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A ML TECHNIQUES TO DETECT DROWSINESS FOR PREVENTING ROAD ACCIDENTS

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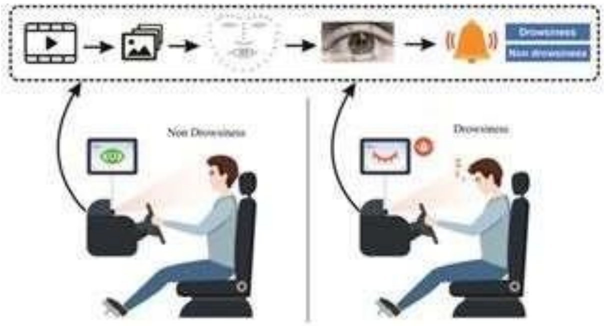
ABSTRACT:

Drowsy driving is one of the common causes of road accidents resulting in injuries, even death, and significant economic losses to drivers, road users, families, and society. There have been many studies carried out in an attempt to detect drowsiness for alert . In this research, we therefore propose two efficient methods with three scenarios for doze alert systems. The former applies facial landmarks to detect blinks and yawns based on appropriate thresholds for each driver. The latter uses deep learning techniques with two adaptive deep neural networks based on MobileNet-V2 and ResNet-50V2. The second method analyzes the videos and detects driver's activities in every frame to learn all features automatically. We leverage the advantage of the transfer learning technique to train the proposed networks on our training dataset. This solves the problem of limited training datasets, provides fast training time, and keeps the advantage of the deep neural networks. Experiments were conducted to test the effectiveness of our methods compared with other methods. Empirical results demonstrate that the proposed method using deep learning techniques can achieve a high accuracy of 97%. This study provides meaningful solutions in practice to prevent unfortunate automobile accidents caused by drowsiness.

INTRODUCTION:

The American National Highway Traffic Safety Administration (https://www.nhtsa.gov (accessed on 4 August 2021)) has an estimated 100,000 accidents reported each year mainly due to drowsy driving [1]. This results in more than 1550 deaths, 71,000 injuries, and 12.5 billion dollars of property damage. According to the National Safety Council (https://www.nsc.org (accessed on 4 August 2021)), 13% of drivers admitted to falling asleep behind the wheel at least once a month and 4% of them resulted in accidents [2]. Morgenthaler et al. announced that drowsiness is one of the main causes of traffic accidents in their study [3]. It is estimated that about 10–15% of car accidents are related to lack of sleep [4]. The sleep questionnaire obtained from professional drivers showed that more than 10.8% of drivers are drowsy while driving at least once a month, 7% had caused a traffic accident, and 18% had near-miss accidents due to drowsiness [5]. These alarming statistics point to the need for capable systems for monitoring drowsy drivers to prevent unfortunate traffic accidents that may occur [6].

In recent years, building intelligent systems for drowsy driver detection has become a necessity to prevent road accidents. Therefore, it requires a lot of research to design robust alert methods to recognize the level of sleepiness while driving [7]. Many studies focused on constructing the smart alert techniques for intelligent vehicles that can automatically avoid traffic accidents caused by falling asleep, as illustrated in Figure 1. Rateb et al. introduced real-time driver drowsiness detection for an android application using deep neural networks [8]. A minimal network structure was proposedbased on facial landmarks to identify drowsy drivers. The method presented a lightweight model and achieved an accuracy of more than 80%. This study focused only on eye facial landmarks without detecting the yawning of the drivers. Moreover, the method was based on a multilayer perceptron classifier with three hidden layers, which is a limitation that leads to low accuracy [9]. Fatigue detection using Raspberry Pi 3 was provided by Akalya et al. by processing driver's faces and eyes images. A Haar cascade classifier was applied to detect the blink duration of the driver, and the eye aspect ratio(EAR) was computed by the Euclidean distance between the eyes.



