Deep Learning Models for Classifying Driver Eyes: A Comparative Study

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Abstract

Driving a vehicle with drowsiness is a very serious and widespread problem in society, because drowsiness has a negatively influence on the driver's reaction time. And therefore, when the level of drowsiness increases in the driver, he loses control of his vehicle. He can unexpectedly veer off the lane, colliding with an obstacle or causing a car to overturn. In this paper, we present a low-cost, non-intrusive, more accurate, and better solution for detecting driver drowsiness in real-time in real-world driving conditions, whenever the drowsiness is detected, and the system activates an audible alarm to alert the driver before he falls asleep. In the proposed method, we used the most important facial components that are considered the most effective for sleepiness. We used the Viola-Jones algorithm to detect the driver's face and eyes area. Then we inserted the resulting image into the deep convolutional neural network to detect driver drowsiness in real-time. The purpose of this paper is to arrive at the performance of five deep learning models: AlexNet, ResNet50, GoogleNet, VGG16, and DenseNet201, which detects sleepy using RGB footage of drivers as input. The experimental results indicate that all these models produce excellent detection accuracy but DenseNet201achieves the highest detection accuracy compared with others.

Keywords: Deep learning CNN AlexNet, ResNet, GoogleNet, VGG16, DenseNet, driver drowsiness.

نماذج التعلم العميق لتصنيف عيون السائق: دراسة مقارنة

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الملخص:

تعد قيادة السيارة في حالة النعاس مشكلة خطيرة للغاية ومنتشرة في المجتمع، لأن النعاس له تأثير سلبي على وقت رد فعل السائق. وبالتالي، عندما يزداد مستوى النعاس لدى السائق، يفقد السيطرة على سيارته. يمكنه أن ينحرف عن المسار بشكل غير متوقع، أو يصطدم بعائق أو يتسبب في انقلاب السيارة. في هذا البحث، نقدم حلًا منخفض التكلفة وغير تدخلي وأكثر دقة وأفضل لاكتشاف نعاس السائق في الوقت الفعلي في ظروف القيادة الواقعية، فعند اكتشاف النعاس، يقوم النظام بتنشيط إنذار مسموع للتنبيه السائق قبل أن ينام. في الطريقة المقترحة استخدمنا أهم مكونات الوجه التي تعتبر الأكثر فاعلية للنعاس. استخدمنا خوارزمية Viola-Jones لاكتشاف منطقة وجه وعين السائق. ثم أدخلنا الصورة الناتجة في الشبكة العصبية التلافيفية العميقة لاكتشاف نعاس السائق في الوقت الفعلي. الغرض من هذه الورقة هو الوصول إلى أداء خمسة نماذج للتعلم العميق: AlexNet وResNet50 وGoogleNet وVGG16 وDenseNet201، التي تكتشف النعاس باستخدام لقطات RGB للسائقين كمدخلات. تشير النتائج التجريبية إلى أن جميع هذه النماذج تنتج دقة كشف ممتازة ولكن DenseNet201 تحقق أعلى دقة كشف مقارنة بالآخرين.

Introduction

Accidents in traffic pose a serious threat to people's lives. According to the National Highway Traffic Safety Administration report (NHTSA), 22 to 42 percent of car accidents occur when a driver drives while in a drowsy state, and this lack of alertness leads to a four-to-six increase in collisions compared to an alert driver [1]. Evaluations conducted by the United States (the National Highway Traffic Safety Administration) showed that driver drowsiness is a major cause of approximately 100,000 traffic accidents annually, causing 1550 deaths, 71,000 injuries, and costing more than 12.5 billion dollars [2]. A series of studies were conducted by many foundations to indicate the accident state; the National Sleep Foundation in the United States of America reported that 54 % of drivers drove during sleepiness, and 28% of them fell asleep completely [3]. National Transportation Safety Board (NTSB), indicating that drowsiness is the main cause of heavy vehicle accidents, with a rate of approximately 52% [4]. The "Ministry of Road Transport and Highways" reported in a report that 4,552 accidents in India annually resulted in thousands of people losing their lives due to the drowsiness of the drives [5]. The Road Safety Board in Germany (DVR) (Deutsche Verkeh Rswacht) stated that temporary drowsiness was the cause of 25% of fatal car accident [6]. According to proven statistics issued by the General Directorate of Dhi Qar Traffic in Iraq, it stated that the total number of road accidents in the last ten years (2010-2020) in Dhi Qar Governorate has reached 4,410 accidents, most of which were due to drowsiness. And, statistics issued by the General Traffic Directorate in Iraq indicate that the number of accidents for the year 2019 in Iraq, except for the Kurdistan region, reached 10,753 accidents, 11,651 injured, and 2,636 deaths. For that reason, car manufacturers in the world are eagerly developing a system that can prevent drowsy driving.

