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DRIVER DROWSINESS DETECTION SYSTEM BY REAL TIME EYE STATE IDENTIFICATION

Hajra Asif[*1], **Dr. Ghulam Mustafa**[2]

[*1] *Student, Faculty of Information Technology & Computer Science, University of Central Punjab, Lahore, Pakistan.*
[2] *Assistant professor, Department of computer science and information technology, University of Central Punjab, Lahore, Pakistan.*

[*1]L1F22MSDS0002@ucp.edu.pk, [2]ghulammustafa02@ucp.edu.pk,

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Corresponding Author: *
Hajra Asif

Abstract
The paper proposes a new architecture which plies eye states of a live video feed and receives at 97 percent accuracy; followed by sending signals at the right time before instances of accidents occur and this is an immense problem in the globe since traffic accidents by fatigued drivers are a huge menace. It is a combined CNN and RNN based system. A comprehensive dataset of 4,760 images, comprising 2,380 closed-eye and 2,380 open-eye images captured under diverse driving conditions, is used to train the model.

INTRODUCTION

Drunk driving is a major contributor to the epidemic of road accidents that affects every region of the globe. Attempting to translate the traditional methods of identifying driver fatigue into a real-life setting, many measuring the behavior patterns of the car or physiological changes experience the effect of being distractive or simply ineffective. The use of a combination of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) is the basis of this thesis's novel method for real-time tire identification in drivers [1]. Convolutional neural networks (CNNs) excel at extracting spatial data from images, making them ideal for tasks like identifying tiredness based on eye closure and facial expressions. However, it is critical to seek time trends in terms of driving behavior in order to detect sleepiness. The temporality of such sequence of picture frames is captured by this system using an RNN, in particular LSTM network. This combination means that the model can be trained on static images and dynamic patterns of driver behavior [2].

The proposed solution uses a non-invasive method because a camera is used to record the face of a driver in real-time. To investigate the time dimension, suppose that the CNN part extracts spatial features of each frame and sends them to the LSTM layer. By adopting this hierarchy, sleepiness may be better comprehended, and thus detection will be more exact and timely. Because of its real-time nature, the device can immediately identify indicators of fatigue, such as extended eye closures, and transmit notifications [3]. This dissertation details the process of creating, implementing, and testing a system to detect driver sleepiness using convolutional neural networks (CNNs). Issues with the real-time sleepiness detection are presented, and the way to get rid of them or take account of them is being considered, such as different lightings around and the peculiarities of drivers. The capacity of the system to resist adverse effects, impairment and loss of reliability under a set of circumstances are assessed by examining the performance under varying conditions. Moral implications of being monitored by drivers at all times will also be discussed, especially in terms of how this puts personal data in danger. This innovation contributes to the growing field of smart driver help system as it is a potential solution to the issue about drowsy drivers and safety in the road [4].

There are numerous ways of detecting drowsy drivers and they all do possess their strengths and shortcomings. The most common categories into which such approaches fit would be methods based on vehicle, physiological and behavioral parameters. Weakness detection models have shown promise in using a mix of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), especially Long Short-Term Memory (LSTM) networks, to enhance accuracy and consistency. Among these methods, this literature review examines CNN-RNN architectures with an eye towards their improvements and future usage in dependable sleepiness detection.

Behavioral approaches look at visual cues indicating that someone is tired through computer vision algorithms. Most often, these methods monitor the head movements which are caught by the camera, eye expressions, and facial emotions [5]. Generally, most people, when they are feeling sleepy, depict it in their body language and expressions. These consist of such characteristics as droopy eyelashes, long eye blinks, yawning and nodding of the head. These techniques offer a non-invasive direction of detecting sleepiness, which, however, is not always accurate and can be influenced by alterations in the light conditions, facial properties, and personal manner of interaction. Moreover, the manual assessment in the real-life scenario may be not easy to capture and recognize slight alterations in the head motions and facial expressions during driving sessions.

The fundamental physiological technique is the use of sensors to pick up physiological measures related to sleepiness. These involve aspects of physiological states such as skin conductance, core temperature, brainwave patterns, and heart rate variability, among others that may try to give a more direct and objective assessment of driver attentiveness by monitoring aspects of physiological reaction patterns [6]. However, not everyone is going to be ready to accept the usage of the sensors because it is very invasive. Besides the sleepiness, the other variables such as worry, stress or other health conditions might affect the physiological signs and lead to false alarms. The other barrier to wide adaptation is the cost and inconvenience of putting physiological sensors in vehicles.

