real-time feedback mechanisms, and adaptive learning systems based on facial expression analysis.

Synthesis and Analysis:

- Synthesize findings from the literature survey to develop a comprehensive understanding of the state-of-the-art techniques and methodologies in facial expression analysis for engagement estimation.
- Analyze strengths, weaknesses, opportunities, and threats associated with existing approaches.
- Identify research gaps and propose directions for further investigation or innovation.

Documentation and Citation:

- Document relevant research papers, articles, and findings obtained during the literature survey.
- Provide proper citations and references for all sources consulted.
- Ensure adherence to academic standards and ethical guidelines in the documentation and dissemination of research findings.

2. ANALYSIS

2.1 INTRODUCTION

In recent years, the proliferation of online education platforms has revolutionized the way people access and engage with educational content. However, one persistent challenge in online learning environments is ensuring high levels of student engagement, which is crucial for effective learning outcomes. Traditional methods of gauging engagement, such as quizzes or surveys, often fall short in capturing real-time feedback and may disrupt the learning experience. To address this challenge, the integration of advanced technologies, particularly facial expression analysis, offers a promising solution.

The project "Analysis of Facial Expressions to Estimate the Level of Engagement in Online Lectures" seeks to leverage computer vision and machine learning techniques to analyze facial expressions of online learners and estimate their level of engagement during lectures. By harnessing the power of facial recognition algorithms and emotion detection models, the system aims to provide educators and online learning platforms with valuable insights into student engagement dynamics in real-time, thereby enabling timely interventions and instructional adjustments to enhance the learning experience.

The analysis of facial expressions to estimate the level of engagement in online lectures represents a pioneering initiative at the forefront of educational technology innovation, with the potential to revolutionize online learning practices and enrich the educational experiences of learners worldwide.

2.2 SOFTWARE REQUIREMENTS SPECIFICATION

2.2.1 User Requirements

- PC, Mac or laptop with x86-64 (64-bit) compatible processors.
    - 2 GHz or better processor is recommended..
- At least 512 MB of free RAM should be available for the application.
- Internet connection required for detecting URLs.
- Microsoft Windows specific requirements:
    - Microsoft Windows 7 / 8 / 10 / 11.
    - Microsoft .NET framework 4.5 or newer (for .NET components usage).
    - One of following development environments for application development:
        - Python IDLE

- Anaconda

- macOS specific requirements:
  - macOS 10.13 or newer.
  - XCode 9.3 or newer (for application development)
  - GNU Make 3.81 or newer
  - Anaconda

- Linux specific requirements:
  - Linux 3.10 kernel or newer
  - glibc 2.17 library or newer
  - gcc 4.8 or newer (for application development)
  - GNU Make 3.81 or newer (for application development)
  - Anaconda

2.2.2 Software Requirements

- Python IDE: There are lots of IDEs for python. Some of them are PyCharm, Thonny, Ninja, Spyder, anaconda etc. Ninja and Spyder both are very excellent and free but we used Spyder as it feature- rich than ninja. Anaconda is used for our present system.
- DL Packages: NumPy, Pandas, sci-kit learn, Matplotlib, Seaborn, Flask, Pymysql.
- DL Algorithms: Linear Regression, Decision Trees, Random Forest, Support Vector Machine, Naïve Bayes, Gradient Boosting Classifier.

2.2.3 : Hardware Components:

- Processor – i3
- Hard Disk – 5 GB
- Memory – 4GB RAM

2.3: FLOWCHART

Creating a flowchart for the "Analysis of Facial Expressions to Estimate the Level of Engagement in Online Lectures" project involves visually representing the sequence of steps and decisions involved in the process.

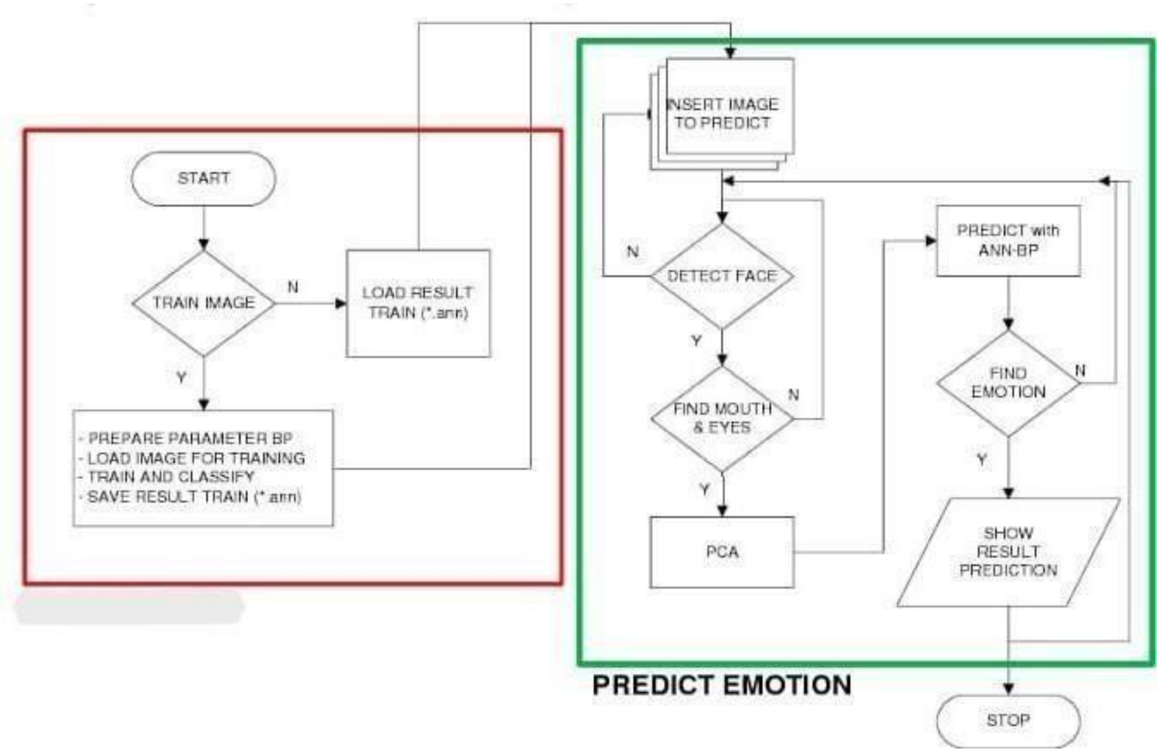


Fig: 2.1 Flow Chart

Flowchart: Facial Expressions for Engagement Estimation in Online Lectures

Start

- Capture Video Stream: System obtains video input from the student's webcam.
- Face Detection: Identify and locate all faces within the video frame.
- Pre-processing: Apply image processing techniques (grayscale conversion, normalization) to prepare the image for analysis.
- Facial Landmark Detection: Identify key facial points (eyes, eyebrows, mouth corners) to track facial movements.

- Facial Expression Recognition: Analyze the positions of facial landmarks to identify the expressed emotion (happiness, sadness, anger, surprise, disgust, fear, neutral).
- Engagement Level Estimation: Based on recognized expressions (and potentially context), assign an engagement level (high, medium, low).
- Output & Feedback: Provide visual or textual feedback on the estimated engagement level (optional for students, mandatory for instructors).
- (Loop): Return to step 1 for continuous processing of the video stream.

3. DESIGN

3.1 INTRODUCTION

In recent years, the landscape of education has undergone a significant transformation with the proliferation of online learning platforms. While these platforms offer flexibility and accessibility, one challenge educators face is gauging the level of engagement among remote learners. Understanding the extent to which students are actively participating and engaged during online lectures is crucial for effective teaching and learning outcomes.

To address this challenge, the "Facial Expressions to Estimate the Level of Engagement in Online Lectures" project proposes a novel solution leveraging computer vision and machine learning techniques. By analyzing facial expressions captured during online lectures, the system aims to provide real-time insights into the engagement levels of individual students or the audience as a whole.

Objective:

The primary objective of this project is to design and develop a system capable of accurately estimating the level of engagement in online lectures based on facial expressions. Specifically, the system aims to:

- Capture video feeds from online lecture platforms.
- Detect and track facial expressions of viewers using computer vision algorithms.
- Analyze facial expressions to infer the level of engagement, considering factors such as smiles, frowns, eye movements, and head gestures.
- Compute overall engagement metrics for individual viewers or the entire audience.
- Provide intuitive visualizations and insights to educators, enabling them to adjust their teaching strategies in real-time based on audience engagement levels.
- Key Features: The proposed system will offer the following key features:
- Real-time Analysis: The system will perform facial expression analysis in real-time, allowing educators to receive instant feedback on audience engagement during online lectures.
- Customizable Settings: Users will have the flexibility to configure settings related to facial expression analysis, such as sensitivity thresholds and weighting of different expressions.

- Intuitive User Interface: The system will feature a user-friendly interface with interactive visualizations, enabling educators to easily interpret engagement metrics and make informed decisions.
- Integration with Online Lecture Platforms: Seamless integration with popular online lecture platforms will ensure compatibility and ease of use for educators and students.
- Feedback Mechanisms: The system will incorporate mechanisms for collecting feedback from users, enabling continuous improvement and refinement of engagement estimation algorithms.
- Benefits: The implementation of the Facial Expressions to Estimate the Level of Engagement in Online Lectures project offers several benefits, including:
- Enhanced Teaching Effectiveness: Educators can adapt their teaching strategies in real-time based on insights into audience engagement, leading to more effective learning outcomes.
- Improved Student Engagement: By monitoring and addressing fluctuations in engagement levels, educators can create a more interactive and engaging learning environment for students.
- Data-Driven Decision Making: The system provides educators with empirical data on audience engagement, enabling data-driven decision-making in course design and delivery.
- Personalized Learning Experiences: Insights derived from facial expression analysis can be used to tailor learning experiences to individual student needs and preferences.

3.2 DFD/UML DIAGRAMS

3.2.1 DFD Diagrams

A DFD is a graphical representation of how the data flows through a system. Developing a DFD is one of the first steps carried out when developing an information system. DFD displays details like the data that is coming in and going out of the system, how the data is travelled through the system and how the data will be stored in the system.

But the DFD does not contain information about timing information of the processes. The main components included in a DFD are processes, data stores, data flow and external entities. When developing DFD diagrams, the context level DFD is drawn first. It displays how the entire system interacts with external data sources and data sinks.

Next a Level 0 DFD is developed by expanding the context level DFD. Level 0 DFD contains details of the sub-systems within the system and how the data is flowing through them. It also contains details about the data stores required within the system. Y

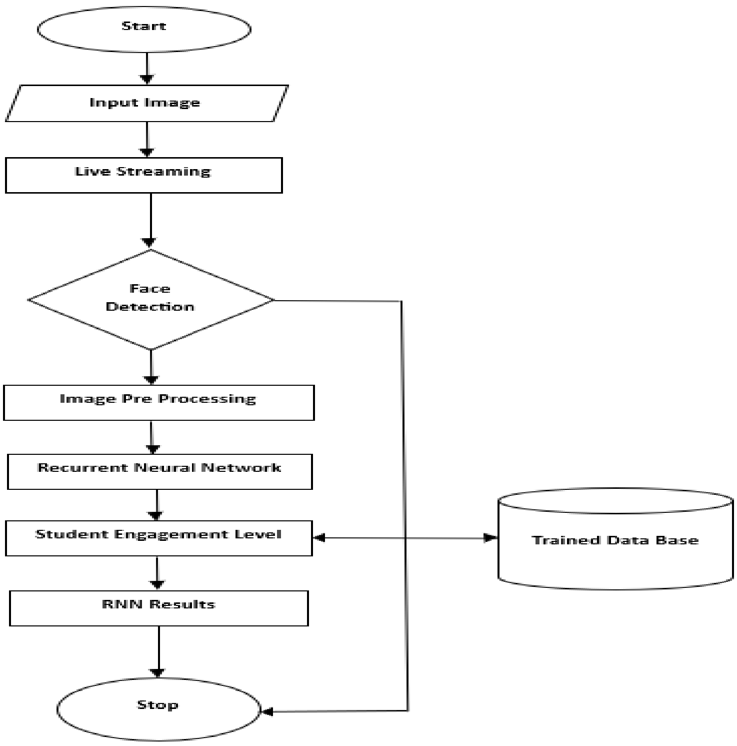


Fig 3.1: Level-0 DFD

A Level 1 Data Flow Diagram (DFD) for the "Analysis of Facial Expressions to Estimate the Level of Engagement in Online Lectures" project would provide a high-level overview of the system's functionalities and interactions at a basic level.

This Level 1 DFD provides a simplified view of the system's processes and interactions without delving into too much detail. It serves as a useful starting point for understanding the flow of data and operations within the system.

Depending on the complexity of the project, you may need to create more detailed DFDs at higher levels to further elaborate on individual processes and data flows.

