

Car Assistance System with Drowsiness Detection

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ABSTRACT

Experts say that while driving long distances, drivers who don't stop often run the risk of becoming drowsy, which they often don't catch early enough. As indicated by studies, Tired drivers who require time off are responsible for approximately 25% of serious accidents on motorways, making them more risky than plastered driving. Because its sensitivity can be adjusted, Attention Assist can tell drivers how tired they are right now and how long they have been driving since their last break. Consideration Help will likewise show close by administration regions in the COMAND route framework if a warning is given. In a wide range of speeds, Attention Assist can indicate drowsiness and inattention. Using their eyes, face, and head gestures, we will compare and contrast all possible algorithms with regard to their success percentage in this paper. The mouth and eyes are used in our suggested method to give the driver a warning about fatigue. The results of the experiments show that our method is accurate 92% of the time.

Keywords: Drowsiness Detection, Eyes Detection

I. INTRODUCTION

Driver Drowsiness Detection System assumes a vital part in the prevention of traffic accidents by detecting driver drowsiness [1]. Nowadays, a lot of people use cars for daily commute, higher standard of living, comfort, and travel that needs to be done quickly. As a result of this trend, there is a lot of traffic on highways and in metropolitan areas. Due to a variety of factors, it will result in an increase in traffic collisions. Accidents on the road may only be caused by drowsy drivers. Early ID of driver sluggishness and caution alarming are two methods for restricting the rate of mishaps.

The Public Thruway Traffic Wellbeing Organization (NHTSA) gauges that sluggish driving is liable for over 15,000 traffic accidents annually in the United States. The NHTSA says that driver fatigue was a factor in 72,000 traffic accidents, around 800 deaths, and 44,000 wound. In our country, street mishaps killed around 1.47 lakh individuals in 2017. Every year, traffic accidents cause more than a million deaths and more than four times as many injuries. India has seen an annual death toll from road accidents of 1,36,118 on average over the past ten years. Between the ages of 18 and 35, sixty percent of those who were killed in traffic collisions in 2016 did so. On the Yamuna Expressway in India, more than 500 people have died since 2012, and on the Agra-Lucknow Expressway, more than 100 people have died in car accidents. On these expressways, officers and patrol teams discovered that sleep-deprived drivers are to blame for the majority of accidents that occur between 2 and 5 a.m. Drivers' insufficient sleep is a major cause of collisions on roads. Technology for driver sleepiness detection systems is needed to cut down on traffic accidents. The scientific and business communities face a significant challenge in the development of this technology. While driving, a number of symptoms of driver drowsiness can be observed, including the no ability to maintain eye to eye connection, successive yawning, moving the head forward, and other similar behaviors.

The degree of driver drowsiness is measured using a few different techniques. These estimates include vehicle-based, social, and physiological ones. In order to evaluate the circumstances of the driver, physiological measures such as electrocardiograph, electroencephalography, and electrooculogram are utilized [2]. Due to their practical limitations, these tools rarely get used because they produce precise results. In vehicle-based tests, drowsiness is measured by how the steering wheel is moved and how the brakes are applied. These methods rely upon the qualities of the road and the driver's capacities to drive.

The underpinning of social measurements is the individual instead of the machine. Data about the driver is caught here by means of a shrewd camera. The most reliable techniques for distinguishing sluggish driving are conduct measures.

Face regions were extracted from the input photos using a variety of face detection techniques during the Face Detection phase [3]. Face recognition is more of a challenge for humans than it is for computers. There are

image-based and feature-based face detection methods to choose from. In image-based face detection algorithms, statistical, neural network, and liner subspace techniques have been utilized. In the subsequent stage, various eye area discovery methods were utilized to distinguish and separate the eye area of the facial photographs.

Normalization is performed following the discovery of face regions to lessen the impact of illumination during pre-processing. The contrast variations between facial photos can be changed with histogram leveling. In the third stage, highlight extraction was performed on the pictures of the info eye region. Geometric-based The two main methods for extracting features from are appearance-based feature extraction techniques and feature extraction techniques. photos. The mathematical extraction approach extricates measurements from the foreheads and eyes, which are linked to shape and position.

Conversely, appearance-established highlight removal utilizes strategies which include PCA [4], Discrete Cosine Change , and Direct Discriminant Examination to extricate data for the skin's look or facial elements (LDA). These methods can be used to remove facial features from specific areas, or the entire face. Although Gabor wavelets can be used to extract a face's local features, the presence of The main method is high-dimensional feature vectors. drawback. A classifier is utilized in the fourth period of the driver sluggishness discovery cycle to order resting and non-doing photographs in light of the qualities that were separated in the initial two stages. Staked Deep CNN is made to categorize situations that lead to drowsy driving.

