

Online Student Learning Experience

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ABSTRACT

These days, the rise of online education offers unprecedented access to education and learning experiences that copy learning in the classroom. But, student involvement, assessment of learning experiences, and feedback to students have become complex as part of such significant growth. Conventional ways used to measure student attention and affect have become ineffective as educational activities have migrated online requiring new approaches to improve online learning quality. This paper presents a new model for evaluating student engagement and learning experience in online education using computer vision and deep learning. The system assesses student engagement and feelings during lectures through the analysis of real-time facial expressions. To ensure real-time feedback, only comments from attentive students are analysed for sentiment using the VADER tool. The project is planned with sufficient time and towards engagement detector. So, we are focused on enhancement of robustness of engagement detection by using visual analysis of facial expressions in combination with other instruments such as eyetracking technology, physiological sensors (e.g. heart rate variability, skin conductance), and Natural Language Processing (NLP) techniques. The researchers examine machine learning models trained on a large dataset of student interactions and performance data. By leveraging these approaches, teachers will have the data to understand how engaged students and their emotions are during class. This will allow them to improve their way of teaching and online learning in general.

Keywords: Student Engagement, Online Education, Computer Vision, Deep Learning, Sentiment Analysis

INTRODUCTION

As schools seek to improve student engagement today, tools to measure and enhance engagement will help all students. Using the traditional methods to measure a student's attentiveness does not offer timely and fine information on the mental state of the students. To resolve this issue, we proposed a novel model that employs facial expression analysis for the real-time assessment of student attentiveness during an event. We proposed a system that captures facial expression using advanced computer vision and deep learning algorithm which will be effective with lower cost. The model quickly provides teachers with feedback on the attention levels of their students. Also, the model will be able to assess the sentiment through sentiment analysis of student's feedback. Through these attention detection and sentiment analysis this paper outlines the development, validation, and potential applications of our model. Our approach will not only help in improving the teaching methodologies but also in producing an adaptive responsive learning environment through the understanding of the cognitive states and learning experience of students.

Education serves as a fundamental mechanism for molding both individual development and societal progress. Educational researchers utilize technology to study student behavior patterns and improve learning outcomes since technology now forms a fundamental component of educational settings. The research presented in this paper applies computer vision techniques to analyze facial expressions in order to measure student engagement during educational activities. Sentiment analysis of student reviews delivers important insights concerning their overall learning experiences. Students starting their academic paths must consider both the availability of courses and how well these courses deliver quality learning experiences.

Does the online institute match the student's educational needs and personal goals? Does the online institute match their preferred learning methods while supporting academic objectives and personal dreams? These questions highlight the requirement for detailed analysis and comprehensive assessment of the online learning environment.

This research directly addresses these questions by using advanced technologies to examine the complex elements of student learning experiences within online education systems. Our study uses facial expression analysis and sentiment analysis to create an unbiased holistic view of the relationship between students and online educational platforms. While education continues to progress this study analyzes more than just course content by examining all stages of online education including virtual classroom experiences and the assessment techniques used by digital learning institutions. The investigation proceeds from the understanding that selecting an online institution involves an investment in one's academic and Professional trajectory rather than just a simple financial transaction. Educational technology integration must serve dual purposes by both enhancing learning processes and making students feel involved and ready for future challenges.

Join our journey to reveal and analyze the critical elements that define the online learning experience. The research examines teaching methods alongside student- professor interactions and assessment practices to deliver prospective students a complete set of tools for navigating online education. It is a matter of students' educational pursuits as well as academic growth which needs to be done wisely. The study in question emphasizes objectivity and transparency. It seeks to draw a distinction between an online institute that is merely easy to join and one that is truly useful for the overall growth of students. As students begin their educational journey, many questions come to mind. Are these reviews legitimate? Are they a true depiction of the student learning experience or are they a fake? Who is at Fault? A Student-Response Study of a Yes or No Question and Its Implications for Learning Outcomes. As we go through the online education system, these questions guide this enquiry. Peeking behind the curtains of promotional material and testimonials, we must conduct a critical view to gauge the actual learning environment.

Authenticity of reviews:

A large number of reviews available online help students to some extent or the other. It's really important for the reviewers to be real people if the students must rely on them. This study is going to find out the authenticity of online review by using sentiment analysis. Are the reviews just marketing hype or a true display of the student experience? By looking at how people feel about the reviews, this research tries to provide a reliable framework for students to decide whether not to go.

Performance Attribution: Institute vs Student:

The online education system has its own challenges and issues for both teachers and students. When academic performance fails, it is important to know whether the problem lies within the institution or the student.

