

Early Detection of Attention Deficiency Using ML*

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Abstract—Working parents find it difficult to check upon their children’s academic performance and monitor them frequently. AI-based study companion assistants can help reduce the workload of parents by providing an additional support system for their children’s learning. This can take some of the burden off of parents, who may otherwise have to spend time helping their children with their studies or coordinating with teachers and tutors. One promising application of AI is the development of study companion assistants that use machine learning techniques to help students improve their academic performance. These assistants can provide personalized recommendations, feedback, and support based on a student’s learning style, strengths, and weaknesses. In this paper, we present a study companion assistant that uses ML techniques to help students stay organized, manage their time, and develop effective study strategies. The assistant is designed to adapt to a student’s needs and learning progress over time, providing support and guidance as needed. We demonstrate the effectiveness of our approach through a series of experiments and user studies, showing that our AI-based study companion assistant can significantly improve student performance and satisfaction.

Index Terms—Convolutional Neural Network, OpenCV, Eye Aspect Ratio

I. INTRODUCTION

Students require high concentration and productivity to acquire information. However, trying to study for a long time would cause a decrease in attentiveness and his ability to understand concepts. To maximize a student’s concentration, it is necessary to find out how attentive he is while working and is mainly deduced based on one’s attitude and expressions. This helps us understand how much time he can focus on his work and the required remedies to follow such as to take a break when needed. Various behaviors and facial expressions are evaluated to analyze a person’s attentiveness and efficiency. The purpose of this study is to use Machine Learning algorithms that can quantify audience attention by tracking blinks and yawns.

A useful measure of attention status is blinking. People tend to blink less when their degree of attention is high in order to maintain eye contact with the subject of their attention. On

the other hand, an increase in blinking is linked to exhaustion. This is best explained as an end to the attention blinking inhibition. The utilized model is constructed utilizing Keras and consists of Convolutional Neural Networks (CNNs). CNNs are a specific kind of deep neural network that excels in image classification. The architecture of a CNN consists of multiple layers consisting mainly of a input layer, hidden layers and an output layer, each with a specific purpose. The layers undergo a convolution operation where a filter performs a 2D matrix multiplication on the layer and the filter. The Haar Cascade files, in conjunction with OpenCV, are utilized to classify faces, left eyes, and right eyes. OpenCV is employed to capture images from a webcam and feed them into a Deep Learning model for the purpose of determining if a person’s eyes are “Open” or “Closed.”

II. LITERATURE SURVEY

In [1] the study aims to quantify audience attention by using machine learning algorithms. Another study conducted by the authors involved surveying 578 physics students. They used statistical analysis to examine the students’ attitudes, challenges, and advantages of online education [2]. The findings indicated a positive correlation between strong communication skills and effective self-organization with improved perceived learning outcomes. However, the research also revealed that students are frequently distracted by their home environment during remote classes. Based on these results, the authors proposed that special courses should be offered to enhance self-regulated learning, the positive aspects of distance learning should be emphasized, and networking services should be established to support student communication.

Eye tracking systems can be utilized to immediately gauge a student’s gaze for instant feedback [3]. These systems serve as valuable tools to determine the student’s level of attention and cognitive effort during problem-solving. Along with words, human expressions are the primary source of information that can be evaluated for understanding someone’s feelings [4].

Various feelings can be traced from expressions as well as fatigue that is evident on one's face [5]. Yawning can indicate that a person is tired. Particularly facial feature identification, which enables the estimation of vigilance level based on an arbitrary model and indirect data collection regarding actions such, for instance, yawning or blinking. [6]. Another study conducted showed that excessive blinking or frequent closing of eyes can give inaccurate results from the data extracted based on various behavioural patterns. A person tends to blink less indicates good performance that includes high visual attention. And a person tends to blink more when under boring tasks or before sleep. [7]. Another study showed that When individuals experience increasing levels of fatigue, their blink rate and duration tend to rise, indicating that their brain may be having difficulty in sustaining focus and attention on the task. This decline in vigilance can adversely affect their performance, resulting in slower reaction times, reduced accuracy, and impaired decision-making abilities. By keeping track of the changes in blink rate and duration, healthcare professionals and researchers can better understand the individual's level of fatigue and vigilance, which could lead to the development of strategies for enhancing their performance and reducing the likelihood of accidents or mistakes. [8].

