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# REAL-TIME AND DEEP LEARNING-BASED FATIGUE DETECTION FOR DRIVERS

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**Abstract**

*Among the causes of traffic accidents, driver errors are in the first place. Driver faults are generally considered to be situations such as drunk driving and excessive speeding. However, sleep-deprived and tired driving are also among the leading causes of driver faults. Driving while feeling sleepy and fatigued; Effects such as slow reaction time, decreased awareness, and inability to focus occur. Considering this situation, it is understood that driving while sleepy and tired is at least as dangerous as driving under the influence of alcohol. In this study, a system that works in real-time inside the vehicle constantly monitors the driver and works with high accuracy is proposed. This system is deep learning based and low cost. In the study, the driver's eye and mouth movements were analyzed to determine normal, yawning and fatigue. A data set has been created for this. The data set consists of videos taken at different times and in different ways from 129 volunteers. Videos shot in different formats, quality and sizes were collected, and turned into a single format. Grayscale, tilt addition, blurring, variability addition, noise addition, image brightness change, color vividness change, perspective change, sizing, and position change were added to the photographs that make up the data set. With these additions, the error that may occur due to any distortion that may occur from the camera is minimized. Thus, the accuracy rate in the detection process with images taken from the camera in real-time has been increased. At the same time, a new data set specific to the study was prepared. YOLOv5, YOLOv6, YOLOv7, and YOLOv8 architectures were used in the study. The newest and most used architectural results in the literature are compared. As a result of the study, a 98.15% accuracy rate was obtained in YOLOv8 architecture. It is aimed that the study will be highly effective in preventing traffic accidents.*
**Keywords: Deep learning, Driver fatigue detection, Image processing, YOLOv8 architecture**

# SÜRÜCÜLER İÇİN GERÇEK ZAMANLI VE DERİN ÖĞRENME TABANLI YORGUNLUK TESPİTİ

**Özet**

*Trafik kazaları nedenleri arasında sürücü kusurları ilk sırada yer almaktadır. Sürücü kusurları genel olarak alkollü iken araç kullanma, aşırı hız yapma gibi durumlar düşünülmektedir. Fakat uykusuz ve yorgun araç kullanmanın da sürücü kusurlarında ön sıralarda yer almaktadır. Uykusuz ve yorgun şekilde araç kullanımda; tepki süresinde yavaşlık, farkındalığın azalması, odaklanamama gibi etkiler ortaya çıkmaktadır. Bu durum göz önünde bulundurulduğunda uykusuz ve yorgun araç kullanmanın da en az alkollü araç kullanmak kadar tehlikeli olduğu anlaşılmaktadır. Yapılan bu çalışmada araç içeresinde gerçek zamanlı çalışan, sürekli olarak sürücüyü izleyen ve yüksek doğrulukta çalışan bir sistem önerilmiştir. Bu sistem derin öğrenme tabanlı ve düşük maliyetlidir. Yapılan çalışmada sürücünün göz ve ağız hareketleri analiz edilerek normal, esneme ve yorgunluk tespiti gerçekleştirilmiştir. Bunun için bir veri seti oluşturulmuştur. Veri seti 129 gönüllüden farklı saatlerde ve şekillerde çekilmiş videolardan oluşmaktadır. Farklı formatta, kalite veboyutta çekilen videolar toplanark tek bir format haline getirilmiştir. Veri setini oluşturan fotoğraflar üzerinde gri tonlama, eğim eklenmesi, bulanıklaştırma, değişkenlik eklenmesi, gürültü eklenmesi, görüntü parlaklığı değişikliği, renk canlılığı değişikliği, perspektif değişikliği, boyutlandırma ve konum değişikliği eklenmiştir. Bu eklemeler ile kameradan meydana gelebilecek herhangi bir bozulmaya karşı oluşacak hata en aza indirilmiştir. Böylelikle gerçek zamanlı olarak kameradan alınan görüntülerle yapılacak tespit işlemindeki doğruluk oranı arttırılmıştır. Aynı zamanda çalışmaya özgü ve yeni bir very seti hazırlanmıştır. Yapılan çalışmada YOLOv5, YOLOv6, YOLOv7 ve YOLOv8 mimarisi kullanılmıştır. Literatürde en yeni en çok kullaılan mimari sonuçları karşılaştırılmıştır. Çalışma sonucunda YOLOv8 mimarisinde %98.15 doğruluk oranı elde edilmiştir. Yapılan çalışma ile trafik kazalarının önlenmesinden yüksek oranda etkili olacağı hedeflenmektedir.*
**Anahtar Kelimeler: Derin öğrenme, Sürücü yorgunluk tespiti, Görüntü işleme, YOLOv8 mimarisi**

**Cite**

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## 1. Introduction

In many parts of the world, most of the transportation is done by road. Traffic accidents on highways are among the leading causes of death in the world. Traffic accidents are generally defined as events involving one or more vehicles that result in material damage, injury, or death.

Traffic accidents can be significantly reduced by taking the necessary precautions. As a result of research conducted in this context, it has been determined that the rate of driver-related accidents is high. Driving under the influence of alcohol, fatigue, and insomnia significantly affect these rates. Many people know how dangerous it is to drink and drive. However, driving while tired and sleepy is at least as dangerous as driving under the influence of alcohol.

Many different studies have been carried out on the early detection of driver fatigue in order to prevent traffic accidents. It should be noted that in some applications, a few features are more important for detecting fatigue. The most important of these features are the devices used to determine fatigue. It has been determined that biological characteristics will give the most accurate results in fatigue detection studies because they show the internal state of the body exactly. However electrodes and sensors are attached to the body during data collection for biological characteristics. The devices used are expensive, complex, and disturb the driver. When these situations are evaluated, the most suitable feature for detecting driver fatigue is seen as physical features [1-5].

