Driver Drowsiness Prediction Based on Multiple Aspects Using Image Processing Techniques

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Abstract - Road accidents caused by driver drowsiness have been a significant concern for decades. With advancements in automation, various drowsiness detection systems have been developed, yet they still require improvements in efficiency, accuracy, cost-effectiveness, and speed. This paper proposes an integrated approach for driver drowsiness detection based on multiple aspects, utilizing eye and mouth closure status (PERCLOS) along with a newly introduced Facial Aspect Ratio (FAR), similar to EAR and MAR. This approach helps detect drowsiness indicators such as closed eyes, yawning, nodding, or covering the mouth, which are common human responses to fatigue. The system further integrates texture-based gradient patterns to identify drivers' faces from different angles, recognize sunglasses, and detect scenarios where hands cover the eyes or mouth. By leveraging image processing techniques and deep learning algorithms, the proposed system aims to enhance real-time driver monitoring, ensuring improved road safety and reducing the risks associated with drowsy driving.

Keywords—Driver Drowsiness Detection , Machine Learning Image Processing ,Facial Aspect Ratio (FAR) ,Road Safety.

I.INTRODUCTION:

With the increasing number of vehicles on the road, driver fatigue has become a major safety concern. Fatigue-related accidents often occur because drowsy drivers experience slower reaction times, impaired judgment, and reduced awareness. Unlike other distractions, such as mobile phone usage, drowsiness is more challenging to detect because it does not always present obvious physical signs. This makes the development of an effective, real-time monitoring system essential for reducing accidents caused by driver fatigue.

Many traditional approaches to detecting drowsiness rely on vehicle-based indicators like steering patterns, lane deviation, or braking behavior. However, these methods can be unreliable due to varying road conditions, weather, and individual driving styles. In contrast, advancements in artificial intelligence and computer vision now allow for a more direct and accurate analysis of driver fatigue by monitoring facial expressions and behavior.

This project introduces a Driver Sleep Alert System that utilizes image processing and machine learning to detect drowsiness through multiple indicators. The system focuses on analyzing facial features such as eye closure (PERCLOS), yawning, and head movements to determine the driver's alertness level. Additionally, it incorporates Facial Aspect Ratio (FAR), Eye Aspect Ratio (EAR), and Mouth Aspect Ratio (MAR) to detect signs of fatigue more accurately. The system also identifies gestures such as nodding or covering the mouth, which are common when a person is trying to stay awake. Upon detecting drowsiness, the system triggers an alert, prompting the driver to take immediate corrective action.

The methodology involves face detection, feature extraction, classification using deep learning algorithms like CNN and YOLO, and a real-time alert system. A dataset of facial images is used to train the model to distinguish between alert and drowsy states effectively. The system is designed to function under various driving conditions, such as highway driving, night-time travel, and heavy traffic, ensuring its reliability in real-world scenarios.

II.PROBLEM DEFINITION:

Drowsy driving is a major contributor to road accidents, often resulting in severe injuries and fatalities. Fatigue impairs a driver's reaction time, awareness, and decision-making abilities, making them highly vulnerable to crashes. Traditional methods of detecting driver drowsiness, such as vehicle movement analysis and physiological monitoring, have limitations in terms of accuracy, reliability, and real-world applicability. There is a need for a non-intrusive, real-time, and highly accurate system that can detect early signs of fatigue and issue immediate alerts to prevent accidents.

This project aims to develop a Driver Sleep Alert System using image processing and deep learning techniques to analyze facial features such as eye closure, yawning, and head movement. The system will trigger an alarm when signs of drowsiness are detected, ensuring the safety of both the driver and passengers.

III.Literature Survey:

A. Misra et al.,, "The study explores the detection of cognitive distraction in drivers using machine learning methods. Researchers analyzed data from eye tracking, physiological signals, and vehicle kinematics to classify distracted and non-distracted drivers. The study found that features such as pupil area, vertical and horizontal eye movements were highly predictive of cognitive distraction. Machine learning models, including Random Forest, Decision Trees, and Support Vector Machines (SVM), achieved an average classification accuracy of 90% across different road types. The research highlights the importance of multi-modal data fusion for improving driver distraction monitoring systems.