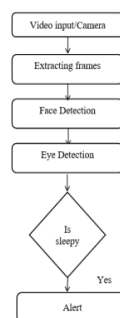


FIGURE1. DROWSINESS DETECTION MODEL

II. RELATED WORK

The entire body of research on identification of facial landmarks, head position, eye gaze, and estimation of action units cannot be examined in this study. As a result, we direct the reader to recent field reviews[5]. All things considered, we give a synopsis of the procedures that can be utilized to finish every responsibility including facial conduct investigation.

Recognition of faces: Face landmark detection in still or moving pictures can be done with a variety of free tools. However, very few of the methods simply provide executable binary files rather than the source code. This makes it possible to repeat experiments with different training sets or landmarks. Comment plans are testing. Additionally, binaries frequently aren't portable, only support a small number of predefined functions, and aren't cross-platform. This makes it difficult to integrate systems in real time, which would necessitate landmark detection. However, there are a few exceptions that do not adhere to these procedures—for interactive systems, enabling real-time landmark tracking in videos is essential. [6]

Gesture of the Head: Compared to facial landmark detection, estimation of head posture has received less attention. A previous delineation of a particular head position assessment is the Watson framework, a Adaptive View-Based Generalized Appearance Model implementation. There are likewise various structures that empower head present assessment utilizing profundity information [7], however they are inconsistent with cameras. The majority of facial landmark detectors do not have the capability to estimate head posture [8].

Estimation of Gaze: There are numerous monetarily accessible instruments and strategies for assessing eye-stare, yet the greater part of them need specific equipment, including infrared cameras or head-mounted cameras [9].

There are a few approaches to webcam-based gaze estimation [10], but they are difficult to use in real-world situations and some necessitate lengthy manual calibration procedures.

Open Face, in contrast to previous technologies, provides training and testing code, making it simple to replicate an experiment. Furthermore, our system displays cutting-edge results based on true information and doesn't need any specific equipment or individual calibration. All of the facial modules for behavior analysis work together in our approach.

There are two types of driver sleepiness detection: non-contact strategies [12] and contact strategies [11]. Drivers in contact strategies use wearable or contactable devices to collect physiological indicators of fatigue. Warwick and co introduced the driver's body's BioHarness 3 [11] to accumulate data and actually take a look at sluggishness. Li and co. An electroencephalographic (EEG) signal serves as the foundation for the smartwatch. 's [13] was used to determine whether a driver was drowsy. Jung and co. changed the wheel of the car. 14] and had a sensor for keeping an eye on the driver's ECG signal.. But, due to the cost of collision methods or installation, some restrictions cannot be enforced universally. The elective strategy utilizes a sans tag approach in which the deliberate item doesn't need to connect with the driver to recognize driver sleepiness. Omidyeganeh et al. [15], for instance, utilized the driver's captured facial expression to identify fatigue, but this method is not live.. Notwithstanding, an intricacy related to the strategy is much more than our calculation. Zhang and Hua [16] utilized weakness look recreation in view of Nearby Parallel Example (LBP) highlights and Backing Vector Machines (SVM) to assess driver exhaustion. Furthermore, Picot et al. [17] proposed a method for detecting fatigue that utilizes the flickering component and electrooculogram (EOG) signal. Akrouit and Mahdi, as well as OyiniMbouna and co. [18]. A fusion system was used by [19] to find drowsiness on the point of head position and eye state. We utilize clear recipes and evaluations, which make the outcomes simple to quantify, rather than these techniques.

III. PROPOSED WORK

3.1 Algorithm for the proposed system

- (1) The Viola-Jones face identification method is utilized in finding faces in images, and the Viola-Jones algorithm for detecting eyes receives the results.
- (2) The Viola-Jones ability to see strategy is utilized to remove the eye district of the facial pictures and give it to CNN as contribution after the face has been distinguished.
- (3) Profound elements are separated from a CNN with four convolutional layers and shipped off a completely associated layer.

- (4) CNN's Delicate Max layer isolates the photographs into drowsy and non-sluggish classifications.

