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DROWSY GUARD REAL TIME DETECTION SYSTEM

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Abstract

Driving while sleepy presents a serious risk to road safety, frequently resulting in collisions and fatalities. The goal of this project is to create a real-time drowsiness detection system that uses non-intrusive video camera technology to track physical indicators of driver fatigue, such as eye closure and head nodding. This approach uses computer vision techniques to analyze changes in the driver's eye state and posture, in contrast to traditional methods that require the attachment of sensitive electrodes to the driver's body, which can be uncomfortable and impractical. According to studies, driving while sleepy can be just as dangerous as driving while intoxicated because it impairs judgment and slows reaction times. Micro sleeps, which are short bursts of sleep lasting two to three minutes and are important markers of drowsiness, are what the system seeks to identify. The system can deliver timely alerts to improve driver awareness and avoid fatigue-related incidents by continuously monitoring the driver's eyes and other physical cues. By guaranteeing that the monitoring procedure is non-invasive while preserving accuracy and dependability, this project highlights the significance of real-world applicability.

Keywords: Eye tracking, Machine learning, Computer Vision

1. INTRODUCTION

Real-time drowsiness behavior related to fatigue manifests through eye closing, head nodding, and changes in brain activity. We can monitor drowsiness by measuring changes in physiological signals, such as brain waves, heart rate, and eye blinking, or by observing physical changes like sagging posture, head leaning, and the open or closed state of the eyes. While the former technique can provide more accurate results, it is impractical, as highly sensitive electrodes would need to be attached directly to the driver's body, which can be distracting and uncomfortable. Additionally, prolonged use may lead to perspiration on the sensors, compromising their accuracy. On the other hand, the second technique—monitoring physical changes (e.g., open and closed eyes)—is more suitable for real-world conditions, as it is non-intrusive. This method uses a video camera to detect changes in eye state. Moreover, "micro sleeps," which are brief sleep episodes lasting 2 to 3 minutes, serve as significant indicators of fatigue. By continuously monitoring the driver’s eyes, we can effectively detect signs of sleepiness and issue timely warnings. By implementing effective drowsiness detection systems, we can significantly improve road safety and reduce the incidence of fatigue-related accidents. Drowsiness significantly impairs a driver’s cognitive abilities, including reaction time, decision-making, and attention span, making it as dangerous as driving under the influence of alcohol. Effective real-time detection systems leverage machine learning models, such as Convolutional Neural Networks (CNNs), to analyze facial features and predict drowsiness states accurately. Integration with IoT devices, including smart sensors and connected cameras, can further enhance these systems by capturing data on steering patterns and lane deviations. Timely alerts, like audio alarms or vibration notifications, play a crucial role in helping drivers regain focus and avoid accidents. However, challenges persist, such as detecting drowsiness in poor lighting conditions, during night driving, or when drivers wear sunglasses. Robust algorithms are needed to account for variations in facial structures. Future solutions may incorporate infrared cameras for low-light detection and hybrid systems combining physiological and behavioral monitoring for higher accuracy. Given that drowsiness contributes to approximately 20% of road accidents globally, implementing comprehensive detection systems is essential for improving road safety and reducing fatigue-related incidents.

2. OBJECTIVE

This project outlines the design and development of a system that focuses on driver's drowsiness detection and prediction.
1.Monitoring the driver behavior by observing the maneuver stability and performance.
2.Validate and measure the progress by using Specific algorithm.
3.Warning the drivers if the behavior beyond the thresholds.
Here we will employ machine learning methods to classify the data of actual human behavior during drowsiness. Devices to detect when drivers are trying to sleep and to provide alert warnings to them of the risk. Drowsiness driving has become a serious concern where even researches are unable to decide which factor lead to the accident. Hence the main objective of the proposed system is to detect drowsiness of the driver using image processing techniques to detect open and closed eye.

