Socio- Technical System for Effective Classroom Learning

Author

Kainat.

Registration Number

00000328240

Supervisor

Dr. Sara Ali

ROBOTICS AND INTELLIGENT MACHINE ENGINEERING

SCHOOL OF MECHANICAL & MANUFACTURING ENGINEERING

NATIONAL UNIVERSITY OF SCIENCES AND TECHNOLOGY

ISLAMABAD

MAY 2023

Socio- Technical System for Effective Classroom Learning

Author

Kainat.

Registration Number

00000328240

A thesis submitted in partial fulfillment of the requirements for the degree

of

MS Robotics & Intelligent Machine Engineering

Thesis Supervisor:

Dr. Sara Ali

Thesis Supervisor's Signature: ____________________

ROBOTICS AND INTELLIGENT MACHINE ENGINEERING

SCHOOL OF MECHANICAL & MANUFACTURING ENGINEERING

NATIONAL UNIVERSITY OF SCIENCES AND TECHNOLOGY,

ISLAMABAD

MAY 2023

FORM TH-4

National University of Sciences & Technology

MASTER THESIS WORK

We hereby recommend that the dissertation prepared under our supervision by: Student Name: Kainat & Regn No. 00000-328240

Titled: Socio-Technical System For Effective Classroom Learning. be accepted in partial fulfillment of the requirements for the award of MS-RIME degree.

Examination Committee Members

1. Name: Dr.Yasar Ayaz Signature: ____________

2. Name: Dr.Khawaja Fahad Iqbal Signature: ____________

3. Name: ____________ Signature: ____________

Supervisor's name: Dr. Sara Ali Signature: ____________

Date: 25/5/23

____
Head of Department

29/05/23
Date

COUNTERSINGED

Date: 29-5-23

____
Dean/Principal

THESIS ACCEPTANCE CERTIFICATE

Certified that final copy of MS thesis written by **Kainat (Registration No. 328240),** of SMME (School of Mechanical and Manufacturing Engineering) has been vetted by undersigned, found complete in all respects as per NUST Statutes / Regulations, is within the similarity indices limit and is accepted as partial fulfillment for award of MS/MPhil degree. It is further certified that necessary amendments as pointed out by GEC members of the scholar have also been incorporated in the said thesis.

Signature: ________________

Name of Supervisor:

Date: 25/5/23

Signature (HOD): ________________

Date: 29/05/23

Signature (Dean/Principal): ________________

Date: 29-5-23

Proposed Certificate for Plagiarism

It is certified that MS Thesis Titled "Socio-Technical System for Effective Classroom Learning" by "Kainat" has been examined by us. We undertake the follows:

a. Thesis has significant new work/knowledge as compared already published or are under consideration to be published elsewhere. No sentence, equation, diagram, table, paragraph or section has been copied verbatim from previous work unless it is placed under quotation marks and duly referenced.

b. The work presented is original and own work of the author (i.e. there is no plagiarism). No ideas, processes, results or words of others have been presented as Author own work.

c. There is no fabrication of data or results which have been compiled/analyzed.

d. There is no falsification by manipulating research materials, equipment or processes, or changing or omitting data or results such that the research is not accurately represented in the research record.

e. The thesis has been checked using TURNITIN (copy of originality report attached) and found within limits as per HEC plagiarism Policy and instructions issued from time to time.

Name & Signature of Supervisor

Signature : ____________

Plagiarism Certificate (Turnitin Report)

This thesis has been checked for Plagiarism. The Turnitin report endorsed by Supervisor is attached.

Signature of Student

Kainat.

00000328240

Signature of Supervisor

Declaration

I certify that this research work titled "*Socio- Technical System For Effective Classroom Learning*" is my own work. The work has not been presented elsewhere for assessment. The material that has been used from other sources has been properly acknowledged and cited.

Signature of Student

Kainat.

2020-NUST-Ms-RIME-00000328240

Acknowledgements

I am thankful to my Creator Allah Subhana-Watala to have guided me throughout this work at every step and for every new thought which You set up in my mind to improve it. Indeed, I could have done nothing without Your priceless help and guidance. Whosoever helped me throughout the course of my thesis, whether my parents or any other individual, was Your will, so indeed none be worthy of praise but You.

I am profusely thankful to my beloved parents who raised me when I was not capable of walking and continued to support me throughout every department of my life.

I would also like to thank my supervisor Dr. Sara Ali for her help throughout my thesis.

I would also like to express special thanks to Dr. Khawaja Fahad Iqbal and Dr. Yasar Ayaz for being on my thesis guidance and evaluation committee. Each time I got stuck in something; they came up with the solution. Without their help, I wouldn’t have been able to complete my thesis.

I would also like to thank my husband for his support throughout my degree.

Finally, I would like to express my gratitude to friends and family who have rendered valuable assistance to my study.

Dedicated to my incredible teachers, exceptional parents, supportive husband, adored siblings, and friends whose tremendous support and cooperation led me to this wonderful accomplishment.

Abstract

Analyzing attention enables educators to assess student engagement and enhance learning experiences. It provides valuable insights for optimizing teaching and managing classroom behavior. Several techniques have been proposed to analyze attention and provide feedback to the instructor for effective learning. These include intrusive and non-intrusive techniques which utilize EEG headsets, eye trackers, Kinect sensors, cameras, non-verbal cues etc. Intrusive techniques provide accurate results only for controlled environments prioritizing precise measurements. Moreover, they cause discomfort to the subjects involved. Whereas non-intrusive techniques using non-verbal features do not cause any discomfort to the user and can be used in any environment. However, none of the studies so far have addressed all non-verbal features simultaneously. This paper presents a multimodal architecture which integrates all non-verbal features including headpose orientation, body posture estimation, emotion detection and Eye Aspect Ratio (EAR) calculation to analyze attention. A deep learning model has been trained on the Facial Expression Recognition Plus (FERPlus) dataset with 94% accuracy. We used Euler angles to determine the head pose which includes up, down, left, right and forward directions. Further EAR is calculated for both eyes using eye key points and Euclidean distance which shows the opening and closing state of the eyes. Finally estimated the body pose of the student by training an SVM model & body key points which include shoulders, elbows, and wrists. The combined result of all these features is displayed in the form of a graph which reflects the level of attentiveness of the students to the teacher in real-time. This system can assist the teacher in addressing concerns such as poor academic performance, disengagement from studies, and high dropout rates among students.

Key Words: *Attention Analysis; Engagement; Non-Verbal Skills; Effective Learning; Multimodal Architecture.*

Table of Contents

List of Figures

List of Tables

CHAPTER 1

INTRODUCTION

The growing importance of Human-Computer Interaction and the widespread integration of smart devices in various aspects of our lives have underscored the need for smart devices to possess human-like abilities. In the realm of education, technological advancements have facilitated greater accessibility, interest, and interactivity, transforming traditional classrooms into dynamic digital learning environments. This shift has brought forth opportunities to enhance auditory, visual, logical, physical, and verbal learning, among other modalities. It is widely acknowledged that the integration of technology in educational settings is crucial as technology continues to shape and influence student learning experiences.

With the advent of machine learning, computer vision, and artificial intelligence, the landscape of technology has witnessed remarkable transformations since the beginning of the 21st century. These advancements have paved the way for the development of intelligent virtual assistants like Apple's Siri, Google's Assistant, Amazon's Echo, and numerous other similar devices and applications. These technologies are built upon the foundations of machine learning and artificial intelligence, delivering interactive and personalized experiences to users.

As technology continues to progress, the traditional practice of carrying heavy bags filled with books and notebooks to classrooms has been replaced by the use of lightweight devices such as iPads and laptops. This shift has revolutionized the learning process, enabling students to access vast amounts of information and resources at their fingertips.

The fields of machine learning, computer vision, and artificial intelligence hold tremendous potential for the future, as they continue to shape and redefine how we interact with technology. By harnessing these advancements, we can create innovative solutions that enhance learning experiences and empower individuals in various educational contexts.

The analysis of attention is an essential and widely recognized application of technology in the field of education. Attention refers to the ability to focus and maintain uninterrupted concentration, and it plays a vital role in student engagement and learning outcomes [1]. A student’s capacity to absorb and retain information is directly linked to their level of attention in the classroom.

In the educational setting, attention holds significant importance for several reasons. Firstly, it enhances the learning process by facilitating information processing and comprehension. When students are attentive, they are more likely to grasp and assimilate new knowledge effectively. Secondly, attention promotes retention, ensuring that acquired information is stored in long-term memory for future recall. Furthermore, attention cultivates critical thinking skills, enabling students to analyze and evaluate information critically.

In addition to its cognitive benefits, attention also contributes to positive classroom behavior. When students are attentive, they are actively engaged in the learning process, exhibiting respectful and cooperative behavior towards both their peers and teachers. Moreover, attention supports effective time management, allowing students to allocate their time efficiently and make the most of their educational experiences.

Fig. 1.1 Attentive Student.

To optimize attention in the classroom, students are encouraged to actively participate in class activities and maintain a high level of concentration throughout the learning process. By doing so, they can maximize their learning potential and derive the greatest benefit from their educational endeavors.

Based on research findings, it has been observed that students tend to experience a decline in concentration after approximately 10 minutes [2]. In large classroom settings, it can be challenging for instructors to accurately gauge the level of concentration and engagement among their students [3]. This lack of awareness regarding student attention can potentially impact their academic progress.

Fig. 1.2 Un-Attentive Student

To address this issue, the real-time visualization of individual student interest during lectures can prove to be invaluable for instructors aiming to enhance student engagement. By having access to visual feedback on each student's level of interest, instructors can make informed decisions and employ strategies that effectively capture and maintain student attention throughout the learning process. Such real-time visualization can serve as a crucial tool in promoting active participation and fostering an interactive classroom environment.

The implementation of a closed-loop teaching system, which incorporates the use of real-time visual feedback on student interest, holds great potential for improving the teaching profession and enhancing students' academic performance [4]. By leveraging this system, instructors can adapt their teaching approaches and tailor their instructional methods to better align with the needs and interests of their students. This personalized and responsive approach to teaching can lead to increased student engagement, motivation, and ultimately, improved academic outcomes.

1.1 Problem Statement

Several attention analysis systems exist, varying in their approach to capturing and analyzing attention. Some systems employ intrusive methods, while others opt for non-intrusive techniques. However, a common limitation among many of these systems is their reliance on only one or, at most, two features to assess attention. To achieve more accurate and comprehensive results, it is crucial to simultaneously analyze multiple features.

In our proposed system, we have developed a multimodal framework that integrates various features to analyze attention. This framework incorporates the integration of head pose, which serves as a natural indicator for gaze direction, along with facial expressions, Eye Aspect Ratio, and body posture. Each of these characteristics offers distinct parameters that exhibit positive or negative correlations with attention levels.

By considering multiple features simultaneously, our system aims to provide a more robust and comprehensive assessment of attention. This approach allows for a more nuanced understanding of the factors influencing attention and enables more precise and accurate results. By leveraging the combined information from these different modalities, we can gain valuable insights into the dynamics of attention and its relationship with various physiological and behavioral indicators.

1.2 Aims, Objectives and Research Questions

This section outlines the aims and objectives of the thesis work and provides conclusion to the research questions posed.

1.2.1 Aims & Objectives:

The primary aims of this thesis are as follows:

- To detect student attention: The thesis aims to develop a system capable of accurately detecting and assessing student attention levels during classroom activities.
- To study and implement how different features participate in analyzing student attention: The thesis aims to investigate and implement various features, such as head pose, facial expressions, Eye Aspect Ratio, and body posture, to understand their roles in analyzing and predicting student attention.
- To help teachers understand student behavior: By providing real-time visualizations and insights into student attention, the thesis seeks to assist teachers in gaining a better understanding of their student’s behaviors and engagement levels. This knowledge can facilitate targeted interventions and instructional strategies to enhance the learning experience.
- To explore different existing models and their workings: The thesis aims to conduct a comprehensive review and analysis of existing models and approaches used for analyzing student attention. By understanding their strengths, weaknesses, and underlying mechanisms, the thesis can contribute to the advancement and refinement of attention analysis methodologies.

By achieving these objectives, the thesis aims to provide valuable insights and practical solutions that can positively impact both teachers and students in educational settings.

1.2.2 Research Questions

This thesis aims to address the following research questions:

1. What are the challenges in detecting student attention?

2. Which is better: intrusive or non-intrusive techniques for detecting student attention?

3. Which features can be used to detect a student's attention

By addressing these research questions, the thesis aims to provide a comprehensive understanding of the challenges and possibilities associated with detecting student attention and offer insights into the integration of machine learning techniques, the comparison of intrusive and non-intrusive approaches, and the selection of appropriate features for attention analysis.

