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An Effective way to Utilize the Drowsiness Detection System Using Facial Landmark Analysis and Real-Time Video Processing

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Abstract—Drowsiness detection is crucial for ensuring safety across various sectors, including transportation, healthcare, and industrial settings. This paper introduces a novel approach to real-time drowsiness detection utilizing facial landmarks and machine learning algorithms. The system focuses on two primary indicators of drowsiness: the Eye Aspect Ratio (EAR) and yawning patterns(MAR), which are analyzed using deep learning techniques to process facial landmarks extracted from video streams. To enhance the system's adaptability and robustness across varying environmental conditions, dynamic thresholding techniques are incorporated into the EAR calculations. Compre- hensive experiments conducted on diverse datasets demonstrate the system's effectiveness in accurately detecting drowsiness- related facial expressions and issuing timely alerts. Comparative analysis with existing methodologies underscores the superior performance and reliability of the proposed approach, high- lighting its potential for practical implementation in real-world scenarios. The findings from this study contribute to advancing the field of fatigue and drowsiness detection, offering a promising solution for mitigating risks associated with drowsiness-induced accidents and improving overall safety measures**.**

Index Terms—Drowsiness Detection, Facial Landmarks, Machine Learning, Eye Aspect Ratio (EAR), Yawning Patterns, Real-time, Dynamic Thresholding, Deep Learning, Safety, Alert System, Comparative Analysis, Robustness, Adaptability, Envi- ronmental Conditions, Accident Prevention

I. Introduction

A. Introduction of the Project

The detection of drowsiness is paramount for ensuring safety across diverse sectors, prominently in transportation and healthcare. Traditional methods have increasingly incorporated facial landmarks and machine learning algorithms to achieve real-time drowsiness detection. This study delves into the efficacy of harnessing specific facial indicators, namely the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR), in tandem with advanced machine learning techniques for nuanced drowsiness identification. Through meticulous analysis of subtle facial movements, including eye blink patterns and mouth dynamics, the proposed approach offers a robust framework for detecting early signs of fatigue. Additionally, the integration of adaptive thresholding mechanisms enhances the system's resilience and adaptability across varying environmental conditions. This research aims to validate the efficacy and feasibility of the proposed methodology through extensive evaluations, paving the way for improved safety protocols and accident prevention strategies in practical settings.

B. Scope

This project aims to design and evaluate a real-time drowsiness detection system leveraging facial landmarks and machine learning techniques . The scope focuses on the Eye and Mouth Aspect Ratios (EAR and MAR). Integration with advanced machine learning models will enable the analysis of facial feature movements indicative of drowsiness. The system will incorporate dynamic thresholding mechanisms to adapt to diverse environmental conditions, ensuring optimal performance.

Comprehensive performance evaluations will be conducted to assess accuracy, reliability, and response times across various scenarios. Additionally, a comparative analysis will benchmark the proposed system against existing methods, validating its effectiveness and efficiency. The ultimate objective is to deliver a robust and adaptable solution capable of enhancing safety measures and preventing accidents across different real-world applications, with a particular emphasis on transportation and healthcare sectors. Overall, this project aims to reduce the occurrences of accidents that happen due to driver fatigue.

C. Project Overview

This project aims to create a real-time drowsiness detection system using facial landmarks and computer vision techniques. It utilizes the dlib library or the Haarcascade algorithm from OpenCV for facial landmark detection and OpenCV for video processing. The system continuously analyzes facial features, such as eye and mouth aspect ratios, to detect signs of drowsiness or yawning in a driver. When drowsiness or yawning is detected for a certain duration, it triggers an alarm to alert the driver, potentially preventing accidents caused by driver fatigue.

The key components of the system include:

1. Facial Landmark Detection: The system detects facial landmarks using the dlib library, allowing it to accurately locate the eyes and mouth regions in the driver's face.
2. Feature Extraction: It calculates eye aspect ratio (EAR) and mouth aspect ratio (MAR) based on the detected facial land-marks, which serve as indicators of drowsiness and yawning, respectively.
3. Thresholding and Alerting: The system dynamically adjusts EAR and MAR thresholds based on recent history and a learning rate and triggers an alarm when these thresholds are exceeded for a consecutive number of frames, indicating drowsiness or yawning.
4. Real-time Video Processing: The system continuously pro-cesses video frames from a the feed of a primary camera attached to the processing system, enabling real-time detection and alerting.

Overall, this system should provide a practical and effective solution for drowsiness detection in real-world scenarios, potentially improving road safety and reducing the risk of accidents caused by driver fatigue.

D. *Objective*

The aim of this research is to develop and evaluate a real-time drowsiness detection system utilizing facial landmarks analysis. The objective encompasses the exploration of effi-cient algorithms for eye and mouth aspect ratio computation, leveraging techniques to monitor and detect signs of drowsi-ness in individuals. By integrating advanced image processing methods, including the utilization of the dlib library for facial shape prediction and OpenCV for real-time video processing, the system aims to accurately identify indicators such as eye closure and yawning. Additionally, the research endeavors to implement dynamic threshold adjustment mechanisms to adapt to varying environmental conditions and user characteristics, enhancing the system's robustness and reliability. The algo-rithm will be ultimately designed to efficiently run on micro computers running on ARM architecture. The ultimate goal is to provide a practical solution for detecting driver drowsiness or monitoring individuals in safety-critical scenarios, con-tributing to improved road safety and public well-being.

