A Novel Approach Distracted Driver Detection System Using ML Techniques

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Abstract— Driver drowsiness and fatigue are significant contributors in traffic accidents globally, leading to a distressing rise in injuries every year. To combat this alarming trend, the implementation of artificial intelligence (AI) coupled with visual data analysis emerges as a promising solution. The primary objective of this system is to autonomously detect signs of driver fatigue, particularly focusing on the monitoring and analysis of eye expressions and eye movements, as these indicators have been validated scientifically to correlate with drowsiness, especially with gradual eye closure. The scientific validation of the selected metrics reinforces the system's reliability and accuracy in assessing driver fatigue. Extensive research has demonstrated a strong correlation between drowsiness and specific ocular manifestations, such as prolonged blink durations and drooping eyelids. By incorporating this knowledge into the algorithm's design, it can effectively differentiate between moments of alertness and instances where the driver's cognitive faculties are compromised due to fatigue. In conclusion, the proposed AI-driven approach to identifying driver fatigue represents major advancement in road safety and reducing the incidence of traffic accidents worldwide due to drowsiness. By harnessing the power of visual data analysis and scientific insights into human behaviour, this innovative system offers a proactive solution to address one of the leading causes of road fatalities and injuries. As technology continues to progress, the integration of AI into automotive safety systems holds immense potential for creating safer and more sustainable transportation ecosystems for generations to come.

Keywords—

Driver fatigue, Drowsiness, Artificial intelligence (AI), Eyes Off Road (EOR), Facial expressions, Eye movements, Analysis, Algorithms, Real-time monitoring

I. Introduction

Transportation systems currently play an important part in human activity. Drowsiness can occur when driving for a variety of reasons, including lack of sleep, physical discomfort, or long trips. Sleepiness reduces a driver's awareness, which can lead to dangerous conditions and increase the probability of an accident. Driver fatigue is one of the leading causes of traffic accidents, contributing to an annual increase in the number of fatalities and injuries worldwide. As a result, it is critical to use emerging technology to develop systems capable of monitoring and measuring drivers' attentiveness throughout the driving process.

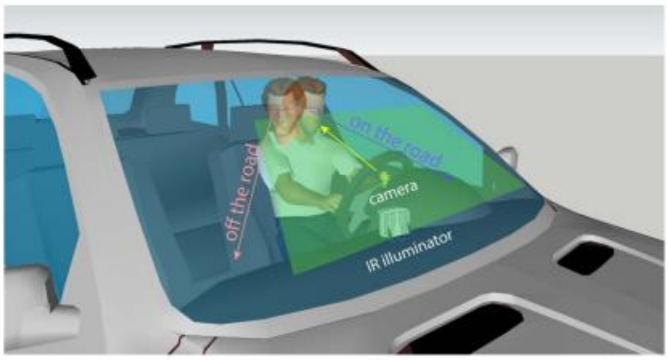

Fig. 1. Eyes off the road (EOR) detection system.

Fig. 1. EOR detection system

Fig. 1 displays the camera module used to detect if eyes are on the road or not.

II. Eyes Localization

Because the eyes always occupy a precise location of the face (defined by facial anthropometric features), our research concentrates on the region between the brow and the mouth, known as the Eye Region of Interest 'eROI' (see Figure 2). The inherent symmetry of the eyes assists detection within the face structure. We begin by vertically traversing the eROI. utilizing a rectangular mask whose width corresponds to the width of the face and whose predicted height is equal to that of the eye, and then calculating the symmetry. The location with a noticeably high symmetry measurement is used to identify the eye area. We recompute the symmetry on the left and right sides within this specified region. The center of the eye is shown by the highest symmetrical value. An illustration of this process's result is provided.

III. Literature Review

Paper 1: Distracted Driver Detection Based on a CNN With Decreasing Filter

This study centers on utilizing advanced deep learning techniques to detect distracted driving. The D-HCNN model demonstrates commendable accuracy in classifying driver postures. To address the conflicting demands outlined above, the design of D-HCNN takes into account the following two factors:

1. Reduction in parameter quantity while enhancing accuracy: Initially, the original images contain significant background noise, such as variations in clothing color and lighting, whereas our focus lies solely on discerning the driver's posture.
2. Emphasis on speed: The majority of parallelism in a convolutional network occurs within each layer's computations, with minimal parallelism observed between layers.

