DRIVER DROWSINESS DETECTION BASED ON JOINT MONITORING USING MACHINE LEARNING

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ABSTRACT - Road traffic crashes that cause fatalities and serious injuries are still a major global concern, and current forecasts suggest that this problem will not go away for some time. Every year, car crashes result in over 1.3 million fatalities, and many of these are caused by fatigued drivers. We provide a methodology for identifying driver tiredness during lengthy trips in order to reduce the likelihood of such occurrences. Our solution maximizes performance without introducing intrusive measures that could cause driving distractions by combining image processing techniques with driver-vehicle interface methods. A monitoring system is required to identify indicators of driver drowsiness because it is a significant contributing element to traffic accidents. Three categories of data are usually analyzed by driver monitoring systems: driver graphical data, vehicle behavior patterns, and biometric signs. This analysis summarizes recent improvements in sleepiness detection systems with multiple approaches, including as arousal level detecting technologies applicable to driverless situations. Rather than being used for real-time accident avoidance, such technologies might guarantee that drivers are enough rested to reach their destinations safely and comfortably in autonomous driving levels 4 and 5, where the driver is not actively engaged in major driving activities.

1. INTRODUCTION

Every year, traffic accidents cause hundreds of thousands of fatalities worldwide. When cars get into the wrong hands and become weapons of mass destruction, even something as simple as a tiny error can have disastrous consequences. One Driving while fatigued is a critical form of negligence that is linked to a high number of accidents. This project aims to improve implementations targeted at preventing accidents caused by driver tiredness by offering new viewpoints and data. This will help address the issue and provide extra insights for enhancing current systems. For example, car accidents claimed the lives of 148,707 people in India in 2015 alone; at least 21% of these deaths were the result of mistakes made by tired drivers. These numbers probably understate the real impact of weariness as an accident-causing factor, especially in developing nations with poor infrastructure. Fatigue is difficult to quantify or monitor objectively, unlike substances like cocaine or alcohol, which have obvious tests and symptoms. Increasing public awareness of tiredness related accidents and motivating drivers to recognize their own exhaustion as a serious safety risk are two effective ways to address the issue. But raising general awareness is difficult and expensive. Although there are already a number of products available to evaluate driver weariness, sophisticated methods for detecting vehicle drowsiness provide increased safety advantages along with higher accuracy. In addition to identifying early indicators of drowsiness, these systems warn drivers when their level of exhaustion approaches a certain threshold, which may help avoid accidents. When someone is drowsy, they often feel close to sleep and have a strong desire to go to sleep. It presents serious risks, particularly when driving or performing other duties that call for prolonged concentration. Extended periods of driving without sufficient sleep can cause poor judgment and delayed reaction times, which raises the possibility of collisions. This project's main objective is to replicate drowsiness detection systems by keeping a watch on the driver's mouth, eyes, and head position. Through examination of these indicators, It is possible to identify early indicators of sleepiness in order to avert mishaps. For example, yawning detection is a good way to tell when you're tired because it signals that you need to get some oxygen before you start to feel sleepy. Analyzing facial picture sequences to track whether the lips and eyes are open or closed is one method of detecting exhaustion. Methods such as PERCLOS calculate the proportion of time that the driver's eyes are closed, providing information about their level of attentiveness. In conclusion, combating driver fatigue continues to be a major global road safety concern. Putting in place efficient detection systems—possibly with the help of vision-based techniques that capitalize on advances in image analysis—can greatly increase the safety of motorists, passengers, and pedestrians.

OBJECTIVE

The project's goal is to:

- Decrease the number of accidents on the road that are brought on by tired drivers.
- To identify and notify drivers when they become sleepy.
- To improve general traffic safety.
- To create a system that can identify tiredness and drowsiness by using yawning and eye closure.
- To put in place a system that recognizes shifts in head posture that suggest sleepiness while driving.

II. PROBLEM STATEMENT

The objective is to create a system that can accurately detect drowsiness in drivers by combining multiple monitoring inputs—specifically visual cues like facial expressions and head movement along with physiological data (such as EAR and MAR. The lack of a robust, real-time system that integrates these modalities limits the effectiveness of current drowsiness detection solutions.

