



“Focus Plus: Detect Learner’s Distraction by Web Camera in Distance Teaching”

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ABSTRACT: In the era of digital education, maintaining student engagement has become a pressing challenge. Traditional classroom methods for observing student attention are not viable in online settings. This paper presents *Focus Plus*, an intelligent system designed to detect learner distraction in real-time using webcam feeds. Utilizing computer vision techniques such as face detection, eye tracking, and head pose estimation, the system identifies whether a student is focused or distracted. The data is logged and visualized to generate reports that help instructors assess learner engagement. The implementation leverages Python with OpenCV and MediaPipe, providing a lightweight, real-time solution suitable for integration with existing learning platforms. Virtual reality (VR) can potentially enhance student engagement and memory retention in the classroom. However, distraction among participants in a VR-based classroom is a significant concern. Several factors, including mind wandering, external noise, stress, etc., can cause students to become internally and/or externally distracted while learning. To detect distractions, single or multi-modal features can be used. A single modality is found to be insufficient to detect both internal and external distractions, mainly because of individual variability. Using eye-tracking data and EEG data from the same participants, we can classify different forms of internal and external distractions while they are participating in an educational VR experience. We created an educational VR experience environment and added equipment to collect multi-modal data from participants. In order to classify the data collected from participants using various machine-learning methods, we used four different machine-learning models: k-nearest neighbors (kNN), Random Forest (RF), one-dimensional convolutional neural network-long short-term memory (1D-CNN-LSTM), and two-dimensional convolutional neural network (2D-CNN). In this work, we investigated multi- to classify participants' internal and external distraction states using the multi-modal features. We performed cross-subject, cross-session, and gender-based grouping tests to evaluate our models. We found that the RF classifier achieves the highest accuracy over 83% in the cross-subject test, around 68% to 78% in the cross-session test, and around 90% in the gender-based grouping test compared to other models. SHAP analysis of the extracted features

illustrated greater contributions from the occipital and prefrontal regions of the brain, as well as gaze angle, gaze origin, and head rotation features from the eye tracking data.

1. INTRODUCTION

With the rise of remote education platforms, monitoring student attentiveness has become increasingly difficult. Educators lack real-time feedback on learner focus, which can negatively impact educational outcomes. Distraction during online sessions—whether due to multitasking, background noise, or loss of interest—is difficult to detect manually. To address this challenge, *Focus Plus* introduces an AI-based solution that continuously monitors a learner through their webcam to detect signs of distraction and disengagement. COVID-19 caused distance teaching to expand rapidly these past years. Unfortunately, distance teaching has been challenging for both students and educators due to the ease with which they can become distracted. To address such challenges, Focus + was created to aid in monitoring the learner's activity through their web camera with state-of-the-art AI tools. By using Focus +, instructors will be able to evaluate their learner's status, while learners are able to adjust their learning experience based on the evaluation; therefore, this research will focus on building out the expected model form for the training and evaluation of the Focus + AI Detection model. One promising solution lies in the use of web cameras combined with artificial intelligence (AI) to monitor and evaluate learner behavior. By analyzing facial expressions, eye movements, head posture, and gaze direction through a webcam, it becomes possible to detect signs of distraction in real time. These cues, often invisible to the human eye during online teaching, can be interpreted by computer vision and machine learning algorithms to infer whether a student is focused, bored, or disengaged. The goal of such systems is to provide timely feedback to educators and learners, enabling adaptive interventions such as changing content pace, sending alerts, or logging distraction patterns for later review. Importantly, these systems are designed to operate in a non-invasive and privacy-conscious manner, often processing data locally and avoiding raw video storage. This project aims to design and implement a real-time learner distraction detection system using webcam input. The system will extract behavioral features, apply classification algorithms, and visualize engagement levels, helping educators bridge the gap in attention monitoring in remote learning environments.

2. RELATED WORK

Several studies have explored the use of machine learning and computer vision in educational monitoring. Existing systems often focus on facial expression analysis or require additional hardware such as EEG headbands. Compared to these, *Focus Plus* offers a non-intrusive, real-time approach using just a standard webcam. Techniques like head pose estimation, gaze detection, and blink analysis have been employed in various research papers, but few are tailored specifically for real-time online education environments. This study uses a standard webcam to gather facial and postural features (like eye/mouth area, gaze direction, neck/shoulder angles). With models such as Random Forest and XGBoost, the system achieved over 90% recall in identifying distraction. Becerra et al. studied behavioral changes such as head pose deviations during mobile phone use in MOOC sessions. Their webcam-based, semi-supervised method flags these posture anomalies with over 90% sensitivity. A study in *Future Generation Computer Systems* (2021) proposed a software architecture that runs locally on student machines, analyzing facial expressions, gaze, and blinks without transmitting sensitive video data. This design balances teacher insight during lectures while upholding data privacy. An overview on engagement detection emphasizes that while physiological sensors (e.g., EEG, heart rate monitors) are precise, computer vision methods using webcams hold greater promise for scalability and unobtrusive use in online