Paper 2: Towards a Context-Dependent Multi-Buffer Driver Distraction Detection Algorithm

Driver distraction detection systems typically rely on three main types of data: lateral and longitudinal driving performance metrics, electrophysiological data, and gaze tracking information. In the case study presented, the outputs of AttenD2.0 and AttenD exhibit similar trends, indicating periods of inattention during non-driving related activities (NDRA) and higher alertness during other times. AttenD2.0 shows slightly more sensitivity to the driver's actions when confirming control handover, likely due to its delay in classifying distractions from off-forward glances, influenced by the decrement function's shape and the predominant effect on the forward buffer over the mirror buffers.

Paper 3: A Triple-Wise Multi-Task Learning Framework for Distracted Driver Recognition

Distracted driving poses a significant danger to society. The Triple-wise Multi-task Learning (TML) technique generates sets of triplets consisting of a raw image, a positive sample, and a negative sample. In these triplets, the positive sample preserves the overall spatial layout of the raw input while refining the local texture within the human body region. Conversely, the negative sample maintains the local details from the raw input but disrupts the overall spatial arrangement. Subsequently, TML mitigates the local bias of Convolutional Neural Networks (CNNs) by leveraging information across the triplets through a multi-task learning approach.

Paper 4: A Hybrid CNN Framework for Behavior Detection of Driver Distracted

In the context of vehicles, recognizing distracted driver behaviors poses challenges due to physical constraints and obstructed body gestures. Nonetheless, leveraging modern camera technology allows for the application of convolutional neural networks (CNNs) to analyze visual data. This study introduces a hybrid CNN framework (HCF) designed to identify distracted driving behaviors through deep learning-based image feature processing. By employing three pretrained CNN models, features are extracted at various scales and combined to generate comprehensive feature maps. Subsequent training involves fine-tuning the fully connected layer to classify different distracted driving behaviours, with dropout techniques utilized to prevent overfitting. Additionally, Class Activation Mapping (CAM) is employed to highlight regions of interest for behaviour detection. Experimental results demonstrate the effectiveness of the proposed HCF, achieving a high classification accuracy of 96.74% in recognizing distracted driver behaviours.

Paper 5: Distracted Driver Detection using Stacking Ensemble

While operating a vehicle, drivers often engage in secondary tasks that divert their attention from driving. Reducing driver distraction is a crucial aspect of an intelligent transportation system aimed at lowering accidents and enhancing safety. This research introduces a method for detecting distracted drivers using various CNN architectures such as VGG19, InceptionV3, Xception, and ResNet50. The suggested model outperforms pre-existing models and requires less computational time. Consequently, employing a stacked ensemble approach yields superior performance compared to previously studied models. This system holds promise for real-world implementation to prevent road accidents by issuing alerts to drivers.

IV. Face Detection

One essential face feature is symmetry. We describe symmetry in digital images by using an accumulator vector, a one-dimensional signal that equals the width of the image. The values that this vector produces correspond to the vertical axes of the relevant objects in the picture. A pixel in the edge image having a value of 1 is referred to in this context as a white pixel. We have implemented improvements to the symmetry calculation technique for facial recognition. Instead, then calculating symmetry just between the two white pixels in the picture. These modifications are designed to maximize the symmetry.

Within this section, we elaborate on our developed system designed for detecting driver drowsiness. The comprehensive flowchart outlining our system is depicted in Figure 2.

Steps:

1. Receive frame from camera (input).
2. Check for face detection.
3. Check for eyes detection.
4. Evaluate the input.
5. Check for driver attentiveness.
6. Play sound if driver is inattentive.