There are different studies using devices to detect driver fatigue. One of these was made during the journey of the high-speed train. Pressure, force, strain, and non-contact temperature values were measured and examined through devices placed on the seat. The most successful results were obtained from pressure and temperature values. As a result of the study, 66% accuracy of existing driver fatigue detection systems was determined [6]. Another study was conducted in the field of aviation. They stated that the majority of aviation accidents are caused by human factors such as fatigue or tiredness. A flight simulation was carried out with the participation of 10 pilots. During this flight, Electroencephalography (EEG) and Electrooculography (EOG) sensors were added to the 10 participating pilots. The study was carried out on the data coming from the sensors. In the study, in addition to mental state classification as sleepy and awake, classification procedures were also carried out for 5 fatigue levels. This was determined using 5 fatigue levels (very alert, fairly alert, neither alert nor sleepy, sleepy but not trying to stay awake, and very sleepy). Classification processes were carried out using deep learning methods, and as a result of the study, it was determined that using only EEG signals for fatigue classification processes provided sufficient performance [7].

Fatigue detection has also been applied to vehicle drivers with Electroencephalography and Electrooculography sensors. An ECG sensor has been added to the driver. To detect driver fatigue; First, the driver's electrocardiogram (ECG) data was examined. Then, heart rate variability was classified into neural networks using the Fast Fourier Transform. This study detected driver fatigue with 90% accuracy [8]. They stated that heart rate variable-based fatigue technique can be used as a precaution against fatigue [9]. They examined the connections between fatigue and EEG by analyzing EEG data during driving experiences performed in a virtual reality driving simulator. In the study, analyses were performed on data taken from electrodes on parts of the scalp that do not contain hair. [10]. Another study was based on the driver's heart rate. In the study, they used a portable measuring device that can be attached to the fingertip to measure the driver's heart rate, unlike other studies. With this method, they calculated the driver's respiratory rate. The study generally includes two different validation studies: the accuracy of the respiratory rate calculated from the heart rate and the accuracy of the fatigue detected based on the respiratory rate. As a result of the study, it was concluded that the calculated respiratory rate was consistent with the actual respiratory rate, but the accuracy value should be increased in systems where the respiratory rate will be used for fatigue detection [11-12].

There are driver fatigue detection studies based on vehicle parameters. Fatigue causes greater variability in lane position and steering movements. Studies have shown that this variability can be used in driver fatigue detection studies. Studies have been conducted to determine driver fatigue using vehicle telemetry data. In the study, operations were carried out using various machine-learning methods. Data were recorded during rides on a gaming console integrated into a desktop computer. First of all, feature selection was made, and the most meaningful data that could determine driver fatigue was extracted. As a result of this process, it was decided that steering angle, lateral speed and derivatives of these variables could be effective in driver fatigue detection studies and that these data should be used. It is aimed to achieve optimum results by using various combinations of these features. Logistic Regression-LR, Multilayer Perceptron-MLP, and Random Forest-RF machine learning methods were used for fatigue detection. SVM was preferred due to its better performance, greater computational efficiency, and higher precision. As a result of the study, it was determined that the feature set in which steering angle, lateral speed and their derivatives were evaluated simultaneously showed the best performance [13].

The most preferred driver fatigue detection methods are methods based on behavioral parameters. The fact that it is a method that is easily applicable, low-cost, not affected by external factors and does not interfere with the driver can be considered among the reasons for its preference [14]. The most used in this technique is the PERCLOS technique. PERCLOS; visual parameters such as eye closing time, blinking frequency, driver's head nodding frequency, facial position, and fixed gaze. These parameters are used with a Fuzzy Classifier. They stated that the experimental results obtained by using multiple visual parameters and combining the parameters yield more accurate and stable results compared to the use of a single parameter [15]. A new real-time eye tracking based on the Kalman filter is proposed for driver fatigue detection. It is also stated that driver fatigue can be detected using PERCLOS calculated under realistic driving conditions. This study accurately predicted driver fatigue 99% of the time [16]. An accurate drowsiness detection method has been developed for images acquired using low-resolution consumer-grade webcams under normal lighting conditions. The drowsiness detection method used a combination of Directional Gradient Histogram (HOG) features with a Haar-based cascade classifier for eye tracking and a Support Vector Machine (SVM) classifier for eye blink detection. It was determined that the system matched the human observer with 91.6% accuracy [17]. Machine learning was used to classify spontaneous human behavior data, which they used to detect driver fatigue. Data including eye blinking and yawning movements were classified with learning-based classifiers such as AdaBoost and Multinomial Ridge Regression. This study detected driver fatigue with over 90% accuracy [18]. A drowsy driver monitoring and accident prevention system based on monitoring changes in eye blink duration has been designed. In their proposed method, changes in eye positions were detected by using the horizontal symmetry feature of the eyes. As a result of their experimental results using a standard webcam, 94% of blinking movements were detected [19].