The technics grounded on vehicular parameters evaluate the level of attentiveness of the driver as based on the analysis of vehicle driving habits and dynamics. These methods typically monitor such aspects as lane change, speed variation, braking pattern and wheel movement. Drunk driving occurs in various forms such as hitchy steering, drifting of the lanes or suddenly applying brakes. Despite the fact that these methods involve less physical intrusion in comparison with physiological methods, they are still prone to external forces such as traffic levels, harsh weather conditions, and poor road conditions. There is also the difficulty of coming up with single thresholds in the detection of sleepiness by use of vehicle characteristics because it could be that individual driving habits and styles could vary immensely.

Improving driver tiredness detection has been made possible by the integration of CNNs and RNNs, namely LSTMs. The findings have been positive. One of the strongest areas in which convolutional neural networks (CNNs) excel is facial image analysis and minor changes in expressions recognition. Actively tracking the growth or change of driver behavior in sequential data requires temporal models, and RNNs, especially LSTMs, are excellent temporal dependencies models. Integration of the abilities of the two architectures has enabled scholars to develop sleepiness detection algorithms that are more particular and robust [8]. Convolutional neural networks (CNNs) process the video frames sequentially and capture the spatial attributes of head positions, visual manner of eyes, and facial points. Once the features are retrieved, LSTM network or another RNN is applied to analyze the temporal associations of the features. By representing a combination of spatial-temporal analysis, the algorithm can learn complex patterns and associations on driver behaviors, ultimately becoming more accurate and reliable in detecting sleepiness [9].

The working focus at the moment in this direction is the improvement of CNN-RNN architectures, the exploration of new networks structures, and the design of more efficient training algorithms. Researchers are looking at multimodal data, which combines optical data with data from other sensors including physiological signals and vehicle factors, to make drowsiness detection systems even more accurate and resilient. The implementation of such cutting-edge technology into vehicles to provide practical use is the ultimate goal of other ongoing breakthroughs in the design and development of real-time embedded systems that detect driver tiredness. [10]. By adding the attention mechanisms, which narrows down to the most significant traits, the accuracy of the detection has been increased [11].

Random cropping, rotation, and color jittering are data augmentation approaches that have been used to improve the model's resilience [12]. By reducing the likelihood of overfitting, dropout regularization improves the model's capacity to generalize [13]. Results from enhancing detection performance using transfer learning and fine-tuning pre-trained models have also been encouraging, particularly in situations when training data is scarce [14].