EXISTING SYSTEM

• **Daytime travel:** Driving just during the day takes advantage of the best visibility, which reduces the risk of accidents caused by fatigue. Natural light increases general driver vigilance and encourages alertness.

•**Companion interaction:** Talking to a passenger helps maintain driver attention since it stimulates the brain and allows for social connection. This is especially helpful on long trips.

•**Nap breaks:** Fighting weariness with frequent breaks—even quick naps—proves to be beneficial. The driver's mental clarity and level of focus can be restored by finding a safe place to stop and taking a quick break.

•**Caffeine consumption:** Caffeine-containing beverages, such tea and coffee, provide a mild stimulant effect that momentarily increases alertness and cognitive function. This technique is frequently used to prevent fatigue when driving.

•**Auditory engagement:** If you're going on a long drive and need to keep your concentration while driving, listening to music, podcasts, or other aural content might help you stay engaged and relieve boredom.

•**Physical activity:** In order to improve blood circulation and lessen stiffness and discomfort, which can lead to driver fatigue, drivers should stretch or take brief walks during breaks.

PROPOSED SYSTEM

To successfully detect driver tiredness, the suggested method integrates three facial features: Eye Aspect Ratio, Mouth Aspect Ratio, and Head Pose, which is identified via Optical Flow. The vertical and horizontal distances between face landmarks, like the mouth and eyes, are measured by EAR and MAR. The technology may identify signs of tiredness such as eye blinking and yawning by continuously monitoring EAR and MAR. Optical Flow-based head position detection detects when a motorist nods, which is a major indicator of driving weariness. Following the successful computation of EAR, MAR, and head posture using Optical Flow, these features are merged to serve as the input for K-Nearest Neighbors and Multi-Layer Perceptrons, two classification models. These algorithms for machine learning are used to to determine, depending on the combined attributes, whether the driver is alert or sleepy. In contrast to conventional threshold-based methods, KNN and MLP employ leverage the continuous monitoring of various facial features to improve the system's efficiency in identifying drowsiness. This method enhances the system's accuracy in various driving scenarios and lighting situations, making it appropriate for real-time use in a range of driving environments. Through the integration of several facial feature analyses and sophisticated classification algorithms, the proposed system seeks to mitigate the hazards associated with driver drowsiness and improve overall road safety by means of proactive alerts to drivers.

ADVANTAGES OF PROPOSED SYSTEM

● Enhances driving safety for drivers.
● Real-time fatigue detection and prompt action to prevent mishaps.
● Accurately determine the head position, eye aspect ratio, and mouth aspect ratio.
● Prevents fatigued drivers from causing accidents on the road.
● Integration of selected techniques.
● Development and testing of the code.
● Full testing and enhancement.

III. METHODOLOGY

The Proposed system consists of five steps to detect the drowsiness of the driver.

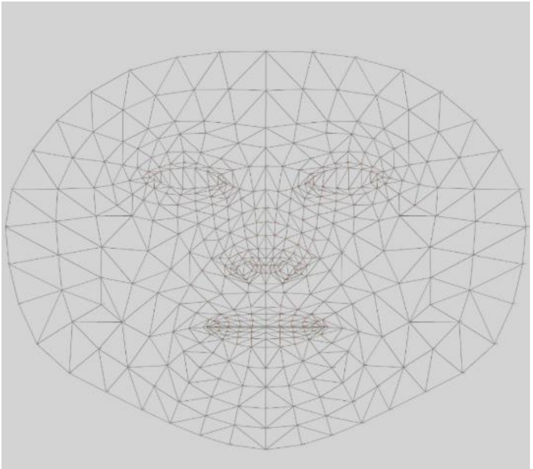
● Every input frame must first undergo preprocessing.
● Face detection and alignment
● Every frame's features are extracted
● Features are merged before being sent into a supervised classifier
● MLP and KNN are used to classify the inputs and to ascertain the driver's state; the prediction outcome of each frame is a binary value that indicates whether the driver is sleepy or not.