The developments made by deep learning algorithms in recent years have an impact on many areas of our lives. In parallel with these developments in deep learning, image classification techniques are developing rapidly every day. For this reason, deep learning methods have begun to be frequently preferred in behavior detection studies. A non-intrusive autonomous driver fatigue system based on computer vision and artificial intelligence has been developed. The system analyzed the driver's eye condition in real-time. The system they classified by analyzing yawning, blinking frequencies, and head movements detected driver fatigue with an accuracy of over 60% [20]. Deep learning and fuzzy logic were used in the study on driver fatigue detection from facial expressions. While the Caltech10k Web Faces dataset was used for training in mouth and eye detection, the FDDB dataset was used for testing. Yawning frequency and eyelid closing frequency are calculated to determine the driver's fatigue state. After calculating the driver's yawning and eye-closing frequency, the fuzzy inference system determines the driver's fatigue status. The success rate of the developed model, in which the mouth and eyes were analyzed together, was found to be 85.9% in yawning and 93.4% in eye closing. The success rate of the fatigue detection model was found to be 96.5% in normal situations and 94.7% in slightly fatigued situations [21]. In the study on real-time driver fatigue detection from eye-opening ratio, multi-layer perceptron random forest and support vector machines algorithms were used. In the study, multilayer perceptron random forest and support vector machine algorithms were used for reasons such as low hardware requirements and short training time. Among the algorithms used, the support vector machines algorithm has shown the best performance with a success rate of 94.9% [22].

For fatigue detection, only the eye was taken into account because taking into account facial features other than the eye would result in unnecessary information and increased computational power. In the study, a success rate of 94.44% was achieved on a challenging test data set such as DROZY [23]. A compact face descriptor was used for fatigue detection. In the study, the regression tree ensemble algorithm was used because it is sensitive and effective in detecting facial images. A descriptor based on perceived level of care was used to detect distinctive features in the images. Support vector machines algorithm was used to classify the images. In the article, driver status is discussed in four categories; not sleepy, sleepy, yawning, and nodding. The Principal component analysis method was used to reduce unnecessary areas in the data set. The developed model achieved an average accuracy rate of 76.77% without using the principal component analysis method. When the principal component analysis method was used, the accuracy rate of the model was 76.92% [24]. A Java-based mobile application was developed for fatigue detection using OpenCV. For fatigue detection, only the right eye was focused. In this way, fewer images are analyzed and processing power is reduced. The accuracy of the application developed in the study was tested with three different methods. The first method is fatigue detection through photographs. The photographs were made dynamic using the Adobe Animate program and the test was performed by opening and closing the eyes. In the second method, a scenario in which two people slowly closed their eyes was tested in a laboratory environment. The phone was placed in the a laboratory environment with a distance of 30 cm between the phone camera and the driver. The last test was made with a phone placed on the steering wheel of the vehicle. In the application, the OpenCV library was used for classification. To detect the face and eyes, the image classifier algorithm Haar classifier in OpenCV was used. Fatigue is calculated based on the white-pixel ratio. If the white pixel ratio falls below the 5% and 50% limits, fatigue is detected. The application is not affected by short-term pixel changes such as blinking. In case of prolonged eyelid closure, the alarm sounds continuously and requests feedback from the driver. In practice, if the eyelid remains closed for more than 3 seconds, the alarm works [25]. A combination of convolutional neural networks and bidirectional long-short-term memory methods was used for driver fatigue detection. The proposed method works in three stages. First, the driver's face image is determined. Then, the frequency of eye-opening and closing is monitored with the Euclidean algorithm. In the last stage, closed or open eye detection is made. Convolutional neural networks and bidirectional long-short-term memory methods were used together for classification. InceptionV3 convolutional neural network algorithm was used in the study. The model was generalized with the Adam optimization method to improve the driver fatigue detection accuracy rate. When the convolutional neural network model was used alone, the accuracy rate was achieved at 85% [26].

Unlike other studies, the study is deep learning based and low cost. A camera and Raspberry Pi were used in the study. The study proposes a solution that detects driver fatigue with high accuracy by taking into account the driver's facial and eye movements as well as mouth movements. The solution offered aims to minimize human-caused traffic accidents, as well as ensure safe transportation and protect human life in traffic. In this context, a deep learning-based system was developed that monitors the driver in real-time in the vehicle and can detect the driver's fatigue state. With the developed system, the driver is monitored instantly and if fatigue or insomnia is detected, the driver is warned. Thus, it is thought that the proposed system will be very effective in preventing possible traffic accidents.

The contributions of the study can be listed as follows. The study created a new data set. As a result of the study, a very high level of accuracy was achieved. A cheap and easy system has been developed.

## 2. Material and Method

People experience moments during the day when they feel extremely sleepy or tired. This condition is defined as fatigue. If the state of fatigue increases and intensifies, falling asleep during the day may occur. This situation is called microsleep.

Microsleep is a temporary episode of sleep that lasts between 1-30 seconds. When people are tired, parts of their brains fall asleep, even though they're technically awake. People who fall into microsleep are usually not even aware of this situation. Even if people think they are awake, the brain does not work at full capacity because a part of the brain turns off or sleeps during microsleep. While driving, drivers cover high distances during their micro sleep period. At these distances, it is long enough to violate situations such as red lights, lane changes, and stop signs. In addition, fatigue also affects decision-making skills, reaction time, and driving ability. Even if falling asleep does not occur, a tired driving can lead to many dangers. With the study carried out, real-time fatigue detection of drivers was achieved using deep learning. Figure 1 shows the general schematic of the system.