In [9] a research is done to analyze and comprehend student behavioral patterns to offer customized services and management. The proposal involves a framework for unsupervised ensemble clustering of student behavioral data using the DBSCAN and k-means algorithms to detect patterns. The framework is tested on behavioral data from undergraduate students in a Beijing university, and its effectiveness is assessed by examining the relationships between behavioral patterns and grade point averages (GPAs). The results demonstrate that the framework can identify both exceptional and regular behavioral patterns, which can be beneficial for student services departments in offering psychological counseling and academic guidance. Based on various studies, the students identified several key challenges such as being easily distracted by text messages or social media, feeling bored and exhausted, and coming across content that is uninteresting and drab, making it challenging to sustain their focus. [10]

III. PROPOSED METHODOLOGY

In a classroom setting, teachers can easily observe students and gauge their understanding and engagement. From the facial cues, the teachers could identify if the person is attentive to what he is learning. But self study sessions are what differentiates between a successful student and a mediocre one. Attention span pertains to the duration of time that an individual usually remains engrossed in a particular activity before losing interest. It could differ among individuals, but on average, the attention span of a person would be between 30-50 minutes. After that, he would lose interest and his productivity decreases exponentially according to proven research. There are several problems that students may face during self study, such as distractions, boredom, and difficulties with self-regulation. In this project, we are proposing a system

that uses machine learning algorithms to analyze the videos captured by the built-in cameras on their laptops by the students, during a study session. The goal of this system is to provide the teachers as well as the parents with aggregated information on the efficacy of the a study session, without the need for students to share their video recordings. The adoption of additional solutions like this one is essential as it would lead to better productivity of the students. Our proposed system, includes a software module that runs on students' computers and analyzes their video streams to extract indicators of attention and engagement of the student during self study. In the initial phase, we are planning to run the system on the students' PC, but in the future we would be migrating the system to a Raspberry Pi based system. It would be sitting on desk as a device with a small form factor, analysing the students. The system also involves a smart AI assistant that interacts with the students to help them. The factors that would be used to determine the productivity would be

- Blink rate - We would detect how many times the eyes of the subject would blink in a given time frame
- Yawn rate - How many times the subject would yawn in a given time frame
- Gaze - The gaze of the person, where the subject is looking
- Head movement

The module runs in the background and does not require a graphical user interface on the student side, in order to minimize distractions. The system uses machine learning approaches, specifically computer vision techniques, to analyze the video frames captured by the student's camera and detect various behaviors such as blinks, yawns, and expressions. The system also uses microphone that would be used to facilitate the interaction of the student with the AI assistant. We are planning on using the open source AI assistant project for our virtual assistant. The user could ask interact with the assistant for clearing doubts and casual chatting. If our device finds that the student is distracted and his productivity level has fallen, the assistant would recommend activities that would benefit him. The device might ask him to take a walk, play his favourite music , play podcast etc. That way we might be helping him to avoid burn out. For capturing the eye parameters, we would be using a measure known as Eye Aspect Ratio (EAR) as given below.

