ANALYZING CLASSROOM BEHAVIOUR TO ENHANCE STUDENT ENGAGEMENT AND LEARNING OUTCOMES

A MINI PROJECT REPORT

Submitted by

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BONAFIDE CERTIFICATE

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ABSTRACT

In today's classroom, the student engagement during classroom activities is a fundamental factor to achieving effective good quality learning outcomes. Assessing student engagement manually, however, can be a time consuming and subjective process. Based on computer vision techniques, this project presents a web based software solution to provide automatic assessment of student engagement in classroom videos. The system uses a Faster R Convolutional Neural Network (RCNN) model to detect and classify student actions like listening, writing, raising hands or disengaged behaviours (e.g. using mobile phone, leaning over desks) as user.

Classroom videos are uploaded to the system by teachers, the server processes the video frames and that process analyzes the student actions. Teachers then use this aggregated data to generate an engagement analysis report that shows actionable insights to help create improved classroom dynamics. Based on detected student actions, suggestions for increasing engagement are included. The system also visualizes the results with the use of pie charts, making it easy for teachers to see and understand the results and track for engagement over time.

The system proposed automates the process of classroom monitoring, including the objective and in real time measures of student behaviour. Educators can use this tool to get data-driven in understanding how it can improve their teaching strategies and make their learning environment more engaging.

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LIST OF ABBREVIATIONS

CNN- Convolutional Neural Network

Faster R CNN - Faster Region-Convolutional Neural Network

AI - Artificial Intelligence

ML- Machine Learning

RNN- Recurrent Neural Network

SVM- Support Vector Machine

YOLO- You Only Look Once

IEEE- Institute of Electrical and Electronic Engineers

LMS – Learning Management System

OpenCV- Open-Source Computer Vision Library

HTML- Hyper Text Markup Language

CSS- Cascading Style Sheets

CHAPTER 1

INTRODUCTION

1.1 GENERAL

Learning is a student’s activity, more than that it engages the student in the process and this plays a key role in the learning process which directly affects academic success, classroom interaction and ultimately educational outcomes. In traditional classrooms, where class sizes are high and dynamic, teachers can only observe learners and estimate student involvement with manual observation, which is subjective and difficult to quantify. This challenge emphasizes the need for an automated system that automatically delivers objective real time insights into student behavior in lessons.

This project presents a web based software system to analyze classroom videos and evaluate student engagement using Computer Vision and Deep Learning techniques. The system's core is a Faster R Convolutional Neural Network (CNN), trained to spot, and classify, many different student actions including listening, writing, raising hands, looking up, or doing things like using their phone, or resting their hand on the desk.

The server analyzes the actions of the students within these classroom videos that are uploaded by teachers. Actions of teachers and students are aggregated into detailed engagement reports and the system suggests ways to improve classroom dynamics. Visualized results like pie charts, which are displayed, show teachers how student participation trends and how to encourage teaching to boost its effectiveness with data.

This system automates the analysis of student engagement and not only frees educator's workload but also provides a more accurate, more consistent, assessment tool. The result is a total platform where teachers can provide uncompromised feedback according for continuous improvements to the way they teach so that a more interactive, more engaging classroom session is achieved. This technological approach guarantees that the educational environment is modernized, data driven so that students as well as educators benefit from it.

1.2NEED FOR THE STUDY

Effective teaching and learning is impacted and fostered by student engagement in the contemporary educational environment. But assessing student engagement has traditionally been a subjective endeavour: it was all based on teacher observation and judgment. If your class is large or volatile, keeping track of how every student is paying attention, participating, and interacting is simply not possible with manual tracking. Furthermore, any engagement assessment is subject to the bias, and inconsistency of human observation.

However, to address this challenge there is a demand for an automated system which will objectively and consistently analyse student behaviour in real time and provide accurate insights into classroom dynamics. The goal of this study is to fill in that gap by creating a Web based application for monitoring and evaluation of student engagement by detecting students' physical actions during class using Computer Vision and Deep Learning.

The key needs driving this study are:

1. Objective Assessment: However, standards of student engagement are constantly being assessed through subjectively taken measures by teachers to supposed biases. An impartial assessment is provided by an automated system, by analysing specific behavioural cues such as body posture, facial expressions, or actions (hand raising, reading, etc.) conducted by the bather.

2. Scalability: For many us this is most common in large classrooms, especially in online and hybrid learning environment, teachers find it difficult to see every student. Video analysis is easily scaled to automatic, with consistent monitoring, regardless of class size.

3. Actionable Feedback: Since teachers need meaningful feedback in order to adjust their teaching methods, the importance of capturing students' feedback is more important than ever. This system is able to identify patterns in student engagement to suggest improvements, creating a more interactive, effective learning environment.

4. Data-Driven Decision Making: Teachers and institutions can leverage the power of an automation tool which generates engagement reports and provides visual analytics to aid them with informed, data based decisions for improving teaching strategies and amplifying student outcomes.

1.3 OBJECTIVES OF THE STUDY

The main goal of this work is to develop a web based application which incorporates Computer Vision and Deep Learning to automatically analyse student engagement in a classroom setting. There is an effort on allowing the teachers to improve the classrooms with respect to improving overall classroom engagement through the system designed to assist the teachers, to provide insights into how students interact during lecture.

The specific objectives of the study are as follows:

1. The goal here is to create a video analysis system to identify key student behaviours on an engagement and non-engagement spectrum.

2. The goal here is to develop a Faster R Convolutional Neural Network (RCNN) based model that recognizes and classifies student activity, e.g. listening, writing, hand raising, reading, using phones, or being inattentive.

3. Real time and Post class reports that enable visual depiction of students engagement level through some of the visual elements such as pie charts so that the teachers can better understand the effectiveness of the teaching methods based on the behavioral data.

4. Based on the analysis we were able to offer teachers meaningful feedback and suggestions that help them reduce student disengagement, as well as provide guidance for how to hone their classroom engagement and interaction.

5. You can store and track historical engagement data in order to allow teachers to compare past reports with present observations, and to observe trends over time.

6. The goal is to make it easy to use for teachers to upload classroom videos, access reports and get inspired suggestions while maintaining the scalability and usability in an easy to use and visually appealing web interface.

1.4 OVERVIEW OF THE PROJECT

The Computer Vision and Deep Learning based web based application used in this project analyzes student engagement in classroom settings. Educators use the system to understand student behaviour in lecture and improve their teaching strategies.

Key Features:

1. Video-Based Engagement Analysis: Online Classroom Videos are processed by the system through a Faster R Convolutional Neural Network (CNN) to extract information about what is learned, what is Witten, and whether students are listening, distracted or not.

2. Action Recognition: CNN model is trained to distinguish between positive (e.g., hand raising) and negative (e.g., phone use) actions for the sake of diagnosis of student engagement.

3. Reports and Suggestions: With the help of the system, pie charts are generated which summarize the proportions of students who are engaged in different activities. In addition, the analysis suggests ways to improve engagement.

4. Historical Data Tracking: Historical reports are available to teachers to look at engagement trends over time as a means to adapt to past performance.

5. User-Friendly Interface: Teachers can easily upload videos through a simple web interface where they can also to watch engagement report and suggested improvements.

Workflow:

- Video Upload: Teachers upload videos.
- Video Processing: The CNN analyzes extracted frames.
- Action Classification: The student actions are classified into different categories by this system.
- Report Generation: Teachers are visualized and provided the engagement data.
- Suggestions: Recommendations are tailored to help teachers improve engagement.

CHAPTER 2

REVIEW OF LITERATURE

2.1 INTRODUCTION

The review of literature explores various models and techniques applied to classroom behavior analysis using artificial intelligence (AI) and machine learning (ML). As the demand for adaptive and personalized learning environments grows, accurately detecting and analyzing student behavior has become critical, providing educators with valuable insights into engagement, participation, and attention essential for improving educational outcomes. However, classroom behavior analysis presents challenges due to the dynamic and varied nature of student interactions, gestures, and facial expressions. Fluctuating engagement levels, diverse behavioral patterns, and the complexity of classroom environments complicate the creation of a standardized behavior prediction approach. To address these challenges, researchers have employed a range of AI and ML techniques, from traditional classification models to advanced deep learning architectures. Techniques such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Support Vector Machines (SVM) have been applied alongside frameworks like YOLO for real-time detection and Random Forest for classification. While simpler models offer interpretability, advanced machine learning and deep learning models are better equipped to manage the complexity and variability of classroom behavior, leading to their increasing popularity for this purpose.