The proposed architecture for the Deep CNN-based Drowsiness Detection System is depicted in Figure 2. Three stages make up the proposed model. 1. Pre-handling stage, 2. the extraction of features, and Deep Classifier Using CNN

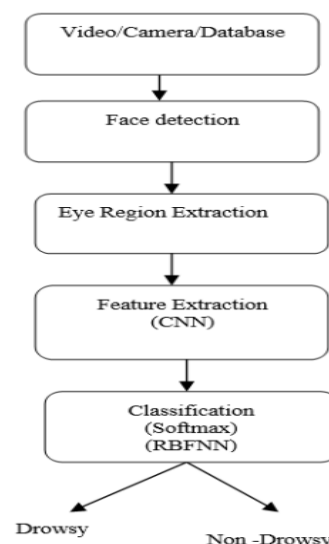


Figure 2. Plan for the system's architecture

3.2 Identifying faces and extracting the eye region

To recognize fatigue, only the area around the eyes is necessary; the whole facial district may not be essential. The Viola-Jones face identification strategy is utilized to initially finds a face from the photographs. After the face has been identified, the eye district is removed from the facial images using the Viola-Jones eye location calculation. The Viola-Jones object detection method [20, 21], was the first face recognition algorithm. It uses three methods to detect faces: Overflow classifier, Ada support, and Haar-like elements The Viola-Jones object area procedure using the Haar flood classifier was utilized in this paper and was created utilizing Python's OPEN CV. characteristics that Haar uses to recognize faces in pictures. Figure 3 shows the pictures of the Eye area that were taken from the facial picture.

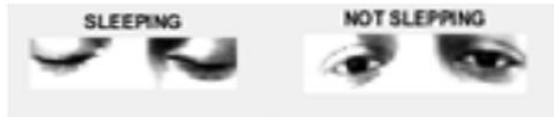


Figure 3. Eye images

3.3 Classification and extraction of features

Extracting the feature, in which important parts of a picture are shown as feature vectors, is one way to reduce dimensionality.

In this review, a convolutional brain organization (CNN) is utilized to remove data from photographs of the eye locale

3.3.1 Neural network with convolutions

The proposed system uses a convolutional neural network to identify driver drowsiness. due to the fact that a feature vector that is comparable to other feature vectors in a database to determine whether an image is drowsy is required for each drowsy image. Preprocessing is required because CNNs typically require images of a fixed size as input. In the preprocessing, the critical edges from the video are separated in light of worldly changes and put away in a data set. Convolutional layers of CNN make include vectors from these saved pictures. These element vectors are then used to recognize the driver's sleepiness. Pooling, fully connected, convolutional, and ReLU layers are a few of the layers in CNN. The convolution layer contains portions. with the width, depth, and height of each kernel. By measuring the multiplication between the kernels and local parts of the picture, this layer creates feature maps. To accelerate estimations, CNN utilizes pooling layersto decrease the size of the component maps. Before moving on to the next step, the layer bifurcates the input image into a number of different areas. When Max Pooling is used, a greatest worth is chosen for every area, and they were put in the output in the right place. RLU is the name of an online layer. The ReLU actuation capability is portrayed in the accompanying condition.

(1) The completely associated layers used to create class rankings from the actuations utilized for characterization. $f(x)=\max(0,x)$.

3.3.2 The proposed deep CNN model's layer architecture

A new Deep CNN model in light of Eye State is created to involve profound figuring out how to recognize driver sleepiness in the review we propose. The developed CNN model used in this study is depicted in Figure 4.. The suggested approach makes use of one fully linked layer in addition to four convolutional layers. Convolution layer 1 (Conv2d_1) utilises extricated key pictures with a high resolution. The info picture was convolved utilizing 84 3x3 channels by Conv2d_1. Batch Normalization, ReLU non-linear transformation, Max pooling over two cells, and others are added in the design dropout with 0.25%, and convolution after convolution. There are 840 required parameters for Conv2d_1. Batch_normalization_1 has been completed with 336 parameters. Convolution layer's outcome 1 (Conv1) is received by convolution layer 2 (Conv2d_2). Conv2d_2 convolves input by means of 128 channels, each estimating 5x5. MaxPooling more than 2 2 cells with step 2 after convolution, cluster Standardization, non-direct change ReLU, and dropout with 0.25% applied. There were 268928 boundaries for conv2d_2. 512 boundaries were expected for batch_normalization_2. The output of convolution layer 2 (Conv2) is received by convolution layer 3 (Conv2d_3). Conv2d_3 uses 256 5x5 filters to convolve the input. After convolution, bunch standardization, non-straight change ReLU, Conv2d_3 required 819456 boundaries for

MaxPooling across two cells using stride 2 and dropout with 0.25 percent applied. 1024 boundaries were expected for batch_normalization_3.