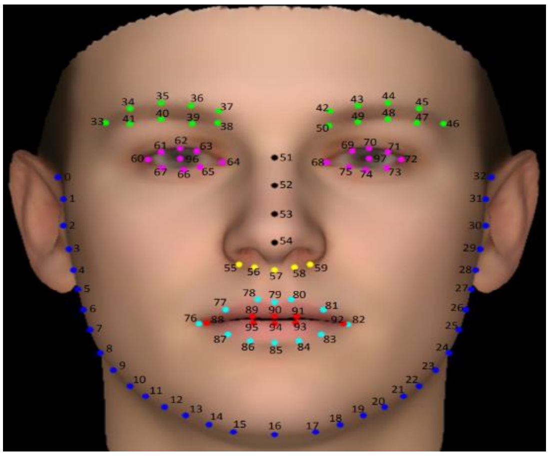
PREPROCESSING

To prepare each image and frame of the incoming video for Landmarks detection, preprocessing is applied. The process is known as gamma correction. Gamma correction regulates an image's overall brightness. It is employed to adjust for discrepancies in how a camera records images, how a display shows those images, and how our visual system interprets light.

FACE DETECTION AND ALIGNMENT

Regression tree assemblies are employed in this standard technique for face alignment, which is based on the extraction of 68 coordinates of facial landmarks. The technique identifies the facial landmarks under situations of wearing light. A solution that estimates 468 3D face landmarks in real-time, even on mobile devices, is Media Pipe Face Mesh, Instead of requiring a separate depth sensor, it uses machine learning to infer the 3D facial surface from a single camera input. Making use of lightweight model architectures in conjunction with GPU augmentation The solution provides real-time performance necessary for live experiences throughout the pipeline. It uses transfer learning to train a network with multiple goals for 3D face landmarks: the network simultaneously predicts 2D semantic contours on annotated real-world data and 3D landmark coordinates on synthetic rendered data. The resultant network gave us accurate 3D landmark predictions based on both synthetic and real-world data.

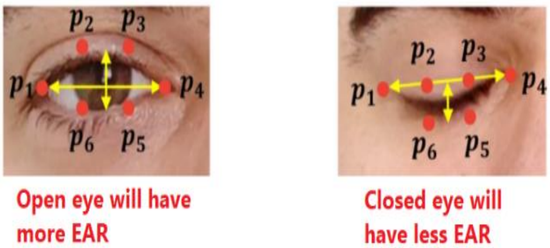




FEATURE EXTRACTION EYE ASPECT RATIO

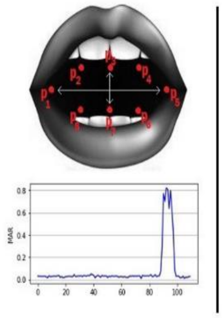
The Czech Technical University proposes the Eye Aspect Ratio. It is a scalar quantity that may be acquired by identifying a face in an image, figuring out the eye coordinates' Euclidean distance, and then entering that value into the formula

$$EAR = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{2\|p_1 - p_4\|}$$



MOUTH ASPECT RATIO

The driver drowsiness systems employed this measurement to determine how wide open the mouth is during yawning. We can't rely solely on EAR because drivers' eyes can occasionally be obscured. Yawning is the next sign of exhaustion and sleepiness. It is an indication of fatigue. One way to address yawning is to measure the mouth aspect ratio, MAR rises when the mouth opens. The motorist is considered drowsy when the MAR is higher than a predetermined threshold.



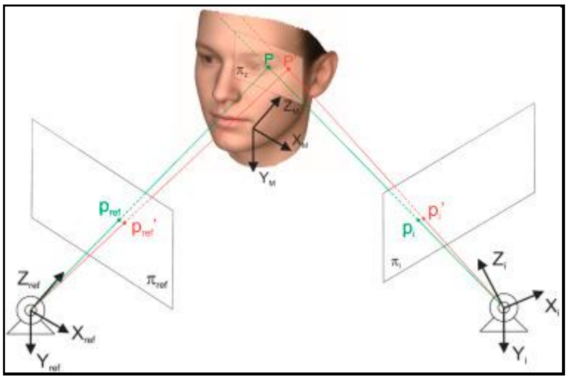
$$MAR = \frac{\|p_2 - p_8\| + \|p_3 - p_7\| + \|p_4 - p_6\|}{2\|p_1 - p_5\|}$$

