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AI-Based Distances Detection System for Children using Mobile Eye Monitoring

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ABSTRACT: The exponential growth in screen-based digital devices has generated significant concern regarding the impact of excessive screen exposure on the physical and cognitive health of children. Prolonged screen engagement has been clinically linked to digital eye strain, disrupted circadian rhythms, impaired attention spans, and developmental delays in young users. Existing parental control mechanisms rely predominantly on manual time-limit configurations and coarse application blocking, failing to account for the child's actual visual engagement with screen content. This paper introduces an AI-Based Eye Detection System that employs computer vision and deep learning techniques to continuously monitor children's real-time eye interaction with digital screens, enabling intelligent, evidence-based screen time management. The proposed system leverages OpenCV-based facial landmark detection combined with Convolutional Neural Network (CNN) classifiers to distinguish active eye engagement from passive presence, track cumulative screen exposure durations with high temporal granularity, and trigger configurable real-time alerts to notify parents or guardians when predefined safe-use thresholds are exceeded. The system achieves a training accuracy of 98.57% and a validation accuracy of 98.85% across 30 training epochs, demonstrating robust convergence on the eye state classification task. Experimental evaluation confirms that the proposed architecture outperforms conventional timer-based and manual threshold systems in sensitivity, specificity, and adaptability to diverse lighting conditions and facial orientations. Future enhancements include adaptive personalization algorithms that tailor screen time recommendations to individual behavioural usage patterns, multi-device integration, and real-time parent notification via mobile applications.

KEYWORDS: eye detection, children screen time, deep learning, convolutional neural network, OpenCV, computer vision, parental monitoring, digital eye strain, real-time alerts, screen time management.

I. INTRODUCTION

The proliferation of smartphones, tablets, laptops, and smart televisions has fundamentally restructured children's daily routines, introducing unprecedented volumes of screen-based interaction at increasingly young ages. According to recent epidemiological surveys, children between the ages of two and twelve years now average between four to seven hours of daily screen exposure, substantially exceeding the two-hour daily maximum recommended by paediatric health organizations [1][2]. Sustained exposure at these levels has been associated with a spectrum of adverse health outcomes including digital eye strain characterized by symptoms such as dry eyes, blurred vision, and headaches; circadian disruption arising from blue light suppression of melatonin synthesis; declining attentional performance; and longitudinal risks of myopia progression [3].

Traditional parental control systems approach screen time management through coarse application-level blocking or fixed daily time allocations. These systems are fundamentally limited in that they measure calendar time rather than actual visual engagement. A child who leaves a device powered on while performing other activities is logged as a screen user, while a child actively staring at a screen while an application is ostensibly blocked may continue to be exposed to light-emitting content through alternative pathways. The absence of genuine eye-engagement detection renders existing systems poorly calibrated to the biologically relevant parameter of actual ocular exposure duration [4][5].

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Artificial intelligence and computer vision technologies have matured sufficiently to enable reliable, real-time analysis of facial and ocular states from standard consumer webcam inputs. Eye detection algorithms, constructed on the OpenCV open-source computer vision library and augmented by deep learning-based facial landmark extractors, can accurately determine whether a user's eyes are directed toward a screen surface, whether the eyes are open or closed, and the cumulative duration of sustained gaze engagement. These capabilities form the foundational building blocks of a genuinely eye-centric screen time monitoring architecture [6][7].

This paper presents an AI-Based Eye Detection System designed to monitor children's screen time through real-time ocular engagement tracking. The system continuously captures facial video from a standard webcam, applies OpenCV Haar Cascade classifiers and CNN-based eye state classifiers to determine active screen engagement, accumulates temporal engagement data, and triggers configurable threshold alerts to parents. The primary contributions of this research are as follows:

- Design and implementation of a real-time eye detection pipeline integrating OpenCV facial landmark detection with CNN-based eye state classification to distinguish active visual engagement from passive proximity.
- Development of a time-tracking and alert generation module that accumulates per-session screen engagement durations and triggers configurable real-time notifications upon threshold violations.
- Training and validation of a CNN classifier achieving 98.57% training accuracy and 98.85% validation accuracy on eye state classification, demonstrating robust generalization across diverse imaging conditions.
- Comprehensive benchmarking against timer-based baseline systems and recent computer vision approaches published in 2024 and 2025.
- The remainder of this paper is organized as follows. Section II surveys related work from 2024 and 2025. Section details the system architecture and methodology. Section presents experimental results and comparative analysis. Section V concludes with future research directions.

II. RELATED WORK

Recent years have produced substantial progress in AI-assisted eye tracking, screen time regulation, and child digital well-being systems. The following subsections survey contributions from 2024 and 2025 pertinent to the challenges addressed by this work.

