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Real-time driver fatigue detection system with deep learning on a low-cost embedded system

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ABSTRACT

Road traffic accidents result in significant life and property losses, which are caused by various factors including driver fatigue and drowsiness. Therefore, real-time monitoring of the driver's state inside a vehicle and accurate detection of fatigue is essential to reduce the number of accidents. However, achieving high accuracy with low-cost embedded devices has been a challenge. This study proposes a novel approach that uses deep learning to accurately detect driver fatigue in real-time on the Nvidia Jetson Nano embedded device. The proposed system utilizes deep learning architecture, specifically Convolutional Neural Networks (CNNs), to classify four different situations by analyzing the eye and mouth areas of the driver. In addition, the dlib library is employed to precisely locate the driver's eye and mouth regions. The system is trained and tested on the YawDD dataset and achieves an accuracy of 93.6% and 94.5% for the eye and mouth models, respectively. The system operates at an average speed of 6 fps on the Nvidia Jetson Nano embedded device. The proposed system contributes to the field of driver fatigue detection by addressing the challenges of achieving high accuracy in real-time on a low-cost embedded device. This system aims to minimize the number of accidents and protect human life during transportation by detecting driver fatigue and issuing an alert. The classification results demonstrate the success of the proposed system, which accurately classifies four different states of the driver and detects driver fatigue states with high accuracy. Overall, this study presents a significant contribution to the field of driver fatigue detection by proposing a real-time, low-cost, and accurate system that can be installed in vehicles to ensure safe transportation and prevent accidents.

1. Introduction

Traffic accidents are a big social problem and cause material and moral losses. 2018 traffic accidents occurred in Turkey Referring to the distribution and characteristics; 84.81% of the accidents are material damage, 14.66% are injured and 0.53% are fatal traffic accidents [1]. In addition, TSI (Turkey Statistical Institute) by the number of vehicles in traffic according to published reports has been increasing in [2]. This increase causes an increase in traffic accidents. In addition to the increasing number of vehicles, the main factors that cause traffic accidents are the mistakes of the drivers, the carelessness of the pedestrians, and unsafe roads. Accordingly, according to the Highway Traffic Accident Statistics, it was stated that a total of 1.229.364 traffic accidents occurred in Turkey in 2018. When the flaw rates of 217.898 traffic accidents with fatal and injuries are examined, it is stated that 89.5% of the flaws are caused by the drivers [3]. In driver defects, the rate of accidents due to sleepiness while driving is 1%–16% in Europe, while this rate reaches up to 70% in Turkey [4]. According to the data of the US National Highway Traffic Safety Agency (NHTSA), there are approximately 100.000 accidents (1.5% of all accidents) and 1500 deaths (4% of all fatal accidents) each year due to fatigue and drowsiness. In the graphical image in Fig. 1, it is seen that the highest defect rate in accidents belongs to the driver with an average of 90%.

Traffic accidents can have a significant impact on society, and measures need to be taken to prevent them. Extensive research and analysis have been conducted to determine the factors that contribute to accidents, and it has been found that a high proportion of accidents are caused by driver-related factors. Driving under the influence of alcohol, fatigue, or sleep deprivation has been identified as a significant contributor to the incidence of accidents.

It is well-known that alcohol impairs driving performance, but the dangers of driving while fatigued or sleep-deprived are often overlooked. These factors are equally dangerous and can lead to serious accidents. The negative impact of insomnia on driving performance has been demonstrated in several studies, and it has been found to be as detrimental as driving under the influence of alcohol or drugs [5].

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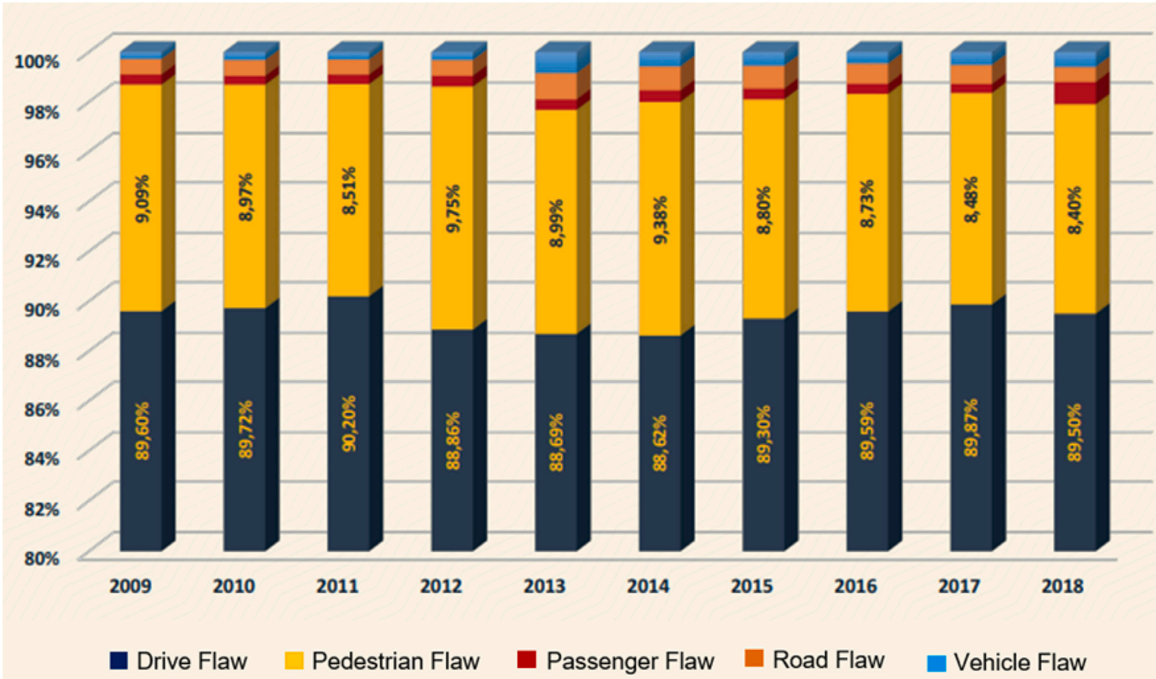


Fig. 1. Flaw rates of driver, passenger, pedestrian, road and vehicle causing 2009–2018 traffic accidents [1].

Driver fatigue detection is a critical problem in the transportation industry. Driver fatigue and drowsiness can lead to a significant number of accidents, which can result in severe injuries and loss of life. The problem involves accurately detecting the driver's state in real-time to issue timely warnings and prevent accidents. Detecting driver fatigue is challenging due to the varying symptoms, and it is essential to accurately monitor both the face and eye regions of the driver to detect early signs of fatigue, such as drooping eyelids, yawning, and changes in facial expressions.

