

Real-Time Drowsiness Identification Based on Eye State Analysis using Efficientnetb7 Deep Learning Technique

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ABSTRACT

The amount of road accidents caused by driver drowsiness is one of the world's major challenges. It is critical to prevent catastrophic accidents and reduce the financial burden on society caused by driver drowsiness. In these occurrences, this research endeavors to optimize efforts towards the real-time identification of drowsiness in drivers under authentic driving conditions, with the overarching objective of mitigating the incidence of traffic accidents.

We propose a novel system aimed at alerting drivers to instances of distraction or drowsiness. Image processing techniques and Convolutional neural networks (CNNs) based on EfficientNetB7 version is employed in real-time applications. the camera continuously monitors the driver's facial features and eye movements, with a particular emphasis on eye tracking as a key indicator of drowsiness. We used Dlib toolkit to provide a new, more stable parameter for evaluating the status of the driver's eyes.

The database used is **Driver Drowsiness Dataset (DDD)**, which contains image of drivers with different levels of drowsiness. The proposed model was evaluated in terms of accuracy, precision and Loss in detecting drowsiness in the eye region. The results of the study show that the EfficientNetB7 model have high accuracy in detecting drowsiness in the eye region.

Keywords: Driver drowsiness; behaviour-based methods; Deep learning; CNN models; EfficientNetB7.

INTRODUCTION

The drowsiness of the driver is widely recognised as a major risk factor that reduces road safety and poses a threat, not only to drivers, but to all road users. Recent studies estimate that around 20% of car crashes have been caused by drowsy driver. The UN revealed that 1.19 million people lose their lives each year due to these types of accidents which occur daily across the world, including Algeria. During 2023, Algeria recorded no less than 24,751 traffic accidents on the roads which injured 33,995 people and caused the death of 3,628 people, according to a recent report revealed by the National Delegation for Road Safety (DNSR) [1].

Nowadays, one of the main goals in the development of new advanced driver assistance systems is the trustworthy drowsiness detection. As figure 1 the Global Driver Drowsiness Detection System Market size is expected to be worth around USD 24.4 Billion by 2033, from USD 8 Billion in 2023.

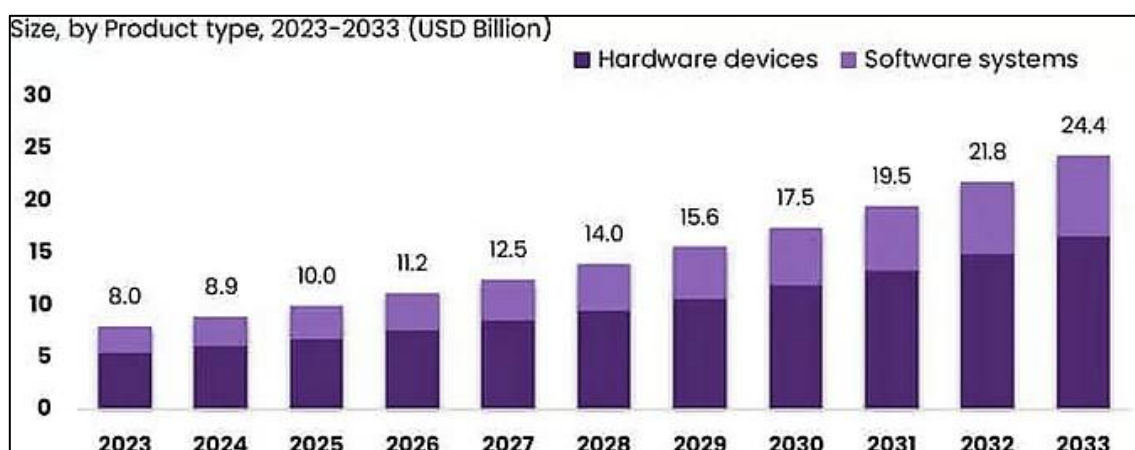


Figure 1. Global Driver Drowsiness Detection System Market [2]

The Driver Drowsiness Detection System Market refers to the segment within automotive safety technology dedicated to preventing accidents caused by driver fatigue. It encompasses systems utilizing various sensors and algorithms to monitor driver behavior, such as eye movement, steering patterns, and vehicle position [2].