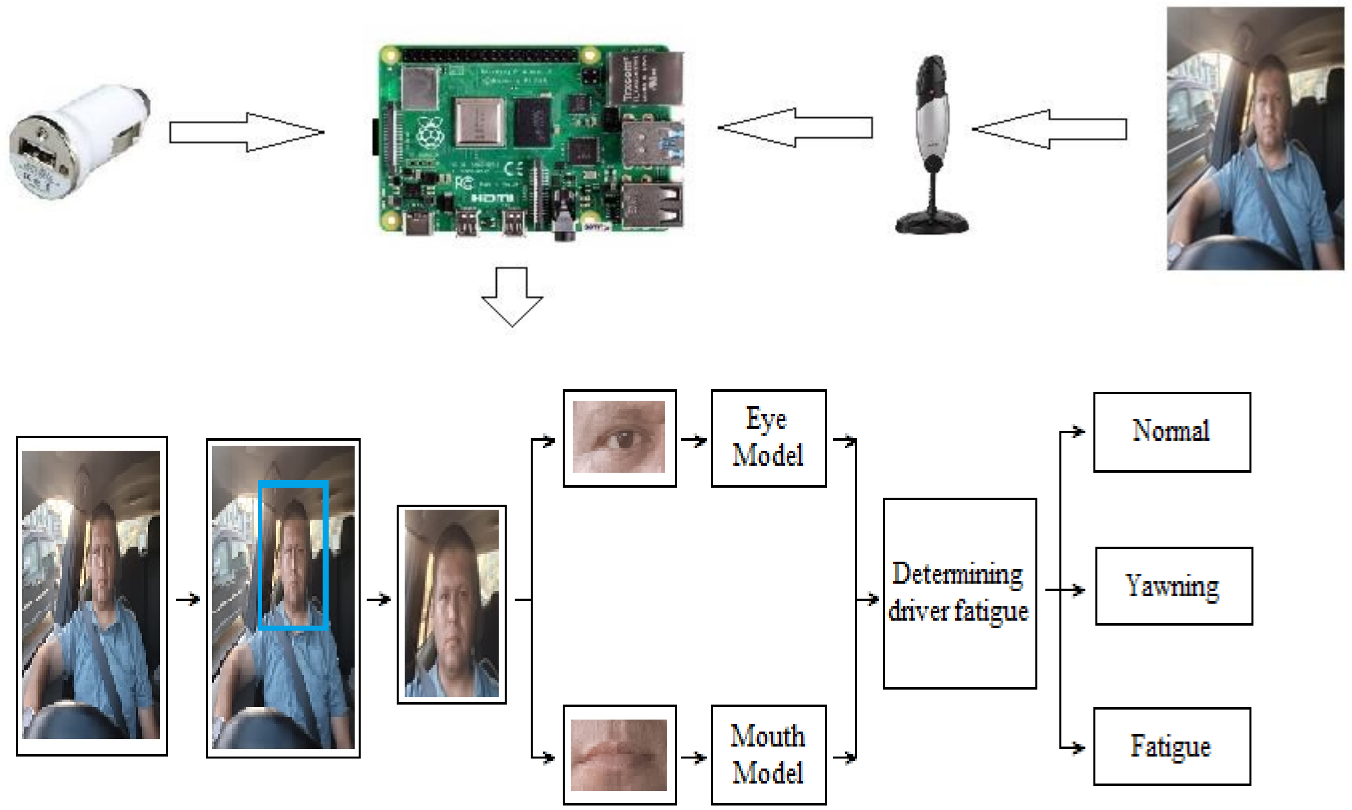


Figure 1. The general schematic of the system.

### 2.1. Dataset

The first process in deep learning is the creation of the data set. The accuracy rate increases the more the data set is created in accordance with the real environment. Many different ready-made data sets are used. Table 1 shows the data sets used in literature studies.

Table 1. The data sets used in literature studies.

| Data set | Number of Participants | Experimental Environment | Situation |
|---|---|---|---|
| DROZY | 14 | Lab | Normal/Tired |
| NTHU-DDD | 36 | Game Simulation | Yawning/Nodding/ Slow Blinking/ Laughing/ Speaking/ Looking Both Sides |
| RLDD | 60 | Home/ University | Awake/Low Alert/Tired |
| YAWDD | 107 | In a Parked Vehicle | Normal/Talking or Singing/Yawning |
| NCKUDD | 25 | In the Vehicle While Driving | Normal/Sleepy/Distracted/Talking/Eating/ Playing on Phone/ Other |
| SMIC | 16 | In a Closed Room | Sad/Angry/Disgusted/Scared/Happy/ Surprised |
| SAMM | 32 | In a Closed Room | Angry/Disdainful/ Frightened/Disgusted/ Happy/Sad/Surprised |

When the data sets are examined in general; while data is collected in most datasets, it is seen that the videos are shot in a laboratory or simulation environment rather than a real vehicle. Some data sets were created outside real environments such as home, school, and social environment. When the recordings made in the vehicle in the real environment were examined, the vehicle was parked and an artificial driving simulation was performed. During the video recordings that make up the data set, participants are asked to role-play by giving instructions such as yawning, nodding, and laughing. It is predicted that the creation of artificial expressions in data sets cannot be used to detect real driver fatigue.

When the data sets in the literature are evaluated, it is seen that there is a need for a data set consisting of real and safe driving moments. In this study, a data set consisting of the participants' driving experiences in their own vehicles and on their own routes was created. 129 people, 122 men and 7 women, between the ages of 18-70, participated in the data set study.

A phone holder was placed on the windshield of the participants' cars. The phones placed in the holders are adjusted to face the drivers' faces. Participants were asked to record videos while driving. Each driver was given one month for these procedures. This allowed them to shoot videos without pressure, at a time when they felt really tired/normal. Participants were not asked to follow any route while driving. They recorded some of their driving on camera, without any additional sanctions, during the routes they were supposed to follow in the normal course of the day, according to their own wishes. Depending on the preference of the participants, the videos are generally shot during the hours when people feel more vigorous, such as going to work, for normal driving, and at the time of returning from work when end-of-day fatigue is intense for tired driving, and there are also videos recorded at the beginning (normal) and near the end of intercity journeys (tired). . Each participant shot at different times and times. Since each participant shot in their own vehicles with their own phones, a video recording that was more appropriate to the real environment was recorded. Since each participant recorded their video with their own phone, there are differences in the quality of the videos. There are differences in format, size and quality between videos depending on the phone's features and camera. All videos have been converted to mp4 format. Since the videos contain sound, they are large in size. Since only the image will be processed in the detection process, sound has been deleted from all videos. Thus, the size of the videos has been reduced. In this way, a shortening of the processing time and a slight increase in accuracy was achieved.