Is a student's struggle a reflection of deficiency in the teaching of an institute or the individual learning styles and efforts of a student? This study looks at the relationship between institutes and students to find out the reason for poor performance in online learning.

Holistic Evaluation for Informed Decision Making:

When it comes to learning about a program, students are usually keen to know what goes on in the institution, the promises made by the institution, and so on. However, students must also get a deeper insight into the experience of virtual students who got to know about the institution through the introduction. If students spend time knowing about how the previous students experienced the program and what they learnt from it, it will benefit them for sure. Through the investigation of review authenticity and the determinants of student performance, this research aims to yield useful insights into the online educational landscape.

Background:

Understanding the Significance of Student Learning Experience in Online Education

In education, the term "student learning experience" describes the various things that affect a student's journey and development. More than just the classroom, it refers to all the ways that someone acquires knowledge, skills, and competencies. With the onset of online education, things that seemed impossible and difficult are happening and becoming easy at our doorsteps. The immense number of courses and institutions available online presents both

opportunities and challenges for students. As the variety satisfies numerous academic interests, the complex aspect is finding out the things that are real and have depth. The dynamic landscape of online education fairgrounds the need for a comprehensive evaluation framework that looks beyond the standard parameters.

In today's fast-paced, digitized world, maintaining focus and paying attention is crucial for any student to succeed in classes and schools. For learners, which mostly means students, the ability to pay attention in lectures and study hours affects his learning outcome and performance. But there are many distractions students face with other things like fatigue and technology which limits their ability to focus. Knowing how important learning environment is, teachers and parents are trying out different ways to help students become focused or attentive. One way includes keeping an eye on the attention span of the students regularly by teachers. They can focus on improving/increasing their attention by monitoring the attention of students in the school and at home in order to enhance their learning experience.

A. Online Education and Student Decision Making:

The rise of popularity in online education gave birth to many education platforms and institutions. As students look at their options, the decision-making process of selecting an institute is critical. Reviews are critical to guiding students toward institutes that are aligned with their learning preferences and desires. The usefulness of reviews is determined by their authenticity and credibility or else any biased opinions can steer to a wrong institute.

B. Unbiased Evaluation through Facial Expression and Sentiment Analysis:

The main aim of this study is to provide a solid and impartial assessment of the student learning experience in online education. By using facial expression analysis and sentiment analysis, this study intends to add another objective measure for assessing the online education experience, so that students may make an informed choice.

C. Curriculum and Academic Content:

An educational program's curriculum is the tool that drives the learning experience. This section will delve into:

- 1) Teaching Methodologies: Evaluating the effectiveness of teaching strategies in online courses.
- 2) Academic Content: Asses quality and relevance of course material, management of delivery and practice sheets.

Interaction between Professors and Students:

The relationship between the teachers and learners impacts the online mode of learning. This section will explore:

- 1) Communication and Availability: Assessing the ability and willingness of professors in the online setting.
- 2) Engagement and Interaction: Evaluating the engagement between students and professors, and its effect on learning.

Assessments and their Importance:

The assessment process is an important part of measuring student understanding and development. This section will focus on:

- 1) Evaluation Methods: A comprehensive review of all the assessment tools used in online courses.
- 2) Feedback Mechanism: Reviewing the loop created by assessments and feedback for continuous improvement.

Enhancing Student Focus and Performance:

In addition, the latest area of research in the online education world is identifying and increasing the attention capacity of students in online classes. As focusing is important in online learning, this research will help know how a student can discover and enhance his attention in class. The research aims to help students improve their attention in class, which will help enhance their performance in class. This will be assisted by facial expression analysis. This new method is in line with the goal of the research not just to assess institutions but also to improve each learner's growth and performance in online education.

1) **Attention Capacity Identification:**

- Employing facial expression analysis, the study seeks to identify patterns related to student attention during virtual classes.
- Understanding variations in attention spans allows for tailored interventions and support to enhance student engagement.

2) **Individualized Learning Strategies:**

- Through the analysis of attention data, the research aims to provide insights into individualized learning strategies.
- Tailoring instructional approaches based on identified attention patterns can foster a more effective learning environment.

3) **Impact of Course Structure on Focus:**

- Analyzing how the structure of online courses affects student attention and focus.
- Identifying optimal course designs that promote sustained engagement and reduce distractions.

4) **Technological Interventions for Focus Enhancement:**

- Exploring the integration of technology-driven interventions to enhance student focus.
- Investigating the effectiveness of tools such as real time quizzes, interactive elements, or adaptive learning platforms.

5) **Time Management and Attention Allocation:**

- Studying how students allocate their attention across different tasks during online learning.
- Providing insights into effective time management strategies that contribute to sustained focus.