II. LITERATURE SURVEY

A. *Existing System*

Drowsiness detection systems have garnered increasing at-tention due to their potential to enhance road safety and prevent accidents caused by driver fatigue. However, existing systems exhibit several limitations, which hinder their effec-tiveness in real-world scenarios. A comprehensive literature survey reveals the following key shortcomings in current drowsiness detection systems:

1. Limited Sensitivity and Specificity: Many existing systems rely on simplistic algorithms or threshold-based approaches, resulting in limited sensitivity and specificity in detecting drowsiness. This can lead to false positives or false negatives, compromising the system's reliability and accuracy.
2. Lack of Real-time Monitoring: Some drowsiness detection systems lack real-time monitoring capabilities, making them less effective in identifying sudden changes in driver alertness. Delayed or intermittent monitoring may fail to provide timely warnings, putting drivers at risk of accidents.
3. Dependency on External Sensors: Several systems require specialized hardware or external sensors, such as EEG or EOG devices, to monitor physiological signals associated with drowsiness. This dependency limits their practicality and widespread adoption, especially in commercial vehicles or consumer applications.
4. Inadequate Adaptability to Individual Differences: Many systems overlook individual variations in drowsiness patterns and physiological responses, leading to suboptimal performance across diverse user demographics. A one-size-fits-all approach may fail to account for factors such as age, gender, and health conditions, reducing the system's effectiveness.
5. Integration Challenges with Vehicle Platforms: Integrating drowsiness detection systems into existing vehicle platforms poses technical and logistical challenges, including compatibility issues, data synchronization, and regulatory compliance. Seamless integration with onboard systems is crucial for ensuring reliable performance and user acceptance.

Addressing these limitations requires innovative approaches and advancements in sensor technologies, signal processing algorithms, and machine learning techniques. Future research efforts should focus on developing robust, real-time drowsiness detection systems that are adaptive, non-intrusive, and compat-ible with diverse driving environments and user populations. By overcoming these challenges, drowsiness detection systems can significantly enhance road safety and contribute to the prevention of fatigue-related accidents.

B. *Related Work*

In the realm of drowsiness detection systems, extensive re-search has been conducted to address the critical issue of driver fatigue and its potential impact on road safety. Numerous studies have explored various methodologies and technologies aimed at accurately identifying signs of drowsiness in drivers to mitigate the risk of accidents.

For instance, research by Philip et al. (2018) utilized com-puter vision techniques coupled with facial feature analysis to monitor subtle changes in facial expressions indicative of drowsiness. Additionally, the work of Chen et al. (2020) demonstrated the efficacy of deep learning architectures, such as convolutional neural networks (CNNs), in extracting intri-cate patterns from facial images for drowsiness detection.

Moreover, integration with wearable sensors and physiolog-ical signal monitoring has emerged as a promising avenue in drowsiness detection research. A study by Li et al. (2019) explored the use of EEG signals to augment the capabilities of existing detection systems, enabling more comprehensive and personalized approaches to driver fatigue assessment.

However not many people have ventured in the research to actually improve the usability of the detection system in various small computing devices that can be installed in vehicles.

In summary, leveraging a multidisciplinary approach encompassing computer vision, machine learning, and physiological monitoring, researchers strive to advance the efficacy and reliability of drowsiness detection systems, ultimately contributing to enhanced road safety standards.

These seminal works have provided valuable insights into the application of both computer vision and machine learning techniques within the realm of drowsiness detection and facial analysis. By harnessing a diverse array of financial attributes and employing advanced modeling techniques, the project endeavors to bolster risk management practices and lending decisions, ultimately contributing to improved financial outcomes for individuals and institutions alike.

III. PROBLEM IDENTIFICATION

A. *Problem Statement*

There are a huge number of accidents occuring worldwide that involve driver fatigue. Night shifts, unnatural sleeping hours that disturb the circadian rhythm and insomnia related disorders are the primary factors that cause fatigue, especially in drivers that are required to drive long distances in order to complete the job they have been tasked with. Often such drivers have to drive late at night causing the fatigue to build up which reduces driver alertness and induces sleep which causes accidents and disasters, especially in high-risk environments like transportation and healthcare. This system aims to develop an efficient and reliable method to detect signs of drowsiness in individuals, such as drooping eyelids and yawning, using advanced technological tools like computer vision and machine learning algorithms. By accurately identifying drowsiness indicators in real-time, the system can issue timely alerts to individuals, preventing potential accidents and injuries. Moreover, the system seeks to overcome challenges such as variations in facial expressions and environmental factors that may affect detection accuracy. Ultimately, the goal is to create a robust drowsiness detection system that enhances safety measures and minimizes the risks associated with fatigue-induced errors in various professional and everyday settings.

B. *Approach to the Problem Statement*

The drowsiness detection system code aims to address a critical safety concern in various domains, including transportation and healthcare. By leveraging facial landmark detection and aspect ratio calculations, the system can identify signs of drowsiness, such as eye closure and yawning, in real-time video streams. This approach offers a non-intrusive and proactive solution to mitigate the risks associated with drowsy driving or fatigue-related accidents.