All videos that make up the data set were examined and divided into 3 classes: normal, yawning and tired. In this separation process, the records are separated for 1 minute in length. Since people have normal, yawning and tired states during a recording, these should be separated. For this purpose, the entire data set was examined and separated. As a result of this process, a total of 1347 videos were created. Of the 1347 videos, 685 of them consist of normal driving, 489 of them in the stretching state, and 173 of them in the tired state of the driver. 259 of the videos that make up the data set consist of drivers with glasses.

In the proposed method, the data set is first pre-processed. At this stage, the samples in video format are first divided into frames. Then, the frames sequentially create the singular image. Grayscale, tilt addition, blurring, variability addition, noise addition, image brightness change, color vividness change, perspective change, dimensioning, and position change were added to each individual image. With these additions, the error that may occur due to any distortion that may occur from the camera is minimized. Thus, the accuracy rate in the detection process with images taken from the camera in real-time has been increased. Figure 2 shows the changes applied to the photographs in the data set.

Figure 2a)Normal, b) Sizing and position change, c)Grayscale, d)Adding slope, e)Blurring, f)Adding variability, g) Adding noise, h)Image brightness change, i)Colour vividness change, k)Perspective change, l) Hue, m) Cutout

Figure 2a shows the normal photo without modification. In Figure 2b, 25% variability has been added to the positioning and sizing of the images that make up the database. This process was done because the model is more durable depending on the camera position. Detection works the same way after the camera shakes or changes its position. There is no decrease in accuracy rates after the detection process. In Figure 2c, the images in the database have been converted to grayscale. The system will continue to work in case of color loss that may occur in the camera. In Figure 2d, +15% and -15% slope was added to the images. The car is mostly in motion. During these times, cars shake. The camera attached to the car is also shaking. This creates shifts in the images. +15% and -15% slope was added to the images in the database to ensure that the system always performs detection. In Figure 2e, Gaussian blurring was applied to the images in the database. Gaussian blurring was done randomly. In this way, it is ensured that the camera focus is more resistant. In Figure 2f, +15% and -15% variability has been added to the rotations to be more robust against camera roll. In this way, the effect of errors that may occur on the edges of the images is minimized. In Figure 2g, noise has been added to make it more robust to camera artifacts. There are electronic devices for the car, especially mobile phones. This causes noise in the camera. To prevent this, noise was added to the images. In Figure 2h, +15% and -15% changes were made in the image brightness to make the model robust to light and camera changes. The image taken from the camera is not always clear. Especially at sunset and sunrise, very clear pictures cannot be taken. To prevent this, changes were made to the brightness of the images. In Figure 2i, the vividness of the colors in the images is randomly adjusted. Perspective variability has been added to Figure 2k to make it more robust to camera, subject pitch, and aberration. Perspectives change when the car turns or bends. At this time, a perspective change was added to the database for the detection process to work properly. It was used to randomly adjust the vividness of the colors in the images in Figure 2l. The camera cannot always take normal images. Sometimes the sun hits the camera directly or from the side. In this way, color change has been added to the image taken from the camera. In Figure 2m, truncation has been added to help the model be more resilient to object occlusion. Some areas are not visible when taking pictures from the camera. Because a piece comes in front of the violin, that part of the picture appears black. At such times, images were cropped to ensure the detection process worked properly.

A computer with an AMD Ryzen 1500X 3.5 GHz processor was used in the study. NVIDIA GeForce GXT 1050Ti 4GB GDDR5 was preferred as the graphics card. Memory speed is 16 GB 3000 MHz.

### 2.2. Deep Learning

Deep Learning is one of the sub-topics of the field of machine learning and is also the most current topic. Deep Learning methods are used as artificial neural network algorithms inspired by the structure of the human brain. Deep Learning is part of a broader family of machine learning methods based on learning data representations, as opposed to task-specific algorithms. Deep Learning, along with studies in the field of machine learning, has also pioneered the expansion of the scope of artificial intelligence. Compared to superficial learning, the concept of deep learning has the advantage of building deep layers to reach more abstract information. Deep learning-based methods are used successfully in many fields. One of these is automatic object detection.

YOLO is a deep learning-based object recognition algorithm developed by Joseph Redmon. YOLO performs object detection using a single neural network to estimate class probabilities along with bounding boxes. YOLO's architecture is convolutional neural network-based and has a fast structure.

YOLOv8 is equipped with more advanced post-processing techniques than its previous versions. These techniques are applied on estimated bounding boxes and object scores produced by the YOLOv8 neural network. With YOLOv8, it refines detection results, removes unnecessary detections and improves the overall accuracy of predictions. These techniques include Soft-NMS, a variant of the non-maximum suppression (NMS) technique used in YOLO architectures. Instead of completely deleting overlapping bounding boxes, Soft-NMS applies a soft threshold to them. YOLOv8 passes the image through the convolutional ANN at once and performs group normalization. This gives a frame processing speed that can vary from 5 FPS to 160 FPS. Figure 3 shows the general structure of the YOLOv8 architecture.

