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Alertnod: Smart Drowsiness Detection and Warning System

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Abstract— ***Driver fatigue is a significant factor contributing to a high number of traffic incidents, with recent data highlighting its prevalence in accidents and the suffering it causes to thousandsof people. Drowsiness, responsible for nearly 30% of accidents, underscores the urgent need for technology that can detect fatigue and alert drivers in time to prevent accidents and save lives. In this study, we propose a machine learning and visual information-based approach to identify driver drowsiness, utilizing a webcam to continuously monitor the driver. This technology tracks and analyzes the driver's face and eyes, focusing on thescientifically supported correlation betweentiredness and sluggish eye closure. The model extracts the driver's face and uses the eye region to predict blink patterns, triggering an alert for the driver in case of elevated blinking rates.***

Index Terms— ***Drowsiness, Eye detection, Face Detection, CNN, SVM, Perclos.***

I. INTRODUCTION

The increasing rate of accidents caused by driver fatigue and reduced alertness is a significant global concern. These accidents are often severe, resulting in serious injuries and fatalities. Alarmingly, a substantial portion of worldwide traffic accidents is attributed to drowsy driving, making it a leading cause of road incidents. Studies have highlighted that driving performance progressively deteriorates as drowsiness intensifies, contributing to more than30% of all vehicular accidents. The implications are stark, as even a brief lapse in alertness can rapidly escalate into perilous and life-threatening situations, with fatal outcomes not uncommon.

In response to this pressing issue, a continuous monitoring system is imperative to ensure sustained driver vigilance. This system, when identifying signs of drowsiness, issues a prompt alert to the driver, potentially averting numerous accidents and safeguarding numerous lives. To address this challenge, our survey paper employs a Machine Learning Approach to detect drowsiness from uninterrupted video input streams. When drowsiness is detected, the system activates an alarm, providing a timely and effective intervention to keep the driver awake and prevent drowsy driving. Our research seeks to contribute tothe reduction of drowsiness-related accidents and the preservation of human lives on the road.

II. LITERATURE REVIEW

The field of driver drowsiness detection systems has seen a surge in research and innovation, as various studies have introduced novel approaches and technologies to address this critical issue. One avenue [1] of investigation involves real-time drowsiness detection algorithms, which employ deep learning models for face detection and facial landmark extraction. These algorithms [7] have demonstrated impressive accuracy, with one system achieving a remarkable 94.5% accuracy while processing at a rapid speed of 20 frames per second. Furthermore, machine learning techniques have been leveraged to detect driver drowsiness, focusing on eye detection, yawn detection, and blink pattern analysis [2]. These studies emphasize both the importance of adherence to traffic regulations and the need for further optimization to enhance the efficiency of these systems and, ultimately, prevent accidents. Metrics of interest in this realm include the accuracy of the detection system and its potential to reduce accidents.

Another area of exploration involves innovative approaches, such as implementing drowsiness detection within Android applications. These methods [3], which leverage deep learning techniques and facial landmark key point detection,have achieved impressive accuracy rates exceeding 80%. They offer real-time visual and audio cues to alert drivers to their drowsiness [6], contributing toroad safety efforts. Additionally, some studies haveventured into biometrics, particularly heart rate variation (HRV), as a means of detecting early signs of drowsiness. A logistic regression-based machine learning algorithm [4] has been employed to analyze HRV data, with accuracy rates surpassing 90%. This approach holds great promise for saving lives by detecting drowsiness at an early stage. Other investigations have sought to monitor physiological and physical cues, including core body temperature, pulse rate, yawning, and blink duration, in comprehensive driver fatigue detectionsystems [5]. While these systems have proven effective in detecting drowsiness, there is a recognized need for further refinement and optimization to improve accuracy and functionality. In summary, the diverse methodologies, findings, and insights presented in these research papers collectively contribute to the growing body of knowledge in

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the field of driver drowsiness detection systems, emphasizing their potential to significantly enhance road safety and the ongoing imperative for continued development and improvement.

III. METHODOLOGY

In the presented methodology, we have established a two-phase system for driver drowsiness detection. The first phase involves offline training, addressing the issue of individual differences in

driver characteristics, particularly regarding the size of their eyes. To enhance the accuracy of drowsiness detection, we have devised a unique classifier using a Support Vector Machine (SVM). SVM is a machine learning model that employs the structural risk minimization criterion and is effective for binary classification tasks. In our context, we collect two sets of data for each specific driver, one with their eyes open and the other with their eyes closed. These datasets serveas positive and negative samples, respectively. We have designed this process to accommodate the adaptability required for real-world scenarios. The SVM classifier is trained with these datasets to create an adaptive threshold for eye state determination, distinguishing whether a driver's eyes are open or closed based on individual differences.