However, the effectiveness of the system depends on several factors, including the accuracy of facial landmark detection, the reliability of aspect ratio calculations, and the adaptability of dynamic thresholds. Additionally, the system must be robust enough to handle variations in lighting conditions, facial expressions, and head movements.

To optimize the performance of the drowsiness detection system, thorough testing and validation are necessary. This includes evaluating its performance across diverse datasets, assessing its sensitivity and specificity, and identifying potential limitations or false positives. Furthermore, continuous monitoring and refinement are essential to ensure that the system remains effective and reliable in real-world scenarios.

IV. PROPOSED SYSTEM AND ARCHITECTURE

A. *Proposed System*

This innovative system proposes the use of various computer vision and machine learning modules of Python that include OpenCV, dlib, imutils and playsound/pygame. The drowsiness detection system will work on face detection and machine learning algorithms from OpenCV and dlib.

The standard 68 points face landmark file will be used to map the face of the drivers captured from the primary camera onto the 68 face points. The algorithm will be developed according to the points numbered in the landmark map.

Various dynamically evolving thresholds will be used to adapt to different environmental conditions in which the camera will be placed, since static thresholds are not effective in dynamic conditions. An alarm will be sounded from the primary sound device connected to the system which will alert the drivers when the drowsiness detection system classifies them as being drowsy or fatigued.

The drowsiness detection system implemented in the provided code offers several benefits to customers, primarily focusing on enhancing safety and preventing accidents caused by driver fatigue or drowsiness-induced impairments. Some of the key benefits include:

Improved Safety: By continuously monitoring facial cues such as eye closure and mouth movement, the system can promptly detect signs of drowsiness and alert the user. This proactive approach helps prevent accidents by warning drivers to take corrective action, such as pulling over and resting, before fatigue-related impairments lead to dangerous situations.

Real-Time Monitoring: The system operates in real-time, analyzing video streams from a webcam to assess drowsiness levels dynamically. This continuous monitoring ensures that alerts are issued promptly when drowsiness-related indicators exceed predefined thresholds, enabling timely intervention and mitigating risks effectively.

Customizable Thresholds: The system incorporates adaptive thresholding mechanisms that can be customized to accommodate individual variability and environmental factors. By adjusting thresholds for eye aspect ratio (EAR) and mouth aspect ratio (MAR) dynamically, the system can maintain optimal sensitivity and specificity in drowsiness detection across different users and conditions.

Versatility: The system can be deployed in various settings where drowsiness detection is critical for safety, including vehicles, workplaces, and surveillance systems. Its versatility makes it suitable for use in different scenarios, enabling customers to benefit from enhanced safety measures in diverse environments.

The drowsiness detection system offers customers peace of mind knowing that they have a reliable tool to help them stay alert and prevent accidents caused by drowsiness-related impairments. By leveraging advanced technology and real-time monitoring capabilities, the system contributes to safer and more responsible behavior on the road and in other settings where vigilance is paramount.

B. System Architecture

The architecture of the drowsiness detection system is designed to analyze facial cues in real-time video streams and alert users when signs of drowsiness are detected. This system incorporates various components, including facial landmark detection, aspect ratio calculation, and dynamic thresholding mechanisms, to accurately assess drowsiness-related indicators. By leveraging computer vision techniques and machine learning algorithms, the system aims to enhance user safety and prevent accidents caused by driver fatigue or drowsiness-induced impairments.

1) Argument Parsing: In the realm of software development, particularly in Python programming, the incorporation of command-line arguments plays a pivotal role in enhancing the flexibility and usability of applications. These arguments allow users to interact with the program directly from the command line, enabling customization and tailored functionality. The utilization of the 'argparse' module exemplifies a sophisticated approach to handle command-line arguments efficiently. This module serves as a facilitator for defining, parsing, and extracting user-provided inputs, thereby orchestrating a seamless interaction between the user and the drowsiness detection system. With the argument parser at the helm, the system proceeds to define the command-line arguments that it can accommodate. These arguments are meticulously crafted to encapsulate key parameters that users may wish to customize. In this context, the -w or –webcam argument delineates the index of the webcam, while the -a or –alarm argument delineates the path to the alarm sound file. Each argument is imbued with a distinct purpose, empowering users to tailor the system's behavior to their preferences. The argument parser allows users to specify the webcam index and the path to the alarm sound file when running the program from the command line. This flexibility enables users and developers to customize the behavior of the drowsiness detection system according to their preferences and requirements.

