MACHINE LEARNING BASED DRIVER MONITORING SYSTEM

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Abstract - *The creation of efficient driver monitoring systems has become essential due to the rise in traffic accidents and driver-related safety issues. In order to improve road safety, this project introduces a machine learning-based Driver Monitoring System (DMS) that continuously evaluates and warns drivers of potential hazards. The DMS analyses driver behaviour in real-time, including gaze tracking, head movement, eye closure, and facial expressions, by utilizing cutting-edge computer vision and machine learning techniques. The system uses a range of sensors, such as cameras and in-cabin sensors, to gather information on the driver's movements and environment. Machine learning models are utilised to identify and categorise a range of safety-critical occurrences, including fatigue, inattention, and lack of focus. To avoid collisions, the technology promptly warns the driver when it detects a risk. Facial expressions are used in the proposed study to implement a Support Vector Machines (SVM) based emotion identification algorithm. When evaluated in situations of varying brightness, the algorithm performed more accurately than existing research.*

Key Words: Machine learning, Gaze tracking ,Real time analysis, machine learning model, Eye closure, Driver monitor system, computer vision

1.INTRODUCTION

The use of machine learning has brought about revolutionary changes in our daily lives in this day and age of swift technology advancement and increasing focus on road safety. One noteworthy application is in the field of intelligent transportation systems, where Driver Monitoring Systems (DMS) based on Machine Learning have become an essential part. These technologies, which continuously monitor and warn drivers of possible problems like weariness, sleepiness, and distraction, represent a significant advancement in improving road safety.Road accidents continue to be a major problem despite advancements in car safety, with a significant percentage of the cause being driver behaviour. Globally, drowsiness and attention have been identified as the main causes of traffic accidents. It is essential to create technology that can both detect and react to the nuances of human behaviour when driving. A creative approach to this problem is machine learning-based DMS, which provides proactive interventions and real-time monitoring to reduce risks and improve driving enjoyment.

The significance of road safety cannot be overstated, and cutting-edge driver monitoring and support systems are essential to creating safer roadways. Significant advancements in modelling and improving these systems have been made in the last ten years, which have enhanced driver performance and decreased the frequency and severity of accidents. One prominent example is the Advanced Driver Assistance System (ADAS), which was developed to improve driving conditions while making a major contribution to traffic safety overall. Among the many capabilities included in ADAS are automated parking, road sign recognition, pedestrian identification, and—most importantly—driver tiredness detection. As one of the main factors contributing to traffic accidents, driver weariness has sparked a lot of study into mitigation and assessment techniques. In contrast to other factors that contribute to accidents, driver weariness has a progressive effect that results in both detectable psycho-physiological indicators and a noticeable deterioration in driving performance. The progress in technology has led to the development of novel methods for assessing and calculating driver fatigue.

These methods include measuring head and eye movements, using electroencephalography to monitor brain activity, and examining a range of driver performance metrics, including lane monitoring, steering wheel movements, and blinking. The creation of an affordable drowsiness detection system based on the PERcentage of eye CLOsure (PERCLOS) approach is presented in this research. Crucially, the PERCLOS approach has proven to be accurate in identifying tiredness and is non-intrusive while being pleasant for the driver. It can identify microsleeps based on a preset threshold value and, unlike some other approaches, is resistant to environmental influences like road conditions.The positioning of a camera to record a live video feed of the driver's face is part of the PERCLOS method's operational architecture.

1.1 Problem Definition

In order to solve this crucial issue for road safety, the focus of the current project is on the early identification and detection of driver fatigue. To this end, a hybrid machine learning technique will be utilised. Driver fatigue continues to be a major contributing factor in collisions, endangering both individual motorists and the general public's safety. Drivers' reaction times and general driving skills degrade with fatigue and distraction, raising the possibility of collisions. The main obstacle is creating a reliable and accurate system that can detect drivers' symptoms of tiredness in real time. This entails examining a variety of physiological, behavioural, and environmental elements, including eye movements, facial expressions, vital signs, car information, and ambient elements including lighting and road quality.