Many studies based on the deep learning approach using convolutional neural networks (CNNs) have been introduced to detect drowsy drivers. A drowsiness detection method using CNN-based machine learning for android applications was introduced by Rateb et al. [10]. The method detected facial landmarks by a camera and passed through a CNN model to detect drowsy driving, with an average accuracy of 83.33%. Zuopeng et al. introduced a driver fatigue detection method using a proposed EM-CNN to detect the states of the eyes and mouth from the region of interest images. The proposed algorithm, EM-CNN, showed an accuracy of 93.62%. Biswal et al. proposed an IoT-based smart alert system for drowsy driver detection using Raspberry Pi3 and Pi camera modules to make a persistent recording of face landmarks for eye detection. This method was based on the idea of determining blinks through an eye aspect ratio (EAR) and Euclidean distance of the eye. Although this method reached a high accuracy of 97.1% for the experiment, it had many limitations for practical systems because it only focused on eye detection, and an EAR threshold was pre-defined and unchanged for all drivers (EAR<0.25 <0.25) to detect drowsiness. Ajinkya et al. introduced a driver drowsiness detection method using deep learning with an average accuracy of 96%. This method included two stages of the pre-processing and drowsiness detection. Haar feature-based cascade classifiers, a machine learning-based approach, were used to detect the mouth and eye regions of the drivers in pre-processing [11]. To identify drowsiness, the frames of the mouth and eye regions werethen forwarded to the proposed CNN models, which were the basic CNN models using four conv2d, four max-pooling layers, and two dense layers to identify the state of blinks and yawns in the given time threshold. There were only two features of the eyes and mouth trained on these two CNN models for drowsiness detection without considering other physiological factors. Moreover, experiments were implemented on a small dataset of 2423 subjects, including 1192 people with closed eyes, and 1231 people with open eyes. In addition, Madhav et al. presented a deep learning approach to detect driver drowsiness. This method extracted the characteristics of the driver's eyes on each frame using Dlib's APIand passed through a classification model to predict the state of drowsiness. Adam was used as the optimizer and the average accuracy reached 94% [12].

BACKGROUND

Drowsiness

Sleep is the natural cyclical rest state of the body and mind. In this state, people often close their eyes and lose consciousness partially or completely, thereby reducing their response to external stimuli. Sleep is not an option. It is necessary and inevitable to help the body rest and restore energy. The term "microsleep" or "drowsiness" is defined as brief and involuntary intrusions of sleep that can occur at any time due to fatigue or a prolonged conscious effort. Microsleep can last for a few seconds, and during this time, the brain falls into a rapid and uncontrolled sleep, which can be extremely dangerous, especially in the case of driving or in situations demanding focused attention. There are some signs that show that drivers are not awake: yawning, blinking repeatedly and difficulty opening eyes, the inability to concentrate, the inability to keep the head straight, a distracted mind, feelings of tiredness, and blurred vision.

Identification of Facial Landmarks

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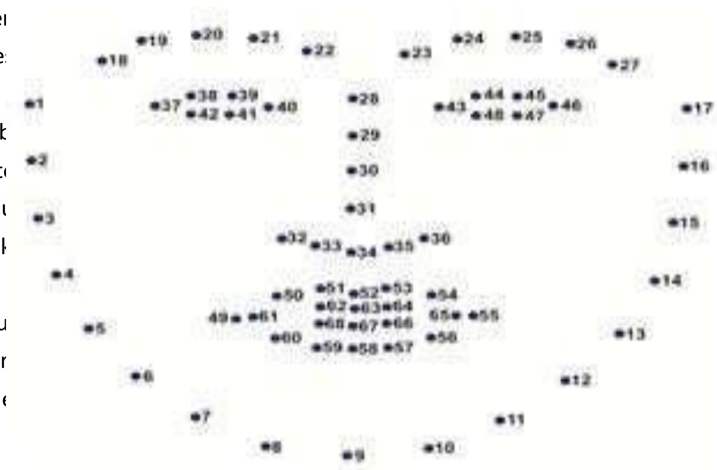
Kazemi and Sullivan presented a method that precisely estimates the positions of facial landmarks using a training set of labeled facial landmarks on images. This method can be used for real-time detection to identify the facialfeatures afte… 8 main positions (x,y coordinates) on human face…