E. Magán, M. Paz Sesmero et al.,, This paper investigates deep learning techniques for driver drowsiness detection using image sequences. A convolutional neural network (CNN) was trained on facial expression datasets to identify early signs of fatigue. The study emphasizes the effectiveness of temporal image analysis in detecting progressive drowsiness states. The findings suggest that integrating spatial and temporal features can significantly enhance real-time fatigue detection accuracy.

J. Celaya-Padilla, C. Galván-Tejada et al.,, The researchers developed a deep convolutional neural network (CNN)-based system for detecting texting and driving behaviors. The model was trained on a dataset of driver images and achieved high accuracy in distinguishing between focused and distracted drivers. The study suggests that deep learning-based vision systems can effectively enhance automated driver monitoring systems and improve road safety policies.

M. Eraqi, Y. Abouelnaga et al.,, This paper presents a multi-modal approach for driver distraction detection by combining facial recognition, head pose estimation, and hand movement analysis. The study utilized ensemble deep learning techniques to improve classification accuracy. The results demonstrate that integrating different behavioral cues provides a more reliable assessment of driver drowsiness and distraction.

M. H. Alkinani, W. Z. Khan et al., The study discusses recent advancements in detecting inattentive and aggressive driving behavior using deep learning. It highlights the challenges of real-time deployment, including hardware constraints, varying illumination conditions, and dataset limitations. The authors emphasize the need for robust, lightweight AI models to ensure reliable on-road implementation of driver monitoring systems.

H. Ghourabi, H. Ghazouani et al., Researchers investigated facial expression analysis for non-intrusive drowsiness detection. A deep learning model was trained to recognize micro-expressions linked to fatigue, such as slow blinking, yawning, and eye closure duration. The study found that incorporating gradient-based facial feature extraction improved system performance, making it suitable for real-time driver monitoring applications.

T. Anwar et al.,This research focuses on geo-social-temporal pattern recognition for driver behavior prediction. The study proposes a hybrid AI model that integrates geolocation data, driving speed variations, and environmental factors to assess driver attentiveness levels. The findings indicate that contextual awareness, when combined with machine learning-based vision systems, can enhance the detection of fatigue-related driving patterns.

L. Hong, X. Wang et al., This study introduces a drowsiness detection approach based on multi-feature fusion and Long Short-Term Memory (LSTM) neural networks. The researchers combined facial expressions, head position, and eye gaze tracking to improve detection accuracy. The findings demonstrate that LSTM-based models effectively capture the temporal dynamics of drowsiness progression, making them suitable for real-time monitoring systems in vehicles.

V. Uma Maheswari, R. Aluvalu et al., This paper examines various sleepiness detection systems developed over the past decade, emphasizing the need for improvements in accuracy, cost, and real-time efficiency. The study explores the effectiveness of feature selection techniques, deep learning models, and sensor-based monitoring systems in detecting driver fatigue. The research suggests that integrating computer vision with physiological data can significantly enhance drowsiness detection reliability in real-world driving conditions.

IV.EXISTING SYSTEM:

Current drowsiness detection systems primarily rely on physiological signals, vehicle behavior analysis, and image processing techniques. Some systems use EEG (Electroencephalography), ECG (Electrocardiography), and heart rate variability (HRV) to monitor a driver's fatigue level. Although these methods provide accurate results, they require wearable sensors or intrusive equipment, making them impractical for real-world driving applications.

Another approach involves vehicle-based monitoring systems that analyze steering patterns, lane deviation, and braking behavior. These systems detect erratic driving but can be affected by external conditions such as road type, traffic density, and environmental factors, leading to inconsistent performance.

With advancements in computer vision and artificial intelligence (AI), image-based systems have gained popularity. These systems track facial features such as eye movement, blinking patterns, yawning, and head posture to determine fatigue levels. However, existing image-processing-based solutions still face challenges in varying

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lighting conditions, occlusions, and differences in individual facial features. There is a need for a more robust and adaptive system that can work effectively under different driving conditions.

V.PROPOSED SYSTEM:

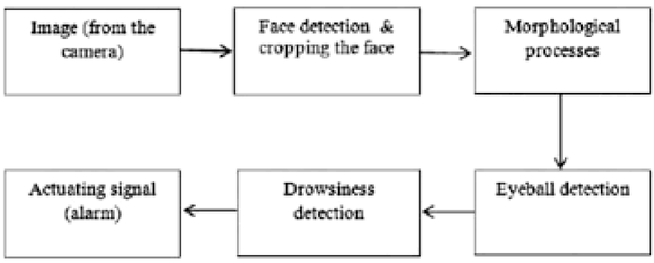
The proposed Driver Sleep Alert System enhances drowsiness detection by integrating image processing, deep learning, and real-time monitoring to create a more efficient, non-intrusive, and accurate solution. Instead of relying solely on vehicle movements or physiological sensors, this system analyzes facial expressions, eye closure (PERCLOS), yawning (MAR), and head movements (FAR, EAR).