1.2 Objective

Our machine learning driver monitoring system's main goal is to increase road safety by continually seeing and evaluating driver behaviour in real-time, identifying problematic behaviours including diversions and sleepiness. It will build precise models for behaviour detection while enabling customisable alerts and user-friendly interfaces by utilising a variety of data sources, including video and sensor data. Our goals include adhering to safety laws, being flexible enough to work with various car kinds and sectors, improving continuously by retraining models, and placing a high priority on data security and privacy. Another important factor is cost-effectiveness, which enables the system to be used for a variety of purposes and, in the end, promotes safer and more responsible driving practises as well as fewer traffic incidents.

Support Vector Machine (SVM) methods and PERCLOS (Percentage of Eye Closure) analysis are two novel components that work together to form the hybrid machine learning driver monitoring system. PERCLOS is used to track how much a driver is sleeping by examining how much of their eyes are closed, which is a good sign of exhaustion. The system is therefore better able to identify and categorise different driving behaviours once this data is fed into SVM, a potent machine learning algorithm. SVM is trained to identify not just other important factors like awareness, distractions, and possibly risky actions, but also tiredness. When PERCLOS and SVM are used together, they provide a reliable and flexible driver monitoring solution that enhances road safety by precisely recognising and reacting to different driver states and behaviours.

2. LITERATURE SURVEY

A technique based on Adaboost and Haar-like features was developed by the authors in [9] to train a cascade classifier that demonstrated excellent face detection performance. The fundamental idea behind this feature-based method is that the face in the picture is recognised using a set of fundamental traits, independent of the surrounding lighting, the face's direction, or the subject's posture.

Over time, machine learning has shown to be a reliable foundation for classifying eye states and detecting faces. Convolution neural network (CNN)-based deep learning has quickly become a potent technique in face detection, especially for drowsiness detection [10]. In order to identify driver tiredness, a multitasking Convolutional Neural Network model was created in [11]. To identify tiredness, the model makes use of alterations in the driver's mouth and ocular characteristics. The authors of [12] suggested a CNN-based spatiotemporal strategy for real-time driver state monitoring, in which action recognition is derived from temporal data in addition to geographical data.

A combination of a two-level attention bidirectional LSTM network and a 3D conditional generative adversarial network forms the basis of a deep learning model for accurate sleepiness prediction that is shown in [13]. In order to retrieve short-term spatial-temporal features with a variety of fatigue-related data, a 3D encoder-decoder generator was created to raise high-resolution fake image patterns and implement a 3D discriminator to predict fatigue incidents from the spatial-temporal domain. The use of a two-level attention strategy to direct the bidirectional LSTM to recognise the importance of temporal data for long-term spatial-temporal fusion and memory data for brief intervals was also examined by the researchers.

A machine learning-based real-time image classification and sleepiness system was put into place by Altameem et al. [14]. An emotion recognition method based on Support Vector Machines (SVM) is developed using facial features. High performance was shown by the algorithm under various brightness conditions. Because the system is connected to the vehicle's circuitry, it can track the vehicle's data and produce more accurate results. Sensors in autonomous vehicles must be able to identify whether a driver is weary, agitated, or going through strong emotional swings like rage. These sensing devices need to continuously track the driver's face and identify facial landmarks in order to determine the driver's condition and determine if they are driving safely.

Through interactive simulations, Esteves et al. explored the application of machine learning and signal processing techniques in connected automobiles to detect driver weariness. Using the electrocardiogram and facial recognition, extensive biometric research has made it possible to continue developing subject-specific tiredness frameworks for accurate prediction. Cheng et al. proposed a multi-pronged method to identify whether the driver's facial landmark sequence changes from alert to tired. The simulation tool was used in the design and execution of the investigation. The eye aspect ratio and mouth aspect ratio patterns are generated based on face landmarks. We gathered data on blink rate, average blink duration, closing and reopening frequencies, percentage of closed eyes over a predetermined period of time, and percentage of yawning. A sleepiness evaluation methodology is proposed after the features that were extracted. Several machine learning approaches were used in the development of the fatigue assessment system. Koohestani et al.'s main goal is to use a range of machine learning techniques to analyse the driving experience. There are two main stages in the optimisation component of the proposed system. During the first stage, K-nearest neighbours, support vector machines, and naïve Bayes algorithms are optimised for maximum efficiency using bagging, boosting, and voting ensemble learning approaches. Subsequently, four innovative optimisation methods (the grey wolf optimizer, particle swarm optimisation, whale optimisation algorithm, and ant lion optimizer) are applied to increase the system's overall functionality by enhancing its variables. In [8], a sleepiness detection system for driver monitoring is proposed that may be customised for use in trucks and buses.

