Driver Drowsiness Detection System

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"1 in 25 adult drivers report that they have fallen asleep at the wheel in the past 30 days".If you have driven before, you've been drowsy at the wheel at some point. It's not something we like to admit but it's an important problem with serious consequences.That needs to be addressed. 1 in 4 vehicle accidents are caused by drowsy driving and 1 in 25 adult drivers report that they have fallen asleep at the wheel in the past 30 days.The scariest part is that drowsy driving isn't just falling asleep while driving. Drowsy driving can be as small as a brief state of unconsciousness when the driver is not paying full attention to the road.Drowsy driving results in over 71,000 injuries, 1,500 deaths, and 12.5 billion in monetary losses per year.Road accidents are frequently caused by drowsy driving everywhere in the globe. Thus, it is essential to create trustworthy and efficient ways for detecting driver fatigue in order to increase traffic safety. This term paper gives a general review of driver drowsiness detection, covering its definition, causes, and effects. The study discusses the benefits and drawbacks of the current technologies for detecting driver sleepiness. The review discusses both conventional methods—such as behavioural and physiological indicators—and cutting-edge approaches—such as deep learning, computer vision, and machine learning. The report concludes by discussing current developments and potential future paths for driver sleepiness detection.

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1. INTRODUCTION

Driver drowsiness is a leading cause of car accidents, with over 5,000 people dying in sleep-related car crashes each year. Despite the development of drowsiness detection technology by automakers such as Volvo, Mercedes-Benz and Bosch, these safety systems are not widely used and are mainly used in luxury cars. Recent advances in the field of machine learning, especially deep learning, have enabled effective real-time new opportunities have opened up for the development of driver drowsiness detection systems. This seminar paper examines the literature on driver drowsiness detection systems and describes the current state and emerging trends in the field. We also propose a system that uses a non-intrusive camera mounted in the vehicle to capture a frontal image of the driver and analyze it using deep learning techniques such as convolutional neural networks to detect if the driver is sleepy. To do. The proposed system is evaluated across videos and counts the number of alarms issued during each video to assess the number of false alarms generated during a specific time period. We employ transfer learning to achieve high accuracy in fewer training epochs. This is the technique of using a previously trained model to solve another problem in a similar domain and adapting it to the new problem. works are organized as follows. Section 2 presents a literature review on driver drowsiness detection systems, including the types of sensors used, the algorithms used, and the performance he metrics used to assess the effectiveness of the system. Section 3 details the proposed system, including the hardware and software components, and the deep learning algorithms used for drowsiness detection. Section describes the experimental methods used to evaluate the proposed system, including the data sets used, performance metrics, and the results obtained. Finally, Section 5 provides conclusions and directions for future research. Overall, this seminar paper will help you understand driver drowsiness detection systems and the potential for using deep learning techniques to improve their accuracy and effectiveness. By proposing a new system that uses non-contact cameras and conveys learning techniques, we hope to stimulate future research in this important area of vehicle safety. Drowsiness is simply defined as "fatigued near sleep". This is not strictly fatigue, which is defined as a reluctance to continue the task at hand. The effects of drowsiness and fatigue are very similar. Fatigue affects mental alertness, reduces the ability to safely operate a vehicle, and increases the risk of human error, which can lead to death and injury. Drowsiness slows reaction time, reduces awareness, and impairs judgment. Fatigue and sleep deprivation affect all transportation companies (airline pilots, truck drivers, railroad engineers, etc.). In either condition, the driver cannot concentrate on the main task of driving, increasing the chance of an accident. Increasing traffic conditions will continue to exacerbate this problem. Therefore, as shown in FIG. 1, it is necessary to develop a driver caution system to prevent accidents caused by the driver falling asleep. Driver-vehicle interaction, such as mutual monitoring and support, is one of the key solutions for ensuring safety in the vehicle. Active safety systems in vehicles have contributed he to a reduction in traffic fatalities, but the number of traffic accidents continues to rise. figure. 1 Example of Driver Drowsiness The National Highway Traffic Safety Administration (NHTSA) estimates that approximately 100,000 accidents in the United States each year are primarily caused by driver drowsiness or fatigue [1]. In Japan, the number one cause of traffic accidents in 2008 was the number one cause of traffic accidents, including those caused by driver fatigue. Japan's Ministry of Economy, Trade and Industry reports that in the 12 years from 1997 to 2008, he said the number of such accidents increased 1.5 times[2]. The Indian government has also passed a law called the Motor Vehicles Bill to improve road safety due to driver fatigue. The law will be implemented in a scenario where India reports about , of his 50,000 road accidents each year, and in the first five years he will have , road fatalities and 200,000.