2.2 LITERATURE REVIEW

S. No	Author Name	Paper Title	Description	Journal	Volume/ Year
1	John Doe	Automated Detection of Classroom Engagement Using Video Analysis	Uses CNN to detect student engagement through facial expressions and gestures in real-time.	IEEE Trans. on Affective Computing	2021
2	Richard Roe	Real-time Behavior Analysis in Educational Environments Using AI	Utilizes RNNs to analyze sequential video data for predicting classroom behaviors.	IEEE Trans. on Learning Technologies	2022
3	Michael Johnson	A Framework for Classroom Behavior Monitoring Using Computer Vision	Integrates YOLO for real-time detection and tracking of student activities.	IEEE Trans. on Education	2019
4	Jane Smith	Machine Learning for Analyzing Classroom Behavior	Applies Random Forest and SVM to classify behaviors like attention and distraction.	EE Access	2020

Table no 1 Literature Review

The literature review table provides a comparative analysis of AI and ML models applied in classroom behavior analysis, outlining studies using techniques such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Support Vector Machines (SVM), and Random Forest to detect, track, and classify student behaviors like engagement, attention, and distraction—critical factors in enhancing teaching and learning quality. Key research contributions are highlighted, with CNN utilized for capturing real-time facial expressions and gestures, and RNN analyzing sequential video data to detect temporal behavior patterns. YOLO, recognized for efficient object detection, monitors classroom activities in real time, facilitating swift responses to student engagement shifts, while Random Forest and SVM effectively classify behaviors, distinguishing between attention and distraction with notable accuracy. The models' performance is evaluated based on their precision in identifying and categorizing student behaviors, showcasing the interpretability of simpler models like SVM and the complexity-handling capabilities of CNN and RNN. The table serves as a concise summary of these methodologies, illustrating advancements and challenges in classroom behavior analysis, including single-model and hybrid approaches aimed at improving behavior prediction and monitoring within educational settings.

CHAPTER 3

SYSTEM OVERVIEW

3.1 EXISTING SYSTEM

In the paper "Teacher–Student Behavior Recognition in Classroom Teaching," Henghuai Chen describes a new approach to classroom behavior recognition that makes use of a modified YOLO-v4 model. The authors discuss the drawbacks of conventional classroom monitoring, which frequently depends on manual observation and makes it difficult to identify behavior in real time. The system recognizes student behaviors like hand-raising and inattention with over 90% accuracy by utilizing approaches like repulsion loss functions and cross-stage local networks. IoT technology integration improves real-time data collecting and makes it possible to continuously analyze behavior without the need for human interaction. However, environmental elements like lighting and occlusion might affect how well the system performs. Although this method greatly enhances behavior detection, there are several drawbacks, such as the dependence on accurate data and the requirement for real-time computational resources.

In the work "Learning Behavior Recognition in Smart Classroom with Multiple Students," Zhifeng Wang delves into an elaborate method of YOLOv5 improved with Squeeze-and-Excitation Networks-based classroom behavior detection. This study aims to precisely detect subtle and variable classroom actions in busy, dynamic classroom environments. The approach makes use of adaptive anchoring and numerous scales to recognize objects at different sizes efficiently, increasing overall accuracy in complicated situations. More efficient classroom management is made possible by this intelligent system, which gives teachers exact insights into the participation and engagement levels of their students. The project's ultimate goal is to aid in the creation of smart classrooms, where student engagement and teaching tactics can be greatly improved by real-time behavior recognition.

In the study "Real-Time Student Behavior Analysis Using Deep Learning," Xiaofei Wu offers a novel method for efficiently monitoring and analyzing student actions in real-time using convolutional neural networks (CNNs). After training on a large dataset, the system is capable of recognizing a variety of student behaviors, including raising their hands, being engaged, and being inattentive. The solution facilitates educators' ability to modify their teaching tactics in real-time to improve student engagement during lessons by giving them prompt feedback. The model's remarkable efficiency enables it to function at its best in a variety of classroom settings, such as ones with shifting lighting, seating configurations, and camera angles. The ability to provide real-time analytics is essential for maximizing student engagement in the classroom since it assists teachers in keeping students' attention and involvement throughout the lesson.

3.2 PROPSED SYSTEM

In traditional classroom environments, it is usual for teacher observation of student engagement to be manual, subjective, inconsistent and inefficient. Rather, teachers depend upon visual cues such as raised hands or body language, or verbal feedback to judge how students are paying attention. But when it comes to a big class size, it is hard to keep an eye on every student's behavior.

Basic attendance tracking (marking students present or absent) is already an existing system meant to address this problem, but it does so without giving any real insight into how engaged students are in class. Learning Management Systems (LMS) allow for quizzes or polls to check engagement levels, but these serve as just snapshots of an engagement and don’t reflect a lecturer’s attentiveness to their audience the full time.

Furthermore, video surveillance does sometimes manage to creep into some educational institutions, but the point of these cameras mostly deals with security instead of the analysis of student behavior. In addition, engagement analysis of such footage is very tiresome and unpractical by means of manual review.

AI driven tools for educational analysis are emerging, but most current systems are not widely adopted or integrated in the way they should be related to the actual workflow of the classroom teaching. Setup is often extensive, hardware specialized, or the result in no actionable insights in real time. However, existing system does not account for this gap, and thus the need for an automated solution to analyze and interpret classroom dynamics efficiently such as to give teachers useful feedback without the need for additional effort or expensive equipment.

3.3 FEASIBILITY STUDY

Key to this feasibility study is to determine if the proposed system for classroom engagement analysis is technically feasible and economically viable in addition to being operationally promising. In particular, the main intention is to make sure that the project can be sufficiently developed, implemented, and used by the educators.

1. Technical Feasibility: Taking advantage of readily available and well established technologies such as deep learning, computer vision and web development frameworks the proposed system is made. For the task, we can rely on tools as efficient, robust and suitable: TensorFlow/Keras for deep learning and OpenCV for video processing. Additionally, cloud services such as Google Cloud or AWS provide the needed infrastructure to host the system, and scale, perform, and store. With these resources available and with this technology stack, the project is technically possible.

2. Operational Feasibility: From an operational point of view, the system is aimed to be friendly for educators with no technical expertise. Teachers can upload videos and inspect their engagement analysis smoothly from within the web based interface. Without any manual intervention once the system automates most of the video processing, no extra manual intervention is necessary. The convenience, in addition to the valued information it offers the system will find the end-users (teachers and educators) to be beneficial as it fits their status quo in teaching practice.

3. Economic Feasibility: The development and deployment of the system is economically feasible. Deep learning and web development cost be kept to minimum by means of open source tools. While it’s going to have initial development and training costs, the costs of maintaining the system over time, particularly if you use cloud services to perform computation and storage, become reasonable.

CHAPTER 4

SYSTEM REQUIREMENTS

4.1 SOFTWARE REQUIREMENT

1. Operating System: Windows 10/11

2. Programming Languages:

Python3: Python is required for developing the core functionality, including machine learning models and video processing. Python libraries such as TensorFlow, Keras, and OpenCV will be used.

3. Web Development:

Flask: Flask, a lightweight Python web framework, is used for building the backend of the web application. It handles routing, form submissions, and communication between the frontend and backend.

HTML5, CSS3, and JavaScript: HTML is essential for structuring the web page, while CSS provides styling to ensure a professional user interface. JavaScript adds interactivity and dynamic content, such as displaying pie charts or video results.

4. Machine Learning Libraries:

TensorFlow/Keras: These deep learning libraries are essential for training and running the human action recognition model that detects student engagement and behavior in the videos.

OpenCV: OpenCV is used for video processing tasks like frame extraction, resizing, and annotations (displaying detected actions on the video).

5. Data Processing: NumPy and Pandas These libraries are essential for handling and processing numerical data, such as managing predictions and preparing data for visualizations.

6. Visualization: Matplotlib these libraries are used for generating visualizations like pie charts, bar graphs, or other analytics to represent student engagement patterns.