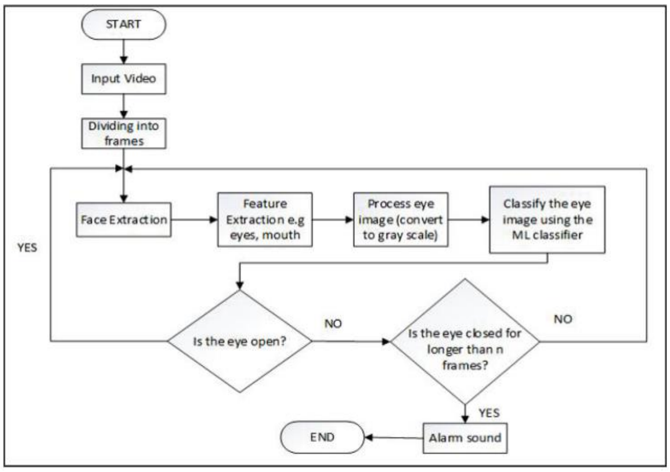
Several sub-systems of the design include head-pose estimation, face identification, eye detection, eye-state classification, and fatigue estimate. There are two primary steps involved in implementing the suggested system. For eye state classification, a fusion model is employed after spectral regression has been applied for eye tracking. The next step is to use PERCLOS to identify if the eye is open or closed.

3. METHODOLOGY

The suggested solution comprises of a camera mounted in a bus so that it can monitor the driver's face. The driver's face is detected by the camera, which also localises their eyes, which are then classed as open or closed. The camera records the live-stream footage and feeds the data into the machine learning programmed. The driver monitoring system alerts the driver with an alarm when it detects that the eyes have been closed for a longer duration than predetermined.

The system receives a live-stream video of the driver's face as input; it outputs the driver's state—alert or drowsy—and sounds an alarm if it detects drowsiness. The movie was divided into frames, face detection was applied to each frame, and the ocular region of each discovered face was localised. The driver's alertness or drowsiness was then determined by applying eye state analysis to the eye area. The project's algorithms are described in more detail below.

The Viola-Jones technique, which makes use of scalar products between the image and a few Haar-like templates, was used to recognise faces. The four primary steps of the Viola-Jones approach are: choosing Haar-like features, building an integral image, doing AdaBoost training, and building classifier cascades. The analysis of eye state encompasses the duration and rate of blinks, as well as the open and closed states of the eyes. Blink and open/close eye state detection were implemented using a convolutional neural network. The driver's eye was closed for a certain number of consecutive frames, which resulted in a high enough departure from the threshold value to cause an alarm. This method of detecting drowsiness was then applied.



. **Fig -1**: System Model Flow Diagram

3.1 System Description

An advanced technology called a Driver Monitoring System (DMS) monitors and evaluates a driver's behaviour and condition while operating a vehicle using a variety of sensors and data processing techniques. A DMS's major objective is to improve road safety by making sure that drivers are focused, aware, and in a condition that allows for safe driving. This is a driver monitoring system description. By collecting data from drivers in real-time under various settings using in-car sensors and cameras, the proposed driver drowsiness monitoring system seeks to improve road safety. Machine learning models, such as Convolutional and Recurrent Neural Networks, are trained to predict sleepiness levels after preprocessing and feature extraction. When abnormal behaviour is noticed, ongoing monitoring sets off haptic, aural, and visual alerts. Data logging and adaptive alert levels help drivers and monitoring systems alike, and an intuitive user interface gradually enhances system performance. A reliable and efficient method for averting mishaps and sparing lives is ensured by privacy and security precautions, regulatory compliance, frequent model upgrades, and possible vehicle integration.