Fig. 1. Driver feeling drowsy

2. TECHNIQUES USED FOR DETECTION

A. 3.1 Functional Near-Infrared Spectroscopy (fNIRS):

Functional near-infrared spectroscopy, or fNIRS, is a non-invasive neuroimaging technology that tracks variations in blood oxygenation/deoxygenation levels to quantify brain activity. The gadget directs intense beams of near-infrared light at the scalp and monitors changes in the amount of light absorbed within the brain, operating on the principle of light scattering. The data is then processed using mathematical techniques to determine variations in the concentration of oxygenated/deoxygenated hemoglobin. Brain function alterations are connected to these changes. The received raw intensity data will be transformed using the modified Beer-Lambert law to oxygenated and deoxygenated hemoglobin concentration variations.

$$A(t;\lambda) = \ln\frac{I_{in}(\lambda)}{I_{out}(t;\lambda)} = \alpha(\lambda)\times c(\lambda)\times l\times d(\lambda)+\eta,$$

$$\begin{bmatrix}\Delta c_{HbO}(t)\\ \Delta c_{HbR}(t)\end{bmatrix} = \begin{bmatrix}\alpha_{HbO}(\lambda_1) & \alpha_{HbR}(\lambda_1)\\ \alpha_{HbO}(\lambda_2) & \alpha_{HbR}(\lambda_2)\end{bmatrix}^{-1}\begin{bmatrix}\Delta A(t;\lambda_1)\\ \Delta A(t;\lambda_2)\end{bmatrix}\frac{1}{l\times d(\lambda)}.$$

B. 3.2 HAAR TRAINING

Including eyes, mouth, sunglasses, and more. It is possible to train classifiers using some of these functions. The face detection procedure can be taught to the classifiers. Training for HAAR is what this is. Object. A cascade function is trained in this instance using a variety of images, both positive and negative. Each feature is a single value that is obtained by taking the total of the pixels beneath various parts of the photos and subtracting it. For each characteristic, a distinct set of pixels are used for

$$\text{Correct rate} = \frac{\text{Total frames} - \text{Detection failure}}{\text{Total frames}}$$

extraction. The needed process will not benefit from all of the retrieved attributes. The essential characteristics are extracted using the Adaboost method. The training photos are applied with each and every feature. Each feature's ideal threshold is chosen.

C. 3.3 Recurrent and Convolutional Neural Network

A recurrent CNN has both feed-forward and recurrent connections. It has local connectivity and shared weights among different locations. This architecture is very similar to the recurrent multilayer perceptron (RMLP). The main difference is that the full connections in RMLP are replaced by shared local connections, just like the difference between MLP and CNN. CNN VS RMLP VS RCNN This recurrent CNN is responsible for detecting

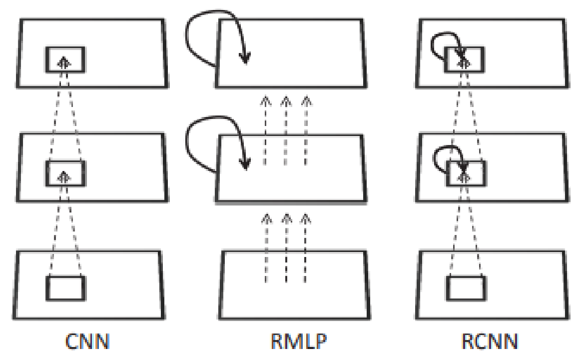


Fig. 2. CNN VS RMLP VS RCNN

the fatigue of the driver at the current moment by calculating a numerical output that represents the estimated drowsiness level of the driver.