1.3 Motivation

After conducting a thorough review of publications and research articles on attention analysis systems in education, I developed a strong interest in contributing to this field. Recognizing the potential impact of such technology on our educational system, I became motivated to make a meaningful contribution. These systems have the potential to enhance the performance of both teachers and students by providing valuable insights through data analysis.

There are numerous attention analysis systems available that employ either intrusive or non-intrusive methods. These systems utilize various techniques and technologies to assist students and instructors in understanding and improving attention levels. While each system has its unique approach to analyzing attention, our research has revealed that combining multiple non-intrusive features yields superior results.

The main objective of this research is to provide evidence and demonstrate the effectiveness of combining multiple non-intrusive features for attention analysis. By conducting a comprehensive investigation, we aim to support the notion that a multimodal approach can yield more accurate and reliable results in assessing student attention. Ultimately, this research seeks to contribute to the advancement of attention analysis systems and their practical application in educational settings.

1.4 Research Contributions and Evaluation process

The primary contribution of this study lies in the development and implementation of a multimodal approach that incorporates facial expressions, body posture, and head orientation to assess student attention levels. To detect facial expressions, we utilized a widely recognized dataset called FERPlus with 94.68% accuracy. As direct measurement of gaze was not feasible, we leveraged head orientation as an indicator by calculating the face angles for each student. Additionally, we acknowledged the importance of body language and incorporated posture detection into our system. By integrating these three features, our proposed system comprehensively analyzes pupil attention. This holistic approach allows for a more accurate and comprehensive assessment of student engagement and attention in educational settings.

1.5 Upcoming Chapters

The latter part of the thesis document is organized in the following chapters.

1.5.1 Literature Review

This chapter offers a comprehensive overview of attention, highlighting its different categories and shedding light on the substantial progress made in recent years in detecting students' attention through diverse technological and traditional approaches. The literature review encompasses a wide range of studies and research conducted in this field, providing valuable insights into the methods and techniques employed to assess student attention. By examining the advancements in attention detection, this chapter serves as a valuable resource for understanding the current state of the art in this area and sets the stage for the subsequent chapters of this thesis.

1.5.2 Methodology

In this chapter, we present our proposed method for detecting student attention, which leverages facial features, head orientation, and pose estimation. We provide a detailed description of the workflow followed by our system, outlining the step-by-step process of how attention is detected and analyzed.

1.5.3 Results, Experiment and Analysis

This chapter presents the conducted experiments along with the obtained results. It offers a comprehensive analysis of the results, including detailed comparisons with relevant examples.

1.5.4 Conclusion and Future Work

This chapter presents the final conclusive remarks and offers insights into the future directions for the research community. It highlights the key findings and contributions of the study and discusses potential areas for further research and development.

CHAPTER 2

Literature Review

The relationship between attention and behavior plays a crucial role in students' engagement during lectures. A student's behavior in the classroom directly influences their ability to concentrate and absorb information effectively. Attention and behavior are interconnected elements that significantly impact a student's learning experience during a lecture. By actively maintaining focus, practicing attentive listening, displaying appropriate behavior that is non-disruptive and respectful, and actively participating in class activities, students can optimize their learning outcomes and enhance their overall academic performance.

Successful learning requires student participation in classrooms. Engaged students have better academic performance [5]. Another study indicated that teacher load, collaboration, and student discipline attitudes were the most strongly connected with teacher job satisfaction [6]. These factors may affect student concentration and engagement. Attention analysis study has been popular for decades. Attention is the ability to focus without interruptions. Student engagement is students' attention, interest, and class participation [1]. According to research, after 10 minutes, students start losing concentration [2].

According to Jecker et al. [7], teachers must rely on nonverbal input like facial expressions and body gestures during classroom lessons. These subliminal cues improve teaching and learning. Nonverbal and verbal cues accompany this unconscious activity [8][9]. The most important "Honest Signals" [10] for assessing a student's center of attention include gaze patterns, auditory aspects, and body languages, such as hand-raising and head posture. They can show student involvement and instruction quality [11]. Despite not specifically mentioning student attention analysis, understanding variables that affect student well-being and academic success can help educators establish a good learning environment that fosters student involvement and attention.

2.1. Types of engagement

In the study conducted by Fredricks et al. [12], they categorized attention into three distinct dimensions, known as the multidimensional engagement model. These dimensions include behavioral engagement, emotional engagement, and cognitive engagement.

2.1.1. Behavioral engagement

Behavioral engagement in the context of student learning refers to the observable actions and active involvement of students in academic activities and tasks [12][13]. Extensive research has demonstrated a significant and positive correlation between behavioral engagement and academic performance [14][15]. Furthermore, behavioral engagement is consistently associated with higher levels of academic motivation among students [16].

Numerous scientific studies have focused on the characteristics that influence behavioral engagement. For instance, difficulties in attention and behavior in children have been found to have a negative impact on their level of engagement and commitment to learning [17][18]. Additionally, gender differences have been observed, with girls in late middle childhood and adolescence displaying higher levels of behavioral engagement compared to boys[19][20].

These findings emphasize the importance of promoting and fostering behavioral engagement among students, as it plays a vital role in their academic success.

2.1.2. Emotional engagement

Emotional engagement in the realm of student learning involves the emotional experiences and states of learners. It encompasses various aspects such as interest, boredom, happiness, anxiety, and other factors that influence students' level of commitment and sustained effort in their learning activities and tasks. Emotional engagement extends beyond the mere cognitive aspect of learning and encompasses the affective domain.

One key element of emotional engagement is the experience of interest, which can greatly enhance students' motivation and involvement in the learning process. When students find a topic or activity interesting, they are more likely to invest their time and effort into understanding and exploring it further. Conversely, experiences of boredom can hinder engagement and lead to disinterest and disengagement from the learning environment.

Another important facet of emotional engagement is the sense of belonging and worth within the learning community [21]. When students feel connected and valued in their classroom and school environment, they are more likely to be emotionally engaged. This sense of belonging fosters a positive emotional climate that supports students' motivation, well-being, and overall commitment to learning.

2.1.3. Cognitive engagement

Cognitive engagement in the classroom refers to the psychological state in which students exert considerable effort to comprehend the subject matter and demonstrate persistence in their learning. This aspect of engagement is closely tied to the cognitive processes involved in understanding, analyzing, and applying knowledge.

One context in which cognitive engagement has been extensively studied is problem-based learning (PBL) classrooms [22]. In PBL, students are actively involved in solving authentic, real-world problems, requiring them to engage in critical thinking, problem-solving, and a deep understanding of the subject matter. Cognitive engagement in this context involves students actively processing information, analyzing complex problems, and generating solutions through their cognitive efforts. Furthermore, cognitive engagement also encompasses the level of effort that students willingly invest in their learning tasks [23] while maintaining a sense of perseverance [24][25]. This includes the motivation to exert mental energy, focus attention, and persist in the face of challenges or setbacks. Students who are cognitively engaged demonstrate a high level of involvement in their learning activities and possess the determination to overcome obstacles and achieve their learning goals.

Traditionally, cognitive engagement has been measured through various indicators, including students' completion of homework assignments, regular attendance, participation in extracurricular activities, interactions with teachers, and motivation exhibited during class discussions [26]. These measures provide insights into the extent to which students actively participate in the cognitive aspects of the learning process and demonstrate their commitment to their academic pursuits.

By understanding the different dimensions of engagement, educators gain a more comprehensive view of students' behaviors, emotions, and cognitive processes during their learning experiences. This understanding allows them to tailor their instructional practices, create supportive learning environments, and design interventions that target specific aspects of engagement.

For example, if a student is lacking behavioral engagement and shows minimal participation in classroom activities, educators can employ strategies such as incorporating interactive learning tasks, providing opportunities for student collaboration, and using engaging instructional materials to stimulate active involvement. Addressing emotional engagement may involve fostering a positive classroom climate, cultivating a sense of belonging, and recognizing and validating students' emotions to enhance their motivation and connection to the learning environment. When it comes to cognitive engagement, educators can focus on designing challenging and meaningful learning tasks, promoting critical thinking, and offering support and scaffolding to foster deep cognitive processing.

2.2. Previous Work

Educational institutions have increasingly embraced the use of student attention analysis systems to enhance teaching and learning experiences. These systems utilize advanced technologies such as eye-tracking and gesture recognition to monitor and analyze classroom behavior and participation.

Eye-tracking technology plays a crucial role in understanding how students engage with textual materials. By tracking students' eye movements, these systems can identify specific areas where students may lose attention or encounter difficulties in information retention [27]. This information can be valuable for educators as they can identify problematic sections of texts and make necessary adjustments to improve comprehension and engagement.

Gesture recognition technology is another powerful tool employed in student attention analysis systems. It enables the identification and interpretation of various student behaviors, such as raising hands, standing up, or even instances of drowsiness. By capturing and analyzing these gestures, the system can provide insights into student engagement and the overall quality of teaching. Educators can use this data to assess their instructional methods, identify areas of improvement, and make informed decisions to optimize student engagement and participation [6].

By integrating these technologies into educational settings, attention analysis systems contribute to a more comprehensive understanding of student behavior and engagement. They provide educators with valuable insights that can inform instructional strategies, curriculum development, and individualized support. Ultimately, these systems aim to create an enriched learning environment that promotes active engagement, improves teaching effectiveness, and enhances student learning outcomes and uncovers research gaps.

2.3. Techniques and methods

Student attention analysis systems utilize a combination of traditional and modern technological techniques to monitor and assess student engagement in educational settings.

2.3.1. Traditional Approach to Measure Attention

Traditionally, teachers have relied on their observational skills to monitor students' behavior and attitude in the classroom. They would adjust their lessons and teaching methods based on their observations. However, this approach has limitations, as it is challenging for a teacher to closely monitor and provide personalized attention to each student simultaneously.

Our educational system has several conventional ways of gauging student attention or engagement. Benefits and downsides vary in each.

2.3.1.1. Student Self- Reporting

Student Self-reporting is the easiest way to evaluate student classroom engagement. In this, each student gets a survey questionnaire. The survey asks about emotional and cognitive engagement. Researchers say these self-report methods are suitable for indirectly measuring emotional and cognitive engagement since they are not readily visible and must be deduced from behaviour. Their report methods are popular because they are practical and easy to apply [28]. But it is possible students may lie while self-reporting [26]. Primacy and recency effects may influence self-reports. Students may also have quite diverse ideas of engagement. Despite these restrictions, self-reporting might reveal students' classroom participation and attentiveness.

2.3.1.2. Instructor rating Checklist

Instructors evaluate student performance to assess teacher efficacy and student learning. Instructors evaluate students' classwork like essays, assignments, class notes, involvement, and progress [29]. These assessments can show instructors' "added value" to students [30]. This method lets educators track student performance against learning outcomes and gives students feedback [31]. The teacher rating scale or inventory asks questions about behavioural, emotional, and cognitive engagement. These studies show a substantial link between instructor and student perceptions of behavioural involvement, unlike emotional engagement. Because students can conceal their emotions [28][32].

2.3.1.3. Interviews

Few studies measure student involvement using interviews [33]. Interviews can detail students' involvement experiences. Students can give longer, unstructured answers while interviewed. However, the interviewer's knowledge, skills, and prejudices may affect the results. Interview reliability is another issue [34]. Written feedback surveys also proved reliable. Useful information can be retrieved from the student's free-text answer using cutting-edge supervised machine learning and unsupervised clustering [35].

2.3.1.4. Observation

Attention is measured through individual and classroom observation. Student conduct determines behavioural engagement. For better understanding, students must be watched in various academic circumstances, such as working alone, in groups, etc. Observation can verify survey or interview results. The observation method's main drawback is its reliance on the observer's analytical skills [28].

It is very difficult to exactly conclude on the state of the student because though a student seems to listen to the teacher, he/she might be in a different mental state rather than listening to the teacher. The cognitive state is not easy to identify even for a human observer. Here, we are considering coarse indicators of engagement state as perceived by the external observers [Jonathan Bidwell and Henry Fuchs. 2011 [36]. The inference is done based on facial analysis. Even though there is a variety of factors that contribute to the engagement factor like teaching style, peer students, environmental factors etc., a naive human observer can understand the level of engagement of the students from their faces, mainly from facial expressions, head pose and eye gaze to a great extent.

In a traditional classroom setting, where there are limited resources and time constraints, it becomes difficult to create a fully customized learning environment for every student [37]. Teachers may not be able to address the specific needs, preferences, and learning styles of each student effectively. As a result, some students may not receive the optimal level of support and engagement they require to thrive academically.

2.3.2. Technological Approach to Measure Attention

Researchers have categorized these methods into two main types that work in various settings [38]. The first method, intrusive techniques entail physical contact with the subject's body, like measuring body temperature, heart rate, brainwaves etc. However, these measurements are frequently uncomfortable for the participant and are extensive, which can contribute to data collection errors. The second non-intrusive technique analyses attention using auditory characteristics, and non-verbal cues like facial expressions, gaze, head direction and body pose. Each strategy differs in scope, cost, and complexity. These techniques are discussed in depth in the sections that follow.