Drowsiness detection can be divided into three main categories: -1- Vehicle based; -2-Behavioural based; -3- Physiological based. Vehicle based methods analyse information about the car position inside the lane, speed, usage of the steering wheel, brakes and gear changes [3]. The main weakness of this method is the variation in accuracy for particular characteristics of the vehicle and driving conditions.

The Behavioural based methods focus on driver's body analysis. These systems process eye-state information by calculating percentage of eye closure, eye closure duration and the frequency of eye closure [4-5]. Other systems combine this information with head-movement, yawning and facial expression [6].

The disadvantage of these approaches is collecting eye-state information properly when the driver wears dark sunglasses, which does not allow measuring these features properly.

Physiological based methods used the biomedical multi-signal acquisition and processing, such as electroencephalogram (EEG), electrocardiogram (ECG), galvanic skin response and respiration. These biomedical signals provide useful information about the physiological response during sleep stages [7]. But these methods suffer from some serious limitations it requires sensors and cables on the body that disturbs the driver. On the other hand, the mechanical car vibrations may introduce artifacts in the skin-electrode interface, which also complicates the signal detection.

The study presented a deep-learning-based drowsiness detection system for exploring the state of the eyes (open or closed) in order to detect driver drowsiness in real time. This detection system is based on convolutional neural networks (CNNs) essentially EfficientNetB7 model. The concept of the CNN originated in [8], and it was motivated by the brain's visual cortex and interpretation of visual data. Typically, a CNN's nonlinear and subsampling layers introduce other convolution layers. A new baseline architecture called EfficientNetBo was designed initially and it is scaled up to generate family of EfficientNet by compound scaling method. Powered by this approach, there are eight variants of the EfficientNets, namely EfficientNetBo to EfficientNetB7. The basic building block of the EfficientNet architecture is mobile inverted bottleneck convolution (MBConv) [9] with squeeze and excitation optimization. EfficientNetB7 strikes an optimal balance among accuracy, inference duration and model size, rendering it suitable for real-time applications. Additionally, this proposed detection technique used a method for the selection of the region of interest based on Haar cascade classification algorithm.

For the prediction of driver's drowsiness in a real environment, the probability of the Eye Aspect Ratio EAR belonging to the drowsiness class is evaluated and subsequently used, which consists of counting the score of a normal blinking eye from 1 to 10 frames; when the eyes are closed for more than 10 frames it is considered a drowsy state.

This approach is used to provide a warning with a sound alarm to prevent road accidents in the case of drowsiness.

The organization of the paper is classified into 5 sections with Section 2 describing the previous research works related to the driver drowsiness monitoring systems, followed by section 3 that narrates the proposed system. The experimental results were analysed in Section 4 and finally the conclusion in Section 5.

RELATED WORKS

In recent years, machine learning methods, especially deep learning, have been gaining attention, and more and more research is being done to apply deep learning to the detection of drowsiness.

The first paper dealing the drowsiness detection is since 1994 it is presented in [10]. The authors have proposed a system that uses image processing technology to analyse images of the driver's face. drowsiness is detected on the basis of the degree to which the driver's eyes are open or closed. Actually, there are many significant results and literature about driving drowsiness detection methods.

In [11], authors present a panorama of the existing methods of driver drowsiness detection with comparative study and give a detailed analysis of widely used classification techniques in this context.

Authors in [12] illustrate and review recent systems using different measures to track and detect drowsiness. Each system presented in this research is associated with a detailed description of the features, classification algorithms, and used datasets. In addition, an evaluation of these systems is presented, in terms of the final classification accuracy, sensitivity, and precision.

In [13] this paper, a module for Advanced Driver Assistance System (ADAS) is presented to reduce the number of accidents due to drowsiness and hence increase the transportation safety; authors develop an algorithm to locate, track, and analyse both the drivers face and eyes to measure PERCLOS associated with slow eye closure.

In [14], the research concentrates on examining the applications of EEG features and deep learning methods in detecting driver drowsiness. It addresses the unresolved challenges and potential advancements in enhancing driver drowsiness detection using EEG.