To prevent driver-related accidents, numerous studies have been conducted in the literature. These studies have focused on developing interventions to reduce the incidence of accidents caused by driver-related factors. Some of the interventions include the use of technology such as driver fatigue detection systems, education and training programs, and legislative measures. In recent years, deep learning methods have been increasingly employed to develop more advanced safety systems [6]. For example, deep learning algorithms have been used to improve the accuracy of speech recognition systems, which can reduce driver distraction and improve hands-free communication [7]. In the field of automotive cybersecurity, deep learning can be used to detect and prevent cyber-attacks on connected vehicles [8]. Additionally, deep learning has been applied to improve the accuracy of object detection systems, which can assist with a range of tasks such as parking assistance and obstacle detection [9]. Deep learning models have also been used in the development of real-time image enhancement for automatic automobile accident detection through CCTV [10]. Outside of the automotive industry, deep learning models have been used in a variety of applications, such as medical imaging [11], fake news detection [12], and gesture recognition [13]. In conclusion, it is crucial to explore the potential of advanced technologies such as deep learning to prevent accidents caused by driver-related factors and to consider its potential applications in other areas such as healthcare, media, and entertainment. The literature provides a range of interventions, both technological and non-technological, that can be employed to reduce the incidence of these accidents.

Girit proposed a system to analyze the video portions recorded by the camera to determine if the driver is awake or sleepy [14]. Suryaprasad and his/her friends worked on video data to detect real-time driver sleep status in their studies [15]. Parmar et al. proposed a system that tracks the eyes and head actions to detect the drowsiness of the driver [16]. Golgiyaz et al. in their study, presented a system that decides whether to warn the driver by looking at the driver's perspective and blink status [17]. In another study, Dwivedi et al. proposed a simple CNN-based drowsy driver detection system with 78% accuracy using customized data sets [18]. In the study done by Park et al. a deep CNN of AlexNet, VGG-FaceNet and FlowImageNet networks were handled to detect driver drowsiness on RGB video [19]. When evaluating the detection system, it is stated that it works with an accuracy of 73% for NTHU-drowsy driver detection dataset. In another study, Reddy et al. provided a faster and more precise real-time drowsiness detection system with 89.5% accuracy by converting the basic model to produce a lighter model that can be placed in an embedded system [20].

Yan et al. developed a real-time system based on PERCLOS and gray scale image processing for fatigue detection [21]. Approximate position of driver's face and eye positions on gray scale images were used in the study. Deng and Wu proposed a driver fatigue system called DriCare that works with 92% accuracy in their study [22]. In the study, similar to other studies, the face and eye areas were handled and discussed. Mehta and his/her colleagues developed an Android-based real-time driver fatigue system that works with an accuracy of 84% using image processing techniques, machine learning, and the important points of the face, Eye Aspect Ratio (EAR) and Eye Closing Ratio (ECR) [23].

Galarza et al. developed a method with an accuracy rate of 93.37% [24]. In this method, the behavior of the driver's eyes, head movements and yawning situations are taken into account to detect drowsiness. In the study of Ravi et al. he proposes an automatic real-time driver fatigue detection system based on image processing technique as well as a cloud-based management platform running on Raspberry PI [25]. It was also stated that location details were learned using the GPS receiver module. Liu et al. proposed a driver fatigue detection algorithm using two stream network models with multiple facial features [26]. Multitasking cascading convolutional neural networks (MTCNNs) were used for the positioning of the mouth and eye areas. It was stated that an accuracy of 97.06% was obtained in the National Tsing Hua University Driver's Drowsiness Detection (NTHU-DDD) dataset. Savas and Becerikli proposed a multitasking Convolution Neural Network (ConNN) model for the detection of driver drowsiness in their study [27]. It was said that driver fatigue was determined by calculating the eye closing time/Percentage eye Closure (PERCLOS) and the Frequency Of Mouth (FOM). In addition, it was stated that the proposed model worked with 98.81% accuracy in YawDD and NthuDD data sets.

The present study makes a significant contribution to the field of driver fatigue detection by proposing a solution that effectively addresses the problem of detecting driver fatigue with high accuracy, including the detection of yawning, using a low-cost embedded system. The system monitors both the face and eye regions of the driver in real time and aims to enhance transportation safety by reducing the incidence of traffic accidents and protecting human life during transportation. The proposed solution offers instant monitoring of the driver's condition and provides timely warnings to prevent accidents resulting from driver fatigue or drowsiness. This research is unique in its approach and offers valuable insights into developing low-cost, high-accuracy solutions for driver fatigue detection.

The proposed model offers several advantages and contributions to the field of driver fatigue detection. The system uses a deep learning architecture and library to accurately monitor the driver's eye and mouth regions, which can provide a more reliable measure of fatigue. The use of two separate CNN models for the mouth and eye areas also allows for more accurate detection of specific types of fatigue, such as yawning with open eyes or closed eyes. The system has been successfully implemented in real-time on an embedded device, which is a practical and convenient solution for monitoring fatigue in vehicles.

The main contribution of the proposed model is its ability to accurately detect driver fatigue in real time, which is critical for ensuring the safety of drivers and passengers. The use of deep learning techniques and the dlib library in this system demonstrates the potential of machine learning and computer vision in addressing safety concerns in the transportation industry. The proposed model also contributes to the field by presenting an approach that is more successful in detecting fatigue and yawning of drivers compared to other existing methods.

The remainder of this article is organized as follows: Section 2 provides information about the system architecture developed in this study. Section 3 presents discussion and real-time test results of the proposed system. Last section includes the conclusions and the future works regarding this paper.

2. System architecture

The block diagram of the proposed system is illustrated in Fig. 2. The system begins by detecting the face region in the video frame captured by the camera. Subsequently, the eye and mouth local regions are extracted from the detected face region. The system utilizes two deep learning models to concentrate on the driver and promptly detect the states of the eyes and mouth in real-time. This approach allows for the separate determination of whether the eyes are open/closed or whether the driver is yawning. The proposed system incorporates both visual and auditory warnings to alert the driver when signs of fatigue are detected. Specifically, if the driver's eyes are closed with an open mouth, or if the driver is yawning with open eyes, or if both eyes are closed with yawning, the alarm is triggered, and the driver is alerted. Conversely, if the driver's eyes are open without any indication of yawning, the system detects the driver's condition as normal and does not activate the alarm. The proposed system provides an efficient approach to accurately detecting driver fatigue and offering timely warnings to prevent potential accidents.