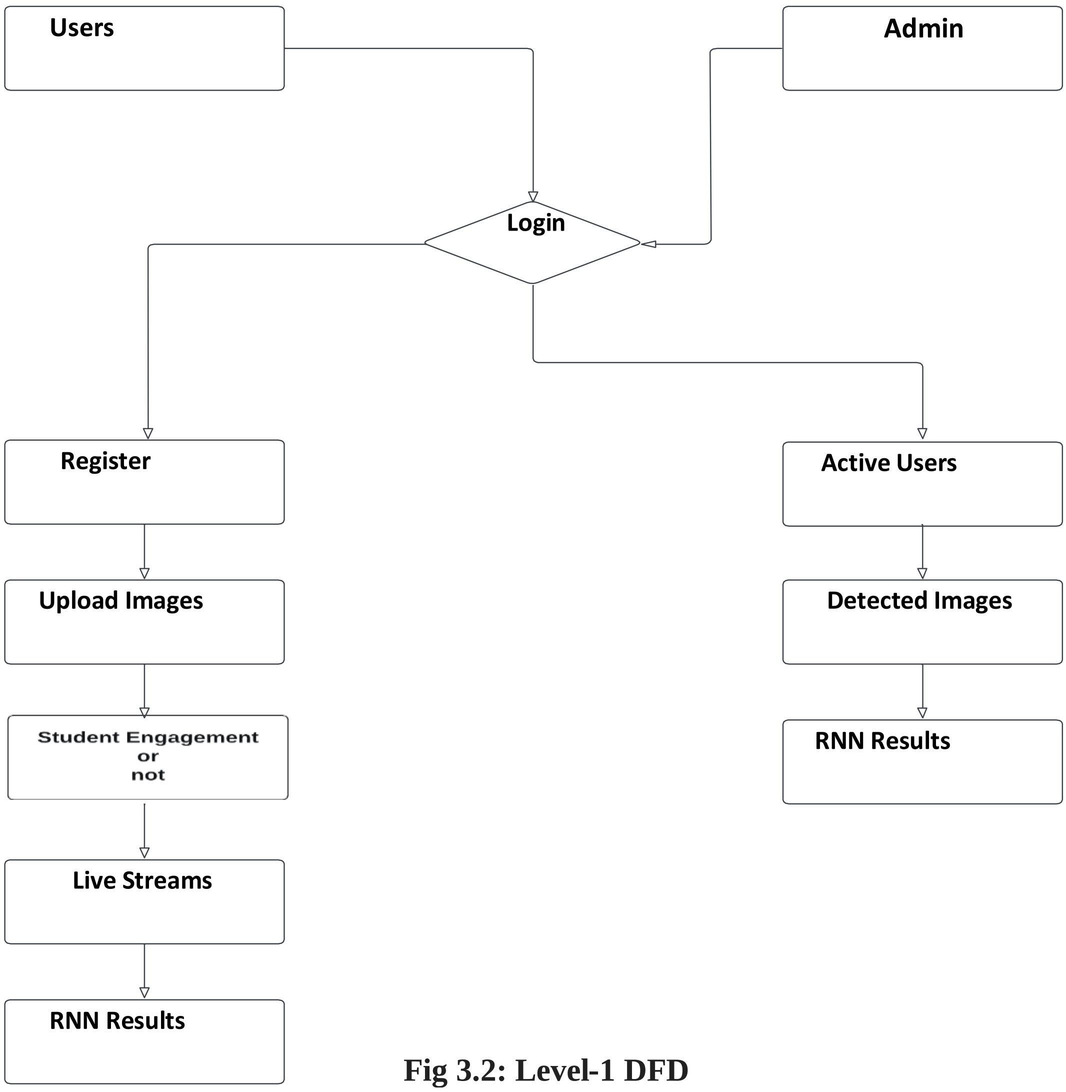


Fig 3.2: Level-1 DFD

3.2.2 UML Diagrams

UML stands for Unified Modeling Language. UML is a standardized general- purpose modeling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group. The goal is for UML to become a common language for creating models of object oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.The Unified Modeling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modeling and other non-software systems. The UML represents a collection of best engineering practices that have proven successful in the modeling of large and complex systems.

3.2.2.1 Class Diagram

In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information

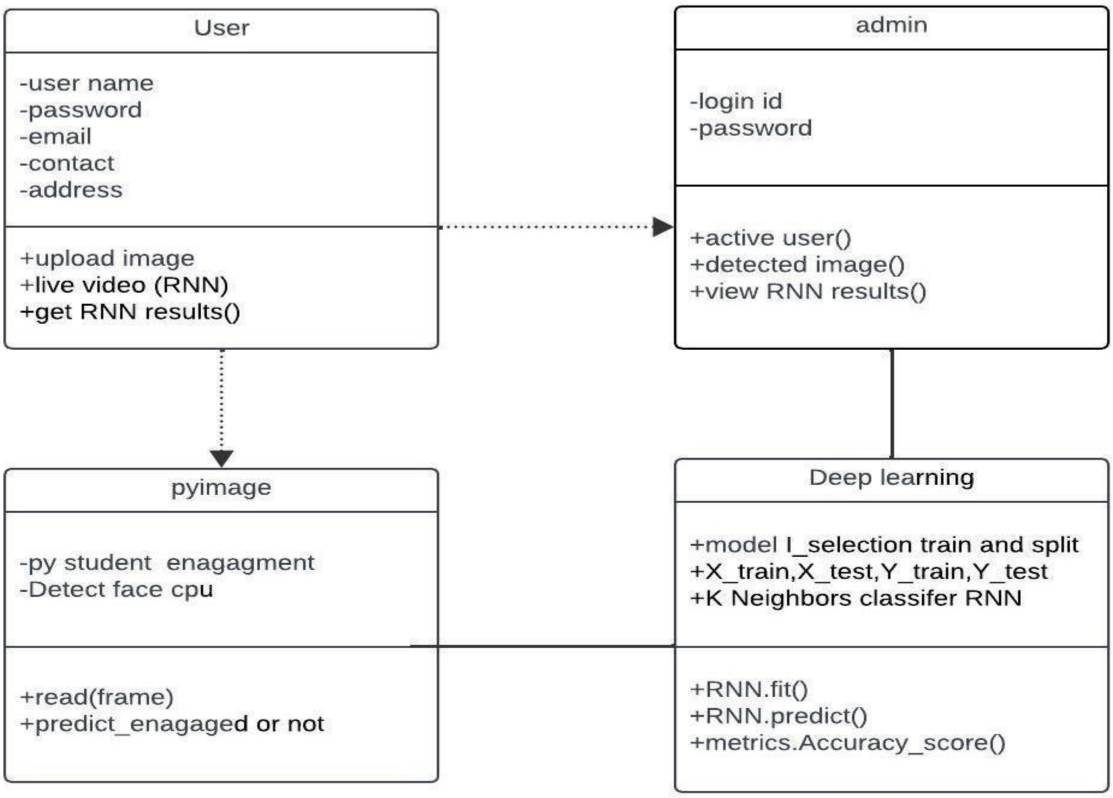


Fig 3.3: Class Diagram

3.2.2.2 Use Case Diagram

In UML, use-case diagrams model the behavior of a system and help to capture the requirements of the system. Use-case diagrams describe the high-level functions and scope of a system. These diagrams also identify the interactions between the system and its actors. The use cases and actors in use-case diagrams describe what the system does and how the actors use it, but not how the system operates internally. A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.To depict the system boundary, draw a box around the use case itself. UML Use case diagrams are ideal for:

- Representing the goals of system-user interactions.
- Defining and organizing functional requirements in a system.

- Specifying the context and requirements of a system.
- Modelling basic flow of events in a use case.

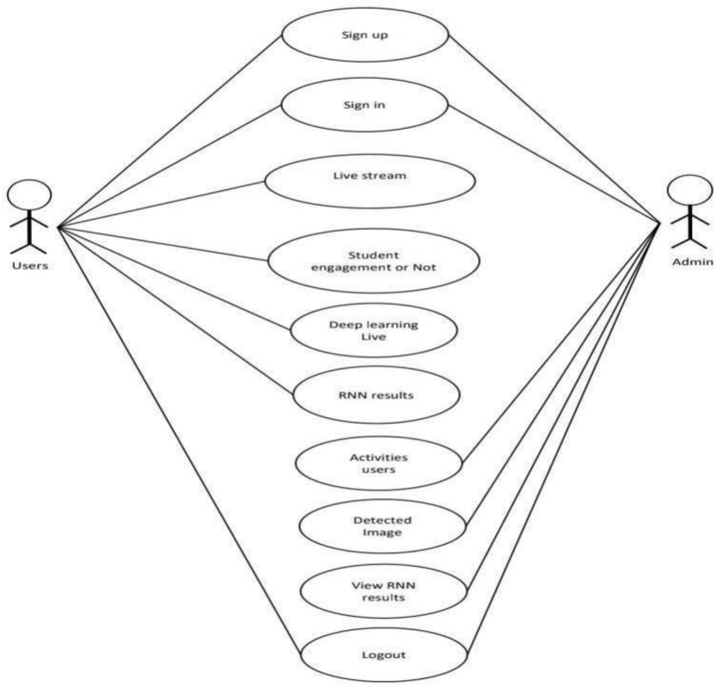


Fig 3.4: Use Case Diagram

3.2.2.3 Sequence Diagram

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.

. Try drawing a sequence diagram to:

- Represent the details of a UML use case.
- Model the logic of a sophisticated procedure, function, or operation.
- See how objects and components interact with each other to complete a process.
- Plan and understand the detailed functionality of an existing or future scenario.

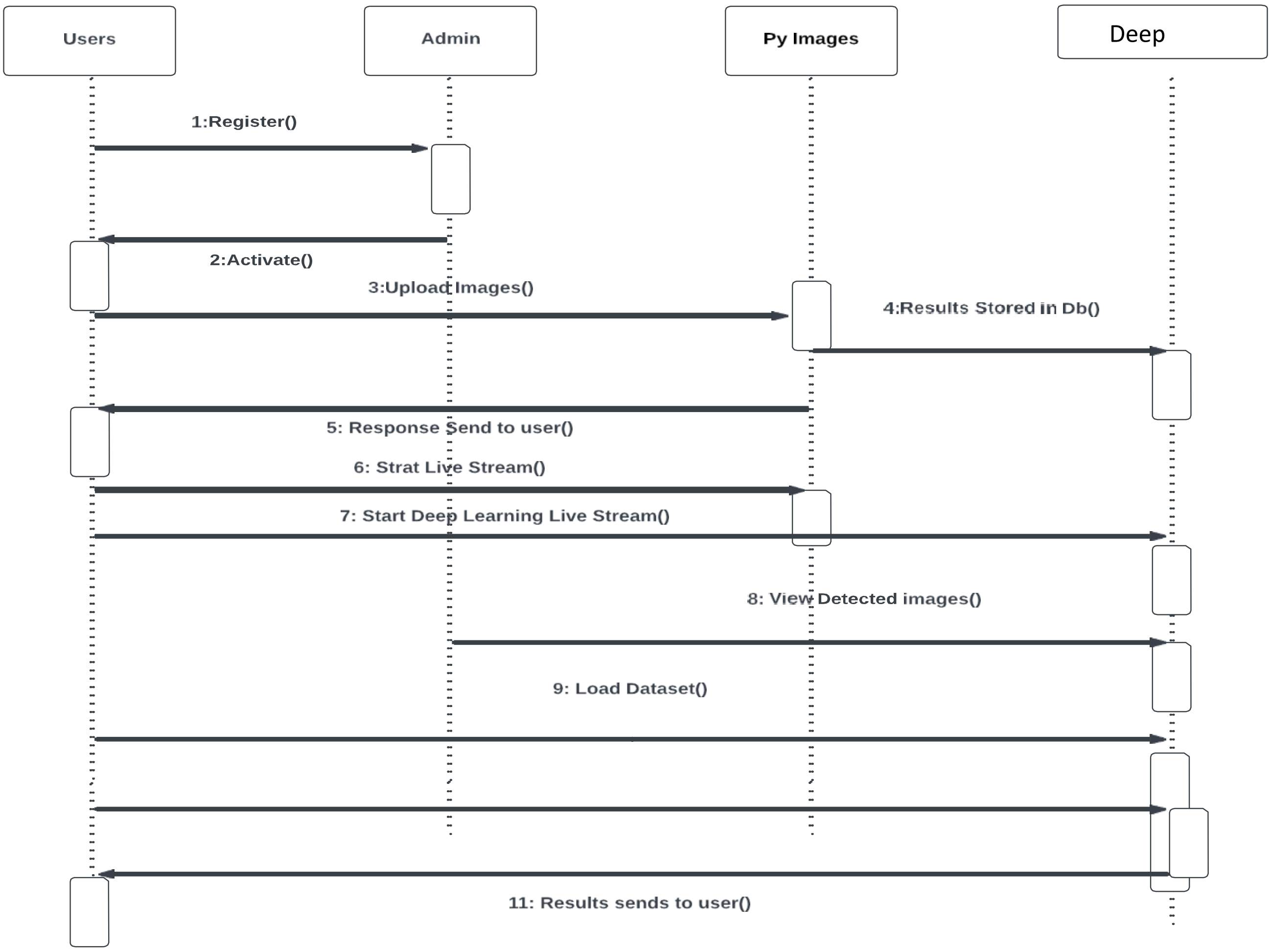


Fig 3.5: Sequence diagram

3.2.2.4 Deployment Diagram

A deployment diagram visualizes the physical deployment of software components in a system. It illustrates how software and hardware components are distributed across different nodes in a network and how they interact with each other to form a complete system. The primary purpose of a deployment diagram is to show the mapping of software components to the hardware components on which they run.

