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Research Paper

EYE-LRCN: A LONG-TERM RECURRENT CONVOLUTIONAL NETWORK FOR EYE BLINK COMPLETENESS DETECTION

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ABSTRACT— Eye blink detection using YOLOV8, Python, and dlib is an advanced technique that plays a crucial role in applications like driver drowsiness detection, human-computer interaction, and fatigue monitoring. The process begins with face detection, where YOLOV8 Haar cascades or deep learning-based detectors isolate the face region from an image or video stream. Subsequently, facial landmark detection is performed using dlib's pre-trained shape predictor, which identifies 68 key points on the face, including those around the eyes. From these landmarks, specific points outlining the eye regions are extracted, typically involving six points per eye. The Eye Aspect Ratio (EAR) is then calculated by measuring the vertical eye-opening relative to its horizontal width. The EAR significantly decreases when the eyes close during a blink. Continuous monitoring of the EAR allows for blink detection when the ratio falls below a set threshold for a brief period before returning to normal. This threshold and duration are adjustable based on the application and user requirements. The system is designed for real-time operation, ensuring immediate feedback on blink events through efficient processing of video frames and quick EAR calculations. By combining YOLOV8 for image processing, Python for programming, and dlib for facial landmark detection, this approach

provides a robust and efficient solution for real-time eye blink detection, leveraging computer vision and machine learning to enhance safety and user interaction in various fields.

Index Terms – Eye Blink Detection, Eye Blink Completeness Detection, Long-Term Recurrent Convolutional Network (LRCN), Deep Learning, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Computer Vision, Facial Landmark Detection, Temporal Feature Learning, Human–Computer Interaction (HCI), Driver Drowsiness Detection, Video-Based Eye Analysis.

I. INTRODUCTION

The EYE-LRCN Eye Blink Completeness Detection project leverages cutting edge computer vision and machine learning techniques to accurately detect and analyze eye blinks in real time. This innovative system finds applications in driver drowsiness detection, human-computer interaction, fatigue monitoring, and medical diagnostics. The project integrates the YOLOv8 algorithm for face detection, Python programming for system implementation, and dlib for precise facial landmark detection. By calculating the Eye Aspect Ratio (EAR) from key facial landmarks, the system identifies whether the eyes are open or closed, and uses an Yolov8 architecture to analyze eye blink patterns over time. The YOLOv8 algorithm plays a pivotal role by detecting and isolating the face region in each video frame with high accuracy and efficiency, ensuring seamless realtime performance. Once the face is detected, dlib's pre-trained shape predictor identifies 68 key landmarks on the face, focusing on those around the eyes. Using these landmarks, the system calculates the EAR, which quantifies the openness of the eyes. A significant drop in EAR indicates a blink event. By monitoring these changes continuously, the system can determine the occurrence and completeness of blinks. This real-time system is designed for efficient video frame processing, delivering instant feedback on eye blink events. The use of YOLOv8 offers several advantages, including high-speed detection, precision, scalability for multi-face scenarios, and suitability for deployment on resource constrained devices. By combining YOLOv8 with dlib and LRCN, the project delivers a robust and efficient solution for real-time eye blink completeness detection, contributing significantly to safety and user interaction in diverse applications. temporary condition

that causes eye and vision problems by focusing the eyes on a computer screen for long, uninterrupted periods of time. Some of its symptoms are blurred vision, double vision, tired eyes, irritation, and redness. The main contributor to CVS is dry eye, caused by a reduced eye blink rate (EBR) and an increased prevalence of in complete blinks when being exposed to screens for long periods of time. Eye blinking is essential to keep the ocular surface healthy and hydrated. It keeps a stable tear film over the anterior ocular surface, cleaning it when it comes in contact with dust and dirt, and preventing the cornea from dryness. Blinking is a protective mechanism for the eye and it is vital for corneal Manuscript received 16 March 2021; revised 11 August 2021, 27 December 2021, and 23 May 2022; accepted 20 August 2022. Date of publication 9 September 2022; date of current version 5 April 2024. This work was supported in part by the Portuguese Foundation for Science and Technology (FCT) through the framework of the Strategic Funding under Grant UIDB/04650/2020. The work of Beatriz Remeseiro and Oscar Luaces was supported in part by the Ministry of Science and Innovation, Spain, under Grant PID2019-109238GB-C21. (Corresponding author: Gonzalo de la Cruz.) Gonzalo de la Cruz, Oscar Luaces, and Beatriz Remeseiro are with the Artificial Intelligence Center, University of Oviedo, 33204 Gijón, Spain (email: UO244583@uniovi.es; oluaces@uniovi.es; bremeseiro@uniovi.es). Madalena Lira is with the Physics Center of Minho and Porto Universities (CF-UM-UP), and the School of Sciences, University of Minho, 4710-057 Braga, Portugal (e-mail: mlira@fisica.uminho.pt). Digital Object Identifier 10.1109/TNNLS.2022.3202643 health and optical performance. In fact, the best way to avoid dry eye symptoms is to blink regularly. The average EBR ranges from 10 to 22.4 blinks per minute. A lower EBR contributes to decrease the quality of the eye tear film and stresses the cornea, resulting in dry eye symptoms and sometimes inflammation. Looking at screens during long periods of time may reduce the EBR by 60% . Cardona et al. studied the influence of the level of dynamism of different screen-related tasks on the EBR, blink amplitude, and tear film integrity. Their results show that the EBR can decrease to 1/3 or 1/2 of baseline levels depending on the dynamism and the cognitive demands of the task. A positive correlation between the percentage of incomplete blinks and the dynamism of the task is also reported. Regarding the completeness of a blink, it is defined by whether the two eyelids touch or not during