There are two main categories for driver drowsiness detecting methods: a. approaches that concentrate on driver’s performance (depend on the condition of the vehicle), and b. methods focusing on the driver’s state, which are divide into techniques Using Physiological Signals and techniques utilizing Computer Vision. It is found that methods focusing on driver’s performance are efficient but require a large time to analyze the driver's performance, and thus the accuracy will decrease, and in some cases where the driver sleeps for a moment, the vehicle’s condition will not change, and therefore you will not be able to detect the drowsiness that did not affect the vehicle’s condition. Therefore, the system is confused in detecting partial sleep [7]. As for techniques Using Physiological Signals (the physiological rather than apparent signs of drowsiness in the driver's body are relied upon, such as Electroencephalography (EEG), heart rate variability (HRV), pulse rate, Electrocardiography (ECG), Electrooculogram (EOG), and respiration) [8] . Although these methods are characterized by high accuracy, they are not recommended because they are intrusive where many tools are connected to the driver, and then the recorded values are verified [9]), expensive, annoying to the driver, and thus distracting attention. Besides, driving for a long time causes the sensors to sweat, which negatively affects the ability of the sensors to close monitoring. As for methods depend on computer vision using image processing, as the image processing techniques are one of the methods that are most acceptable to researchers because it is non-intrusive (the device is not delivered to the driver), does not cause any inconvenience to the driver, and is characterized by speed, accuracy, ease of use and low cost compared to other methods. Sleepiness leaves a group of prominent effects on the driver's face, which is essential for detecting sleepiness inroads based on computer vision, and in most cases, the first stage in image-based methods is to discover the person's face in the image [10]. After looking at statistics like these, many researches proposed systems and algorithms to detect driver drowsiness in real-time to reduce the number of vehicle accidents. These algorithms may be divided into Convolution neural network-based and computer vision-based. R. Jabbar, et al. [11]. The framework of their work was able to recognize facial landmarks in images taken on a mobile device and pass them on to a CNN-based qualified Drowsy driving behavior is detected using a deep learning algorithm.. M. Hashemi, et al. [12]: Convolutional Neural Networks (CNN) are utilized for driver's eye-tracking. They have proposed a dataset to discover driver lethargy and investigated multiple networks to improve drowsiness detection based on eye state accuracy and reduce computational time. Three networks are proposed as possible networks for eye status classification, one of which is a completely developed neural network (FD-NN), while the others take use of transfer learning. With VGG16, and VGG19 with additional designed layers (TL-VGG). M. Dua et al. [13]: They proposed a method made up of four deep learning AlexNet, FlowImageNet, VGG-FaceNet, and ResNet are that use RGB videos of drivers as an entrance to identify drowsiness. In addition, these models take into account four distinct categories of functionality for implementation: hand motions, head motions, facial expressions, and behavioral characteristics. The performance of these models is fed into an ensemble algorithm, which then runs them through a SoftMax classifier, which returns a positive (sleepy) or negative response. V. Reddy Chirra, et al. [14]: In their work, the driver is classified as sleep or non-sleep using a SoftMax layer in a CNN classifier. M. Tanveer, et al. [15]: they identified the drowsiness utilizing deep learning algorithms and practical near-infrared spectroscopy for a passive brain-computer interface. They have used a CNN on the functional brain maps, which had a 99.3% accuracy, and discovered thirteen distinct channels that are most involved during drowsiness, as well as a new area made up of the channels with the best classification accuracy. T. VU, et al.[16]: Was presented a DDD system that is extremely accurate and doing in real-time. The DNN sequentially processes frames from the video flow at inference time without resetting Conv CGRNN states, resulting in a very quick inference time. M. Tayab Khan, et al. [17]: In real-time driving surveillance videos, a method for image-based drowsiness detection is proposed, where many classical image operations and filters were used to detect and classify the eyes as open or closed. A. McDonald, et al. [18]: designed and evaluated a contextual and temporal algorithm for detecting drowsiness-concerned lanes. M. Poursadeghiyan, et al. In 2018 [10]: was used image-processing methods. With a driving simulator a virtual reality-based driving simulator, to identify degrees of tiredness was carried out on five suburban drivers