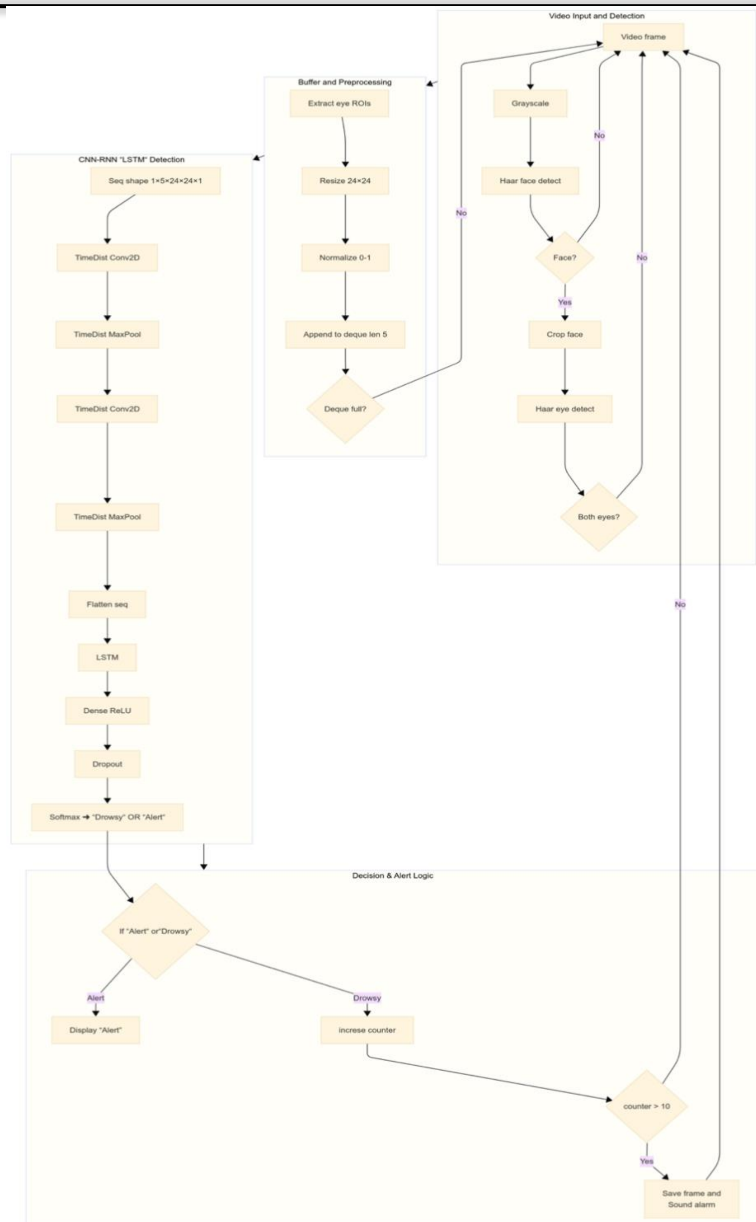

Figure 1 Research Model

2. Research Methodology

In order to classify if the driver is in drowsy state, the suggested approach builds a robust framework that makes use of CNNs and RNNs, in particular LSTM networks, for their strengths. Our dual-architecture system collects spatial and temporal data from live video feeds to detect driver drowsiness quickly and reliably.

2.1 Dataset Collection

A publicly available Human Eyes Open/Close dataset [15] used in this study is a clean and complete dataset presented on Kaggle. The dataset contains many high-quality visuals in the PNG format, explicitly prepared and labeled for eye state classification. The data set is strategically sliced so that there is an 80-20 ratio of the data images used to train the data and 20% of the data used during the test. The training set contains 2,380 images in closed and open states of the eye, and the testing set has 510 images in closed and open eye states. Such a balance between the training and testing data is a sturdy and reliable validation of the model's performance. More importantly, the dataset also includes expert annotations on each image, and this feature is highly valuable because correct labels will offer the capability to perform the classification tasks accurately and reliably. Such an organized and expertly commented meal plan is crucial in training and checking the results of the above method of conveying CNN-RNN in constructing an exact and resilient program for measuring driver exhaustion.

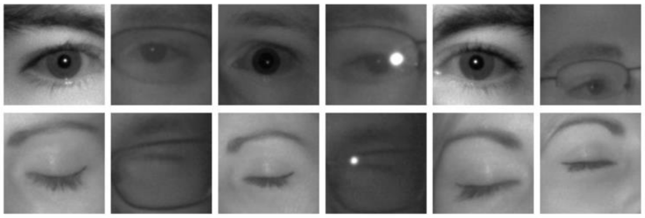

Figure 2. Non-Drowsy and drowsy images from dataset

2.2 Data Augmentation

The model's generalizability and resilience were enhanced using many data augmentation methodologies. Some of these operations included moving along the width and height dimensions, scaling, rotating, shearing, and horizontal flipping. By incorporating transformational approaches into the dataset, the likelihood of overfitting was decreased and the model's capacity to generalize to new, unknown data was enhanced.

2.3 Image Preprocessing

Greyscale conversion, scaling to a standard dimension, and pixel value normalization are all part of the picture preparation procedure. By standardizing the input data, these preprocessing steps decrease computational complexity and enable the model to focus on the most important visual elements for accurately detecting signs of driver tiredness.

2.4 Segmentation of Drowsy Eyes

An important part of the whole procedure for identifying driver tiredness is the detection of the driver's fatigued eyes. Using Haar cascade classifiers, which can distinguish and identify important visual features like the eyes and face in subsequent video frames, simplifies this phase. The system has the option of studying the health of the eyes and their patterns of behavior by analyzing areas surrounding the eyes of the driver in real-time.