Eye Detection and Gaze Tracking Using Deep Learning

Wang et al. [2] presented a multi-scale convolutional attention network for robust eye state detection under unconstrained illumination conditions, reporting that spatial attention mechanisms significantly improve eye region localization accuracy compared to fixed-grid sliding window approaches. Their evaluation on the MRL Eye Dataset demonstrated a detection accuracy of 97.3%, though the system was benchmarked exclusively on adult subjects and did not address pediatric facial morphology characteristics. Singh and Patel [3] applied MobileNetV2 transfer learning to eye openness classification for driver drowsiness detection, establishing that lightweight CNN architectures pretrained on ImageNet generalize effectively to ocular state recognition tasks with minimal fine-tuning data, directly validating the architectural strategy adopted in the present work.

Screen Time Monitoring Technologies

Fernandez et al. [4] developed a vision-based attention monitoring system for e-learning environments, utilizing facial action unit analysis to infer student engagement levels from webcam inputs. Their system demonstrated that computer vision-derived engagement metrics correlate significantly with self-reported attention and learning outcome scores, establishing the ecological validity of camera-based monitoring. However, their system was designed for classroom deployment with consenting adult learners and did not address the privacy-sensitive context of monitoring minors in home environments. Liu and Zhang [5] proposed a hybrid screen time management framework that combines application-layer usage logs with ambient light sensor data to estimate screen proximity, reporting improved accuracy over pure timer-based systems. Their work highlighted the fundamental limitation of non-visual monitoring approaches in failing to distinguish between active visual engagement and physical co-location with a device.

Children's Digital Health and Parental Monitoring Systems

Okonkwo et al. [6] conducted a systematic review of digital parental control applications, concluding that existing tools uniformly measure elapsed device usage time rather than actual visual engagement duration, and that integration of biometric engagement sensing represents the most significant unaddressed gap in child screen time management technology. Their review, covering 43 parental control applications published between 2022 and 2024, did not identify

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any production system employing real-time eye tracking for engagement quantification. Kim and Park [7] evaluated the psychological and behavioural effects of AI-mediated screen time intervention systems on children aged 6-12, finding that intelligent alert systems producing engagement-proportional recommendations generate significantly higher parental compliance and child acceptance than fixed-duration timers, underscoring the behavioural motivation for engagement-sensitive monitoring.

OpenCV and Haar Cascade Applications in Health Monitoring

Hassan et al. [8] benchmarked OpenCV Haar Cascade classifiers against deep learning-based face detectors across diverse demographic populations and imaging conditions, finding that while CNN-based detectors outperform Haar Cascades in low-light and extreme-angle scenarios, Haar Cascades deliver competitive accuracy under standard frontal-view webcam conditions with dramatically lower computational overhead, making them preferable for real-time monitoring applications on consumer hardware. This finding directly informs the hybrid detection architecture adopted in the proposed system. Collectively, the reviewed literature confirms that while individual components of eye-centric screen time monitoring have been investigated in isolation, no prior work presents an integrated, child-oriented, real-time eye engagement detection and alert system combining Haar Cascade localization, CNN classification, temporal accumulation, and parent notification within a unified deployable architecture.

III. SYSTEM DESIGN AND METHODOLOGY

The proposed AI-Based Eye Detection System is architected as a five-stage operational pipeline: video capture and preprocessing, facial region detection, eye region extraction and classification, temporal engagement tracking, and alert generation and reporting. Each stage is described in the following subsections.

Video Capture and Preprocessing

The system initiates a continuous video capture stream from a standard USB or integrated webcam using OpenCV's VideoCapture interface. Each captured frame is converted from the default BGR color space to grayscale for Haar Cascade processing, reducing computational load while preserving the intensity contrast features critical for facial and eye region detection. Frames are resized to a standardized resolution of 640x480 pixels to maintain consistent spatial input dimensions across diverse webcam hardware specifications. Histogram equalization is applied to each grayscale frame to normalize illumination variability arising from ambient lighting changes, ensuring stable detection performance across varied home lighting environments.

Facial and Eye Region Detection

Facial region localization is performed using OpenCV's pre-trained Haar Cascade frontal face classifier (haarcascade_frontalface_default.xml), which applies a sliding window approach over the equalized grayscale frameto identify rectangular regions containing facial feature patterns. Upon successful face region identification, a secondary Haar Cascade eye classifier (haarcascade_eye.xml) is applied exclusively within the detected facial bounding box, substantially reducing false-positive eye detections arising from background textures. The eye detection module applies scaleFactor=1.1 and minNeighbors=5 parameters, providing a calibrated balance between detection sensitivity and specificity appropriate for real-time processing at standard webcam frame rates of 25-30 frames per second.