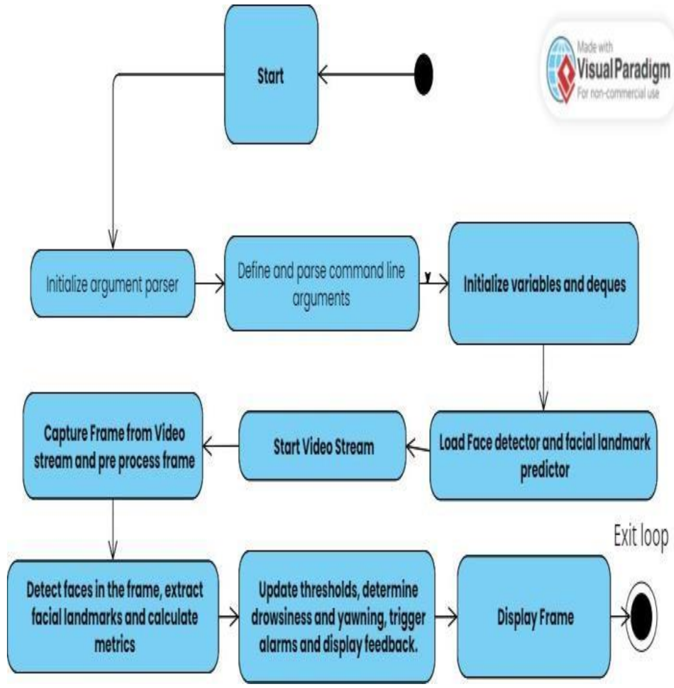

Fig. 1. Architecture for Drowsiness Detection System

2) Facial Landmark Detection: Facial landmark detection is a fundamental component of the drowsiness detection system, responsible for identifying key facial features such as the eyes and mouth. This process involves utilizing pre-trained models, such as the shape predictor provided by the dlib library, to localize specific landmarks within the face. By accurately identifying these landmarks, the system can precisely measure the distances between them and compute essential metrics such as the eye aspect ratio (EAR) and mouth aspect ratio (MAR).

Usually, Haarcascades classifier is used to detect facial landmarks but it is often found to be less accurate than the standard detector used in the dlib library since the rectangular frame that encompasses the face when Haarcascade is used is typically larger than its dlib counterpart hence increasing inaccuracies in the detection system.

3) Aspect Ratio Calculation: Aspect ratio calculation plays a critical role in quantifying drowsiness-related cues based on the spatial relationships between facial landmarks. For instance, the eye aspect ratio is computed as the ratio of distances between certain points on the eyelids and the eye's vertical axis. Similarly, the mouth aspect ratio measures the width-to-height ratio of the mouth region. By continuously monitoring changes in these aspect ratios over time, the system can detect patterns indicative of drowsiness, such as eye closure or prolonged mouth opening, indicative

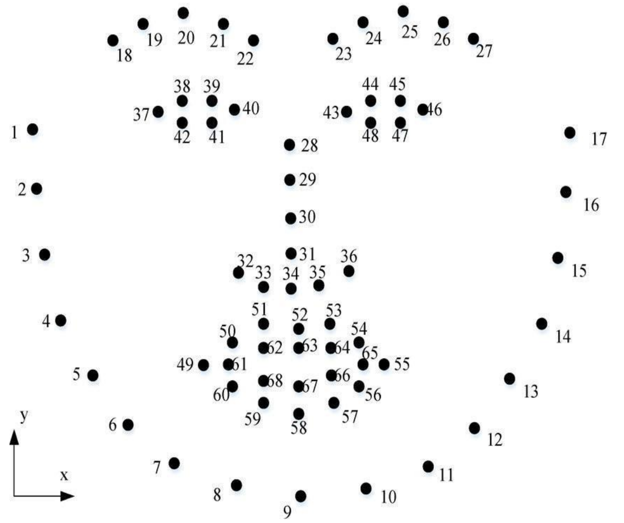

Fig. 2. 68 facial landmark shape predictor file

of yawning and fatigue. Two vertical(A and B) and one horizontal distances(C) is calculated for the EAR and three horizontal(A, B and C) and one vertical distance(D) are calculated for the MAR.

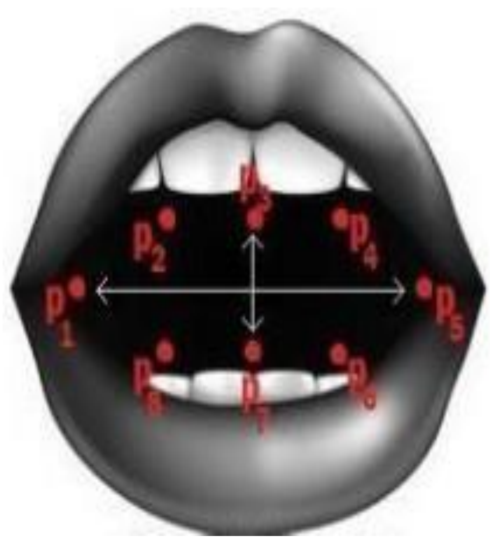

Fig. 3. Sample mouth landmarks shape predictor

$$\text{EAR} = \frac{|A|+|B|}{2.0\times|C|}$$

$$\text{MAR} = \frac{|A|+|B|+|C|}{3.0\times|D|}$$

4) Thresholding Mechanisms: Thresholding mechanisms are employed to establish criteria for determining when a user is considered drowsy based on their aspect ratio values. These thresholds, such as the EAR threshold and