6) **Instructor Strategies for Engagement:**

- Analyzing the role of instructors in maintaining student engagement and focus.
- Identifying effective pedagogical strategies that promote active participation and attentiveness.

7) **Peer Interaction and Collaborative Learning:**

- Exploring the impact of peer interaction on student focus and overall performance.
- Assessing the role of collaborative learning environments in sustaining interest and motivation.

8) **Feedback Mechanisms for Focus Improvement:**

- Implementing feedback mechanisms based on facial expression analysis to guide students in improving their focus.
- Fostering continuous feedback loop for both educators and learners to optimize the online learning experience.

9) **Stress and Cognitive Load Analysis:**

- Investigating the relationship between stress levels, cognitive load, and attention in online learning.
 - Understanding how factors beyond course content influence student focus and performance.

10) **Long-Term Impact on Academic Success:**

- Examining the correlation between sustained focus during online learning and long-term academic success.
- Providing insights into how enhanced attention capacity contributes to improved learning outcomes.

Role of Parents: Parents can help their child develop and do well in school. By actively engaging with their kids and giving them advice and encouragement, parents can help kids form habits and strategies to sustain their attention. Parents can help their kids in overcoming their distractions by establishing a productive home environment. Besides, parents can consult teachers together to discuss the attentional requirements of their child and any individualized strategies or materials that can help their child.

Exploring Techniques for Attention Enhancement: There are different evidence-based techniques and practices that the student can explore to enhance their attention in class. They may include mindfulness meditation, cognitive behavior strategies, sensory integration exercises, etc. Students can develop more resilience to distractions and monitor attention over the school day by including these techniques in their school day.

Benefits of Improved Focus and Attention: Having better focus and attention will not just improve the academics, but students will also be more engaged, productive and well-being overall in life. When students are able to focus well in class, they find it easier to absorb, retain, and understand/acquire information. Also, when you focus on attentional skills, you can learn a lot of things and utilize them for life.

MOTIVATION AND OBJECTIVES

This model was developed based on the understanding that student focus, attention, and feedback are important for student achievement. In today's education, we see that students do get distracted in class. Also, they do receive selective and biased feedback. Students may receive misleading feedback that affects their progress and confidence.

The student is unaware of his attention span and hence, does not optimize his learning process. We are developing a model that helps the students monitor their attention span and receive genuine feedback. This will help empower students academically.

Today's education system is filled with a journey towards success which is very challenging. Students face numerous challenges, including distractions outside the classroom and difficulties with self-awareness and feedback inside of it. Receiving feedback that is inaccurate, misleading, or biased can impact the confidence and self-perception of students. As well as the above, many students are unaware of their own abilities and don't know where to improve. It is necessary to provide students with a solution to these issues. The model with facial expression recognition, sentiment analysis, and attention span monitoring will help them overcome these issues and facilitate students to excel in studies.

We wish to create a fun and easy-going environment where students can learn easily and increase their efficiency in doing academic work. Our model aims at generating confidence and self-belief in students by providing them with truthful and actionable feedback. Also, we understand that self-awareness and self-regulation can help in academic success. We want students to control their attention span and emotions. Therefore, the goal of this model is to establish a culture of mindfulness that helps students overcome challenges & persist in learning despite those challenges. At the end of the day, we believe every student can succeed regardless of their background and circumstances. We want students to be able to notice their feelings and attention spans through tech while staying aware of what they are doing. This small implication will help them stay calm when over-excited and act mindfully. We hope that our contribution will help create a future where every student will get what they deserve.

Sentiment analysis on student reviews is getting popular in educational evaluation and feedback. However, it can be tricky due to all the biases and subjectivity in it. There are many sentiment analyses currently built that do not account for student engagement and involvement in activities. Therefore, it makes the feedback untrustworthy which may lessen its applicability for the teacher as well as the student.

In addition, classical ways of looking at the level of student engagement, such as self-reporting surveys or observation assessment, are subjective and biased. Classroom engagement assessments provide accurate measures of student attention and emotional responses to take appropriate informative decisions on the learning process. We came up with the idea of creating a model to recognize facial expression and attention span because of the problems we mentioned above. Our model is a sentiment analysis tool that is based on the real time data of a student's facial expressions and attention to a particular educational activity.