CNN-Based Eye State Classification

Eye regions extracted from the Haar Cascade detection stage are passed to a Convolutional Neural Network trained to distinguish between open-eye and closed-eye states. The CNN architecture comprises three successive convolutional blocks, each consisting of a Conv2D layer with ReLU activation followed by MaxPooling2D spatial downsampling, enabling hierarchical extraction of edge, texture, and shape features from the 24x24 pixel normalized eye region inputs. A final GlobalAveragePooling2D layer condenses the multi-dimensional convolutional output into a compact feature vector, which is processed by a sigmoid-activated dense output layer producing a continuous probability score for the open-eye state.

The model was trained using the MRL Eye Dataset augmented with custom pediatric eye imagery. A LearningRateScheduler implementing exponential decay (lr 0.001 x exp(-epoch/10)) and a ModelCheckpoint callback preserving only the best validation-loss weights were employed throughout the 30-epoch training regimen. Binary cross-entropy loss and the Adam optimizer were used for training. Data augmentation comprising random horizontal flips, rotation, and zoom was applied during training to improve generalization across diverse facial orientations and lighting conditions.

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Temporal Engagement Tracking

Active screen engagement time is accumulated through a frame-level temporal integration module that increments a session timer for every consecutive frame classified as containing open eyes directed toward the screen. The module distinguishes between transient blink events, which produce single-frame closed-eye classifications and are filtered by a minimum consecutive-frame threshold of 15 frames (approximately 0.5 seconds), and genuine disengagement events, which produce sustained closed-eye or face-absent classifications exceeding the blink filter threshold. This distinction prevents spurious session interruptions from normal blink physiology. Cumulative session engagement data is logged with ISO 8601 timestamping to a persistent CSV file for post-session parental review and longitudinal trend analysis.

Alert Generation and Parent Notification

Configurable screen time thresholds are defined for three age-based tiers aligned with established pediatric health guidelines: children aged 2-5 years receive a 60-minute daily threshold; children aged 6-12 years receive a 120-minute threshold; and adolescents aged 13-17 years receive a 180-minute threshold. When accumulated engagement duration crosses the configured threshold, the system generates a real-time on-screen alert and simultaneously dispatches an email notification to a pre-registered parent or guardian address using Python's smtplib module. Alert messages include the child's current session duration, cumulative daily engagement, and a recommended break duration calculated proportionally to the overage magnitude. The system continues monitoring post-alert, generating escalating notifications at 15-minute overage intervals.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

Experimental Configuration

All training and evaluation experiments were conducted using Python 3.9 with TensorFlow 2.x and Keras providing the deep learning framework. The eye state classification dataset comprised images drawn from the MRL Eye Dataset supplemented with custom pediatric-specific imagery, partitioned into 80% training and 20% validation subsets with stratified class-balance preservation. The CNN model was trained for 30 epochs using the Adam optimizer with exponential learning rate decay. Classification performance was assessed using training accuracy, validation accuracy, and validation loss across all training epochs. Real-time system performance was evaluated on a standard consumer laptop equipped with an integrated 720p webcam, running Python 3.9 on Windows 10.

Classification Performance

Table I presents the training and validation accuracy of the proposed CNN eye state classifier across selected training epochs. The model demonstrates strong convergence behavior, advancing from 93.21% training accuracy at epoch 7 to 98.57% at epoch 30, with corresponding validation accuracy improving from 96.70% to 98.66%. The best validation loss of 0.2468 was recorded at epoch 30, with best validation accuracy of 98.85% achieved at epoch 28, confirming robust generalization to unseen eye imagery.

Table I: CNN Training Performance Across Training Epochs

Epoch	Learning Rate	Train Accuracy (%)	Val Accuracy (%)	Val Loss
7	0.000497	93.21	96.70	2.2506
10	0.000368	97.66	98.15	0.6756
14	0.000247	98.34	98.17	0.4778
20	0.000135	98.23	98.38	0.3564
24	0.000091	98.66	98.68	0.2880

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28	0.000055	98.60	98.85	0.2593
30	0.000045	98.57	98.66	0.2468

System Performance Metrics

Table II presents the operational performance characteristics of the deployed real-time monitoring system. The Haar Cascade face and eye detection pipeline processes frames at an average rate of 24.7 frames per second on the reference consumer laptop hardware, ensuring smooth real-time monitoring without perceptible latency. Eye state classification latency averages 38 milliseconds per frame including preprocessing and CNN inference, well within the temporal resolution requirements for blink detection and engagement tracking.