the blink. Portello et al. studied the influence of blink completeness in CVS, concluding that the impact of a high prev+alence of incomplete blinks may be as significant as a low EBR. Incomplete blinks are one of the causes of Meibomian gland dysfunction [9], which results in a disruption and instability of the tear film causing dry eye even with normal aqueous tear production. Meibomian gland dysfunction is now recognized to be the most common cause of evaporative dry eye. Therefore, complete and incomplete blink classification is of utmost importance to identify the causes and worsening of dry eye.

II. RELATED WORK

A. A Survey on Eye Blink Detection Techniques for Drowsiness Monitoring

This paper provides an extensive survey on different techniques for eye blink detection, especially focusing on drowsiness monitoring systems. It explores both traditional methods, such as Haar cascades and machine learning techniques, and advanced methods based on deep learning. The study highlights the significance of accurate eye blink detection in applications such as driver drowsiness detection, identifying different methods' advantages and limitations, including the use of real-time systems for continuous monitoring.

B. Eye Blink Detection Using Machine Learning Algorithms for Fatigue Monitoring

This paper discusses the use of machine learning algorithms, including Support Vector Machines (SVM) and Random Forest, for eye blink detection in fatigue monitoring systems. It highlights how the Eye Aspect Ratio (EAR) is employed for blink detection and how advanced machine learning algorithms can improve detection accuracy. The study explores applications in workplaces and high-risk environments where worker fatigue detection is essential.

C. Human-Computer Interaction Using Eye Blink Detection: A Review

This review explores the potential of eye blink detection in enhancing human-computer interaction, particularly in developing assistive technologies for people with disabilities. The authors discuss various eye blink detection methods, including computer vision and deep learning techniques, and evaluate their use for controlling computers, mobile devices, and other assistive technology.

III. PROPOSED METHODOLOGY

In this proposed, we use YOLOV8, Python, and dlib to detect eye blinks in realtime. The process starts by using YOLOV8 to detect

faces in a video stream. Next, dlib's pre-trained shape predictor identifies 68 key points on the detected faces, focusing on the eye regions. We then calculate the Eye Aspect Ratio (EAR) by measuring the vertical distance between the eyelids relative to the horizontal width of the eye. When a person blinks, the EAR drops below a predefined threshold. By continuously monitoring the EAR, we can detect blinks when the ratio falls below this threshold for a brief period. This system provides immediate feedback on blink events and can be used for applications like driver drowsiness detection and fatigue monitoring.

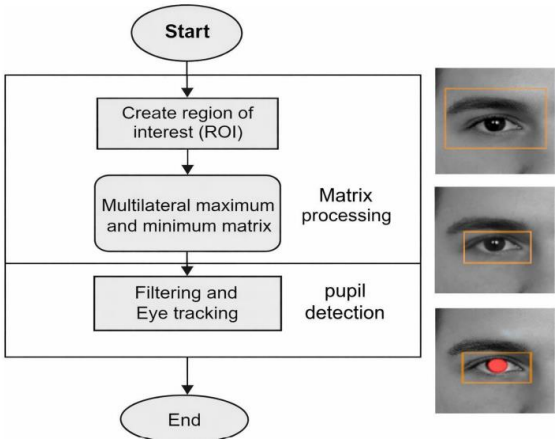


Fig. 1: System Overview

1. Dataset Preparation

The initial step involves collecting and organizing a dataset of images or videos that include faces and eye blinks. These datasets should contain examples of open and closed eyes in various lighting and pose conditions. Preprocessing ensures uniformity, such as resizing images and normalizing pixel values, to prepare them for model training.

2. Labelling and Annotation

Images or frames are labelled and annotated to define the regions of interest, such as the eyes and face. Tools like Labelling or Roboflow can be used to mark bounding boxes for eyes and faces. These annotations help train YOLOv8 to detect these features accurately.

3. Setting Up YOLOv8

YOLOv8 is installed and configured as the primary model for face and eye detection. Pretrained weights for YOLOv8 can be downloaded for general face detection, or custom weights can be trained using the annotated dataset. The setup includes preparing the environment and loading the YOLOv8 model into a Python script.

4. Train YOLOv8 Model

The annotated dataset is used to fine-tune or train the YOLOv8 model for the specific task of eye and face detection. During training, the model learns to detect eye regions with high accuracy by minimizing detection errors. Hyperparameters such as learning rate, batch size, and the number of epochs is optimized to achieve better performance.