In this paper, we presented a low-cost, non-intrusive, more accurate, and better solution for detecting driver drowsiness in real-time in real-world driving conditions. This model takes into account the condition of the driver and since it is there is a strong relationship between sleepiness and eye activity, and the state of the driver's eyes is a reliable indicator for detecting drowsiness. The rest of the paper is organized as follows. Section 2 presents the Problem statement, Section 3 explains the proposed system, Section 4 presents the experimental results, and in Section 5 the conclusion was presented.

1- Problem statement

Driving a vehicle with drowsiness is a very serious and widespread problem in society, because Drowsiness has a negatively influence on the driver's reaction time. Therefore, when the level of drowsiness increases in the driver, he loses control of his vehicle. He can unexpectedly veer off the lane, colliding with an obstacle or causing a car to overturn. So the main problem may be formulated as to detect the face of the driver from multi-environment, then detecting his/her eyes from various styles – with medical glasses, sunglasses with many degrees of the blackout, finally decide is the driver sleep or awake.

2- The proposed system

Our system uses a video camera installed in front of the driver and the camera captures a live video of the driver and in different lighting conditions. In the proposed method, we used the most important facial components that are considered the most effective for sleepiness. We used the Viola-Jones algorithm to detect the driver’s face and eyes area, then cut the driver’s eyes region from the video frame and changed the size of the eyes area. Then we inserted the resulting image into five models of CNN, and compare their performance to detect driver drowsiness in real-time, the system has been tested and implemented in a real environment. The essential goal of this research is to know the accuracy of each of the performances: AlexNet, DenseNet 201, Googlenet, ResNet50, and Vgg16 in driver drowsiness detection, to view whether the outcomes will obtain more than 90% accuracy or not.

1- The Face detection algorithm Viola-jones is utilized to detect the nearest face in the frame then given as an input to the Viola-jones algorithm to eyes detection.
2- Following the detection of the face, utilized Viola-jones eyes detection algorithm to elicit the eyes region of the facial image and feed it to above mentioned CNN models.
3- Then CNN models convolutional layers are utilized to excerption the features and those features are passed into the fully connected layer.
4- Softmax layer in CNN models classify eyes images to awakened eyes images or drowsy eyes images.
5- If classify eyes images as drowsy eyes images the system activates an audible alarm to alert the driver before he falls asleep.

Our proposed system, as shown in Figure (1), our proposed system consists of three phases: the first phase is the pre-processing, The second phase is done using CNN, and The third phase is the classification phase.

