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Deep convolutional network based real time fatigue detection and drowsiness alertness system

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ABSTRACT

Fatigue and drowsiness detection techniques based on the external features are under progress, and the methods of facial feature extraction require further development. This paper discusses the innovative processes, efficient methods, and recent advancements in the field of drowsiness and fatigue detection. In this proposed model, a wide application is planned in the field of artificial intelligence by defining the fundamentals of human-computer interaction, facial expression recognition and driver fatigue-sleepiness determination. This research outlines an efficient and effective three-phase strategy for detecting drowsiness. Viola Jones is used to detect facial traits in these three phases. Detection of yawning and tracking once the face has been identified, the segmenting the skin, the system becomes lighting invariant portion by itself, focusing on the chromatic components based on skin, and to reject most of non-face image backdrops. The color eye tracking and yawning detection are carried out by template matching with the correlation coefficient. The vectors of features based on each of the above phases is concatenated, and a binary result is obtained. The analysis of sound and successive frames into fatigue and non-fatigue states has been classified. If the time in fatigue state exceeds the threshold, the system will sound an alarm.

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1. INTRODUCTION

Nowadays, modern computing technologies have major advances in artificial intelligence. Brightness, blurring, individual variances in skin tone, and environmental variables all affect eye closure detection. It is a difficult process. Eye closure detection has various applications. Recently, driver assistance systems, smart car development and enhancement. Control and warning systems are examples. All artificial intelligence driverless vehicles are built in step with the information era. While research for driver assistance systems continues, solutions are generated based on need. Google, Manufacturers including Toyota, Nissan, BMW, and Tesla are continuing system R&D [1].

Currently available advanced driver-assistance systems (ADAS) Studies in numerous areas are seen when studied. The continual movement of road, car, and people generates life-threatening accidents [2]. Between 2009 and 2016, Turkey Statistics Institute (TSI) explained driver errors in road accidents as [3]. NHTSA (National Sleepiness is said to be the cause of 56,000 road fatalities and injuries per year [4]. Various studies to detect driver fatigue-sleepiness. These studies use body temperature, heart rate, and brain electrical signals to assess driver alertness [5]. Studies on the human body auxiliary equipment like electroencephalography (EEG) header affects drivers and is difficult to integrate in real life.

Another study [6] is to perceive the driver's vehicle's reactions. These parameters are used to diagnose fatigue. These parameters are determined by the vehicle's accelerator pedal and sensors such as the steering wheel's driving type and driver status. It is used in [6]. This type of job varies widely depending on the driver's attributes and the success rate is poor. Also, putting the sensors in the right places on the vehicle is difficult and requires expertise. These systems also have procedures that require maintenance and repair. Whether you're asleep or not. There are many studies on determining absence in the literature. Another way devised to determine driver attention is to instantaneously examine and evaluate the driver's condition. It is founded on will [7].

The "urge to nod off" is defined. This operation is the result of a natural human sleep-wake cycle. They both represent the sleep-wake cycle. The greater the alertness length, the more weight and problem sleep works [8]. A circadian pacemaker is an intrinsic biological clock that cycles. Homeostatic components detect sleepiness and treatment with circadian factors. These procedures normally occur 12 hours after the mid-sleep cycle (in the evening for the great majority of sleepers) and before a combined sleep period (mostly in the evening, before sleep) [9]. These cycles must be understood as normal and inevitable, not as something to be emulated or ignored.

2. ALGORITHM

These mechanisms result in deep learning and multilayer feed forward neural networks. Since its inception, deep learning models with many hidden layers have been dubbed this. It is used in image classification, description, split-split, video analysis and interpretation, audio detection and processing, and natural language learning. A multi-level neural network is constructed by using deep learning to extract major attributes from unlabeled education data.

Convolutional neural networks (CNN's) local connection, weight sharing, and pooling sampling have made it a popular choice in image processing and voice semantics. In image processing, the original image can be immediately input into the network without complicated pre-processing. Convolutional neural networks are used to process images. It is a non-connected multi-layer neural network. Too many parameters overfit the network, preventing useful learning. Here is the convolution formula:

$$a_{i,j} = f\left(\sum_{m=0}^{2}\sum_{n=0}^{2}\omega_{m,n}x_{i+m,j+n} + \omega_b\right) \tag{1}$$

It has many convolution layers, pooling capabilities, and fully connected layers. Each layer of the fully linked neural network has one dimension, while the three-dimensional neurons have width, height, and depth. The neurons are arranged in a layer structure of a fully linked neural network. The presence of a convolutional layer in the convolutional neural network is crucial. The convolutional layer's weight sharing reduces the number of network structure parameters. The local linkage to the convolutionary layer reduces the complexity of network computing. The input layer has a 1000×1000= node for a 1000×1000 picture. Only that layer assumes 100 nodes are the initial hidden level (1000=1000+1).