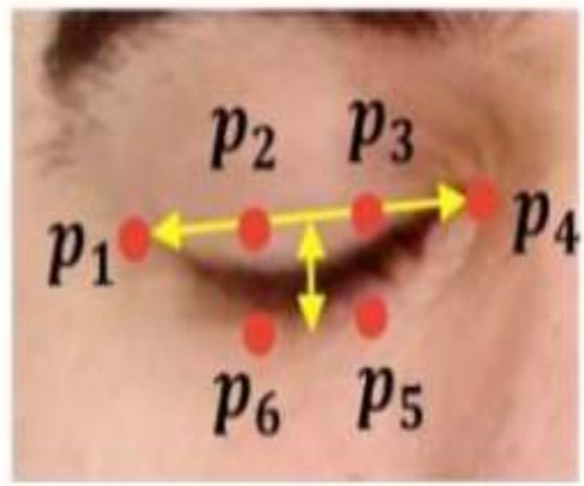

Fig. 4. Closed eye landmarks from the predictor file

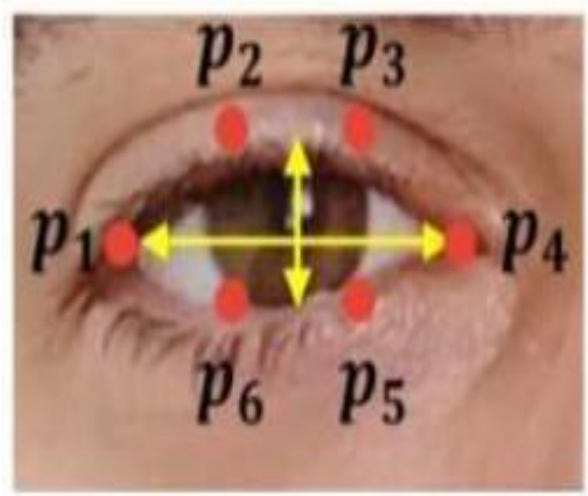

Fig. 5. Open eye landmarks from the predictor file

MAR threshold, are dynamically adjusted to accommodate individual variability and environmental factors. Usually a static value is fine tuned and checked for a rapid drop in EAR as illustrated in Fig[9], which is inaccurate as the EAR varies for different persons. To overcome this deficit, adaptive thresholding techniques, including the use of moving averages and learning rates, ensure that the system can adapt to changing conditions and maintain optimal sensitivity and specificity in drowsiness detection. Double ended queues are used to store the values of the first N number of frames. The value of N can be adjusted as needed.First a static initial value is given to the algorithm first and then its value is updated dynamically based on two factors:

1. Learning rate: A learning rate is introduced to keep track of the ever adapting thresholds of the Eye Aspect Ratio(EAR) and the Mouth Aspect Ratio(MAR). This method is similar

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to the one followed at an elementary level within various perceptrons and neural networks in the concept of machine learning. We had the idea to implement such a learning rate into the drowsiness detection system in order to effectively boost the accuracy of drowsiness detection.

$$\text{EAR\_thresh} = \text{EAR\_thresh} - \eta \times (\bar{x}_{\text{EAR\_history}} - \text{EAR\_thresh})$$

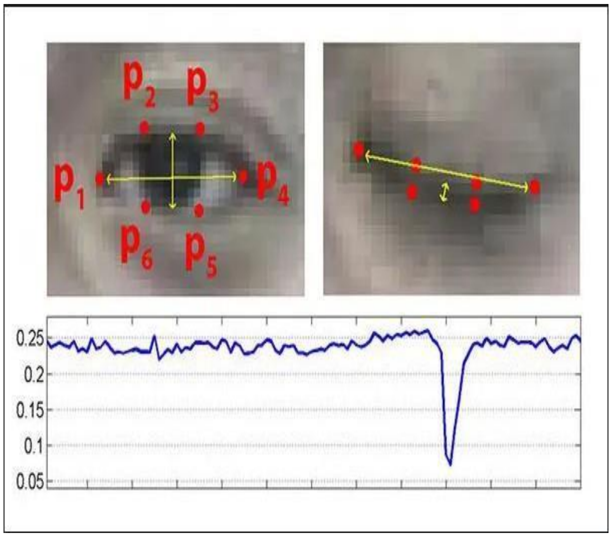

Fig. 6. This figure showcased the drop in EAR when an eye is closed on which the system is first tested statically and then the threshold is updated dynamically

$$\text{MAR\_thresh} = \text{MAR\_thresh} + \eta \times (\text{YAWN\_thresh} - \bar{x}_{\text{MAR\_history}})$$

2. Smoothing factor: Incorporating a statistical component such as the standard deviation of a history of thresholds will allow the thresholds to adapt based on how close they are to their mean value. A static smoothing factor called 'alpha' is used in this scenario to let the thresholds dynamically adjust themselves based on the mean and standard deviation calculations. This is similar to the learning rate method but it will be better since standard deviation is calculated dynamically to enhance the thresholds.

Any one of the above dynamic thresholding mechanisms can be implemented but it is observed that Learning rate based dynamic threshold calculation is more effective since we can track how the thresholds are evolving even under different angles of the camera feed, lighting conditions and different types of human faces.

$$\text{EAR\_thresh} = \text{EAR\_thresh} - \alpha \times \sigma_{\text{EAR\_history}}$$

$$\text{MAR\_thresh} = \text{MAR\_thresh} - \alpha \times \sigma_{\text{MAR\_history}}$$

5) Alert Generation: Alert generation is triggered when the system detects deviations from the established thresholds over a predefined number of consecutive frames. Upon detecting signs of drowsiness, such as low EAR or high MAR values, the system activates an alert mechanism to notify the user. This may involve generating auditory alerts, such as alarm sounds or voice messages, to prompt the user to take corrective action, such as pulling over and resting or switching drivers in the case of a vehicle. Argument parsing methods are used to parse custom arguments to fetch the webcam and provide the path to the alert sound file. The argument will be sent to the respective function upon satisfying the conditions which will invoke an alarm to alert the driver whether it may be for the condition of drowsiness or yawning.