Authors in [15] develop a model for predicting the driver drowsiness using Artificial Neural Networks. The system works on the heartbeat rate analysing principle which is fed as the input to the Artificial Neural Network (ANN) to detect the drowsiness. The system accuracy is about 80%.

In [16] McDonald et al. designed a contextual algorithm for detecting driver drowsiness. The algorithm was integrated with the Dynamic Bayesian Network algorithm (DBN) and the algorithm yields a lower false-positive rate than the existing PERCLOS which is the present standard for the driver drowsiness detection system.

In [17], a drowsiness detection method based on changes in the respiratory signal is proposed. The respiratory signal, which has been obtained using an inductive plethysmography belt, has been processed in real time in order to classify the driver's state of alertness as drowsy or awake. The proposed algorithm is based on the analysis of the respiratory rate variability (RRV) in order to detect the fight against to fall asleep. Moreover, a method to provide a quality level of the respiratory signal is also proposed. Both methods have been combined to reduce false alarms due to the changes of measured RRV associated not with drowsiness but body movements. A driving simulator cabin has been used to perform the validation tests and external

Saini and Rekha [18] and Ramzan et al. [19] present a new approach for drowsiness detection based on machine learning. These review papers are from 2014 and 2019, respectively. In the last decade, there have been significant advances in machine learning methods and in autonomous driving technology. Certainly, the review by Saini and Rekha, Ramzen et al. helps us understand the traditional and new methods of drowsiness detection.

The important review in [20] summarizes the research and development trends of drowsiness detection systems based on various methods. Drowsiness detection methods based on the three

types of information: biometric information, vehicle behavior, and driver's graphic information are discussed. A prospect for arousal level detection and estimation technology for autonomous driving is also presented.

Varun et al in [21] present a novel model of multi-level distribution of detecting the driver drowsiness using the Convolution Neural Networks (CNN) followed by the emotion analysis. The emotion analysis, in this proposed model, analyses the driver's frame of mind which identifies the motivating factors for different driving patterns. These driving patterns were analysed based on the acceleration system, speed of the vehicle, Revolutions per Minute (RPM), facial recognition of the driver. The facial pattern of the driver is treated with 2D Convolution Neural Network (CNN) to detect the behavior and driver's emotion.

Paper in [22] proposes a model that combines Behavioral measures as a non-intrusive approach and sensor-based physiological measures as an intrusive approach to detect driver drowsiness. The proposed hybrid model uses AI-based Multi-Task Cascaded Convolutional Neural Networks (MTCNN) as a behavioral measure to recognize the driver's facial features, and the Galvanic Skin Response (GSR) sensor as a physiological measure to collect the skin conductance of the driver that helps to increase the overall accuracy. The proposed hybrid model is capable of identifying the transition from awake to a drowsy state in the driver in different conditions.

Research in [23] introduces a cutting-edge approach that combines facial recognition and drowsiness detection technologies with Internet of Things capabilities, including 5G/6G connectivity, aimed at bolstering vehicle security and driver safety. This work has been developed in two fundamental stages. The first phase was designed to carry out facial recognition of the driver when attempting to start the vehicle, rigorously verifying whether the driver possesses the required authorization to operate it. The second phase involved the constant monitoring of the driver's characteristic signs of drowsiness throughout the journey, using facial features and the condition of their eyes as reference points, aided by IoT sensors.

In [24], due to the high-dimensional nature of EEG signals and the subtle temporal patterns of drowsiness, there is increasing recognition of the need for deep neural networks (DNNs) to capture the dynamics of drowsy driving better. Authors investigate the use of two human-inspired algorithms—teaching learning-based optimization (TLBO) and student psychology-based optimization (SPBO)—to optimize convolutional neural networks (CNNs) for EEG-based drowsiness detection. Results demonstrate strong predictive performance for both CNN-TLBO and CNN-SPBO, with area under the curve values of 0.926 and 0.920, respectively.