The developed system was implemented on the Nvidia Jetson Nano embedded device. The camera attached to the device captures the images, which are then processed by the dlib[1] library to detect the face, eyes, and mouth regions. Subsequently, the deep learning models and decision-making block are employed to determine the fatigue state of the driver in real-time. To further enhance safety, the system also incorporates a feature to monitor the duration of vehicle usage. In the event of prolonged usage, the alarm system is activated to alert the driver. The implementation of this system on an embedded device offers a practical and convenient solution for fatigue detection in vehicles.

2.1. Hardware infrastructure

The training of the deep learning-based models in the proposed system was carried out on the computer with Intel® Core ™ i7-7500 CPU, Nvidia GeForce 950M GPU, and 16 GB RAM hardware. Two deep learning-based CNN models used for eyes and mouth regions have been tested on both the computer and the embedded device. The Nvidia Jetson Nano embedded device used in the designed system is a developer kit developed to run artificial intelligence algorithms with 4 GB 64 bit LPDDR4 25.6 GB/s memory, 4-Core ARM A57 CPU, and 128 CUDA core NVIDIA Maxwell ™ GPU [28]. Fig. 3 shows the Nvidia Jetson Nano board and its specifications. With Nvidia Jetson Nano, images that come in real-time from the camera are pre-processed with image processing methods and given as input to deep learning-based models. Based on the output received from the models, an audible and visual alarm system is activated. Specifically, the system employs an RGB LED to provide a visual warning and a buzzer to deliver an audible warning.

To ensure portability of the designed system, power was sourced from the cigarette lighter of the vehicle. Typically, such lighters generate voltage within the range of 12–24 V (DC). The Nvidia Jetson Nano device employed in the study, however, operates on a 5 V voltage. Hence, to power the system, a charging converter was used, which is capable of converting the 12–24 V (DC) input to 5 V output. The buzzer and LEDs used in the alarm system were also supplied from the same voltage.

2.2. Software infrastructure and data set

In this study, two CNN models trained with a deep learning network were used. The CNN model basically consists of five main layers (Fig. 4). These are the convolution layer, the non-linearity layer, the pooling layer, the flattening layer, and the fully connected layer. In the literature, it is possible to come across many different CNN models such as LeNet-5 [29], AlexNet [30], ResNet [31], VGG-16 [32,33], PolyNet [34], Xception [35].

In this study, one model detects whether the eyes are open, while the other model finds out whether there is yawning. Both models have the same architecture comprising of 4 convolution layers, 4 pooling layers, 1 flattening layer, and 1 fully-connected layer. The CNN models take fixed-size RGB images of 150×150 pixels as inputs during training. Convolutional layers with $3 \times 3 \times 32$ filters are used in the initial layer, while a filter with $3 \times 3 \times 64$ is used in the second convolution layer. The third and fourth convolution layers use filters with $3 \times 3 \times 128$. ReLU activation function is applied after each convolution layer, followed by a max-pooling layer over a 2×2 pixel window. The same dropout value of 0.5 is applied in all layers. The output of the fourth max-pooling layer, which is an $8 \times 8 \times 128$ matrix, is flattened into a one-dimensional vector of size 8192 and is fed as input to the fully-connected layer. The Sigmoid function is applied to the output of the last layer, which provides values between 0 and 1 for classification into the open or closed eye state or yawning or normal mouth state. The training data was processed in groups, and the batch size (epoch) was set to 64. The learning rate was set to 10^{-4} and RMSprop (root mean square error probability) was used for reducing oscillation during training.

In Fig. 5, the flowchart of the real-time driver fatigue detection system is shown. According to the proposed system's flowchart, the

[1] http://dlib.net/.

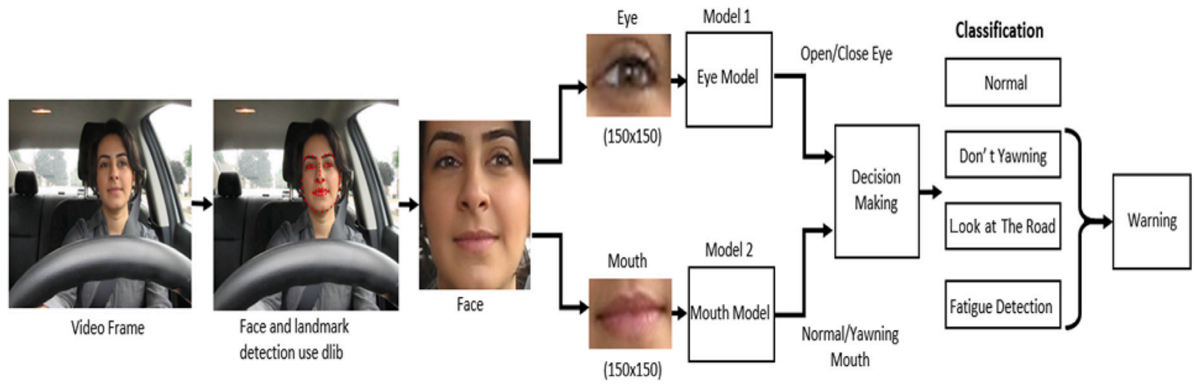


Fig. 2. The developed system block diagram.

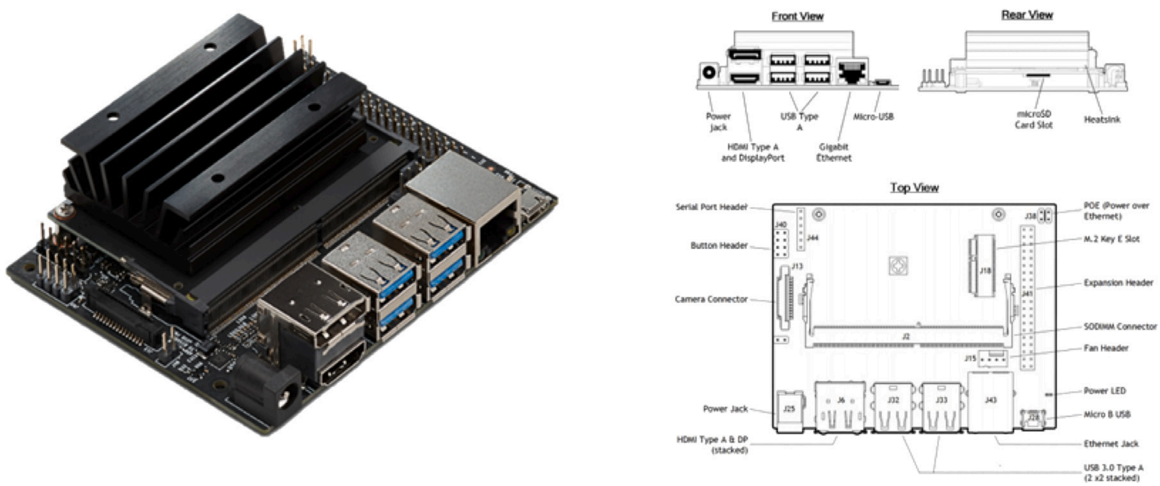


Fig. 3. Nvidia Jetson Nano [28].