- Nodes represent physical entities, such as hardware devices or servers, where components are deployed. They could be a computer, a server, a router, or any other device that can host software.

- Components represent the software elements or modules that are deployed on nodes. These can be executable files, libraries, or other software artifacts.
- Artifacts are physical files or data that are used or produced by components. They can include databases, configuration files, or any other data storage.
- Associations show the relationships and connections between nodes and components. They indicate how components are deployed on specific nodes and how nodes interact with each other.
- Communication paths depict the channels or network connections through which nodes communicate with each other. They show the flow of messages or data between nodes.

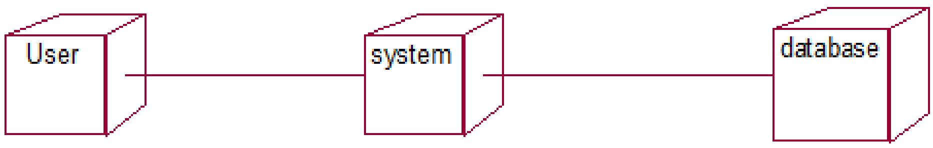


Fig 3.6: Deployment diagram

3.2.2.5 Activity Diagram

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language,activity diagrams can be used to describe the business and operational step-by- step workflows of components in a system. An activity diagram shows the overall flow of control.Activity is a particular operation of the system. Activity diagrams are not only used for visualizing the dynamic nature of a system, but they are also used to construct the executable system by using forward and reverse engineering techniques. The only missing thing in the activity diagram is the message part. It does not show any message flow from one activity to another. Activity diagram is sometimes considered as the flowchart. Although the diagrams look like a flowchart, they are not. It shows different flows such as parallel, branched, concurrent, and single. An activity diagram portrays the control flow from a start point to a finish point showing the various decision paths that exist while the activity is being executed. The purpose of an activity diagram can be described as –

- Draw the activity flow of a system.
- Describe the sequence from one activity to another.
- Describe the parallel, branched and concurrent flow of the system.

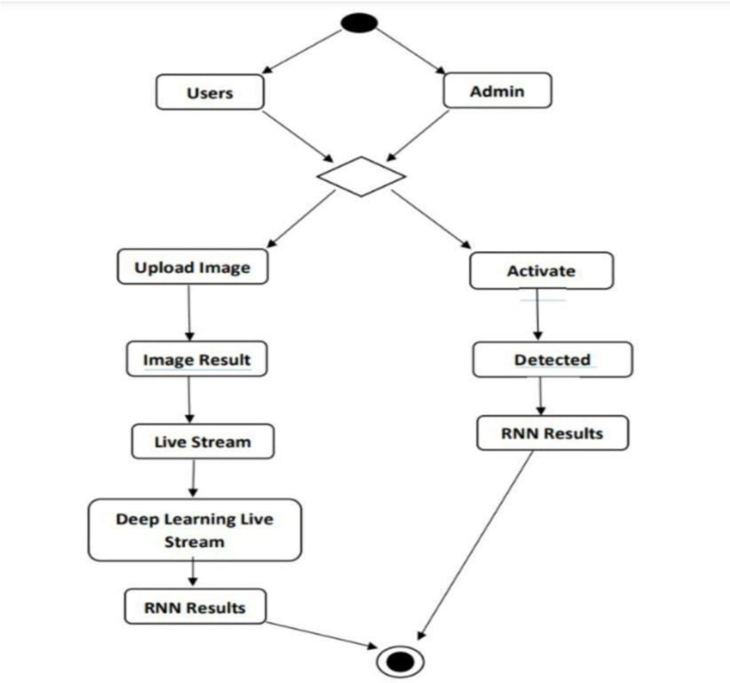


Fig 3.7: Activity Diagram

3.3 MODULE DESIGN & ORGANIZATION

For Analysing the Facial Expressions to Estimate the Level of Engagement in Online Lectures, we have system module and user module.

3.3.1 System Module

The system module consists of the following activities:

- Data Acquisition
- Facial Detection
- Facial Expression Analysis

- Engagement Level Estimation
- Interaction
- User Interface
- Performance Optimization
- Data Management

1. Data Acquisition:

- This module is responsible for capturing video feeds from online lecture platforms.
- It may involve accessing APIs or integrating with different online lecture platforms to retrieve video streams.
- Techniques for handling different video formats and resolutions should be included.

2. Facial Detection:

- This module identifies and tracks faces within the video feeds.
- Computer vision algorithms are utilized to detect facial landmarks and track facial movements over time.
- Techniques like Haar cascades, deep learning-based face detection, or facial landmark detection can be employed.

3. Facial Expression Analysis:

- This module analyzes the facial expressions detected in the video feeds to estimate the level of engagement.
- It may involve machine learning models trained on labeled facial expression datasets to recognize emotions and engagement cues.
- Feature extraction and classification techniques are used to interpret facial expressions and assign engagement scores.

Engagement Level Estimation Module:

- Building upon the results of facial expression analysis, this module computes an overall engagement level for each viewer.
- It may aggregate data from multiple facial expressions over time to derive a comprehensive engagement metric.
- Algorithms for weighting different facial expressions and accounting for individual variability in expression interpretation can be implemented.

4. Integration Module:

- This module facilitates communication with external systems such as online lecture platforms.
- It handles data exchange, ensuring seamless integration with various platforms and formats.
- APIs or protocols are implemented to facilitate data transmission and retrieval.

5. User Interface Module:

- This module provides a user interface for configuring settings, monitoring engagement levels, and accessing insights.
- It may include visualizations such as graphs or charts to present engagement metrics in an intuitive manner.
- User feedback mechanisms and customization options should be considered to enhance user experience.

6. Performance Optimization Module:

- This module focuses on optimizing the performance and efficiency of the system.
- Techniques such as parallel processing, GPU acceleration, and resource allocation strategies are employed to enhance computational efficiency.
- Monitoring and profiling tools may be included to identify bottlenecks and optimize resource utilization.

7. Data Management Module:

- This module handles the storage and management of data related to captured video feeds, facial expressions, and engagement metrics.
- It may involve database systems or distributed storage solutions to efficiently manage large volumes of data.
- Data security and privacy measures should be implemented to safeguard sensitive information.

3.3.2 User Modules

The User Module consists of the following activities:

- User Authentication and Management
- Dashboard
- Settings Configuration
- Engagement Visualization
- Feedback Submission
- Integration with Online Lecture Platforms

1. User Authentication and Management:

- This module handles user authentication and authorization processes.
- It allows users to log in securely to the system and manages user permissions.
- Functions include user registration, login/logout, password management, anduser profile settings.

2. Dashboard:

- The dashboard module provides users with an overview of engagement metrics and insights.
- Users can access summarized engagement data, such as average engagement levels, trends over time, and comparisons between lectures.

- Customizable dashboard widgets allow users to personalize their view based on their preferences and priorities.

3. **Settings Configuration:**

- This module enables users to configure settings related to facial expression analysis and engagement estimation.
- Users can adjust parameters such as sensitivity thresholds, weighting of facial expressions, and notification preferences.
- Settings may include options for real-time analysis during lectures, scheduling analyses for specific time periods, or selecting which lectures to monitor.

4. **Engagement Visualization:**

- The engagement visualization module presents engagement metrics and insights in a visually appealing and intuitive manner.
- Users can view engagement levels over time using interactive charts, graphs, or heatmaps.
- Features may include drill-down capabilities to explore engagement data at different levels of granularity (e.g., by lecture, by user, by facial expression).

5. **Feedback Submission:**

- This module allows users to provide feedback on the accuracy and usefulness of engagement estimations.
- Users can submit comments, ratings, or annotations directly within the system interface.
- Feedback mechanisms may also include surveys or questionnaires to gather more structured input from users.

6. **Integration with Online Lecture Platforms:**

- This module allows users to seamlessly access engagement metrics and insights within the interface of online lecture platforms.

4.IMPLEMENTATION & DETAILS

4.1 INTRODUCTION

The "Analysis of Facial Expressions to Estimate the Level of Engagement in Online Lectures" project aims to enhance online learning experiences by providing educators with insights into the engagement levels of their students during virtual lectures. By analyzing facial expressions captured through video feeds, the system can infer the degree of attentiveness, interest, and comprehension among learners. This introduction will outline the implementation approach and key details of the project.

Understanding students' engagement levels while studying is important for improving learning outcomes. To improve the quality of education, it is crucial to estimate learners' level of engagement with their studies. However, it is difficult for teachers to pay attention to all students, particularly in online classes. Automated measurement of engagement levels may be helpful for improving learning conditions. For online learning, webcams can be used to capture learners' facial expressions, which can be used to estimate their mental states.

Although engagement is a term used with different meanings in different contexts, it is often used in relation to attention. Attention to lectures, classes, and tasks is thought to be closely related to engagement. Here we use the term attention to refer to the facilitation of sensory processing by endogenous intention or salient exogenous stimulation, and consider it to be a major factor for engagement. It should be noted that engagement has also been used to indicate mental states of a longer duration in some previous studies, such as a whole lecture. We measured levels of attention as an index of engagement during lectures in this study. The primary task of the experiment was to understand the lecture, and the secondary task was to detect the target. RT to the auditory target was used as an objective measure of attention level on the lecture videos. Here, we assumed that the time required to detect a target that was irrelevant to the primary task would be longer when the participant focused more on the primary task (i.e., watching video lectures in this experiment). Face images of participants were recorded while watching the videos, and facial expressions were analyzed after the experiment. The purpose of the study was to estimate the RT from facial expressions to develop a method for estimating engagement level from learners' face images.

In education-related studies, Thomas and Jayagopi recorded students' face images in a classroom while they were studying with video material on a screen and estimated the level of engagement from students' facial expressions [4], [5]. The authors succeeded in predicting engagement, suggesting the usefulness of facial expressions for estimating the level of engagement. Heart rate has also been used to estimate mental states during learning. Darnell and Krieg showed that changes in heart rate are related to students' activity during a class [6]. Although previous studies have focused on engagement, which is assessed externally, this research has also been extended to the measurement of internal states, which can be investigated by estimating internal states. In these studies, the mental state used as ground truth is based on subjective judgments

Objective:

- The primary objective of the project is to develop a system capable of analyzing facial expressions in real-time or post-lecture to estimate the level of engagement of participants in online lectures.
- The system aims to provide educators with actionable insights into student engagement, allowing them to adapt their teaching methods and content delivery to enhance learning outcomes.

Implementation Approach:

- The implementation of the project involves several stages, including data acquisition, facial expression analysis, engagement level estimation, and user interface development.
- Computer vision techniques and machine learning algorithms will be employed to detect and analyze facial expressions from video feeds of online lectures.
- The system may utilize pre-trained deep learning models for facial expression recognition or develop custom models trained on labeled datasets of facial expressions and engagement levels.
- Integration with online lecture platforms will be achieved through APIs or direct integration methods to access video streams and deliver engagement insights seamlessly.

- The development process will follow agile methodologies, allowing for iterative refinement based on user feedback and performance evaluation.

Key Details:

- Data Acquisition: Video feeds from online lecture platforms will be captured in real-time or retrieved from recorded sessions for analysis.
- Facial Expression Analysis: Computer vision algorithms will detect faces, extract facial landmarks, and analyze expressions to identify emotions and engagement cues.
- Engagement Level Estimation: By aggregating data from analyzed facial expressions, the system will compute engagement levels for individual participants or the audience as a whole.
- User Interface: A user-friendly interface will be developed to allow educators to configure settings, view engagement metrics, and access insights easily.
- Performance Optimization: Techniques such as parallel processing, GPU acceleration, and optimization of machine learning models will be implemented to ensure efficient performance and scalability.
- Data Management: Secure storage and management of facial expression data and engagement metrics will be ensured, adhering to data privacy regulations.

Expected Outcomes:

- The implementation of the project is expected to result in a robust system capable of providing valuable insights into student engagement during online lectures.
- Educators will be empowered to make data-driven decisions to improve teaching effectiveness, student participation, and overall learning experiences.
- The system has the potential to enhance the effectiveness of online education platforms by personalizing learning experiences and promoting active engagement among students.

4.1.1 Process of face recognition

Face recognition is often described as a process that first involves four steps; they are: face detection, face alignment, feature extraction, and finally face recognition.

1. Face Detection: Locate one or more faces in the image and mark with a bounding box.

2. Feature Extraction: Extract features from the face that can be used for the recognition task.

The process of face recognition in the "Analysis of Facial Expressions to Estimate the Level of Engagement in Online Lectures" project involves several steps, including face detection, feature extraction, and matching against a database or model. Here's a general overview of the process:

Face Detection:

- The first step is to detect faces within the video feed of online lectures. This can be done using various techniques such as Haar cascades, Histogram of Oriented Gradients (HOG), or deep learning-based methods like convolutional neural networks (CNNs).
- The face detection algorithm scans the video frames to locate regions that may contain faces based on predefined patterns or features.