2.3.2.1. Intrusive Techniques for attention analysis

The method described involves the use of physiological sensors integrated with wearable devices to measure a student's attention. This approach utilizes various biological parameters, such as brainwaves, heart rate, body temperature, and gaze pattern, as input data. By monitoring these physiological signals, the system can gain insights into the student's attention levels.

This method is often referred to as an invasive technique because it requires the use of physiological sensors that directly interact with the student's body. These sensors capture and record the biological responses and signals, which are then analyzed to infer the student's attention state.

By leveraging wearable devices equipped with physiological sensors, this method provides a more direct and objective measurement of a student's attention compared to other non-invasive approaches. The data collected from these sensors can provide valuable insights into the student's physiological responses and patterns, which can be further analyzed to understand their attention levels and cognitive states.

However, it is important to note that the use of physiological sensors and invasive techniques raises ethical considerations and privacy concerns. Proper informed consent and ethical guidelines must be followed to ensure the protection of students' privacy and well-being.

Additionally, the deployment and interpretation of such invasive techniques require expertise in data analysis and an understanding of physiological responses.

In the year 2012, Yaomanee et al. [39] analyzed EEG (Electroencephalography) data for attention analysis. A previous study suggests Alpha and Beta EEG waves are linked to relaxation and attentiveness. These pulses indicate alertness or relaxation. Three sub-experiments involved 10 people. Three 10-minute pieces comprised the 30-minute inquiry. The experiment used the Emotive EPOK EEG headset. It is a low-cost commercial device and fewer EEG channels were the study's main goals. Thus, channel 2 (F7), channel 13 (F8), and channel 11 (FC6) are recommended for Alpha and Beta wave detection.

In the year 2013, Liu et al. [40] recorded EEG readings using a mobile brainwave sensor. The experiment involved 15 college students. The students' foreheads were scanned for EEG signals from the cerebral cortex, which controls emotions, mental states, and attention. After collecting EEG data, some similar traits were retrieved. To determine attentiveness, an SVM-based classifier calculated and analyzed these characteristics. The suggested approach recognized human attention with 76.67% accuracy.

In the year 2015, Wang and Cesar [41] presented an E-learning attention study using Galvanic Skin Response (GSR) sensors. GSR sensors detect consumer epidermis electrical conductivity. The experiment included two 17-student groups. The first group attended class physically, whereas the other group attended class remotely. Self-reports and GSR sensors measured both groups' attentiveness and comfort. After class, a test was given, and the reports and sensor findings were compared to the exam result to know the authentication of the sensor data.

In the year 2016, Monkaresi et al. [38] proposed a technique to assess students' engagement during a writing activity. They replicated Whitehill et al.'s [42] video-based study on student involvement during cognitive training. Besides the audio recording, a Microsoft Kinect observed the 23 students. Computer vision-based video-based heart rate sensing detected engagement. A heart rate detector was placed on the participant’s body. Both results were compared. Remote heart rate measurement allowed them to identify engagement.

In the year 2018, Sethi et al. [43] used a single-channel electrode headset, Neurosky Mindwave to collect EEG signals and offer real-time attention-based biofeedback on user concentration and performance. An online SAT preparation course case study is investigated. The experiment started with reading the provided passage and answering questions. Participants' phones were Bluetooth-connected to the earpiece. The headset stored EEG and attention readings at 512 Hz and 1 Hz. After a one to two-day break, the participants repeated the activity with real-time attention-based neurofeedback on the headset. The notice shows the user's attentiveness is below the threshold. After comparing pre- and post-neurofeedback outcomes, 36 of 42 individuals' attention levels rose.

In the year 2020, N-gage a classroom sensing system by Gao et al. [44], uses a multi-dimensional model of engagement, diverse data for engagement prediction, classroom environment data and ubiquitous sensor watches. The four-week trial has 144 lectures in eleven courses. N-gage uses two sensory inputs. One of the ubiquitous devices that may record physiological and physical signals (e.g., EDA (electrodermal activity), HRV (heart rate variability), ACC (accelerometer)). Secondly, indoor weather stations capture environmental changes (e.g., temperature, sound). Using this n-gage predicted emotional engagement.

2.3.2.2. Intrusive Techniques for attention analysis

Non-intrusive techniques, also known as non-invasive techniques, are widely employed by researchers to measure student attention. These methods focus on evaluating facial features and non-verbal cues, such as gaze direction, head pose, and body movements. Various technologies, including cameras, eye-trackers, Kinect sensors, computer vision, and machine learning techniques, are utilized in this regard. Cameras are commonly used to capture visual data of students in the classroom. By analyzing facial expressions and non-verbal cues, researchers can infer the level of attention and engagement exhibited by students. Eye-trackers, specialized devices that monitor eye movements, are employed to track gaze patterns and identify areas of visual focus or distraction.

Kinect sensors, which utilize depth-sensing technology, can detect and track body movements and gestures. These sensors provide valuable information about students' physical engagement and participation in the classroom.

Computer vision techniques, combined with machine learning algorithms, are used to process the visual data captured by cameras and Kinect sensors. These techniques enable the identification and analysis of specific facial features, head pose, and body movements associated with attention and engagement.

By employing non-intrusive techniques, researchers aim to gather data without directly interfering with the students' natural behavior or personal space. These methods provide valuable insights into students' attention and engagement levels, allowing for the development of interventions and strategies to enhance their learning experience.

It is important to note that while non-intrusive techniques do not involve direct physical contact or invasive measurements, ethical considerations and privacy concerns still apply. Proper consent and privacy safeguards should be in place to protect the rights and well-being of the students involved in these studies.

In the year 2013, Fanelli et al. [45] formulated the estimation of posture as a regression problem. They predicted head posture using depth data to train a random regression forest. The random regression forest algorithm estimates nose tip 3D coordinates and rotation angles to detect head pose.

In the year 2014, Whitehill et al. [46] detect student attention using facial expressions. Facial expressions may reliably predict engagement levels, according to the study. This system is for the e-learning setting with a single student at a time in a video frame, they employed machine learning to determine engagement. The system was trained using student facial expressions from learning activities.

In the year 2015, Raca et al. [47] explored unobtrusive measures and social signal processing. Researchers monitored students and teachers to improve education. They presume that students with varying attention levels will behave differently in class. Recording lectures with cameras and eye trackers. They also link head orientation to gaze direction. The questionnaire supported video-derived assumptions. Students' head orientation matched the teacher's position.

In the year 2017 Zaletelj and Koir [48] proposed a system which used Kinect to identify face and bodily traits and a machine learning algorithm to predict the attention of 18 students. The study outcomes are validated by a human observer who assesses the gathered data through visual observation. This involves combining various Kinect data such as gaze, head position, and skeleton joints with calculated attributes like mouth openness and eye status (open or closed). Additionally, observable behavioral cues like taking notes, supporting the head with a hand, and yawning are integrated into the analysis process.

In 2019, Qiu et al. [49] proposed a facial landmark/action unit-based facial emotion recognition framework. A total of six primary facial expressions and one neutral expression were identified as indicators of student engagement. To predict these expressions, a technique utilizing coordinate distance vectors was developed. Remarkably, this technique demonstrated comparable performance to the well-established convolutional neural network (CNN) architectures like VGG-16 and ResNet, which are widely used in computer vision applications and the development of visual object recognition software.

Researchers in Intelligent Tutoring Systems (ITS) have dedicated their efforts to enhancing student learning through the development and evaluation of intelligent technologies. In this context, the focus has shifted towards prioritizing engagement in e-learning settings over traditional classroom environments. By leveraging the predictive capabilities of these technologies, early identification of factors such as emphasis within Massive Open Online Courses (MOOCs), withdrawal rates, and course cancellations has become possible. This enables prompt assessment of student performance and facilitates the provision of corrective techniques and policies aimed at mitigating attrition rates [50].

In the year 2020, Luo, Z., et al. [51], presented a novel approach for assessing student engagement in the classroom. Their method involved the utilization of a 3D model combined with hierarchical and conditional random forest algorithms. Additionally, an interactive platform was developed, incorporating measures such as head posture, facial expressions, and the use of cell phones instead of a camera.

The primary objective of this approach was to accurately determine the level of student engagement during classroom activities. The classification accuracy achieved by their model was reported to be 87.5%, indicating its effectiveness in accurately assessing and distinguishing various levels of student engagement.

In the year 2021, by Datta et al. [52] an enhanced convolutional neural network (CNN) implementation was developed for image classification, utilizing the FashionMNIST dataset consisting of sixty thousand fashion-related photos for model training. In addition, the MNIST dataset, containing handwritten numbers, was also utilized in the training process.

To improve the efficiency of the CNN model, parallel processing techniques were employed. This approach resulted in a significant reduction in operating time, leading to increased productivity during the training phase. By leveraging the power of parallel processing, the model was able to handle large volumes of image data more efficiently, allowing for faster model training and improved overall performance.

In the year 2021, Zheng et al. [11] trained their model using the student behaviour dataset and the public PASCAL VOC [39] dataset. Hand-raising, standing, and sleeping were the behaviors. The lightweight MobileNetV2-SSD approach reduces GPU reliance on the behaviour detector. The public PASCAL VOC dataset yields 74.5% mean Average Precision (mAP) and the real student behaviour dataset 75.2%.

In the year 2023, Trabelsi et al. [53] offer a deep learning system that recognizes student behaviour and emotions to assess classroom attention. Seven students tested YOLOv5 deep learning. They classify student activities as high or low attention. Focused and raised hands show attention. Restlessness, eating/drinking, laughing, reading, phone usage, and distraction were low-attention behaviour. For emotions, they used angry, sad, neutral, happy, and surprised by training the AffectNet dataset [54].

Overall, student attention analysis systems are an important tool for educators and researchers to better understand student engagement and behavior in the classroom. By using various technologies and techniques, these systems can provide valuable insights that can help improve teaching methods and materials, and ultimately enhance learning outcomes for students.

2.4. Proposed Solution

The aforementioned systems analyze attention in various ways. Some researchers use EEG and pulse rate, and some employ emotions, body posture, head direction, etc. None of these systems evaluates student attention to all these features simultaneously. For more accurate findings, the suggested model would use a multi-model architecture to use all three key features of the non-intrusive technique simultaneously i.e., emotions, body posture, and head direction. Gaze traction is another important feature recommended by Sharma and Abrol's eye gaze estimate approach survey on gaze monitoring techniques [55]. If the eye gaze cannot be directly observed, the head position is assumed to indicate a cue to gaze. Stiefelhagen [56] showed that 87% of the time, gaze fixation matched head orientation. Should we utilize all three functionalities at once?

Many researchers have used head position, gaze direction, and body posture to assess student attentiveness in the classroom [48][57][58][59]. Emotional identification with these methods can improve student attention analysis [60]. A student who sits up straight takes notes, and smiles at the lecturer may be attentive and interested [57]. Researchers can give teachers feedback on student involvement and attention by studying body posture, head orientation, and emotions [57][59]. This promotes accurate instruction and tailored student learning [59].

CHAPTER 3

Methodology

In this chapter, we provide a comprehensive overview of our methodology, experimental procedures, and the implementation of our system. The proposed architecture, as illustrated in Figure. 3.1.1, outlines a multimodal framework designed to detect head orientation, recognize facial features, and estimate posture. The primary objective of this architecture is to enhance student attentiveness and engagement during classroom activities.