Objectives:

- 1) **Facilitate Genuine Feedback:** The aim of this model is to give the students real and comprehensive feedback on their performance and engagement. The model seeks to effectively analyze the attention spans and sentiments of the students during educational activities by using facial expressions and sentiment analysis.
- 2) **Enhance Student Awareness:** Another key objective is to develop recognition of one's attention span and sentiment during learning sessions. The model aims to enhance the ability of students to understand their attentional patterns and emotional states so that they can use this information to make decisions.
- 3) **Improve Academic Performance:** The design helps students assess their attention span, get individual feedback and improve their academic performance. If students are able to increase their focus and attention, they would be able to enhance their performance levels.
- 4) **Objectives for Constructive Feedback and Institutional Improvement:**
 - a) **Enhance Instructional Strategies:** The model aims to offer insights into the effectiveness of instructional strategies employed by educators. The model will be able to help in refining strategies or methods of Instruction by identifying patterns and trends from the quantitative assessment of students' attentiveness and emotions during various activities.
 - b) **Optimize Classroom Environment:** In terms of the classroom environment, the model may be able to identify features that are influencing students' learning by assessing attention span and emotions. This brings in things like classroom layout, lighting, noise level, seating arrangement. The model gives feedback to teachers and administrators on how to create the best learning environment that helps in the engagement of students.

c) **Identify Support Needs:** By looking at students' attention and feelings, this model can identify those who might need help or a change to do well in school. Such students may possess disorders related to attention, emotion, and learning. By pinpointing who these students are and what they need, schools will have the knowledge and understanding to initiate various forms of interventions and support.

d) **Evaluate Program Effectiveness:** The model can help in evaluating the effectiveness of education-related activities or programs. Education institutions can analyze the effect of specific programs, interventions, or policy changes on students' satisfaction, academic performances, and overall learning outcomes using students' feedback and engagement over time. Using this data, colleges can help make effective decisions regarding resource distribution.

e) **Promote Continuous Improvement:** The model promotes continuous improvement in the institution through the ongoing monitoring of student feedback and the data on student engagement. When the feedback given by the model is reviewed and reflected upon regularly, it allows educators and administrators to find areas of growth or innovation, use the proof-based practices, and adjust strategy needs for students and stakeholders.

METHODOLOGY

This research employs a threefold method facilitating the assessment and understanding of students focus, feelings and performance in online education system. Combining facial recognition techniques with state-of-the-art sentiment analysis techniques will give a complete picture of the online learning experience.

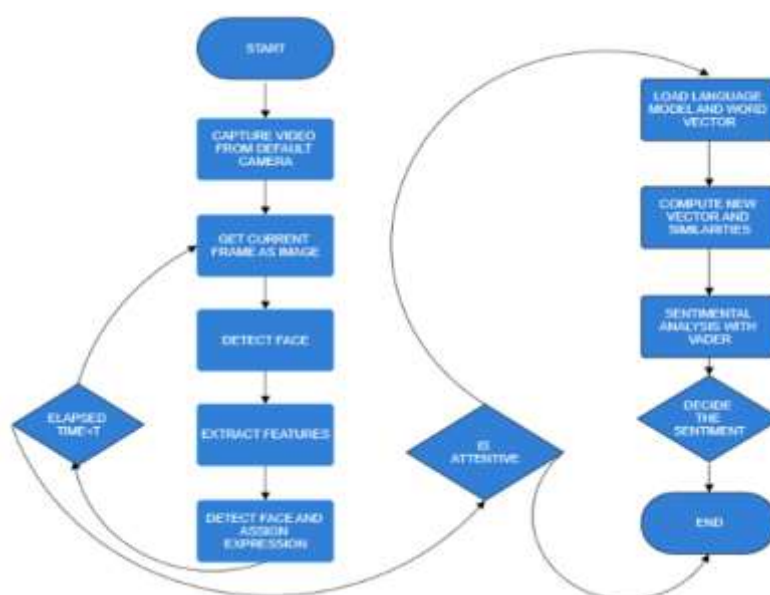


Figure 1. Flow of procedure

A. Facial Recognition:

a) **Import Libraries:** At the beginning of the code, libraries are imported that contains function of the code. OpenCV (cv2) helps in image data processing. For example, you can read video frames using OpenCV and draw on them. NumPy (np) helps with fast number calculations, which are often required for handling images and using data. Keras provides easy mechanism for building neural network. Its high level abstraction helps in loading working model. This facial recognition library allows for face detection which is vital for identifying facial expressions. The time module can access, measure the time taken for program execution, etc.

b) **Load Pretrained Model:** Right after the imports, a facial expression recognition model was loaded. The model is saved in H5 and JSON files. The model file contains the learned weights which help in recognizing the facial expression. By loading this pre- trained model, the code uses the knowledge gained during the learning stage, then allowing it to recognize faces.

c) **Declare Emotions Label:** The emotion labels are stated as a tuple in the code giving a clear understanding of the mapping with predictions. This label's tuple consists of the following: 'angry', 'disgust', 'fear', 'happy', 'sad',

'surprise', 'neutral', which are the basic emotions. The code makes it pretty convincing for users to understand with the help of the predictions that which emotion was predicted.