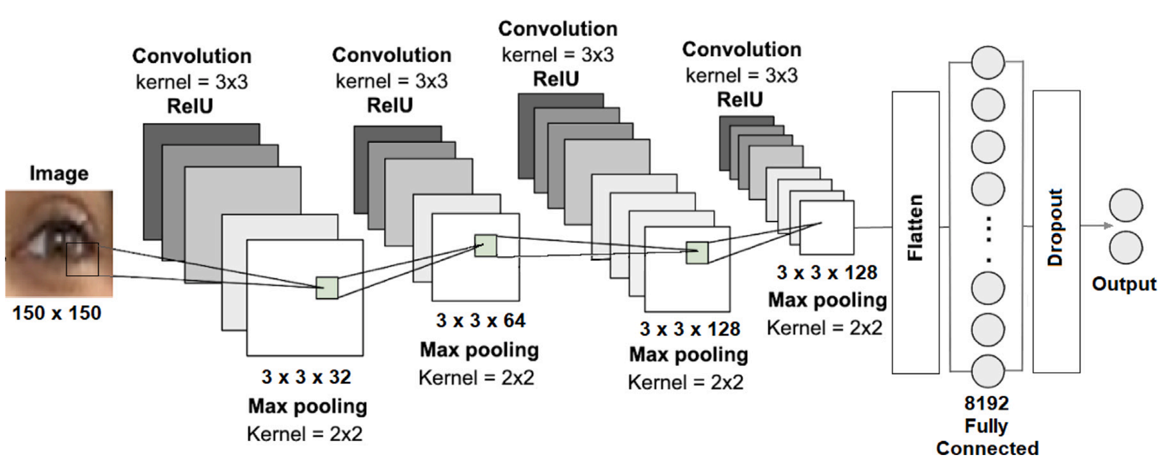


Fig. 4. CNN model architecture.

camera is initialized, and face detection is performed using the OpenCV library. If no face is detected in the video frame, the system waits until a face is detected. Once the face is detected, the regions of the mouth and eyes are determined. Subsequently, the mouth and eye data are used as inputs for the CNN models to determine the driver's status during driving. Driver fatigue is detected based on the state of the driver's eyes and mouth, whether the driver's eyes are open or closed and whether the driver is yawning or not.

YawDD dataset [36] was used in the training of the CNN deep learning models. This dataset includes talking, singing, silent, and yawning videos of drivers (men and women, with glasses/sunglasses and without glasses, different ethnicities) in a real car, which was recorded with a camera. It can be used primarily to develop and test algorithms and models for stretch detection, as well as to recognize and track the face and mouth. The videos were shot in natural and variable lighting conditions. Fig. 6 shows some examples from the YawDD yawning dataset.

Images were obtained from the yawning videos in the dataset, and a special dataset was created by separating the eye and mouth regions. The information regarding the training data sets is summarized in

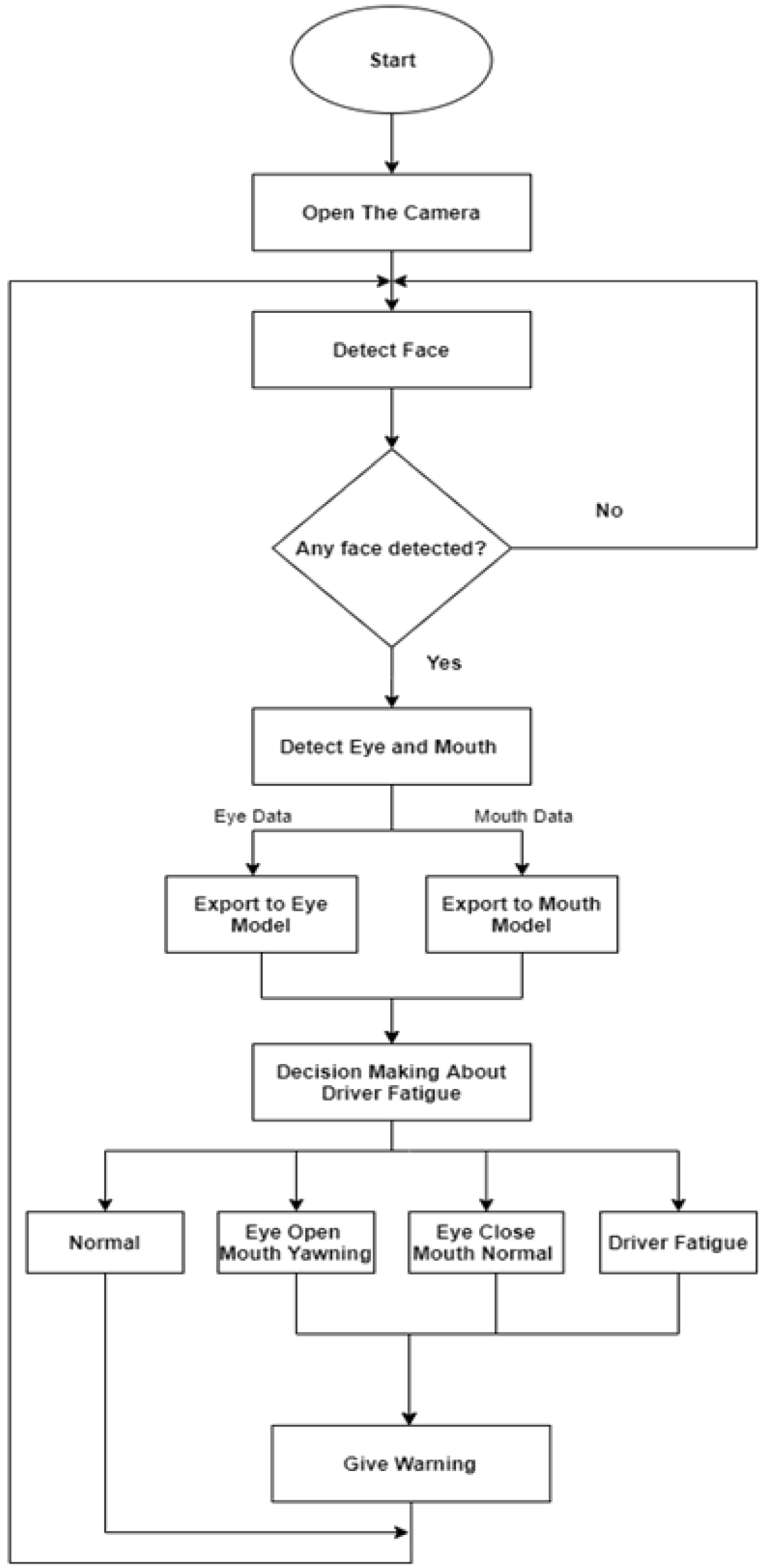


Fig. 5. Flowchart of the real-time driver fatigue detection system.

