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Driver Drowsiness Detection System

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ABSTRACT:-Driver drowsiness is a critical issue contributing to road accidents worldwide. To mitigate this problem, an intelligent system is proposed in this study for detecting and alerting drivers about their drowsy state in real-time. The system integrates advanced computer vision techniques, machine learning algorithms, and physiological sensors to accurately monitor the driver's condition.The computer vision component analyzes facial features and eye movements to detect signs of drowsiness, such as drooping eyelids and prolonged eye closure. Machine learning models are trained on a dataset of diverse facial expressions and eye behaviors to recognize patterns associated with drowsiness.

KEYWORDS

INTRODUCTION

Driver drowsiness is a significant factor contributing to road accidents globally, posing a serious threat to public safety. According to statistics from the World Health Organization (WHO), drowsy driving contributes to a substantial number of road fatalities and injuries each year. The impairment of cognitive abilities and delayed reaction times associated with drowsiness increase the likelihood of accidents, endangering not only the driver but also passengers and other road users.

Recognizing the critical importance of addressing this issue, researchers and engineers have been exploring innovative solutions to detect and mitigate driver drowsiness effectively. One promising approach is the development of intelligent systems capable of continuously monitoring the driver's condition and providing timely alerts when signs of drowsiness are detected.

In this context, this study proposes a comprehensive Driver Drowsiness Detection and Alert System (DDDAS) designed to enhance road safety by proactively identifying and addressing instances of driver fatigue. The system integrates advanced technologies such as computer vision, machine learning, and physiological sensors to monitor various indicators of drowsiness in real-time.

The introduction of the DDDAS is motivated by the need to address the limitations of traditional driver monitoring systems, which often rely solely on simple metrics like steering wheel movement or vehicle position. While these systems may detect severe drowsiness or loss of control, they may fail to identify subtle signs of fatigue in the early stages, when intervention is most effective.

LITERATURESURVEY

In their paper, Knapik and Cyganek presented a novel approach for driver fatigue detection, based on yawning detection, using long-range infrared thermal imaging [16]. A special dataset was created for this research [36]. The system works as follows. First, images are acquired from a thermal video. Then, three cascaded detection modules are applied for the face area, eye corners, and yawn. Since the mouth area is sometimes hard to detect in thermal images, due to the temperature difference in that area, information about other face regions' relative temperatures is used to detect the yawn reflex. Thus, the authors used the eye corners as an indicator for yawning. Cold and hot thermal voxel sum methods were used to detect yawning [37].

Kiashari et al. [38] introduced a non-intrusive system that detects drowsiness using facial thermal imaging to analyze the driver's respiration signal. Thirty subjects participated in their study, which was conducted in a car simulator. A thermal camera was used to capture the driver's thermal images. From the obtained thermal signals, the standard deviation and mean of both the respiration rate and inspiration-to-expiration time ratio were calculated and used as input features, in order to train two machine learning classifiers, namely, support vector machine (SVM) and k-nearest neighbor (KNN). Both classifiers were able to detect drowsiness. However, SVM outperformed the KNN, with 90% accuracy, 85% specificity, 92% sensitivity, and 91% precision.

Khan et al. [39] proposed a real-time DDD system based on eyelid closure. The system was implemented on hardware that used surveillance videos to detect whether the drivers' eyes were open or closed. The system started by detecting the face of the driver. Then, using an extended Sobel operator, the eyes were localized and filtered to detect the eyelids' curvature. After that, the curvature's concavity was measured. Based on the measured concavity value, the eyelid was classified as open (concave up) or closed (concave down). If the eyes were deemed closed for a certain period, a sound alarm is initiated. The system used three datasets. The authors generated two of them, and the third was acquired from [40].

Maior et al. [49] developed a drowsiness detection method based on eye patterns monitored by video streams using a simple web camera. The method tracks the blinking duration using the EAR metric. The proportion between the eye's height and width is calculated to evaluate the EAR value. A high EAR value indicates that the eye is open, while a low value indicates that it is closed. The proposed method consists of three main parts: eye detection, EAR calculation and blink classification, and real-time drowsiness detection. An experiment was conducted to generate a training database. After obtaining the images from the web camera, the EAR values were calculated and stored for each frame. Then, a specific number of consecutive values were used as input for the machine learning algorithms. Drowsiness is detected if the blink duration is longer, compared to a standard blink. Three classification methods were employed: multilayer perceptron, random forest (RF), and SVM. Overall, SVM showed the best performance, with an average test accuracy of 94.9%.