Paper in [25] explores the efficacy of driver drowsiness detection using deep learning (DL) and machine learning (ML) techniques to develop robust systems that enhance road safety. Transfer learning is performed on the pre-trained Convolutional Neural Network (CNN) models- VGG16 and ResNet50 on image dataset. As an alternative approach, the study explores the efficacy of traditional classifiers on facial features extracted from the same image dataset used for transfer learning. Feature extraction is performed using MediaPipe Face Land marker model. These features are then trained and evaluated using traditional classifiers such as Random Forest, Gaussian Naive Bayes, Support Vector Classification (SVC), Decision Tree, XgBoost and a Multi-Layer Perceptron (MLP) neural network with and without Principal Component Analysis (PCA). The study showcases the influence of data format, model architecture, and hyper parameter tuning on model performance. This work also emphasizes the potential for developing a robust drowsiness detection system by adapting trained models to classify video frames in real time. Such a system holds promises for significantly improving road safety and addressing the critical issue of drowsy driving.

MATERIALS AND METHODS

The purpose of this work is to develop a system that is able to detect the drowsiness of a driver by using sequences of images that are recorded in such way that the face of the subject is visible.

The methodology begins with data preparation, including image resizing, normalization, and augmentation, to enhance the generalization capabilities of the models. The **"Driver Drowsiness Dataset (DDD)" dataset available at Kaggle is used** with an 80-20 split for training and testing, ensuring a robust evaluation of the model. **The dataset consists of pictures of drivers under different states labeled as "Drowsy" and "Non-Drowsy". The data set was retrieved using the Kaggle hub library in the Colab environment. All images are rescaled to 227 by 227 pixels[26].**

For data augmentation, the transformations applied to the data are random rotations, shifting, shearing, and zooming, excluding flipping the images horizontally.

For the purpose of evaluating drowsiness, videos are processed by detecting the frames in real time and then classifying them in real time, starting from driver's face to both the left and right eye using Haar Cascade classifiers. The captured eye regions of the driver are preprocessed to conform to the set standards of the model including scaling as well as normalization, once this step has been completed, the model with optimally set parameters derived from the previous workflow is deployed to identify whether the eyes were open or closed. Every drowsiness score starts from zero, a score increases by 1 unit in case closed eyes are detected. The score for drowsiness will be triggered in the case that the score has remained constant for 10 frames, meaning the driver will alert once a frame reaches a certain threshold. If the predictions generated indicate the eyes of the driver are open, then the score is decreased by one.

The overall pipeline of our approach is shown in Figure 2.

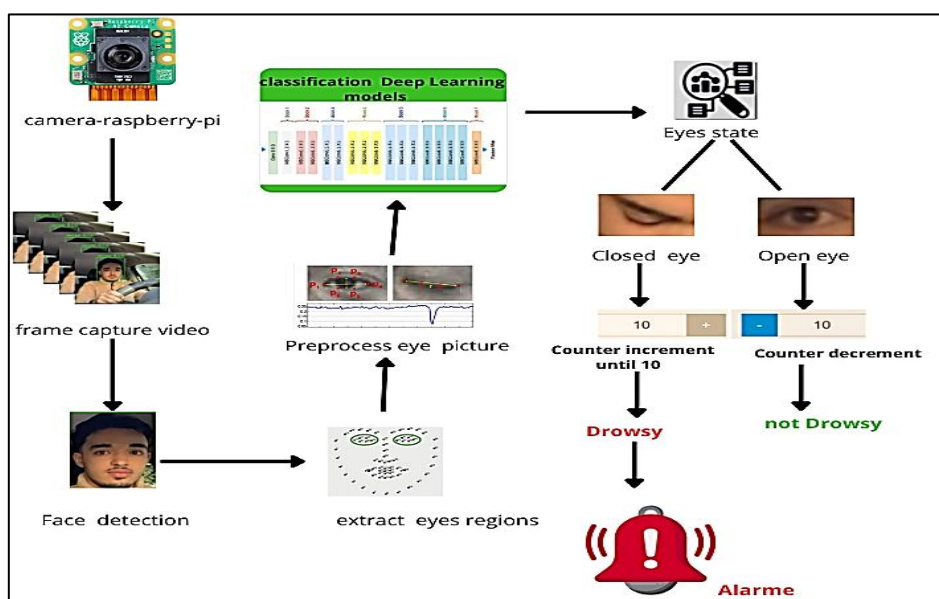


Figure 2. Diagram of the proposed drowsiness detection system.