3. TOOLS REQUIRED

1. **Python**: Python is a high-level programming language known for its readability and simplicity. As an open- source language, it is free to use for both personal and commercial applications. Python is cross- platform, capable of running on Mac, Windows, and Unix systems, and it has been ported to Java and .NET virtual machines. While often categorized as a scripting language alongside Ruby and Perl, Python excels in creating web applications and dynamic web content. Its compatibility with various 2D and 3D imaging software enables users to develop custom plugins and extensions. Notable applications with Python API support include GIMP, Inkscape, Blender, and Autodesk Maya.

2. **OpenCV**: OpenCV, which stands for Open Source Computer Vision, is a robust library licensed under the BSD license that features a comprehensive collection of advanced computer vision algorithms optimized for hardware acceleration. It is widely used in machine learning, image processing, and image manipulation. With its modular architecture, OpenCV offers shared and static libraries, as well as a CV Namespace. In the context of this application, OpenCV facilitates the loading of bitmap files containing landscape images and enables seamless blending operations between two images, allowing for visually appealing overlays with minimal coding effort. For those interested in delving deeper into image processing and machine learning, OpenCV.org is an invaluable resource.

3. **Machine Learning**: Machine learning is a programming paradigm that empowers computers to learn from data automatically, adapting their behaviour without explicit programming. This capability allows machine learning algorithms to evolve based on the information they process. Python is regarded as one of the leading languages for machine learning due to its intuitive syntax and rich ecosystem of libraries. Notable libraries such as SciPy, Pandas, and NumPy provide essential tools for linear algebra and kernel methods, making Python a preferred choice for implementing machine learning algorithms.

4. **DLib**: Dlib is an open-source library that implements a wide range of machine learning algorithms, including classification, regression, clustering, data transformation, and structured prediction. Similar to DMTL, Dlib offers a high-performance toolkit for machine learning, but it is more frequently updated and comes with an abundance of practical examples. Dlib provides

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extensive supporting functionality, making it a versatile choice for developers seeking to incorporate machine learning techniques into their applications.

4. RELATED WORK:

Deep Learning and IoT System for Driver Drowsiness Detection by Phan et al. (2023),[6] proposes an innovative approach to detect driver drowsiness and provide timely alerts using deep learning techniques and Internet of Things (IoT) technology. The main goal is to enhance road safety by promptly notifying drivers when they exhibit signs of drowsiness, such as yawning or heavy eyelids. The proposed system integrates deep learning models with IoT devices installed in vehicles to monitor driver behaviour in real-time. Convolutional neural networks (CNNs) analyze facial images captured by onboard cameras and classify them into drowsy or alert states. These models are trained on a comprehensive dataset comprising diverse facial expressions associated with drowsiness, ensuring robust performance across various driving conditions. In addition to facial analysis, the system leverages IoT sensors to collect supplementary data such as steering wheel movements, vehicle speed, and lane deviation. This multimodal approach enhances the accuracy of drowsiness detection by considering multiple indicators of driver fatigue[6] **Driver Drowsiness Detection using Viola-Jones Algorithm by** J et al. (2020),[4] proposes a driver drowsiness detection system utilizing the Viola-Jones algorithm. The system, developed by Anitha et al. (2019) aims to address the crucial issue of driver drowsiness, which poses significant risks to road safety. By leveraging the Viola-Jones algorithm, which is renowned for its effectiveness in object detection tasks, the proposed method aims to detect signs of drowsiness in drivers. The paper likely elaborates on the implementation details, experimental results, and performance evaluation of the system in accurately identifying drowsy states in drivers, thus contributing to the advancement of intelligent computing applications in the domain of road safety. **EEG-based Driver Drowsiness Detection using Deep Learning by** U et al. (2019),[10] presents a novel approach to detecting driver drowsiness using electroencephalogram (EEG) signals, which measure brain activity. This method comprises three key components. Firstly, it extracts features from both raw EEG signals and their corresponding spectrograms. These features include energy distribution, zero-crossing distribution, spectral entropy, and instantaneous frequency, providing comprehensive insights into the EEG data. Secondly, deep learning techniques, specifically pre-trained AlexNet and VGGNet models, are employed to directly extract features from EEG spectrogram images. This approach leverages the power of convolutional neural networks for efficient feature extraction from complex data representations. Thirdly, the tunable Q-factor wavelet transform (TQWT) is utilized to decompose EEG signals into sub-bands, and statistical features such as mean and standard deviation of instantaneous frequencies are computed from the resulting spectrogram images. These features capture detailed information about different frequency components present in the EEG signals. Subsequently, all extracted features from each building block are fed into long-short-term memory (LSTM) networks for classification, and the LSTM outputs are combined using a majority voting layer. Evaluation using the MIT-BIH Polysomnographic database with ten-fold cross-validation demonstrates the effectiveness of the proposed method, achieving an average accuracy score of 94.31%. Furthermore, comparison with existing literature reveals superior performance, highlighting the efficacy of the proposed approach in driver drowsiness detection. **Driver Monitoring System for Drowsiness Detection by** Schwarz et al. (2019),[7] presents a study focused on detecting drowsiness using a driver monitoring system. The main objective is to develop a system capable of accurately identifying signs of drowsiness in drivers to prevent potential accidents caused by reduced alertness. The proposed driver monitoring system utilizes various sensors and technologies to monitor driver behaviour and physiological indicators associated with drowsiness. This includes monitoring factors such as eyelid closure, head movements, and changes in driving patterns. Additionally, the system may incorporate physiological sensors to detect changes in heart rate and respiration, which can further indicate drowsiness. To analyze the