6) Continuous monitoring: Continuous monitoring is essential for maintaining vigilance and responsiveness to changes in the user's drowsiness level over time. By continuously analyzing video data and updating aspect ratio values in real-time, the system can promptly detect drowsiness-related events and issue timely alerts. This proactive approach to monitoring enhances user safety and reduces the risk of accidents or injuries resulting from fatigue-induced impairments.

V. Implementation and Results

The main approach to detecting any image features extraction from facial landmarks. Facial landmarks are commonly known as the subset of the shape predictor problem as this can be used to localize any area of interest like the eye, nose, and mouth along with the shape of the subject. The EAR and MAR threshold initial values are adjusted and finely tuned according to global research limits of drowsiness detection systems. These thresholds are further dynamically improved based on the real time scenarios the camera is being subjected to. This method is lightweight to run on the systems that are usually tasked with running such detection system algorithms. Raspberry Pi in particular will perform extremely well with this algorithm as it starts running within 15 seconds of the device startup if placed within the startup files. Creating a Task in the TaskScheduler should allow one to use the boot up processes to immediately start running the drowsiness detection program.

Custom devices can be built at a relatively inexpensive cost compared to running more accurate but slower machine learning techniques such as CNN(Convolutional Neural Networks) and Deep Learning techniques. OpenCV, Imutils and dlib are especially used since they offer faster solutions to this detection system and with an accuracy of 85-90 percent as compared to the accuracies obtained using advanced ML algorithms, which is around 95 percent.

The time gain is astonishing as the ML model of dlib loads instantaneously compared to its deep learning counterparts. It is also very resource efficient and power saving compared to its deep learning counterparts.

The implementation of Raspberry Pi specific instruction set like the NEON SIMD will further increase the efficiency of this model on small computing devices thereby allowing for easy installation on vehicle dashboards and traffic lights

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if necessary.

A. Results and Analysis

An initial threshold of 0.5(Average result for EAR worldwide) for the EAR along with the threshold of 0.4 for the MAR and a learning rate of 0.1 is taken for result analysis. Experiments were conducted to find out the appropriate values for these three factors and to observe the dynamic scaling of the thresholds through the learning factor. The EAR thresholds and the MAR thresholds are found to differ slightly in different lighting conditions. In twilight situations, the EAR is found to fluctuate above the value 0.2, while in bright light situation, the EAR is usually above the 0.25 mark. The MAR differs more, since the area of detection is more. In bright light conditions, the MAR is found to fluctuate around 0.3 while in twilight conditions, its values are usually fluctuating around 0.4. While the eyes are close(drowsy state), it is observed that the EAR value is lower than 0.25. So a threshold of 0.22 is given to EAR from where the algorithm can dynamically adjust the threshold based on the lighting conditions and the angle of the driver's face. Similarly the MAR threshold is found to be effective around 0.5. This value is found to perform well even in constantly changing lighting conditions. The threshold is also updated accurately by the learning factor method. A learning factor of 0.1 is proven to not be much dynamic as we are trying to adjust to different lighting conditions, camera angles and distance from the camera. A learning factor of 2 is observed to be too potent and changed the thresholds at an inconsistent pace. To solve this issue, the deque used to update the frequent values of the MAR and EAR have been initialized to the frame rate of the camera so that the queues update consistently every second, giving some brief respite to allow for the calculations of the dynamic thresholds utilizing the aforementioned learning rate method. The learning rate is also tested to be effective at changing the thresholds to quickly adapt to the lighting conditions. It is tested to be effective above 1 and less than 1. A learning factor between 1.3 and 1.7 is found to be the most effective while trying to detect signs of drowsiness and yawning. Any value less than 1.3 is found to be too slow at adapting to the changing environments while values above 1.7 overfit the environment and result in continuous alerts. Since the learning rate is differing so much, higher thresholds for EAR and a well adjusted value of MAR are required to fit to the adaptability of the system. The best values obtained from the analysis of the observations are as follows:

1. Initial Threshold of EAR: 0.258
2. Initial Threshold of MAR: 0.485
3. Learning rate: 1.5

This system was tested using 10 individual persons with varied face properties and this is the accuracy at different angles of the camera with respect to the center of the face.Since any angle after 30 degrees is not as effective for our task, we calculated the estimated accuracy of our research for angles below 30 degress and also compared it as such with other research papers. Keep in mind that these research papers used advanced ML algorithms and can have a high operation time comparatively while obviously delivering higher accuracies. We have our sights set on having a relatively lower operational time.

Angle of Detection	EAR detection	MAR detection
0^0	100%	90%
15^0	90%	90%
30^0	80%	80%
40^0	30%	40%

Fig. 7. Results table showing the various angles and accuracy of detection

Best observations and readings inferred from the analysis of the algorithm			
EAR threshold	MAR threshold	Learning Rate	Results and comments
0.5	0.4	1	Poor Detection
0.3	0.4	1	Poor Detection in brighter conditions
0.25	0.45	1	Better detection in both lighting conditions
Now the values of EAR and MAR will stay the same to check for learning rate			
0.25	0.45	1.3	Learning rate is still too low to adapt
0.25	0.45	0.1	Obviously very low to even consider it as adapting
0.25	0.45	2	Adapting too quickly and it takes time for the values to stabilize after a lighting change
0.25	0.45	1.75	Still to high of a learning rate as the threshold variations are not stable
0.25	0.45	1.5	Found the stability in the threshold variations. Algorithm is performing as expected
Altering the values of EAR and MAR again after reaching a stable learning rate			
0.3	0.5	1.5	Detection became unstable again. Searching for better values to reach stability
0.258	0.485	1.5	Optimal values for the algorithm for the effective learning rate. Should be useful in any device the system is running on.