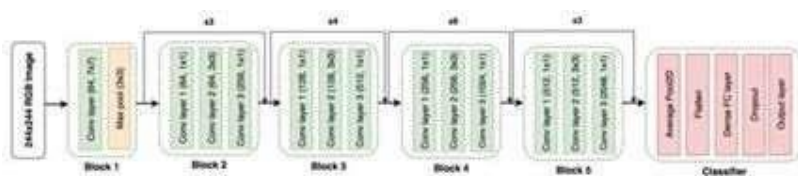
… 1 to 17; right eyebrow: points 18 to 22; left eyeb… o 42; left eye: points 43 to 48; mouth: points 49 t… ates of the left eye, right eye, and mouth to calcu…

Blink…

… including the eyes, eyebrows, nose, ears, and mou… fic parts of a face. For blink detection, we are inter… trated in Figure 3, starting at the left corner of the e…



ResNet won the ImageNet Large Scale Visual Recognition Competition in 2015 for image classification, object localization, and object detection. The main challenge in training deep learning models is that the accuracy decreases with the depth level of the networks. ResNet converges very quickly and can be trained with hundreds or thousands of layers. At the same time, ResNet is easy to optimize and can achieve accuracy gains from greatly increased depth, producing better results . ResNet-50V2 was trained on ImageNet and CIFAR-10 datasets . The ResNet-50V2 network architecture is shown in Figure 5. The results show that ResNet-50V2 performs better and gives better results than ResNet50 and ResNet101 on the same ImageNet dataset. ResNet-50V2 applies the transfer learning technique with ImageNet pre-trained weights, which are used in object classification, such as COVID-19 and pneumonia detection from chest X-ray images and video classification with accuracy up to 94–98%. Taking advantage of ResNet-50V2, we choose this architecture as the training model for driver drowsiness detection.



Accuracy

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When building a classification model, it is necessary to know the accuracy of that model. In general, it is a ratio of correctly predicted observation to the total observations [26]. Accuracy helps us evaluate the prediction performance of a model on a dataset. Accuracy is calculated as Equation (3).

Accuracy=TP+TNTP+FP+FN+TN.

(3)

Precision, Recall and F1

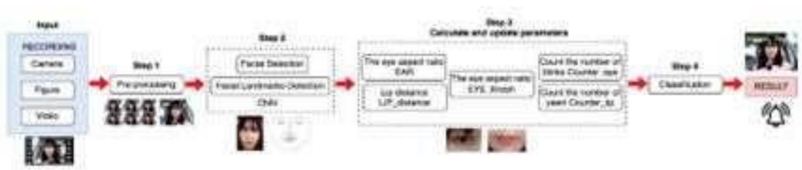
Precision is the ratio of correctly predicted positive observations to the total predicted positive observations. The higher the precision, the better the model is on positive classification. Precision is calculated as Equation (4).

Precision=TPTP+FP.

PROPOSED METHODS:

In this work, we propose two efficient methods for doze alert systems. The first method is based on a combination of two blink and yawn features (EAR, LIP) using facial landmarks. However, adaptive thresholds of blinks and yawns were calculated appropriately for each driver without needing to pre-determine for all drivers. The second method uses advanced deep learning techniques with the transfer learning approach. Facial images are detected with the SSD- ResNet- 10, and then forwarded to the proposed networks to detect drowsiness. We designed and perfected two adaptive deep neural networks developed on the advanced networks of MobileNet-V2 and ResNet-50V2 by making improvements in some layers to adapt the drowsiness detection. In addition, we applied the transfer learning approach to train the proposed networks in order to achieve faster learning, no requirement for large training datasets, and an improvement in classification accuracy. The details of the implementation steps of the two proposed methods are presented below.
Method 1: Drowsiness Detection and Prediction Based on Facial Landmarks