d) **Initialize Variables:** This code sets up many variables which indicate the state and handling. The program sets up important variables for counting detected emotions and monitoring execution time. The code allows us to have insights on the occurrence of various feelings over periods of time. Also, the timer helps with time-based stuff like stopping the program after a certain time.

e) **Capture Video Stream:** After doing the configuration, the code opens a video stream from the default camera (usually camera index 0). The main source of input is this stream which takes video frames from the webcam continuously. The code can process videos one frame at a time due to capturing video in real-time. This is required for dynamic facial expression recognition.

f) **Process Each Frame in the Video Stream:** In a loop, it processes each frame from the video stream. The video frame is resized for efficiency. The video stream frame is run through the face recognition library to detect the face in that frame. Finally, the face is analyzed by predicting the emotion on it. The code can be used to recognize and predict emotions in real time by applying the facial expression recognition model to each frame.

g) **Check Elapsed Time:** To control when the program runs, the code checks the time elapsed since program starts. By observing the time elapsed, it can respond to time logic items such as quitting after certain time. The code checks if 10 seconds have elapsed to limit the running time of the code.

h) **Display the Processed Frame:** With every iteration of the processing loop, the current frame shown on the screen has emotion labels, and bounding boxes around detected faces. The users can see the facial expression recognition process in real-time to understand which emotions are inferred through the video stream.

i) **Release Resources:** After the program is done running, the video stream is released and all OpenCV windows are closed. By handling everything properly we would free up the resources and mitigate potential memory leak. The resources are released by the code which ensures good performance of the system.

j) **Additional Actions based on Neutral Count:** After performing emotion analysis the code will further take action in counting the neutral emotions. If the count is more than a certain threshold then code executes additional tasks like calculation of similarity between words, emotion analysis and review classification. This logic for decision making allows the code to behave accordingly and in an adaptive manner to the user's attention level. If the user is classified as inattentive (neutral count below threshold), the code states the user cannot give a review, thereby implementing a logic based on the user's activity level.

B. Sentiment Analysis of Student Reviews:

a) **Load Language Model and Word Vectors:** To begin with, the code uses the spaCy library which is a complete Natural Language Processing (NLP) library. Loading the `en_core_web_md` model gives access to large word vectors in the model trained on different English texts and documents. The high dimensional numerical representations encoding semantic meanings of words, are referred to as word vectors or word embeddings. They help algorithms understand how closely different words mean the same thing with a neural net.

b) **Compute New Vector and Similarities:** Through a language model, it computes a new vector using vector arithmetic involving the words — 'wolf', 'dog', 'cat'. This process captures the meaning that they share which allows you to determine something that was not included in the initial vocabulary. The next comparison of that calculated vector with the vectors of all other words from the model vocabulary, or the words in the notebook, can provide a list of words with a similar meaning.

c) **Sort and Retrieve Similar Words:** After calculating the similarities, the code stores the results in a sorted list according to cosine similarity values. This sorting helps pick out the words that are most associated to the computed vector and thus reveals more information related to what we are analyzing. The `vector_math` function will keep the code more modular and reusable. It will allow you to experiment with different words' semantic relations easily.

d) **Sentiment Analysis with VADER:** Alongside semantic analysis, the code utilizes VADER, which is a specialized sentiment analysis tool. In contrast to the typical method for sentiment analysis by using machine learning techniques to train predictive models, VADER is rule-based. It uses a set list of words, and other grammatical and meaning based rules to find the polarity of meaning. This technique is particularly good at looking at the feeling in informal texts like tweets, which are when mainstream models do not work well due to the use of emojis and slang.

VADER's distinguishing features from traditional and modern sentiment techniques:

- VADER's strength lies in its adeptness at handling nuanced language expressions commonly encountered in social media texts. It incorporates domain specific lexicons and rules to decipher sentiment in text, including slang, acronyms, and grammatical nuances.
- Old-style sentiment analysis models need massive labelled datasets for training and don't capture the richness and variability of language use across different situations. Unlike other algorithms, VADER's rule-based method has the ability to adapt itself to various forms of languages which can be reused in diverse domains.
- VADER can recognize that some words like 'very' and 'extremely' can intensify the sentiment of a word (in this case, a word like 'good'). Such modifiers make VADER a more sophisticated tool for gauging the overall meaning of someone's sentiment to obtain better results.
- The output of VADER also includes a compound score, which sums up the positive, negative and neutral scores. The overall score gives you a complete view of the sentiment polarity of the text.