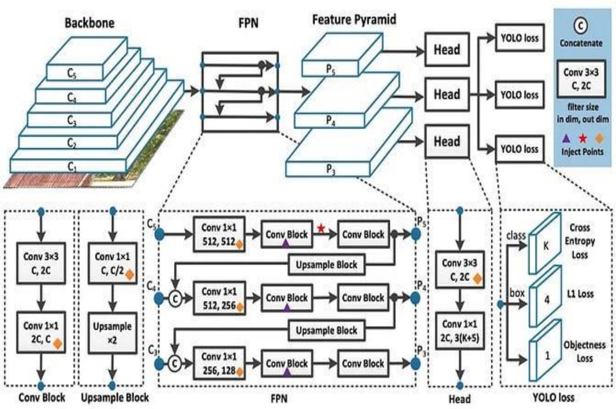


Figure 3. The general structure of the YOLOv8 architecture.

## 3. Result and Discussion

With the study, the normal, yawning and fatigue states of the drivers in the vehicle were determined. For this purpose, the driver's face, eyes, and mouth areas are constantly monitored. First, the driver's face is detected. Finally, after the eye and mouth areas are detected, they are sent to two separate models to detect fatigue. Thus, in cases where eye detection cannot be made, it can be independently determined whether there is yawning in the mouth area. Figure 4 shows the operating algorithm of the system.

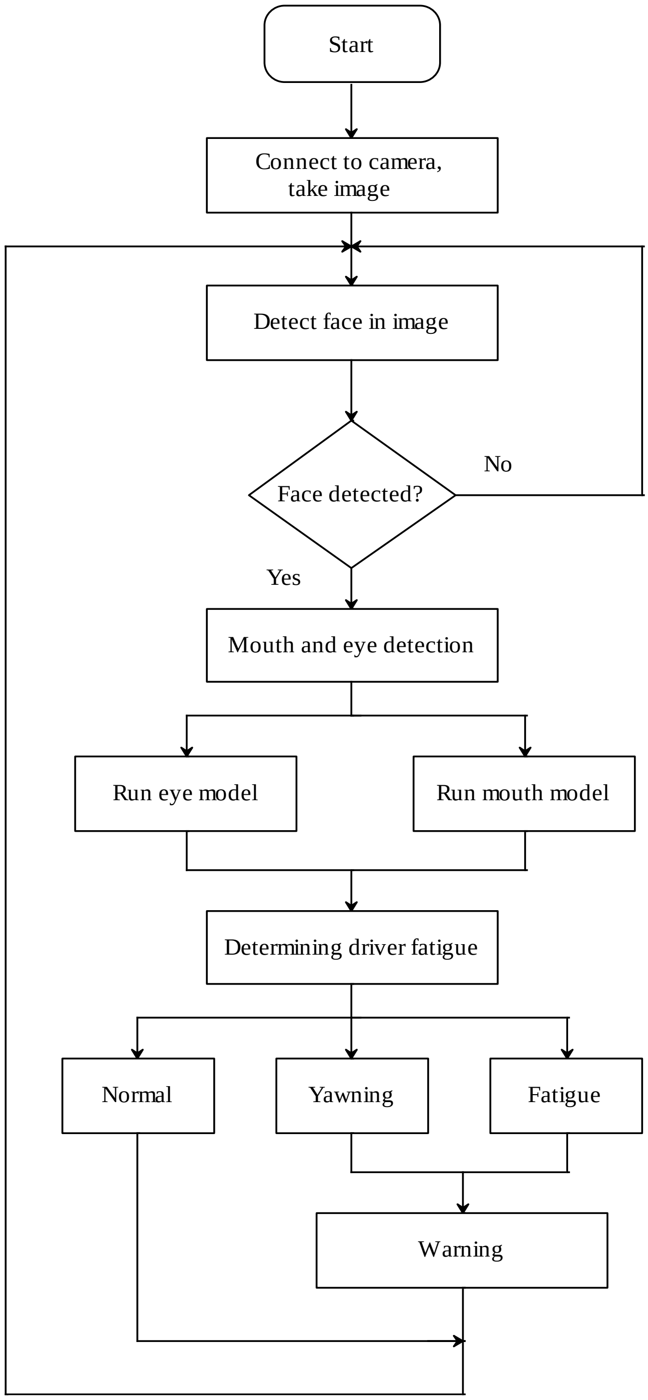


Figure 4. The operating algorithm of the system.

### 3.1. Eye Model

The eye model method is based on operations performed on the eyes within the face. For this, the image taken from the camera is processed. After the facial process is detected in the image, the eye model works. In the eye model, first the eye is detected in the picture. After eye detection, it is determined whether the eyes are open or closed. If the eyes are open, the counter is reset. If the eyes are closed, it is counted with a counter. The number of frames per second (FPS) is checked. The calculation made according to the FPS value is called PERCLOS calculation. Fatigue decision is made with PERCLOS calculation. If the PERCLOS percentage exceeds 80%, a decision of fatigue is made. In other words, in a system where the number of frames per second is 100, a fatigue decision is made if the eyes are closed for at least 80 frames. Figure 5 shows the eye model algorithm.