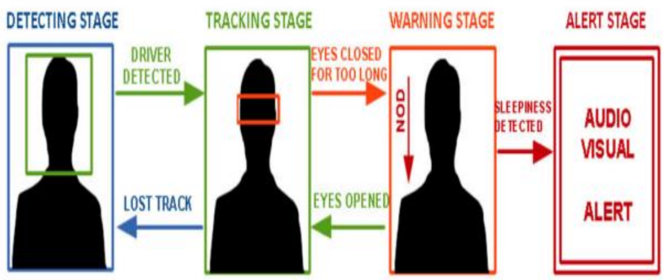


Fig -2: four stages of driver drowsiness system.

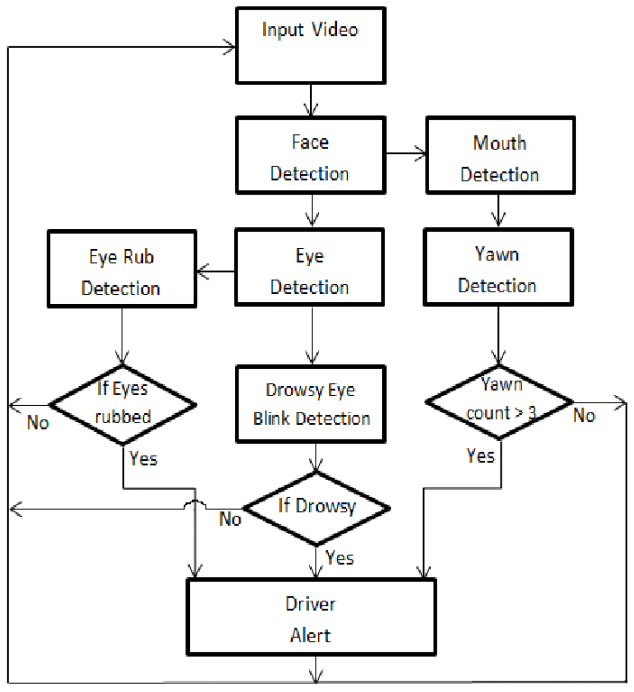


Fig -3: Flowchart of the drowsiness detection system.

3.2 Image and Video Input Stream

The technology would require input from photos and videos in order to detect faces and compare them to a database of recognised individuals. CCTV cameras, cameras worn while moving, and other sources may provide this information.

3.3 Face Recognition

The proposed driver sleepiness monitoring system relies heavily on face recognition, which uses sophisticated algorithms to reliably identify registered users. In particular, the system's facial recognition capabilities is based mostly on the Haar Cascade algorithm.

For the purpose of identifying faces in pictures or video frames, the Haar Cascade algorithm is a trustworthy technique. Its use in this system entails identifying facial features including the mouth, nose, and eyes, which helps the system locate and identify faces with accuracy. By using this technique, the system is able to accurately identify registered users by differentiating them based on face traits. Moreover, the face recognition component plays a major role in the system's overall functionality. It enables tailored monitoring and analysis of individual sleepiness levels by precisely identifying drivers. This customised method improves the efficacy of the sleepiness detection and alert system by enabling it to better adjust alerts and actions based on the driving habits of individual drivers.

Furthermore, the system's emphasis on user-friendliness is in accordance with the face recognition integration. Drivers can have a smooth and customised experience with the system by enrolling individuals and linking their facial data to certain profiles. This guarantees that every registered user's unique demands and features are taken into account by the monitoring and alarm system. Furthermore, the integration of facial recognition technology enhances the privacy and security protocols built into the system. By limiting access to the monitoring functions to just those who are authorised, it protects confidential driver data and complies with privacy laws.

In general, the incorporation of facial recognition algorithms, specifically the Haar Cascade algorithm, enhances the system's capacity to precisely identify persons who have registered, allowing for customised surveillance while upholding strong privacy and security protocols.

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3.4 Facial landmark detection

A key element in the creation of machine learning-based driver sleepiness monitoring systems is facial landmark detection. The training of a model to identify important face characteristics including the lips, nose, and eyes allows real-time tracking of a driver's movements and expressions. The indicators of drowsiness, such as closed eyes, head position, blink rate, yawning, and pupil dilation, can then be evaluated using this data.

Following the identification of these signs, an alerting system is triggered by a predetermined set of rules and thresholds, warning the driver and eventually improving road safety by preventing accidents caused by intoxicated driving.