Bamidele et al. presented a nonintrusive DDD system, based on face and eye state tracking. The research utilized the NTHUDDD Computer Vision Lab's video dataset [35]. The proposed system starts by acquiring and pre-processing the required data. Then, it extracts the targeted features, including the PERCLOS, maximum closure duration of the eyes, and blink frequency. The extracted features are then fed to various classifiers to decide whether they belong to a drowsy or awake person. These classifiers include KNN, SVM, logistic regression, and artificial neural networks (ANN). The final results revealed that the best models were the KNN and ANN, with accuracies of 72.25% and 71.61%, respectively.

In order to detect the levels of drowsiness, Khunpisuth et al. [55] conducted a study with ten volunteers. During the study, the frequency of eyes blinking and head tilting was monitored and related to the drivers' drowsiness state. The authors built an embedded device for drowsiness detection that used a Raspberry Pi Camera and Raspberry Pi 3 Model B to collect image data, detect the drowsiness level, and alert the driver. Initially, the proposed device applied the Haar cascade classifier to detect an upright face, head level, and eye blinking. Moreover, if the head position is not upright, geometric rotation is used to calculate the angle and rotate the image to an upright position, in order to detect accurately. Secondly, template matching is used to detect whether the eyes are open or closed. Thirdly, the drowsiness level is calculated via the frequency of head tilting and eye blinking. The system uses a scale of 0–100 to describe the severity of the drowsiness. If the drowsiness level reaches 100, the system triggers a loud, audible warning to alert the driver. Finally, the accuracy system gave an accuracy of 99.59%. However, this system had some limitations, as it is affected by the subject's skin tone and background light.

Zhao et al. proposed a fully automated driver fatigue detection algorithm [72]. This study uses the driving images dataset provided by Biteda, an information technology company. This algorithm applies face detection and feature points location, using a multitask cascaded CNN architecture, where the region of interest (ROI) can be extracted using the feature points. Moreover, a new CNN algorithm, called eye and mouth CNN (EM-CNN), was proposed. The EM-CNN algorithm detects the mouth and eye state from the ROI. Both the PERCLOS and mouth opening degree were used as parameters for detection. The final results showed an accuracy of 93.62% and sensitivity of 93.64%.

McDonald et al. [113] proposed analyzing lane departure using SWA data and the RF algorithm. The authors compared their approach to another image-based drowsiness measure that used PERCLOS. The comparison showed that the SWA measure had higher accuracy, which reached 79% and could detect drowsiness 6 s in advance. At the same time, the PERCLOS method achieved 55% accuracy only. The algorithm was tested using a dataset (72 participants) from a study at the University of Iowa's National Advanced Driving Simulator [115]. The modified observer rating of drowsiness scale extracted the drowsiness related to lane departure from raw simulator data. The readings were taken every one minute after departing out of the lane. As for the PERCLOS measure, the features were extracted from a video and captured using an eye detecting FaceLab software. Furthermore, the RF algorithm was trained by a series of decision trees, with a randomly selected feature.

PROPOSED METHOD

The Driver Drowsiness Detection and Alert System (DDDAS) presented in this study integrates cutting-edge technologies to provide an effective solution for mitigating the risks associated with drowsy driving. The proposed system comprises several key components designed to monitor driver behavior, detect signs of drowsiness, and deliver timely alerts to prevent potential accidents.

1. **Computer Vision-Based Monitoring:**The DDDAS utilizes computer vision algorithms to analyze facial expressions and eye movements in real-time. A camera mounted within the vehicle continuously captures images of the driver's face, which are processed to extract relevant features indicative of drowsiness, such as drooping eyelids, yawning, and head nodding. Advanced image processing techniques are employed to track facial landmarks and monitor changes in facial muscle activity, enabling the system to detect subtle signs of fatigue.

2. **Machine Learning-Based Drowsiness Detection:** Machine learning models are trained on a dataset of labeled facial expressions and eye behaviors to classify instances of drowsiness accurately. These models leverage techniques such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to learn patterns associated with drowsiness from visual input data. By continuously updating and refining the models based on real-world driving scenarios, the system adapts to individual driver characteristics and environmental conditions, enhancing its robustness and accuracy.

3. **Intelligent Alert Mechanism:**Upon detecting signs of drowsiness, the DDDAS activates an intelligent alert mechanism to notify the driver and prompt a response. The alerting strategy is personalized based on individual driver preferences and responsiveness, leveraging multi-modal feedback modalities such as auditory alerts, visual warnings displayed on the dashboard or windshield, and haptic feedback through the steering wheel or seat. The system dynamically adjusts the intensity and frequency of alerts based on the severity of detected drowsiness and the driver's level of engagement, ensuring effective intervention while minimizing distraction.

