

Driver Drowsiness Detection and Alerting System Using Deep Learning Methods

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Abstract

The drowsiness of a person driving a vehicle is the primary cause of accidents all over the world. Due to lack of sleep and tiredness, fatigue and drowsiness are common among many drivers, which often leads to road accidents. Alerting the driver ahead of time is the best way to avoid road accidents caused by drowsiness. There are numerous techniques to detect drowsiness. In this paper, we have put forward a deep learning-based approach to detect the drowsiness of the drivers. We have used convolutional neural networks, which is a class of deep learning. We used the Eye regions-based dataset to predict the drowsiness.

Keywords: Drowsiness detection, Convolutional neural network, deep learning

Introduction

Networks of transportation are essential to human activities in daily life. Anyone might be involved in a road accident at any time for a number of reasons, but most the accidents were caused by the driver's sleepiness. The main reasons of drowsiness, which makes long journeys exhausting, are lack of sleep and rest. Drivers become less cautious as a result of these factors, which increases the likelihood of hazardous circumstances and accidents. environment, new technologies may be essential in providing a solution to this problem. The National Sleep Foundation USA found that tiredness while driving contributes to 100,000 accidents annually. In fact, analysis research shows that if a person becomes sleepy after an 18-hour sleep deficit. Periodic driving condition observation and considerable feedback (such as alarms or safety automatic measures) required to be put in place in order to improve the security of automotive systems. Fortunately, these problems can be resolved by contemporary technology, such as wearable critical parameter detectors, distributed pressure sensors, and eye sensor cameras. The following tools have been widely used to track drowsiness:

- 1) Vehicle-based measurements Lane deviations, steering wheel rotation, pedal pressure, and other factors are continuously tracked, and any change that exceeds a predetermined level signals that the driver is dozing off.
- 2) Behavioural strategies: The driver's eye closure, eye twitching, head position, and yawning are all captured on camera. The motorist is alerted if any of these signs of tiredness are identified.
- 3) Physiological signs: Several research have looked at the physical symptoms such as ECG, EMG, EoG, and EEG are associated to driver drowsiness. This study aims to recognize and alert a person whose eyes have been closed for a preset period of time. If it detects fatigue, this device will warn the driver.

Related Work

The survey that is conducted comprises the most recent developments and research on the subject of our project. It is an endeavor to comprehend the work that has gone into this area of research and to identify the areas where our project-development efforts should be concentrated. The existing sleepiness detection technologies for facial landmark detection [7], blink detection, and yawn detection have been the subject of this literature review. Drowsiness detection can be done using a variety of methods, including deep CNN [13], computer vision [15], behavioral measurements, and machine learning approaches, all of which have their own benefits and drawbacks as well as varying degrees of accuracy. For the detection of blinks and yawns, research has been done on EAR- and

MAR-based systems. Drowsiness detection for motorized vehicles using computer vision and web push notifications is taken from [1]. They have created a computer vision-based sleepiness system for cars in this study, complete with alert noises and web push notifications. These alerts will let the motorist take action to avoid an accident. Also, the system is built to alert the user about local coffee shops, enhancing driving awareness. As a result, the system successfully recognized the driver's sleepiness during the trial run. To determine whether the eyes are open or closed, the Eye Aspect Ratio was used. The usage of the Raspberry Pi camera was a limitation for the article because it prevented the system from functioning at night. It ought to have been a night-vision camera. "Real-time monitoring of driver drowsiness on mobile platforms using 3D neural networks," from [2]. In this study, they employed real-time face video to identify microsleeps and alert the drivers while simultaneously using depth-wise separable 3D convolution procedures to detect driver tiredness. The outcomes demonstrate that the technique may select the most crucial aspects without needing to be pre-specified by the developer, who may overlook details like nose wrinkles, eyelid movement, and other facial motions.

From [3] titled "The detection of drowsiness using a driver monitoring system". In this paper, they have made use of a driver monitoring system (DMS) to detect drowsiness along with different kinds of sensors. They have also collected data in the form of signals from other vehicle-based sensors. The results obtained show that the models were effective at dividing the drowsiness into three levels - low, moderate, and severe drowsiness. But, while differentiating between moderate and severe levels, the model was not efficient enough. The limitations of the paper are that the model was not effective while differentiating moderate drowsiness from severe drowsiness. Another limitation is that the size of the sample used in this paper is small.

Driver Drowsiness Detection System and Techniques according to the experts it has been observed that when the drivers do not take break, they tend to run a high risk of becoming drowsy. Study shows that accidents occur due to sleepy drivers in need of a rest, which means that road accidents occur more due to drowsiness rather than drink-driving.