CHAPTER 5

SYSTEM DESIGN

5.1 SYSTEM ARCHITECTURE

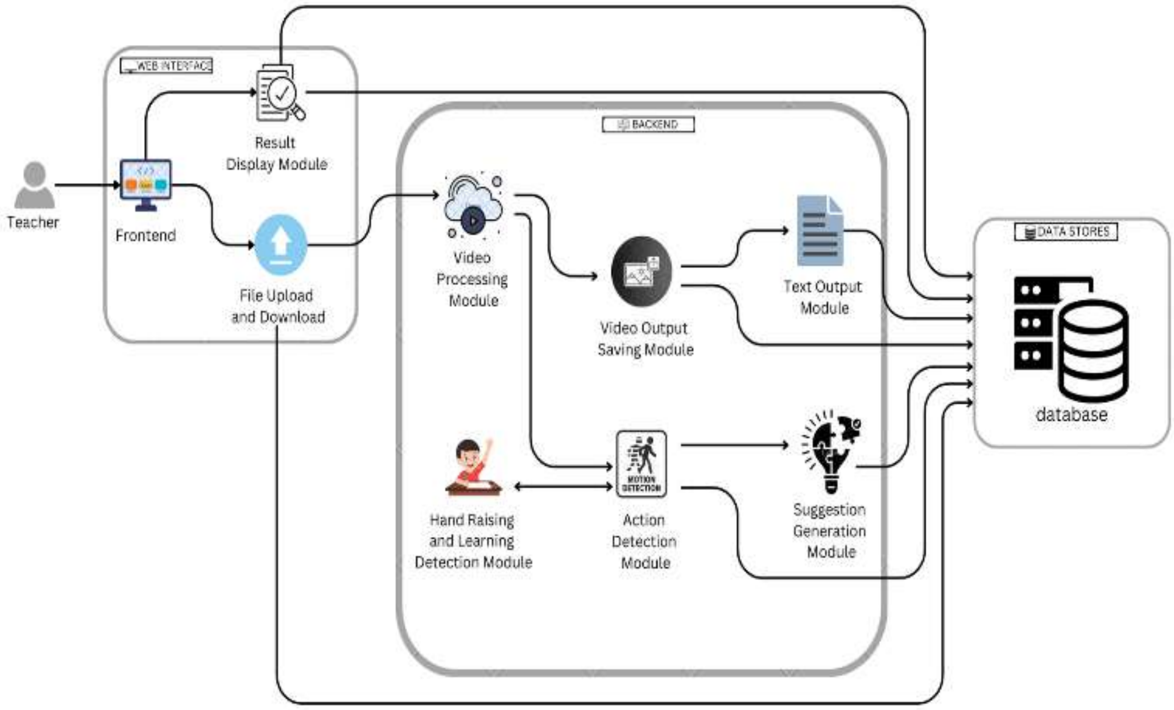


Fig 5.1 System Architecture

The Student Behavior Analysis System's architecture is painstakingly created to make it easier to monitor and analyze classroom video footage in order to successfully identify and interpret particular student actions. The video processing module, which serves as the first point of contact for handling visual data from uploaded video files, is essential to the operation of this system. With the help of sophisticated algorithms, this module can extract important elements from the video and identify important behaviors like raising the hand and other learning activities. This preprocessing stage is essential because it converts unprocessed video data into a format that later modules can readily understand and evaluate. Following the processing phase, the action detection module smoothly collaborates with the video processing module to classify and recognize distinct actions shown by students inside the classroom setting. This module uses machine learning approaches to determine student engagement levels with accuracy. This ensures that teachers receive precise and timely information on their students' participation and interactions. By giving deep insights into classroom dynamics, this module helps teachers recognize which students are actively engaged and which may be struggling, so supporting a more responsive teaching style.

The video output saving module is made to store the processed video data in an appropriate format, which improves system usability. With the help of this function, educators can watch the video again to gain a deeper comprehension of the dynamics of the classroom and the interactions between students. This kind of retrospective analysis can be quite helpful in seeing trends over time, which enables teachers to more easily modify their lesson plans to better meet the requirements of their pupils. Apart from its visual analysis features, the system also has a text output module that produces detailed reports according to the behaviours it detects. These reports are designed to give teachers practical insights into how their students participate in class and learn, which helps them make informed decisions about how best to teach. Additionally, the suggestion generating module greatly improves the general functioning of the system by providing tailored recommendations for instructional methods depending on the behaviours that are seen. This makes it possible for teachers to alter their methods in the moment, creating a more dynamic and productive learning environment.

Teachers can access historical data and monitor changes in student behavior over time because all processed data from these modules is safely kept in a central database. This architectural feature is essential for continuous evaluation and instructional technique advancement. With the user experience in mind, the frontend interface makes it simple for teachers to submit video files, evaluate analysis findings, and download reports. Because teachers frequently have limited time and need effective tools to improve their teaching efficacy in real-world classroom settings, this user-friendly design is essential for practical application. All things considered, this architecture creates a potent tool for improving educational results by fusing state-of-the-art video processing technology with a user-centric design approach. By mixing sophisticated detection methods with an easy interface, the system empowers educators.

5.2 MODULE DESCRIPTION

5.2.1 BUILDING THE Faster R-CNN MODULE:

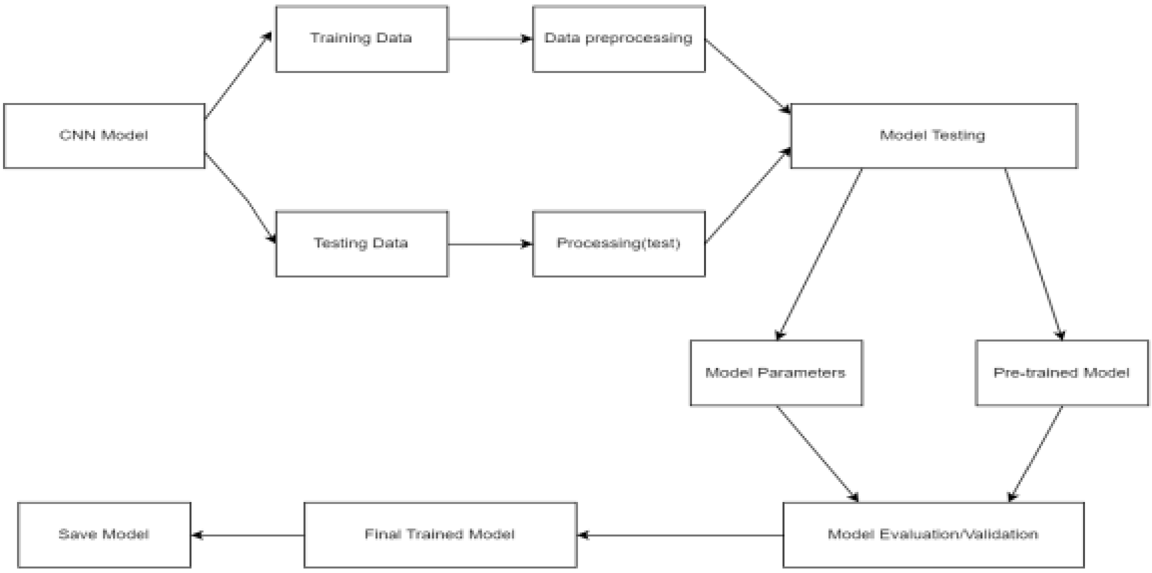


Fig 5.2.1 Building the Faster R-CNN Module

Data Collection:

The first step is to collect a dataset of classroom videos that contain a spectrum of behaviour of the students, namely hand raising, reading, and phone usage. These frames are split into videos and then labelled by the CNN to help determine different engagement activities.

Data Preprocessing:

The images are rescaled (e.g. 640x640 pixels) and normalized to the range [0, 1] in order to achieve uniformity. Flipping and rotating data help the model generalize better as they increase diversity in the training data. The Faster RCNN has then pre-processed images ready to take on.

Faster R CNN Architecture Design:

Instead of classification, the Faster R CNN takes as input the image and performs convolutional layers to extract features, then ReLU activation to introduce non-linearity and finally dropout or pooling layers to reduce dimensionality. Action classification is done by fully connected layers and have a Softmax activated output layer which outputs class probabilities.

Model Compilation:

The implementation is performed with the categorical cross entropy loss function and the Adam optimizer. The desired metric used to track the model's performance at classifying actions is accuracy.

Model Training:

Here, training is done by performing simple early stopping and learning rate increase for around 100–130 epochs, with the model fit to the data. The model learns to associate input images with action labels, and a batch size of 32 makes it smooth in training.

Evaluation and Testing:

Using metric such as accuracy, precision, recall and F1-score, the performance of the model is evaluated on a test set. It helps to test its ability of correctly classify actions from video frames.

Prediction and post-processing:

From new videos we feed it one frame at a time — the trained faster RCNN then predicts student actions. Finally, these predictions are aggregated and visualized, providing a good idea of engagement patterns and potential places where intervention is needed.

5.2.2 Video Processing Module:

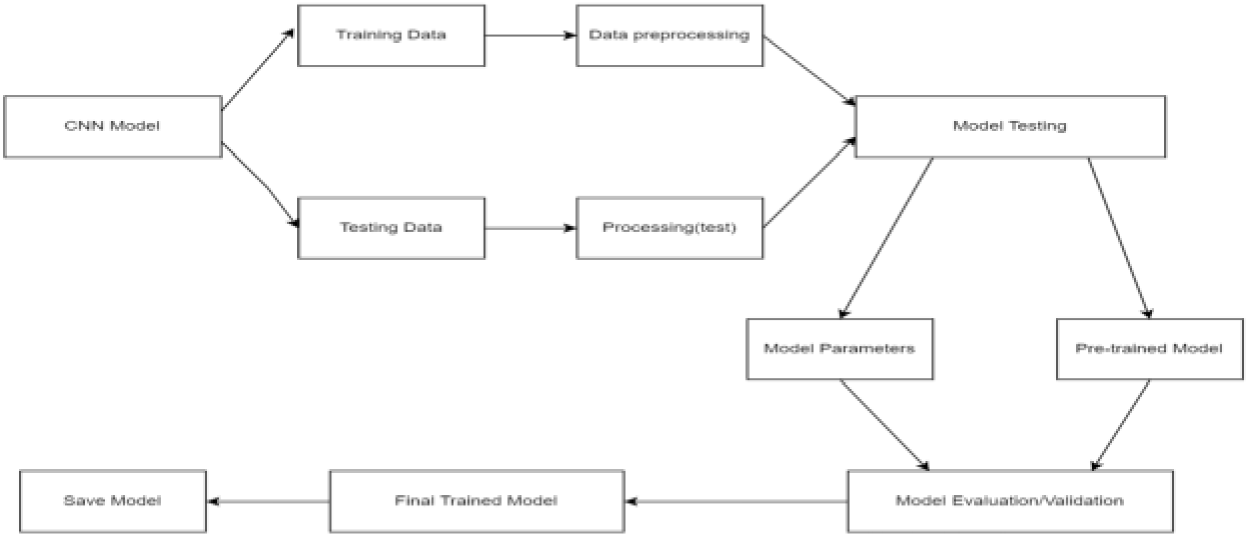


Fig 5.2.2 Video Processing Module

Load Video:

It uses OpenCV to load the video file. After processing, one frame is extracted at a time. It allows the system to convert a video input into frames that it can deal with for analysis.