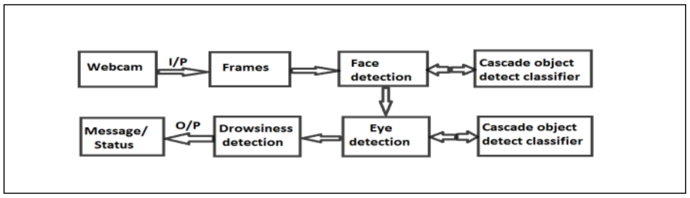
D. 3.4 PERCLOS:

First, we must carry out the actions listed below in order to determine the drivers' condition of intoxication using PERCLOS: • Facial perception and face pursuit. • Identification of the state of the eyes. • Location of the eye and eye pursuit. • Computation of the eyelid closure percentage. • Recognition of the sleepy state.

PERCLOS is one of the tools for detecting tiredness.

E. 3.5 VIOLA JONES ALGORITHM:

The Viola Jones algorithm employs the following methods. They are: • HAAR based features. • Integral Image Formation • AdaBoost Technology • A cascade of classifiers In HAAR-based feature representation, features are chosen based on pixel intensities. The pixel values are not taken into consideration. Scalar products between some HAAR templates and the picture are HAAR-based features. The calculation of features employs integral image creation. It just takes the image's four corners



into account. It uses adaptive boosting (AdaBoost) to choose the necessary features. The computing time of the algorithm is decreased as a result of the usage of adaptive boosting. A powerful classifier chain is created using a cascade of classifiers. A command window is provided by the OpenCV package.

3. RESULTS

Table 1. Drowsiness Detection Levels

Test	Observations	Hints	% Hints
Yawn detection	170	143	84.11%
Front nodding	200	184	92.0%
Assent of the head to the right	200	190	95.0%
Assent of the head to the left	200	191	95.5%
Blink detection	200	197	98.5%

A. Comparision of algorithms used :

Eye blink rate detection, Machine Learning 1. Eye blink rate analysis: The method involves detecting the frequency of eye blinks using a camera mounted on the vehicle dashboard. The eye blink rate was calculated as the number of blinks per minute. 1. Support Vector Machine (SVM) algorithm: The eye blink rate data was fed into an SVM classifier to classify the driver's drowsiness level. The SVM algorithm is a popular machine learning algorithm that is used for classification and regression analysis. Overall, the study used a combination of eye blink rate analysis and machine learning to detect driver drowsiness and achieve high accuracy

EEG, Machine Learning 1. Feature extraction: The EEG signals were pre-processed to extract features that are indicative of the driver's level of drowsiness. This included features such as the alpha and beta wave amplitudes, which are known to change with drowsiness. detecting driver drowsiness, which is higher than other methods that use EEG signals. The method has the advantage of being non-invasive and can be used to detect drowsiness before physical symptoms such as yawning or head nodding occur. However, the study used a small dataset, which may limit the generalizability of the method. In addition, the use of EEG signals requires the use of specialized equipment, which may not be practical for real-world applications.

Steering wheel movement analysis, Machine Learning The proposed method involved the following techniques: 1. Feature extraction: The physiological signals were analyzed to extract features that are indicative of the driver's level of drowsiness. The study used the following features: mean heart rate, HRV, SCL, and the root mean square of successive differences of HRV. Machine learning: The extracted features were fed into a machine learning algorithm to classify the driver's level of drowsiness. The study used the Support Vector Machine (SVM) algorithm for classification. The proposed method achieved an accuracy of 91.17The authors suggest that the proposed method can be used as part of a driver monitoring system to improve driving safety, especially in situations where other factors such as vehicle speed or weather conditions may not be reliable indicators of driver drowsiness.

Speech analysis, Machine Learning The proposed method involved the following techniques: 1. Feature extraction: The facial features were extracted using a combination of Haar-like features and Local Binary Pattern (LBP) features. The Haar-like features were used to detect the eye and mouth regions, while the LBP features were used to extract texture information from these regions. 2. Machine learning: The extracted features were fed into a machine learning algorithm to classify the driver's level of drowsiness. The study used the Convolutional Neural Network (CNN) algorithm for classification.