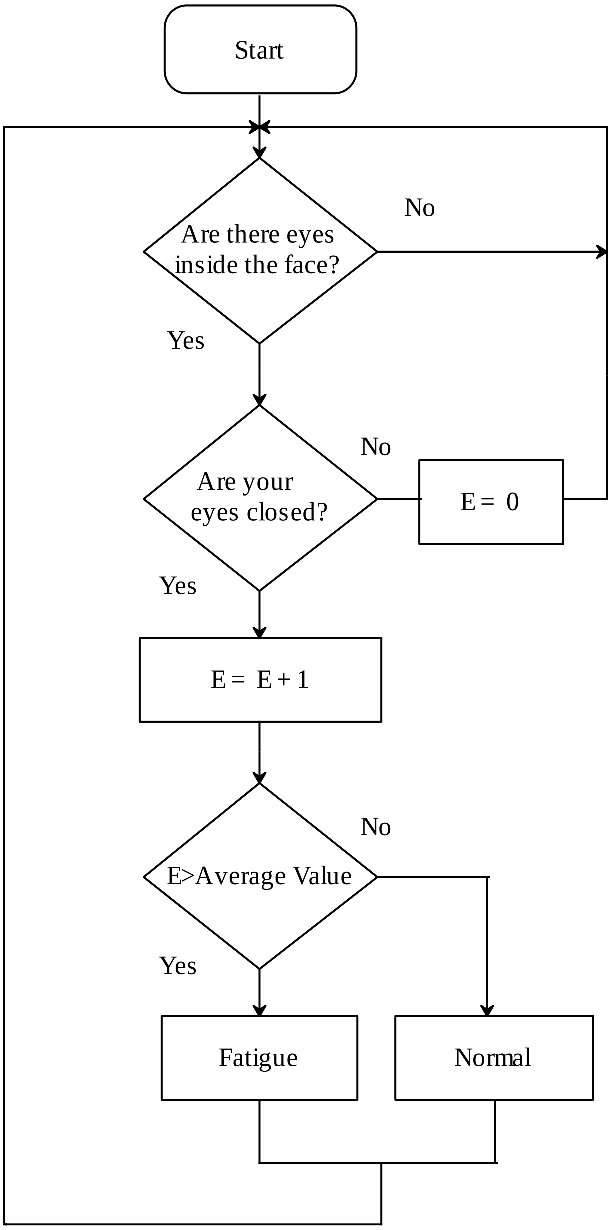


Figure 5. Eye model algorithm.

### 3.2. Mouth Model

The mouth model works just like the eye model. First, it is determined whether there is a mouth in the picture. Later, it is determined whether the mouth is open or closed. If the average value exceeds 80, a relaxation decision is made. Figure 6 shows the mouth model algorithm.

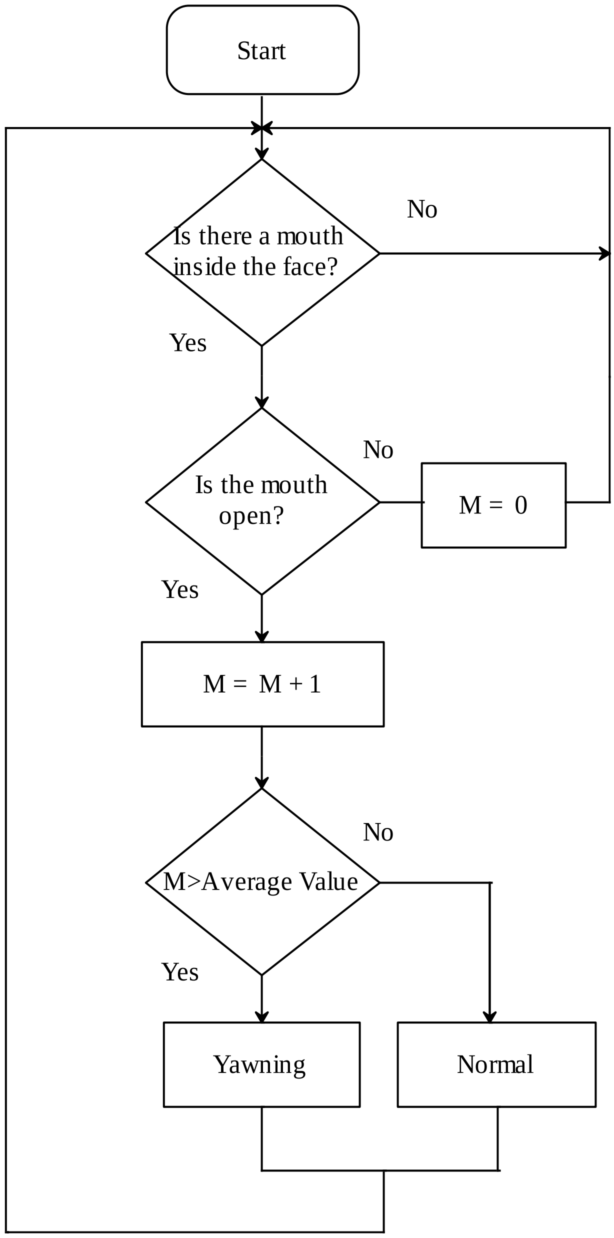


Figure 6. Mouth model algorithm.

YOLOv5, YOLOv6, YOLOv7 and YOLOv8 architectures were used in the study. The results are different due to changes in the internal structures of each architecture. Table 2 shows the average values of the architectural results.

Table 2. Results of the architectures used in the study

| Architecture name | Accuracy % |
|---|---|
| YOLOv5 | %94.15 |
| YOLOv6 | %95.24 |
| YOLOv7 | %96.48 |
| YOLOv8 | %97.50 |

The highest accuracy rate was achieved in the YOLOv8 architecture with 99.75%. For this purpose, YOLOv8 architecture was used.

A total of 3 different states were determined for the YOLOv8 architecture: normal, stretching, and fatigue. In the study, normal detection was 0.99. The accuracy rate of yawning detection was determined as 0.98. The lowest rate was fatigue detection with 0.96. The average detection rate of 3 different cases was 0.975. Figure 7 shows the ROC curve obtained from the study.