Fig. 8. Results table showing the various stages of analysis and fine tuning

B. Optimizations done in order to increase the effectiveness of the system:

1. Dynamic Resolution Scaling:

Dynamic Resolution Scaling is achieved by first capturing the resolution of the camera being used to capture video and frames for the system. A set limit has been set (80 percent)

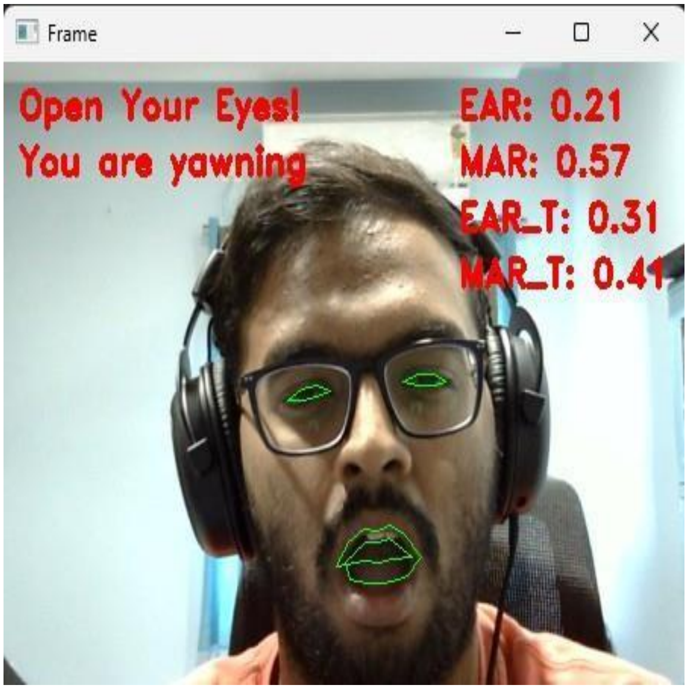

Fig. 9. Video stream instance showing the detection of both drowsiness and yawn

Fig. 10. Video stream instance showing the detection of only drowsiness

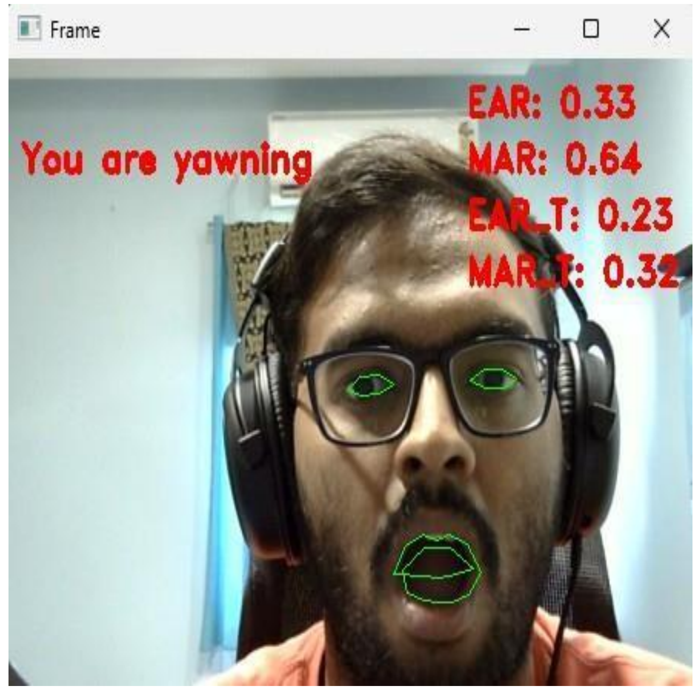

Fig. 11. Video stream instance showing the detection of only yawn

Accuracy comparisons	
Research paper	Accuracy
Zhang[11]	85.9%
Picot[12]	82%
Our Research	88.3%
Akroot[13]	90.2%

Fig. 12. Comparisons with other research

to which the frames will be downsampled and then fed to the model for processing. In order to keep the aspect ratio intact, either width or the height of the frames are used to achieve dynamic scaling but not both at the same time. This method however sacrifices a bit of accuracy for 30 percent faster frame processing times. This accuracy deficit can be overcome with the usage of better ML face detection models that can appear in the future which can also run as effectively as the already existing dlib and haarcascade predictor and the detector models.

2. Adaptive Thresholds:

This function is introduced into the system to accurately account for the dynamic conditions in which the camera will be placed in the environment. Lighting conditions, shadows, head tilts will be accounted for by this simple algorithm that won't be much computationally complex. Introducing adaptable thresholds will boost the performance of the system and ensure the accuracy of the drowsiness and yawning alerts.