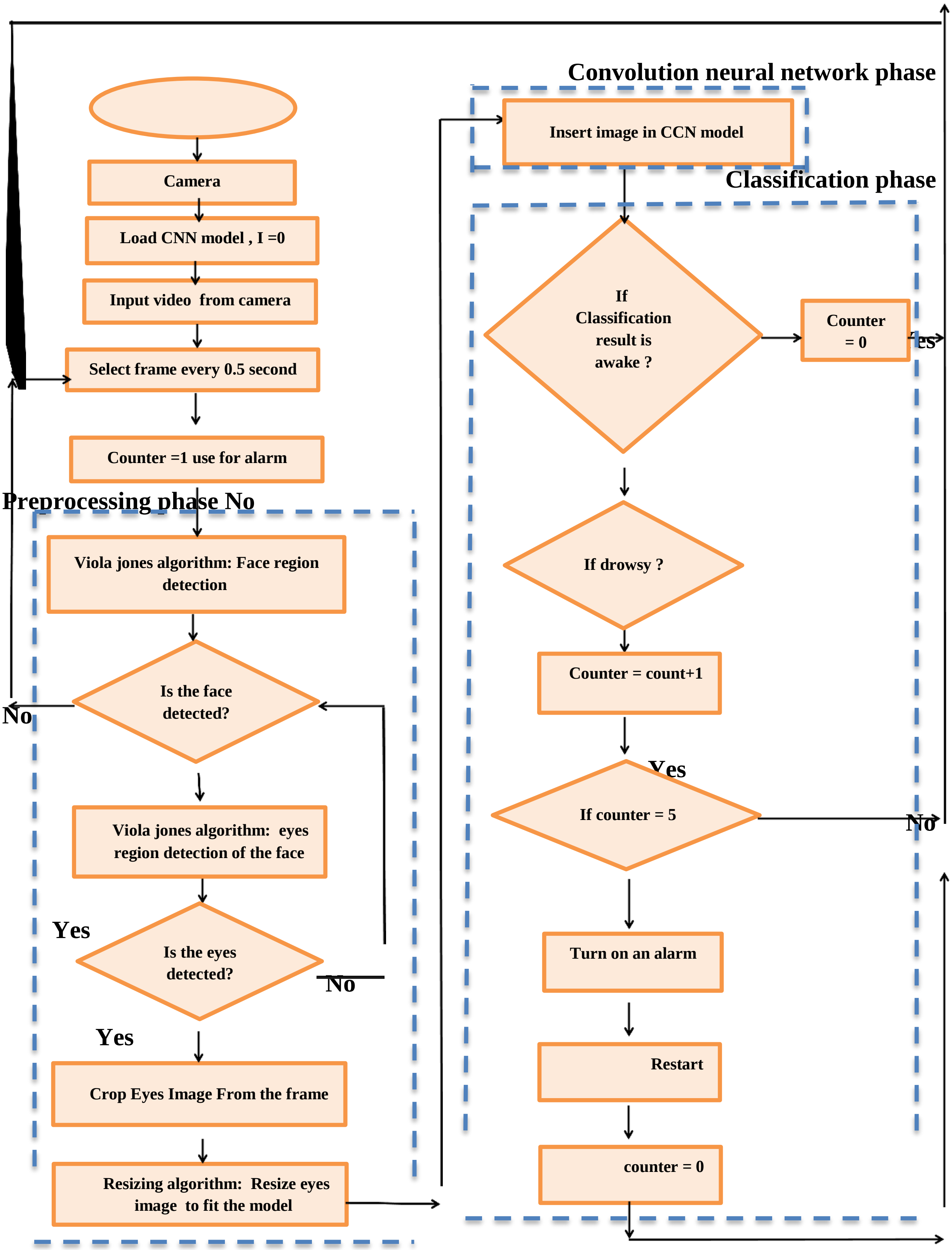


Figure 1: Global algorithm of the proposed system (training phase and testing phase)

3.1 The pre-processing phase

The pre-processing processes required before the use of the proposed system include the following:

3.1.1 Face and eyes detection:

After extracting each frame, it is entered into the Viola-Jones algorithm [19] to determine the driver's face, where we adopted the closest face and considered it the target (due to the possibility of detecting the face of the person sitting behind the driver), then we determine the eyes area from within the face area. The fundamental block diagram of our Face, and eyes Detector module is shown below:

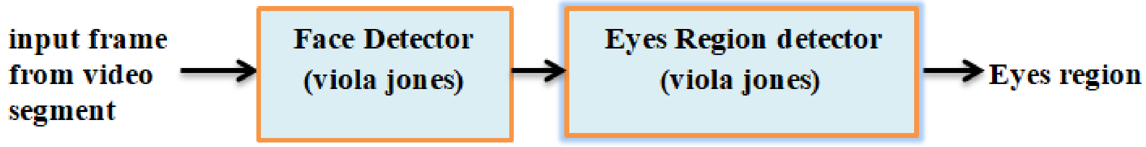
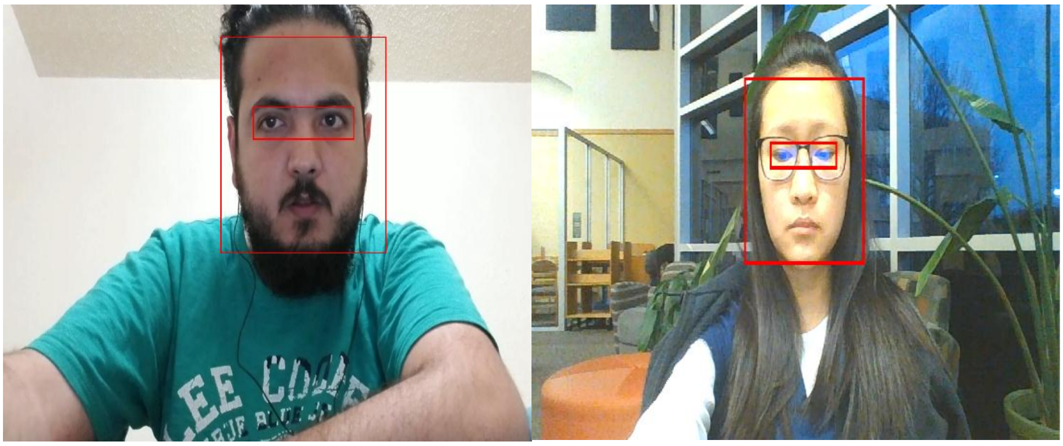