3.1. DATA PREPROCESSING

In our experimental of the proposed model, all the images were scaled to dimensions of 224×224 . The model learning process is improved by reducing the influence of external pixel values. To attain that, each pixel is normalized into the range of $[0,1]$ by dividing each pixel value by 255.

In an effort to prevent overfitting and make the model more generalizable, data augmentation methods are utilized on the dataset throughout the preprocessing phase. Many transformations are done on the training images to keep their main characteristic intact while being changed. The Shift Scale Rotate tools in this case moves random images off center and out of proportion, the model then grows stronger to these changes in the position of the eye. Horizontal Flip is often paired with images to give a reflection to the rest of them to strengthen and prepare the model for different angles. Images Random Brightness Contrast changes the brightness and contrast of images allowing the model to work under different lighting scenarios. Some more tools are rotation_range, width_shift_range, height_shift_range that slightly rotate and move images vertically and horizontally in order to simulate real life movement of the head and the position of the eyes. As a result of editing with these augmentation tools the model became stronger at identifying Open-Eyes and Close-Eyes states giving better real-time drowsiness detection.

3.2. REGION OF INTEREST SELECTION

As seen in figure 3, finding the headbox is the first step in finding the eyes. Both the face landmark approach and head detection used the Haar cascade classification algorithm. This algorithm was applied for object detection, evaluating the intensity distribution of picture pixels. The “extract face landmarks” tool was used to illustrate the

identification of the eye regions, obtaining 68 landmark points matching to distinct facial features. These points, given as (x, y) coordinates, assisted in identify certain facial regions.

By this method, we found optical landmarks, determined the absolute distance between different points, and chose the farthest one. This strategy improved the method's ability to determine if an eye was closed.

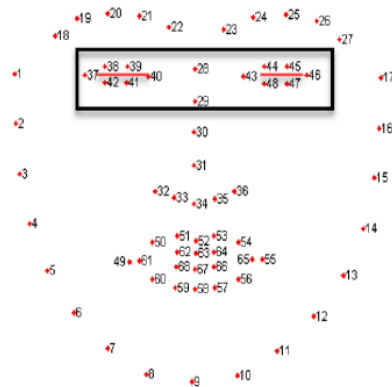


Figure 3. Facial extraction.

3.3. EYE ASPECT RATIO CALCULATION

In this work, we used a more reliable metric for assessing the condition of the driver's eyes using the Dlib toolkit. The Dlib toolset allowed us to gather facial landmarks. Six dots were placed around each eye to determine its location, as seen in Figure 4. There were notable differences in the distribution of ocular landmarks between the open and closed states. Based on the location of eye landmarks, the EAR can be computed using the formula below:

$$EAR = \frac{\|P_2 - P_6\| + \|P_3 - P_5\|}{2\|P_1 - P_4\|} \quad . \quad (eq.1)$$

According to Equation (1), the ocular landmarks' coordinates are P_i , $i = 1, 2, \dots, 6$. As seen in Figure 4, the EAR is more than 0.2 whenever the driver is awake. Conversely, the EAR is less than 0.2. The placement of solid facial landmarks makes this new parameter, the EAR, significantly more robust.

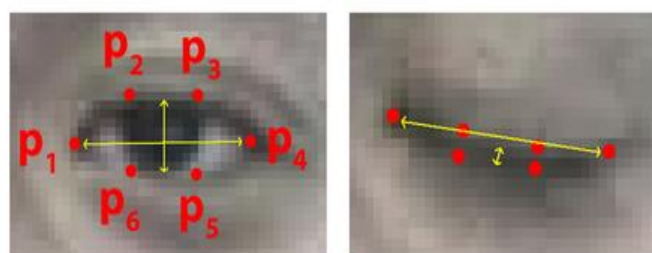


Figure 4. Eye Aspect Ratio Calculation.