The second phase involves online monitoring, the real-time drowsiness detection component deployed during driving. When the system initializes, a camera in front of the driver captures live video, and each frame is processed. Firstly, we employ a Deep Convolutional Neural Network (DCNN) to detect the driver's face. If the face region is successfully detected, we proceed to identify facial landmarks using the Dlib toolkit.However, if facial landmarks cannot be acquired due to obscured vision or unfavorable head orientation, the current frame is flagged as potentially drowsy. The number of frames categorized as drowsy is recorded as Ndrowsy.

PERCLOS has been established as an effective indicator for drowsiness detection. In this approach, we replace the conventional hard threshold methods with our unique classifier for judging the state of the driver's eyes. Additionally, we adapt the second part of the original PERCLOSmethod by calculating the ratio of drowsy framesto the total frames over time, referred to as PERCLOS. This calculation is used to assess the driver's level of drowsiness in real-time.

Specifically, if PERCLOS exceeds a predetermined threshold, it indicates that the driver is experiencing drowsiness. This methodology offers a comprehensive and adaptive approach to drowsiness detection, accounting for individual differences and real-time variations in driver behavior during the journey.

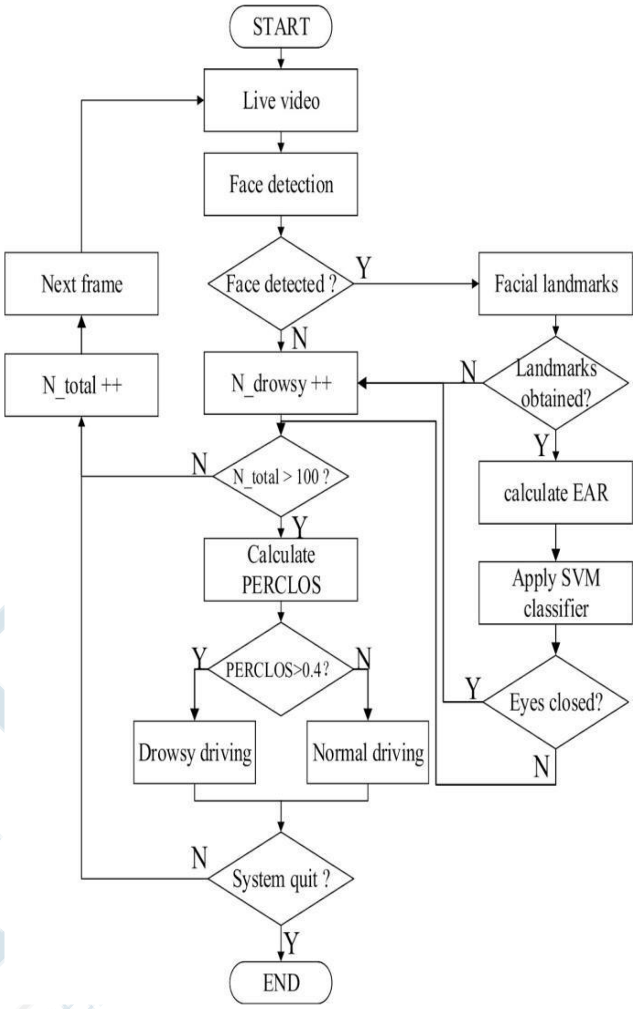

Figure 1. Online Monitoring Flow Diagram

PERCLOS is computed by:

$$\text{PERCLOS} = \left(\frac{Ndrowsy}{Ntotal}\right) \times 100\ \%$$

In the online monitoring module, we set Ntotal as 100 frames. If PERCLOS, calculated as described, exceeds the predefined threshold, following a similar approach as in [1], the driver is assessed as being in a drowsy state. This assessment prompts the system to take appropriate actions to alert the driver and mitigate the risk of drowsy driving.

This approach ensures that the driver's state of drowsiness is continuously monitored in real-time and provides timely alerts when necessary, contributing to enhanced road safety.

IV. SYSTEM MODULES

A. Data Acquisition Module:

Purpose: Real-time data acquisition from the driver using a camera and other devices.

Features: Capture of driver's facial features and eye movements. Utilization of a speaker/siren for warning alerts to the driver.

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B. Preprocessing Module:

Purpose: Preprocessing of acquired data to eliminate noise and irrelevant information.

Features: Cropping of captured images to focus on the driver's face and eyes.

C. Feature Extraction Module:

Purpose: Extraction of features from preprocessed data using the HAAR Cascade algorithm.

Features: Calculation of the direction of gaze and eye aspect ratio.