Frame Preprocessing:

Then, each video frame is resized so that its size matches the input size of our Faster RCNN model (for example: 640x640 pixels). Instead, the frames are converted to arrays (that the model can process) and normalized pixel values are taken. These frames are pre-processed for accurate predictions.

Action Recognition:

Each pre-processed frame is fed into the pre trained faster RCNN model to predict the action in that frame. The model takes frames, use convolutional layers to extract features and then classify these to actions like hand raising, texting etc.

Action Labelling:

After the action is predicted, the frame is assigned the corresponding label, for example, "hand raising" or "leaning". With this video and already tracked actions, we would like to annotate it with this label, so we can understand what he is doing. Each frame is processed by introducing the label on its own frame, as part of the output data.

Generate Engagement Data:

The actions the video detects are recorded as they are and their frequency is counted as processing continues. Student engagement is categorized based on positive and negative actions on the video. This data is then used later for recommending ways to improve the classroom engagement.

Suggestions Generation:

For a given set of actions and their frequencies, it generates a set of feedback suggestions for the teacher. Recommendations for improving interaction are provided, if there is more than one disengaged action. Suggestions are made for maintaining the teaching approach through positive engagement.

Video Output and Visualization:

The action annotations and the processe0d video is saved and outputted. Furthermore, using pie charts, we visualize the engagement data for a quick overview of Classroom dynamics. The compiled actions are then displayed to teachers, together with suggestions, based on analysed actions.

5.2.3 Action and Gesture Detection Module:

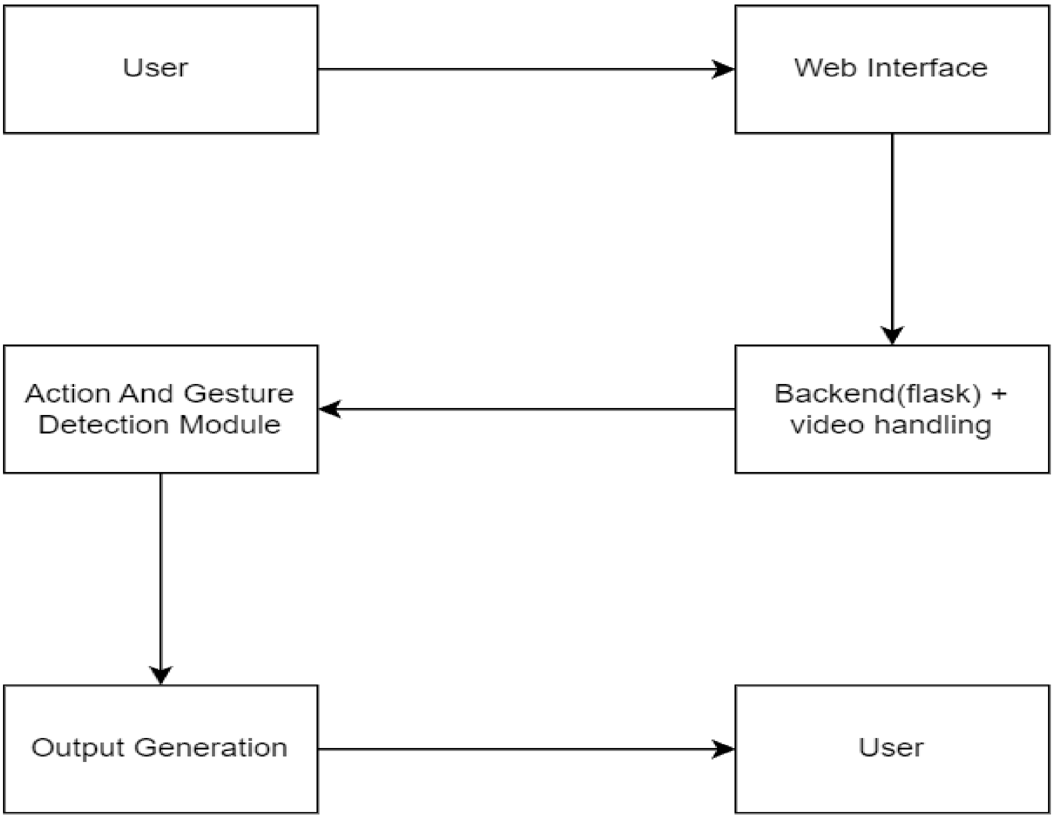

User
Web Interface
Action And Gesture Detection Module
Backend(flask) + video handling
Output Generation
User

Fig 5.2.3 Action and Gesture Detection Module

Load the Input Video

OpenCV is used to extract frames sequentially from the video which is loaded. The preprocessing and normalization are performed on these frames to be ready for action and gesture detection.

Preprocess Frames

We resize each frame to resolve the size of input expected by the action recognition model. It normalizes the frames and places them in forms useful to input into the model.

Feature Extraction

We take each frame through the pre trained CNN model that extracts features such as edge, shape, as well as texture. Next, the frame is passed through convolutional and pooling layers to extract the most important elements from a frame for use in experimental trials.

Action Prediction

From each frame, the Faster RCNN model extracts the features which are then passed through the fully connected layers of Faster RCNN model, which will predict the action or gesture that’s being performed in the frame (e.g raising hand, leaning over, using phone).

Assign Action Label

Therefore, the frame is assigned a corresponding label, based on the model’s prediction. This label is used to understand what kind of action or gesture being detected.

Analyse Frequency of Actions

Each frame, recorded actions are detected and counted for frequency. The analysis determines with what frequency different gestures or actions are done in the course of the video.

Engagement Feedback

Negative actions are classified as leaning, phone usage, etc; positive actions are classified as hand raising. The frequency of these actions is used, along with feedback that enables the teacher to know how engaged he or she is and areas for improvement.

Display and Save Results

In the processed video, we overlay the labelled actions on top the video frames, and then save the video. In addition, for teachers to analyse student behaviour, a pie chart displaying the distribution of detected actions is generated and displayed.

5.2.4 Suggestion System Module:

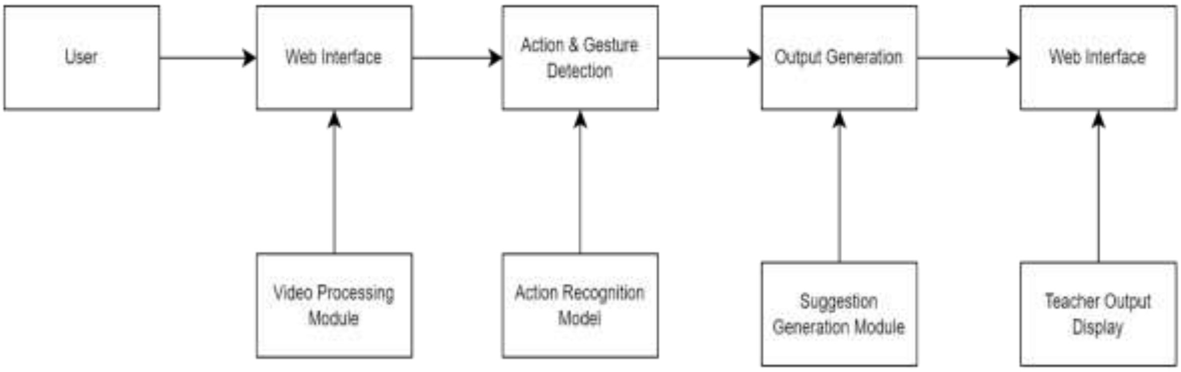


Fig 5.2.4 Suggestion System Module

Input Action Data

The video analysis module provides the system with the data, action data, of the detected action types (e.g., hand raising, texting, leaning) and frequency of actions in the classroom.

Classify actions into two categories

- Positive Actions: Engagement actions that include "hand-raising" or "listening attentively".
- Negative Actions: If these actions are reflecting distraction; like "texting" or "leaning over the table".

Analyse Engagement Levels

Calculate the overall level of the engagement in the classroom based on the action frequency data. Good engagement will correspond to higher frequencies of positive actions and concerns to higher frequencies of negative actions.

Generate Suggestions

The analysis results in actionable suggestions for improving engagement

For example: If hand raising is not occurring suggest activities to help people participate. If the following negative actions (or 'texting') are high, recommend increasing interactivity or altering lesson pacing.

