What are Students Seeing? Insights from Real-Time Eye and Face Tracking in Special Education

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Introduction and Motivation

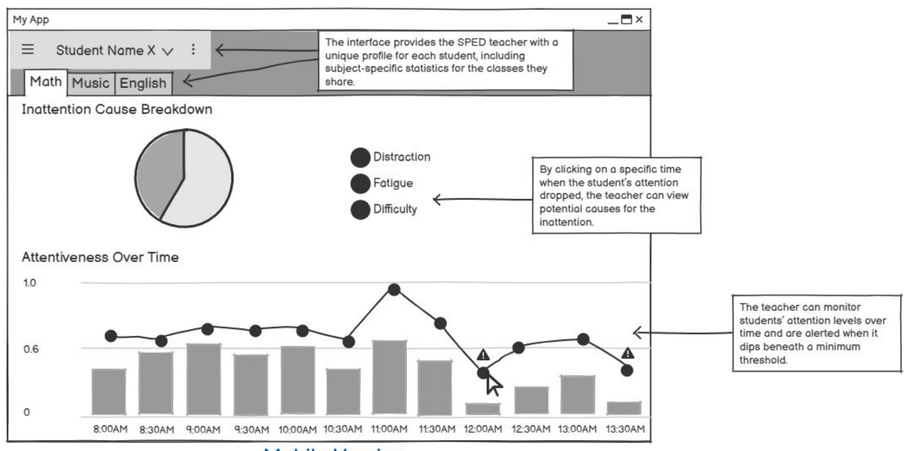
Special education aims to support disabled students, whose disability adversely affects their learning, with specially designed instruction, an instruction built to maximize their learning and functioning [1]. Despite the support provided by various guidelines, policies and programs over time to strengthen efforts in special education, regular schools providing inclusive orientation continue to face numerous obstacles and challenges. A recent study conducted in Ilagan, Isabela, Philippines, aiming to investigate the issues and challenges faced by SPED teachers in teaching children with learning disabilities, discovered that these teachers lacked updated teaching and curriculum guides, Instructional Materials as well as access to seminars on how to effectively handle SPED instruction [1]. In light of these findings and the rapid development of AI and computer vision tools designed to support the field of special education, it is vital to leverage technology to assist SPED teachers in meeting their students' needs.

Proposed Implementation

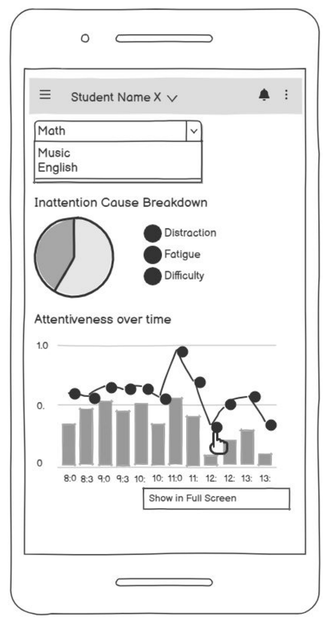
The proposed system leverages standard webcam input to monitor students' behaviour during lessons in real time. Face and eye regions are initially detected using Haar Cascade classifiers, then refined using tools such as Dlib's frontal face detector or Mediapipe's face detection model to enhance robustness under variable lighting conditions and head orientations. For iris and pupil detection, the system integrates multiple techniques; including the Timm and Barth algorithm, centroid and blob detection, and the Hough Circular Transform, to improve detection accuracy and robustness across different face angles and illumination levels [2, 3, 4]. In order to estimate the direction of the gaze, a geometric model, inspired by [3], maps the pupil position to a number of different distinct visual regions in the video frame to keep track of where the student is looking. To interpret engagement, student attention states are then classified into different engagement levels, such as focused, distracted, confused, drowsy and fatigued using a trained machine learning model. This model learns from patterns in gaze direction, blink frequency, and behavioural cues such as yawning, frequent gaze shifts or prolonged off-screen focus, in order to make data-driven predictions. Furthermore, constant fixation on a single point may suggest confusion or difficulty processing a piece of information. These thresholds can be dynamically adjusted using machine learning models that combine contextual data, historical student behaviour, and SPED teacher feedback to personalize engagement analysis for each student.

Captured data is visualised through a dashboard, aimed at SPED teachers, highlighting key engagement insights. This includes real time alerts during moments of inattentiveness or difficulty, visualization of how each student's attention shifts throughout the lesson and simplified, interpretable observations to support well-informed decision-making. Each student has an individual profile that tracks their behaviour across different subjects (e.g. separate profiles for math, music, etc.) enabling SPED teachers to improve their teaching strategies to suit each individual's unique needs. The main priority of the interface is interpretability, providing clear, user-friendly feedback and explanations for all insights the system provides the teachers with.

Desktop Version



Mobile Version



Conclusion

This poster combines machine learning, human-computer interaction, classical computer vision and inclusive education all into a unified system for behaviour interpretation and personalised attention tracking. It empowers SPED educators to better support their students through real-time visual analytics they can engage with. By addressing limitations in existing gaze-tracking approaches, such as sensitivity to lighting and lack of personalization, this system offers a more teacher-friendly, classroom-ready solution. Future works aims to secure the necessary ethical and financial support to bring the system to life, evaluate its effectiveness in real classroom environments, and potentially introduce additional behavioural cues to enrich engagement analysis.

References

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