3.1. Student Attention Analysis System

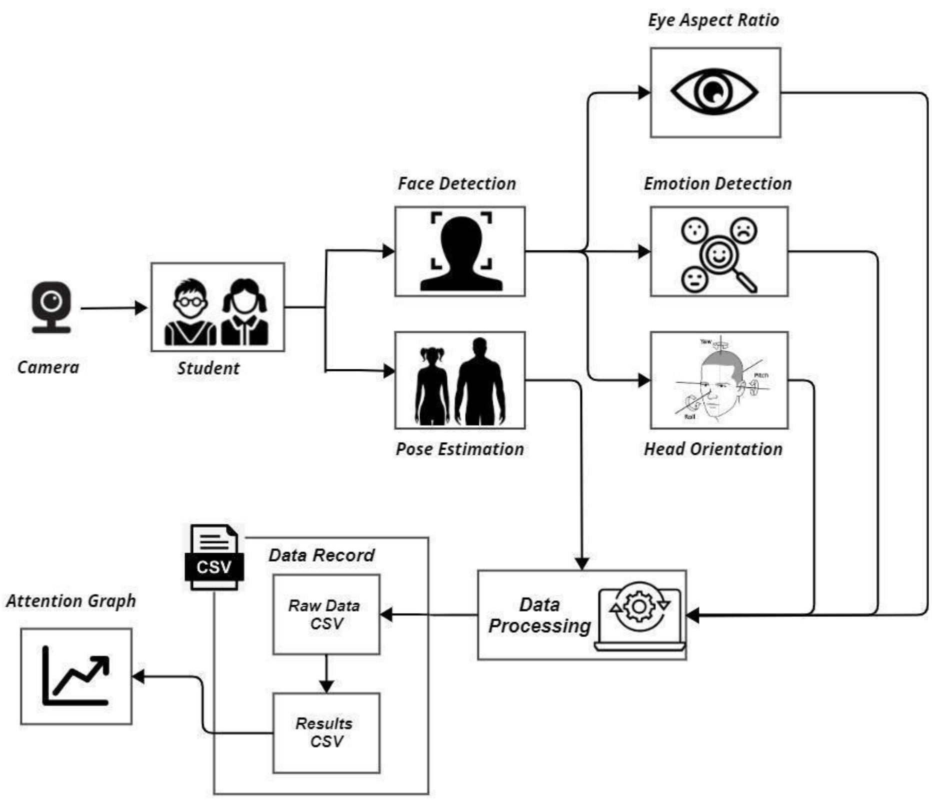

Fig. 3.1.1 Architecture of the proposed system

The proposed architecture consists of four interconnected modules, each serving a specific purpose in the student attention analysis system. This section provides a detailed description of these modules and their functionalities as shown in Figure. 3.1.2.

Module 1: Input Module

The Input Module is responsible for capturing and collecting data from various sources. It operates concurrently and gathers inputs from different sensors, such as cameras, eye-trackers, and other relevant devices. These sensors capture data related to head orientation, facial features, and body movements. The collected data is then passed on to the next module for further processing.

Module 2: Feature Extraction

In Module 2, computer vision techniques are employed to extract relevant features from the collected data. These features can include facial expressions, head pose, gaze patterns, and body posture. The extraction process involves applying algorithms and methods to analyze the captured data and extract meaningful information. Machine learning techniques are utilized to train models that can accurately identify and extract these features. The extracted features are stored in a CSV file for further processing.

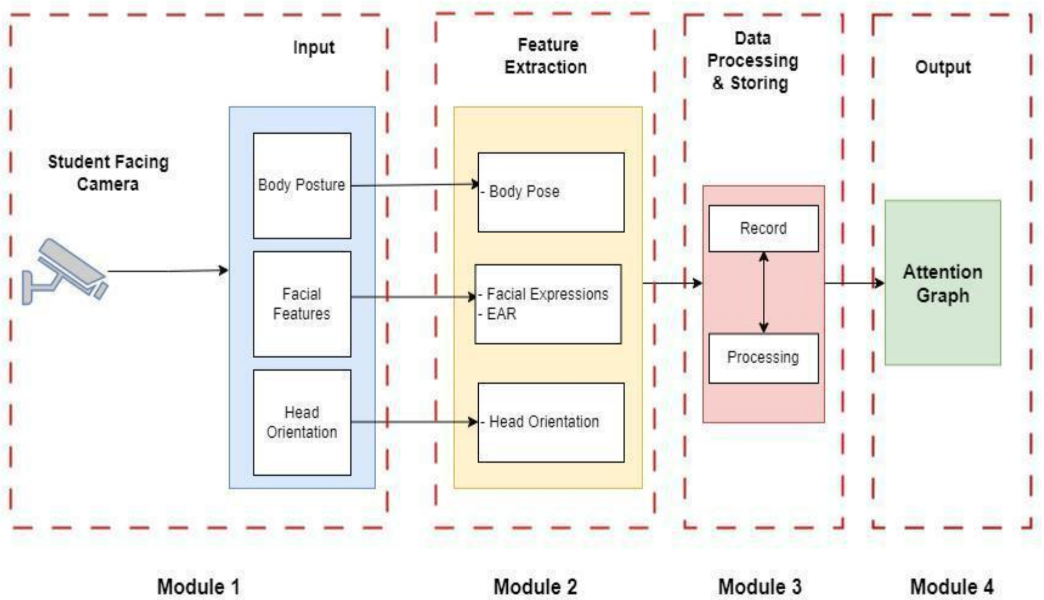

Fig. 3.1.2 Module-wise segmentation of the system

Module 3: Data Processing

Module 3 receives the input data from the CSV file generated in Module 2. This module performs various data processing tasks, including filtering, normalization, and feature aggregation. The processed data is then prepared for analysis and visualization.

Module 4: Output Module

The Output Module analyzes the processed data and generates meaningful insights and results regarding student attention. This module employs various techniques, such as data analysis, statistical modelling, and visualization, to interpret and present the attention levels of students. The results are typically presented in the form of plots, charts, or other visual representations, allowing teachers and researchers to easily interpret and utilize the findings.

Figure 3.1.3 illustrates the flowchart of the system, depicting the sequential order of data processing and analysis across the four modules. The flowchart provides a visual representation of how the data flows through the system.

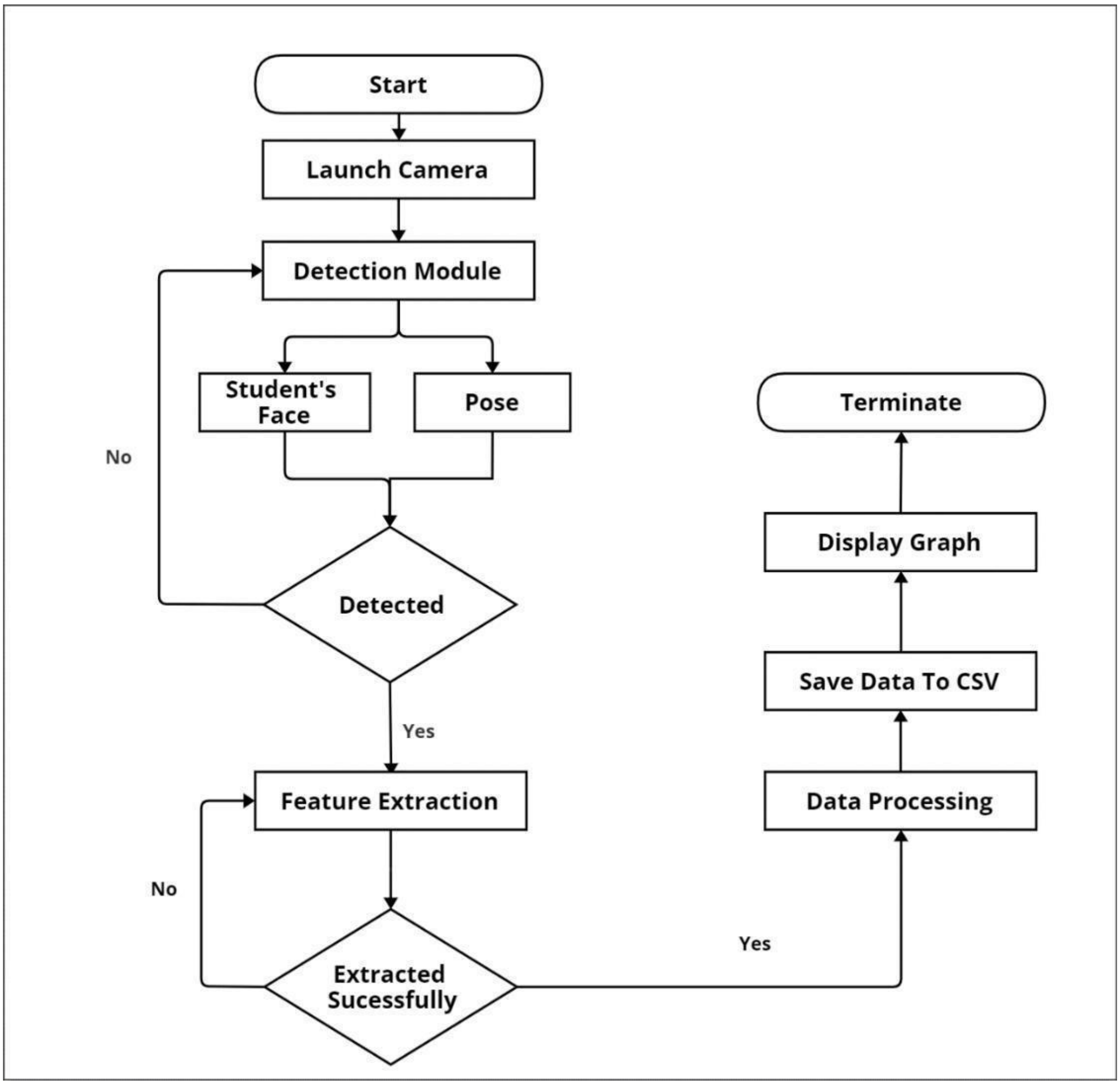

Fig. 3.1.3 System flowchart of the complete architecture explaining student attention analysis.

Overall, this architecture provides a systematic and structured approach to analyzing student attention. By incorporating multiple modules and leveraging computer vision and machine learning techniques, the system aims to provide accurate and insightful information about student engagement and attentiveness during classroom activities. The module-wise explanation of each feature is as follows:

3.1.1. Head-Orientation

The head pose is essential for analyzing students' attentiveness and interest in the class. Using computer vision to extract head poses, researchers can evaluate if a student is paying attention to the teacher or other instructional materials by examining the head orientation and gaze direction. Attention deficiencies reduce head movement intensity [61]. A student's head orientation and the teacher's movements both indicate attentiveness [47]. Figure 3.1.4 shows our head pose module.

Additionally, the orientation of the head provides information regarding the student's gaze. Khorrami et al. [62] stated that the precise location and duration of a person's gaze fixation serve as valuable indicators of attention. While eye trackers offer the highest level of accuracy in detecting gaze, they are costly and impractical for classroom settings [63]. Using computer vision techniques is another method for detecting gaze, but this requires expensive high-resolution cameras, so in this architecture head pose is used as an indicator of fixation.

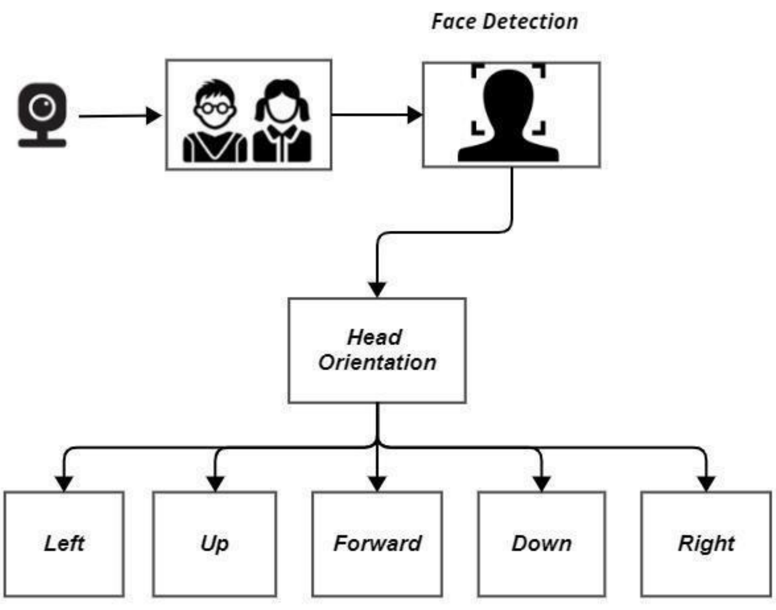

Fig. 3.1.4 Headpose module of student attention analysis system.

We are using a webcam and OpenCV, Numpy, and Mediapipe to detect head orientation in real-time. After launching the camera, Mediapipe FaceMesh is used to identify all facial features. It extracts the 2D and 3D coordinates of facial landmarks, such as the nose, eyes, and ears. Converting the 2D and 3D coordinates to NumPy arrays and defining the camera matrix and distance matrix. The Perspective-n-Point (PnP) problem is addressed in the code by utilizing the OpenCV solvePnP function, which calculates the rotation and translation vectors. As noted by Zheng et al., the PnP problem involves determining the pose of a calibrated camera based on a collection of n 3D point coordinates in the world and their corresponding 2D projections in the image [64]. The vectors are then converted to matrixes and the OpenCV RQDecomp3x3 function is utilized to determine the Euler angles. Depending on the value of the Euler angles, the inclination of the head is determined. Euler angles are illustrated in Figure 3.1.5.