The proposed method is inspired by the methods introduced in preceding studies . However, the threshold of eye-opening is fixed for all drivers, leading to inaccuracies for drivers with large or small eyes. To overcome this problem, we improve the determination of the adaptive eye-opening threshold ($EARThresh\ h\ h$) for each driver. The model of the proposed method is shown in Figure 6. The values of the EAR and $EARThresh\ h\ h$ are first computed for each driver. Then, we determine the drowsiness level of drivers by a comparison of EAR and $EARThresh\ h\ h$. This work is carried out repeatedly during driving. This method does not rely on the yawning frequency, since it would be inaccurate in caseswhere drivers wear a mask or talk while driving



1. Step 1: Pre-Processing

In this step, we extract video frames from input videos. The rate of selecting images from videos is 25 frames per second. These images are flipped to accurately identify the facial landmarks (Figure 7).

Figure 7. Illustration of extracting image frames from input videos.

Step 2: Detection of Facial Landmarks

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We detect and identify facial landmarks on faces in the images as presented in Section 2.2. The facial landmarks considered in this work include the eyebrows, eyes, nose, mouth, and jaw (see Figure 8).

ISSN PRINT 2319 1775 Online 2320 7876

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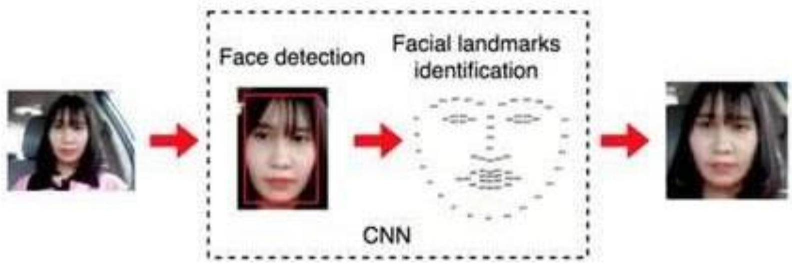

Figure 8. An example of detecting faces and facial landmarks.

. Step 3: Determination of the Eye-Opening Threshold for Each Driver

In this step, we use 32 feature points based on the identification of facial landmarks in step 2 (Figure 9). We determine the coordinates of points on the mouth and eyes.

Algorithm 1 Drowsiness Detection and Prediction

Input: Input video monitored from a camera

Output: Drowsiness_Detection = True/False (state of drowsiness or non-drowsiness)

Begin

▹ video is split into clips with lengths of 300 s

for each clip in video do

$Countereye$=0; =0; ▹ initialize variables to count blinks and yawns respectively.

$Counteryawn$=0; =0;

$Drowsiness\_Detection$ _ = False;

for each i=1...n =1... do ▹ n is the number of image frames extracted from clip

Calculate $EARi$ by Equation (1); Calculate $LIPdistancei$ by Equation (2); end for

▹ compute an adaptive eye-opening threshold for each driver

Calculate $EARThresh$=$Average$(EAR1,EAR2,...,$EARn$) h h= (1, 2,...,);

for each i=1...n =1... do ▹ Count blinks and yawns

if $EARi$>=$EARThresh$ >= h h then

$Countereye$ += 1 ;

end if

if $LIPdistancei$>$LIPThresh$ > h h then

$Counteryawn$ += 1;

end if

end for

▹ $CounterEyeLimit$ and $CounterYawnLimit$ are thresholds of blinks and yawns

if $Countereye$>$CounterEyeLimit$ > then

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$Drowsiness\_Detection$ _ = True; ▹ Turn on a driver drowsiness alarm: Wake up, please!

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end if

if $Counteryawn > CounterYawnLimit$ > then

$Drowsiness\_Detection$ _ = True; ▷ Turn on a driver drowsiness alarm: Wake up, please! end

if

end for

End.