Convolution layer 4 (Conv2d_4) gets the result of convolution layer 3 (Conv3). Conv2d_4 uses 512 5x5 filters to create a convoluted input. The subsequent steps include unique information sources. Batch_normalization_4 needs 2048 arguments.

dense_1 required 8388864 parameters for its fully connected layer. A CNN model that was proposed required 12,757,874 teachable boundaries. Only two outputs exist in the output layer, because the classifier produces two states. Advancement is achieved by employing the Adam method. In this occasion, the information are grouped utilizing a softmax classifier.

The deep features that were extracted from the input eye pictures make up the 256 outputs of the fully connected layer in the CNN framework that we have proposed. The deep features could be combined linearly to produce the final two outputs.

IV. METHODOLOGY

This section provides a description of the primary technologies utilized by our proposed method for facial behavior analysis. To begin, we portray how we recognize and screen face milestones and afterward add a various leveled model to a current calculation. The utilization of these traits for head position assessment and eye stare following is then portrayed. The final section of The subject of our paper is described in detail: method for detecting the intensity and presence of the Facial Action Unit, which adds an original individual adjustment to a current model.

4.1. Facial milestone discovery and tracking

For facial milestone recognition and following, our proposed philosophy utilizes the as of late proposed Restrictive Neighborhood Brain Fields (CLNF). An Obligated Neighborhood Model (CLM) [20] with more modern fix specialists and enhancement capabilities is CLNF. The Point Distribution Model, takes into account Patch Experts, which take into account local variations in each landmark's appearance, and differences in landmark shape are the two fundamental components of CLNF. For additional algorithmic information, it should be consulted.

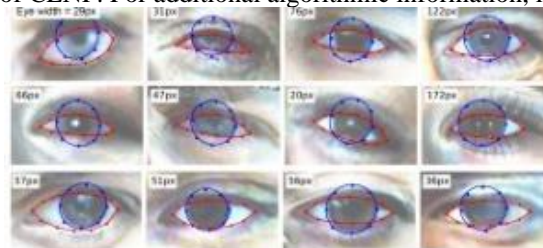


FIGURE 4 EYE GESTURES AND POSITION

4.1.1 Model curiosities

The initial CLNF model that was suggested carries out the simultaneous recognition of every one of the 68 facial tourist spots. By instructing distinct sets of patch expert models and point distribution models for the eyes, lips, and brows, we enhance this model. Afterward, we utilized a joint model to suit the milestones found with individual models (PDM). Face tracking over long periods of time can lead to drift or the subject leaving the area. As a solution, We use a phase for face checking. We utilize a direct, three-layer convolutional brain organization (CNN) that is prepared to foresee the expected milestone ID mistake given a face adjusted by means of a piecewise relative twist.

On the LFPW [21] and Helen [22] preparing sets, which contain both precise and arbitrarily offset milestone positions, we train the CNN. While checking a face in a video, assuming the approval stage fizzles, we know that our model should be reset. We employ a number of initialization hypotheses from various angles and select the one that has the greatest potential for convergence when attempting to identify landmarks in challenging in-the-wild photos. The technique takes more time however is more precise along these lines.

4.1.2 Execution subtleties

The LFPW [21] and Helen [22] preparing datasets were used to prepare the PDM that was utilized in our proposed technique. As a result, a model with 34 non-unbending and 6 inflexible shape characteristics was created. We utilized the Multi-PIE [23], LFPW [21], and Helen [22] preparing sets to prepare the CLNF fix specialists. For each of the four scales, we trained a separate group of patch specialists and seven views, resulting in a total of 28

sets. Because we have experience with multi-scale patching, we are able to be precise on face photos of varying quality. We discovered that the best results are achieved when the face is at least 100 pixels wide. We can recreate self-impediment welcomed on by head pivot and track faces moving out of plane with the assistance of preparing on different perspectives.

Our CLNF model is instated with the assistance of the dlib face identifier from [13]. From the dlib detector's bounding box to the one containing the 68 facial landmarks, we learned a straightforward linear mapping. We instate the CLNF model in view of milestone identifications in the casing before while noticing tourist spots in films. We re-instate the model utilizing the dlib face finder assuming our CNN approval module demonstrates that following fizzled. Furthermore, Our proposed system empowers the acknowledgment of a few countenances in a picture and the checking of various countenances in recordings. This is finished in recordings by monitoring dynamic face tracks and utilizing a direct rationale module to search for people entering and leaving the casing.