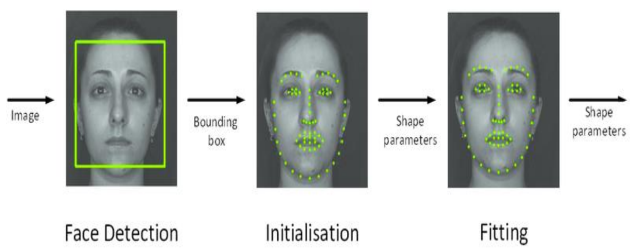

Fig -4: facial landmark system

3.5 Face Segmentation

An essential part of a machine learning-based driver sleepiness monitoring system is face segmentation. In order to precisely analyse facial features and expressions, it entails detecting and isolating the driver's facial region from the entire video feed or image. The technology can efficiently track and monitor important signs of drowsiness, like eye closure, head position, and facial muscle movements, by segmenting the face. For the purpose of precisely determining the driver's level of attentiveness and guaranteeing prompt notifications or interventions to improve road safety, this segmentation procedure is essential.

Fig -5: facial landmark system

3.6 Face Segmentation

A two-stage method is commonly used by machine learning-based driver drowsiness monitoring systems to identify and distinguish between a driver's normal and drowsy states.

The system continuously examines a variety of driver-specific cues during the normal state stage, including head position, eye movements, steering wheel behaviour, and facial expressions. Machine learning models are trained to identify patterns linked to alertness and attentiveness. These models are commonly built on convolutional neural networks (CNNs) and recurrent neural networks (RNNs). The system stays inactive and the driver is free to operate the car as usual when these indicators point to the driver being in a normal state.

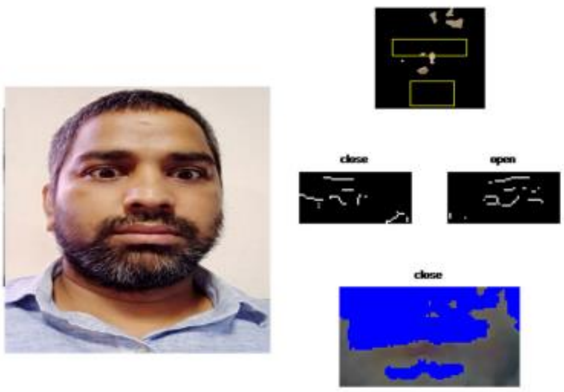

Fig -6: face detection during normal state.

During the sleepy state phase, the system assumes a proactive role and initiates notifications upon identifying indicators of inattention, such drooping eyelids or sluggish reaction times.

Now that these signs have been trained to recognise them, the ML models can inform the driver to take a break or do something to regain consciousness by displaying visual or audible warnings. The driver sleepiness monitoring system can balance convenience and safety with this two-stage method, interfering only when necessary to maintain driver autonomy and promote safer driving.

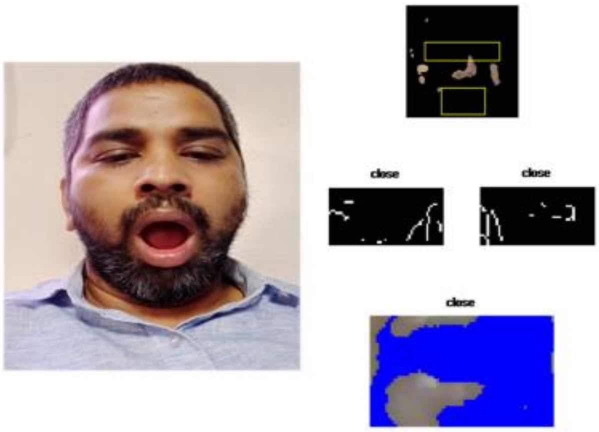

Fig -7: face detection during drowsy state.