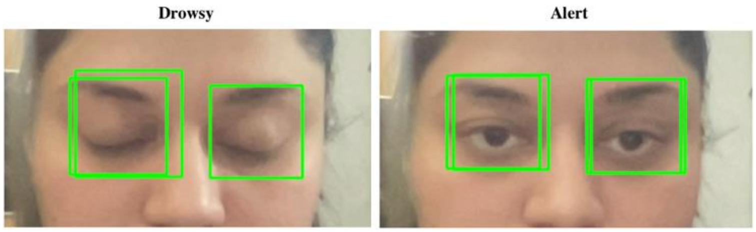

Figure 3. Segmentation of eye regions for drowsy eyes

2.5 Frame Detection

During the border removal, the camera is directed toward the driver in real-time and the camera images are converted to be in grey scale. This greyscale transformation simplifies the computing process of the organization and provides the following study with priorities on the aspects and information of the most significant visual perception relevant to a successful detection of sleepiness signs among drivers.

2.6 Face Detection

To identify the face of the driver in every frame of the video feet, the feature of Haar cascade classifiers is executed. At this point, the system can narrow down on the fact that the driver is sleepy through the analysis of their face and the rest of the visual evidence displayed. The effectiveness of the rest of the pipeline is pegged on the ability to recognize faces correctly in order to make it read the clues of the behavior and appearance of a sleep driver correctly.

2.7 Eye Detection

The system has the capacity to locate the eyes of the driver within the facial regions with the help of Haar cascade classifiers. Such separation of the ocular region enables the detection of signs of sleepiness to be much easier. Since the system measures the condition or the movement of the eyes over a considerable time, it can confidently determine how the driver is attentive based on the changes in his/her condition and movement.

2.8 ROI Selection

Then we merge a greyscale image and normalize and resize the portions of eyes to the same sizes. The CNN-RNN architecture takes a frame buffer that contains the normalized areas of the eyes along with a list of frames. With such an order of things, the model can observe the gaze pattern of the driver over time to determine whether they are getting drowsy.

2.9 Feature Extraction

CNN layers combine the approaches of convolution and pooling in order to extract features out of input pictures. This process in order to amount to the detection of lethargy produces a hierarchy of spatial elements starting with simple visual patterns up to complex representations. The retrieved traits allow the classification stage to identify alert and sleepy very accurately.

2.10 Classification

To track the changes of the ocular region, LSTM networks should be used in the model. Some crucial signs of sleepiness that include blinks frequencies and duration can be detected after studying single series of photographs taken of the eyes.

2.11 Real-Time Detection

In terms of detecting sleepiness, the system applies a pre-trained CNN-LSTM model to decipher the meanings of the video frames recorded in real-time by means of OpenCV. It evaluates one sequence instead of per-frame based on a buffer of stored frames that is recently stored. The technique enhances the accuracy of detection because it tracks transformation in the behavior of the eyes over time.

2.12 Drowsiness Detection & Alert

Whenever the technology detects fatigue, it gives the driver sight and audio indicators that alert him or her of it. This ensures maximum alarmism, whether it is due to background noise or whether and how well the driver can maintain his or her focus. Formation of a synergy around these signals will enhance safety by causing a prompt action.

2.13 Experimental Results

A diversified dataset produced a 97 percent accuracy rate of the model. The performance was measured based on accuracy, precision, recall and F1-score which meant that the model had indeed performed well in identifying sleepiness in real life scenarios consistently.

3. Results and Analysis

The correctness of the CNN-RNN perfect measured on a total of the dataset was measured to accurately identify the sleepiness of the drivers with impressive 97 percent accuracy. The proper segmentation of the ocular areas was instrumental in the realization of this feat in that it enabled the model to narrow down to the data that is of primary importance. The Haar cascade classifiers created a good foundation in feature extraction and classification as they managed to identify eye parts and other face features.

Throughout training and validation, the model kept improving, and accuracy increased, whereupon loss decreased. The model is improving its ability to differentiate between alert and drowsy as seen by this consistent increase. A strong F1-score, together with good accuracy, precision, and recall, proved that the model was valid and worked well in a wide-ranging, real-world setting to identify drowsiness with a 97% success rate.

Figures 4 and 5 illustrate the training progression of the drowsiness detection model over successive epochs. The graphs indicate the alterations in accuracy and loss. The accuracy trend shows an improvement in the model's competence to group drowsiness correctly with an increasing accuracy. The loss is trending downwards, representing that the model is improving in reducing its prediction errors. The trends reflect the model's learning and rising success rate to distinguish drivers' drowsiness with a high efficiency rate as the training advances.