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collected data and detect drowsiness, the authors employ machine learning algorithms trained on a dataset of annotated driving scenarios. These algorithms are capable of recognizing patterns and anomalies indicative of drowsiness, allowing the system to provide timely alerts to the driver or trigger automated safety measures. **CNN-based Facial Analysis for Driver Drowsiness Detection by** Singh et al. (2023),[8] addresses the critical issue of road accidents caused by driver drowsiness, a concern highlighted by the National Highway Traffic Safety Administration (NHTSA). Despite various methods proposed to mitigate this problem, relying solely on vehicle-based parameters may not consistently reflect a driver's alertness level. Hence, the paper advocates for a more effective approach to driver drowsiness detection. It introduces deep learning techniques, particularly convolutional neural networks (CNN), as a structured solution to detect drowsiness by analyzing drivers' facial features. The proposed CNN-based method focuses on the eyes and mouth regions, utilizing the nose as a central reference point. Notably, the CNN model is implemented with a rectified linear activation function (ReLU), achieving an impressive accuracy of 94.95%. This performance surpasses existing methods, even under challenging conditions such as low light, varied angles, and the presence of transparent glasses. Through its innovative use of deep learning technology, the paper offers a promising avenue for significantly improving driver drowsiness detection systems and enhancing road safety outcomes.

Real-time Driver Drowsiness Detection using Deep Learning by Dipu et al. (2021),[3] presents an approach to detect driver drowsiness in real-time using deep learning techniques. The primary aim is to improve road safety by promptly identifying signs of drowsiness, such as yawning or drooping eyelids and alerting the driver to prevent potential accidents. The proposed system employs deep learning models, specifically convolutional neural networks (CNNs), to analyze facial images captured by onboard cameras in real-time. These CNN models are trained on a dataset comprising a wide range of facial expressions associated with drowsiness, ensuring robust performance across different individuals and driving conditions. During operation, the system continuously monitors the driver's facial features, extracting relevant information such as eye closure patterns, head movements, and facial expressions indicative of drowsiness. By analyzing these features using CNNs, the system can accurately classify the driver's state as either alert or drowsy. To enhance real-time performance, the authors optimize the architecture and parameters of the CNN models, ensuring efficient inference on resource-constrained devices commonly found in vehicles. This optimization process aims to minimize computational complexity while maintaining high accuracy in drowsiness detection.