Figure 2: shown the block diagram of the Eyes Region detected



A-without glasses **B- with glasses**

Figure 3: example for eyes region detection

3.1.2 Crop Eyes Images from the Frame.

Cropping is the method of taking a part of a picture, called a sub-image, and cutting it away from the rest of the image [20]. In this stage, the ROI is determined using the auto-cropping approach.

3.1.3 Resize eyes images

We do need to resize the input of the convolution neural network, (in our situation, images of the eyes region) the size of the image entered into any one of the deep learning model (they have already been mentioned) is must be 224 × 224, except in the AlexNet model, we change the input image's size to 227×227.

3.2 Convolution neural network phase:

After completing all the initial treatment operations on the image of the eyes, it is required to assess the condition of the eyes to determine whether it is awake or drowsy. The proposed method uses to classify the condition of the eyes.

3.2.1 Convolution neural network layers

CNN is a sequence of layers, each layer performs its function, where CNN consists of three types of layers:

A- Convolutional layer: The convolution layer generates feature maps, which highlight the unique features of the original image. Where the image entry process through the convolution filters leads to in the feature map [21]. If we have a 2- Dimensional image input, I, and a 2-Dimensional kernel filter, K, the convoluted image is calculated as follows [22]:

$$s(i,j) = \sum_m \sum_n I(m,n)k(i-m, j-n) \quad \dots (1)$$

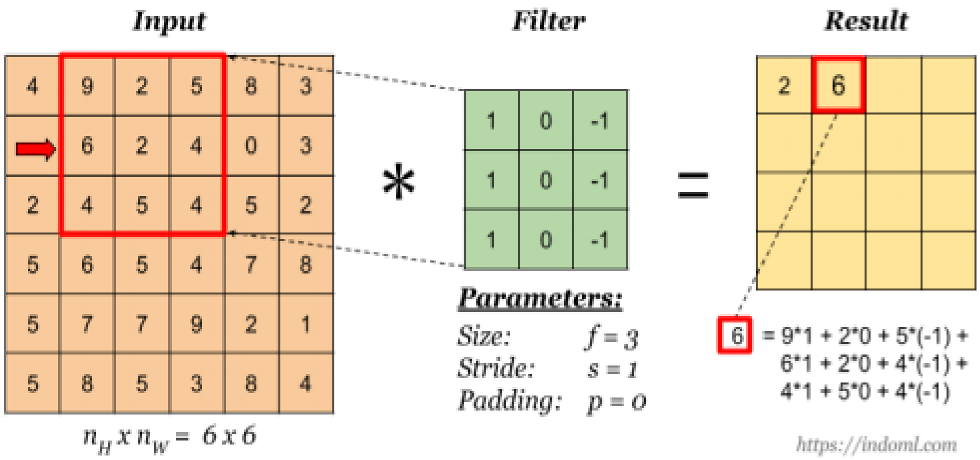


Figure 4: in a convolutional layer, element-wise matrix multiplication, and summation of the results onto feature map [22]

B- Pooling layer (subsampling layer): After the convolution process, the pooling operation is carried out to minimize the number of dimensions. This decreases the number of parameters, which cuts training time. and combats over fitting [23]. This layer keeps the input maps and output maps count as is. This operation can be formulated as in [24]:

$$x_j^l = down\ (x_j^{l-1}) \quad \dots (2)$$

Where, down(.) represents a sub-sampling function.