Fig. 6. YawDD yawning dataset samples [36].

Table 1
YawDD dataset used for training CNN models.

Model name	Female		Male		Total number
	Glasses	No glasses	Glasses	No glasses	
Eye model	4	6	8	5	23
Mouth model	10		13		23

Table 2
Mouth CNN model accuracy results for YawDD dataset.

Reference name	Year	Accuracy
Omidyeganeh et al. [37]	2016	75.00%
Akrout and Mahdi [38]	2016	83.00%
Zhang and Su [39]	2018	88.60%
Zhang et al. [40]	2015	92.00%
CNN model used in this study	**2021**	**94.50%**

Table 1. In the test data sets, 674 frames were used for the eye model and 613 frames were used for the mouth model.

3. Experiment results

The mouth and eyes images obtained from the YawDD dataset are pre-processed using the OpenCV[2] library, and then they are utilized as inputs in the CNN deep learning models. The images are resized to 150 × 150 and then given as input to the deep learning models. Sample images used in the validation data of the eye and mouth CNN models are shown in Figs. 7(a) and 7(b). The labels assigned to the eye and mouth images can be inferred from the figures, where the eye images are classified as either open or closed, while the mouth images are classified as either in a normal state or during a yawn.

The developed driver fatigue detection system consists of two CNN deep learning models to find the states of mouth and eyes. These models were tested separately. To evaluate the performance of the deep learning models, we utilized the accuracy rate metrics as given below:

$$Acc_e = \frac{E_s}{E_t} \tag{1}$$

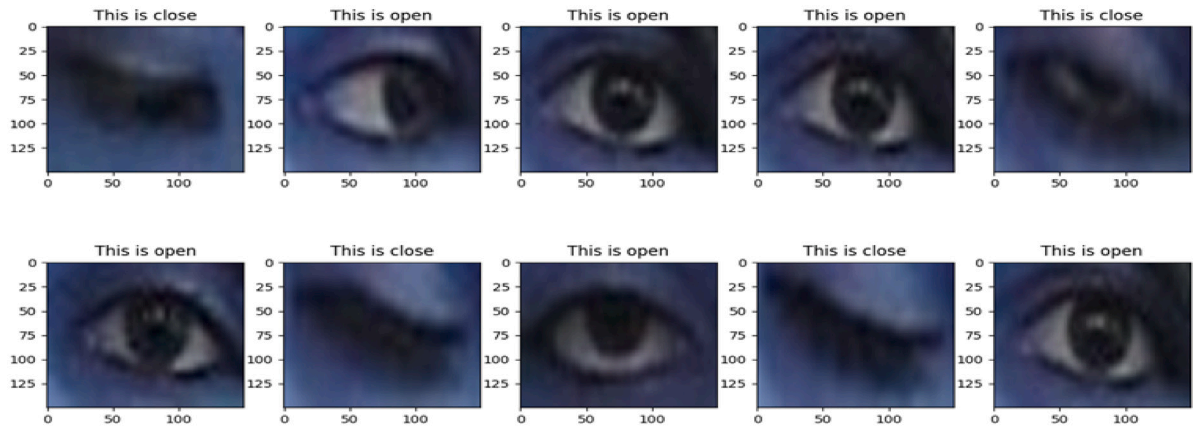
$$Acc_m = \frac{M_s}{M_t} \tag{2}$$

$$Acc_s = \frac{1}{2}\left(Acc_e + Acc_m\right) \tag{3}$$

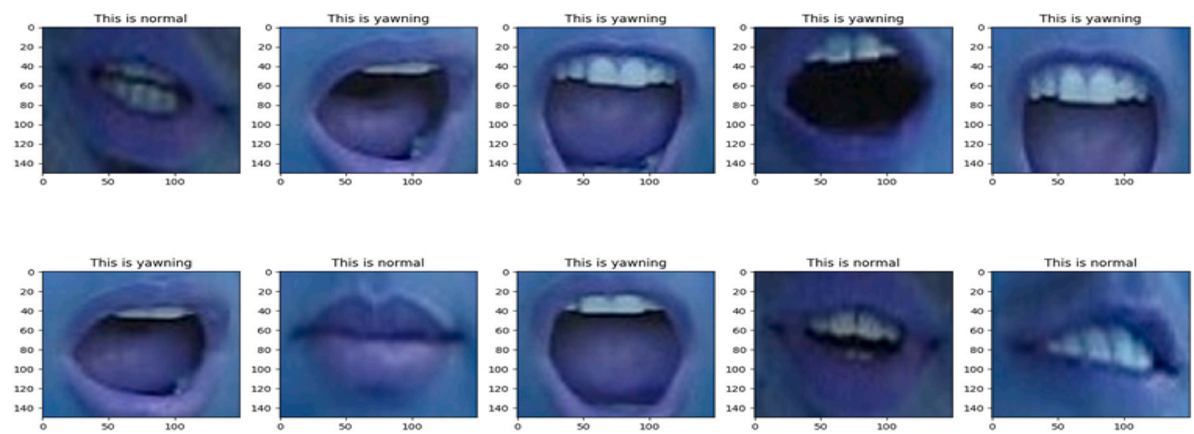
where Acc_e, Acc_m, and Acc_s denote the accuracy rates of the eye model, mouth model, and the system, respectively. E_s and M_s represent the number of successful model test results for eye and mouth deep learning models. E_t and M_t stand for the number of total tests for eye and mouth models. The test results of both models show that the accuracy rate of the eye model was 93.6%, while the accuracy rate of the mouth model was 94.5%. Accordingly, the average total accuracy rate of both models was calculated as 94.05%. Table 2 summarizes the comparison accuracy results between the CNN mouth model and others. The best accuracy score belongs to the CNN mouth model. Fig. 8 shows the loss curves for training and validation of mouth and eye CNN deep learning models.