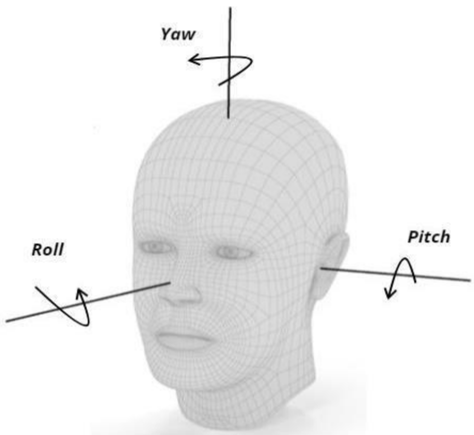

Fig. 3.1.5 Euler Angles showing Roll, Pitch, and Yaw.

Camera and transformation matrixes are as follows:

$$\boldsymbol{Camera\ matrix} = \begin{bmatrix} f & 0 & p_x \\ 0 & f & p_y \\ 0 & 0 & 1 \end{bmatrix} \qquad (\mathbf{1})$$

$$\boldsymbol{Transformation} = \begin{bmatrix} \boldsymbol{r_{11}} & \boldsymbol{r_{12}} & \boldsymbol{r_{13}} & \boldsymbol{t_1} \\ \boldsymbol{r_{21}} & \boldsymbol{r_{22}} & \boldsymbol{r_{23}} & \boldsymbol{t_2} \\ \boldsymbol{r_{31}} & \boldsymbol{r_{32}} & \boldsymbol{r_{33}} & \boldsymbol{t_3} \end{bmatrix} \qquad (\mathbf{2})$$

If a student is looking forward it means he/ she is looking towards the teacher. We set a time threshold and if the time for which the direction of the head is left, right, up, or down is greater than our threshold time then the student is not attentive. If it is less, then threshold time so the student is attentive. He/ she is looking somewhere else (up, down, left, right) for a reason. Maybe a teacher is moving while delivering the lecture or any external stimuli (like a message on the phone) divert the attention for a few seconds.

3.1.2. Face Features Extraction

The module describes two facial traits. One detects facial emotions, while the other calculates EAR (eye aspect ratio). Emotion detection affects student engagement and learning in many ways. Students' attentiveness depends on their emotions[65]v. Educators can measure student engagement by assessing their emotional involvement throughout the study and adjusting their teaching tactics. Facial emotion recognition was used to automatically detect student participation in real-time in e-learning [3]. Analyzing student concentration may improve learning [65]. Happiness and curiosity encourage self-regulated learning and motivation. Frustration and confusion can hamper learning [66].

EAR measures fatigue. The EAR is calculated by dividing the Euclidean distances between the vertical and horizontal eye landmarks. Head posture and EAR were used by Mustafa et al. in 2019 [37] to identify student concentration in e-learning. Their SVM classifier's 72.4% accuracy proves that Head Pose and Eye Aspect Ratio affect students' Visual Focus of Attention and Engagement. Six facial landmarks per eye are used to compute EAR. Drowsiness lowers EAR value. Figure 3.1.6 shows EAR-calculating facial landmarks.

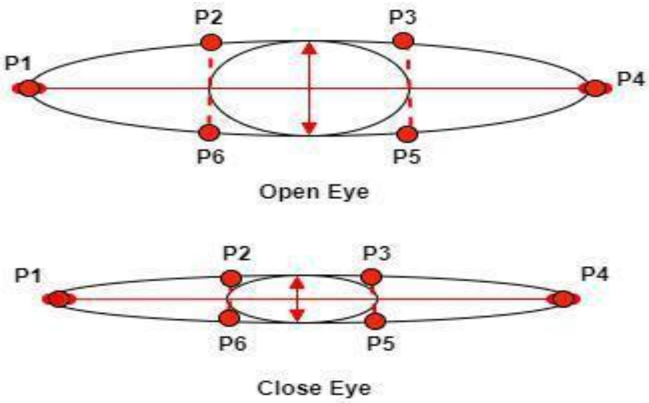

Fig. 3.1.6 Eye Landmarks for open and closed eye, used to calculate Eye Aspect Ratio.

The landmarks are denoted by 1, 2, ..., 6, where 1 and 4 are the corners of the eye, and 2, 3, 5, and 6 are the points on the top, bottom, left, and right eyelids, respectively. The EAR is calculated by dividing the sum of the distances between 2 and 6, and between 3 and 5 by twice the distance between 1 and 4. The vertical distances between 2 and 6, and 3 and 5 represent the height of the eye-opening, while the horizontal distance between 1 and 4 represents the width of the eye-opening.

The face feature module as shown in Figure. 3.1.7 has two sub-modules. First, we train a deep learning model for emotion detection using Keras and TensorFlow on the FERPlus dataset [4]. It is an enhanced and improved version of the FER2013 dataset. The model training involves the following steps:

The code imports required packages, such as OpenCV (cv2) for computer vision tasks and the Keras library for constructing and training the deep learning model. ImageDataGenerator was used to preprocess image data before model training. It rescales the image pixel values to the range of 0 to 1.

We defined the directory paths, the target size, the batch size, the color mode, and the class mode. The images from the specified directories were loaded, resized to the desired dimensions, and converted to grayscale.

Next, the model structure is constructed using the Sequential API from Keras. The model is built by adding convolutional layers, pooling layers, dropout layers, and dense layers. The specified loss function, optimizer, and metrics are used to compile the model. In this case, the categorical cross-entropy loss, Adam optimizer, and accuracy metric are employed.

For model training, the fit_generator method is used. It takes the training and validation generators, the number of steps per epoch, the total number of epochs, and the validation steps as arguments. The provided data is used to train the model, and the training progress is displayed during the process.

Lastly, we used the to_json method, to store the model structure in a JSON file named "emotion_model. json" and the save_weights method, to save the trained model weights in an HDF5 file named "new_emotion_model.h5".

To run the system, we import all the required models and libraries. Dlib's 68 facial landmark predictor and Mediapipe detect faces. These landmarks are used by a pre-trained Keras model to recognize emotions. To determine eye openness, the EAR is computed for both eyes. Two-eye landmarks are (1). Left eye:(37–42). Right eye: (43–48) [65]. Compare the average EAR to the 2.0 threshold [67]. If it's below the threshold for three frames, the student's eyes are closed: otherwise, they're open, showing inattention. We use Happy, Sad, Neutral, and Surprised, to analyze attention since they are most commonly used in academic contexts [65].

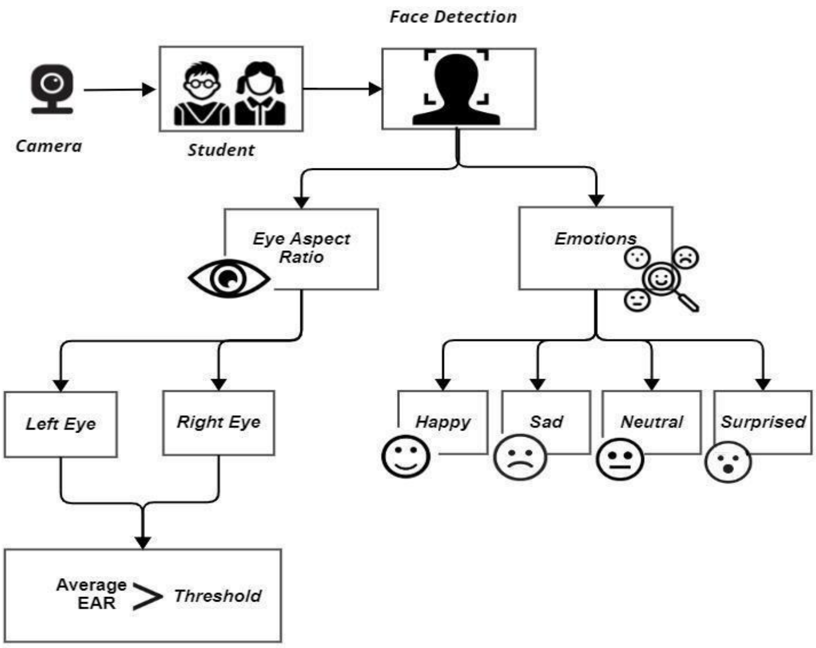

Fig. 3.1.7 Facial feature module of student attention analysis system.

3.1.3. Pose Estimation Module

Body posture plays a significant role in student attention analysis as it conveys information about a person's current state of mind [57]. Head pose, gaze, and body posture can be used to estimate students' classroom attentiveness [58][59][68][69]. Key point estimation can accurately detect and recognize human pose in several experiments [57]. Others use YOLOv3 for object identification and SE-HRNet for pose estimation to recognize several students' classroom stances [58].

Body language says a lot about class concentration and tiredness. A student who is sitting up straight and taking notes is engaged in class, whereas one who is slouching or looking away may be less attentive [43]. Researchers may examine students' attention levels and give teachers feedback on class participation by integrating body posture estimate, head position estimation, and gaze tracking [43][57]. Figure. 3.1.8 shows our pose estimation module.

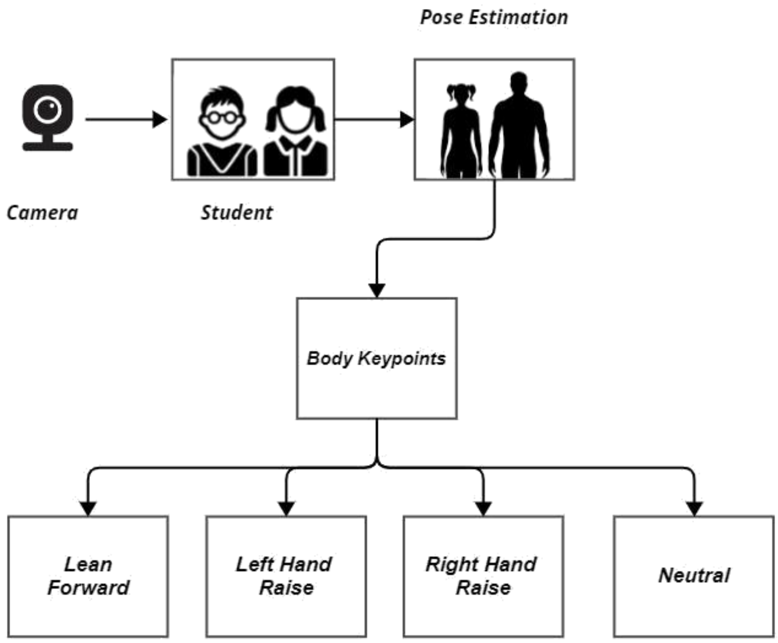

Fig. 3.1.8 Pose estimation module of student attention analysis

An SVM model was trained by using 6 key points of the body to detect the pose. Key points include elbow (2), Shoulder (2), and wrist (2). In this module, the system will execute the pose estimation function and use Meidapipe to extract body key points to determine the posture after launching the camera. Mediapipe is used to extract body key points. I utilized the right-hand raise, left-hand raise, and neutral and forward lean postures. Several studies use these postures to analyze attention [57][70].

The detected key points are passed to the Poselandmark model. It detects the landmark and position of these key points on the body. Then a threshold is used to determine the pose. Text annotations are added to the image and displayed on the screen.

3.2. Participants

The study involved a total of five participants. Each participant was asked to record five videos, each lasting for 20 minutes, while they listened to a lecture. Prior to the video recording session, all participants were fully informed about the purpose and objectives of the study, and they provided written consent to participate.

3.3. Environment Setup

The Figure. 3.3.1 illustrates the experimental environment. A camera was placed 6 feet distance from the subject. We can accurately detect head pose, emotion, and body posture from this distance. The utilized webcam is a Scorpion Marvo MA-MPC01 webcam. The lighting is adjusted using the camera's LED lights and an additional light source. The camera was positioned on a tripod at the same height as the student while seated.

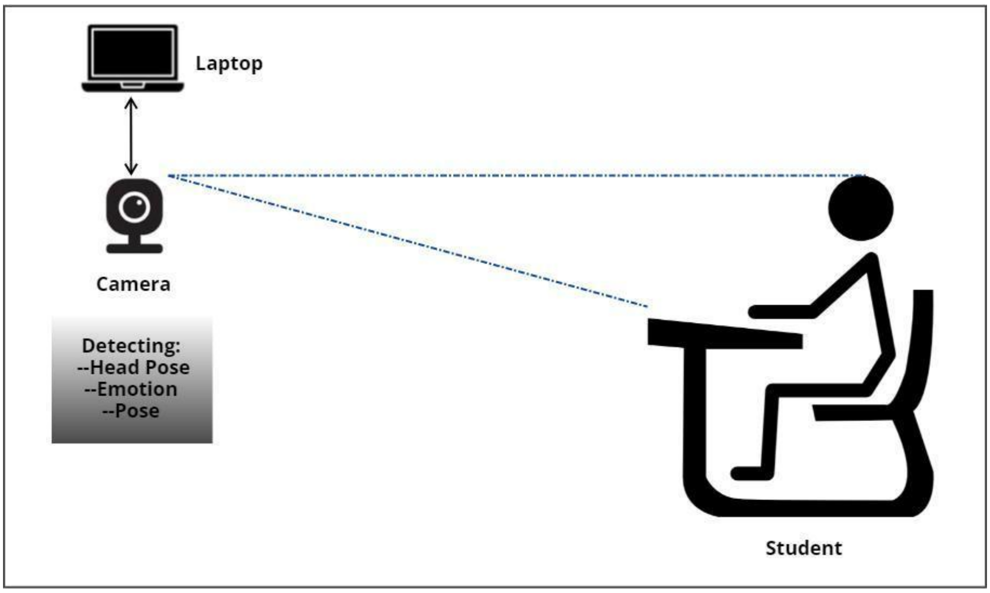

Fig. 3.3.1 Environment setup for measuring student attention.