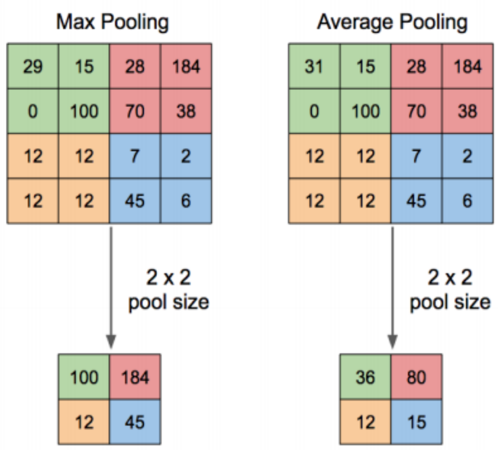


Figure 5: Different types of pooling [22]

C-Fully connected layers: The outlet of the final layer of the CNN (the outlet of the final pooling layer) is utilized as the entrance to the classification layer (which is a fully connected network) [25], [26]. A fully connected layer counted the result of each class from the extracted features from a convolutional layer in the previous steps. The fully connected feed-forward neural layers are utilized as a soft-max classification layer [24].

3.2.2 CNN algorithms:-

A- AlexNet

AlexNet is too famed as a transfer learning sample, knowing is learned from training a big magnitude of datasets [27], is a wider and deeper CNN model introduced in 2012, AlexNet was primarily designed by Alex Krizhevsky. AlexNet consists of 5 Convolutional Layers and 3 Fully Connected Layers. The architecture of AlexNet is display in Figure (6). The first two Convolutional layers keep track by the Overlapping Max Pooling layers. then, The third, fourth, and fifth convolutional layers are linked directly. The fifth convolutional layer is followed by an Overlapping Max Pooling layer, the outlet of which goes inside to a series of two fully connected layers. The second fully connected layer feeds into a softmax classifier with 1000 class labels, the number of parameters is 60 million [27].

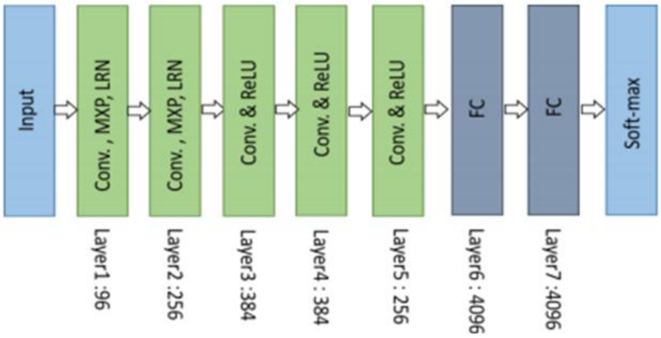


Figure 6: AlexNet's architecture: Convolution, max- pooling, LRN and fully connected (FC) layer [24]

B- VGG16 (The Visual Geometry Group)

This convolutional neural network was offered via Karen Simonyan and Andrew Zisserman, in 2014 from the University of Oxford in the paper "Very Deep Convolutional Networks for Large-Scale Image Recognition" [28]. Consist VGG16 of 16 layers distributed as (13 convolutional layers, 2 Fully connected layers, and 1 SoftMax classifier). For simplicity, used just 3×3 convolutional layers were placed on top of each other. [22].

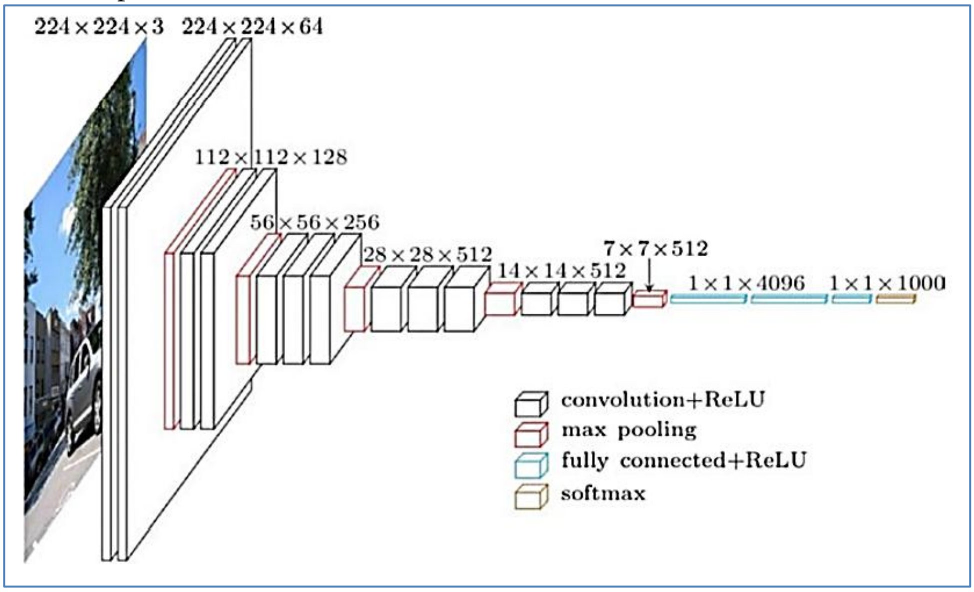


Figure 7: Architecture VGG-16 [22].