The present study describes a system designed for real-time monitoring of driver fatigue by analyzing the face, eyes, and mouth regions. Preprocessing techniques are employed to determine the eye and mouth regions, and two separate deep learning models are used for predicting fatigue. The system is capable of determining fatigue even if eye detection is unsuccessful, by analyzing the mouth region for yawning. The system classifies the driver's status into four different situations based on the combination of open/closed eyes and yawning/non-yawning mouth. In the case of yawning and closed eyes, the system triggers an alarm to alert the driver. A photo of the developed system is shown in Fig. 9. The system operates at an average speed of 22 fps on the computer and 6 fps on the Nvidia Jetson Nano embedded system. It is worth noting that the system's performance is evaluated based on the speed of operation. The system operates at 22 fps on a computer and

[2] https://opencv.org/.



(a) Eye model sample validation dataset



(b) mouth model sample validation dataset

Fig. 7. Sample images used in the validation data of CNN models.

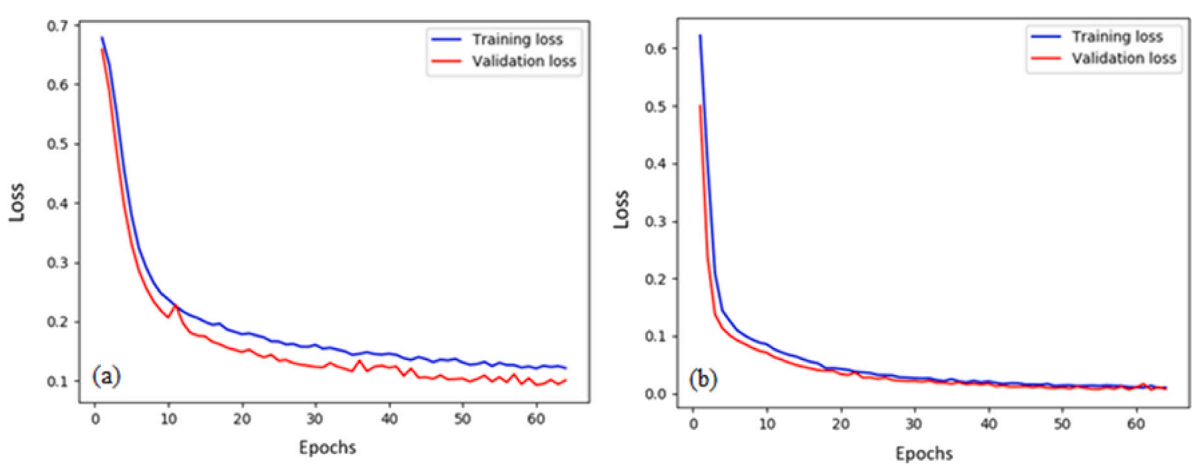


Fig. 8. Training and validation loss curves for eye model (a), mouth model (b).

6 fps on the Nvidia Jetson Nano embedded system. It is observed from the results that the system's performance is acceptable for real-time monitoring applications.

Figs. 10 and 11 depict in-vehicle application photos of the real-time driver fatigue detection system. Two different examples are presented, each showcasing the system's performance under varying lighting conditions. In the first test example, the system's ability to classify the four different fatigue states was evaluated under good light intensity at noon. The second test example presents the system's performance during the evening hours. The real-time driver fatigue system tests were conducted on two different drivers, one wearing glasses and the other without. The results of these tests indicate that the system is capable of accurately detecting four distinct driver situations.

In order to evaluate the driver fatigue detection system developed in this study, different performance metrics derived from the confusion matrix were examined. These metrics are True Positive Rate (TPR) also called sensitivity or recall, True Negative Rate (TNR) also called specificity or selectivity, Positive Predictive Value (PPV) also called

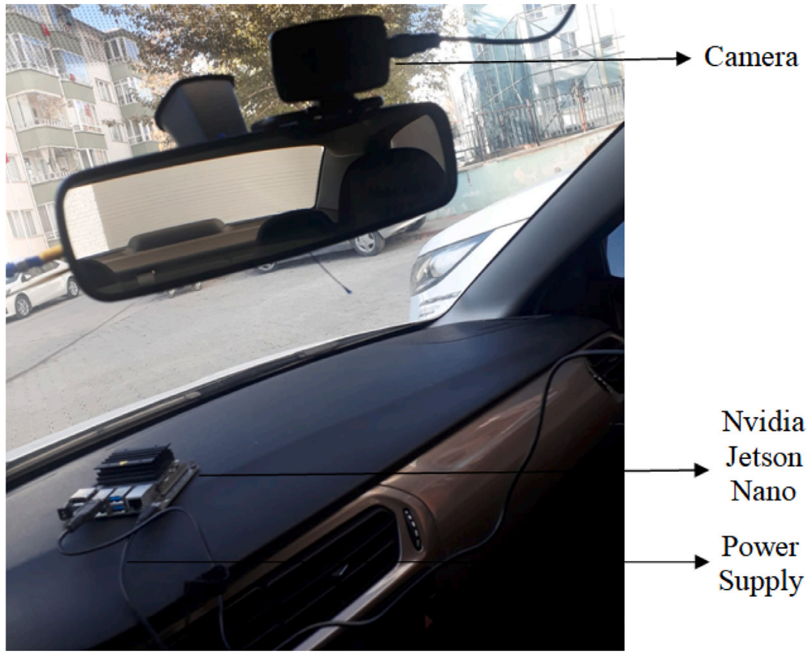
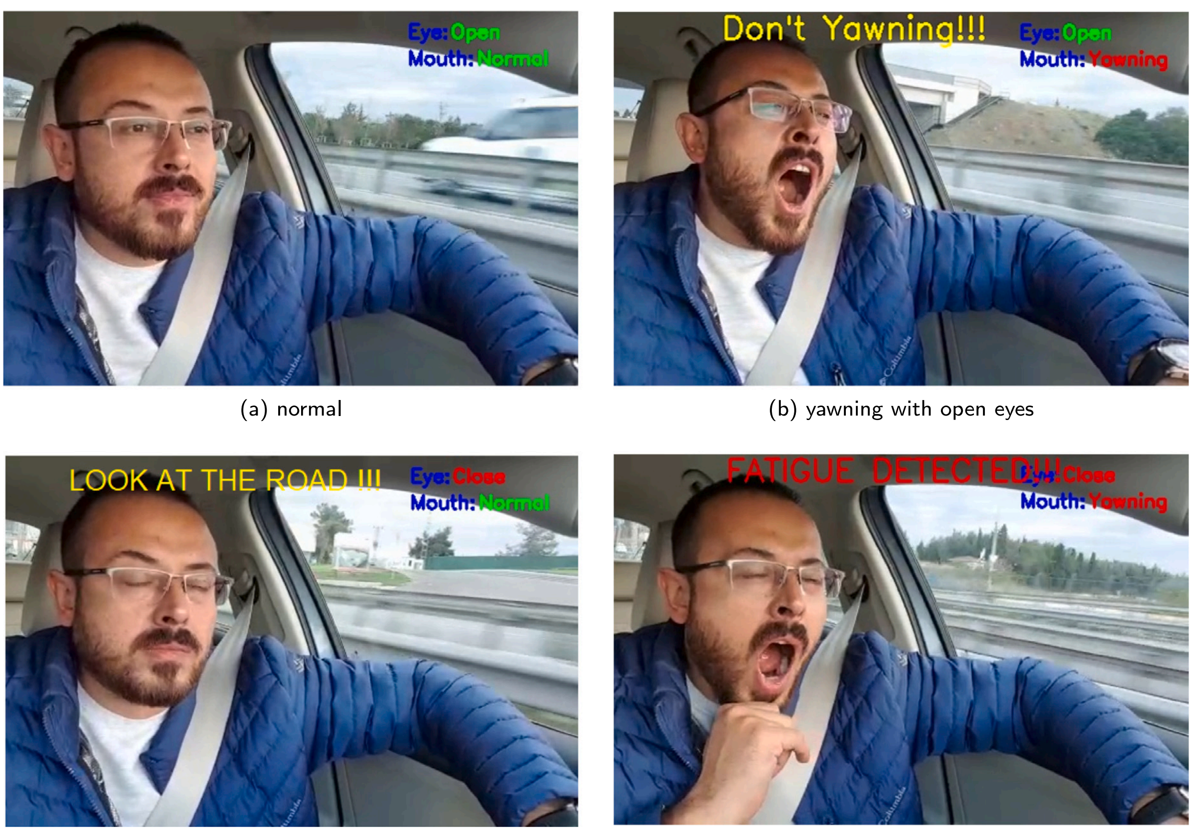