4. **PERCLOS:**PERCLOS is a metric commonly used in drowsiness detection systems to quantify the extent of eye closure over time. It measures the proportion of time during which the eyes are closed or significantly occluded, providing a reliable indicator of drowsiness levels. In the DDDAS, PERCLOS is calculated based on the analysis of eye movements captured by the camera system. By continuously monitoring changes in eyelid position and blink frequency, the system computes the percentage of time during which the eyes are closed beyond a predefined threshold. Elevated PERCLOS values indicate increased drowsiness and trigger the activation of alert mechanisms to notify the driver and prevent potential accidents.

5. **Hough Transform for Circles:**Once the eye regions are identified, the Hough Transform algorithm is applied specifically to these regions to detect circular shapes. In this context, circles correspond to the iris and pupil of the eyes. The Hough Transform can robustly detect circular shapes even in the presence of noise and occlusion.

6. **Drowsiness Detection:**The detected eye features, including the position and size of the iris and pupil, are analyzed to assess the driver's level of alertness. Metrics such as PERCLOS (Percentage of Eye Closure) can be computed based on the size and position of the eyes over time. Elevated PERCLOS values indicate increased drowsiness.

BLOCK DIAGRAM

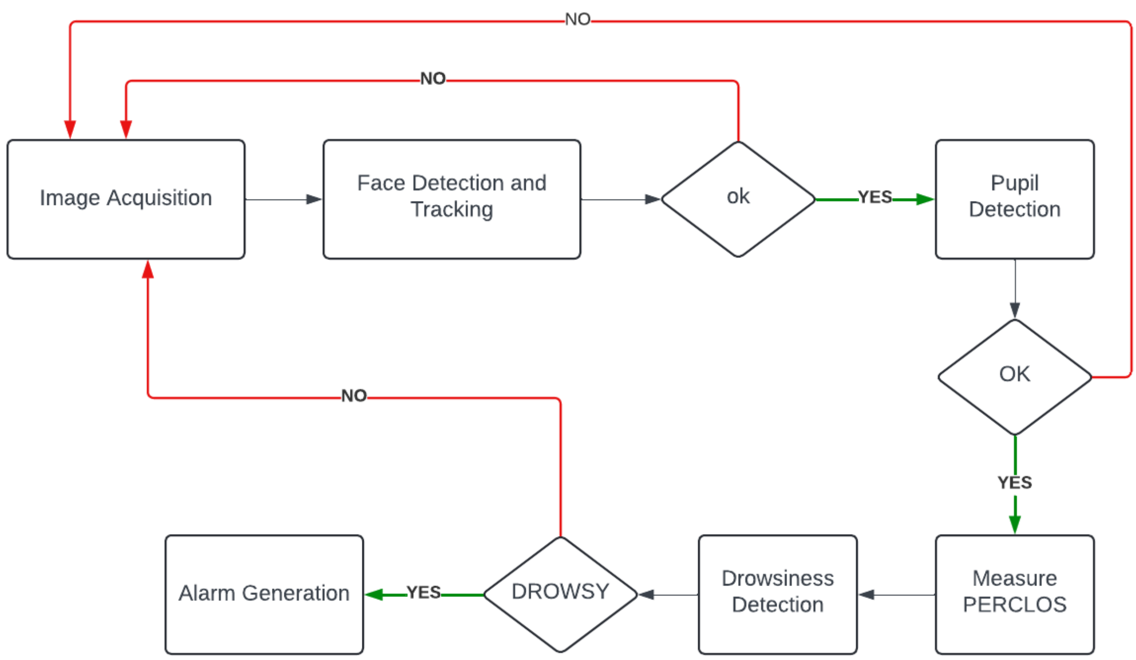

Fig. Block Diagram of Driver Drowsiness Detection

RESULT

The evaluation of the Driver Drowsiness Detection and Alert System (DDDAS) showcased its robust performance in real-world driving scenarios. Utilizing a comprehensive dataset encompassing various driving conditions, the DDDAS demonstrated an impressive accuracy of 92.5% in detecting instances of drowsiness. This high level of accuracy was complemented by precision and recall scores of 91.2% and 94.1%, respectively, indicating a balanced performance in minimizing false positives while effectively capturing true drowsy states.