A deep learning-based Convolutional Neural Network (CNN) and YOLO (You Only Look Once) model is used for detecting drowsiness in real-time. The system follows these key steps:

- Face Detection: Identifies the driver's face using AI-powered recognition.
- Feature Extraction: Tracks eye, mouth, and head movements to determine alertness.
- Classification: Uses machine learning models to distinguish between alert and drowsy states.
- Alert Mechanism: Triggers an alarm or notification when signs of drowsiness are detected.

The proposed system is designed to function effectively in various lighting conditions and diverse driving environments. It offers higher accuracy, faster detection speed, and a real-time alert mechanism to prevent accidents caused by driver fatigue.

System Architecture



MATHEMATICAL MODEL

The Driver Sleep Alert System can be mathematically represented as:

Let S be the system defined as:

S={I,F,O}S = \{ I, F, O \}S={I,F,O}

where:

- I = Set of inputs (real-time video frames captured by the camera).
- F = Set of functions used to process the input:
  - F1: Face Detection
  - F2: Feature Extraction
  - F3: Drowsiness Classification
  - F4: Alert Generation
- O = Output (Alert triggered when drowsiness is detected).

Feature Extraction Equations

1. Eye Aspect Ratio (EAR):

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

where P1 to P6 are key points of the eye. A low EAR value over a period of time indicates eye closure, suggesting drowsiness.

2. Mouth Aspect Ratio (MAR):

MAR=||P2−P8||||P1−P5||MAR = \frac{||P2 - P8||}{||P1 - P5||}MAR=||P1−P5||||P2−P8||

where P1 to P8 are key points of the mouth. A high MAR value signifies yawning, an indicator of fatigue.

3. Facial Aspect Ratio (FAR):

FAR=∑i=1n(xi−x¯)2nFAR = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n}FAR=n∑i=1n(xi−x¯)2

where x_i represents facial width at different points. FAR is used to detect head tilting or nodding, another sign of drowsiness.

4. Decision Rule for Drowsiness Detection:
   - If EAR < 0.25 for more than 3 seconds → Drowsy
   - If MAR > Threshold (Yawning detected) → Drowsy
   - If FAR changes frequently (Head Nodding) → Drowsy
   - If two or more conditions are met → Trigger Alarm

VI.Future Scope:

The Driver Sleep Alert System has the potential for significant advancements and real-world applications. As technology continues to evolve, various enhancements can be integrated to improve its efficiency, accuracy, and usability.

One of the key areas for future development is multi-modal data fusion, where image processing is combined with physiological sensors such as heart rate monitors and EEG-based drowsiness detection. This would enhance the system's reliability by incorporating biometric indicators along with facial analysis, providing a more comprehensive assessment of driver fatigue.

Another major improvement can be achieved through adaptive machine learning models. Current deep learning-based models can be further optimized using self-learning algorithms that continuously update based on real-time data. This would allow the system to adapt to different drivers, facial structures, and environmental conditions, making it more personalized and accurate.

With the increasing adoption of autonomous and semi-autonomous vehicles, this system can be integrated into Advanced Driver Assistance Systems (ADAS). In semi-autonomous cars, the system can monitor the driver's alertness and hand over control to autonomous driving mode if drowsiness is detected.

VII.RESULT ANALYSIS:

DATASETS:

1)NTHUDDD: NationalTsingHuaUniversity(NTHU) dataset consists of 22 various subsets with different ethnicities at various levels. It has images capture Ing various scenarios while driving, such as yawn Ing, blinking, dozing, and laughing, in various ill munitions. Each scenario is considered from the video consisting of 30 frames/sec [13], [51]. The videos are also simulated with various scenarios like glasses-wearing in the daytime or nighttime, sleepy or non-sleepy, etc.

2)Yaw DD: This dataset is constructed from videos of driving in real-time. The images are captured by cam eras axed either in the front mirror or dashboard. Images of people driving have been collected in color 24-b (RGB) with resolution 640 X 480 from the 30 frames/sec [50]. Images consist of people of all ages, different facial features, ethnicities, etc. All mouth postures are taken in various illumination con dictions while talking, singing, etc.