C. Dataset:

The dataset from Udemmy courses is a source used for training the facial expression recognition model. This dataset provides an extensive collection of facial expressions that occur as educational content is delivered. It contains expressions that are generally observed while presenting course content. This dataset helps our model learn from a wide array of facial features. Thus improving its ability to accurately detect and classify expressions indicating student engagement, attention and mood. Giving the citation for the dataset we are using, which will help in transparency and unbiased findings of our research without any plagiarism.

D. Equations:

This section goes over the math behind the facial recognition and sentiment analysis methods we use in this study. The equations distill the complexities of extracting valuable information from the expressions and feedback of students into a concise format.

Facial Landmark Detection using dlib:

$L = \text{dlib.detect_facial_landmarks}(I)$, Where L is the detected facial landmarks, and I is the input image.

$E = \text{face_recognition.face_encodings}(I, \text{dlib.rectangle}(L))$, Where E is the facial encoding we got with the help of face_recognition library, with I as the input image and L as the detected facial landmarks.

Object Detection using cv2:

$\text{Objects} = \text{cv2.CascadeClassifier}(\text{haarcascade})$

$\text{Objects.detectMultiScale}(I, \text{scaleFactor}, \text{minNeighbors})$

This equation shows how the object detection takes place and how this include use of Haar cascades, HOG, SSD and others.

RESULTS

In lectures, facial expressions of the audience are recognized for logging in to behaviors of the audience in a real-time. This segment addresses the different sections of the research document. Before observing the results, we briefly recap the methodology of the real time facial expression analyzing system. We used various computer vision techniques and machine/deep learning models to detect and classify. We used the OpenCV library to process live videos. We implemented a pre-trained CNN from Keras library for facial expression recognition.

Facial Expression Analysis Results: The real-time facial expression analysis during lectures gave an insight into the emotion of the students. We monitored video feed during lectures to track the frequency and duration of different facial features present in students. We looked at 3 major emotions in people- Neutral, happy and sad.

Time-Based Analysis: To get a better understanding of students' emotional responses over time, we segregated the duration of the lecture into fixed time intervals/frames. For each frame, we measured how much of the time was spent neutral/happy/sad. By analyzing it this way, we found out when they were happy, neutral, or sad.

Quantitative Results: The quantitative analysis revealed the distribution of facial expressions observed during lectures.

- Total duration of neutral expressions
- Total duration of happy expressions
- Total duration of sad expressions.



Figure 2. Facial expression analysis for attention

In **Figure 2.**, the counts of neutral, happy, and sad facial expressions are analyzed over a 10-second video segment. The following counts are observed: Facial expression analysis for attention

- Neutral Count: 1
- Happy Count: 0
- Sad Count: 0

Upon calculating the averages based on these counts, it is evident that none of the emotional expressions dominate the majority of the time frame. Specifically, the neutral count does not surpass 50% of the total duration, and the combined counts of neutral and happy, as well as neutral and sad, do not exceed 60% of the total duration. Additionally, we computed the percentage of time spent in each emotional state relative to the total lecture duration, providing a comprehensive overview of students' emotional engagement.

Discussion of Findings: The findings of the facial expression analysis offer valuable insights into students' emotional experiences during lectures. By identifying the prevalence of different emotional states and their temporal variations, educators can gain a deeper understanding of student engagement and tailor instructional strategies accordingly.

Limitations and Future Directions: One important limitation of the study is the assumption that a positive response in facial expression equates to emotional engagement with the lesson, but in reality, students' facial expressions can be influenced by many external factors. Future examination can be studied combining other forms like bodily signs or stated evaluations to advance knowledge of learner feelings in educational environments.

For the attention assessment of facial recognition results, the methodology follows:

- Analysis of Facial Expression:** Firstly, facial expression recognition is done with the help of a facial recognition model on video data recorded during education activities. The model will identify student facial expressions in neutral, happy, and sad categories throughout the session.
- Counting of Facial Expressions:** The model will count the appearance of neutral, happy, and sad faces for each time-interval or frame. The count will enable an evaluation of the attention of the students and their feelings throughout the session.
- Calculation of Average Expressions:** Over the whole session, the counts of neutral, happy and sad facial expressions will be summed together. Next, the average score for each facial expression type will be calculated to give a summarizing measure of the student's emotional and attentional responses.
- Determining the Threshold:** It will set a threshold based on average expressions that will be calculated. It will check if the number of active and effective facial expressions was maintained. The student will be marked attentive if happy expressions are more than the threshold defined. On the contrary, if the average number of sad expressions exceeds the limit, it will be labeled inattentive.
- Attention Assessment:** According to the averages which were calculated and a fixed threshold, the student's level of attention during the class will be judged. The assessment will determine whether the student is paying attention or not.