Drowsiness Detection Based on Ocular Closing and Yawning Detection" from [5]. In this study, Haar-cascade classifiers are used to follow a driver's eye and lip movements. This will make it easier to spot eye closure and frequent yawning. If the driver is already dozing off, the system will also sound an alarm. As a consequence, the system accurately detects faces and necessary facial traits in 85% of situations. After the face's feature identification is successful, the algorithm quickly detects tiredness. The paper's shortcoming is the observation that the system's accuracy declines in poor lighting.

Result:

Drowsiness and driver fatigue are major factors in many different car accidents. Designing and maintaining methods for accident prevention A significant technological problem is developing tools that can reliably detect or prevent driver fatigue and alert them before an accident. We utilise OpenCV to capture webcam photos, and then a deep learning algorithm is used to determine if someone's eyes are open or closed. We are searching for the person's face and eyes in this instance.

First step: A camera image is used as input.

We'll take pictures with a camera for input. But we developed an unending loop that records every frame in order to acquire access to the webcam. We make use of OpenCV's cv2 function. The camera is accessed and the object is captured using VideoCapture(0) (cap). Each frame is read using cap.read(), and the image is then saved in a Variable.

STEP -2 Construct a ROI in step two by identifying a face in the image. Since the OpenCV object detection algorithm only accepts grayscale images as input, we first transformed the acquired image to grey scale in order to segment the face in it. We don't require colour detail to detect the items. To find the face, we apply the Haar cascade classifier. Face=cv2 is the classifier. With this portion, Cas

is prepared. We utilise cv2 for (x,y,w,h)infaces. (100,100,100), rectangle (frame, (x,y), (x+w, y+h), (x+w, y+h), 1

Step 3: Locate the eyes using the ROI, then provide them to the classifier. The technique for detecting eyes is the same as for detecting ears. Cascade classifier is used in left and right eyes. Then, use left eye =`eye.detectMultiScale(Gray)` to detect the eyes. We extracted only the details of eyes from the captured image. This can be done by first removing the Eye’s boundary box and then using this code to remove the eye image from the picture. `L_eye = frame[y : y+h, x : x+w]`. This information is given to CNN, which decides whether the eyes are closed or not. The right eye also detected in the above manner.

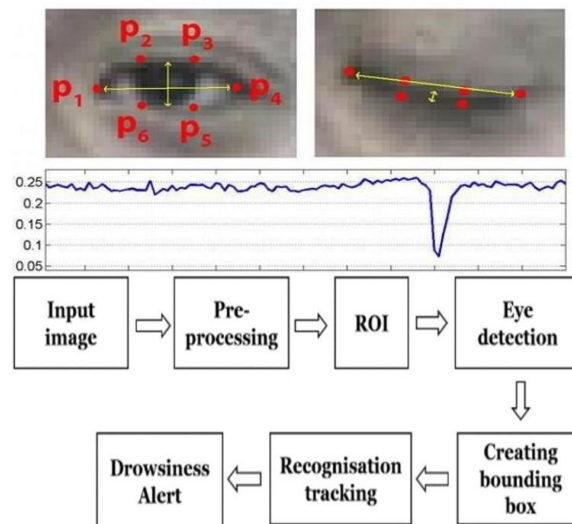
Step 4: The classifier will decide if the eyes are open or closed. A CNN classifier is used to forecast the eye state before the image is sent into the model, as the model needs the right metrics to start with. We start by Grayscale conversion of the colour image.

`R_eye = cv2.cvtColor(r_eye, cv2.COLOR_BGR2GRAY)`. The image is then resized to 24*24 pixels because the model was trained on images with that resolution. `R_eye, (24,24), cv2.resize` the data is normalized for better convergence.

`R_eye equals r_eye/255` `Model = load Model(“models/cnnCat2.h5”)` loads the model. Now, the suggested model predicts each eye. `lpred=model.Predict classes(l_eye)` When `lpred[0] = 1`, it indicates that the eyes are open; when `lpred[0] = 0`, the eyes are closed.

STEP-5: We’ll use the score, which is just a number, to calculate how long the subject has been closed-eyed. As a result, if both eyes are closed, the score will start to rise, and if both eyes are open, the score will fall. The output, which shows the status of the driver or a person, is drawn on the screen using the `cv2.putText()` function. `Font,1,(255,255,255),1,`

`cv2.LINE_AA, frame, “Open”,(10,height20)`, A threshold is established; for instance, if the score is higher than 15, it denotes that the subject’s eyes have been closed for a considerable period of time. The alarm then turned on.