HEAD POSE MULTI LAYER PERCEPTRON

An essential part of head pose estimation is head detection. In this project, nodding is also taken into account as a sleepiness aspect.head position is inferred by examining the optical flow of the frames being taken. First, which may be thought of as an initialization phase, we extract the background depth data. After that, a new depth array's background is subtracted to create a difference matrix. The pixel is set to zero if the difference is less than a threshold; if not, it is kept, producing a matrix with the foreground's depth information. A pixel and its neighbors are on the same item if the depth difference between them is smaller than a threshold of 0.1-0.2m, based on prior information about the human body. A segmented item is deemed inhuman and is rejected if its pixel count falls below a certain threshold.

- First, the face's center point is located.
- The box representing the face bounding is obtained by halving its width and height. The optical flow algorithm developed by Lucas-Kanade is used to identify facial movement. The formula is displayed.

$$\begin{bmatrix} \sum I_x I_x & \sum I_x I_y \\ \sum I_x I_y & \sum I_y I_y \end{bmatrix} \begin{bmatrix} u \\ v \end{bmatrix} = - \begin{bmatrix} \sum I_x I_t \\ \sum I_y I_t \end{bmatrix}$$

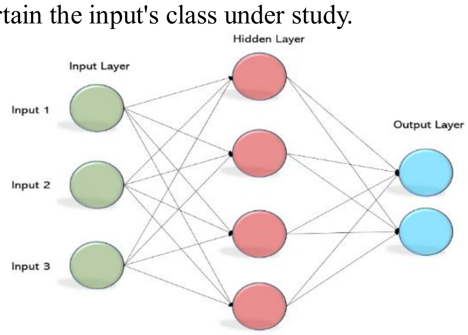


FEATURE COMBINATION

In order to create a more potent feature, feature combination is employed in object classification to combine the strengths of several complementing features. Various researchers typically combine distinct feature sets to produce varying outcomes In order for the three features being assessed in this system to be used as input for the machine learning model, they must be integrated. Since the accuracy of the sleepiness prediction may suffer if thresholding techniques are the only ones used for drowsiness detection The traditional process involves creating linear combinations. Systems become more resilient to the shortcomings of individual procedures when many approaches are used during the decision-making process

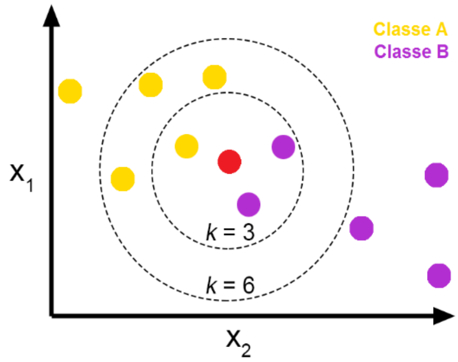
IV. ALGORITHM USED IN THE PROJECT: MULTI LAYER PERCEPTRON

Deep Learning, often known as Deep Neural Networks, is the study of multi-layer artificial neural networks. an ANN is referred to as deep if it contains more than one hidden layer. A common illustration of a feedforward artificial neural network is an MLP. The ith activation unit in the lth layer is shown in below picture as represented as AI. The hyperparameters of a neural network, which include the number of layers and neurons, require fine adjustment. The best values for these must be determined using cross validation techniques. Through backpropagation, the weight correction training is carried out. Deeper neural networks handle information more efficiently. Deeper layers, however, may cause issues with vanishing gradients. It takes special algorithms to solve this problem. Because the input layer in this project has a small size, we are using a single hidden layer with only five neurons, which shortens the training period. We chose the sigmoid function as the activation function since it produces output class labels that range from 0 to 1. However, categorization for the K-Nearest Neighbors is accomplished by locating a new input's closest neighbors and using that information to ascertain the input's class under study.