FIGURE 5 HEAD POSE ESTIMATION

4.2. Head position estimation

In addition to detecting face landmarks, The head posture can be deduced by our model. data. Internal face landmarks are projected onto the image by CLNF employing an orthographic camera projection technique. making this possible. We are able to accurately estimate the head pose by resolving the PnP problem after the landmarks have been identified. For our proposed method to accurately estimate head pose (focal length and principal point), the camera calibration settings must be provided. In their nonattendance, Our proposed approach makes a ballpark estimation in light of the size of the picture.



FIGURE 6 EYE GAZE ESTIMATION

4.3. Eye gaze estimation

Additionally, we use the CLNF framework, a universal deformable shape registration technique, to locate ocular landmarks. The iris, pupil, and eyelids are all included. The SynthesEyes preparing dataset was utilized to educate the PDM and CLNF fix specialists [24]. In the process of registering the eye's region, the eye's location and pupil are identified using our CLNF model, and the eye gaze vector is then computed separately for each eye [24]. We work out where the eyeball circle and a beam terminated from the camera's starting point go through the focal point of the understudy in the picture plane.

This gives the 3D camera bearings to the student region. Our estimated gaze vector is the line that runs from where the pupil is to where the center of the three-dimensional eyeball is located. This is a quick and accurate way to determine a webcam user's eye-stare photographs that is human free.

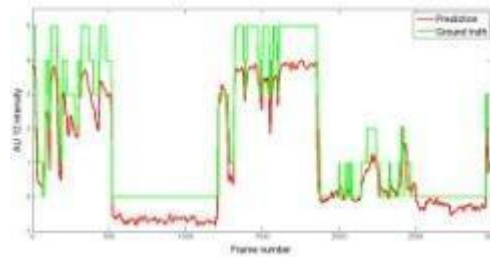


FIGURE 7 EXPERIMENT ANALYSIS

V. OBSERVATIONS

Every one of the Our proposed strategy sub-frameworks — facial milestone acknowledgment, head position assessment, and eye stare assessment — is assessed in this part. We likewise contrast every one of our preliminaries with various as of late introduced strategies for addressing similar issues (albeit not a solitary one of them tackle every one of them on the double). Furthermore, none of the techniques we surveyed offer the total preparation and testing code, just pairs with pre-prepared models (aside from EyeTab [25] and relapse timberlands [7]).

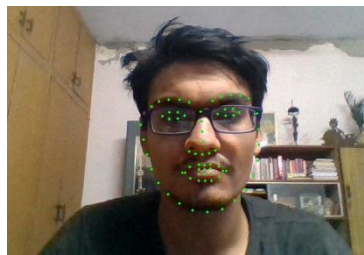


FIGURE 8 FACE ESTIMATION

5.1. Landmark spotting

The facial milestone recognition limit was assessed utilizing the Commented on Appearances in the Wild (AFW)[26], IBUG[27], LFPW[21], and Helen[22] sub-datasets of the 300-W face approval dataset. We utilized the test coordinators' given bounding boxes to introduction.

We began by examining the benefits of our recommended various leveled approach. In 6a, the outcomes are shown. The hierarchical model clearly improves facial landmark detection accuracy.

We compared our method to other algorithms for recognizing facial landmarks in a second experiment that have undergone training to recognize similar landmarks and whose implementations are easily accessible online. The Extended Version of Constrained Discriminative Response Map Fitting (DRMF) [12], Tree-Based Deformable Models (26), Local Models (28) baselines.

Figure 6 depicts the outcomes. For the reporting, we only used the 865 photos for which all of our baselines could recognize faces.

Method	Yaw	Pitch	Roll	Mean	Media
Reg. forests [22]	9.2	8.5	8.0	8.6	N/A
CLM [50]	8.2	8.2	6.5	7.7	3.3
CLM-Z [9]	8.0	6.1	6.0	6.7	3.2
Chehra[5]	13.9	14.7	10.2	12.9	5.4
Our proposed methodology	7.9	5.6	4.5	6.0	2.6

Results of head posture estimation using the Biwi Kinect head pose dataset are shown in Table 3. based on mean absolute degree inaccuracy measurement.

mean absolute degree inaccuracy measurement.