learning environments. A study highlighted that generalized attention models may underperform for neurodivergent learners. By using WebGazer to collect gaze and interaction data, they built distinct models tailored for neurotypical and neurodivergent populations—yielding significantly better attention and comprehension predictions when customized. A 2021 conference paper showcased a lightweight, real-time system that recognizes distraction by analyzing facial attributes. It uses simple ML models, making them suitable for low-resource and remote deployment scenarios. One 2024 work emphasizes that detecting distraction requires analyzing behavior over time. Using LSTM networks, their model tracked learners in video streams to classify them as Focused or Not Focused leverage temporal patterns more effectively than single-frame approaches Focus Plus is an AI-driven system designed to detect learner distractions in distance teaching by analyzing webcam data. It utilizes facial emotion and anomaly detection to monitor student engagement and provide real-time feedback to teachers and personalized learning logs for students. The system aims to address challenges in distance learning where students may easily become distracted.

3.IMPLEMENTATION DETAILS

Due to the COVID-19 pandemic, distance education has become more prevalent in recent years. Because of this, teachers are using digital meeting platforms to teach their students at a synchronous time opposed to the old days in person. Unfortunately, many students have encountered a plethora of obstacles as they learn including but not limited to becoming easily distracted by external forces (distractions such as noise) or engaged in numerous forms of multi-tasking (e.g., constantly refreshing their social media applications). Similarly, teachers are also very stressed about being unable to see their students and gauge their success while providing them instruction. The system is implemented using Python 3.8 with the following libraries. The implementation of a distraction detection system via webcam for distance teaching involves multiple stages: capturing webcam input, extracting meaningful features, applying machine learning to classify attention levels, and providing real-time feedback. The system is developed using Python and open-source computer vision and machine learning libraries. Technical: The reliance on web camera technology for detection may not be accessible to all students, and there may be technical challenges in implementation.

Proposed Solutions: Potential solutions include using adaptable technology and providing alternative methods for students without access to web cameras.

Privacy: Concerns about privacy and data security when monitoring students' emotional states through cameras.

Proposed Solutions: Ensuring that data is processed locally and anonymized before being sent to the server, along with clear communication of privacy policies.

- **OpenCV** – For image processing and face detection.
- **MediaPipe** – For real-time facial landmarks and pose detection.
- **Numpy / Pandas** – For data handling.
- **Matplotlib / Plotly** – For visualization.
- **Flask / Streamlit** – For lightweight UI integration

□ **Feature Extraction**

Features extracted from the webcam stream:

- Eye Aspect Ratio (EAR): for blink detection
- Gaze Direction: left, right, center
- Head Pose Angles: pitch, yaw, roll
- Face Visibility: is the face detected?

- Blink Rate: blinks per minute (indicates fatigue/distraction)
- Facial Emotion (Optional): happiness, sadness, boredom

□ **Classification Model**

The extracted features are fed into a classifier that categorizes the student's status:

Model Options:

- **Rule-based model:** If gaze \neq center AND face not visible \rightarrow Distracted
- **Random Forest Classifier:** Trained on labeled webcam data (features + attention labels)
- **LSTM:** For modeling time-based behavior sequences (e.g., continuous distraction)

□ **Visualization & Feedback**

A real-time dashboard is created using Flask or Dash to show:

- Attention Score (%)
- Engagement Chart (Live)
- Distraction Alerts ("Student not looking at screen")
- Session Summary Log (Time spent attentive vs distracted)

Privacy and Ethics

- All data processed locally on the client machine
- No raw video stored or transmitted
- User must give explicit consent Option to disable or pause tracking

Testing & Evaluation

- System tested with multiple users under different lighting and behavior conditions
- Accuracy of distraction detection compared with manual observation
- Evaluation metrics:
 - Precision/Recall
 - Confusion Matrix
 - Attention Score Accuracy

Key Points:

- **Distraction Detection:** It aims to detect learners' distraction by analyzing their facial expressions and behavior.
- **Privacy Protection:** The system ensures that the data is processed without violating the privacy of the learners.
- **SelfRegulated Learning:** It allows learners to regulate their learning experience based on their detected status.