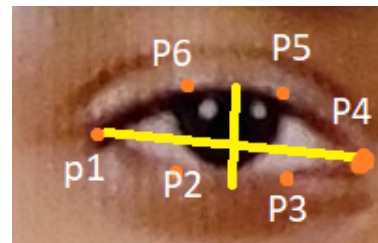


Fig. 1. Eye Aspect Ratio

$$EAR = \frac{||p_2 - p_6|| + ||p_3 - p_5||}{2||p_1 - p_4||}$$

The frequency of the eye blinks can be strictly related to cognitive activity. For calculating the blink rate, we would be using a blink counter. We would be using the EAR values to calculate the blink rate. The number of blinks per minute is termed as the rate at which someone blinks and on average it would be about 17 blinks/minute. The blink duration and the blink amplitude would also be calculated. The yawn rates is another important factor in indicating the lack of attention. It is possible to detect the distances separating the landmarks on the upper and lower lips and estimated to detect the yawn rate. The yawn duration and the yawn amplitude would be calculated as well. For gaze detection, we would be using a Convolutional Neural Network based technique that does not require calibration. We are planning on building an ensemble model that would be able to detect all the mentioned factors. The AI assistant would either be an open source voice assistant project or Alexa API, depending on how much we would be able to complete. Now, the video data from the device camera would be used for analysing the overall productivity of the student. The productivity analysis would be performed only on the basis of this camera feed. The audio data on the other hand would be used to interact the voice assistant. The processing would be done on the PC of the student. The tools that we are going to require are Python and various libraries like OpenCV, Keras, Tensorflow, dlib, speech Recognition, pytsx3, tesseract would be used. After processing, the speech output from the assistant would be produced by the device speaker. The block diagram of our desired system is shown in

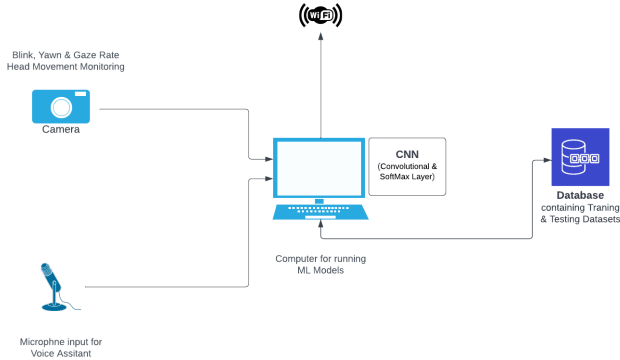


Fig. 2. Block Diagram

IV. RESULTS AND DISCUSSIONS

The models that were analysed includes the detection of blink rates and yawn rates. The number of blinks were found to be an average of 17 per minute. EAR value was calculated to find the blink rates and yawn rates. EAR value tends to be 0 or reduces to a value of zero if a person is feeling drowsy. This helps in determining the attention deficiency in a person.

It is a known fact that a person tends to blink less when their attention level is high. This decreases the number of blinks per minute. so the person monitored is checked thoroughly through a camera. Similarly yawn is also analysed and as a result an alert is sent to the person to wake them up. As of now only yawn detection and blink detection are checked in the proposed system.

Both yawn detection and blink detection were combined to check the attention of a person in the model proposed. The facial landmarks are defined earlier so that the left eye proportion and right eye proportion can be calculated to obtain the EAR value. Similarly the landmarks of the lips are used to calculate to find the EAR value of the lips. In case of yawn detection, the EAR value gets high when the person yawns and an alert is sent to the person to wake up.

Real-time computations were conducted by averaging 5 trials of 16 subjects, recorded at various locations. The results were inclusive of subjects wearing glasses or not. The video frames captured two states, namely sleepy and non-sleepy, for each trial. The highest accuracy percentage achieved was 87.75% for yawn detection, followed by 83.75% for detecting drowsy blinks.

Further two models could be ensembled to detect the attention deficiency in a person. Tracking gaze and head moment could increase performance of the model and help a person in increasing their productivity. Adding these two models might also lessen the inadequacy of the existing model.

V. CONCLUSION

An AI-powered student companion enhances academic performance through the use of various useful tools. We have explored various machine learning models needed to construct an attention tracking system for students. The primary focus of the project involves monitoring student attention levels by analyzing blink frequency, yawn rates, gaze direction, and head movements.

Blinking frequency is a useful measure of attention levels. When someone is paying close attention, they tend to blink less. This helps in focusing and maintaining eye contact on the object. On the other hand, an increase in blinking is associated with exhaustion. The gaze direction can offer insights into how a person perceives information, improving communication and reflecting cognitive processes. Additionally, it can identify regions of interest. If a gaze is fixated on a particular area for an extended period, it could indicate either difficulty in comprehending information or something has piqued up the persons interest.