3.4. PROPOSED CLASSIFIER MODEL : EFFICIENTNETB7

The landmark coordination extracted from images will act as the input to the algorithm, based on CNN Classifier. During this step, a process training will ensue where there will be various predictions from which a model will be formed; corrections are made to the model if the predictions go wrong. The training will be processed till the wanted level of accuracy is reached.

The CNN classifier is based on the EfficientNetBo7 architecture, which presents a lightweight model that is highly precise. Smaller models are processed faster, and EfficientNetBo presents the smallest model of the EfficientNet series [9].

As we go from EfficientNetB0 to EfficientNetB7, depth, width, resolution and model size goes on increasing and the accuracy is also improved [27]. The best performing model Efficient-

NetB7 outperforms earlier state-of-art CNNs in terms of accuracy on ImageNet, and is also 8.4× smaller and 6.1× faster than the best existing CNN [27].

we consider EfficientNetB7 to be the most adequate model for this study case, where the model needs to quickly obtain a prediction.

The EfficientNetB7 architecture is divided into 7 blocks, each of them formed by multiple layers. Figure 5 shows an overview of this architecture, where the 7 main blocks are represented. **A sequential model atop EfficientNetB0 with the addition of a flattening layer, a dense layer with ReLU activation and L2 regularization, a dropout layer for regularization, and a final dense layer with sigmoid activation for binary classification.**

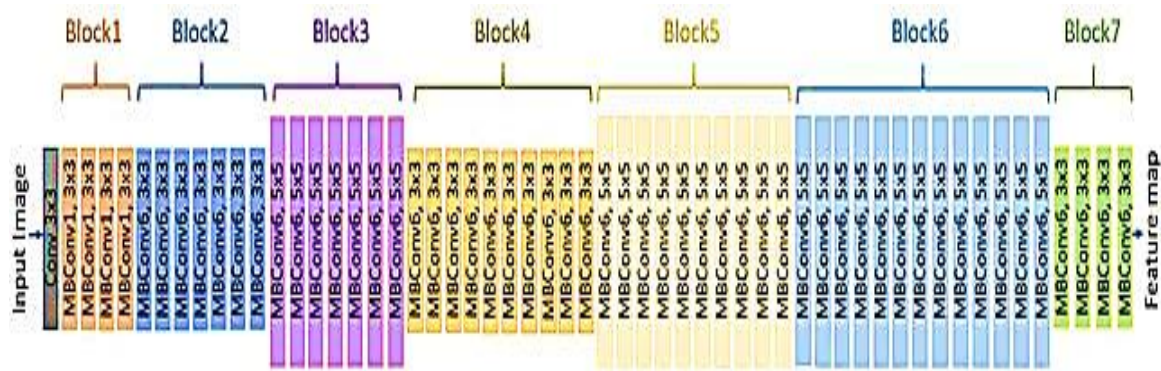


Figure 5. EfficientNetB7 architecture [28]

The EfficientNetB7 network receives the pre-processed frames as input. After that, it extracts high-dimensionality features using a cascade of convolutional layers. These layers gradually reduce the input's spatial dimensions as the number of feature channels rises. In order to intended to learn the intricate nonlinear interactions among the characteristics that have been extracted, a 256-neuron fully connected layer with ReLU activation is incorporated. During training, neurons are randomly deactivated using a 0.5-rate dropout layer to avoid overfitting, which enhances the model's capacity for generalization.

The last layer is a dense classification layer including a single neuron and a sigmoid activation function. This layer transforms the processed feature vector into a probability score ranging from 0 to 1, indicating the possibility of the driver being in a drowsy state.

RESULTS AND DISCUSSION

In this study, to evaluate the proposed model a DDD dataset containing static images of individuals' faces expressing various facial expressions in various lighting conditions, wide eyes, and closed eyes, was utilized.

The evaluation of the model's performance was undertaken utilizing metrics such as accuracy, precision,

and Loss. Additionally, the models were evaluated using real driver data to further assess their adaptability and usefulness in real-world circumstances.

Here, we conducted two distinct sorts of experiments. In the first category, an experiment was conducted by using a DDD dataset. The second form of the experiment was conducted via video.