3. PROPOSED METHOD

Viola Jones' face detection [10]. In order to process the skin segments, the YCbCr algorithm must be set to process the face. In the YCbCr space, the image's color impact can be "wiped out by considering only the chromatic segments." In red, green, blue (RGB) model, each color (red, green, and blue) has a different brightness. A YCbCr picture solely contains red/blue values. Red is the colour of YCbCr, as blue (Cb) and red (Cr) segments have no light. The YCbCr picture is segmented into Y, Cb, and Cr data using the detects. However, despite the fact that the shading is concentrated in the chrominance plane, it appears to be distributed over a tiny area of the chrominance plane. As a result, a large percentage of the non-face image is immediately rejected.

The state of the eyes is the most essential component in determining driver tiredness. When you are sleepy, your eyelids linger nearer to close your eyes. We utilize a computer named "Viola Jones" to position the driver's gaze. Because the eyes are on opposite sides of the brain, they are divided. The focal point of the eyes is governed by their locations. Finally, the understudy is acknowledged. If the person opens his or her eyes and it is normal to the state in which the condition is not tested, it is seen as normal. Table 1 shows that different states' eyes have varied features. The distinction between fully open and half-open eyes is sometimes misunderstood, resulting in erroneous cautions, and the driver's head's fluctuating development might result in disappointment. Figure 1 shows the schematic diagram of the eye positioning and the steps involved in the process.

Table 1. Feature matrix of eye

Variable	Area (No. of pixels)	Avg. Height	Ratio
Full Open	204	7.62	2.87
Half Open	155	6.79	3.04
Closed	117	6.02	3.17

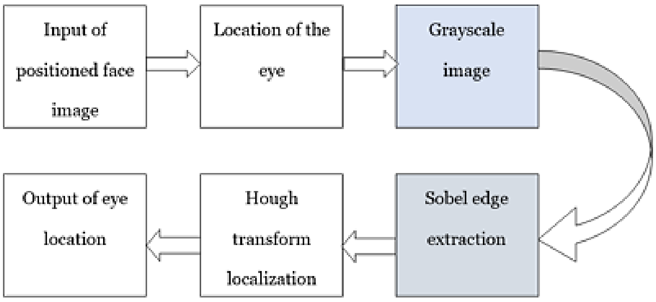


Figure 1. Schematic of the eye positioning

Another unique indicator of fatigue in driving is yawning, which occurs when a person is tired and about to nod off owing to body reactions. When the mouth area is discovered using Viola Jones, the mouth area is split by K, meaning [11] bunching and coordinating the relationship coefficient format [12]. So, protests are closest to each other in each bunch, and farthest from objects in other bunches. Each K group is identified by its centroid. The capacity K-implies conducting K-Means grouping, so that the total of separations from each item to its associated group centroid, total K bunches, is a basis. The target effort is to acquire the base separation between classes or, more fundamentally, between pixels [13]. Figure 2 shows the Sobel edge process of detection of eyes, and the Figure 3 is showing the face detection framework of yawning detection [14].

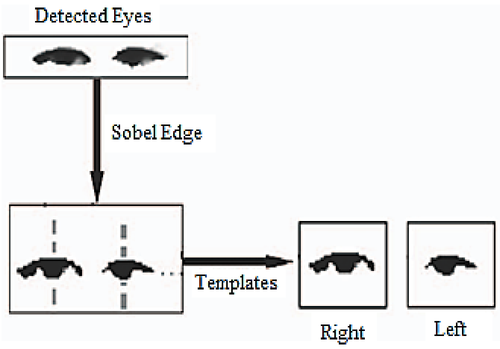


Figure 2. Detection of eyes

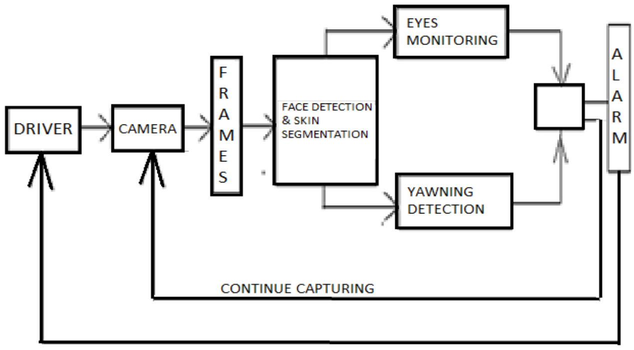


Figure 3. Face detection framework

$$c\,j \;=\; (xi\,|min(\,||xi \;-\; xj||\,)) \qquad (2)$$

argmin Ȉ||cj - xj|| (3)