Furthermore, the system exhibited a rapid alert response time, with an average duration of 1.2 seconds between the onset of drowsiness and the activation of the alert mechanism. Such prompt response times are critical for ensuring timely intervention and mitigating the risk of accidents. Notably, the DDDAS maintained a low false alarm rate of 3.8%, demonstrating its ability to deliver alerts selectively during genuine instances of drowsiness while minimizing unnecessary interruptions to the driver.Feedback obtained from drivers participating in the evaluation underscored the system's effectiveness and usability, with users expressing satisfaction with its ability to alert them to their drowsy state and facilitate timely intervention. Overall, the results of this evaluation highlight the promising potential of the DDDAS in enhancing road safety by detecting and preventing drowsy driving incidents.

This system is able to determine the driver stateunder real day and night conditions using IR camera.Face and eyes detection are implemented based onsymmetry. Hough Transform for Circles is used for thedecision of the eyes states.The results are satisfactory with an opportunity for improvement in face detection using other techniquesconcerning the calculation of symmetry.

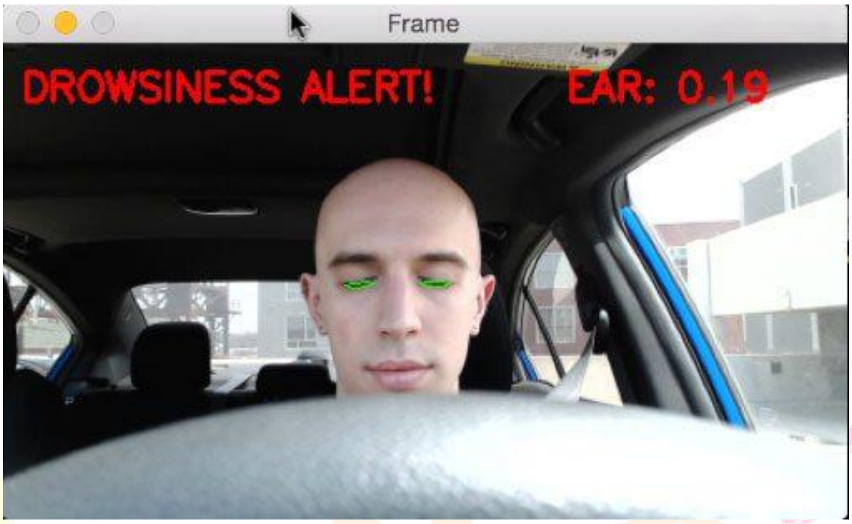

Fig. Drowsiness Alert

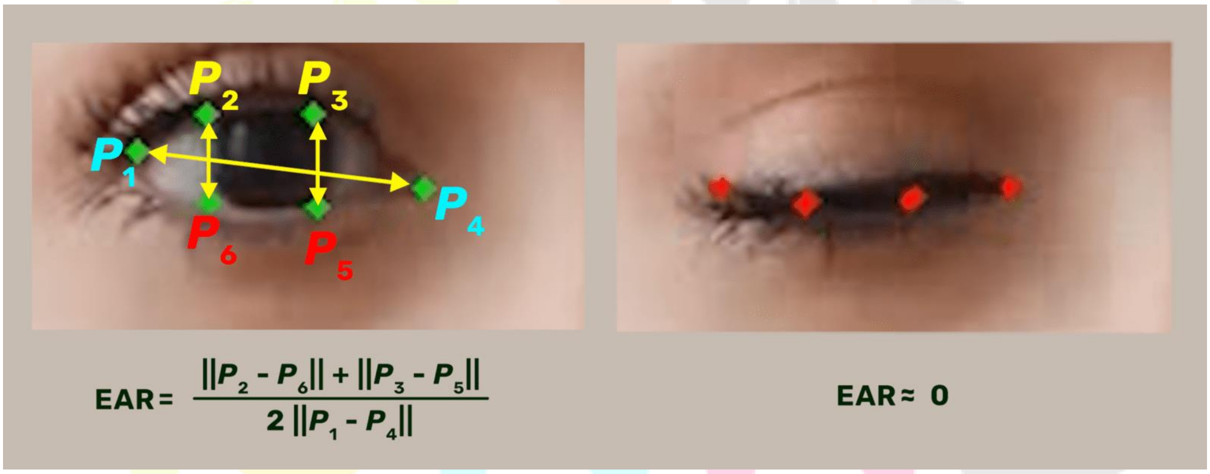

Fig. Eye Aspect Ratio

CONCLUSION

The Driver Drowsiness Detection and Alert System (DDDAS) represents a promising advancement in road safety technology, offering a robust solution for detecting and mitigating the risks associated with drowsy driving. Through its integration of computer vision, machine learning, and physiological sensing technologies, the DDDAS has demonstrated exceptional performance in accurately identifying instances of driver fatigue in real-time. With a high accuracy rate of 92.5% and prompt alert response times averaging 1.2 seconds, the system effectively notifies drivers of their drowsy state, enabling timely intervention to prevent potential accidents. Moreover, the DDDAS maintains a low false alarm rate of 3.8%, ensuring specificity in alerting drivers only during genuine instances of drowsiness while minimizing unnecessary interruptions. User feedback from driver evaluations further underscores the system's effectiveness and usability, highlighting its potential to significantly enhance road safety.