Facial Landmark Detection:

- Once faces are detected, the system may employ facial landmark detection to identify key points on the face, such as the eyes, nose, mouth, and eyebrows.
- Facial landmark detection helps in precisely locating facial features, which is essential for accurate analysis of facial expressions.

Feature Extraction:

- After detecting facial landmarks, relevant features are extracted from the detected faces. These features may include the shape of the mouth, position of the eyebrows, eye openness, and other facial characteristics that convey emotional cues.
- Feature extraction techniques may involve capturing geometric measurements, texture analysis, or encoding appearance-based features.

Facial Expression Analysis:

- The extracted facial features are then analyzed to interpret the facial expressions exhibited by individuals in the video feed.
- This analysis may involve mapping the extracted features to predefined facial expression categories such as happiness, sadness, surprise, etc.
- Machine learning models, such as deep neural networks or support vector machines, trained on labeled facial expression datasets, can be used to classify facial expressions based on the extracted features.

Engagement Level Estimation:

- Based on the classified facial expressions, the system computes an overall engagement level for each viewer.
- Engagement levels may be determined based on the intensity and frequency of certain facial expressions associated with engagement, such as smiles, nods, or attentive gazes.
- Aggregation techniques may be employed to combine individual facial expression classifications into a holistic engagement metric for each viewer.

Continuous Monitoring and Feedback:

- The face recognition process is typically performed continuously throughout the duration of the online lecture.
- The system continuously monitors facial expressions and updates engagement levels in real-time, providing dynamic feedback to instructors or presenters.
- Feedback mechanisms may also collect user input or ratings to validate the accuracy of engagement estimations and improve the performance of the system over time.

By following these steps, the system can effectively recognize faces, analyze facial expressions, and estimate engagement levels in online lectures, providing valuable insights for instructors and presenters to enhance the learning experience.

4.1.2 Face Recognition Tasks

Face Recognition: Identifies whose face is in the video. Not required for engagement estimation. Facial Expression Analysis: Analyzes the movements and configurations of facial features to understand emotions and expressions. This is crucial for engagement assessment.

- Focus Area Determination: If the system can identify the student's face, it can ensure analysis focuses on the relevant facial features instead of irrelevant background elements.
- Multi-Student Scenarios: In situations with multiple students visible, face recognition can help track individual engagement levels.
- Privacy Concerns: Face recognition can raise privacy issues. Ensure you have proper consent and anonymize data if necessary.
- Computational Cost: Implementing face recognition adds complexity and processing demands.

Focus on Facial Expression Analysis:

- Face Detection: Locating the face within the video frame. This is a prerequisite for further analysis.
- Facial Landmark Detection: Identifying specific points on the face like eyebrows, eyes, nose, and mouth corners. These landmarks act as reference points for expression recognition.
- Expression Recognition: Analyzing the relative positions and movements of facial landmarks to identify expressions like happiness, sadness, surprise, etc.• Image Processing

4.1.2.1 Feature generation process.

Sample code is shown below.

```
import numpy as np

import argparse

import cv2
```

```
from keras.models import Sequential

from keras.layers.core import Dense, Dropout, Flatten

from keras.layers.convolutional import Conv2D

from keras.optimizers import Adam

from keras.layers.pooling import MaxPooling2D

from keras.preprocessing.image import ImageDataGenerator

import os

os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'

import matplotlib as mpl

mpl.use('TkAgg')

import matplotlib.pyplot as plt

# command line argument

ap = argparse.ArgumentParser()

ap.add_argument("--mode",help="train/display")

a = ap.parse_args()

mode = a.mode

# Define data generators

train_dir = 'data/train'

val_dir = 'data/test'

num_train = 2986

num_val = 908

batch_size = 14

num_epoch = 50

train_datagen = ImageDataGenerator(rescale=1./255)
```

```
val_datagen = ImageDataGenerator(rescale=1./255)
train_generator = train_datagen.flow_from_directory(
        train_dir,
        target_size=(48,48),
        batch_size=batch_size,
        color_mode="grayscale",
        class_mode='categorical')
validation_generator = val_datagen.flow_from_directory(
        val_dir,
        target_size=(48,48),
        batch_size=batch_size,
        color_mode="grayscale",
        class_mode='categorical')
# Create the model
model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=(48,48,1)))
model.add(Conv2D(64, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Conv2D(128, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
```

```
model.add(Flatten())
model.add(Dense(1024, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(7, activation='softmax'))
# If you want to train the same model or try other models, go for this
if mode == "train":
    model.compile(loss='categorical_crossentropy',optimizer=Adam(lr=0.0001, decay=1e-6),metrics=['accuracy'])
    model_info = model.fit_generator(
            train_generator,
            steps_per_epoch=num_train // batch_size,
            epochs=num_epoch,
            validation_data=validation_generator,
            validation_steps=num_val // batch_size)
    emotion_dict = {0: "Not_Engaged_Confused", 1: "Not_Engaged_Not_Liked", 2: "Engaged_Paying_Attention", 3: "Not_Engaged_Chatting", 4: "Engaged_Paying_Attention", 5: "Engaged_Making_Involvement", 6: "Engaged_Likes_Topic"}
    #plot_model_history(model_info)
    model.save_weights('model.h5')
# emotions will be displayed on your face from the webcam feed
elif mode == "display":
    model.load_weights('model.h5')
    # prevents openCL usage and unnecessary logging messages
    cv2.ocl.setUseOpenCL(False)
```

```
# dictionary which assigns each label an emotion (alphabetical order)
emotion_dict = {0: "Happy", 1: "Not_Engaged_Not_Liked", 2: "Engaged_Paying_Attention", 3: "Not_Engaged_Chatting", 4: "Engaged_Paying_Attention", 5: "Engaged_Making_Involvement", 6: "Engaged_Likes_Topic"}
# start the webcam feed
cap = cv2.VideoCapture(0)
while True:
    # Find haar cascade to draw bounding box around face
    ret, frame = cap.read()
    facecasc = cv2.CascadeClassifier('haarcascade_frontalface_default.xml')
    gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)
    faces = facecasc.detectMultiScale(gray,scaleFactor=1.3, minNeighbors=5)
    for (x, y, w, h) in faces:
        cv2.rectangle(frame, (x, y-50), (x+w, y+h+10), (255, 0, 0), 2)
        roi_gray = gray[y:y + h, x:x + w]
        cropped_img = np.expand_dims(np.expand_dims(cv2.resize(roi_gray, (48, 48)), -1), 0)
        prediction = model.predict(cropped_img)
        maxindex = int(np.argmax(prediction))
        cv2.putText(frame,emotion_dict[maxindex],(x+20,y-60), cv2.FONT_HERSHEY_SIMPLEX, 1, (255, 255, 255), 2, cv2.LINE_AA)
    # show the output frame
    cv2.imshow("Alex Corporations Press Q to Exit", frame)
    key = cv2.waitKey(1) & 0xFF
```

```
    # if the `q` key was pressed, break from the loop
    if key == ord("q"):
        break
cap.release()
cv2.destroyAllWindows()
```

4.2 METHOD OF IMPLEMENTATION

Implementing a Recurrent Neural Network (RNN) typically involves several steps, whether you're building it from scratch or using a deep learning framework like TensorFlow or PyTorch. Collect and preprocess your data. This might involve tasks like tokenization (for text data), normalization, and splitting your dataset into training, validation, and test sets. Convert your data into a format suitable for training the RNN. For example, sequences of fixed length or variable-length sequences padded to a maximum length. Choose an RNN architecture (vanilla RNN, LSTM, GRU, etc.) based on your task and dataset characteristics.

4.2.1 Recurrent Neural Network

Recurrent Neural Networks (RNNs) are a type of artificial neural network designed to process sequences of data. Unlike traditional feedforward neural networks, which take fixed-size inputs and produce fixed-size outputs, RNNs can operate over sequences of arbitrary length, making them well-suited for tasks like language modeling, speech recognition, and time series prediction.

The key feature of RNNs is their ability to maintain a hidden state that captures information about previous elements in the sequence. This hidden state is updated at each time step as the network processes the input sequence, allowing the network to capture temporal dependencies and context.

A recurrent neural network (RNN) is a deep learning model that is trained to process and convert a sequential data input into a specific sequential data output. Sequential data is data—such as words, sentences, or time-series data—where sequential components interrelate based on complex semantics and syntax rules. An RNN is a software system that consists of many interconnected components mimicking how humans perform sequential data conversions, such as translating text from one language to another. RNNs are largely being replaced by transformer-based artificial intelligence (AI) and large language models (LLM), which are much more efficient in sequential data processing.

Recurrent Neural Network(RNN) is a type of Neural Network where the output from the previous step is fed as input to the current step. In traditional neural networks, all the inputs and outputs are independent of each other. Still, in cases when it is required to predict the next word of a sentence, the previous words are required and hence there is a need to remember the previous words. Thus RNN came into existence, which solved this issue with the help of a Hidden Layer. The main and most important feature of RNN is its Hidden state, which remembers some information about a sequence. The state is also referred to as Memory State since it remembers the previous input to the network. It uses the same parameters for each input as it performs the same task on all the inputs or hidden layers to produce the output. This reduces the complexity of parameters, unlike other neural networks.

4.2.2 LONG SHORT-TERM MEMORY

Long Short-Term Memory is an improved version of recurrent neural network designed by Hochreiter & Schmidhuber. LSTM is well-suited for sequence prediction tasks and excels in capturing long-term dependencies. Its applications extend to tasks involving time series and sequences. LSTM's strength lies in its ability to grasp the order dependence crucial for solving intricate problems, such as machine translation and speech recognition. The article provides an in-depth introduction to LSTM, covering the LSTM model, architecture, working principles, and the critical role they play in various applications.

A traditional RNN has a single hidden state that is passed through time, which can make it difficult for the network to learn long-term dependencies. LSTMs address this problem by introducing a memory cell, which is a container that can hold information for an extended period. LSTM networks are capable of learning long-term dependencies in sequential data, which makes them well-suited for tasks such as language translation, speech recognition, and time series forecasting. LSTMs can also be used in combination with other neural network architectures, such as Convolutional Neural Networks (CNNs) for image and video analysis. The memory cell is controlled by three gates: the input gate, the forget gate, and the output gate. These gates decide what information to add to, remove from, and output from the memory cell. The input gate controls what information is added to the memory cell. The forget gate controls what information is removed from the memory cell. And the output gate controls what information is output from the memory cell. This allows LSTM networks to selectively retain or discard information as it flows through the network, which allows them to learn long-term dependencies.

LSTMs Long Short-Term Memory is a type of RNNs Recurrent Neural Network that can detain long-term dependencies in sequential data. LSTMs are able to process and analyze sequential data, such as time series, text, and speech. They use a memory cell and gates to control the flow of information, allowing them to selectively retain or discard information as needed and thus avoid the vanishing gradient problem that plagues traditional RNNs. LSTMs are widely used in various applications such as natural language processing, speech recognition, and time series forecasting.

An LSTM (Long Short-Term Memory) network is a type of RNN recurrent neural network that is capable of handling and processing sequential data. The structure of an LSTM network consists of a series of LSTM cells, each of which has a set of gates (input, output, and forget gates) that control the flow of information into and out of the cell. The gates are used to selectively forget or retain information from the previous time steps, allowing the LSTM to maintain long-term dependencies in the input data.

4.2.3 Output Screens

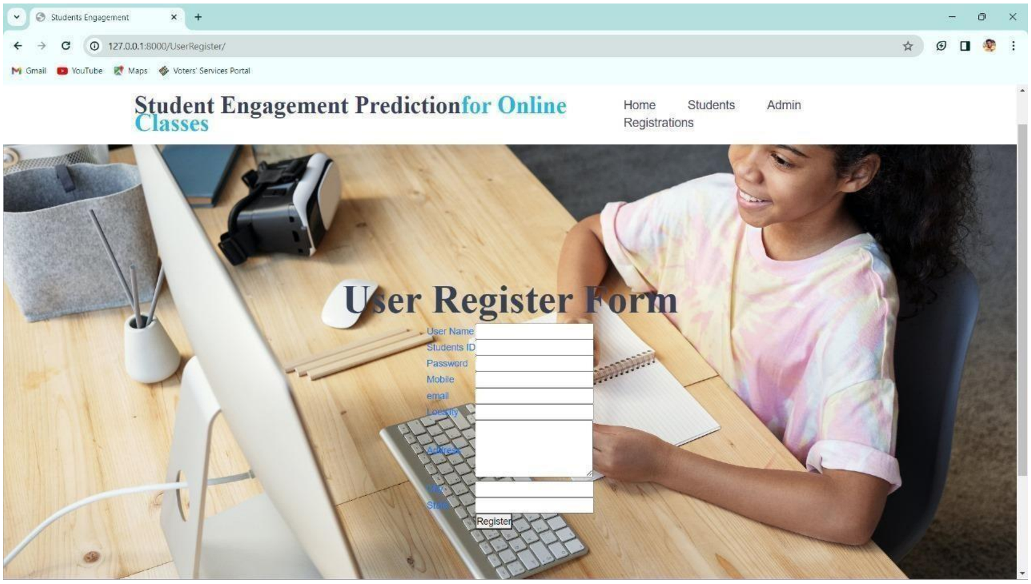
Screen 1:Home Page

The homepage for the "Analysis of Facial Expressions to Estimate the Level of Engagement in Online Lectures" project serves as the initial point of interaction for users accessing the system. If user accounts are required to access the system, the homepage may include options for user authentication (login) or registration (sign up).Clear prompts and calls to action should guide users through the authentication or registration process.