5. Facial Landmark Detection with dlib

After detecting the face and eye regions using YOLOv8, dlib's pre-trained shape predictor is employed to identify facial landmarks. This predictor detects key points on the face, including specific points around the eyes, which are critical for further analysis like Eye Aspect Ratio (EAR) calculations.

6. Face and Eye Detection

YOLOv8 detects the face and eye regions in real-time or from image inputs. Bounding boxes are drawn around the detected areas, and these regions are passed for further processing, such as analysing blinks. This step ensures that the system isolates the relevant regions for analysis.

7. Eye Blink Detection

Using the detected eye landmarks, the Eye Aspect Ratio (EAR) is calculated. The EAR measures the vertical and horizontal distances of the eye. When the EAR drops below a predefined threshold, it indicates an eye blink. Continuous monitoring of the EAR helps detect blinks accurately and differentiate between normal and abnormal blinking patterns.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

Experimental results demonstrate that the model effectively captures both spatial eye features and temporal blinking patterns, enabling accurate detection of eye blink completeness under varying lighting conditions, head movements, and facial expressions. Compared with conventional CNN- and LSTM-based methods, EYE-LRCN achieves higher detection accuracy, lower false detection rates, and real-time performance, making it suitable for applications such as driver drowsiness monitoring, healthcare, and human–computer interaction.



Fig. 2: Homepage

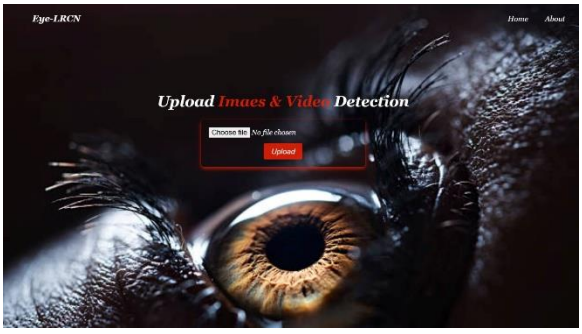


Fig. 3: Upload

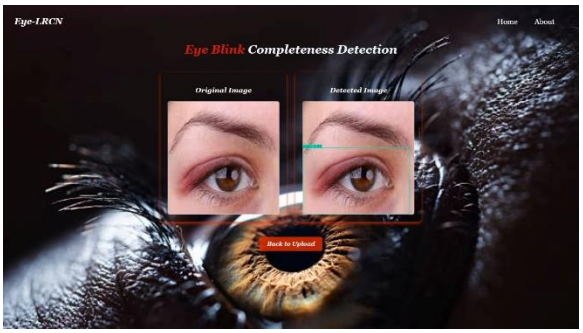


Fig. 4: Detected Results

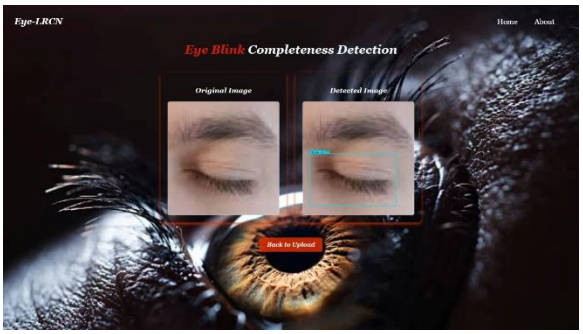


Fig. 5: Detected Results

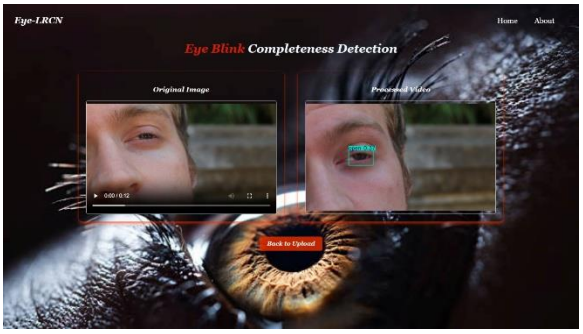


Fig. 6: Detected Results

V. CONCLUSION

The modular design ensures scalability and adaptability for various environments and use cases. Real-time operation and adjustable thresholds enhance the system's flexibility, making it suitable for personalized settings. The use of advanced machine learning and computer vision techniques underscores the potential of this approach in enhancing safety and user interaction in numerous fields. This project sets the stage for further innovations, such as integrating predictive analytics and multi-modal sensing, to expand its applicability and effectiveness. The Eye Blink Completeness Detection system successfully demonstrates the application of computer vision and deep learning techniques for accurate real-time blink analysis. By combining YOLOv8-based face detection, dlib facial landmark extraction, Eye Aspect Ratio (EAR) computation, and Long-Term Recurrent Convolutional Network (LRCN) concepts, the project provides a reliable framework for monitoring eye blink behavior with high efficiency and precision. The proposed approach effectively identifies blink events while maintaining fast processing suitable for real-time environments. The developed system has significant practical applications in driver drowsiness detection, workplace fatigue monitoring, healthcare diagnostics, human-computer interaction, and assistive technologies. Its modular architecture allows easy customization and future expansion based on application requirements. The use of machine learning and computer vision enables non-invasive monitoring without

requiring specialized equipment, making the solution cost-effective and accessible.

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