Computer Vision and Web Notifications for Driver Drowsiness Alerts by Bhope (2019), [2] proposed a computer vision-based solution integrated with web push notifications. The primary objective is to enhance driver safety by promptly alerting them when signs of drowsiness are detected. The proposed system utilizes computer vision techniques to analyze facial features and detect indicators of drowsiness, such as eye closure and head nodding. Specifically, the system employs machine learning algorithms trained on a dataset of annotated facial images to classify driver states as alert or drowsy in real-time. Once drowsiness is detected, the system triggers web push notifications to alert the driver and prompt them to take necessary actions to maintain alertness. These notifications can be sent to various devices connected to the internet, such as smartphones or in-vehicle infotainment systems, ensuring that the alert reaches the driver regardless of their location within the vehicle**. Optimizing CNN Architecture for Drowsiness Detection using Genetic Algorithms** by Jebraeily et al. (2024),[5] introduces a novel approach to drowsiness detection by optimizing CNN architecture through genetic algorithms. The primary objective is to enhance the performance of CNN-based drowsiness detection systems by automatically optimizing the network architecture to achieve better accuracy and efficiency. The proposed methodology involves the use of genetic algorithms to search and evolve the architecture of the CNN model. By encoding various architectural parameters such as the number of layers, filter sizes, and activation functions into a chromosome representation, the genetic algorithm iteratively evolves and evaluates

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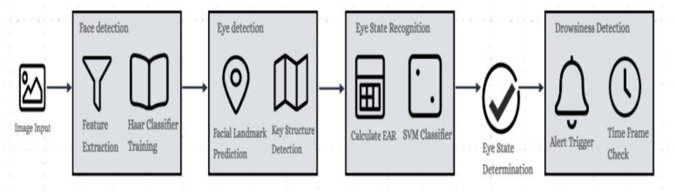
different network configurations to identify the most suitable architecture for drowsiness detection. To train and evaluate the CNN models, the authors utilize a comprehensive dataset containing facial images captured under different lighting conditions and driver states. The dataset includes annotations for drowsy and alert facial expressions, enabling the models to learn and distinguish between these states accurately.

Deep Learning Approach for Classifying Driver Drowsiness States by Suresh et al. (2021),[9] proposes a method for detecting driver drowsiness by leveraging deep learning techniques. The primary objective is to enhance road safety by alerting drivers when they exhibit signs of drowsiness, such as yawning or closing their eyes for extended periods. The proposed system employs a deep learning model trained on facial images to automatically recognize and classify drowsiness-related behaviours. Specifically, the authors utilize CNN to extract meaningful features from facial images, which are then fed into a classification model to distinguish between alert and drowsy states. This approach allows for real-time monitoring of the driver's condition without the need for manual intervention. To train the deep learning model, a dataset containing a diverse range of facial expressions associated with drowsiness is collected and annotated. The dataset includes images of drivers exhibiting various levels of drowsiness, captured under different lighting conditions and driving scenarios. By training the model on this dataset, it learns to effectively recognize subtle cues indicative of drowsiness, such as drooping eyelids or changes in facial expressions.

Wearable EOG-based Continuous Vigilance Estimation for Drivers by WL et al. (2019),[11] introduces a novel method for continuously estimating vigilance levels during driving tasks, aiming to address the critical issue of vigilance decrement that contributes to fatal accidents and jeopardizes public transportation safety. The approach utilizes forehead electrooculograms (EOGs) obtained through wearable dry electrodes, both in simulated and real driving settings. A streamlined electrode placement scheme involving only four electrodes on the forehead is devised to enhance the practicality of the method for real-world deployment. The system incorporates flexible dry electrodes and an acquisition board into a wearable device for EOG recording. Experimental trials involve twenty participants in simulated driving environments and ten in real-world driving scenarios. Accurate eye movement data from eye-tracking glasses are used to calculate the PERCLOS index, which serves as a reference for vigilance annotation. Recognizing vigilance as a dynamic process, the paper introduces continuous conditional random field and continuous conditional neural field models for precise vigilance estimation. Systematic experiments conducted in various illumination and weather conditions, both in laboratory simulations and real-world scenarios, validate the effectiveness of the proposed method. Results indicate that the wearable dry electrode prototype, featuring a comfortable forehead setup, adeptly captures vigilance dynamics. The proposed approach achieves mean correlation coefficients of 71.18% and 66.20% in laboratory simulations and real-world driving environments, respectively. Cross-environment experiments demonstrate simulated-to-real generalization, with a best mean correlation coefficient of 53.96%.