In (2) and (3), *xi* is the i^{th} pixel, *xj* is the class *j* focal point, and *cj* are class *j* pixels. The brilliance power determines pixel classification. Finally, a large chunk of the image reveals the mouth and identifies yawning using *K=2* layouts. The open and close formats are all 38x62 [15].

This deep learning model is taught images from a video device. Yawning, languid pace included sleepy, blinking head gestures, sleepy eyes. Infrared cameras were used to record the event, also night videos.

The result is 9.5 hours of content with 640*480 definition images at 30 frames per second. A convolution neural network (CNN) is made up of layers that are structured to maximize its features [16]. The arrangement of cortical territory is particularly stirring to CNN. Figure 4 depicts a seven-layered neural system with one info layer, five veiled levels employing the first layer objective, and a yield layer. It has two convolutional layers borrowed from Inception and a variety of pooling layers to reduce the computational bundling of layers [17]. Each of the thirty thousand accessible neurons corresponds to an RGB value [100, 100], reachable by the RGB index. The main network layer is a convolutional layer 1 with 64 channels and a 3 to 3-pixel section. The second convolutional layer used for the convolutional classifier has 64 channels with a bit size of three pixels and ReLU [18].

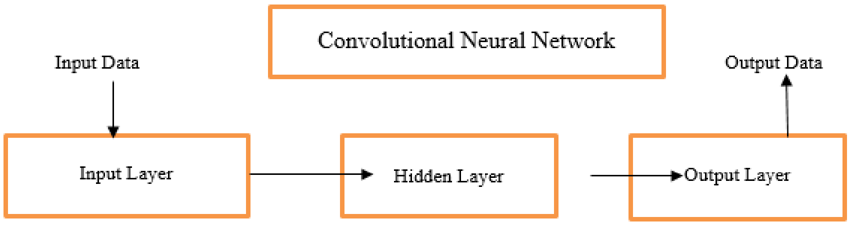


Figure 4. Basic block diagram of CNN

A convolution neural network (CNN) is made up of layers that are structured to maximize its features. The arrangement of cortical territory is particularly stirring to CNN [19]. Figure 4 depicts a seven-layered neural system with one info layer, five veiled levels employing the first layer objective, and a yield layer. It has two convolutional layers borrowed from Inception and a variety of pooling layers to reduce the computational bundling of layers. Each of the thirty thousand accessible neurons corresponds to an RGB value [100, 100], reachable by the RGB index [20]. The main network layer is a convolutional layer 1 with 64 channels and a 3-to-3-pixel section. The second convolutional layer used for the convolutional classifier has 64 channels with a bit size of three pixels and ReLU [21].

4. RESULTS AND DISCUSSION

Figure 5 shows a video of the driver that was captured by the camera. Finally, the video is included. The sections that follow will demonstrate how to keep an eye on an edge. We go over the features, advantages, and algorithms of a prototype system for detecting driver fatigue. It is divided into four sections: the process of getting things started and getting ready using eye-tracking technology to conduct research detection of the early warning signs the fourth stage of the alertness system in order to determine whether or not a driver is fatigued, we look at non-intrusive outside signals. For this project, we are investigating the use of framework engineering in the transition of the current prototyping system into one that can enable further research in this field [22].

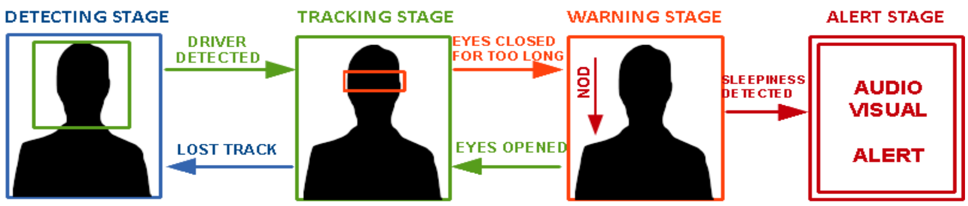


Figure 5. The four stages of our drowsiness detection system

4.1. Image pre-processing

Pre-processing images can impair the system's accuracy. Optical pay is first adjusted using histograms [5], [23]. Here, we add an evening histogram to each area of the shading image, as illustrated in Figure 5. Then a salary image. In order to improve the framework's competence, the repaid picture's priorities are decreased.