Method 2: Drowsiness Detection and Prediction Using Deep Learning

In this method, the drowsiness detection using deep neural networks (DNNs) includes two phases of the training and testing, as illustrated in Figure 10. In the first phase, we train the proposed network models by training a dataset after pre-processing and feature extraction. In the second phase, we evaluate the network models with a test set for drowsiness detection.

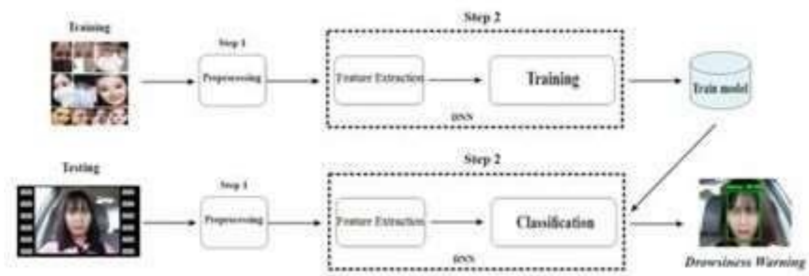

Figure 10. Model of the proposed method 2 for detecting drowsiness using deep lear

EXPERIMENTS:

Dataset and Installation Environment

Dataset Description

It is not safe to make field experiments for driver's drowsiness on real roads. Therefore, in order prevent any risk for drivers, we generate an experimental dataset consisting of drowsy and non-drowsy faces extracted from datasets of Bing Search API, Kaggle, RMFD, and iStock by selecting images and videos recorded from cameras that are related to the driver's drowsy states. The main advantages of this work are its efficiency, low cost, safety, and the ease of data collection. In these images and videos, driving environments are relatively similar to actual road experiments. The dataset contains 16,577 images of faces with 2659 images of drowsy states, 3789 images of non-drowsy states, and 10,129 images of both states. In particular, for method 2, the dataset of 6448 images is divided at the ratio of 80% (5158) for training and 20% (1290) for testing. The dataset directly.

Experimental Results:

Training Model Evaluation

The training phase is only carried out for scenarios 2 and 3 using deep learning techniques. To evaluate the performance of the network models before detecting drowsiness, we use a confusion matrix and compute metrics of the accuracy, Loss_value, and training time.

Metrics of Precision, Recall, and Accuracy

We determine metrics of the precision, recall, and accuracy defined by the confusion matrix, as presented in Section 2.4. Figure 13 shows a confusion matrix for scenarios 2 and 3. In scenario 2, the TP (true positive) and TN (true negative) values of drowsiness and non-drowsiness prediction are 94% and 98%, respectively. In scenario 3, the TP and TN results are 97% and 97% for drowsiness and non-drowsiness, respectively. The metrics of the precision, recall, and accuracy are shown in Table 6. The accuracy of the proposed network models after the training process is 96% for scenario 2 and 97% for scenario 3.