Attention Assessment:

The assessment of the count of facial expressions against the pre-set thresholds for the level of attention shows that the student was not paying attention to the 10 second video. Since none of the emotions dominate in expression, thus the attention does not last, we can say that the student is not sufficiently attentive.

Based on the assessment of student attention, the reviews of this student may not be eligible for inclusion in sentiment analysis. This method ensures that all the feedback collected for the sentimental analysis is only from attentive students. This way no bias creeps in and the end result of the sentimental analysis does turn out to be reliable. The removal of reviews from inattentive students in the analysis allows the focus to be solely on genuine reviews, enabling the teachers and authorities to make valuable decisions for improving instruction and education.

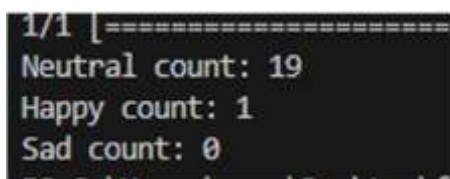


Figure 3. Facial Expression analysis for attention 2

Figure 3. shows the results of face expression analysis conducted during an assessment session of the attention with three values.

- Neutral count: 19 instances
- Happy count: 1 instance
- Sad count: 0 instances

The facial expressions help in assessing whether the student is attending the session or not. The most dominant expression is the neutral expression (19 counts). This could mean giving it sustained attention. Neutral expression suggests concentration and focus on learning. During the session, the student might have found something engaging or worthy of understanding since a happy expression has been recorded. Further, the non- existence of sad expressions (0 counts) indicates no frustration.

With the neutral count that far exceeds those of the other expressions and is over 50% of the total, this student would be labelled as attentive according to the study. So, their comments would be valid for sentiment analysis, which is used in this study to analyze the overall experiences of students.

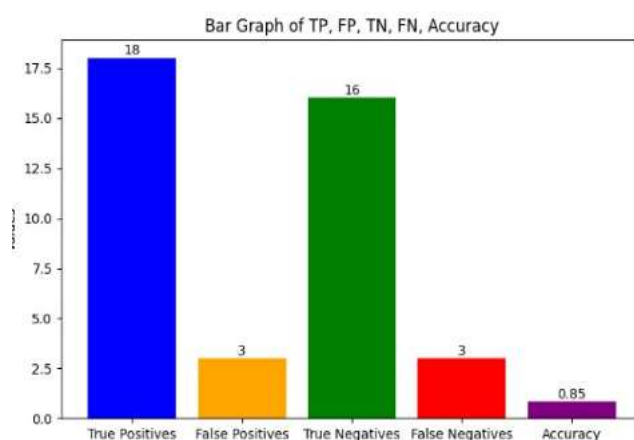


Figure 4. Evaluation Metrics Analysis for Attention Detection Model

Figure 4. illustrates the performance metrics of the facial expression recognition model through a bar graph visualization. The graph presents five key performance indicators:

- 1) True Positives (TP) - shown in blue: Approximately 18 cases where the model correctly identified attentive students.
- 2) False Positives (FP) - shown in orange: Around 3 cases where the model incorrectly classified inattentive students as attentive.
- 3) True Negatives (TN) - shown in green: About 16 cases where the model correctly identified inattentive students.
- 4) False Negatives (FN) - shown in red: Roughly 3 cases where the model incorrectly classified attentive students as inattentive.
- 5) Accuracy - shown in purple: The model achieved an accuracy of 0.85 or 85%

These metrics demonstrate the model's strong performance in classifying student attention levels. The high number of true positives (18) and true negatives (16) compared to the low number of false positives and false negatives (3 each) indicates good model reliability. The overall accuracy of 85% suggests that the model is highly effective in distinguishing between attentive and inattentive students, making it a reliable tool for filtering student feedback before sentiment analysis.

Attention Assessment:

Upon calculating the averages based on these counts, it is evident that the neutral count significantly surpasses 50% of the total duration, while the counts of happy and sad expressions remain minimal. The dominance of neutral expressions indicates a sustained level of attention and engagement by the student throughout the analyzed period.

Considering the assessment of the student's attentiveness, it can be inferred that the student was attentive during the session, as the neutral count exceeds the predetermined threshold. Therefore, any reviews provided by this attentive student will be considered in the sentiment analysis process. By including reviews from attentive students, the analysis ensures a comprehensive understanding of student sentiments and perceptions, facilitating informed decision-making and instructional improvements.

Sentiment Analysis Outcome:

Using the earlier explained methods for sentiment analysis, the score obtained from each review done by students is known as a sentiment score. In other words, the lower the score, the more negative the sentiment, and vice versa. To help understand the results of the sentiment analysis, we calculated the average sentiment score. The average sentiment score gives a summary indicator of the student feedback's overall sentiment.