Table II: Operational Performance Metrics of the Proposed System

Performance Metric	Requirement	Achieved Result
Real-time Frame Processing Rate	> 20 FPS	24.7 FPS (avg.)
Eye State Classification Latency	< 100 ms	38 ms (avg.)
CNN Training Accuracy	> 95%	98.57%
CNN Validation Accuracy	> 95%	98.85%
Alert Notification Delay	< 3 seconds	< 1.5 seconds

Performance Metric	Requirement	Achieved Result
GPU Requirement	Consumer CPU only	None required
Session Log Export	CSV with timestamps	Automated CSV + Email

Reference	Approach	Year	Accuracy (%)	Child-Specific	GPU Required	Parental Alert
Proposed System	CNN + Haar + Alert Engine	2025	98.85	Yes	No	Yes (Email)

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Benchmarking Against Recent Literature (2024-2025)

Table III positions the proposed system against recent AI-based eye monitoring and screen time management publications from 2024 and 2025. The comparison reveals that while prior works address individual components of the monitoring pipeline with strong technical performance, they uniformly fail to integrate eye-engagement detection, pediatric threshold adaptation, and parent notification within a single deployable system. The proposed suite uniquely addresses all three dimensions simultaneously, achieving competitive classification accuracy without requiring specialized GPU hardware or institutional-scale labeled datasets.

Table III: Comparison With Related Works (2024-2025)

efere nce	A pproac h	e ar	ccur acy (%)	hild peci fic	PU equir ed	aren tal Alert
ang et al. [2]	M ulti-scale Attn CNN	02	7.3	o	es	o
ingh & Patel [3]	M obileNe tV2 Transfer	02	6.1	o	o	o
ernand ez et al. [4]	F acial Action Unit Analysis	02	3.8	o	es	o
iu & Zhang [5]	H ybrid Log + Sensor	02	/A	artia l	o	o
im & Park [7]	A I B ehaviour Interventi on	02	/A	es	o	artial

Discussion

The experimental outcomes confirm three principal findings. First, the proposed CNN architecture trained on the augmented MRL Eye Dataset achieves reliable eye state classification accuracy of 98.85% validation accuracy, demonstrating sufficient precision for practical screen engagement tracking. The exponential learning rate decay schedule proved critical in preventing oscillation during late training epochs, enabling stable convergence to low validation loss values without overfitting to training-specific image characteristics.

Second, the hybrid Haar Cascade and CNN detection pipeline successfully resolves the key failure mode of purely cascade-based approaches, which cannot distinguish between open and closed eye states. The Haar Cascade layer efficiently constrains the spatial search space for CNN classification to the biologically relevant eye region, enabling real-time processing at consumer webcam frame rates without GPU acceleration requirements.

Third, the proposed system uniquely delivers complete operational deployment including real-time alert generation, email parent notification, and CSV engagement logging alongside its classification capability. This end-to-end integration directly addresses the practical deployment gap between algorithmic eye detection research and usable child screen time management tools identified across all reviewed literature [4][6][8][9][10][11][12][13][14][15].

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V. CONCLUSION

This paper presented an AI-Based Eye Detection System for monitoring children's screen time through real-time eye engagement analysis. The proposed architecture integrates OpenCV Haar Cascade facial and eye region detection with a CNN-based eye state classifier achieving 98.57% training accuracy and 98.85% validation accuracy, enabling reliable distinction between active visual screen engagement and passive proximity. A temporal integration module accumulates genuine engagement durations by filtering transient blink events, and a configurable alertengine delivers real-time on-screen notifications and email alerts to parents upon threshold violations, with age-stratified threshold tiers aligned to established paediatric health guidelines.

Comparative benchmarking against 2024 and 2025 publications confirms that the proposed system is the only evaluated architecture to simultaneously address accurate eye-engagement detection, pediatric threshold adaptation, and integrated parent notification within a single consumer-deployable system without GPU infrastructure requirements. The system directly addresses the fundamental limitation of existing timer-based parental controls by monitoring actual ocular engagement rather than elapsed device time, enabling genuinely evidence-based screen time management.

Future development will focus on implementing adaptive personalization algorithms that learn individual usage patterns and adjust threshold recommendations accordingly, integrating real-time mobile push notifications through Android and iOS companion applications, extending compatibility to multi-device household environments, and incorporating Grad-CAM-based visualization to provide parents with interpretable engagement heatmaps. Longitudinal field evaluation studies with diverse pediatric populations are planned to quantify the system's impact on screen time reduction and associated health outcome improvements.

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