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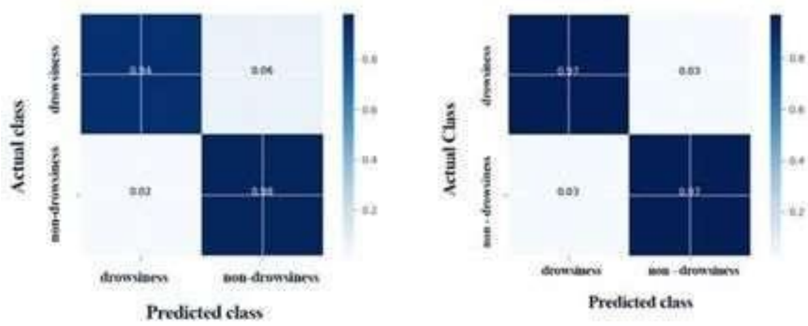
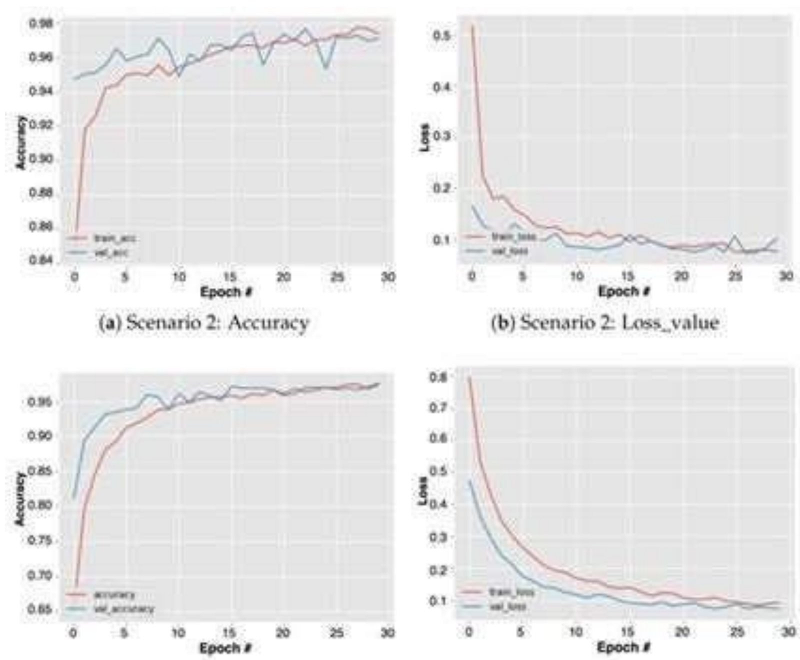


(a) Scenario 2 (b) Scenario 3

Figure 13. Confusion matrix for scenarios 2 and 3.



(a) Scenario 2: Accuracy (b) Scenario 2: Loss_value

(c) Scenario 3: Accuracy (d) Scenario 3: Loss_value

CONCLUSIONS:

Most of the traditional methods for drowsiness detection are based on behavioral factors, while some require expensive sensors and devices to measure sleepiness, and may even interfere with the driving process, distracting drivers. Therefore, in this paper, we propose two methods with three scenarios for driver's drowsiness detection systems. The proposed method with scenario 1 uses facial landmarks to detect drowsiness. This method analyzes the videos and detects drivers' faces in every frame using image processing techniques. Facial landmarks are determined in order to compute the eye aspect ratio (EAR) and the mouth-opening value ($LIPdistance$) to detect drowsiness based on adaptive thresholds. We propose an improvement of the eye-opening threshold for each driver without using a pre-defined threshold for everyone, as in preceding studies. The driver is alerted when the blink and yawn thresholds reach the adaptive maximum thresholds. However, the drowsiness detection based on blinking and yawning is not accurate enough, since drowsiness has different surrounding factors. Therefore, we propose method 2, with two scenarios for a drowsy alert system using deep learning techniques with the transfer learning approach. We design twoadaptive deep neural networks developed from MobileNet-V2 and ResNet-50V2 for scenarios 2 and 3, respectively. Method 2 analyzes the videos and detects the driver's activities in every frame to automatically learn all features for drowsiness detection. It takes advantage of deep neural networks to extract all features and movements of the head and face. This method does not require the definition of input thresholds as in method 1, especially the eye-opening and

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Research paper UGC CARE Listed (Group -I) Journal Volume 10, Iss 3, 2021

yawning thresholds. Additionally, method 2 uses a combination of many typical signs of drowsiness to give accurate results, such as eye-opening, head movements, eyebrows, mouth, etc. Moreover, we leverage the advantage of transfer learning to pre-train the proposed networks on datasets of Bing Search API, Kaggle, and RMFD. We then use the pre-trained weights and re-train them on our training dataset to fine-tune the parameters of these networks. This helps to solve the problem of small training datasets and gives a fast training time

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