Based on the average sentiment score, we can say that the sentiment of the student feedback is positive. We classified the sentiment as positive if the average sentiment score was above a threshold. On the other hand, a below threshold average sentiment score would categorize the feedback as negative.

This method helps us to summarize the results of sentiment analysis thus helping the teachers to understand the sentiments of the students. The classification of the sentiment scores as negative or positive, depending on whether it crossed the threshold value or not, will help summarize the sentiment analysis.

- a) **Attention Assessment:** Using the outcome of facial recognition derived from the test process, we identify those students who displayed attentive behavior. This selection criterion ensures the reviews collected for sentimental analysis are from students who were focused and attentive.
- b) **Review Collection Form:** A feedback form is provided to the attentive students to give feedback and their views on the session. The form has parameters like clarity of instructions, usefulness of the content and overall satisfaction along with an extra open-ended framework for students to share any comments or suggestions.
- c) **Sentimental Analysis:** Sentiment analysis of the review forms responses is done using the various techniques of natural language processing. They analyze each review to extract features related to sentiment like tone, emotion and polarity. Each review is assigned a sentiment score through the application of sentiment analysis algorithms that indicate the student's sentiment.

d) **Scoring and Evaluation:** Analysis of sentiment score gives reviews positivity, neutrality or negativity. The scores from the sentiment analysis measure the students' feelings and attitudes on the educational session. Reviews that received high scores means they received positive feedback. Reviews that received low scores means there is a room for improvement.

e) **Interpretation and Feedback Utilization:** The results of the sentiment analysis are interpreted for educational administrators and teachers for taking action. The good reviews show the strengths and effective practices of the teacher. The bad ones and the neutral ones show the things we could improve or enhance further. The feedback from the sentimental analyses helps to know what teacher can do and brings about other changes too.

By adopting this modified technique for sentimental analysis, educational institutes can utilize insightful feedbacks by attentive students to find out the quality and effectiveness of educational sessions. Through selective review collection, the sentiments being analyzed will be those reflected by learners who are paying attention. In the end, using the results of sentiment analysis helps improve the educational experience for all students.

```
def review_rating(string):  
    scores = sid.polarity_scores(string)  
    if scores['compound'] == 0:  
        return 'Neutral'  
    elif scores['compound'] > 0:  
        return 'Positive'  
    else:  
        return 'Negative'  
  
review_rating(review)  
  
'Neutral'
```

Figure 5. Sentiment Analysis

```
Neutral count: 23  
Happy count: 10  
Sad count: 0  
attentive  
[nltk_data] Downloading package vader_lexicon to  
[nltk_data] C:\Users\user\AppData\Roaming\nltk_data...  
[nltk_data] Package vader_lexicon is already up-to-date!  
Enter the review about the Lecture The lecture was pretty amazing with innovative approaches that were crystal clear  
the review is classified as  
Positive
```

Figure 6. Sentiment Classification Output

In Figure 5.:

- The function `review_rating` takes a string input of a review.
- The `sid.polarity_scores()` function from the VADER sentiment analyzer is used to get a dictionary containing sentiment scores for the string. The function returns scores for how positive, negative, neutral, and mixed the string is.
- Based on the compound score obtained, the function provides a sentiment label to the input string:
 - If the compound score is exactly 0, the function returns 'Neutral', which means that the text sentiment is neither positive nor negative.
 - If the compound score is greater than 0, the function returns 'Positive', indicating that the sentiment of the text is positive.
 - If the compound score is less than 0, the function returns 'Negative', indicating that the sentiment of the text is negative.

This method makes it easy to determine if the sentiment of review texts is positive, negative help or neutral based on the VADER sentiment score.

CONCLUSION

This study shows that using facial expression recognition and sentiment analysis together can help improve the quality of assessment in online learning. The model that did facial recognition achieved accuracy of 85% with 18 true positive, and 16 true negatives for classifying student attention with 3 false positives and 3 false negatives. The use of sentiment analysis along with filtered student feedbacks on online courses helps in rating the learning experience.

The research findings indicate multiple applications for educational institutions. Instructors can identify patterns of engagement in real time during an online session with the attention monitoring system. Second, filtering the reviews to selective students who were paying attention offers more reliable feedback. A look at how many students had a neutral expression (19 counts), happy (1 count), and sad (0 counts) provides valuable insights into students' engagement.

Future programs could add on-eye-tracking and physiological sensors for getting a better detection of the attention of the user. Educational institutions could create automated feedback systems that give teachers rapid suggestions according to student engagement levels. We could also build a personalized learning experience based on individual students' attention and emotional response patterns using the methodology.

This research will help in enhancing online education on the basis of data which includes student engagement and satisfaction with e-learning.

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