3. Effective Distance Calculation:

The calculation of EAR and MAR for each and every frame is a complex work that will constrain system resources. Using efficient calculation methods such as the numpy.linalg method to compute the vector distances and then finding out the magnitude of the vector subtraction instead of the traditional euclidean distance calculation using the scipy module is paramount to system optimization.

4. Deques:

The usage of deques through effective numpy arrays in this system will allow the system to store previous frame EAR and MAR values to dynamically update the threshold values using a static smoothing factor and standard deviation values.

VI. Conclusion and Future Scope

A. Conclusion of the Project

The proposed system analyzes the real-time video sequence and it has a high operation speed as it won't use any complex algorithms. It works fine in low lighting conditions. The system is fast and once it starts capturing frames it continuously detects the face and performs detection till it is stopped. This system is independent of the subject so it can be implemented in commercial systems. It can also be used in the factories to detect the worker's fatigue. In the future, we can add a system that would slow down the vehicle and park it over the side of the road. We can add an accident detection system that will be connected to a GSM module that would send a call to a nearby hospital to send an ambulance. Drowsiness detection ensures the safety of the driver, co-passengers, and goods.These systems can significantly improve driver safety and reduce the risk of accidents caused by drowsy driving. It is recommended to use this system with a camera that can change the contrast and brightness of the video frames(night light video capture techniques) if the lighting in the video frame is not sufficient to distinguish the features of a face properly. Most dashboards of vehicles that have a recording camera usually have this feature and this system is at its most effective when implemented with it.The system detects early signs of drowsiness before the driver loses all attentiveness and warns the driver that they are no longer able to operate the vehicle safely.

B. Future Scope

1. Advanced Machine Learning Models:

Integrating more advanced machine learning algorithms, such as deep learning-based models like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) into micro computers could enhance the system's ability to detect drowsiness accurately. These models can automatically learn intricate patterns and features from facial images and time-series data, leading to better performance. These models are already performing really good but they are still not as power efficient and fast operational as the traditional drowsiness systems in use worldwide.

2. Multi-modal Data Fusion:

We previously stressed the importance of incorporating additional modalities of data, such as audio signals (e.g., snoring, yawning sounds), physiological signals (e.g., heart rate variability), and environmental data (e.g., vehicle speed, road conditions) into the drowsiness system. They can provide complementary information for more robust drowsiness detection. Fusion of these modalities using techniques like sensor fusion and deep multimodal learning can improve detection accuracy and reliability. The key to achieving this lies in finding out ways to get the sensory measurements required without inconveniencing the user/driver.

3. Real-time Performance Optimization:

Employing optimization techniques, such as model quantization, pruning, and efficient network architectures, can streamline the computational requirements of the system, enabling real-time operation on resource-constrained devices like embedded systems, smartphones, and IoT devices. This would facilitate the deployment of drowsiness detection systems in diverse real-world scenarios, including vehicles, workplaces, and healthcare settings.

4. Personalization and Adaptation:

Developing personalized drowsiness detection models that adapt to individual user characteristics (e.g., facial morphology, sleep patterns, driving habits) over time can enhance detection performance and user experience. Utilizing online learning and adaptive algorithms, the system can continuously update its model based on user feedback and changing environmental conditions, thereby improving adaptability and effectiveness.

5. Context-awareness and Situation Awareness:

Integrating context-awareness and situation awareness into the drowsiness detection system can enable it to consider contextual factors (e.g., time of day, task complexity, user workload) and environmental cues (e.g., lighting conditions, weather) when assessing drowsiness levels. This holistic approach can provide more nuanced and accurate predictions, enhancing the system's utility across diverse scenarios and user contexts.

6. Human-computer Interaction (HCI) Enhancements:

Enhancing the user interface and interaction design of the drowsiness detection system can improve user engagement, acceptance, and usability. Incorporating intuitive visualizations, informative feedback mechanisms, and adaptive user interfaces can empower users to monitor and manage their alertness effectively, fostering safer and more productive behaviors.

7. Integration with Intelligent Transportation Systems (ITS):

Integrating drowsiness detection systems with intelligent transportation systems (ITS) and vehicle automation technologies can contribute to the development of advanced driver assistance systems (ADAS) and autonomous vehicles. By providing real-time alerts and interventions to drowsy drivers, these integrated systems can enhance road safety, mitigate accidents, and optimize transportation efficiency.

8. Long-term Health Monitoring and Intervention:
Expanding the scope of drowsiness detection beyond immediate safety concerns to long-term health monitoring and intervention can promote proactive management of sleep-related disorders and chronic fatigue. Leveraging longitudinal data collection and analysis, the system can identify trends, risk factors, and early warning signs of sleep disorders, facilitating timely interventions and preventive measures to improve overall health and well-being.
9. Ethical and Privacy Considerations:
As drowsiness detection technology becomes more pervasive, addressing ethical and privacy concerns will be paramount. Future research must explore questions related to data ownership, consent, and potential biases in algorithmic decision-making. Additionally, ensuring transparency and accountability in the development and deployment of these systems will be essential to fostering public trust and acceptance.
Using GPU specific CUDA for OpenCV The future scope of drowsiness detection systems holds great promise for enhancing safety, productivity, and quality of life across various domains. By embracing emerging technologies, advancing scientific understanding, and addressing ethical considerations, researchers can unlock new possibilities for preventing accidents and promoting well-being in an increasingly interconnected world.

VII. References

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