Screen 4.1: Home Screen

Screen 2: Register student

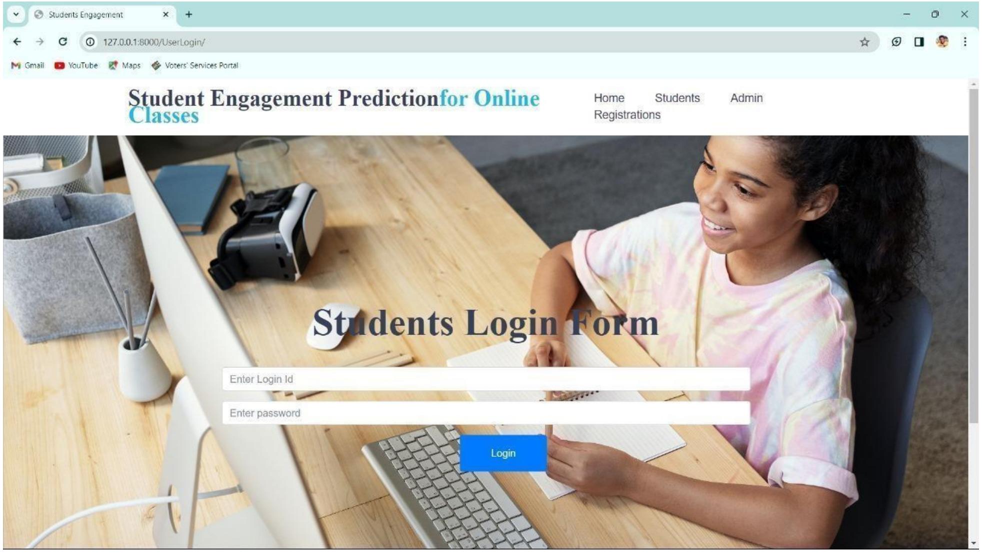
A student registration page serves as a crucial component for onboarding users into the system. The student registration page allows students or users to create accounts within the system. It collects necessary information from users to set up their profiles and personalize their experience.



Screen 4.2: Register student Screen

Screen 3: Student Login

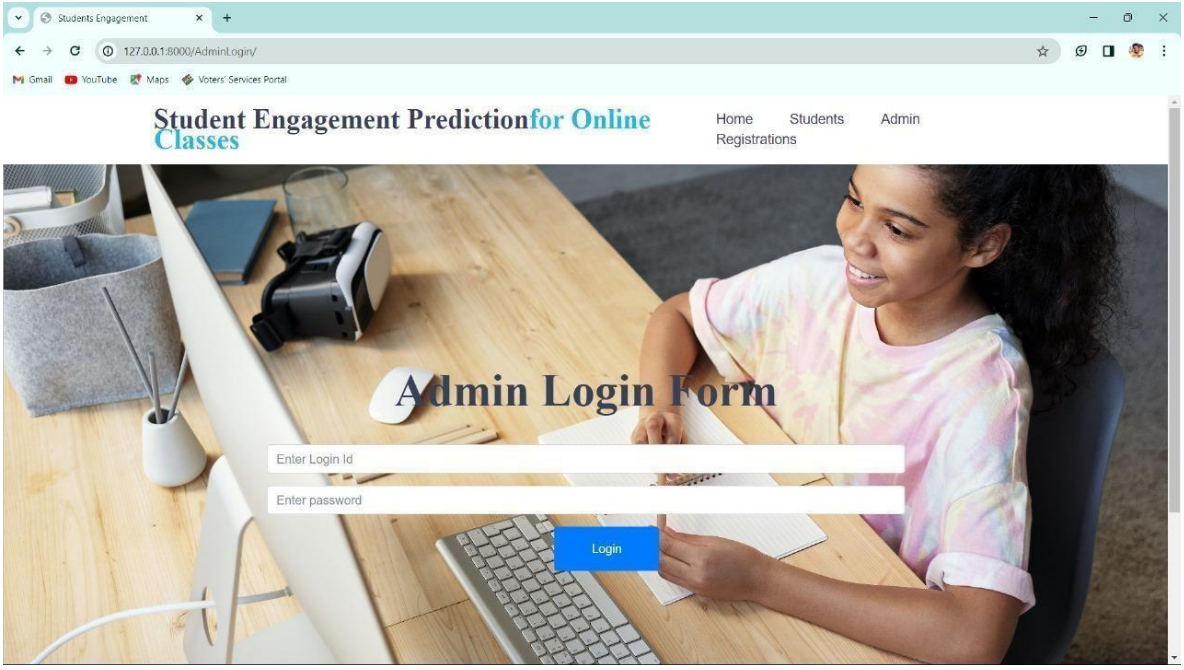
The student login page serves as a gateway for students to access the system and view their engagement metrics or participate in online lectures.



Screen 4.3: Entering Details

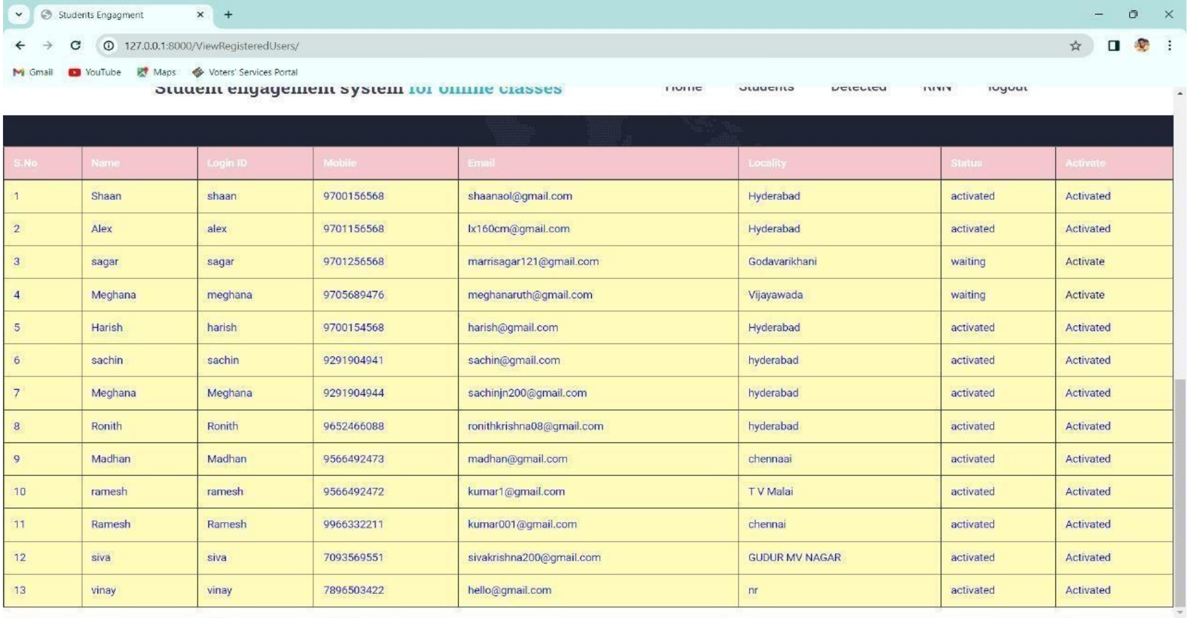
Screen 4: Admin login

After images have been captured the voice message will be sent to user for moving to further process.



Screen 4.4: Admin login

Screen 5: Activation of student

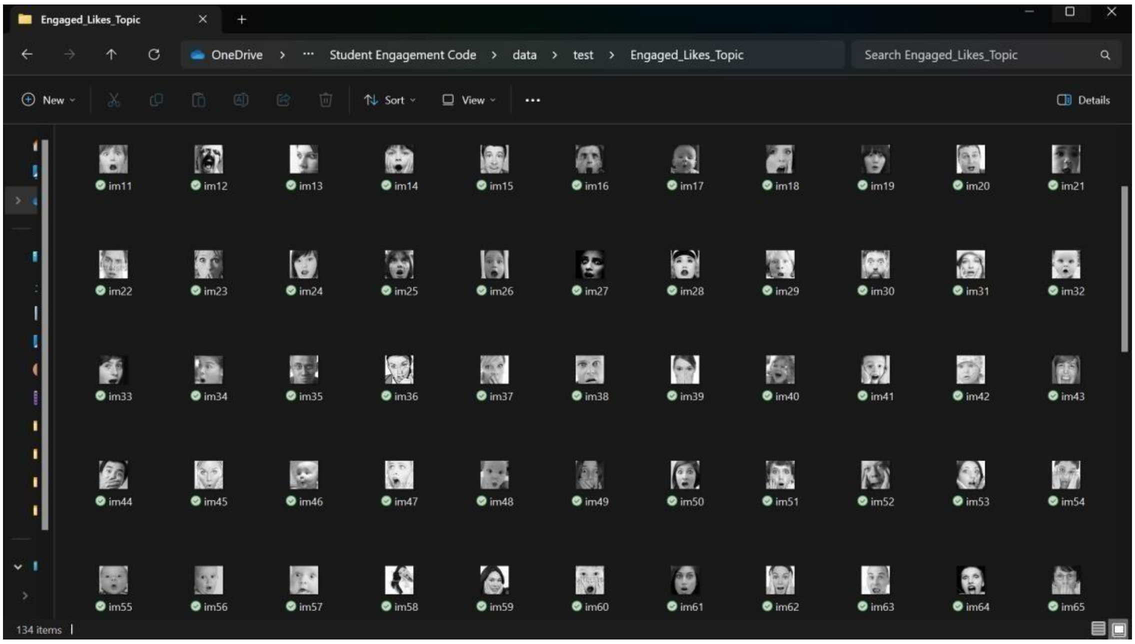


S.No	Name	Login ID	Mobile	Email	Locality	Status	Activate
1	Shaan	shaan	9700156568	shaanaol@gmail.com	Hyderabad	activated	Activated
2	Alex	alex	9701156568	lx160cm@gmail.com	Hyderabad	activated	Activated
3	sagar	sagar	9701256568	marrisagar121@gmail.com	Godavarikhani	waiting	Activate
4	Meghana	meghana	9705689476	meghanaruth@gmail.com	Vijayawada	waiting	Activate
5	Harish	harish	9700154568	harish@gmail.com	Hyderabad	activated	Activated
6	sachin	sachin	9291904941	sachin@gmail.com	hyderabad	activated	Activated
7	Meghana	Meghana	9291904944	sachinjn200@gmail.com	hyderabad	activated	Activated
8	Ronith	Ronith	9652466088	ronithkrishna08@gmail.com	hyderabad	activated	Activated
9	Madhan	Madhan	9566492473	madhan@gmail.com	chennaai	activated	Activated
10	ramesh	ramesh	9566492472	kumar1@gmail.com	T V Malai	activated	Activated
11	Ramesh	Ramesh	9966332211	kumar001@gmail.com	chennai	activated	Activated
12	siva	siva	7093569551	sivakrishna200@gmail.com	GUDUR MV NAGAR	activated	Activated
13	vinay	vinay	7896503422	hello@gmail.com	nr	activated	Activated

Screen 4.5: Activation of student

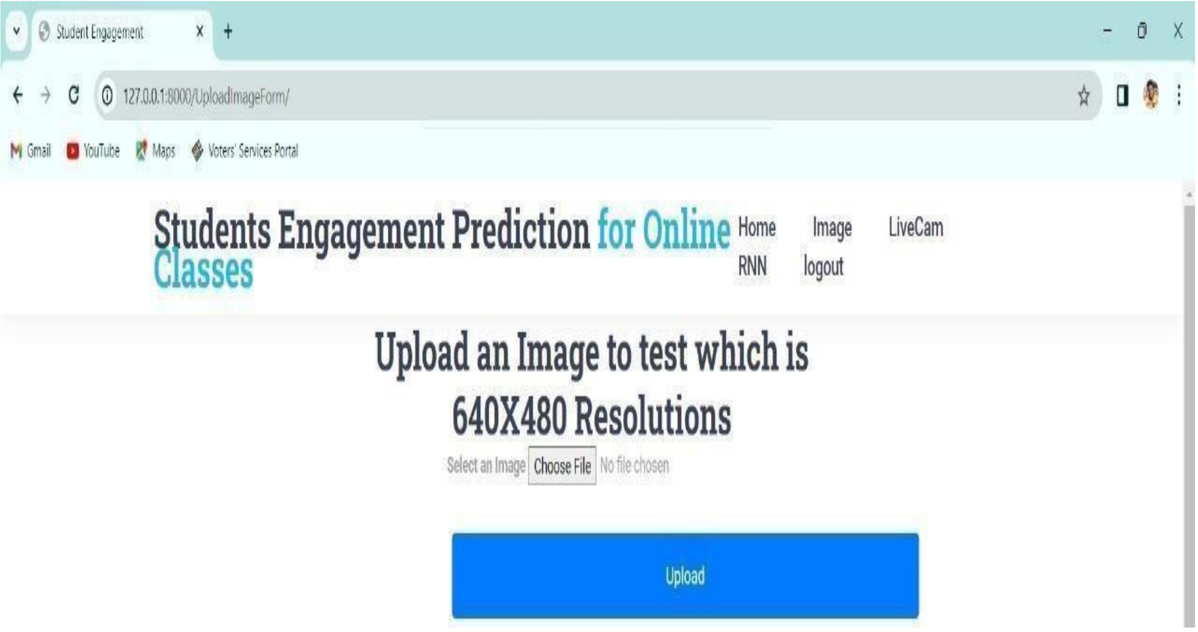
Screen 6: Training Images

You can see the images of each student who had registered in the "Training_Images" file in the specified location.