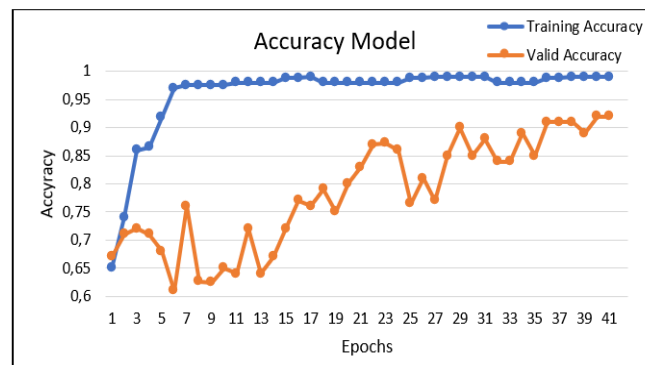
The dataset distribution for the first experiment including 33,435 images for training and 8,358 images for validation, divided into two balanced classes: "Drowsy" and "Non-Drowsy". In simpler terms, out of the total dataset 80% was allocated for training and 20% reserved for testing.

The following Table 1 summarizes the different Hyper-parameters of the model training values used in experiments. The batch size is configured to 64 to enable the model to process a defined number of samples during each training iteration, hence optimizing training performance and memory utilization. Employing a learning rate of 0.001 is essential for facilitating smooth training and rapid convergence.

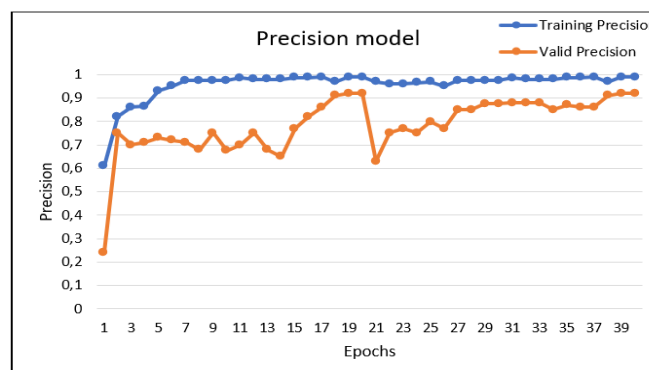
Table 1. Training parameters

Hyper-Parameters	Value
Optimizer	ADAM
Learning rate	0.001
Epochs	40
Batch size	64
Number image for training	33435 images belonging to 2 classes
Number image for validation	8358 images belonging to 2 classes
Number of experiments	10

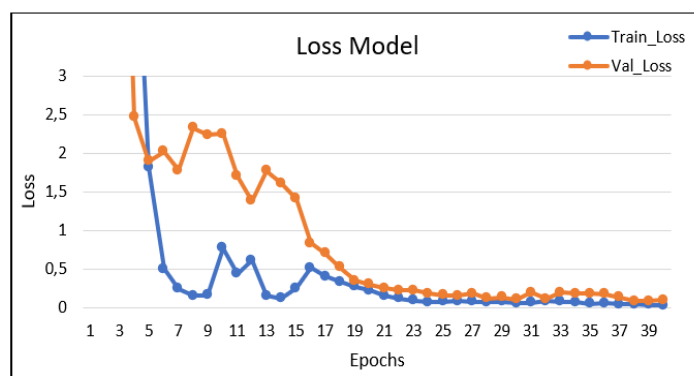
The accuracy, precision, and Loss classification at each epoch of the proposed model are presented in Figures 6.



(a): Accuracy training presentation



(b) Precision training presentation



(c) : Loss training presentation.

Figure 6. Metrics evaluation: Accuracy, Precision and Loss.

The accuracy, which measures the proportion of correct predictions, gradually increases, reaching a value of 0.99 in the last epoch. And slightly lower accuracy, but always impressive 0.93 on validation data. This means that the model has properly predicted the driver's drowsiness state for 93% of the instances in the validation set. These results demonstrate that the model has effectively learned from training data and is well generalized to validation data. The model has shown its ability to make precise predictions on unknown data.