Yawning is a mostly involuntary reflex that can indicate a variety of things. When a person is tired, the body can trigger yawns to stay alert. Yawning can also be a sign of boredom or disinterest in something and it can help the body to release tension and anxiety. Head movement detection can also have several benefits for monitoring student attention, such as providing real-time feedback on focus and engagement. This can help students develop better study habits.

Understanding the correlation between different physiological indicators and attention levels is crucial in developing an attention monitoring system for students. The analysis of blink frequency, gaze direction, yawning, and head movements can provide valuable insights into a student's attention and engagement levels, ultimately improving their academic performance.

Two models such as blink and yawn detection were integrated to create a system that can both assist and monitor a student's academic performance and improve their productivity. The system analyzes the student's engagement and attention using machine learning and computer vision techniques. At the end of the analysis, an evaluation report on the student's academic performance is generated, providing real-time feedback. The system gathers statistics on the student's attention and engagement levels and provides quantitative analysis and measurements on the rates of blinks and yawns. This allows the student to quickly assess their understanding of the learning material and address any issues.

The system can identify patterns in a student's attention levels and suggest strategies or interventions to improve focus and retention. However, it is important to note that the system is not a replacement for traditional teaching methods or the role of a teacher or parents. Another potential drawback is that the system requires a reliable network to run. Although the system has the potential to be a useful tool for improving focus and engagement during learning activities, it is important to consider the limitations and ethical concerns associated with using such a system. It should be viewed as a supplement to traditional teaching methods, and the ultimate responsibility for learning remains with the student.

tiveness of online recitations, and online laboratories, *Phys. Rev. Phys. Educ. Res.* 17 (1) (2021) 010117.

REFERENCES

- [1] Abate, A. F., Cascone, L., Nappi, M., Narducci, F., & Passero, I. (2021). "Attention monitoring for synchronous distance learning". *Future Generation Computer Systems*, 125, 774–784.
- [2] P. Klein, L. Ivanjek, M.N. Dahlkemper, K. Jeličić, M.-A. Geyer, S. Küchemann, A. Susac, Studying physics during the COVID-19 pandemic: Student assessments of learning achievement, perceived effectiveness of online recitations, and online laboratories, *Phys. Rev. Phys. Educ. Res.* 17 (1) (2021) 010117.
- [3] S.J. Hansen, J.R. VandenPlas, Eye tracking in chemistry education research: Study logistics, in: *Eye Tracking for the Chemistry Education Researcher*, ACS Publications, 2018, pp. 11–23.
- [4] S. Umer, R.K. Rout, C. Pero, M. Nappi, Facial expression recognition with trade-offs between data augmentation and deep learning features, *J. Ambient Intell. Humaniz. Comput.* 1–15
- [5] C. Bisogni, C. Pero, IFEPE: On the impact of facial expression in head pose estimation, in: *International Workshop on Biometric Data Analysis and Forensics IWBDFA*
- [6] M. Knapik, B. Cyganek, Driver's fatigue recognition based on yawn detection in thermal images, *Neurocomputing* 338 (2019) 274–292.
- [7] R. Martins, J. Carvalho, Eye blinking as an indicator of fatigue and mental load – a systematic review, 2015, <http://dx.doi.org/10.1201/b18042-48>.
- [8] Detection of vigilance performance using eye blinks, *Applied Ergon.* 45 (2, Part B) (2014) 354–362, <http://dx.doi.org/10.1016/j.apergo.2013.04.020>.
- [9] R. Daza, A. Morales, J. Fierrez, R. Tolosana, MEBAL: A multimodal database for eye blink detection and attention level estimation, 2020, arXiv preprint arXiv:2006.05327.
- [10] P. Klein, L. Ivanjek, M.N. Dahlkemper, K. Jeličić, M.-A. Geyer, S. Küchemann, A. Susac, Studying physics during the COVID-19 pandemic: Student assessments of learning achievement, perceived effec-