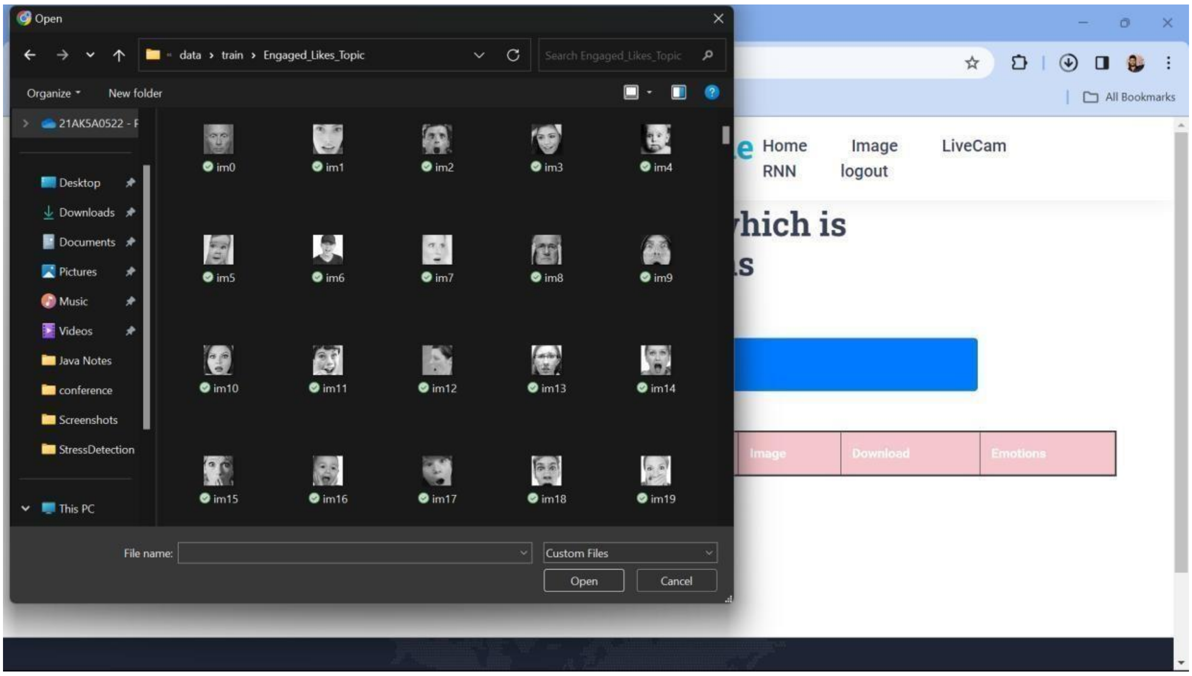
Screen 4.6: Training Images

Screen 7: Upload Images



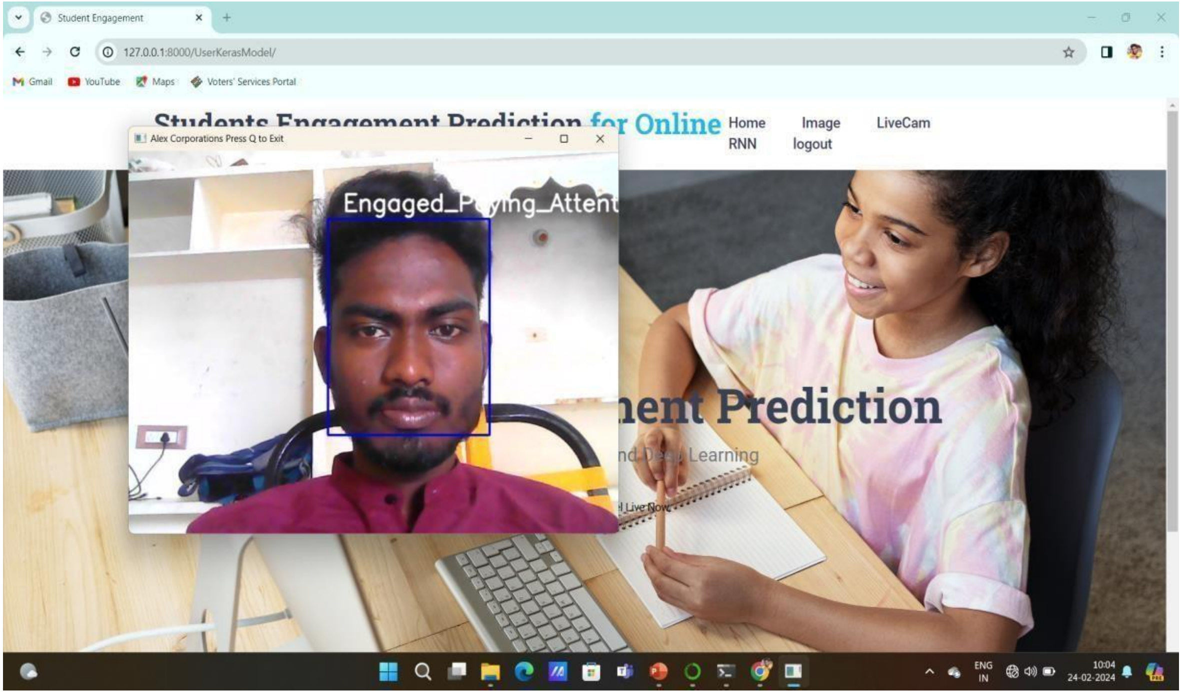
Screen 4.7: Upload Images

Screen 8: Select Image



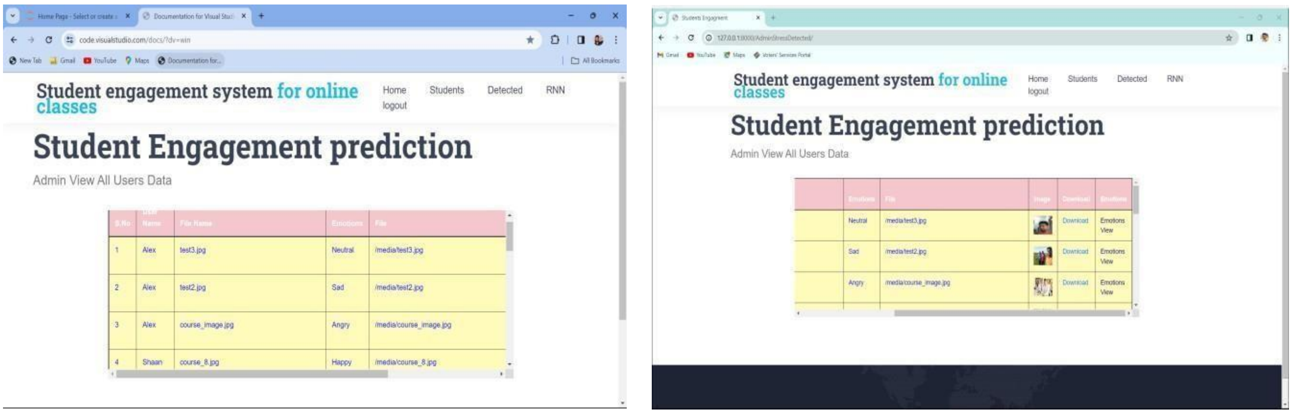
Screen 4.8: Select Image

Screen 9: Live cam results



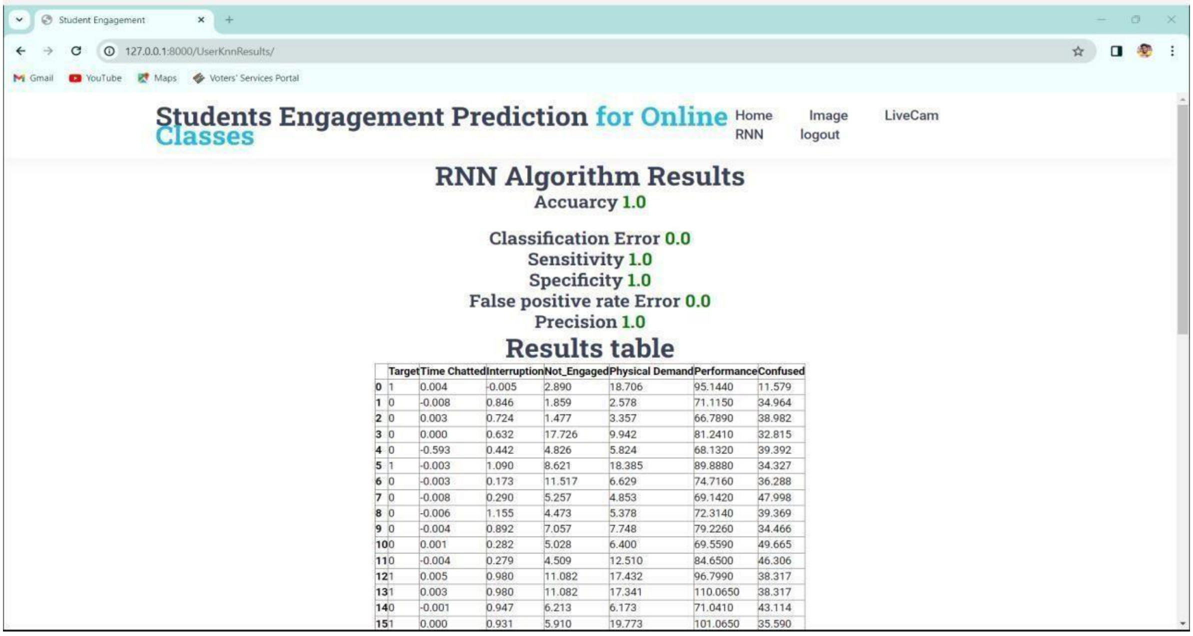
Screen 4.9: Live cam results

Screen 10: Admin results



Screen 4.10: Admin results

Screen 11: RNN algorithm results



Screen 4.11: RNN algorithm results

4.2.4 Result Analysis

The result analysis of the "Analysis of Facial Expressions to Estimate the Level of Engagement in Online Lectures" project involves evaluating the effectiveness, accuracy, and usability of the system in estimating engagement levels based on facial expressions. Here's how the analysis might be structured:

1. **Accuracy of Engagement Estimation**:

   - Evaluate the accuracy of the system in estimating engagement levels compared to ground truth data or human judgment.
   - Conduct statistical analysis to measure the correlation between estimated engagement levels and actual engagement indicators (e.g., self-reported feedback, quiz scores, participation rates).
   - Use metrics such as precision, recall, and F1-score to quantify the system's performance in identifying different levels of engagement.

2. **Comparison with Alternative Methods:**

- Compare the performance of the facial expression-based engagement estimation system with alternative methods or existing systems for assessing engagement in online lectures.
- Evaluate the advantages and limitations of facial expression analysis compared to other approaches, such as surveys, quizzes, or interaction tracking.

3. **Impact on Teaching and Learning Outcomes:**

- Assess the impact of using the engagement estimation system on teaching effectiveness and student learning outcomes.
- Analyze whether instructors can use engagement metrics to adjust their teaching strategies and content delivery in real-time to improve student engagement.
- Measure changes in student participation, attentiveness, and academic performance associated with the implementation of the system.

4. **Usability and User Experience:**

- Evaluate the usability of the system's user interface and interaction design.
- Assess factors such as ease of use, clarity of presentation, and intuitiveness of navigation.
- Gather feedback from users on their overall experience with the system and identify areas for improvement.

5. **Ethical Considerations:**

- Consider ethical implications related to the collection and analysis of facial expression data.
- Ensure compliance with privacy regulations and guidelines for handling sensitive personal information.
- Address concerns related to consent, transparency, and data security in the deployment of the system.

6. **Scalability and Performance**:

- Evaluate the scalability of the system to handle large volumes of video feeds and concurrent users.
- Measure system performance in terms of processing speed, resource utilization, and response times.
- Identify potential bottlenecks or scalability challenges and propose strategies for optimization.

5.TESTING & VALIDATION

5.1 INTRODUCTION

The purpose of testing is to discover errors. Testing is the process of trying to discover every conceivable fault or weakness in a work product . It provides a way to check the functionality of components, sub assemblies, assemblies and/or a finished product . It is the process of exercising software with the intent of ensuring that the Software system meets its requirements and user expectations and does not fail in an unacceptable manner. There are various types of test. Each test type addresses a specific testing requirement.

5.1.1 Testing Phases:

1. Performance Testing:

Objective: Evaluate the model's performance under various conditions, such as live streaming video qualities, different images.