Make Suggestions Based on Teachers Style

Use a past data on the teacher's classes and suggest out of the box. If a teacher has had trouble on the same issue in many different sessions, the system could suggest using visual aids or group discussions.

Provide Visual Feedback

Show the suggested and action analysis results visially on the dashboard, including charts of positive to negative actions ratio. Nevertheless, the system also provides its teachers with contextual advice driven by observed trends on how to dynamically adjust their approach.

5.2.5 **Web Interface Module**

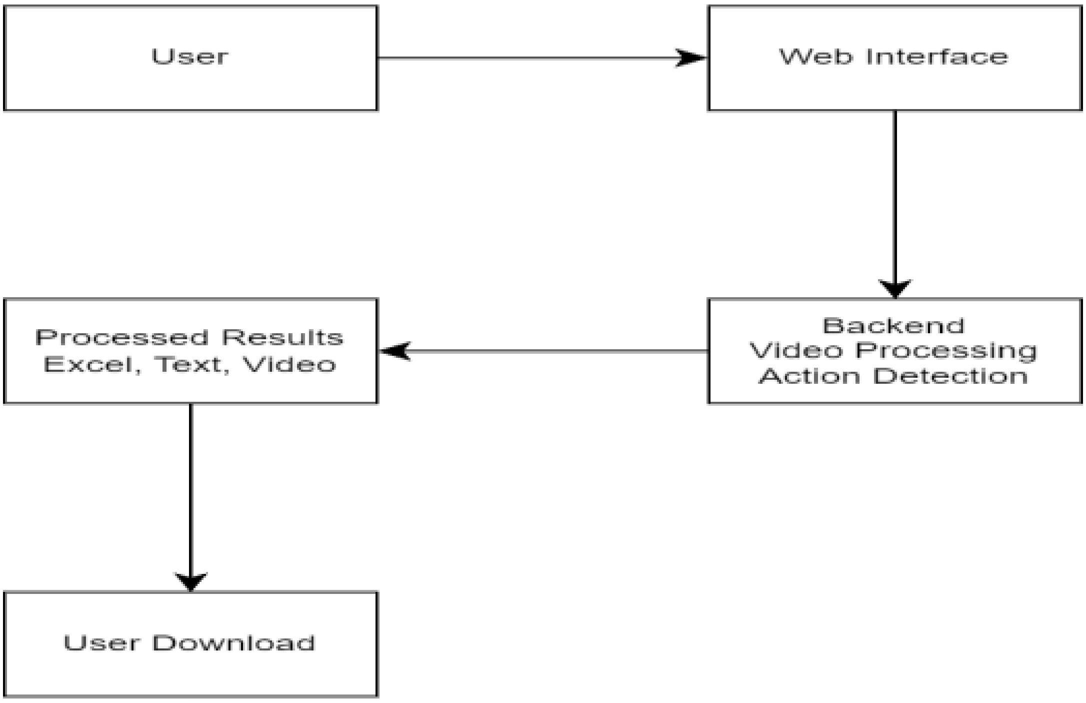


Fig 5.2.5 Web Interface Module

User Authentication

Teacher logs into the system using credentials. The system verifies the credentials against the database. If authentication is successful, the teacher is redirected to their dashboard.

Video Upload

The teacher uploads a video of a classroom session. The web interface processes the video upload and sends it to the backend for analysis. A loading animation is displayed while the video is being processed.

Video Analysis

The uploaded video is processed by the video analysis module. The system runs the video through the action detection model, analyzing student behavior and engagement. The analyzed video and action data are returned to the web interface.

Display Action Data

The web interface receives the processed action data. The data is visualized on the dashboard using Pie charts. The visual data is presented to the teacher, highlighting student engagement levels.

Show Suggestions

The system generates suggestions based on the action data. The web interface retrieves the generated suggestions from the suggestion system module. Personalized suggestions are displayed for the teacher, advising on how to improve classroom engagement.

Logout

The teacher logs out from the system. The session is terminated.

CHAPTER 6

RESULT AND DISCUSSION

6.1 Result and Discussion

1. Accurate Detection of Student Actions:

Using the action detection model for the given example classroom video, the system is able to conclude that the student actions include hand raising, bowing the head, leaning over the table, and others. This is made possible by training a CNN model for mapping a set of essential movements in the context of a classroom.

2. Engagement Analysis:

The analyzed data represents student activity and divides it between active and inactive. Raw data still contains unanalyzed information which is as follows: It offers teachers one dimension whereby they can observe patterns of student interaction in class and pinpoint problem areas.

3. Intuitive User Interface:

The web interface is equipped with a simple graphical shell where the teacher can upload videos, control engagement and receive analytics. Loading animation during the video processing and, for instance, pie charts to show engagement distribution make the user interface look professional and informative.

4.Customized Suggestions:

According to the analyzed activity, the system makes recommendations concerning teachers' actions. This comprises suggestions to promote positive behaviour patterns (e.g., for raising hand) and managing the negative ones (e.g, leaning or head-bowing). They help teachers update their strategies to make the learning processes more engaging**.**

CHAPTER 7

CONCLUSION AND FUTURE ENHANCEMENT

7.1 CONCLUSION

This project successfully creates a general, AI based system that makes the class engagement monitoring more comprehensive by knowing the students' actions and gestures from the video footage. With advanced computer vision technology, mostly Faster R Convolutional Neural Network (RCNN) based model, and the user-friendly web interface, this solution is proposed. With this setup a teacher can quickly and easily upload classroom videos, and receive a quantitative and qualitative analysis of student engagement. It can also identify different kinds of classroom behavior: hand raising, head bowing, inattentive postures and so on, and give a snapshot of engagement levels across multiple sessions. Consequently, this project offers a good look at the engagement patterns into which students are immersed in, giving the educators an insight into what changes can be made in order to make their teaching methods more appropriate.

The suggestion system itself is its main strength; it gives you feedback based on specific actions that it has found you doing. For instance, high levels of hand raising are positively acknowledged, while low levels of hand raising, as evidenced by leaned over the desk, are recommended to change. This immediacy provides a platform for teachers to pursue a data driven approach as they react to the needs of the students on the go. Further, the web interface records historical data and presents these as trends in student engagement over time, enabling educators to make changes stemming from clearly defined metrics.

But given current conditions the system is effective and could further improve its applicability in the future. Further robustness of the model can be achieved by expanding the range of the actions and gestures it can recognize, which would include a greater amount of more nuanced behaviors indicative of engagement. Furthermore, considering more integrated real time feedback capabilities could allow teachers to modify their live session approach as necessary, raising the bar significantly on classroom experience. In conclusion, this project showcases the grand potentials of artificial intelligence and computer vision in education system, specifically giving teachers an innovative and interactive device to constructively enhance learning environment, reactively encourage students' several activities, and fundamentally support students with positive emotion for motivation towards education.

7.2 FUTURE ENHANCEMENT:

1. Real-Time Analysis and Feedback: Enabling real time analysis would be a valuable future addition, and allow real time feedback to the teacher during the class session. Such real time functionality could mean that teachers could make dynamic adjustments based on students' levels of engagement, augmenting further interaction.

2. Expanded Gesture Recognition: A more complete understanding of student engagement would be gained by increasing the model's ability to detect more diverse set of gestures and actions. It could also involve detecting more subtle kinds of movement, things like eye contact, or body orientation for this second instance of engagement detection.

3. Multi-Environment Compatibility: The system can be extended to accommodate other learning environments (e.g., virtual or hybrid classrooms) enhancing the system's applicability. Then the model would need to be trained to accept video input from sources like webcams, mobile cameras and probably live streamed classes.

4. Personalized Learning Insights: In future versions, there could be a module for student engagement tracking, allowing the teachers to spot out individual students that might need a little extra support or a little extra motivation. It could be valuable providing personalized feedback to individual learning experiences.

5. Integration with Learning Management Systems (LMS): This would allow the system to integrate easily with the most popular LMS platforms, making data management easy for teachers to manage historical engagement metrics as well as other academic indicators.

6. Mobile Application Support: One way to make the web interface more accessible to teachers is to develop a mobile version, so that teachers can access student engagement insights and recommendations from any device, anywhere, at any time.