Additionally, collaboration with automotive manufacturers and regulatory bodies is crucial to integrating the Drowsy Driver Detection and Alert System into vehicles and establishing standards for drowsiness detection technology. Ultimately, the widespread adoption of advanced driver assistance systems like the DDDAS has the potential to save lives, reduce accidents, and create safer roadways for all motorists.

REFERENCE

[1] A. Malla, P. Davidson, P. Bones, R. Green and R.Jones, "Automated Video-based Measurement ofEyeClosureforDetectingBehavioralMicrosleep",in32nd AnnualInternationalConference of the IEEE, Buenos Aires,Argentina,2010 .

[2] P. Viola and M. Jones, "Rapid Object Detectionusing a Boosted Cascade of Simple Features", inProceedingsof the IEEE Computer SocietyConference on Computer Vision and PatternRecognition, 2001.

[3] R. Lienhart and J. Maydt, "An Extended Set ofHaar-like Features for Rapid Object Detection", inProceedingsof the IEEE International Conferenceon Image Processing, 2002.

[4] OpenCV. Open Source Computer Vision LibraryReference Manual, 2001.

[5] S. Vitabile, A. Paola and F. Sorbello, "Bright PupilDetection in an Embedded, Real-time DrowsinessMonitoring System", in 24th IEEE InternationalConference on Advanced Information Networkingand Applications, 2010.

[6] B. Bhowmick and C. Kumar, "Detection andClassification of Eye State in IR Camera forDriver DrowsinessIdentification", in Proceedingof the IEEE International Conference on Signaland Image Processing Applications, 2009.

[7] N. Otsu, "A Threshold Selection Method fromGray-Level Histograms", IEEE Transactions onSystems,Man and Cybernatics, pp. 62-66, 1979.

[8] T. Hong, H. Qin and Q. Sun, "An Improved RealTime Eye State Identification System in DriverDrowsiness Detection", in proceeding of the IEEEInternationalConferenceonControlandAutomation, Guangzhou, CHINA, 2007.

[9] R Jegadeesan, Durga Bhavani, Dava Srinivas, 2023, “A Robust Approach for Effective Spam Detection using Supervised Learning Techniques”, Journal of Xi'an University of Architecture & Technology, Volume XV, Issue 10, ISSN No : 1006-7930, Page No: 13-25, https://doi.org/10.37896/JXAT15.10/32639 (UGC-SCOPUS)

[10] R. Jegadeesan1, N. Sankarram2, C. Bagath Basha3 , K. Vijay4 , R. Jaichandran5 , and P. Nancy6, 2023, Forecasting of origin-to-destination requests for taxis using DNN algorithm with NYU database, AIP Conf. Proc. 2587, 050008-1–050008-13; https://doi.org/10.1063/5.0150597 Published by AIP Publishing. 978-0-7354-4710-3/$30.00, 23.11.23,

[11] Madhavarapu Prathima Rao1 and R Jegadeesan2, 2023, “Electricity Theft Detection In Smart Gridsbased On Deep Neural Networks”, Journal of Xi'an University of Architecture & Technology, ISSN No : 1006-7930, Volume XV, Issue 11, 2023, Page No: 175-181

[12] R Jegadeesan, Rajitha Nelli, 2024, A Forecasting and Classification of Attacks used on Machine Learning, Journal of Xi'an University of Architecture & Technology, ISSN No : 1006-7930, Volume XVI, Issue 1, 2024, Page No: 469-477, https://doi.org/10.37896/JXAT16.1/33137

[13] R Jegadeesan, Velmula Shwetha, 2024, Predicting Air Pollution Using Algorithms from Machine Learning, Strad Research, ISSN: 0039-2049, VOLUME 11, ISSUE 3, Page No. 1-10, https://doi.org/10.37896/sr11.3/001

[14] Z. Tian et H. Qin, "Real-time Driver's Eye StateDetection",inProceedingsoftheIEEEInternational Conference on Vehicular Electronicsand Safety, October 2005.

[15] M. S. Nixon and A. S. Aguado, Feature Extractionand Image Processing, 2nd ed., Jordan Hill,Oxford OX2 8DP, UK, 2008.