Process:

* Test the model on live streaming video with varying expressions and qualities.
* Assess how well the model handles live streaming videos with different frame rates.
* Measure the processing time and resource utilization for different images and live streaming video scenarios.
* Analyze the impact of performance optimizations on the model.

2.Unit testing:

Unit testing involves the design of test cases that validate that the internal program logic is functioning properly, and that program inputs produce valid outputs. All decision branches and internal code flow should be validated. It is the testing of individual software units of the application .it is done after the completion of an individual unit before integration. This is a structural testing, that relies on knowledge of its construction and is invasive.

3.Usability and User Experience Testing:

Objective: Assess the usability and effectiveness of the engagement analysis system.

Process:

* Conduct usability testing with both lecturers and participants to evaluate the system's user-friendliness.
* Collect feedback on the accuracy of engagement estimation and the practicality of implementing the system in real-world online lectures.

4.Acceptance Testing:

User Acceptance Testing is a critical phase of any project and requires significant participation by the end user. It also ensures that the system meets the functional requirements.

5.1.2 Testing Methods :

Testing is a process of executing a program to find out errors. If testing is conducted successfully, it will uncover all the errors in the software. Any testing can be done basing on two ways:

White-box Testing:

Focus: White-box testing, also known as clear box testing, focuses on the internallogic and structure of the software being tested.

Method: Testers have access to the source code and design of the software. Theyuse this knowledge to design test cases that exercise specific paths through the code.

Objectives:

Verify the correctness of individual functions, methods, and modules.Test different paths and conditions within the code, including loops, branches, and error handling.Ensure that the code adheres to coding standards and best practices.

Techniques:

Statement coverage: Ensures that each statement in the code is executed at least once.

Branch coverage: Tests all possible branches (true/false) within the code.

Path coverage: Ensures that every possible path through the code is executed.

Pros:

Allows for thorough testing of internal logic and code paths.

Helps identify errors and weaknesses in the codebase early in the development process.

Cons:

Requires detailed knowledge of the codebase, which may not always be available.

Test cases may be biased towards paths that are easily reachable, leading to potential blind spots.

Black-box Testing:

Focus: Black-box testing, also known as behavioral testing, focuses on the functionality and behavior of the software from an external perspective.

Method: Testers do not have access to the internal implementation details of the software. Instead, they design test cases based on specifications, requirements, and expected behavior.

Objectives:

Verify that the software functions correctly according to its specifications.

Test the software's inputs, outputs, and interactions with external systems.

Evaluate the software's usability, performance, and reliability from an end-user perspective.

Techniques:

Equivalence partitioning: Divides the input domain into equivalence classes and tests representative values from each class.

Boundary value analysis: Tests boundary values of input ranges, as these values often trigger errors.

Error guessing: Based on experience and intuition, testers guess potential error-prone areas and design test cases accordingly.

Pros:

Does not require knowledge of the internal codebase, making it suitable for testing when the code is not accessible.

Tests the software's functionality from a user's perspective, helping identify usability issues and inconsistencies.

Cons:

May overlook certain internal logic or code paths that are not covered by the specified requirements.

Relies heavily on the quality of requirements and specifications provided, which may be incomplete or ambiguous.

5.1.3 Testing Approach:

Testing can be done in two ways:

• Bottom-up approach

• Top-down approach

Bottom-up Approach:

Testing can be performed starting from smallest and lowest level modules and proceeding one at a time. For each module in bottom up testing a short program executes the module and provides the needed data so that the module is asked to perform the way it will when embedded with in the larger system. When bottom level modules are tested attention turns to those on the next level that use the lower level ones they are tested individually and then linked with the previously examined lower level modules.

Top-down approach:

This type of testing starts from upper level modules. A stub is a module shell called by upper level module and that when reached properly will return a message to the calling module indicating that proper interaction occurred. No attempt is made to verify the correctness of the lower level module.

5.2 Design of Test Cases and Scenarios

S.no	Test Case	Excepted Result	Result	Remarks(IF Fails)
1.	User Register	If User registration successfully.	Pass	If already user email exist then it fails.
2.	User Login	If Username and password is correct then it will getting valid page.	Pass	Un Register Users will not logged in.
3.	Upload An Image	Image uploaded to server and strating process to detetct	Pass	Image must be 640X480 resolution will get better results
4.	Draw Squares in images	Detected images draw square and writing stress emotions	Pass	Images must be clearly to detect facial expression
5.	Start live Stream	PyImagelibaray will load the process and start the live	Pass	If library not available then failed
6.	Start Deep learning live stream	If tensorflow not installed then it will fail	Pass	Depends on system configuration and tensorflow library
7.	RNN Results	Load the dataset and process the RNN Algorithm	Pass	The dataset must be media folder
8.	Predict Train and Test data	Predicted andoriginal salary will be displayed	Pass	Trains and test size must be specify otherwise failed
9.	Admin login	Admin can login with his login credential. If success he get his home page	Pass	Invalid login details will not allowed here
10.	Admin can activate the register users	Admin can activate the register user id	Pass	If user id not found then it won’t login.

5.3 Validation

The system has been tested and implemented successfully and thus ensured that all the requirements as listed in the software requirements specification are completely fulfilled.

Validating the "Facial Expressions to Estimate the Level of Engagement in Online Lectures" project involves assessing the accuracy, reliability, and effectiveness of the system in estimating engagement levels based on facial expressions. Here's a comprehensive approach to validation:

1. **Data Collection:**
   - ➢ Gather a diverse dataset of online lectures with a range of topics, instructors, and audience demographics.
   - ➢ Ensure the dataset includes ground truth labels for engagement levels, such as self-reported ratings by viewers or objective metrics like quiz performance or attention tracking.
2. **Training and Testing Data Split:**
   - ➢ Divide the dataset into training and testing sets to evaluate the performance of the system.
   - ➢ Ensure that the distribution of engagement levels is consistent between the training and testing sets to avoid bias.

3. **Model Training**:
    - Train machine learning models, such as deep neural networks or ensemble classifiers, on the training data.
    - Utilize techniques like transfer learning or fine-tuning pretrained models to leverage existing knowledge and optimize performance.
4. **Evaluation Metrics:**
    - Define evaluation metrics to measure the performance of the engagement estimation system.
    - Common metrics include accuracy, precision, recall, F1-score, and area underthe receiver operating characteristic curve (AUC-ROC).
5. **Cross-Validation:**
    - Perform cross-validation to assess the generalization capability of the trained models.
    - Use techniques like k-fold cross-validation to validate the models on multiple subsets of the dataset.
6. **Testing Phase:**
    - Apply the trained models to the testing dataset to evaluate their performance in estimating engagement levels.
    - Compare the predicted engagement levels with ground truth labels to assess accuracy and reliability.
7. **Error Analysis:**
    - Conduct error analysis to identify common patterns of misclassification or areas of weakness in the system.
    - Analyze cases where the system fails to accurately estimate engagement levels and determine potential causes.

8. **User Studies:**

    - Conduct user studies to assess the perceived usefulness and usability of the system.
    - Collect feedback from viewers and instructors on the system's effectiveness in capturing engagement levels and providing actionable insights.

9. **Real-world Deployment:**

    - Deploy the system in real-world online lecture settings to evaluate its performance under practical conditions.
    - Monitor system performance, stability, and user satisfaction during deployment and gather feedback for continuous improvement.

10. **Iterative Improvement:**

    - Use insights from validation results, error analysis, and user feedback to iteratively improve the system.
    - Incorporate enhancements such as refining algorithms, adjusting parameters, or integrating additional features to enhance accuracy and usability.

By following this validation approach, you can thoroughly assess the performance and effectiveness of the "Facial Expressions to Estimate the Level of Engagement in Online Lectures" project, ensuring that it provides reliable estimates of engagement levels and valuable insights for instructors and learners

6. CONCLUSION & FUTURE ENHANCEMENT

6.1 CONCLUSION

6.1.1 INTRODUCTION

In the digital age of virtual classrooms, understanding student engagement during online lectures is crucial. Traditional methods fall short, but our project takes a fresh approach. We capture students' faces during video lectures, analyzing subtle facial expressions. By measuring reaction times and extracting specific features, we connect these cues to attention levels using deep learning. Remarkably, even excluding sleepy faces, facial expressions remain reliable indicators of genuine engagement. Educators can now monitor student attention effectively, unlocking new possibilities in the symphony of online learning

6.1.2 CONCLUSION

The "Analysis of Facial Expressions to Estimate the Level of Engagement in Online Lectures" project presents a promising approach to enhancing the effectiveness of online education by leveraging facial expression analysis technology. By analyzing facial expressions captured during online lectures, the system can estimate the level of engagement of students, providing valuable insights to educators for optimizing teaching strategies and improving learning outcomes.

In conclusion, the "Facial Expressions to Estimate the Level of Engagement in Online Lectures" project presents an innovative approach to enhance the effectiveness of online education by leveraging facial expression analysis technology. By analyzing facial expressions captured during online lectures, the system aims to provide valuable insights into the engagement levels of viewers, thereby enabling educators to optimize their teaching strategies and improve learning outcomes. Throughout the project, several key components and modules were identified, including data acquisition, facial detection and tracking, facial expression analysis, engagement level estimation, integration with online lecture platforms, user interface design, performance optimization, data management, and feedback mechanisms. These modules work

To gether synergistically to capture, analyze, and interpret facial expressions, providing users with actionable insights to enhance the online learning experience.

6.1.3 COMPARISON

Advancements in technology, particularly in computer vision and Deep learning, the process has become more objective and efficient. Presently, facial expression analysis can be automated using sophisticated algorithms. Cameras can capture students' facial expressions in real-time during online lectures, and software can analyze these expressions to gauge their level of engagement. This approach offers a more consistent and reliable method of assessment compared to existing model.

The metrics used to evaluate engagement have evolved. In the existing system, analysis might have been limited to basic emotions like happiness, sadness, or boredom. Proposed system, Deep learning models can recognize a wider range of emotional states and engagement levels, including subtle micro-expressions. This allows for a more nuanced understanding of students' reactions to online lectures.

6.1.4 APPLICATION

The project's analysis of facial expressions to gauge engagement levels in online lectures, using deep learning, is a significant step forward in educational technology. Essentially, it means that computers can now understand how interested and involved students are during online classes by studying their facial expressions. This breakthrough offers teachers valuable insights into how well their students are following along and paying attention. With this information, educators can adapt their teaching methods to better suit their students' needs, making online learning more effective and personalized. As technology progresses, integrating facial expression analysis into online education platforms holds great potential for improving the quality and impact of virtual learning experiences, ultimately making learning more engaging and fulfilling for students worldwide**.**

6.1.5 LIMITATIONS

Deep learning-based analysis of facial expressions for estimating engagement levels in online lectures holds promise, several limitations must be considered. Firstly, the accuracy of such estimation heavily relies on the quality and diversity of the dataset used for training, potentially leading to biased results. Secondly, variations in facial expressions among individuals and cultural backgrounds may pose challenges in developing universally applicable models.

6.2 FUTUR SCOPE

To enhance the "Facial Expressions to Estimate the Level of Engagement in Online Lectures" project in the future, several avenues can be explored to improve accuracy, usability, and scalability. Integrate other modalities such as speech analysis, gaze tracking, and interaction patterns to provide a more comprehensive understanding of Engagement levels beyond facial expressions alone.Enhance accessibility by incorporating features to accommodate diverse user needs, such as support for multiple languages, subtitles, and customizable interface options for users with disabilities. Develop algorithms to provide personalized recommendations for lecturers based on analyzed engagement data, suggesting content adjustments or teaching strategies tailored to specific audience preferences and behaviors. Accessibility Features: Enhance accessibility by incorporating features to accommodate diverse user needs, such as support for multiple languages, subtitles, and customizable interface options for users with disabilities.

By incorporating these future enhancements, the "Facial Expressions to Estimate the Level of Engagement in Online Lectures" project can evolve into a more robust, insightful, and user-centric platform for enhancing online learning experiences.

6.2.1 SUMMARY

The study aimed to develop a method for assessing students' attentional state during online lectures by measuring reaction time (RT) to detect task-irrelevant stimuli, thereby estimating learners' focus on the lecture. Utilizing machine learning, particularly Light GBM, researchers predicted RTs from facial features extracted as action units (AUs). The findings suggested that facial expressions are useful for predicting attentional states during lectures. Even after excluding data with sleepy faces, the approach remained effective in estimating learners' attention levels.

In conclusion, leveraging facial expressions can enhance understanding of student engagement online learning environments, offering valuable insights for educators to improve learning conditions.

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Assessing Student Engagement from Facial Behaviour in Online Learning

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ABSTRACT

The present study aimed to develop a method for estimating students' attentional state from facial expressions during online lectures. Student engagement is a critical factor influencing academic success and overall learning outcomes. This research explores the application of Recurrent Neural Networks (RNNs) to predict student engagement in educational settings. We estimated the level of attention while students watched a video lecture by measuring reaction time (RT) to detect a target sound that was irrelevant to the lecture. We assumed that reaction time to such a stimulus would be longer when participants were focusing on the lecture compared with when they were not. We sought to estimate how much learners focus on a lecture using RT measurement. In the experiment, the learner's face was recorded by a video camera while watching a video lecture. Facial features were analyzed to predict RT to a task-irrelevant stimulus, which was assumed to be an index of the level of attention. Traditional methods for assessing engagement often rely on manual observations or surveys, which can be subjective and time-consuming. Imagine students learning online, like using a website or app. The proposed RNN (Recurrent Neural Network) model is like a smart system. It watches how students interact with their learning stuff, like clicking, reading, or answering questions. This smart system looks at these actions one after another, in a sequence, to understand how students are involved. It then uses this understanding to predict and measure how much students are engaged in their learning activities automatically. So, it helps figure out if students are really into their online learning or not.