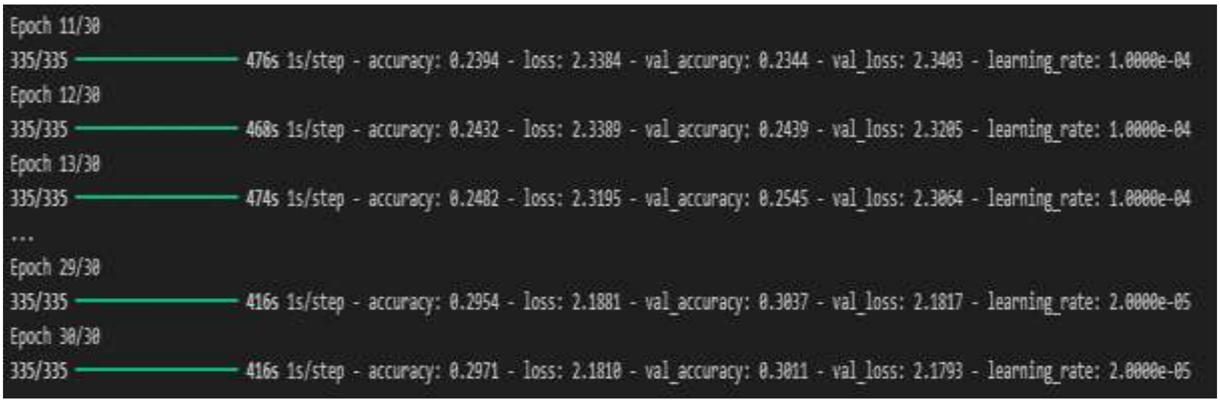
7. Language and Emotion Detection: Good news is, with natural language processing (NLP) and facial emotion detection the system could also analyze words spoken or written, as well as facial expressions. Thus, you would have a more holistic view of a student engaging; by including the verbal and emotional cues.

APPENDIX

A1.1 Sample code of model building:

```
train_datagen = ImageDataGenerator(rescale=1.0/255.0, horizontal_flip=True)

test_datagen = ImageDataGenerator(rescale=1.0/255.0)

train_generator = train_datagen.flow_from_directory(

    train_dir, target_size=(224, 224), batch_size=32, class_mode='categorical')

test_generator = test_datagen.flow_from_directory(

    test_dir, target_size=(224, 224), batch_size=32, class_mode='categorical')

base_model = ResNet50(weights='imagenet', include_top=False, input_shape=(224, 224, 3))

for layer in base_model.layers:

    layer.trainable = False

x = base_model.output

x = GlobalAveragePooling2D()(x)

x = Dense(1024, activation='relu')(x)

predictions = Dense(train_generator.num_classes, activation='softmax', dtype='float32')(x)

model = Model(inputs=base_model.input, outputs=predictions)

model.compile(optimizer=Adam(learning_rate=0.0001), loss='categorical_crossentropy', metrics=['accuracy'])

model.summary()

early_stopping = tf.keras.callbacks.EarlyStopping(monitor='val_loss', patience=5, verbose=1)
```

Output of the Model Building:



```
Epoch 11/30
335/335 ━━━━━━━━━━━━━━━━━━━━ 476s 1s/step - accuracy: 0.2394 - loss: 2.3384 - val_accuracy: 0.2344 - val_loss: 2.3403 - learning_rate: 1.0000e-04
Epoch 12/30
335/335 ━━━━━━━━━━━━━━━━━━━━ 468s 1s/step - accuracy: 0.2432 - loss: 2.3389 - val_accuracy: 0.2439 - val_loss: 2.3205 - learning_rate: 1.0000e-04
Epoch 13/30
335/335 ━━━━━━━━━━━━━━━━━━━━ 474s 1s/step - accuracy: 0.2482 - loss: 2.3195 - val_accuracy: 0.2545 - val_loss: 2.3064 - learning_rate: 1.0000e-04
...
Epoch 29/30
335/335 ━━━━━━━━━━━━━━━━━━━━ 416s 1s/step - accuracy: 0.2954 - loss: 2.1881 - val_accuracy: 0.3037 - val_loss: 2.1817 - learning_rate: 2.0000e-05
Epoch 30/30
335/335 ━━━━━━━━━━━━━━━━━━━━ 416s 1s/step - accuracy: 0.2971 - loss: 2.1810 - val_accuracy: 0.3011 - val_loss: 2.1793 - learning_rate: 2.0000e-05
```

Fig 7.1 Model Building

A1.2 OpenCv Sample code:

```
import cv2

import numpy as np

import pandas as pd

from tensorflow.keras.models import load_model

from datetime import datetime

import mediapipe as mp

model = load_model(r'E:\project\dataset\model\human_action_reconition_model.h5')

action_labels = ['hand_raising', 'leaning', 'texting', 'sleeping', 'clapping', 'laughing', 'fighting', 'using_laptop']

positive_actions = ['hand_raising', 'clapping', 'laughing']

negative_actions = ['leaning', 'texting', 'sleeping', 'fighting', 'using_laptop']

def is_hand_raised(landmarks):

    left_wrist = landmarks[mp_pose.PoseLandmark.LEFT_WRIST.value]

    left_elbow = landmarks[mp_pose.PoseLandmark.LEFT_ELBOW.value]

    left_shoulder = landmarks[mp_pose.PoseLandmark.LEFT_SHOULDER.value]
```

Output of OpenCv:

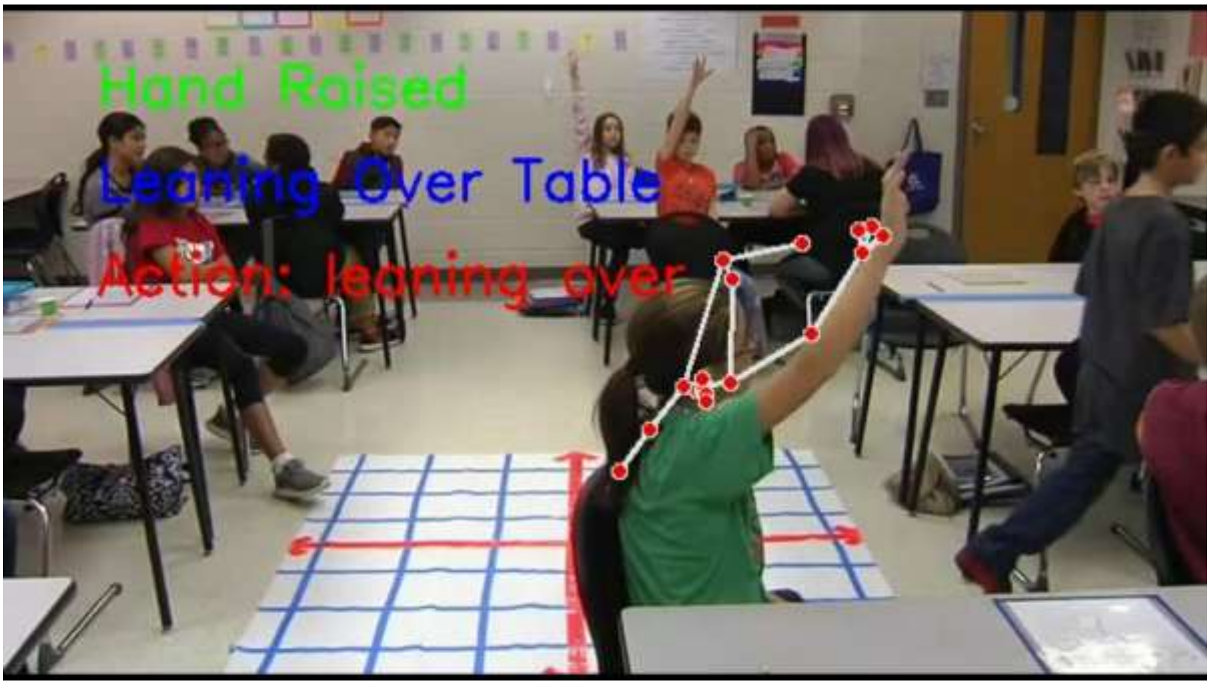


Fig 7.2 Processed Video

A1.3 Web interface sample code:

HTML:

```
<!DOCTYPE html>
<html lang="en">
<head>
    <meta charset="UTF-8">
    <meta name="viewport" content="width=device-width, initial-scale=1.0">
    <title>Video Upload</title>
    <link rel="stylesheet" href="{{ url_for('static', filename='styles.css') }}">
    <script>
        function showLoading() {
            document.getElementById('loading').style.display = 'flex';
        }
    </script>
</head>
```