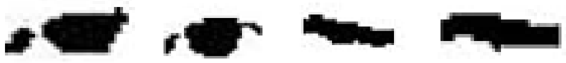
4.2. Face detection
Face detection is used to reduce the number of false positives in the recognition of exterior appearance. The positioning of the eyes and lips is critical. Make sure that the face has been marked before moving the image to YCbCr [11], [24].

4.3. Eye location and recognition
In order to identify driver fatigue, the condition of the eye must be switched on or off. The eyelid muscles can help you fall asleep faster when you're drowsy. Using Viola Jones [25] to find the driver's eyes. At that point, separate the two eyes by their symmetry [26]. The eye's focus is set [27]. The understudy was identified. If the eyes are open, they are seen as normal and no warning is issued. If the eye is closed, it is perceived as a fatigue of caution. Edge recognition can be used to detect changes in pixel capacity [28]. Some approaches, like Sobel, identify edges. This method is designed to detect image alterations. The suggested work's Sobel edge detection strategy outperforms other techniques [29].

The eye's attributes are separated to determine its condition. Normally, the left eye's state is equivalent to the right eye's. In this manner, we consider the status of one eye in one edge. This idea also helps reduce computing complexity [30]. This progression uses two strategies: double mode and Canny edge discovery. Figure 6 shows some binary pattern of Figures 6(a) and 6(b) an open eye and Figures 6(c) and 6(d) closed eye. When the conversion of the eye image is completed, the height of the eyelids is utilized to determine the eye's state [31].

$$T = \frac{\sum_{i=1}^{n} x_i}{n} \quad (4)$$

$$P(X,Y) = \begin{cases} 1, gray(X,Y) \geq T \\ 0, gray(X,Y) < T \end{cases} \quad (5)$$



(a) (b) (c) (d)

Figure 6. Binary pattern of (a), (b) an open eye and (c), (d) closed eye

$$g(X,Y) = I(X,Y) * G_{\emptyset}(X,Y) \quad (6)$$

$$G_{\emptyset}(X,Y) = \frac{1}{2\pi\emptyset^2} e^{\frac{(x^2+y^2)}{2\emptyset^2}} \quad (7)$$

The Canny's edge detection algorithm is well known for its ability to generate a continuous edge. First, the image is smoothed by Gaussian convolution [32]. Where Ø can be used to adjust the scale. At this stage, the differential channel determines the magnitude and introduction of the edge. Edge data of various scales is used to obtain the final edge picture [33]. Edge focuses are summed together for the purpose of determining the eye's condition. Classification is done using a double support vector machine (SVM) classifier with a straight bit [34]. It has been used to generate video outlines using a 15 fps 5-MP camera in MATLAB 2017. In the suggested approach, the driver's facial weakness indications are taken into account to determine if they are properly executed [35]. The approach was tested in both low and high light circumstances in order to verify its performance. The first analysis was performed in broad daylight at a distance that was as close to ideal as possible. Accuracy was found to be between 85% and 95% when the program was run in normal daylight conditions [36]. This can be seen in Figure 7 where the percentage of yawns detected was higher than the percentage of eye movements detected as signs of sleepiness. It was done in low light and close proximity for this second analysis [37]. When compared to scenario-1 daylight, which had an accuracy of 75 to 80 percent, the software ran and executed with an average accuracy of 10 to 15 percent. The percentage detection of yawning was likewise shown to be higher than the % detection of eye movement for drowsiness, as was previously noted [38]. Figure 7 depicts a drowsy and a normal sample in a similar state of alertness. The final study was done in artificial light at night with the best possible proximity. Compared to scenario-1 and scenario-2, the program's execution and performance was found to be between 90 and 93 percent accurate. As previously noted, the detection of yawning was found to be more accurate than the detection of eye movement as a sign of sleepiness. A drowsy sample and a normal one is depicted in Figure 8 for comparison. It was decided to conduct the final analysis under low-light conditions and in close proximity to the samples. The program was found to have the lowest accuracy % compared to scenarios 1 and 2, as well as scenarios ranging from 65 to 68 percent. The percentage identification of yawning was also found to be better than the percentage detection of eye movement for tiredness, as previously reported. As depicted in Figure 8, one sample was tired, and the other was awake. Image capture and analysis rely heavily on proximity, and it has been found that in certain settings, the closest possible proximity is required to improve performance and detect eye and lip gestures [39]. We found that the camera and feature should be as close as possible to each other as to avoid any interference. As part of the first step in the detection procedure, a support vector machine classifier is used to identify the eye and mouth movements [40]. Table 2 shows the accuracy analysis of scenario versus trial, where percentage accuracy is given for trial 1 to trial 4 according to scenario 1 to scenario 4. Table 3 show the results of a statistical study of the accuracy % for all trials in each situation.

