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Designing an Eye-Gaze Tracking System with Computer Vision to Enhance Children's Intention in BCI

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Introduction: BCI, while a promising solution for communication and interaction for children with severe disabilities, also introduces complexities in its use. Such children often suffer from impaired eye and head movement control as well as attention, decreasing efficacy of vision-dependent BCI paradigms. Often, the "good" electroencephalographic (EEG) signals obtained during visual fixation that are required for BCI to work are "contaminated" by noisy EEG signals when gaze is diverted. This study addresses these challenges by leveraging computer vision to analyze children's eye-gaze patterns. We aimed to develop an eye tracking system able to inform when the user is looking at the screen to integrate with BCI and reinforce children's intention.

Material, Methods and Results: Data were collected from 10 healthy control participants focusing on 17 predefined gaze positions (on- and off-screen) for 30 seconds each. Additionally, 10 five-minute frontal videos were recorded of 5 children with complex physical disabilities (GMFCS Levels 4 and 5) using the BCI through a motor imagery paradigm, where they mentally simulated movements without physically moving, during a training session with visual feedback on a screen. The videos were labelled to indicate on-screen and off-screen gaze moments. Eye-gaze features were extracted using Mediapipe's face blendshape function [1], an open-source component of Google's pre-trained models for markerless facial landmark detection. Although Mediapipe does not directly provide a dedicated eye-gaze model, a set of 14 eye-related features were extracted. These features were used to train a CatBoost model [2], a gradient-boosting framework known for its efficiency with categorical features and its ability to handle large datasets. To further enhance model performance, hyperparameter optimization was conducted using Optuna [3]. The model's performance was evaluated using Stratified K-Fold Cross-Validation and Group K-Fold Cross-Validation. The optimized CatBoost model trained with data from both healthy and children with complex physical disabilities was then deployed for real-time use. It detected landmarks from the integrated camera and used a sliding window of 30 frames (14 features each) to generate single output predictions aligned with on/off-screen eye-gaze intentions. The Stratified K-Fold Cross-Validation achieved an accuracy of 0.9558 ± 0.0010, this approach ensures that the distribution of class labels was preserved across all folds [4]. While the Group K-Fold Cross-Validation achieved an accuracy of 0.6851 ± 0.0523 by splitting data based on participant groups, ensuring that data from the same individual did not appear in both training and testing sets [5]. Our findings show that, despite lower accuracy, the Group K-Fold Cross-Validation approach reflects real-world variations by accounting for individual differences. This is crucial for developing models that generalize effectively to new participants.

Conclusion: Computer vision can detect eye-gaze on/off screen patterns, even in children with severe disabilities. This provides a foundation for integrating eye-gaze tracking with BCI systems, potentially improving accessibility and participation for these children.

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