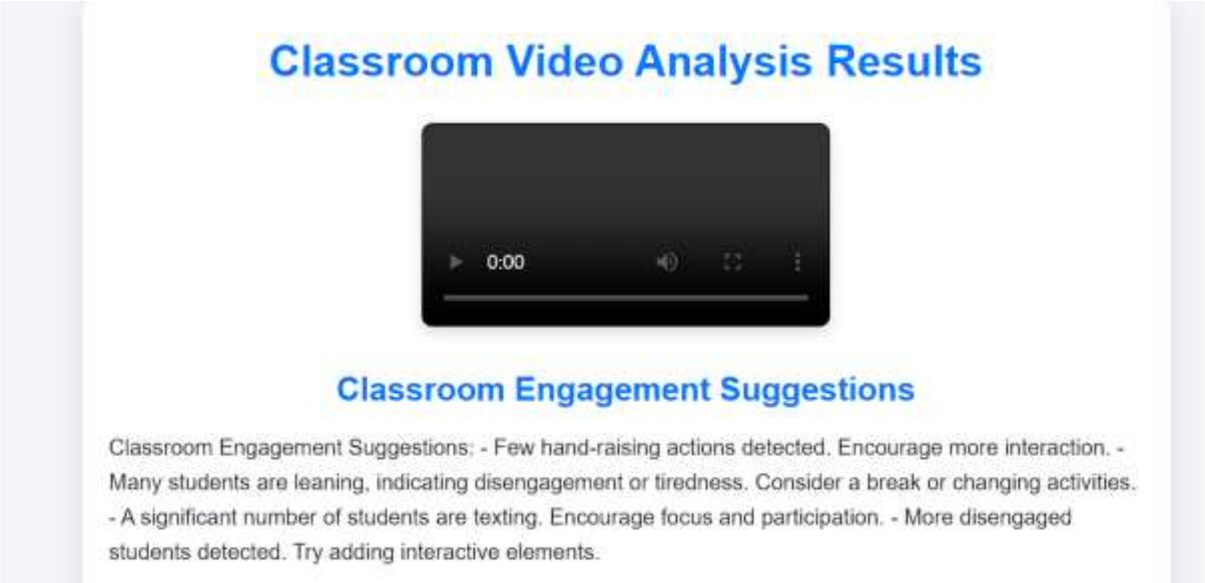
```
<body>
    <div class="container">
        <h1>Upload Classroom Video for Analysis</h1>
        <form action="/upload" method="post" enctype="multipart/form-data"
onsubmit="showLoading()">
            <input type="file" name="file" accept="video/*" required>
            <button type="submit">Upload and Analyze</button>
        </form>
    </div>
    <div id="loading" class="loading-overlay" style="display:none;">
        <img src="{{ url_for('static', filename='loading.gif') }}" alt="Loading...">
        <p>Analyzing the video. Please wait...</p>
    </div>
</body>
</html>
```

CSS:

```
.container:hover {
    transform: translateY(-5px);
    box-shadow: 0 10px 30px rgba(0, 0, 0, 0.2);
}
h1, h2 {
    color: #007bff;
    text-align: center;
}
h1 {
    margin-bottom: 20px;
}
```

```
h2 {
    margin: 20px 0 10px;
}
button {
    padding: 10px 20px;
    font-size: 16px;
    color: white;
    background-color: #007bff;
    border: none;
    border-radius: 5px;
    cursor: pointer;
    transition: background-color 0.3s ease, transform 0.2s ease;
}
```

Output of the Web Interface:



Classroom Video Analysis Results

Classroom Engagement Suggestions

Classroom Engagement Suggestions: - Few hand-raising actions detected. Encourage more interaction. - Many students are leaning, indicating disengagement or tiredness. Consider a break or changing activities. - A significant number of students are texting. Encourage focus and participation. - More disengaged students detected. Try adding interactive elements.

Fig 7.3 Suggestion System

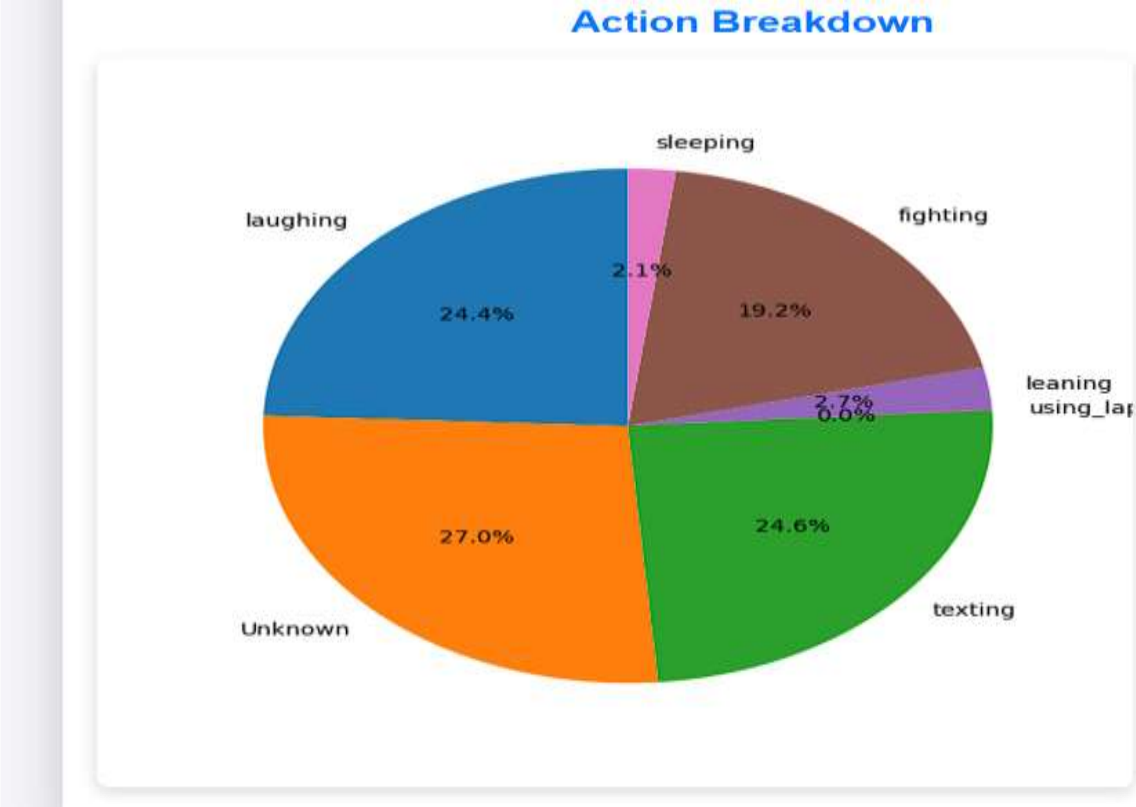
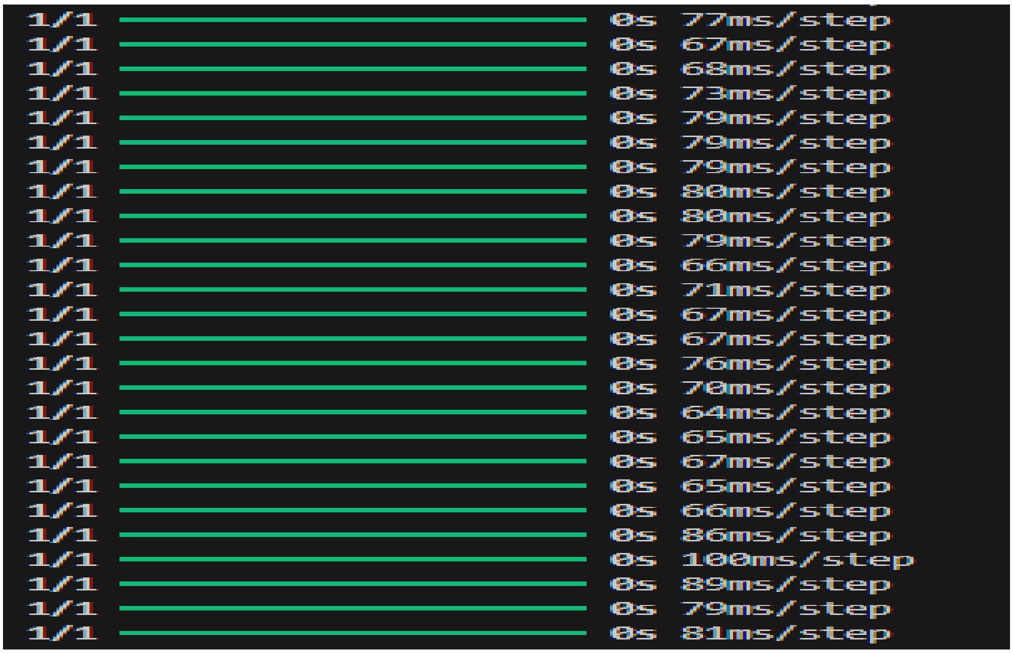


Fig 7.4 Pie Chart



```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 77ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 67ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 68ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 73ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 79ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 79ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 79ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 80ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 80ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 79ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 66ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 71ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 67ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 67ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 76ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 70ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 64ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 65ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 67ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 65ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 66ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 86ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 100ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 89ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 79ms/step
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 81ms/step
```