The decreasing values of loss indicate that the model has managed to converge on optimal parameter values during training. Regarding precision measure, it follows a similar trend with constant improvement. The precision, which represents the proportion of correct positive predictions among all the positive predictions, reached 99% in the last epoch on training data and 91% on validation data.

The outcomes from earlier studies conducted in this field are compared to the research findings in Table 2.

Table 2. comparison of the proposed model' accuracy with that of various approaches when using DDD dataset.

Research	Year	Model	Accuracy
[29]	2021	Deep-CNN-based ensemble	85%
[30]	2022	CNN + LSTM	97.3%
[31]	2023	RF, SVM, and sequential NN	RF: 99%, SVM: 80%, 4D: 96%
[32]	2024	VGG19	96.51%
Proposed model	2025	EfficientNetB7	99% in training and 93% in test

The accuracy of the methods ranged from 85% to 99%, while the proposed method reached an accuracy equal to 99% in training and 93% in test. However, as illustrated, the proposed model outperforms the other techniques available in the literature using the similar dataset.

Considering the results, the CNN based on EfficientNetB7 was used to perform driver drowsiness detection in real case. In Figure 7, consecutive scene analyses are shown, being a sequence of the process with drowsiness. In the examples it is observed that the driver starts in a normal state (Figure 7a), then goes into a state of drowsy (Figure 7b), closing his eyes with a time of approximately 4s.

Despite the driver's inclined face position, which made it difficult to accurately trace the eye region, the proposed model was able to detect the case of drowsiness. The model's usefulness and generalizability are demonstrated by validating it with unknown data, which guarantees that it can function well with new inputs.

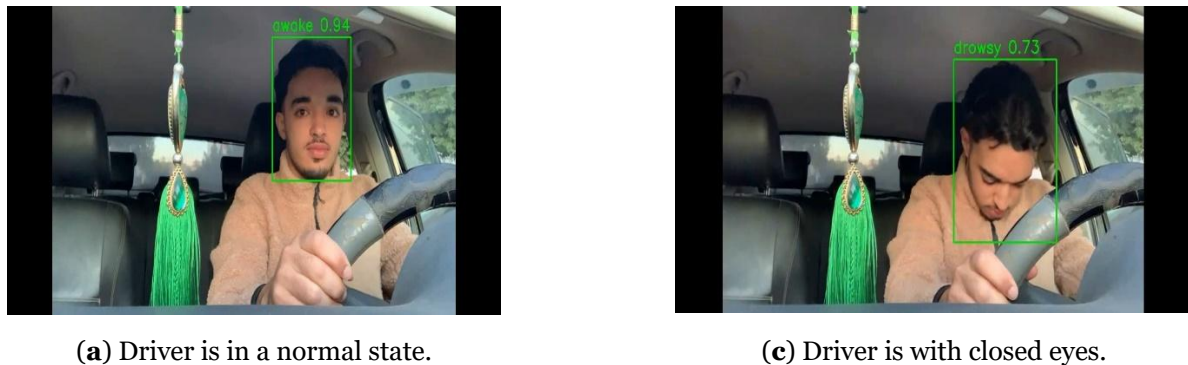


Figure 7. Driver drowsiness detection in a real environment.

CONCLUSIONS AND FUTURE WORKS

This research presents an approach for real time drowsiness detection, where an improvement CNN method is proposed as a basis: EfficientNetB7 version. For the experiments, a DDD database was used. The results were obtained from 10 experiments performed and showed an exceptionally high accuracy in drowsiness detection, with values around 93% in test phase. Additionally, for the prediction of driver's drowsiness in a real environment this proposed detection technique used a method for the selection of the region of interest based on Haar cascade classification algorithm and probability of the Eye Aspect Ratio EAR.

Nevertheless, there are challenges including dim lighting, eyeglasses, and inconsistent image formats. In order to improve the system's performance and dependability under a variety of real-world circumstances, future research should go beyond these limitations by retraining models using a variety of photos, incorporating physiological inputs, and investigating cutting-edge technologies.

Furthermore, we must test the models more on some other diverse datasets, which would make them better applied to real-world driving situations.

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