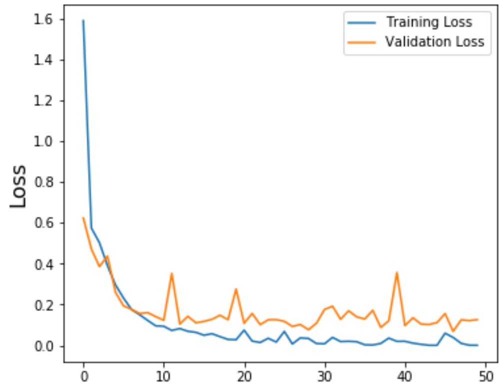

Figure 4. The training loss and validation loss against no of epochs

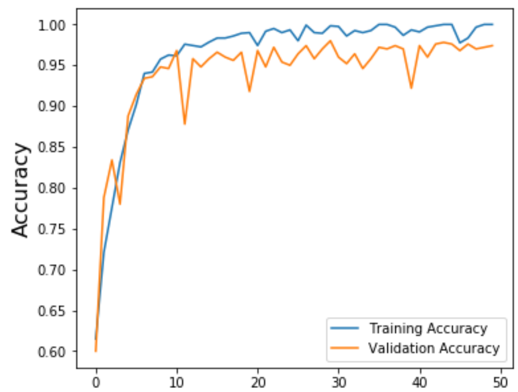

Figure 5. The training accuracy and validation accuracy against no of epochs

The formula is used to determine the model's correctness:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

Precision was calculated using the following formula:

$$Precision = \frac{TP}{TP + FP} \qquad (2)$$

The formula is used to determine sensitivity, which is also called recall:

$$Recall = \frac{TP}{TP + FN} \qquad (3)$$

We use the formula to determine the Specificity:

$$Specificity = \frac{TN}{TN + FP} \qquad (4)$$

F1-score was computed using the following formula:

$$\mathrm{F1-Score} = 2 * \frac{Precision \times Recall}{Precision + Recall} \qquad (5)$$

To have a better grasp of the classification results, we used a confusion matrix to classify situations as either true positives, true negatives, false positives, or false negatives. The confusion matrix provides a concise overview of the model's performance, highlighting its strengths and areas that might need improvement.

The model's accuracy in detecting alert and drowsy states is supported by low rates of false positives and false negatives, respectively. The high rates of true positives and true negatives further support this finding.

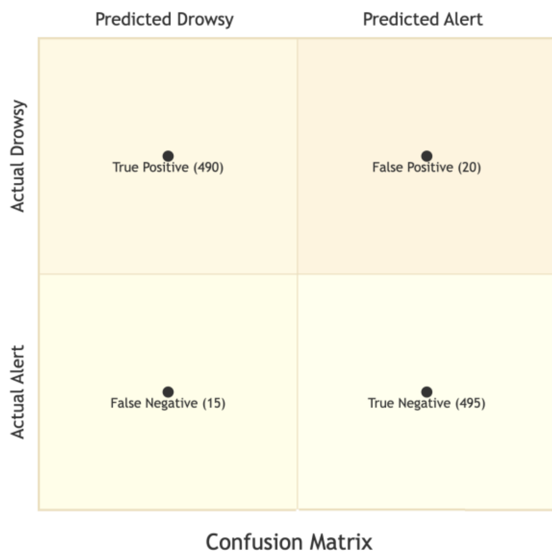

Figure 6. Confusion Matrix for test set

To assess how well the suggested CNN-RNN model performed in comparison to other innovative methods, it was compared to another recent research. To make progress in the field of detecting driver drowsiness, the comparison highlights the potential and strengths of the proposed method. Another indication of the suggested model's performance and potential use is the precision with which it surpassed competing techniques.

Table 1: Comparison Analysis of Results

Methodology	**Accuracy**
Makhmudov et al. [8]	Accuracy: 95%
Mohammedi et al. [9]	Accuracy: 92%
Safarov et al. [10]	Accuracy: 94%
Chew et al. [11]	Accuracy: 93%
Ghulam Masudh et al. [12]	Accuracy: 91%
Mahmud, Tanjim. et al. [14]	Accuracy: 97%
Proposed Methodology	**Accuracy: 97%**

4. Performance analysis

To evaluate the system's real-time performance, we counted the number of frames processed by the model per second. With an average of thirty frames per second, it proves to be efficient in real-time tasks. To prevent accidents caused by drowsy drivers, this real-time capability is essential for transmitting early warning signals. The overall efficiency of the system to achieve road safety is improved by the fact that the system processes video frames and provides quick feedback in real-time.