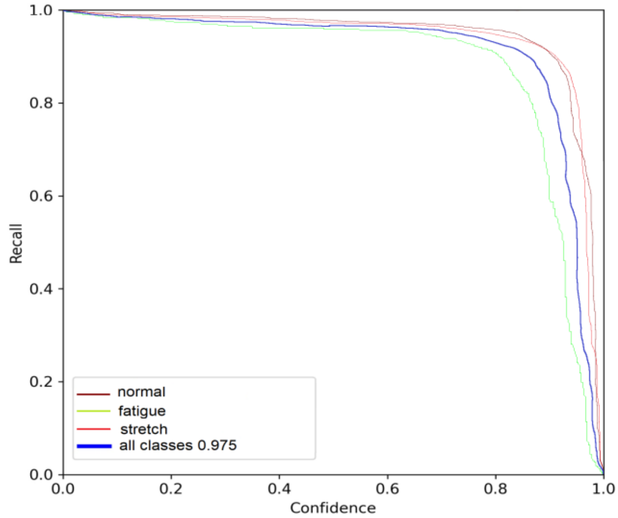


Figure 7. ROC curve

In the conducted study, three different classification situations were identified. As the first situation, normality was considered. In this case, the eye is open and the mouth is in a normal shape. Figure 8a shows the normal situation. The second situation is the stretching situation. In this case, the situation where the eyes are open and yawning occurs is considered. Figure 8b shows the stretching situation. In the third case, fatigue was detected. In this case, it is considered that there is no yawning and the eye is closed for a certain period of time. Figure 8c shows the fatigue condition.


Figure 8a) Normal, b) Yawning, c) Fatigue.

There are many different studies on driver fatigue detection in the literature. Different data sets and different methods were used in these studies. Table 3 shows literature studies.

Table 3. Literature studies.

| Writer | Dataset / Model | Accuracy rates % |
|---|---|---|
| Omidyeganeh et al. [27] | YawDD/Perclo | 75 |
| Yarlagadda et al. [28] | Conv-LSTM | 96.25 |
| Akrout and Mahdi [29] | YawDD/CNN | 83 |
| Lui et al. [30] | Drozy/EAR-SWM | 94.44 |
| Zhang and Su [31] | YawDD/CNN | 88.60 |
| Flores et al. [32] | D2CNN/FLD | 83.33 |
| Zhang et al. [33] | DROZY/CNN | 92.00 |
| Jie et al. [34] | YawDD/CNN | 96.43 |
| Kassem et al. [35] | RLDD/CNN | 96.20 |
| Guo and Markoni [36] | YawDD/CNN | 91.48 |
| Geng et al. [37] | SMIC/CNN | 92.10 |
| You et al. [38] | YawDD/CNN | 94.32 |
| Jabbar et al. [39] | NthuDDD/CNN | 80.93 |
| Vu et al. [40] | NthuDDD/CNN | 84.81 |
| Ayachi et al. [41] | NthuDDD/EEG | 96.05 |
| Çevik et al. [42] | YawDD / CNN | 94.50 |
| Şafak et al. [43] | CNN | 95.62 |

When literature studies were examined, ready-made data sets were used. These data sets give very good results in simulation results. But in the study, detection was made in real-time. For this reason, the data set must be very suitable for the real environment. For this reason, a ready-made data set was not used in the study. The data set was prepared with different people in a real driving environment. Grayscale, tilt addition, blurring, variability addition, noise addition, image brightness change, color vividness change, perspective change, sizing, and position change were added to the photographs that make up the data set. With these additions, the error that may occur due to any distortion that may occur from the camera is minimized. Thus, the accuracy rate in the detection process with images taken from the camera in real-time has been increased. In order for the study to work faster, face detection was first performed in the image taken from the camera. If there is face detection, the system works. Eye and mouth modeling works only in the detected area. In this way, detection was made in a small area, not in the entire picture. In this way, results were obtained both faster and with higher accuracy.

## 4. Conclusion

In the study, the driver's fatigue, yawning and normal conditions were determined to ensure driving safety. Real-time hardware has been developed to warn the driver if a danger situation is detected. The face area of the driver driving in traffic was first detected with the help of images obtained from the camera. If there is no face detection, the system does not work. In face detection, only that region is studied. In this way, the system works both faster and with higher accuracy. After face detection, mouth and eyes are detected in that area. The detection process is carried out by running mouth and eye models on the YOLOv8 architecture. No ready data set was used in the study. A data set suitable for the real environment was prepared with the help of 129 people. Detection will be made on the images taken from the study camera. Therefore, many changes were made to the photographs that make up the data set. In this way, precautions have been taken against image distortions that may occur in the camera.

The difference of in the study from other studies is that a special data set was prepared for the study. The videos for this dataset were shot in real environments. Changes were later made to prevent possible distortions in the camera. Secondly, YOLOv5, YOLOv6, YOLOv7, and YOLOv8 architectures, which are the most used in the literature, were used. As a result of the study, the highest detection rate was achieved with an average accuracy of 0.975 in the YOLOv8 architecture. Yawning detection rate was 0.98 and fatigue detection was 0.96.

For detection, mouth and eye movements must be detected. The size of the eye is smaller than the size of the mouth. At the same time, there is a spatial difference between mouth movement and eye movement. For this reason, detecting mouth movement is a little easier. This causes changes in accuracy rates.

The performance of the system needs to be improved in future studies. The accuracy rate should be increased by expanding the data set. Additionally, features such as detecting distracting actions such as phone calls, eating, and smoking need to be added to the system.

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