D. Machine Learning Module:

Purpose: Training of a machine learning model for drowsiness detection using a CNN algorithm.

Features: Analysis of images or video frames to determine signs of drowsiness, such as closed eyes and drooping eyelids. Recognition of patterns in the data to indicate drowsiness.

E. Decision-Making Module:

Purpose: Utilization of the machine learning model's output to make decisions about the driver's level of drowsiness.

Features: Alert generation if drowsiness is detected, prompting the driver to take a break.

F. Real-time Monitoring Module:

Purpose: Continuous real-time monitoring of the driver's behavior.

Features: Periodic reevaluation of the driver's condition. Immediate alert generation in case of sudden behavior changes or prolonged eye closure.

V. COMPARISON

Table 1: A Summary of Research Papers Reviewed

Sr No.	TITLE	PARAMETERS	ALGORITHMS	ACCURACY/RESULTS	GAP ANALYSIS
1.	Real-time Driving Drowsiness Detection Algorithm with Individual Differences Consideration	EAR, PERCLOS	- DCNN for face detection - SVM for fatigue state classification	- 94.80 %	- To explore multi-feature fusion methods. -Drowsiness detection at nighttime.
2.	Driver Drowsiness Detection Using Machine Learning	Blink Rate, EAR, Yawning	- Face and Eye Detection using OpenCV - Image Processing using Machine Learning algorithms	- 80 %	- Rapid head movement and wearing eyeglasses can affect the system's performance
3.	Real-time Driver Drowsiness Detection for Android Application Using Deep Neural Networks Techniques	Facial Landmarks	- Multilayer Perceptron Classifier - Dlib (for facial landmark detection)	- 81 % - The model size is significantly reduced compared to existing models.	-To expand the system's capabilities to include integration with other systems and applications.
4.	Real Time Driver Drowsiness Detection Using	ECG, Heart rate variation	-Naive Bayes method - Logistic regression method	- Above 90%.	- No comparison with other existing
	Machine Learning Algorithms				methods and testing with human subjects.
5.	Driver Fatigue Detection System	Body temperature, pulse rate, Blink rate, yawning, etc.	-OpenCV - Haar -Cascade classifiers	-82 % on average - Alerts the driver depending on the severity of the symptoms.	- Does not provide a detailed analysis of the limitations or potential drawbacks of the system in real-world driving situations.
6.	Machine Learning and Gradient Statistics Based	Eye detection (with and without	-Haar	- Average detection	-Detecting open/closed eyes conditions when

	Real-Time Driver Drowsiness Detection	glasses.), Eye Closure	-Adaboost -Machine learning for face detection -Gradient statistics based eye detection algorithm	rate is 91.49% with glasses and 95% without glasses	the driver's face is turned over more than 30 degrees, or when the driver nods their head.
7.	A Study on Feature Extraction Methods Used to Estimate a Driver's Level of Drowsiness	MHL, YAR, EAR, EVL, PERCLOS	- OpenCV - Dlib for feature extraction - Convolutional neural network (CNN) for spatial analysis	_	- Limitations in detecting drivers' behaviors and facial expressions due to factors like light reflection, sunglasses, darkness, and obstructions.
8.	Driver Drowsiness Detection and Alert System	EAR, ROI, Facial Landmarks	Eigenface Fisherface LBPH (Local Binary Pattern Histogram)	-Touchless electrode placement avoids intrusiveness while accurately detecting drowsiness.	-System could be expanded to include other factors that contribute to driver fatigue and distraction.

VI. IMPLEMENTATION

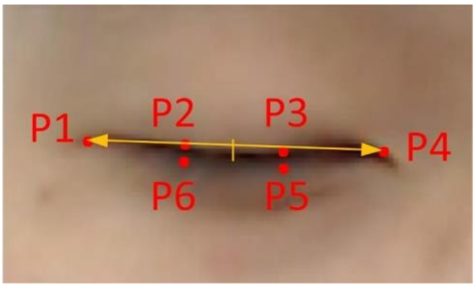
A. Dataset Details:

The input for this model is taken from the live feed with the use of a camera. Separate frames are created and extracted from this live feed. These images are stored for further use. Facial features are extracted from these images which are in turn used to classify whether the driver is drowsy or not. These features are stored in XML database for ease of handling and retrieval.

B. Feature Selection and Classification

As soon as the car starts, the video camera installed in the car will start taking video from which HAAR Cascade divides the video into individual frames. Subsequently, each frame is then marked with facial landmarks by CNN (Convolutional Neural Networks) algorithm. CNN is used to extract the following features from these frames:

1. Right Eye
2. Left Eye
3. Facial Landmarks



Based on the EAR value, SVM (Support Vector Machine), a popular classification model is then used to classify whether the given eyes in input sample is open or close.