5. SYSTEM DIAGRAM



6. WORKING PRINCIPLE

1. Face Detection: The face detection component utilizes Haar feature-based cascade classifiers, an effective object detection technique introduced by Paul Viola and Michael Jones in their 2001 paper,

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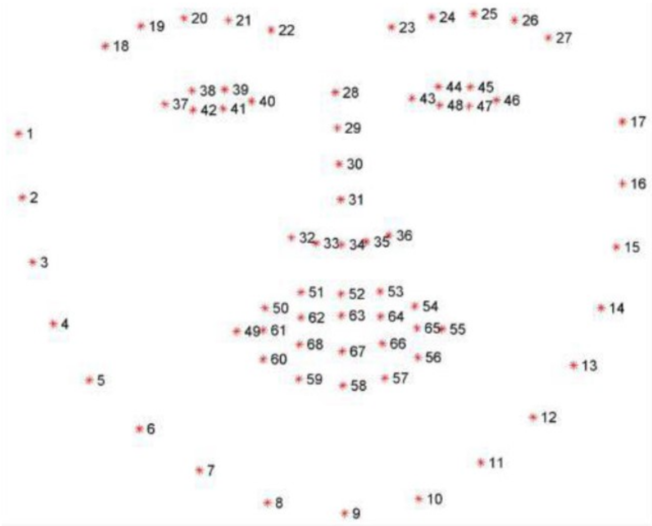
"Rapid Object Detection using a Boosted Cascade of Simple Features." This method employs a machine learning approach in which a cascade function is trained using a large dataset of positive images (images containing faces) and negative images (images without faces). Once trained, this classifier.



2.Eye Detection: In this system, eye detection is performed using facial landmark prediction, which identifies and localizes key regions of the face, including: eyes, eyebrows, nose, mouth, jawline. Facial landmarks have applications in various tasks such as face alignment, head pose estimation, face swapping, and blink detection. The objective of using facial landmarks here is to accurately detect essential facial structures through shape prediction methods. The process of detecting facial landmarks involves two main steps:
1.Face Localization :The face is localized in the image using Haar feature-based cascade classifiers, as discussed in the face detection section.
2.Detection of Key Facial Structures: After localizing the face, various facial landmark detectors are employed to identify and label critical facial regions. The facial landmark detector used in this system is based on the "One Millisecond Face Alignment with an Ensemble of Regression Trees" paper by Kazemi and Sullivan (2014). This method begins with a training set of labelled facial landmarks, where each image is manually annotated with specific (x, y) coordinates indicating the positions of facial structures. Additionally, prior probabilities concerning the distances between pairs of input pixels are utilized. Using the pre-trained facial landmark detector from the Dlib library, the system estimates the locations of 68 (x, y) coordinates corresponding to various facial features. Specifically, the eye regions can be detected using the following landmark indices:
Right eye: [36, 42], Left eye: [42, 48].
These indices are derived from the 68-point iBUG 300-W dataset, on which the Dlib facial landmark predictor was trained. It’s worth noting that alternative facial landmark detectors exist, such as the 194- point model trained on the HELEN dataset.
3.Eye State Recognition: Eye state determination is accomplished through the Eye Aspect Ratio (EAR) calculation, which quantifies the relationship between the height and width of the eyes. The EAR remains relatively constant when the eye is open and approaches zero when the eye is closed. This metric is somewhat invariant to individual differences and variations in head pose. Since eye blinks typically occur synchronously in both eyes, the EAR is averaged across the two eyes for accuracy.
4.Drowsiness Detection: The final step involves determining the driver's condition based on a predefined criterion for drowsiness. The average blink duration is generally between 100-400 milliseconds (0.1-0.4 seconds). To assess drowsiness, the system monitors whether the eyes remain closed for an extended period. A threshold of 5 seconds is set; if the eyes are detected to be closed for five or more seconds, an alert is triggered.