3.7 Blink detection

By determining the coordinates of the eye landmarks on the face, the distance between the vertical and horizontal eye landmarks may be calculated . The eye aspect ratio (EAR) is calculated using the two sets of distances between the various eyes. In this study, the blink detection algorithm uses facial landmark detectors for the localization of eyelid contours and eyes. The eye state is then identified as open or closed using the eye aspect ratio, which is obtained from the eye contours. The ocular landmarks are identified and located for every frame in the film as shown in Figure

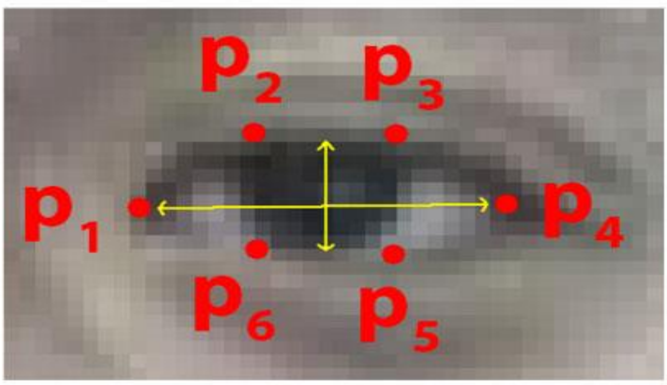

Fig -8: Segmenting image of eye

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

It is evident from the figure in Figure that the width and height of the coordinates are related. Equation, which is derived from equation, describes the connection between the width and height of the coordinates and is known as the Eye Aspect Ratio (EAR). where the 2D face landmark positions shown in Figure are P1, P2,..., P6. This equation's numerator calculates the separation between vertical eye landmarks, while its denominator calculates the separation between horizontal eye landmarks. The studies' suggested EAR threshold of 0.3 was used. A blink is detected if the EAR drops below 0.3 and then climbs above it. Three was chosen as the EAR consecutive frames threshold. This suggests that for a blink to be recorded, three consecutive frames with an EAR below the EAR threshold must occur. The output frame displays the number of blinks.

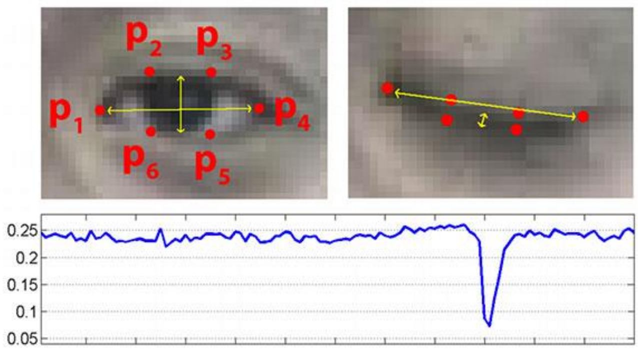

Fig -9: analyzing graph

4. DRIVER MONITORING SYSTEM

A sophisticated technology called a Driver Monitoring System (DMS) monitors and evaluates a driver's behaviour and condition while operating a vehicle using a variety of sensors and data processing techniques. A DMS's main objective is to improve road safety by making sure that drivers are focused, aware, and in a condition that allows for safe driving. This is an explanation of a driver monitoring system.

4.1 Haarcade Algorithm for face detection and Recognition

In computer vision applications, the Haar Cascade algorithm is a reliable and popular technique for face identification and recognition. Its efficacy stems from its capacity to precisely identify faces in pictures or video clips, which makes it useful in a variety of industries including biometrics, surveillance, and human-computer interaction. The algorithm's training phase begins with a sizable dataset of faces in positive photos and Faceless negative photographs are employed. In this stage, the algorithm examines these pictures and extracts characteristics that resemble Haar. Rectangular patterns known as Haar-like features are used to represent several aspects of images, including edges, lines, and textures. After that, integral ages are computed to expedite the feature extraction procedure. Calculating the sums of pixel intensities inside rectangular sections may be done quickly and efficiently with integral pictures.

The most illuminating Haar-like feature subset is then chosen using the Adaboost method. Each characteristic is given a weight by Adaboost depending on how well it can distinguish between positive and negative samples. Face and non-face areas may be distinguished by the algorithm by concentrating on the most discriminative attributes.