C- GoogleNet

GoogleNet is famed as (Inception-V1) [27], [29]. The GoogLeNet architecture introduced in the ImageNet Large Scale Visual Recognition Challenge 2014 (ILSVRC14) developed by researchers at Google, Solving image classification and object identification challenges in computer vision. It accomplished a top-5 error rate of 6.67%, this was very close to human-level performance [27]. Their architecture is composed of 22 layers of deep CNN (27 layers including pooling layers), and part of these layers are a total of 9 inception modules, However, the number of parameters is lowered from 60 million (AlexNet) to 4 million (Googlenet).

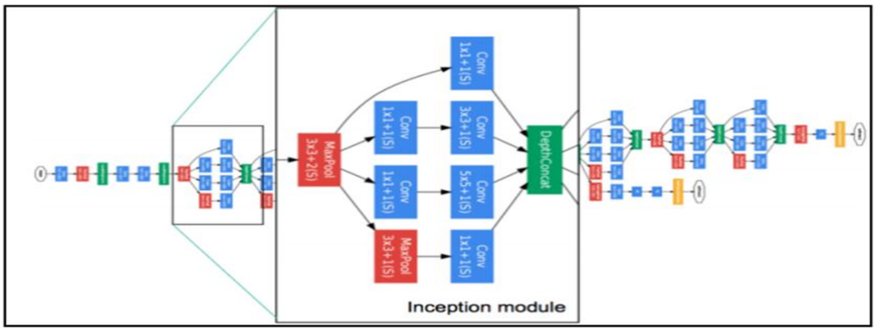


Figure 8: depicts the GoogleNet layers [27]

D- The ResNet-50 model

The ResNet-50 model is composed of 5 phases, Each one includes a convolution and an Identity block. There are three convolution layers in each convolution block, and three convolution layers in each identity block. The ResNet-50 contains approximately 23 million trainable parameters, and after 25 epochs of training, it achieves an 86 percent test accuracy [30].

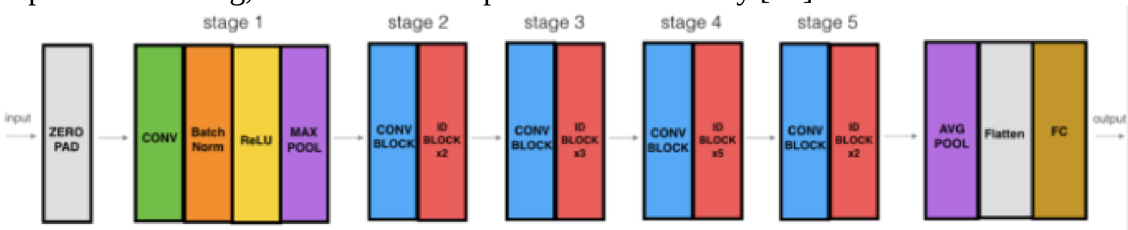


Figure 9: ResNet-50 Model [30]

E- DenseNet-201

DenseNet-201 is a convolutional neural network that is 201 layers deep. The network has an image input size of 224-by-224. Every layer in DenseNet201 has direct access to the original input image and gradients from the loss function. this caused the computational cost to drop significantly, which makes DenseNet201 a best option for image classification, and the figure below shows the DenseNet201 architecture [31]:

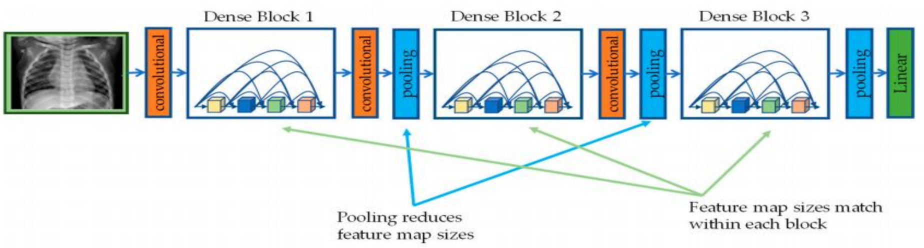


Figure 10: DenseNet201 architecture [31]