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7.MODULE USED

1.Webcam: The webcam is used mainly to capture the static image or the video stream. This captured image or video stream is given as input to the system.
2.Detect Drowsy: This module includes the following things: image processing, face detection, eye region detection, detect closeness of eye.
3.Image Processing: The image processing module will process the obtained image or video input fed into the system. It processes the input and convert it into frames for further processing.
4.Face Detection: The face detection technique is used to locate the face from the image. The video stream which is given as input is converted into frames and the face is detected from those frames. Haar classifier in Viola Jones algorithm is used to detect the face from a given image.
5.Eye Detection: The position of the driver's eye is determined by using appropriate threshold. In this work, edge detection of the eyes region is considered.
6.Detect Closeness of Eye: After locating the eye region in the frame the system finds out whether the eye is in a closed state or in the open state. If the eye remains open then the
system gives the message that the driver is not feeling drowsy. If the eyes remain closed then the system gives the message that the driver is feeling drowsy.
7.Output: The output from the system includes: alert, message to the cab owner, indication to nearby vehicles. The indication is given in order to prevent road accidents which occur due to the drowsiness of the cab drivers.
8. Alert: The system continuously checks whether the driver is feeling drowsy or not. If the driver feels drowsy then an alert signal in the form of an alarm sound or a beep sound is generated. This is done in order to make the driver to wake up from a sleepy state.

8.RESULTS AND DISCUSSION

8.1.Results

The results demonstrate the accuracy and reliability of the drowsiness detection system. Experimental findings indicate that the use of image processing techniques, specifically the Eye Aspect Ratio (EAR) calculation, achieved an 80% success rate in detecting driver drowsiness in varied lighting conditions.
The system successfully triggered alerts when the driver's eyes remained closed beyond a threshold duration of 5 seconds. The non-intrusive video-based monitoring approach proved to be effective without causing distractions to the driver.

8.2.Discussion

The proposed system's performance shows promise for real-world applications. While the 80% accuracy rate is commendable, improvements can be made to account for scenarios involving sunglass usage or low illumination environments.
The current approach effectively overcomes challenges associated with sensor-based systems by leveraging machine learning algorithms for facial feature detection. However, false positives during sudden head movements or brief blinks present areas for further refinement.

CONCLUSION

The Drowsy Guard Real-Time Detection System addresses the critical issue of driver fatigue by leveraging non-intrusive video-based monitoring. The system's ability to detect prolonged eye closure and issue timely alerts contributes to improving road safety. The findings confirm that real-time image processing can provide a practical solution for drowsiness detection with minimal interference to the driver. Future enhancements could further refine the system's performance, making it adaptable to diverse environmental conditions.

FUTURE WORK

For future work, we will extend our application to detect drowsiness even when the subject is using

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sunglass or color spectacles. Another future study can be done to detect drowsiness is to develop a system which can detect drowsiness in the night or with very low illumination.
Real-time data are always unconstrained and with unconstrained nature of the subject/driver, it becomes very difficult to find facial landmarks. Therefore, to overcome this constraint a more reliable application can be developed which can detect face even when user/subject is not friendly.
We can also provide the user with an Android application which will provide with the information of his/her drowsiness level during any journey. The user will know Normal state, Drowsy State, the number of times blinked the eyes according to the number of frames captures.

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