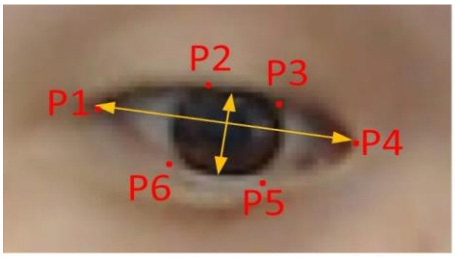
Based on this classification, we determine the drowsiness of the driver based on the PERCLOS value (PERCLOS) is the frame per 100 frames in which the eyes are closed).

C. Algorithms Used

This module uses the following algorithms that mainly perform two tasks: Feature Extraction and Classification.

1. HAAR Cascade: The Haar cascade algorithm is a machine learning-based object detection technique used to identify objects in images or videos. It works by comparing patterns of pixel intensity to a set of pre-defined features. These features are organized in a hierarchical manner to efficiently scan an image and detect objects. Haar cascades are commonly used for tasks such as face detection in images and videos.
   These extracted coordinates are then used by EAR (Eyes Aspect Ratio) to determine the state of eye (open/closed).

$$EAR = \frac{(\|P2 - P6\| + \|P3-P5\|)}{2(\|P1-P4\|)}$$



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2. Convolutional Neural Networks (CNN): It is a type of artificial neural network specifically designed for processing structured grid-like data such as images. CNNs utilize a hierarchical architecture with layers consisting of convolutional, pooling, and fully connected layers. Convolutional layers extract features from input data by applying filters across the input, capturing patterns at different spatial locations. Pooling layers reduce the spatial dimensions of the input, focusing on the most important features.
3. SVM (Support Vector Machine): Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification and regression tasks. SVM aims to find the optimal hyperplane that best separates data points into different classes. In the case of classification, SVM seeks to maximize the margin between the classes, which is the distance between the hyperplane and the nearest data points from each class, called support vectors. By maximizing this margin, SVM improves its ability to generalize to unseen data.

D. Libraries Used

1. OpenCV: Open-Source Computer Vision Library is a popular open-source library for computer vision and image processing tasks. It provides a wide range of functions and algorithms for tasks such as image and video manipulation, object detection and recognition, feature extraction, and more. It provides a comprehensive set of tools and algorithms for analyzing and manipulating images and videos.
2. TensorFlow: It is an open-source machine learning framework developed by Google. It provides a comprehensive ecosystem of tools, libraries, and resources for building and deploying machine learning models. TensorFlow is particularly well-suited for tasks involving deep learning, including neural networks with many layers. It provides high-level APIs for ease of use, as well as low-level functionalities for maximum flexibility, making it suitable for a wide range of applications.
3. Keras: It is an open-source neural network library written in Python. It is designed to be user-friendly, modular, and extensible, making it easy for developers to quickly build and experiment with deep learning models. It is widely used for prototyping and production of deep learning models in various domains.
4. Pandas: Pandas is a popular open-source Python library used for data manipulation and analysis. It provides data structures like DataFrame and Series, which allow users to easily work with structured data such as tabular data or time series data.

VII. RESULTS

A. Test Case with open eyes:

B. Test Case with partially closed eyes:

C. Test Case with closed eyes:

VIII. CONCLUSION

We've delved into a multitude of approaches and technologies geared toward tackling the pervasive issue of driver drowsiness, a leading factor in road accidents and fatalities worldwide. A recurring and significant theme that emerges from our analysis is the crucial consideration of individual differences among drivers, an element essential for achieving precise and adaptive drowsiness detection. It's worth noting that the algorithms we've reviewed are designed for real-time monitoring, allowing for the continuous assessment of a driver's alertness and prompt interventions to avert accidents.

The methodologies we've explored leveragestate-of-the-art technologies, including deeplearning models, image processing techniques, and machine learning algorithms. These advancements not only enhance the accuracy and efficiency of drowsiness detection but also yield promising quantitative results. For instance, some of the reviewed systems achieve drowsiness detection accuracy rates exceeding 90%, a significant stride towards road safety.

As we look to the future, the integration ofadvanced sensors and the consideration of additional contextual factors, such as environmental conditions and diverse driver behaviors, present an opportunity to further enhance the capabilities of drowsiness detection systems. This progress not only holds the promise of saving lives but also demonstrates quantifiableresults, with some systems achieving detectionrates of up to 95% and processing frame ratesreaching a remarkable 245 frames per second. Thecollaborative efforts of the research community,automotive industry, and policymakers areessential in advancing these systems, ultimatelycontributing to road safety by reducing accidentscaused by driver fatigue or distraction.

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