Fig. 9. A photo of the real-time driver fatigue detection system inside the vehicle.



(a) normal (b) yawning with open eyes

(c) closed eyes & not yawning (d) fatigue detection

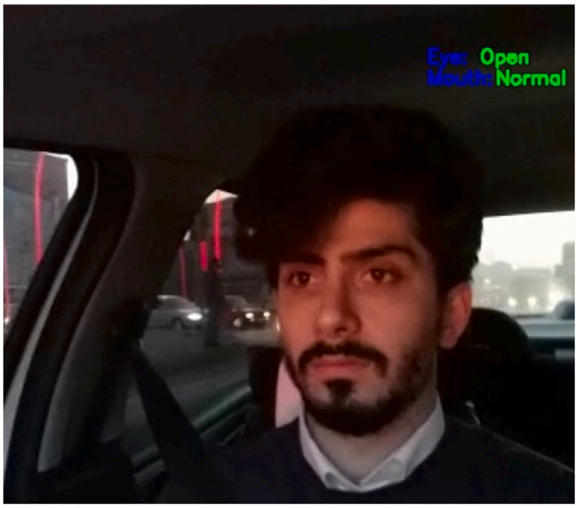
Fig. 10. Real-time driver fatigue detection system application example 1.

precision, Negative Predictive Value (NPV), False Negative Rate (FNR), False Positive Rate (FPR), Accuracy (ACC), and F1 score (F_1). These are calculated by using the following equations:

$$TPR = \frac{TP}{TP + FN} \tag{4}$$

$$TNR = \frac{TN}{TN + FP} \tag{5}$$

$$PPV = \frac{TP}{TP + FP} \tag{6}$$



(a) normal

(b) yawning with open eyes

(c) closed eyes & not yawning

(d) fatigue detection

Fig. 11. Real-time driver fatigue detection system application example 2.

$$NPV = \frac{TN}{TN + FN} \tag{7}$$

$$FNR = \frac{FN}{FN + TP} \tag{8}$$

$$FPR = \frac{FP}{FP + TN} \tag{9}$$

$$ACC = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

$$F_1 = 2 \times \frac{PPV \times TPR}{PPV + TPR} \tag{11}$$

where TP represents True Positive, FP denotes False Positive, TN stands for True Negative, and FN is False Negative. The confusion matrix obtained by applying the proposed driver fatigue detection system to a part of the test dataset (100 sample test data) is shown in Fig. 12. In this study, all classification results in terms of the metrics given above are summarized in Table 3. It is observed that there are 20 driver fatigue samples, 22 yawning samples with open eyes, 26 samples without yawning with closed eyes, and 32 normal samples in the testing data set with a sample size of 100. In terms of the sensitivity or recall metric (TPR), the class regarding fatigue detection has the best score (100%) with the class yawning with open eyes.

Upon examining the precision metric (PPV) results of the real-time driver fatigue detection system, it is observed that the fatigue detection class had the lowest score value (83.33%), as anticipated from the high sensitivity (TPR) results. This outcome can be attributed to the high false positive value (FP = 4) for the fatigue detection class, implying that the developed driver fatigue detection system has predicted four situations as fatigue that are, in reality, normal. However, given that the primary objective of this system is to detect fatigue and prevent accidents, a high sensitivity and low precision warning to the driver is critical. As such, the driver's actual fatigue status is determined precisely, and the risk of accidents is reduced. The accuracy metric revealed that the best result (99%) was obtained for the third class without yawning and closed eyes. Furthermore, the accuracy metric result for the fatigue detection class was 96%, as demonstrated in Table 3. The F1 score, which combines precision (PPV) and sensitivity (TPR), was determined to be 90.9% for driver fatigue detection based on the classification results presented in Table 3.

In Table 4, a comparison of the yawning detection accuracy values (2nd class) obtained by the driver fatigue detection system developed in this study for the YawDD dataset is presented along with different models taken from the literature. The results indicate that the proposed system has achieved the best result among other models with an accuracy of 98% in yawning detection for the YawDD dataset. Furthermore, Table 5 provides a comparison of the accuracy results

Table 3
Classification results of the real-time driver fatigue detection system.