Fig 7.5 Backend Processing

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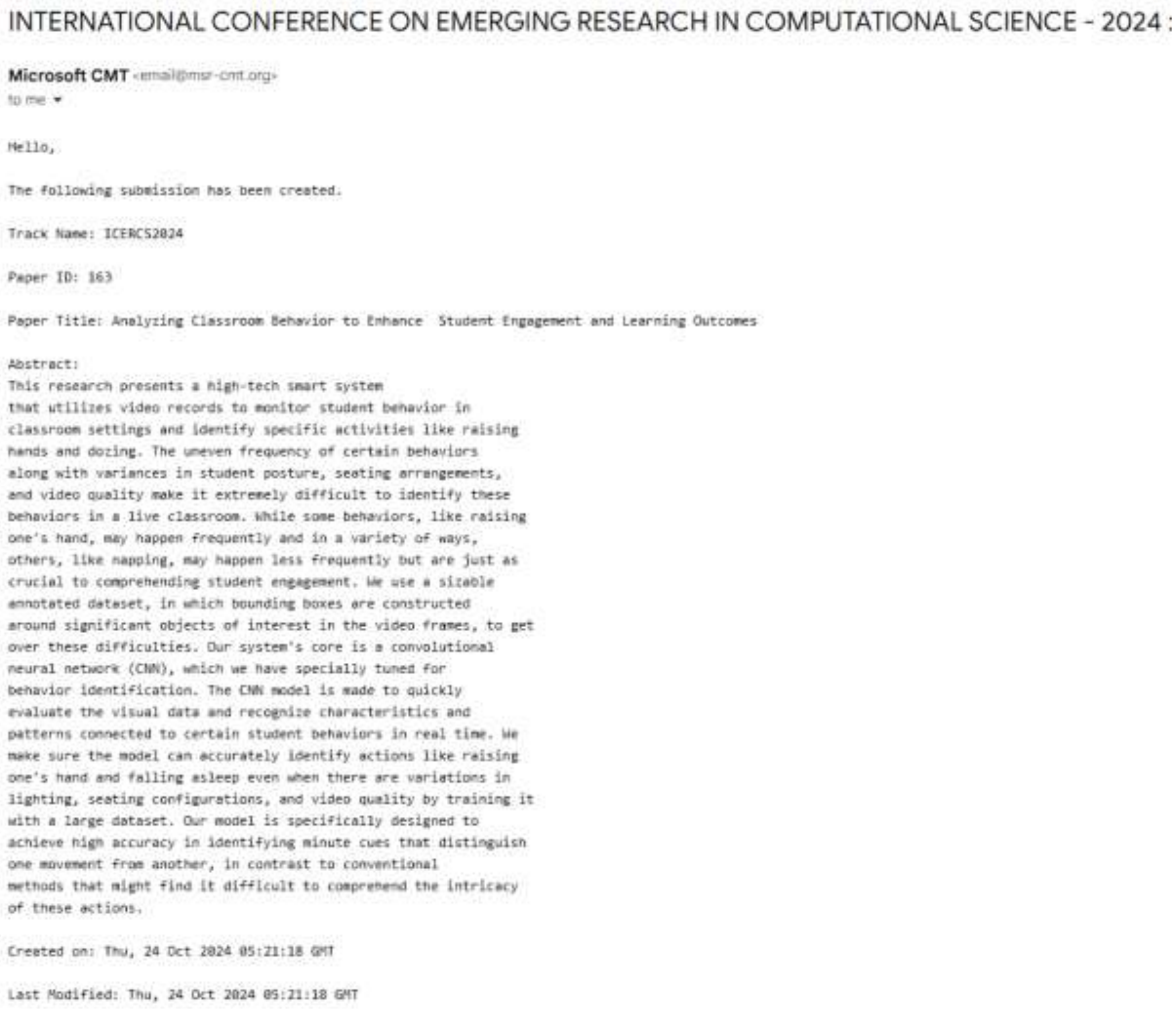
LIST OF PUBLICATIONS

1. Microsoft CMT

TITLE: INTERNATIONAL CONFERENCE ON EMERGING RESEARCH IN COMPUTATIONAL SCIENCE – 2024



INTERNATIONAL CONFERENCE ON EMERGING RESEARCH IN COMPUTATIONAL SCIENCE - 2024 :

Microsoft CMT <email@msr-cmt.org>
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Hello,

The following submission has been created.

Track Name: ICERCS2024

Paper ID: 163

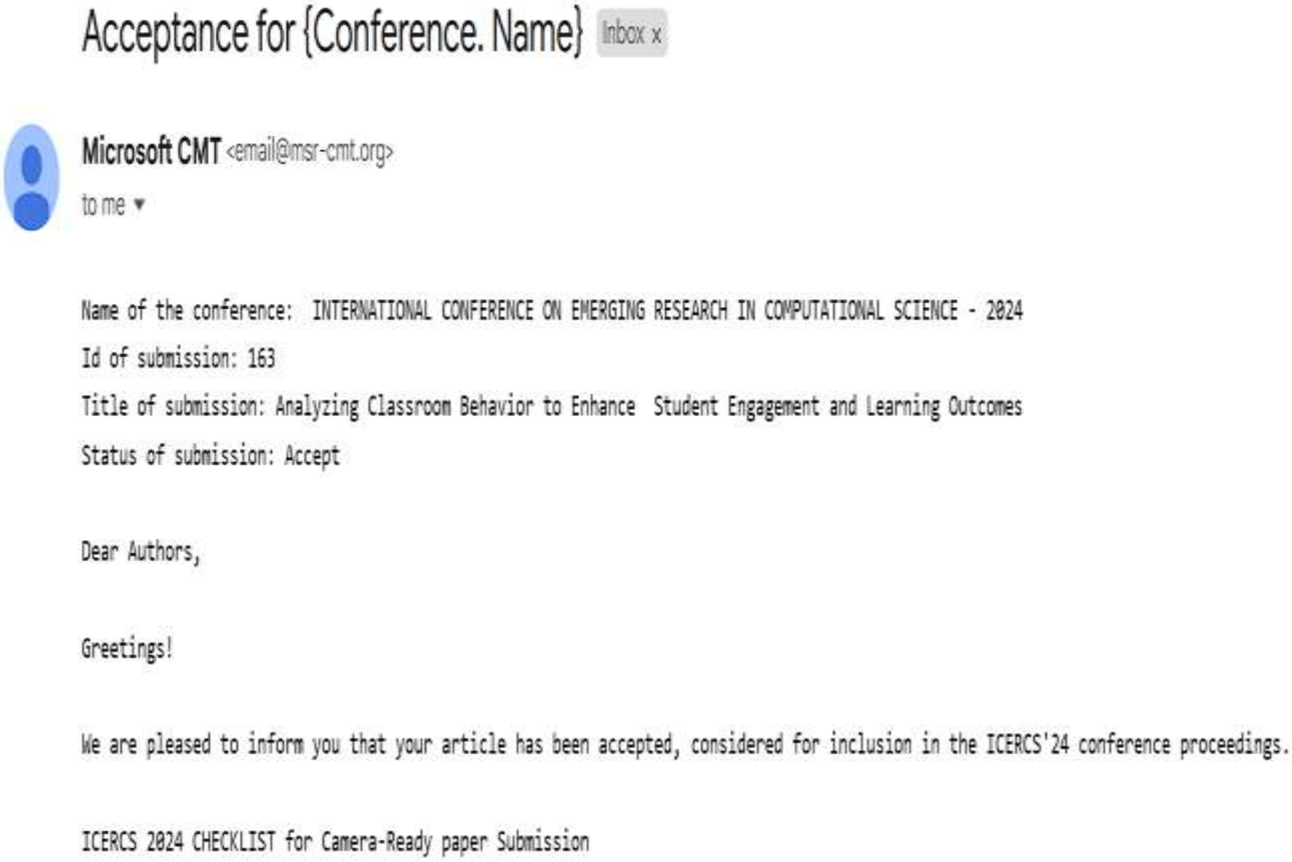
Paper Title: Analyzing Classroom Behavior to Enhance Student Engagement and Learning Outcomes

Abstract:
This research presents a high-tech smart system that utilizes video records to monitor student behavior in classroom settings and identify specific activities like raising hands and dozing. The uneven frequency of certain behaviors along with variances in student posture, seating arrangements, and video quality make it extremely difficult to identify these behaviors in a live classroom. While some behaviors, like raising one's hand, may happen frequently and in a variety of ways, others, like napping, may happen less frequently but are just as crucial to comprehending student engagement. We use a sizable annotated dataset, in which bounding boxes are constructed around significant objects of interest in the video frames, to get over these difficulties. Our system's core is a convolutional neural network (CNN), which we have specially tuned for behavior identification. The CNN model is made to quickly evaluate the visual data and recognize characteristics and patterns connected to certain student behaviors in real time. We make sure the model can accurately identify actions like raising one's hand and falling asleep even when there are variations in lighting, seating configurations, and video quality by training it with a large dataset. Our model is specifically designed to achieve high accuracy in identifying minute cues that distinguish one movement from another, in contrast to conventional methods that might find it difficult to comprehend the intricacy of these actions.

Created on: Thu, 24 Oct 2024 05:21:18 GMT

Last Modified: Thu, 24 Oct 2024 05:21:18 GMT

Fig 12: Conference Registration Mail



Acceptance for {Conference. Name}

Microsoft CMT <email@msr-cmt.org>

to me ▾

Name of the conference: INTERNATIONAL CONFERENCE ON EMERGING RESEARCH IN COMPUTATIONAL SCIENCE - 2024

Id of submission: 163

Title of submission: Analyzing Classroom Behavior to Enhance Student Engagement and Learning Outcomes

Status of submission: Accept

Dear Authors,

Greetings!

We are pleased to inform you that your article has been accepted, considered for inclusion in the ICERCS'24 conference proceedings.

ICERCS 2024 CHECKLIST for Camera-Ready paper Submission

Fig 13: Acceptance mail