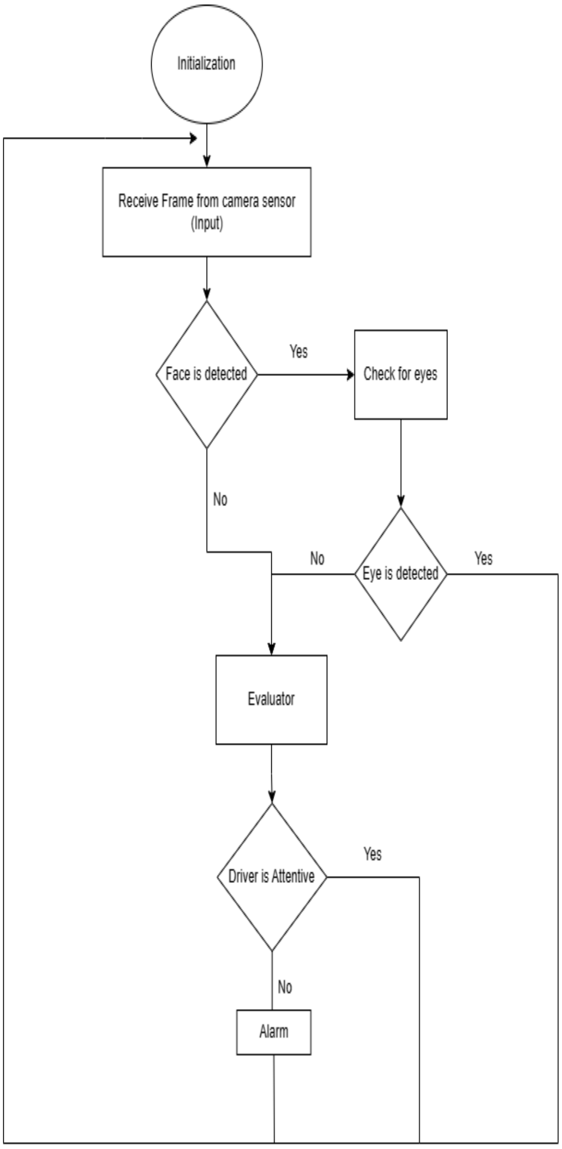

Fig. 2. Flowchart

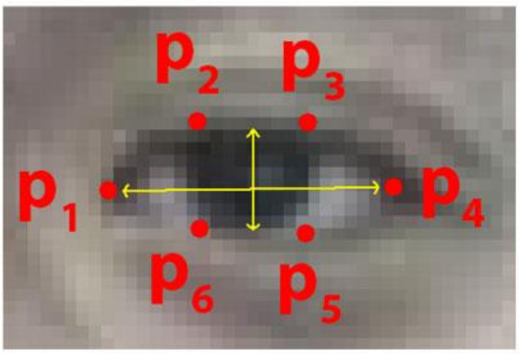

Fig. 3. Eye Aspect Ratio Points

calculation for eye point analysis, offering a more accurate evaluation of facial symmetry and EAR. In the context of EAR (Eye Aspect Ratio) technology for drowsiness detection systems, the eye is divided into six points: p1, p2, p3, p4, p5, and p6(fig3). These points correspond to specific locations on the eye, such as the inner and outer corners, top, bottom, and midpoint. To calculate the EAR, the formula used is:

$$\mathrm{EAR} = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2\|p_1 - p_4\|}$$

Where:

- ||p2−p6||||p2−p6|| represents the Euclidean distance between points p2 and p6 (horizontal eye width).
- ||p3−p5||||p3−p5|| represents the Euclidean distance between points p3 and p5 (vertical eye width).
- ||p1−p4||||p1−p4|| represents the Euclidean distance between points p1 and p4 (average of the horizontal and vertical eye widths). This ratio is used as a measure of the eye's openness, which can be an indicator of drowsiness when it decreases over time.

V. Eye Tracking

Eye tracking, which is used in sleepiness detection systems, is tracking an individual's eye movements, and using metrics such the eye aspect ratio (EAR) and the threshold for closed eye identification. The ratio of the distances between different facial landmarks, such as the nose tip and the corners of the eyes, is used to compute the EAR, a measure of eye openness. When the EAR (Eye Aspect Ratio) drops below a specific threshold, it indicates potential drowsiness or fatigue, sometimes manifesting as closed or partially closed eyes. The device can identify indicators of drowsiness and send out notifications to prevent mishaps, particularly when driving or using machinery, by continuously monitoring the EAR and eye closure duration.

VI. Algorithm

The face and eyes are detected to extract their respective sections, which starts the system's startup phase. These regions function as templates for tracking the future between frames. To decide if the tracking performance is sufficient or insufficient, each tracking instance is evaluated. If tracking is insufficient, the system goes back to the initialization phase. But after tracking is effective, the system moves on to the next steps, which include determining the eye's condition and evaluating the driver's condition.

VII. Conclusion

Distracted driving is a major contributor to traffic accidents, underscoring the importance of devising effective methods for identifying such behavior. Various approaches include:

1. Employing a hybrid framework to detect distracted driving behaviors.
2. Utilizing data from the built-in accelerometer and gyroscope in smartphones to classify instances of distracted driving, particularly during phone usage.
3. Categorizing drivers based on factors such as experience and age to assess the degree of distraction.
4. Implementing a triple-wise multi-task learning framework to enhance the accuracy of identifying distracted driving behaviors.
5. Developing a real-time system, such as an Eyes-Off-Road (EOR) system, using live video from a monocular camera mounted on the steering wheel column to aid in prevention.
6. Demonstrating that a stacked ensemble approach outperforms other models in terms of performance.

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