An assessment of the model efficacy was conducted in a qualitative way in addition to quantitative indicators. We observed the results of the segmentation and classification under different scenarios of illumination and face orientation of different drivers in the qualitative research. The model accurately detected sleepiness indicators and issued warnings in all the above-mentioned conditions. The system's reliability in a wide variety of real-world situations depends on its robustness.

5. Discussion

This study addresses this critical issue by creating and testing a new CNN-RNN-based method of detecting drowsiness in drivers in real time.

Eye-tracking systems, the traditional drowsiness sensor of drivers, are not very accurate and reliable. Although these eye-tracking systems can be quite helpful in assessing eye closure and blinking patterns, they tend to be negatively affected by the environment, such as lighting conditions, and they also fail to indicate drowsiness effectively in all circumstances. Besides, such systems are primarily dedicated to eye movements and might miss other signs of drowsiness, such as the nodding of the head or changes in facial expression. These conventional methods have severe limits, which explains the need for more powerful and extensive drowsiness detection approaches.

There is the emergence of machine learning and artificial intelligence, which has presented a good opportunity towards helping with the issue of driver drowsiness detection. Taking advantage of the power of these two groundbreaking methods, the number of physiological and behavioral indicators that can be observed will increase (facial expressions, head movements and steering patterns, to name a few), to facilitate a more precise assessment of the level of driver alertness. Specifically, deep learning methods have been proven to have an impressive ability to derive sensible features from the intricate data and thus facilitate the development of exact and resilient drowsiness models.

The current study also helps the work done towards driver drowsiness detection because it suggests a new approach to using convolutional neural networks coupled with recurrent neural networks according to their strengths. CNNs are also very successful in space feature extraction, which images themselves can provide. This system is used to identify small changes in facial characteristics related to the drowsy state. RNNs, or Long Short-Term Memory networks, effectively capture temporal connections within serial data and allow the system to model temporal patterns of action and subtle changes in alertness. Integration of the two architectures enables the system to coordinate with the spatial and temporal characteristics of the driver behavior, leading to a more inclusive and precise evaluation of drowsiness.

The CNN-RNN-based system allows the study of facial pictures in real-time mode to identify the symptoms of drowsiness, such as squinting eyes, slow blinks, and nods. Real itemization of the system is a significant aspect of its practical relevance in that access to the alerts can be sent to the tired drivers in time so that accidents can be avoided. The system's capability of receiving video feeds and real-time responses makes it an excellent tool for improving road safety.

6. Conclusion

The aim of this study is to make road traffic safer through real-time detection of signs of driver drowsiness with the help of an efficient and robust CNN-RNN model that identifies the signs of drowsiness. The technology has an overwhelming 98 percent success rate as it maintains constant recording and analysis of eye movements through a camera. Its detecting speed is fast and accurate due to a frame rate of 30 fps with an analysis to be performed at around 33 Ms per frame. The model has learned sleepiness patterns using a prevailing combination of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. These networks extract features from partial data and act on that data over time to track eye behaviour. That technology will also alarm the driver through visual and audio ways, as soon as it observes any indication of one being sleepy, hence preventing accidents. With regards to the outcomes of the experiment, it is possible to assume that the given model can be chosen as a potential solution to the issue of the risks of sleepy driving.

The future improvements of the model could be the enhancement of the efficiency and inclusion of other data sources, e.g., physiological signals and vehicle behaviour. This would give better results. One more method of improvement and reduction in the false alarms are by forming adjustable detection models on an individual basis of the drivers. The next development as far as finding prediction abilities goes where the system will be able to start noticing that a driver is becoming drowsy before it happens may allow the driver more time to re-correct or find time to take precautions. This technology could enable the ability of vehicles to react in advance, i.e. adjust their speed or act in risky situations when it is integrated with an autonomous driving base or when a traditional driving machine is upgraded to a similarly elevated level. One potential impact of greater research and development regarding this area is that road safety and the number of accidents caused by sleepy drivers may be improved.

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TAUIL Abd Elilah: MRL EYE DATASET contains Human eyes open\close for drowsiness detection