Conclusion:

The paper described an improved drowsiness detection system based on CNN-based deeP Learning. The system was able to detect facial landmarks from images captured on a mobile device and pass it to a CNN-based trained Deep Learning model to detect drowsy driving behavior. The achievement here was the production of a deep learning model that is small in size but relatively high in accuracy. The model that is presented here has achieved an average of 83.33% of accuracy for all categories

where the maximum size of the model did not exceed 75KB. This system can be integrated easily into dashboards in the next generation of cars to support advanced driver-assistance programs or even a mobile device to provide intervention when drivers are sleepy. There are limitations to this technology, such as obstructing the view of facial features by wearing sunglasses and bad lighting conditions. However, given the current state, there is still room for performance improvement and better facial feature detection even in bad lighting conditions.

References:

- [1] N. C. for Statistics and Analysis, “Crash Stats:DrowsyDriving2015,”October2017.[Online].Available: <https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812446>.
- [2] M. Walker, *Why We Sleep: Unlocking the Power of Sleep and Dreams*. Scribner, 2017. [Online].Available: <https://books.google.com.qa/books?id=8bSuDgAAQBAJ>
- [3] W. H. Organization, “The top 10 causes of death.”[Online].Available: <https://www.who.int/news-room/factsheets/detail/the-top-10-causes-of-death>
- [4] M. Benz, “Mercedes Benz safety - s class.” [Online].Available:<https://www.mercedes-benz.co.uk/passengercars/mercedes-benz-cars/models/s-class/saloon-w222/safety/intelligent-drive.module.html>
- [5] Muze, “Eyesight.” [Online]. Available: <https://www.eyesight-tech.com/>
- [6] A. D. McDonald, J. D. Lee, C. Schwarz, and T. L. Brown, “A contextual and temporal algorithm for driver drowsiness detection,” *Accident Analysis & Prevention*, vol. 113, pp. 25–37, Apr. 2018. [Online]. Available:<https://www.sciencedirect.com/science/article/pii/S0001457518300058>
- [7] U. S. F. M. C. S. A. T. Division, “PERCLOS: A Valid Psychophysio-logical Measure of Alertness as Assessed by Psychomotor Vigilance,” October 1998.
- [8] C. S. Wei, Y. T. Wang, C. T. Lin, and T. P. Jung, “Toward Drowsiness De-tection Using Non-hair-Bearing EEG-Based Brain-Computer Interfaces,”*IEEE Transactions on Neural Systems and Rehabilitation Engineering*,2018.
- [9] V. J. Kartsch, S. Benatti, P. D. Schiavone, D. Rossi, and L. Biennia sensor fusion approach for drowsiness detection in wearable ultra-low-power systems,” *Information Fusion*, vol. 43, pp. 66–76, Sep.2018. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S1566253517306942>
- [10] S. Tateno, X. Guan, R. Cao, and Z. Qu, “Development of Drowsiness Detection System Based on Respiration Changes Using Heart Rate Monitoring,” in 2018 57th Annual Conference of the Society of Instrumental Control Engineers of Japan, SICE 2018, 2018, pp. 1664–1669.
- [11] A. Kamila is and F. X. Prenafeta-Bold, “Deep learning in agriculture:A survey,” *Computers and Electronics in Agriculture*, vol. 147, pp. 70– 90, 2018. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0168169917308803>
- [12] M. Tayab Khan, H. Anwar, F. Ullah, A. Ur Rehman, R. Ullah, A. Iqbal,B.-H. Lee, and K. S. Kwak, “Smart Real-Time Video Surveillance Platform for Drowsiness Detection Based on Eyelid Closure,” *Wireless Communications and Mobile Computing*, vol. 2019, pp. 1–9, 2019.
- [13] M. F. Shakeel, N. A. Bajwa, A. M. Anwaar, A. Sohail, A. Khan, and. urn Rashid, “Detecting Driver Drowsiness in Real Time Through Deep Learning Based Object Detection,” 2019, pp. 283–296. [Online].Available: <http://link.springer.com/10.1007/978-3-030-20521-8{ }24>
- [14] L. Celona, L. Mamma, S. Bianco, and R. Schettini, “A multi-task CNNframework for driver face monitoring,” *IEEE International Conference on Consumer Electronics - Berlin, ICCE-Berlin*, vol. 2018-Septe, pp. 1–4,2018.
- [15] C.-H. Weng, Y.-H. Lai, and S.-H. Lai, “Driver drowsiness detection viaa hierarchical temporal deep belief network,” in *Asian Conference on Computer Vision*. Springer, 2016, pp. 117–133.