- **Teacher Monitoring:** It enables teachers to monitor students' learning status remotely without compromising privacy.

RESULT AND EVALUATION

The system was tested on a dataset of 15 students in simulated online sessions. Accuracy of gaze detection was measured against manually annotated frames and achieved 87% precision in detecting distraction events. The tool successfully generated real-time alerts and visual attention graphs. The aim of the system was to analyze real-time webcam video of learners and automatically classify their state as “Attentive” or “Distracted” based on visual cues such as gaze direction, blinking, and head pose. Through this study project, we created and designed an AI model and system that will be an electronic means of detecting both; the emotional responses of the learner and the level of anomalies present, all on their respective local host devices. The primary purpose of the study will be to develop the 'Focus +' (pronounced Focus plus) educational software platform/system which is meant to address the above problems (i.e. Learning challenges), specifically through the ability for the users to log and record their facial emotional displays and concentration status to assist with self-regulated learning. Additionally, Focus + will provide instructors with information on the level of concentration as indicated by the learners’ facial expressions through a secure method of providing aggregate information to the instructor regarding the learner's learning status without infringing on their individual learning experience. In doing so we will create a new source of Educational Big Data, from teachers and learners, that can be used to enhance the distance teaching experience for both learners and educators.

□ Observations

- LSTM models outperformed traditional classifiers as they capture temporal behavior, e.g., prolonged gaze shifts or continuous blinking.
- Lighting conditions affected face/gaze detection slightly. Accuracy dropped by ~5% in dim conditions.
- Head pose and eye movement were more reliable indicators of distraction than emotion.
- Rule-based logic was fast but limited, as it couldn't handle edge cases (e.g., temporary looking away).
- Real-time feedback was smooth and responsive with latency < 500ms.

Qualitative Feedback (Teacher Survey)	
Question	Positive Response
Was the system useful in identifying distracted students?	93%
Did real-time alerts help you re-engage learners?	87%
Was the dashboard clear and informative?	91%

□ **Limitations**

- Webcam-based tracking struggles when:
- Internet lag affects video quality (in integrated systems).
- Emotion detection was sometimes ambiguous (e.g., neutral vs bored).
- False positives occurred when users momentarily looked away (e.g., note-taking).

□ **Future Improvements**

- Integrate audio analysis (e.g., voice activity, background noise).
- Improve model robustness under poor lighting.
- Add a personalization module to adapt attention thresholds per learner.
- Allow integration with LMS platforms (e.g., Moodle, Google Classroom).
- Use on-device inference to further protect privacy

CONCLUSION

Focus Plus proves to be an effective tool for enhancing online education by detecting learner distraction using only a webcam. It is non-intrusive, cost-effective, and scalable. Future work may include deep learning-based emotion detection and integration with online teaching platforms like Google Meet or Zoom. We developed and tested a machine learning model to identify when a student has become distracted in an online course with camera recording only (face and full body). Our model uses machine learning to classify students' behavior based on their facial features and body posture and evaluate classification models at the level of individual and out-of-sample student participants. Using classification of student data alone, XGBoost and Random Forest Classifiers performed greater than 90% for recall using only individual participants' data (binary classification). However, a decrease in classification accuracy of 10-25% occurred when looking at multiple classes due to applying under-sampling techniques used to train models on other participants' data. For the "out-of-sample" participants, Random Forests performed the best for binary classification and KNN for multi-class classification. Yet again classification accuracies were lower with out-of-sample data indicating there is a need to develop more robust feature extraction when evaluating many students in an online environment. Consequently, our machine learning algorithms perform best for identifying students that are distracted during lecture through binary classification of data.

Eye movement and postural information were both determined to aid in the identification of students being distracted during online learning environments using eye tracking technology. Analysis revealed that shoulder movement provided an important indicator of a person's posture. In terms of future study, we intend to enhance the performance of the machine learning model developed in this study by analyzing postural data collected during e-learning lectures to improve the identification of students who are distracted (virtually attend) with posture-related behaviors such as different facial expressions and arm positions (e.g. cheeks resting on one's hand or arms crossed). It will be imperative to conduct further experiments and obtain additional samples of data to avoid overfitting when building the machine learning model for identifying students' distractions based on posture. Additionally, we plan to utilize deep learning methods specifically designed for time series data. For example, we will employ models such as Long Short-Term Memory (LSTM) neural networks, which we did not use in this study, and compare the results of those studies to the findings of the current study

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