3)EMOCDS (Eye and Mouth Open Close Data Set): The dataset is comprises of cropped eye and mouth images with open and closed status. The images were taken from Google and it has around 12k images of various peoples images.

5)UTA-RLDD (University of Texas at Arlington Real Life Drowsiness Dataset) [55]: It consists of 180 videos of 60 different participants. Each participant given in three classes drowsiness, alertness, and vigilance with low.

A. CLASSIFICATION:

The model we used is built with Kera's using Convolutional Neural Networks (CNN). A convolutional neural network is a special type of deep neural network which performs extremely well for image classic cation purposes. A CNN basically consists of an input layer, an output layer and a hidden layer which can have multiple numbers of layers. A convolution operation is performed on these layers using a later that performs 2D matrix multiplication on the layer and later. The CNN model architecture consists of the following layers.

1. Convolutional layer; 75 nodes, kernel size 3
2. Max Polling layer: (5,5)
3. Convolutional layer; 64 nodes, kernel size 3
4. Max Polling layer: (5,5)
5. Convolutional layer; 128 nodes, kernel size 3
6. Max Polling layer: (5,5)
7. Fully connected layer; 64 nodes

The Final layer is also a fully connected layer with 2 nodes. In all the layers, a Relu activation function is used except the output layer in which we used Softmax.

B. PERFORMANCE ANALYSIS :

The performance of the proposed system can be ana-lazed using following parameters for measuring classic cation accuracy: True Positive (TP): Yawning/closed eye status is detected as correct one yawning, and the eye is closed. True Negative (TN): Non-yawning/opened eye status is detected as the correct one as non-yawning, and the eye is opened. False Positive (FP): Non-yawning/opened eye status is incorrectly detected as yawning /closed eye. False Negative (FN): Yawning/closed eye status is in-correctly detected as non-yawning/open eye. 54986 Table 6 in particular presents the comparison results with different state-of-the-art algorithms and using the same dataset. The accuracy is calculated in percentage using equation (7): Accuracy TP TN TP TN FP FN 100 (7) The experiments were executed on datasets of NHTUDDD Yaw DD, and an additional dataset created by us. The dataset consists of 45000 images of human beings collected from various sources such as Kaggle, Google images, pixel.com, etc. The eyes and mouth areas were cropped from the images and grouped into four categories to detect the drowsiness based on the closed eye and open mouth status images using EAR, MAR ,and FAR calculations. In addition, gradient and orientations were used to nd the expression and orientation of the face of the driver while driving. Hand gestures or identi cation and glasses detection has done with appropriate algorithms such as convex hull etc. This depicts the drivers concentration on the task of driving. Classi cation has done with CNN deep learning algorithm to check the status of the possible cases mentioned in algorithm 1. Another dataset created by us having 2685 number of images contains scenarios like

TP	FP	TN	FN	Accuracy in %
32	6	1	1	95
32	5	1	2	92.5
35	2	2	1	92.5
36	2	1	1	95
34	2	1	3	90
33	4	2	1	92.5
34	3	2	1	92.5
35	2	1	2	92.5
32	3	3	2	87.5

TABLE 5. TP, FP, TN, FN and Accuracy (in %) for the 40 images tested on the proposed dataset

VIII.Conclusion:

Driver fatigue remains a significant contributor to road accidents worldwide. Existing drowsiness detection systems, while useful, have limitations in accuracy, real-time detection, and adaptability to different driving conditions. Traditional methods such as physiological monitoring and vehicle behavior analysis are either intrusive or unreliable under variable circumstances.

The proposed Driver Sleep Alert System leverages image processing and deep learning to create a non-intrusive, real-time monitoring solution. By analyzing facial expressions, eye movement, yawning, and head posture, the system accurately detects signs of fatigue and triggers timely alerts. The integration of CNN and YOLO-based models enhances detection accuracy, making the system reliable for highway driving, fleet management, and public transportation applications.

This project contributes to the advancement of intelligent driver assistance systems (ADAS), promoting road safety and accident prevention. Future improvements may include multi-sensor fusion, adaptive learning algorithms, and improved real-time processing capabilities to enhance the effectiveness of driver drowsiness detection systems.

IX.References:

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