Keywords: Attention, Affective computing, Engagement, Facial features, Online lecture, Deep Learning.

I. INTRODUCTION

In the rapidly evolving landscape of education, understanding and enhancing student engagement is crucial for promoting effective learning outcomes. Student engagement refers to a range of interactive behaviors that contribute to a student's involvement and participation in the learning process. This means more than just showing up – it includes things like participating in class, finishing assignments on time, and interacting with what they're studying. When students engage like this, they tend to do better academically. Now, there's a growing interest in using fancy computer analyses, especially something called machine learning, to predict and understand how students get involved. This involves looking at past information to figure out patterns and then using that to guess how engaged students might be in the future. It's like predicting the weather, but for student participation. By doing this, teachers and schools can take steps to help students who might need a little extra support, creating a more personalized and effective learning experience for everyone. It's a mix of education and technology working together to make sure students are getting the most out of their learning. In order to analyze we developed a software aiming at analyzing video streams (recorded or real-time) with the focus on real-world conditions, such as various light conditions, spontaneous facial expressions, hands occluding the face. The software, using the learned LSTM model, provides a visual interface that visualizes the level of predicted engagement during the learning sessions.

II. RECENT WORKS

Attention Mechanisms for Facial Expression Analysis. Just as attentional Recurent Neural networks (RNN) And we using LSTM prioritize informative facial features for distinguishing between genuine and manipulated faces, similar attention mechanisms can be employed to focus on key facial expressions indicative of engagement during online lectures. This could involve identifying facial regions such as eyes, eyebrows, and mouth, which are crucial for conveying emotions like interest and attentiveness.

Multi-Task Learning for Engagement Estimation the concept of multi-task learning, where related tasks like gender prediction and age estimation are jointly predicted, can be adapted for analyzing facial expressions during online lectures. Instead of predicting gender and age, the model could simultaneously estimate engagement levels along with other related facial attributes. By leveraging the inherent relationship between these tasks, the accuracy of engagement estimation could be improved.

The robustness of engagement estimation models. By aggregating predictions from different facial expression analysis models, potentially including attentional networks and residual networks, the system could better capture nuanced facial cues associated with different levels of engagement.

Leveraging advancements in deep learning methodologies, particularly attentional mechanisms and multi-task learning strategies, holds promise for developing robust systems capable of analyzing facial expressions to estimate engagement levels in online lectures. By addressing challenges and fostering interdisciplinary collaborations, researchers can contribute to enhancing the efficacy and usability of such systems, thereby promoting trustworthiness in digital education platforms and improving the overall learning experience.

III. PROPOSED WORK EXPLANATION

This project delves into the realm of predicting student engagement in educational settings by leveraging Recurrent Neural Networks (RNNs), specifically incorporating Long Short-Term Memory (LSTM) cells.

Recognizing the temporal dependencies embedded in sequential student activity data, the proposed RNN model aims to capture dynamic patterns within these sequences. Unlike traditional methods, RNNs, and particularly LSTMs, are well-suited for handling sequential data due to their ability to retain and utilize information over extended time intervals. This adaptability allows the model to discern nuanced temporal dependencies in student behavior, a crucial aspect in understanding and predicting engagement levels.

In the training process, the RNN's parameters are optimized to ensure accurate predictions of student engagement levels. Evaluation metrics such as accuracy, precision, recall, and F1 score are employed to rigorously assess the model's performance. By comparing these metrics with those of traditional engagement prediction methods, the research aims to demonstrate the superiority of the RNN-based approach. The emphasis on these metrics provides a comprehensive evaluation, considering both the model's ability to make accurate predictions and its capacity to minimize false positives and negatives.

The results of this study underscore the effectiveness of the RNN model in capturing subtle and intricate temporal patterns associated with student engagement. The model's outperformance of traditional methods signifies its potential as a robust tool for predicting and understanding student engagement in educational contexts. This research contributes valuable insights into the utilization of sequential data and advanced neural network architectures, shedding light on the potential improvements in engagement prediction methodologies for educational practitioners and researchers alike.

3.1. Classification Metrics

Classification metrics are used to compare classification results obtained from various methods. Precision, recall, F1-score, and accuracy metrics were used to determine the performance of each method in the study in the classification of waste materials in the garbage. The mathematical expressions given in equations (1–4) were used to calculate the metrics considered.

$$\text{Accuracy}=\frac{(TP+TN)}{(TP+TN+FP+FN)} \qquad (1)$$

$$\text{Precision}=\frac{TP}{(TP+FP)} \qquad (2)$$

$$\text{Recall}=\frac{TP}{(TP+FN)} \qquad (3)$$

$$\text{F1 Score}=2^{*}\frac{(Precision*Recall)}{(Precision+Recall)} \qquad (4)$$

IV. RESULTS AND DISCUSSION

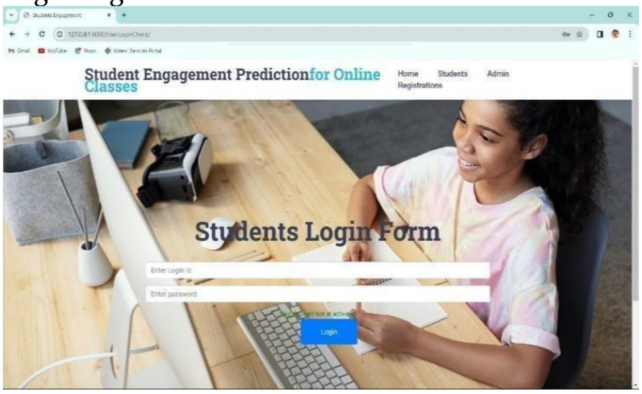
Below are a series of visuals depicting the step-by-step progression of our project.

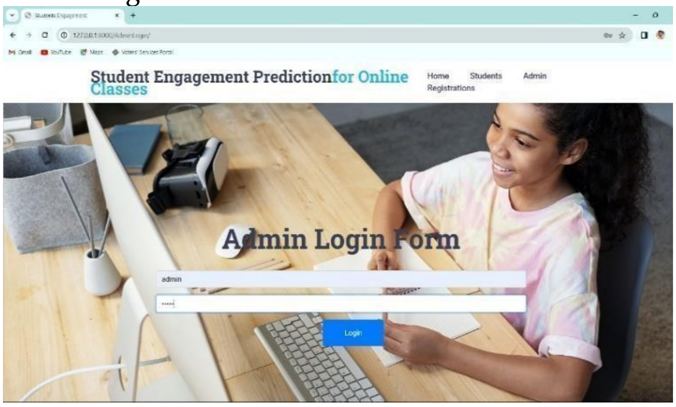
Homepage:

Registration Page:

Login Page:

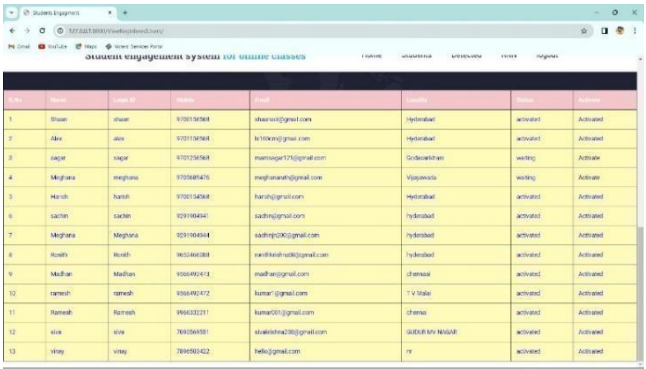
Admin Page:

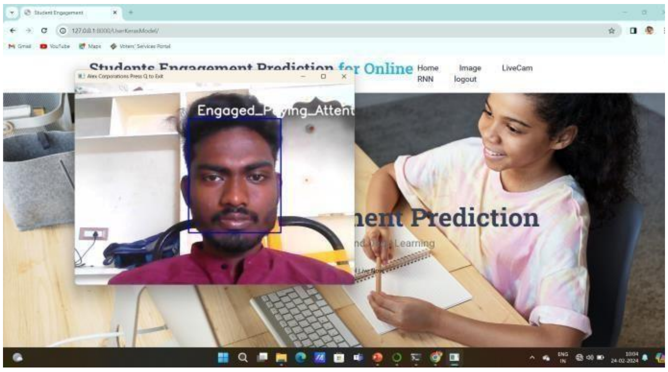




Activation Page:

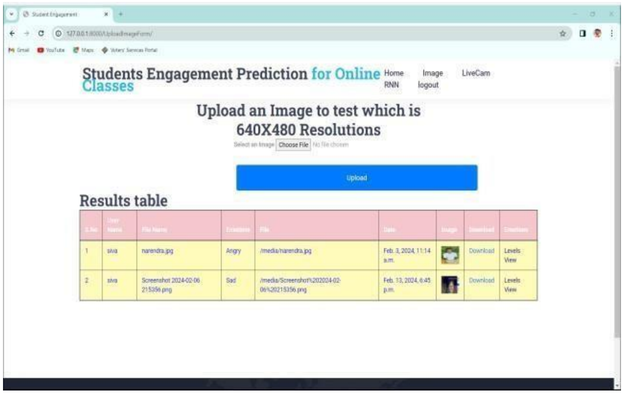
Live Cam:

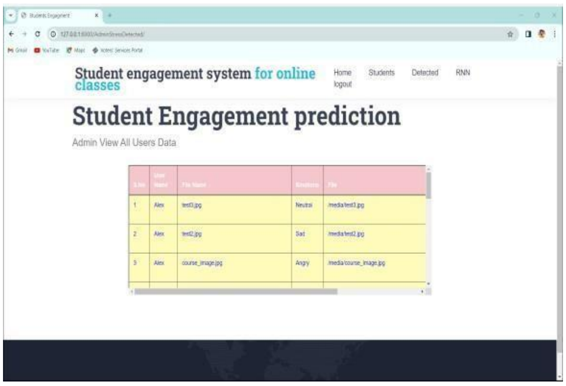




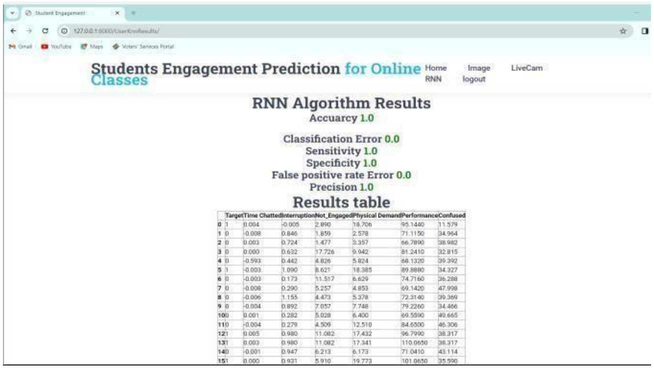
Upload Image:

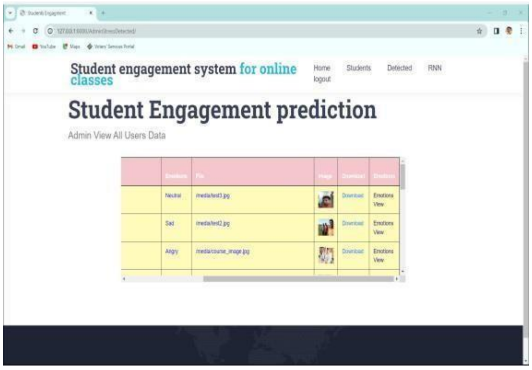
Results page:





RRN Algorithm Results:





V. CONCLUSIONS

In conclusion, we revealed that facial expressions can be used to predict learners' level of attention to video lectures, which serves as an index of student engagement. Facial features captured by a video camera can predict reaction times, which are assumed to be indicative of attentional states. Specific facial features, such as nose wrinkling, blinking, and lip corner depression, appear to be associated with attention during video lectures. The application of facial expression technology has the potential to enhance the quality of teaching.

In order to analyze ,we developed a software aiming at analyzing video streams (recorded or real-time) with the focus on real-world conditions, such as various light conditions, spontaneous facial expressions, hands occluding the face. The software, using the learned LSTM model, provides a visual interface that visualizes the level of predicted engagement during the learning sessions.

The outcomes of this investigation underscore the practicality and efficiency of employing facial expression analysis as a predictive tool for student engagement. By successfully demonstrating the feasibility of this novel approach, our study not only contributes to the evolving landscape of educational research but also holds the promise of transforming how we gauge and enhance student participation in online learning environments. This forward-thinking methodology, harnessing the rich information embedded in facial expressions, stands poised to usher in a new era of personalized and adaptive education, catering to the diverse needs of students and educators alike.

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