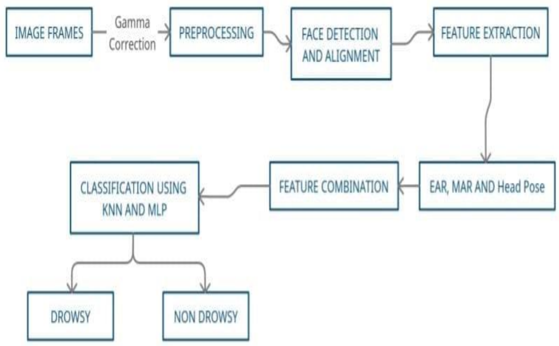


K-NEAREST NEIGHBOR

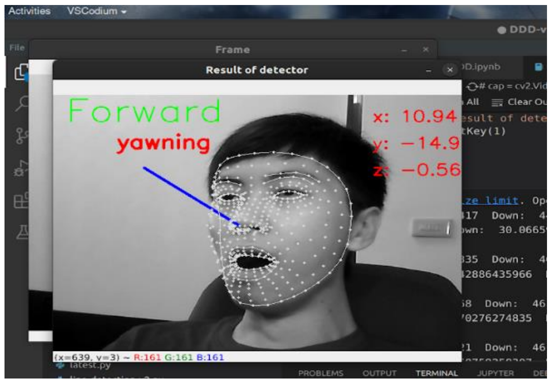
A supervised learning technique called K-nearest neighbors is applied to both regression and classification. By computing the distance between the test data and all of the training points, KNN attempts to predict the proper class for the test data. Next, decide which K points are closest to the test data. The KNN algorithm determines which class has the highest likelihood of being chosen by calculating the probability that the test data will belong to each of the classes of the "K" training data. The mean of the "K" training points that were chosen is the value in the regression scenario. KNN uses the mean/average approach to forecast the value of fresh data. It would take into consideration all of the closest neighbors based on the value of K. The algorithm makes an effort to Once every nearest neighbor has been found within a specific range of the K value, compute the mean for each neighbor's value. The KNN method makes the assumption that similar objects are nearby.

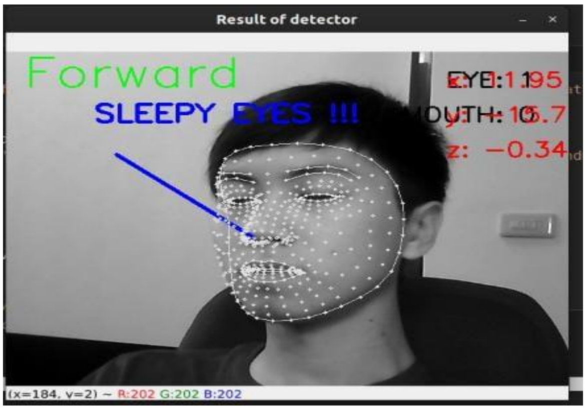


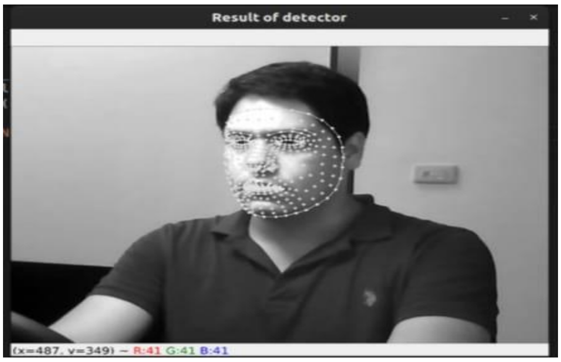
V. SYSTEM ARCHITECTURE



VI. RESULT AND DISCUSSION







VII. FUTURE ENHANCEMENT

A. Combining Data from Multiple Sensors

• Cameras: Use infrared cameras with high resolution to track head positions, eye movements, and facial expressions.

• Vehicle Data: To give sleepiness indicators context, combine information from in car sensors such as steering angle and lane departure alarms.

B. Contextual Analysis

• Behavioral Patterns: Create models to identify patterns over time and differentiate between more significant sleepiness and transient exhaustion.

C. Real-Time Monitoring Systems and Feedback

• Visual/Auditory Alerts: Give users instant feedback via alerts that are audible or visually shown on the dashboard.

D. User Interaction and Engagement

• Industry Partnerships: To stay up to date on industry best practices and advances, cooperate and interact with automakers, tech companies, and researchers.

• User Interaction: Include automatic water spraying on the driver's face anytime the driver becomes sleepy. This will assist the driver in maintaining alertness during the trip.

VIII. REFERENCES

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