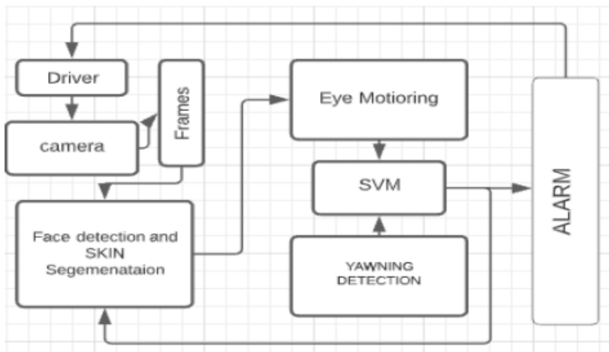

Fig -10: face detection framework

Due to its effectiveness and precision, the Haar Cascade technique is frequently used for face detection applications. It is appropriate for real-world applications due to its capacity to manage changes in lighting conditions, partial occlusions, and face positions. However, it might not work well in situations involving significant position fluctuations or low-resolution photos. However, for face identification and recognition in computer vision, the Haar Cascade method continues to be an essential tool.

In the context of a driver drowsiness monitoring system, Support Vector Machine (SVM) is a supervised machine learning method that may be used to categorise and identify sleepy and alert states of a driver based on attributes taken from pictures or video frames. The following explains how SVM may be used to this system:

1. Data collection and feature extraction: The driver's face is collected in pictures or video frames, and pertinent features are retrieved for analysis, such as the length of the driver's eye closure and facial landmarks.

2. Data Labelling: Depending on the driver's real state at the time of data collection, the obtained data is categorized as "alert" or "drowsy."

3. Data Splitting: To train an SVM model, the dataset is split into two parts: a training set and a testing set. The testing set is used to assess the model's performance.

4. Training the SVM: Using the training data, the SVM algorithm learns to identify the optimal hyperplane that divides the "alert" and "drowsy" classes.

5. Kernel Functions: To help identify intricate correlations between characteristics, kernel functions may be used to turn the data into higher-dimensional spaces.

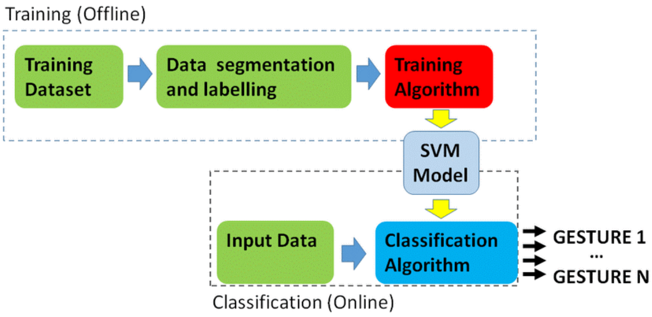

Fig -11: Support Vector machine

6. Testing the SVM: To evaluate the trained SVM model's accuracy in classifying sleepy and awake states, it is tested on a different testing dataset.

7.Evaluation: To determine how well the model identifies drivers, measures such as accuracy, precision, recall, F1-score, and ROC curves are used to assess the model's performance.

8. Real-time Inference: To generate predictions in real-time, the SVM model is utilised. identifying whether the driver is "alert" or "drowsy" based on real-time video frames.

9.Alert Mechanism: The system sends out notifications to the user based on the SVM's predictions. when a driver exhibits signs of fatigue, such as haptic feedback, auditory alerts, or visual input to improve the safety of the roads.

5. CONCLUSIONS

To sum up, the present condition of Machine Learning Based Driver Monitoring Systems signifies a noteworthy progression in augmenting traffic safety and customising the driving encounter. These devices provide in-the-moment driver behaviour monitoring, which helps avert accidents brought on by intoxication, weariness, or impairment. Nonetheless, issues with accuracy and privacy must be resolved. These systems are probably going to be common in cars in the future because to legal regulations and customer desire for safer and more convenient driving. According to our study, real-time Drowsiness Detection Techniques perform effectively in a range of illumination scenarios. Hardware was used as input for our support vector machine and image processing methods for video analysis. The ideal camera distance and lighting conditions were ideal for the algorithm's performance. With increased camera distance and in poor light, accuracy dropped. It is possible to test this proposed algorithm under various brightness conditions and with an improved camera. Several datasets and modern deep learning techniques may be used to test this approach.

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The authors can acknowledge any person/authorities in this section. This is not mandatory.

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