3.4. Experiment Design

The system adheres to the architecture described previously. It incorporates three characteristics employed in numerous studies. 1) Head pose 2) Emotion Detection and Ear Estimation, and 3) Pose Estimation. The results from these three modules are combined to determine the attention level of students. In the introduction section, we observed that several researchers use these features singly or in tandem. Utilizing all three will significantly enhance the results. Five students total participated in this experiment. Each participant was subjected to the experiment five times, yielding a total of thirty experiments.

3.5. Software and Hardware Specifications

In Table 1. Starting with the specifications of the Computer System used to run out student attention analysis system.

Table. 1 Hardware Requirements

OS	Windows 11 Pro
Processor	Intel(R) Xeon(R) CPU W3670 @ 3.20GHz 3.19GHz
Graphic Card	NVIDIA GeForce GTX 960
Ram	16GB
Memory	1TB
Webcam	Scorpion Marvo MA-MPC01

The system is developed using the Python programming language (version 3.9) and the PyCharm Community Edition 2021.3.3 IDE (Integrated Development Environment). Multiple libraries, including OpenCV, were used to analyze the incoming video input for data processing. Google's Mediapipe is an open-source framework that provides pre-built machine-learning models and processing modules for tasks such as object detection, pose estimation, face detection, etc. Keras is used for model training and evaluation, Matplotlib is used to plot the attention graph, Dlib is used to extract facial landmarks, and many other libraries are used for the system's seamless operation.

3.6. Data Processing

Data processing is the foundation of system design. This describes how your system will function. How data will be transmitted and processed. I utilised a 5 MP webcam with a transmission rate of 1920 x 1080 and a frame rate of 30 fps for video input. The data frame was converted from BGR color space to RGB for processing and, when necessary, to grey image format. Adjusting the color space of incoming frames and resizing and scaling them are components of data preprocessing.

For head pose estimation, no model was trained. It applied a PnP function in which the 2D and 3D features of the face are extracted and used to calculate Euler angles, which determine the head's inclination direction. These angles include Roll, Pitch, and Yaw.

We train a Deep learning model for emotion detection using the FERPlus dataset. It consists of 48 x 48 black and white images. Therefore, to process received frames, they must be converted. Before activating the camera, all relevant model files and prediction functions were imported. The mathematical equations for EAR calculation are:

$$EAR = \frac{||p_2 - p_6|| + ||p_3 - p_5||}{2||p_1 - p_4||} \quad \textbf{(3)}$$

$$\text{Avg\_EAR} = {}^{1}\!/_{2} * (\text{EAR}_{\text{left}} + \text{EAR}_{\text{right}}) \quad \textbf{(4)}$$

For pose estimation, we gathered data from a variety of participants in the necessary poses. Using those data, we extracted 7 key points from the body and trained an SVM. The camera video was given to the Pose estimation model which detects the pose.

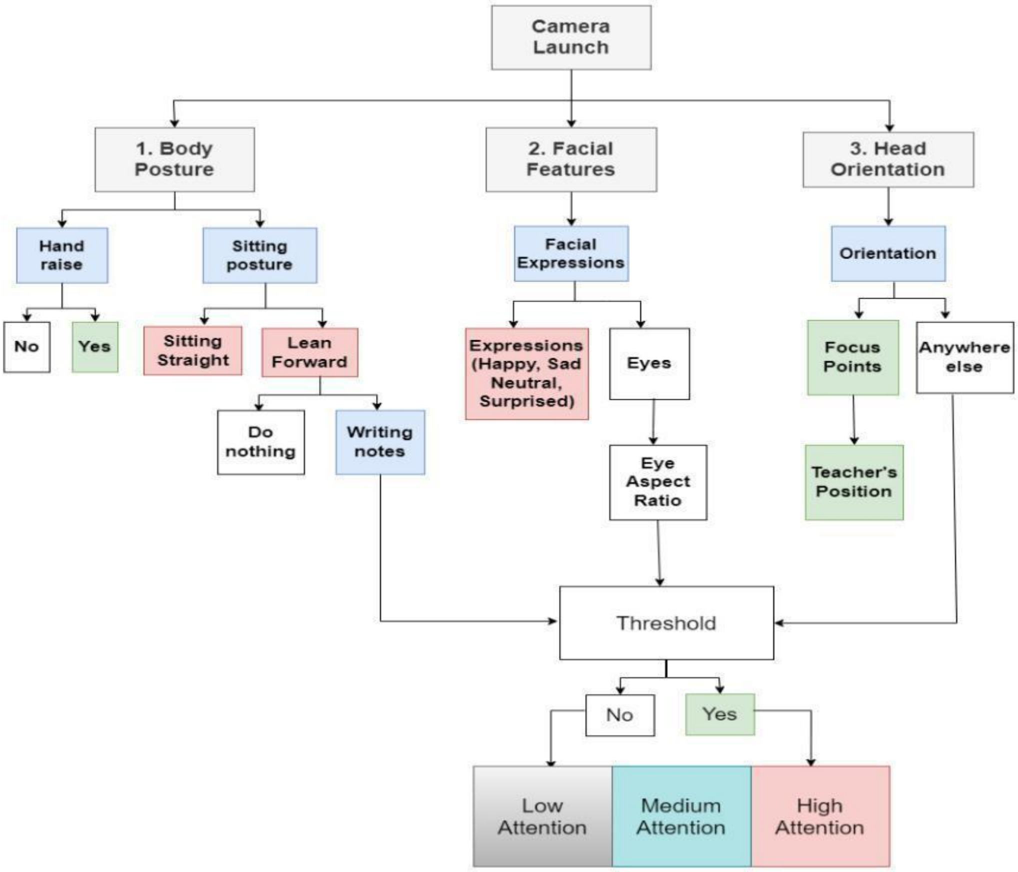

Fig. 3.6.1 . Flowchart of features and sub-features of each module.

CHAPTER 4

Results and Discussion

4.1. Head Pose

This module detects and displays real-time head direction. Mediapipe and OpenCV are the main libraries. We retrieved the participant's facial characteristics in real-time using Mediapipe FaceMesh. The algorithm retrieves 2D and 3D coordinates of nose, eye, and ear landmarks for the next step. A built-in function solves Perspective-n-Point. The motion of the head along the x and y axes can be described using Euler angles. Specifically, the vertical rotation of an object is referred to as pitch, while yaw represents the rotation during horizontal motion. Roll, on the other hand, refers to the circular rotation of an object, either clockwise or anticlockwise. To identify certain features, a threshold was applied to the amount of yaw movement. This threshold helped distinguish between left-skewed and right-skewed orientation. Similarly, variations in pitch were used to identify upward and downward orientations.

Table. 2 User Input Vs Results

User Input	**System Results**
Forward	Forward
Looking Left (positive change in yaw angle)	Looking Left
Looking Right (negative change in yaw angle)	Looking Right
Looking Down (negative change in pitch angle)	Looking Down
Looking Up (positive change in pitch angle)	Looking Up

4.2. Emotion Detection and EAR

This module's purpose is to analyze the participant's emotions and calculate EAR (Eye aspect ratio). We trained a model for emotion detection using the FERPlus dataset, which includes four emotions: happy, sad, neutral, and surprised. In 2022, Sharma, P. et al. [65] presented an e-learning system that combines head movement and eye-tracking with seven fundamental emotions. They categorized engagement as

"very engaged," "somewhat engaged," and "not engaged at all." During a session in which the student is viewing a video, they extract all of these characteristics and group students to exhibit the same emotions together. Later, they took an exam about the video. Then, compare the assessment results to the student's emotion group. Neutral received the maximum weight, followed by joyful and surprised at the same weight. The remaining emotions received low weights, indicating that the students were not attentive.

Our model was trained with four emotions; neutral has the most weight, happy and surprised has average weights, and sad has the least weight; we will analyze the attention based on these four emotions. Our system's accuracy is..., and the figure displays the predicted sentiments. We use Dlib to extract facial landmarks, followed by the FER prediction function to determine the sentiments. The results are determined by combining the student's emotions with the output of the other two modules. The following Figure. 4.2.1 shows the accuracy of the model and Figure 4.2.2 shows confusion matrix of the model.

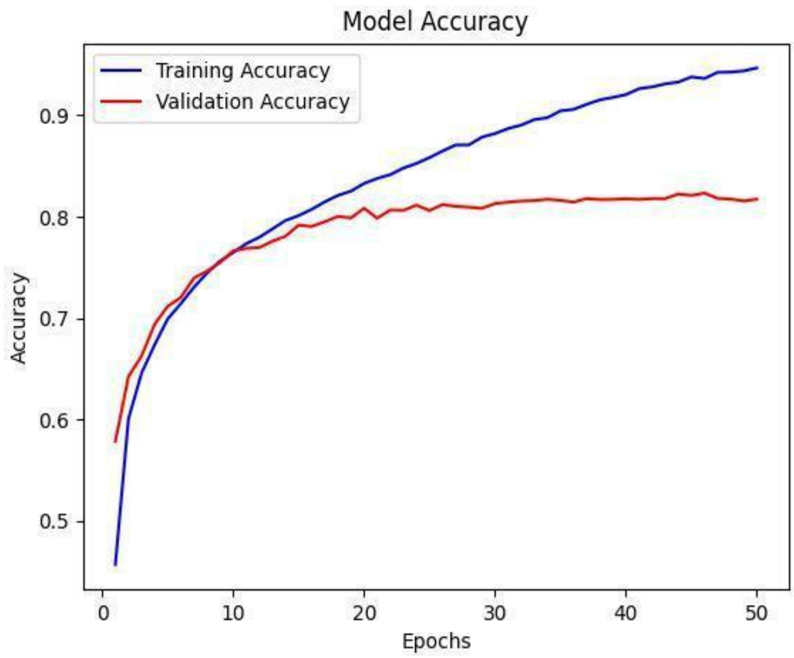

Fig. 4.2.1 Training and Validation Accuracy plot of FERPlus

The EAR is calculated to determine whether the eye is open or closed. The criterion is fixed at 2.0. Each frame's EAR is calculated, and then three consecutive frames are used to determine the eye's state. Using the EAR formula and average, a function is developed to compute EAR. EAR is also calculated using the formula described previously. Which was contrasted with the threshold every three frames. If the student's eyes remain closed (Avg_EAR < threshold) for three consecutive frames, they are inattentive and asleep. If EAR is not calculated because the student is gazing down, it is also deemed that the student is not attentive.

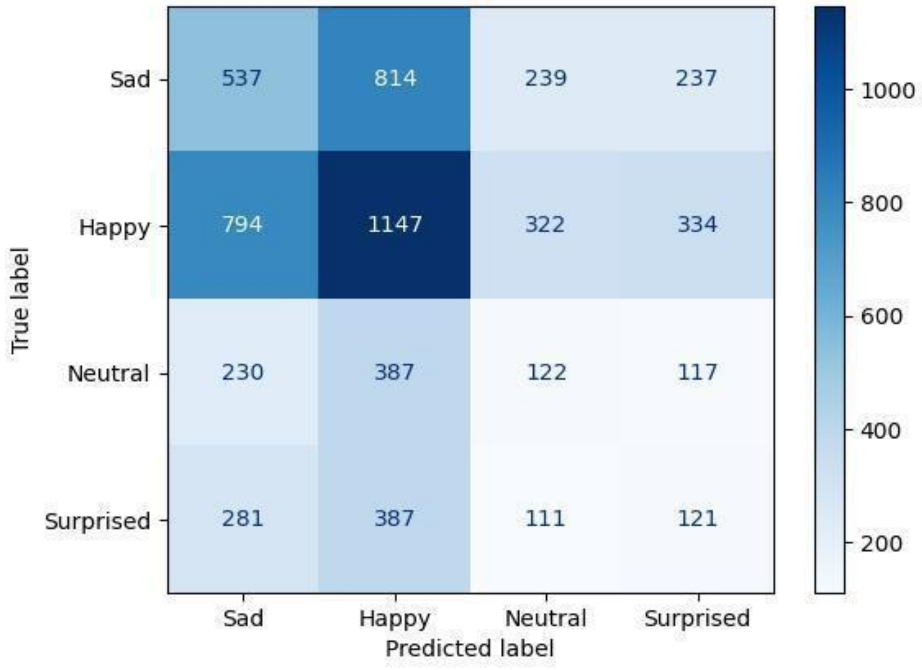

Fig. 4.2.2 Confusion Matrix of the trained model.