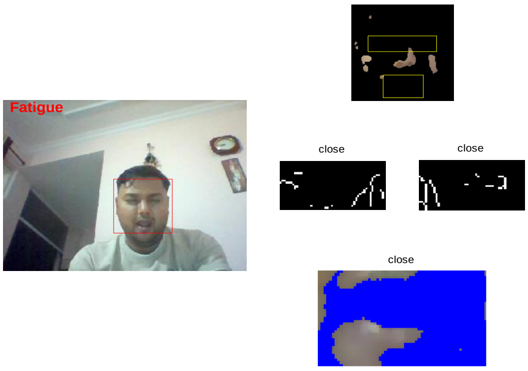


Figure 7. Face detection for alert and drowsy state

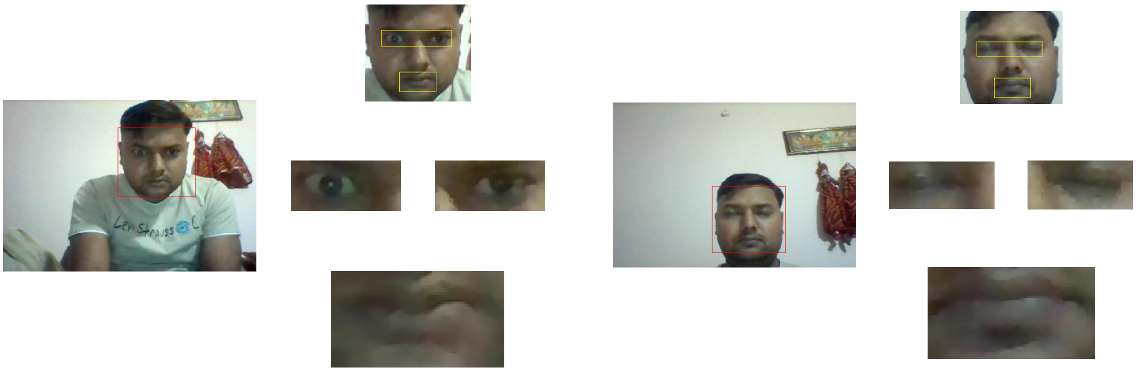


Figure 8. Face segmentation of eyes and lips

Table 2. Accuracy analysis of scenario vs trial

Scenario	Percentage Accuracy			
	Trial-1	Trial -2	Trial -3	Trial -4
Scenario-1	91 %	90 %	91.5 %	92.10 %
Scenario-2	77 %	80 %	83 %	82 %
Scenario-3	91 %	92.5 %	93 %	94 %
Scenario-4	65 %	68.50 %	66 %	72 %

Table 3. Average accuracy per scenario

Scenario	Percentage Accuracy
Scenario-1	91 %
Scenario-2	81 %
Scenario-3	93 %
Scenario-4	68 %

5. CONCLUSION

Due to the high efficiency and good performance under different circumstances, the real-time implementation of drowsiness detection which is invariable to illumination and performs well under various lighting conditions. Tracking the eyes and mouth is made simple using a design matching type of medical signal processing. The proposed framework achieves a high degree of accuracy in the four test cases, surpassing the accuracy of the approaches used in the recent past. Through using a device that is able to identify the aura of the fire substantially accurately, the machine will also reduce the number of casualties per year. With its model, the device could not say if the person was nodding off from getting their head to the side or if their body was slipping out from under them. The head lowering forecast might also need to be included within some form of threshold. The accuracy also decreases when wearing glasses. Future attempts will be made to make it so "swing" will continue to be the same.

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