3.3 The classification phase:

The video enters to the convolutional neural network models to obtain a classification result. If the frame test result indicates drowsiness (the driver's eyes are closed), the system adds one to the counter and the system will start a sound alarm to alert the driver if the counter reaches 5 consecutive frames classified as drowsiness. Else, the counter keeps for the following frame, and when the eyes are classified as awake, the counter is reset. To put it another way, the objective of this counter is to count consecutive frames to discriminate between blinking and drowsy.

3- Experimental results

4.1 Dataset Description.

Eyes pair images used in this study were provided by the researcher. A total of 2000 Eyes pair images, 1800 it was cut from frames videos from http://vlm1.uta.edu/~athitsos/projects/drowsiness) and the remaining 200 images compiled by the researcher (real database). The datasets were sorted into two categories: open eyes 1000 images (700 training samples and 300 test samples), and closed eyes images 1000 images (700 training samples and 300 test samples). Figure (11) shows examples of training sets, test sets are like to the training sets, but with various drivers.

4.2 Implementation Details

The testing procedure begins after completing the training. The "CNN" classifiers created during the training process are used to test for the new unlabeled (unclassified) eyes image. The picture of the eyes would then be listed as either positive or negative. During the training phase, 70% (1400 images) of all training samples were randomly selected to conduct the CNN models training process. The remaining 30% (600 images) of the total samples were randomly selected to perform a performance test of the proposed algorithm. The tests were conducted under different lighting conditions, and at various times of the day: five o'clock in the morning, one o'clock in the afternoon, eleven o'clock at night, and two o'clock at night. Also, at this stage, standards are calculated by comparing the results with the actual images.

Training and testing of CNN models based on MATLAB R2020a language to easily implement the code of CNN. A computer DELL that has specifications such as Intel(R) Core (TM) i7- 2670QM @ 2.20 GHz for CPU, 12 GB windows10 of RAM, and 64-bit Operating System.

Figure 11: Training set examples

4.3 Performance of CNN models

Using the proposed models, we achieved an accuracy of more than 90% by using 15 videos for users with different skin colors, with or without glasses and beards, at different times of the day and in different places. (Ten Realistic videos obtained from an ordinary camera, and five videos from the following site http://vlm1.uta.edu/~athitsos/projects/drowsiness) The duration of each video was one minute, so we tested two frames per second and therefore the total frames tested for each video was 120 frames The table below presents a summary of the results we obtained for each of the aforementioned models.

Table 1: shows the main classification criteria for the proposed models.

Metrics / Model	Accuracy	Precision	Recall	F-measure
AlexNet	98%	96%	100%	97.9%
DenseNet 201	99%	98%	100%	98. 9%
GoogleNet	98.5%	97%	100%	98.4%
ResNet50	98.8%	97.6%	100%	98.8%
Vgg16	98.1%	96.3%	100%	98.1%

4- Conclusion

They CNN based models for identifying driver drowsiness is anticipated to serve a key role in avoiding automotive accidents caused by driver's sleepy. For face detection then eyes region detection (ROI) from inside face region, we use the viola jones algorithm, which outputs the facial bounding box, and eyes bounding box.

The suggested method showed good accuracy and robustness in real-world driving situations. the experimental results show the following:

1- The results indicate that all our suggested models can give a correct rating even if the driver wears medical glasses, or if the driver has a beard and mustache.
2- Our suggested models are unable in most cases to detect driver drowsiness in the dark, so we recommend in future studies the use of a system based on infrared light.
3- Only DenseNet 201 and ResNet 50 to abilities to detect sleepiness in the case of wearing driving glasses at night and in the case of wearing sunglasses (which accounted for 25%), while all our suggested models were unable to detect sleepiness in sunglasses whose rate was higher than that. Therefore, we recommend not wearing sunglasses with a rate higher than 25 % while driving.
4- For future work, we will focus on developing our current system so that it collects the largest number of sleepiness indicators, such as tracking the movement of the head and yawning.

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