4.3. Pose Estimation

The purpose of this module is to detect the pose of the participant. Pose give information about the mental state of the student. The 6 key points used in this study were shoulders, elbows, and wrists. The six key points of the lower body (pelvis, knees, and ankles) were excluded because they were occluded by the tables. Four poses from the upper body are classified. Sitting straight, lean forward and hand raise right & left. The keypoints are detected using Mediapipe and then those keypoints are fed to the prediction function which provides the results.

4.4. Student Attention Analysis System

After extracting data from all the modules. Data is saved to a CSV file. A function reads that data and checks for correlations in the data. For example, if a student is sitting actively with a neutral face, eyes are open as well and he/she is looking towards the teacher so this shows he/she is active [48][57][60].

Table. 3 shows the traits and their positive and negative correlation with attention. Intermediate correlation means these features can relate both positively and negatively when used in combination with some other trait. For example. If a student is leaning forward and his/her head is down.

There are two possibilities either he/she is writing notes which shows attentiveness (positive), or he/she is busy with some other tasks like using the phone or doodling on the paper (negative). This difference is measured using a threshold value to know how much time the student was in this position. The faces in Figure. 4.4.2 are hidden because of privacy concerns. The Attention graph of the system is displayed in Figure. 4.4.1

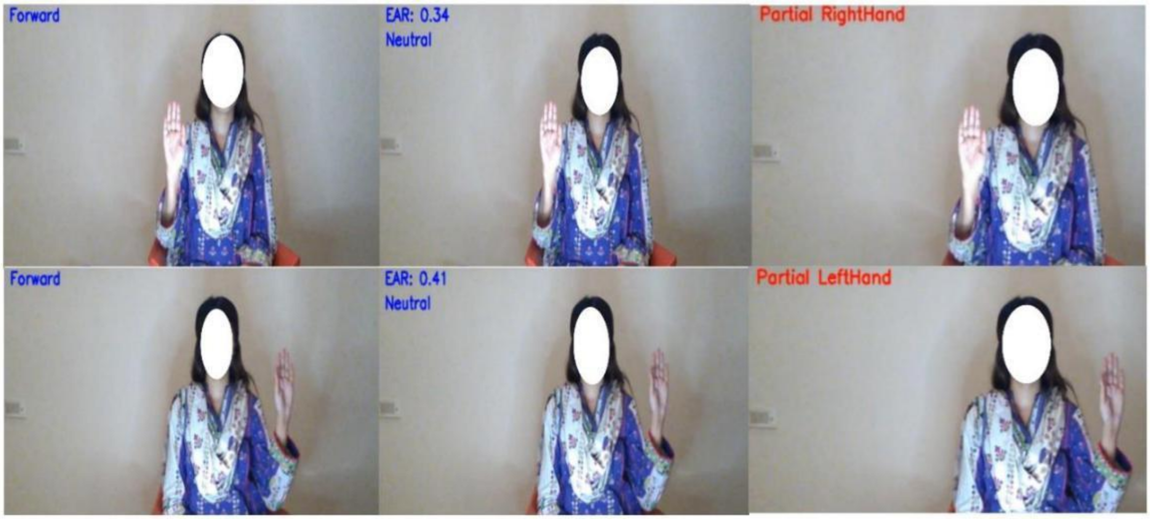

Fig. 4.4.2 Labeling of different modules using a camera during attention analysis

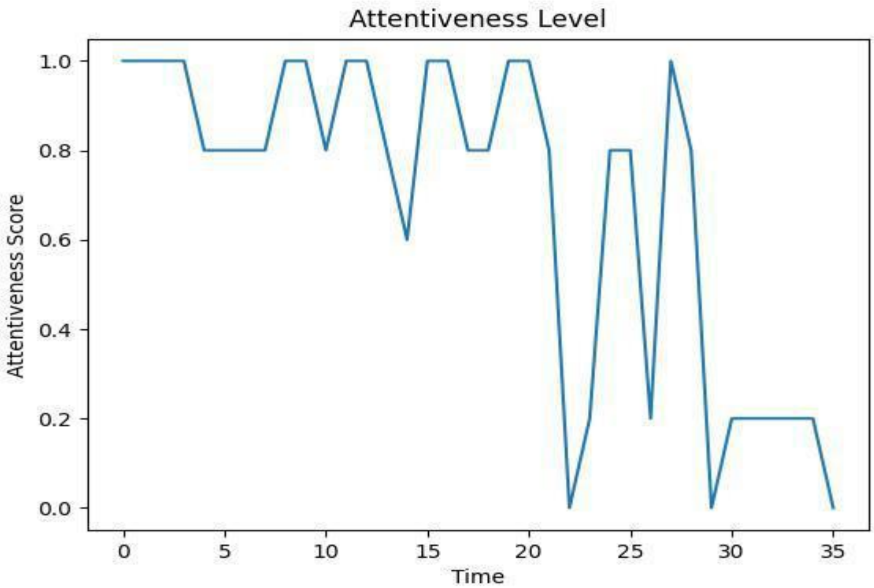

Fig. 4.4.1 The attention graph presents the level of attentiveness exhibited by the student.

Table. 3 Correlation of features extracted from Headpose, Emotion and Pose Modules

EMOTION	RELATED TO ATTENTION	BODY POSTURE	RELATED TO ATTENTION	HEAD ORIENTATION	RELATED TO ATTENTION
Happy	Positive	Sitting Straight	Positive	Forward	Positive
Neutral	Positive	Lean Forward	Intermediate	Left/ Right	Negative
Sad	Negative	Partial Hand Raise	Positive	Up	Intermediate
Surprised	Intermediate	Full Hand Raise	Positive	Down	Intermediate

4.5. Privacy policy

Automated video-based emotional AI and powerful computers raise ethical and privacy problems. These include system design, openness, data use, and privacy. Transparency requires informed permission before collecting participants' visual data. Adult participants and minor participants' parents or legal guardians should give consent. The utilization of data in research must adhere to ethical principles and ensure that visual data is not misused or misappropriated. Data privacy plays a crucial role in safeguarding participants' data and ensuring their identities are protected.

To address these concerns, the proposed method adopts several solutions. Firstly, the system does not store complete classroom videos. Instead, incoming video frames are temporarily held in a cache for analysis purposes only and are automatically destroyed afterwards. This approach minimizes the storage of sensitive visual data [71].

Furthermore, the system is designed to prioritize student privacy. It does not involve the recognition, analysis, or publication of visual data that could potentially compromise the privacy of the individuals involved. By refraining from these activities, the system ensures that student identities are not disclosed or exposed [53].

These measures aim to strike a balance between utilizing visual data for research purposes while upholding ethical standards and respecting participants' privacy.

CHAPTER 5

Conclusion and Future Work

Attention analysis helps the teacher to have a better understanding about the student's state. Our research has been focused on developing a multimodal architecture that aims to analyze student attention. The system has undergone effective testing on a small group of five students, yielding positive results. The architecture encompasses various features, including head orientation detection, emotion detection, EAR calculation, and pose estimation. Our long-term objective is to implement this architecture in an offline classroom setting, enabling simultaneous analysis of the attention levels of multiple students. We envision that this system has the potential to transform the traditional classroom into a sensing environment by providing valuable guidance and feedback to both teachers and students. Teachers can benefit from insights and recommendations on how to enhance their teaching methodologies based on real-time analysis of student attention. Similarly, students can receive feedback on their classroom behavior, allowing them to improve their engagement and, ultimately, enhance their academic performance. By leveraging this system, we aim to create a collaborative and supportive educational environment that empowers both teachers and students to optimize their roles and interactions in the classroom, leading to improved learning outcomes.

Reference

[1] . K., S. Ali, K. F. Iqbal, Y. Avaz, and M. Sajid, “A Review on Different Approaches for Assessing Student Attentiveness in Classroom using Behavioural Elements,” 2022, pp. 152–158, doi: 10.1109/ICAI55435.2022.9773418.

[2] N. A. Bradbury, “Attention span during lectures: 8 seconds, 10 minutes, or more?,” *Adv. Physiol. Educ.*, vol. 40, no. 4, pp. 509–513, 2016.

[3] S. Gupta, P. Kumar, and R. K. Tekchandani, “Facial emotion recognition based real-time learner engagement detection system in online learning context using deep learning models,” *Multimed. Tools Appl.*, vol. 82, no. 8, pp. 11365–11394, 2023.

[4] E. Barsoum, C. Zhang, C. C. Ferrer, and Z. Zhang, “Training deep networks for facial expression recognition with crowd-sourced label distribution,” in *Proceedings of the 18th ACM international conference on multimodal interaction*, 2016, pp. 279–283.

[5] R. M. Carini, G. D. Kuh, and S. P. Klein, “Student engagement and student learning: Testing the linkages,” *Res. High. Educ.*, vol. 47, pp. 1–32, 2006.

[6] A. Toropova, E. Myrberg, and S. Johansson, “Teacher job satisfaction: the importance of school working conditions and teacher characteristics,” *Educ. Rev.*, vol. 73, no. 1, pp. 71–97, 2021.

[7] J. D. Jecker, N. Maccoby, and H. S. Breitrose, “Improving accuracy in interpreting non-verbal cues of comprehension.,” *Psychol. Sch.*, 1965.

[8] K. Ahuja *et al.*, “EduSense: Practical classroom sensing at Scale,” *Proc. ACM Interactive, Mobile, Wearable Ubiquitous Technol.*, vol. 3, no. 3, pp. 1–26, 2019.

[9] N. Dhingra, C. Hirt, M. Angst, and A. Kunz, “Eye Gaze Tracking for Detecting Non-verbal Communication in Meeting Environments,” in *15th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP 2020)*, 2020, pp. HUCAPP20--RP.

[10] A. Pentland, *Honest signals: how they shape our world*. MIT press, 2010.

[11] R. Zheng, F. Jiang, and R. Shen, “GestureDet: Real-time student gesture analysis with multi-dimensional attention-based detector,” in *Proceedings of the Twenty-Ninth International Conference on International Joint Conferences on Artificial Intelligence*, 2021, pp. 680–686.

[12] J. A. Fredricks, P. C. Blumenfeld, and A. H. Paris, “School engagement: Potential of the concept, state of the evidence,” *Rev. Educ. Res.*, vol. 74, no. 1, pp. 59–109, 2004.

[13] C. Suárez-Orozco, A. Pimentel, and M. Martin, “The significance of relationships: Academic engagement and achievement among newcomer immigrant youth,” *Teach. Coll. Rec.*, vol. 111, no. 3, pp. 712–749, 2009.

[14] I. Archambault, M. Janosz, J. Morizot, and L. Pagani, “Adolescent behavioral, affective, and cognitive engagement in school: Relationship to dropout,” *J. Sch. Health*, vol. 79, no. 9, pp. 408–415, 2009.

[15] J. N. Hughes, W. Luo, O. Kwok, and L. Loyd, “Student-teacher support, effortful engagement, and achievement: A 3-year longitudinal study,” *J. Educ. Psychol.*, vol. 100, pp. 1–14, 2008.

[16] H. Patrick, A. M. Ryan, and A. Kaplan, “Early adolescents’ perceptions of the classroom social environment, motivational beliefs, and engagement.,” *J. Educ. Psychol.*, vol. 99, no. 1, p. 83, 2007.

[17] J. A. Baker, T. P. Clark, K. S. Maier, and S. Viger, “The differential influence of instructional context on the academic engagement of students with behavior problems,” *Teach. Teach. Educ.*, vol. 24, no. 7, pp. 1876–1883, 2008.

[18] J. T. Downer, S. E. Rimm-Kaufman, and R. C. Pianta, “How do classroom conditions and children’s risk for school problems contribute to children’s behavioral engagement in learning?,” *School Psych. Rev.*, vol. 36, no. 3, pp. 413–432, 2007.

[19] L. S. Pagani, C. Fitzpatrick, and S. Parent, “Relating kindergarten attention to subsequent developmental pathways of classroom engagement in elementary school,” *J. Abnorm. Child Psychol.*, vol. 40, pp. 715–725, 2012.

[20] C. Furrer and E. Skinner, “Sense of relatedness as a factor in children’s academic engagement and performance.,” *J. Educ. Psychol.*, vol. 95, no. 1, p. 148, 2003.