Metric name	Normal	Yawning with open eyes	Closed eyes & not yawning	Fatigue detection
TP	27	22	25	20
TN	68	76	74	76
FP	0	2	0	4
FN	5	0	1	0
TPR	84.38%	100.00%	96.15%	100.00%
TNR	100.00%	97.44%	100.00%	95.00%
PPV	100.00%	91.67%	100.00%	83.33%
NPV	93.15%	100.00%	98.67%	100.00%
FNR	15.63%	0.00%	3.85%	0.00%
FPR	0.00%	2.56%	0.00%	5.00%
ACC	95.00%	98.00%	99.00%	96.00%
F1	91.53%	95.65%	98.04%	90.91%

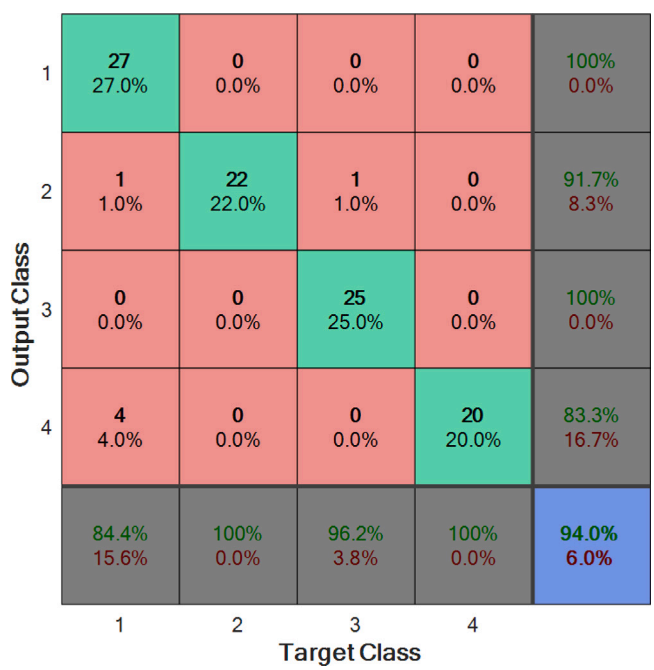


Fig. 12. Confusion matrix of the proposed system: (1) normal, (2) yawning with open eyes, (3) closed eyes & not yawning, (4) fatigue detection.

Table 4
Yawning detection accuracy results for YawDD dataset.

Reference name	Year	Accuracy
Zhang et al. [40]	2015	92.00%
Omidyeganeh et al. [37]	2016	75.00%
Zhang and Su [39]	2018	88.60%
Jie et al. [41]	2018	94.63%
Kassem et al. [42]	2020	96.20%
Our system in this study	**2022**	**98.00%**

Table 5
Comparison of driver fatigue detection for YawDD dataset.

Reference Name	Method	Year	Accuracy
Zhang et al. [40]	CNN + TLD	2015	92.00%
Guo and Markoni [43]	CNN + DF_LSTM	2019	91.48%
Geng et al. [44]	AdaBoost + CNN	2018	92.10%
You et al. [45]	YOLOv3 + FFT	2020	94.32%
Our system in this study	**CNN**	**2022**	**96.00%**

of the proposed system with some methods presented in the literature for driver fatigue detection. The comparison reveals that the proposed system has achieved better accuracy than other methods.

We evaluated the performance of our model on the Nthu-DDD dataset employed in previous research studies. The Nthu-DDD dataset is a public dataset for driver drowsiness detection research. It was created by the National Tsing Hua University in Taiwan and contains video data of 44 subjects in a driving simulator. The videos include both normal and drowsy driving states, and the dataset also provides ground truth labels for each video segment indicating whether the driver is drowsy or not [46]. Table 6 presents the comparison of the performance between the proposed system and previously published some real-time driver fatigue systems for this dataset. The results demonstrate that the proposed system exhibits superior performance compared to the prior works.

Table 6
Comparison of driver fatigue detection for Nthu-DDD dataset.

Reference name	Year	Accuracy
Jabbar et al. [47]	2018	80.93%
Vu et al. [48]	2019	84.81%
Ayachi et al. [49]	2021	96.05%
Our system in this study	**2022**	**96.13%**

4. Conclusion

The system proposed in this study successfully detects driver fatigue in real-time using the Nvidia Jetson Nano embedded device. The system employs a CNN deep learning architecture with Keras deep learning library and dlib library for accurate identification of the driver's eye and mouth regions. Two separate CNN models were developed for the mouth and eye regions, which were trained and tested on the YawDD dataset. The system continuously monitors and classifies the driver's eye and mouth areas into normal, yawning with open eyes, closed eyes & not yawning, and driver fatigue detection.

The CNN models used in the driver fatigue detection system achieved an accuracy rate of 93.6% and 94.5% for the eye and mouth models, respectively. While the developed driver fatigue detection system runs at 22 fps on a computer, it has an average speed of 6 fps on the Nvidia Jetson Nano embedded device. However, the location of the camera in the vehicle has a significant impact on the system's operation rate and accuracy.

To evaluate the performance of the driver fatigue system, we calculated and analyzed various metrics for 100 samples from the YawDD dataset. Based on the classification results derived from the confusion matrix, the accuracy metric for the fatigue detection class was 96%. Furthermore, we compared the accuracy metric results of the proposed system and other methods for two classes from the YawDD dataset. The comparison results demonstrate that the proposed system is more successful in detecting fatigue and yawning of drivers. However, it is important to note that the proposed system has some limitations, and its operation in various scenarios requires further investigation.

The proposed real-time driver fatigue detection system has certain limitations. Firstly, the system requires good lighting conditions and may not work well under low-light conditions. Secondly, the system can only detect fatigue based on the facial and eye regions, and other factors such as body posture and behavior are not taken into account.

To address the limitations, further research and development are needed to improve the system's performance and expand its capabilities. For example, incorporating additional sensors such as accelerometers and heart rate monitors may provide a more comprehensive assessment of driver fatigue. Additionally, conducting experiments with different lighting conditions and diverse datasets can help improve the system's robustness and generalizability. In conclusion, while the proposed system has shown promising results in detecting driver fatigue in real-time, further research is necessary to address its limitations and enhance its performance in various scenarios.

CRediT authorship contribution statement

Esra Civik: Conceptualization, Methodology, Software, Writing. **Ugur Yuzgec:** Supervision, Writing, Review, Editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Esra Civik reports equipment, drugs, or supplies was provided by CuteSafe Technology Company. Esra Civik reports a relationship with CuteSafe Technology Company that includes: employment.

Data availability

Data will be made available on request.

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