Method	Yaw	Pitch	Roll	Mean	Median
CLM [50]	3.0	3.5	2.3	2.9	2.0
Chehra[5]	3.8	4.6	2.8	3.8	2.5
Our proposed methodology	2.8	3.3	2.3	2.8	2.0

Table 4 shows the BU dataset's head posture estimation findings. based on mean absolute degree inaccuracy measurement. Due to the fact that the The BU dataset contains only RGB images., comparisons with CLM-Z and Regression forests were made.

Method	Yaw	Pitch	Roll	Mean
Reg. forests [22]	7.2	9.4	7.5	8.0
CLM-Z [9]	5.1	3.9	4.6	4.6
CLM [50]	4.8	4.2	4.5	4.5
Chehra[5]	13.9	14.7	10.3	13.0
Our proposed methodology	3.6	3.6	3.6	3.6

Table 5: Estimation of the Head position results on ICT-3DHP. Measured in mean absolute degree error.

of 49 results from landmark detection. We occasionally are unable to change the face detector that is used, so this is another issue with given binaries (not the code). The main model that offers both model preparation and fitting source code, along with tree-based models [26], is Open-Face, which displays state of the art execution.

5.2. Head pose estimation

Our proposed method's performance on a head pose estimation task using three datasets that are freely accessible were used to evaluate the results—BU, Biwi, and ICT-3DHP—each of which contained ground truth head position data.

We present the Chehra framework, CLM, CLM-Z, and regression forests for comparison results. The outcomes are shown in Tables 3, 4, and 5. The results show without a doubt that, when applied to all three datasets, our approach performs at the forefront.

5.3. Eye gaze estimation

Using the challenging MPIIGaze dataset, In order to test appearance-based gaze estimation, we evaluated our proposed method's ability to estimate eye gaze vectors. MPIIGaze presents a challenge because it was collected in actual laptop use settings but useful challengefor estimating eye contact. The example photos from the dataset are displayed in the right two sections of Figure 4.

750 face photos from the dataset were used to test our method, and 1500 eye images were produced. We used the entire Open-Face workflow rather than just the manually location of the annotated eye corner in the dataset. Our model's error rates are shown in Table 7.

MODEL	GAZE ERROR
EyeTab	47.1
CNN on UT	13.91
CNN on <u>SynthesEyes</u>	13.55
CNN on <u>SynthesEyes</u> + UT	11.12
Our proposed methodology	9.96

Table 7: Results Mean absolute degree error is used to measure the difference between our approach and other work on MPIIGaze for cross-dataset gaze estimation.

5.4 PERFORMANCE OF DETECTION METHODS

We contrast our strategy for surveying the state of the eye with different techniques to test the viability of our assessment calculation. Figure 16 depicts the outcome, which demonstrates that the 95:2% angle of eye opening is the highest of the evaluated approaches. Moreover, with an acknowledgment pace of 93:5, shut eye acknowledgment is awesome. Our methodology essentially builds the achievement pace of recognizing a shut eye; It surpasses HoughCircle by 10%.

The ability to recognize mouth states and eye in both normal and drowsy conditions is shown in Figures 17(a) and (b). The opening of the eyes is depicted on the left vertical axis, with 1 representing an open eye and 0 representing a closed eye. The horizontal axis indicates the total number of video frames. The right upward pivot portrays the proportion of the mouth's level to width. The exploratory findings indicate that the driver's flicker recurrence and eye-shutting time are low while they are conscious. But when a driver is tired, they tend to blink more often, close their eyes for longer, and sometimes yawn.

VI. CONCLUSION AND FUTURE WORK

In this review, we presented constant facial conduct examination that is totally open source. The communities of affective computing, machine learning, and computer vision can benefit from the method we propose. Additionally, it will encourage research into the interpretation and analysis of facial activity. In addition, the tool will continue to be developed in the future with the intention of incorporating the most recent and dependable solutions to the central issue while keeping up with its open source straightforwardness and constant abilities. We trust that by giving this device, different analysts in the field will be enlivened to share their code.

For determining the extent of driver fatigue, we propose a method based on facial key point identification and face tracking.To develop the first KCF calculation, we propose the MC-KCF calculation that utilizes CNN and MTCNN to follow the driver's face. Using key facial points, we define the face's detection zones. In addition, based on the state of the lips and eyelids, we present a novel method for determining sleepiness. It's almost like a real-time system.because of its rapid operation. The results of the trial indicate that it is versatile and capable of providing consistent performance.

We have accomplished the tiredness recognition utilizing eyes, head and face signals. We used opencv to detect eye gestures, taking an image and using the CNN model to classify gestures. We used an open face library-based pose estimation model to detect facial and head gestures.

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