[21] X. Ge and D. Ifenthaler, “Designing engaging educational games and assessing engagement in game-based learning,” in *Gamification in Education: Breakthroughs in Research and Practice*, IGI Global, 2018, pp. 1–19.

[22] J. I. Rotgans and H. G. Schmidt, “Cognitive engagement in the problem-based learning classroom,” *Adv. Heal. Sci. Educ.*, vol. 16, pp. 465–479, 2011.

[23] L. Corno and E. B. Mandinach, “The role of cognitive engagement in classroom learning and motivation,” *Educ. Psychol.*, vol. 18, no. 2, pp. 88–108, 1983.

[24] J. C. Richardson and T. Newby, “The role of students’ cognitive engagement in online learning,” *Am. J. Distance Educ.*, vol. 20, no. 1, pp. 23–37, 2006.

[25] C. O. Walker, B. A. Greene, and R. A. Mansell, “Identification with academics, intrinsic/extrinsic motivation, and self-efficacy as predictors of cognitive

engagement," *Learn. Individ. Differ.*, vol. 16, no. 1, pp. 1–12, 2006.

[26] J. J. Appleton, S. L. Christenson, D. Kim, and A. L. Reschly, "Measuring cognitive and psychological engagement: Validation of the Student Engagement Instrument," *J. Sch. Psychol.*, vol. 44, no. 5, pp. 427–445, 2006.

[27] M. Tóthová and M. Rusek, "use of eye-tracking in science textbook analysis: a literature review," *Sci. Educ.*, vol. 12, no. 1, pp. 63–74, 2021.

[28] J. A. Fredricks and W. McColskey, "The measurement of student engagement: A comparative analysis of various methods and student self-report instruments," in *Handbook of research on student engagement*, Springer, 2012, pp. 763–782.

[29] J. Parsons and L. Taylor, "Student engagement: What do we know and whatshould we do," *Alberta, Canada Univ. Partners, Univ. Alberta*, 2011.

[30] N. R. Council, *Testing, Teaching, and Learning: A Guide for States and School Districts*. Washington, DC: The National Academies Press, 1999.

[31] A. Education, "Effective student assessment and evaluation in the classroom," *Teach. Dev. Certif. Branch). Retrieved from http//www. eric. ed. gov/PDFS/ED498247. pdf*, 2006.

[32] A. Wigfield *et al.*, "Role of reading engagement in mediating effects of reading comprehension instruction on reading outcomes," *Psychol. Sch.*, vol. 45, no. 5, pp. 432–445, 2008.

[33] P. Blumenfeld *et al.*, "School engagement of inner-city students during middle childhood," in *Developmental pathways through middle childhood*, Psychology Press, 2006, pp. 157–182.

[34] M. M. McCaslin and T. L. Good, *Listening in classrooms*. HarperCollins, 1996.

[35] R. Nawaz *et al.*, "Leveraging AI and Machine Learning for National Student Survey: Actionable Insights from Textual Feedback to Enhance Quality of Teaching and Learning in UK's Higher Education," *Appl. Sci.*, vol. 12, no. 1, p. 514, 2022.

[36] J. Bidwell and H. Fuchs, "Classroom analytics: Measuring student engagement with automated gaze tracking," *Behav Res Methods*, vol. 49, no. 113, 2011.

[37] M. Uçar and E. Özdemir, "Detecting Student Engagement in e-learning Environment Based on Head Pose Estimation and Eye Aspect Ratio," 2019.

[38] H. Monkaresi, N. Bosch, R. A. Calvo, and S. K. D'Mello, "Automated detection of engagement using video-based estimation of facial expressions and heart rate," *IEEE Trans. Affect. Comput.*, vol. 8, no. 1, pp. 15–28, 2016.

[39] K. Yaomanee, S. Pan-ngum, and P. I. N. Ayuthaya, "Brain signal detection

methodology for attention training using minimal EEG channels," in *2012 Tenth International Conference on ICT and Knowledge Engineering*, 2012, pp. 84–89.

[40] N.-H. Liu, C.-Y. Chiang, and H.-C. Chu, "Recognizing the degree of human attention using EEG signals from mobile sensors," *sensors*, vol. 13, no. 8, pp. 10273–10286, 2013.

[41] C. Wang and P. Cesar, "Physiological Measurement on Students' Engagement in a Distributed Learning Environment.," *PhyCS*, vol. 10, p. 0005229101490156, 2015.

[42] J. Whitehill *et al.*, "Towards an optimal affect-sensitive instructional system of cognitive skills," in *CVPR 2011 WORKSHOPS*, 2011, pp. 20–25.

[43] C. Sethi, H. Dabas, C. Dua, M. Dalawat, and D. Sethia, "EEG-based attention feedback to improve focus in E-learning," in *Proceedings of the 2018 2nd International Conference on Computer Science and Artificial Intelligence*, 2018, pp. 321–326.

[44] N. Gao, W. Shao, M. S. Rahaman, and F. D. Salim, "n-Gage: Predicting in-class Emotional, Behavioural and Cognitive Engagement in the Wild," *Proc. ACM Interactive, Mobile, Wearable Ubiquitous Technol.*, vol. 4, no. 3, pp. 1–26, 2020.

[45] G. Fanelli, J. Gall, and L. Van Gool, "Real time head pose estimation with random regression forests," in *CVPR 2011*, 2011, pp. 617–624.

[46] J. Whitehill, Z. Serpell, Y.-C. Lin, A. Foster, and J. R. Movellan, "The faces of engagement: Automatic recognition of student engagementfrom facial expressions," *IEEE Trans. Affect. Comput.*, vol. 5, no. 1, pp. 86–98, 2014.

[47] M. Raca, "Camera-based estimation of student's attention in class," 2015.

[48] J. Zaletelj and A. Košir, "Predicting students' attention in the classroom from Kinect facial and body features," *EURASIP J. image video Process.*, vol. 2017, no. 1, pp. 1– 12, 2017.

[49] Y. Qiu and Y. Wan, "Facial Expression Recognition based on Landmarks," in *2019 IEEE 4th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, 2019, vol. 1, pp. 1356–1360.

[50] H. Waheed, S.-U. Hassan, N. R. Aljohani, J. Hardman, S. Alelyani, and R. Nawaz, "Predicting academic performance of students from VLE big data using deep learning models," *Comput. Human Behav.*, vol. 104, p. 106189, 2020.

[51] Z. Luo, C. Jingying, W. Guangshuai, and L. Mengyi, "A three-dimensional model of student interest during learning using multimodal fusion with natural sensing technology," *Interact. Learn. Environ.*, vol. 30, no. 6, pp. 1117–1130, 2022.

[52] D. Datta and S. B. Jamalmohammed, “Image classification using CNN with multi-core and many-core architecture,” in *Applications of Artificial Intelligence for Smart Technology*, IGI Global, 2021, pp. 233–266.

[53] Z. Trabelsi, F. Alnajjar, M. M. A. Parambil, M. Gochoo, and L. Ali, “Real-Time Attention Monitoring System for Classroom: A Deep Learning Approach for Student’s Behavior Recognition,” *Big Data Cogn. Comput.*, vol. 7, no. 1, p. 48, 2023.

[54] A. Mollahosseini, B. Hasani, and M. H. Mahoor, “Affectnet: A database for facial expression, valence, and arousal computing in the wild,” *IEEE Trans. Affect. Comput.*, vol. 10, no. 1, pp. 18–31, 2017.

[55] A. Sharma and P. Abrol, “Eye gaze techniques for human computer interaction: A research survey,” *Int. J. Comput. Appl.*, vol. 71, no. 9, 2013.

[56] R. Stiefelhagen, “Tracking focus of attention in meetings,” in *Proceedings. Fourth IEEE International Conference on Multimodal Interfaces*, 2002, pp. 273–280.

[57] G. K. S. Rao, “STUDENT ATTENTIVENESS CLASSIFICATION USING GEOMETRIC MOMENTS AIDED POSTURE ESTIMATION,” Purdue University Graduate School, 2022.

[58] X. Xu and X. Teng, “Classroom attention analysis based on multiple euler angles constraint and head pose estimation,” in *MultiMedia Modeling: 26th International Conference, MMM 2020, Daejeon, South Korea, January 5--8, 2020, Proceedings, Part I 26*, 2020, pp. 329–340.

[59] H. Xu, J. Zhang, H. Sun, M. Qi, and J. Kong, “Analyzing students’ attention by gaze tracking and object detection in classroom teaching,” *Data Technol. Appl.*, 2023.

[60] L. Lin and L. Shi, “Research on student classroom attention recognition based on multimodality,” in *Third International Conference on Computer Science and Communication Technology (ICCSCT 2022)*, 2022, vol. 12506, pp. 840–845.

[61] M. Raca, L. Kidzinski, and P. Dillenbourg, “Translating head motion into attention-towards processing of student’s body-language,” in *Proceedings of the 8th international conference on educational data mining*, 2015, no. CONF.

[62] P. Khorrami, V. Le, J. C. Hart, and T. S. Huang, “A system for monitoring the engagement of remote online students using eye gaze estimation,” in *2014 IEEE International Conference on Multimedia and Expo Workshops (ICMEW)*, 2014, pp. 1–6.

[63] H. Jarodzka, I. Skuballa, and H. Gruber, “Eye-tracking in educational practice: Investigating visual perception underlying teaching and learning in the classroom,”

Educ. Psychol. Rev., vol. 33, no. 1, pp. 1–10, 2021.

[64] Y. Zheng, Y. Kuang, S. Sugimoto, K. Astrom, and M. Okutomi, "Revisiting the pnp problem: A fast, general and optimal solution," in *Proceedings of the IEEE International Conference on Computer Vision*, 2013, pp. 2344–2351.

[65] P. Sharma *et al.*, "Student engagement detection using emotion analysis, eye tracking and head movement with machine learning," in *Technology and Innovation in Learning, Teaching and Education: Third International Conference, TECH-EDU 2022, Lisbon, Portugal, August 31--September 2, 2022, Revised Selected Papers*, 2023, pp. 52–68.

[66] A. Pentaraki and G. J. Burkholder, "Emerging evidence regarding the roles of emotional, behavioural, and cognitive aspects of student engagement in the online classroom," *Eur. J. Open, Distance E-Learning*, vol. 20, no. 1, pp. 1–21, 2017.

[67] C. Dewi, R.-C. Chen, X. Jiang, and H. Yu, "Adjusting eye aspect ratio for strong eye blink detection based on facial landmarks," *PeerJ Comput. Sci.*, vol. 8, p. e943, 2022.

[68] Y. HATORI, T. NAKAJIMA, and S. WATABE, "Body Posture Analysis for the Classification of Classroom Scenes," *Interdiscip. Inf. Sci.*, vol. 28, no. 1, pp. 55– 62, 2022.

[69] Y. Zhang, T. Zhu, H. Ning, and Z. Liu, "Classroom student posture recognition based on an improved high-resolution network," *EURASIP J. Wirel. Commun. Netw.*, vol. 2021, no. 1, pp. 1–15, 2021.

[70] K. A. Rocca, "Student participation in the college classroom: An extended multidisciplinary literature review," *Commun. Educ.*, vol. 59, no. 2, pp. 185–213, 2010.

[71] K. Ahuja *et al.*, "Classroom Digital Twins with Instrumentation-Free Gaze Tracking," in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, 2021, pp. 1–9.

Appendix A- Consent Form

National University of Science and Technology
Islamabad, Pakistan.

RIME Department

Participant Consent Form

Purpose:
The purpose of this study is to analyze the student's attention in the classroom using non-invasive approach. The study is part of MS thesis, under the supervision of Dr. Sara Ali.

Procedure:
If you agree to be in this study, you will be asked to do the following:

1. Listen to approximately 20 minutes lecture.
2. Perform activities as per instructions.

Benefits/Risks to Participant:
There is no personal benefit from your participation in this, but the knowledge received may be of value to future researchers.

Voluntary Nature of the Study/Confidentiality:
Your participation in this study is entirely voluntary and you may refuse to complete the study at any point during the experiment. You may also stop at any time and ask the researcher any questions you may have.
You will be assigned a number as names will not be recorded. The researchers will save the data file and recordings by your number, not by name. Only members of the research group will view collected data in detail. Any recordings or files will be stored in a secured location accessed only by authorized researchers.

Contacts and Questions:
You can ask any questions you may have regarding this study. If you have questions later, you may contact at kainat.rime20smme@student.nust.edu.pk , or my faculty supervisor, sarahaber@smme.nust.edu.pk.

Statement of Consent:
I have read the above information. I have asked questions I had regarding the experimental procedure, and they have been answered to my satisfaction. I consent to participate in this study.

Name	Signature
Anum	[illegible]
Hajira	[illegible]
M.Ali	[illegible]
Malaika	[illegible]
Kainat	[illegible]

Thanks for your participation!