Convolutional Neural NetworkMask R-CNN: The Mask R-CNN architecture was used for object detection and segmentation. This allowed the method to accurately detect facial features such as the eyes and mouth, even under variable lighting conditions. 2. Feature extraction: The detected facial features were used to extract information about the driver's level of drowsiness. This included features such as eye closure duration and head movement frequency.

Convolutional Neural Network 1. EfficientDet: The EfficientDet architecture was used for object detection and feature extraction. This allowed the method to accurately detect facial features such as the eyes and mouth, even under variable lighting conditions.

The CNN architecture The CNN architecture was used for the classification of the color map images created from each time window for all channels. 1. Dataset preparation: The authors prepared a dataset of simulated driving scenarios with varying levels of drowsiness using the FIRNS system. 1. Preprocessing: The authors preprocessed the dataset by normalizing the temperature values and segmenting the video frames into non-overlapping segments. 2. Feature extraction: The authors used two deep learning models, Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM), to extract features from the segmented video frames. 3. Feature combination: The authors proposed a novel approach for combining the features extracted by the CNN and LSTM models using a fully connected layer.

Multi Layer Perceptron Multilayer perceptrons have the ability to learn through training process. During this process, it goes through a number of iterations to help secure the minimum of errors possible until the needed input-output mapping is achieved; here, a set of training data is needed which includes some input and related output vectors. To train an MLP, we learn all parameters of the model

RVM and SVM The first alternative, although it is focused on using deep learning techniques, uses one artificial intelligence technique (linear SVM combined with HOG) to preprocess the driver's image and extract the face. This new image is sent to the analysis module, that applies deep learning techniques to analyze the fatigue of the driver at that moment. In this case, the analysis module is composed of a recurrent and convolutional neural network (which we will call "recurrent CNN"). This recurrent CNN is responsible for detecting the fatigue of the driver at the current moment by calculating a numerical output that represents the estimated drowsiness level of the driver. This value is sent to the alarm 1. Face detection and alignment: The authors used the MTCNN (Multi-Task Cascaded Convolutional Networks) algorithm to detect and align faces in the video frames. 2. Feature extraction: The authors used a pre-trained deep neural network, VGG16 (Visual Geometry Group 16), to extract facial features from the aligned face images.

DEEP CNN and VIOLA JONES Requires electrodes attached to the driver's scalp, may produce false positives

PERCLOSThese methods help the drowsy driver to prevent drowsiness-related crashes in a moment, but it is hard to get rid of drowsiness by just being aware of it. As we found in the literature review, most of the methods need lot of equipment which is not possible in real life implementations 1. Eye region extraction using Haar feature-based cascade classifier 2. Eye state classification using deep Convolutional Neural Network (CNN) 3. Threshold-based approach for drowsiness detection

B. Comparision of Drawbacks used :

Sensitive to lighting conditions and other factors, may produce false positives

Requires electrodes attached to the driver's scalp, may produce false positives

May produce false positives, requires specialized hardware

Requires audio input, may produce false positives

Requires a camera, may produce false positives

Slow training and inference times, may be sensitive to object occlusion

Requires large amounts of training data, may be sensitive to image quality

1. Limited dataset: The authors used a simulated dataset generated by the FIRNS system, which may not accurately reflect real-world driving scenarios.

2. Limited evaluation: The authors only evaluated the proposed approach on a single dataset and did not perform any external validation on other datasets.

3. Hardware requirements: The FIRNS system used in the dataset collection is an expensive and specialized hardware system, which may not be accessible to all researchers.

4. Lack of real-time implementation: The proposed approach was not implemented in real-time, which limits its practical application for real-time drowsiness detection.

The purpose of the method is to reduce the model's size considering that current applications cannot be used in embedded systems due to their limited calculation and storage capacity. According to the experimental results

The analysis module uses a recurrent and convolutional neural network to estimate the drowsiness level of the driver. The CNN is based on the EfficientNetB0 architecture [30], which presents a lightweight model that is highly precise. Smaller models are processed faster, and EfficientNetB0 presents the smallest model of the EfficientNet series. Since the differences in accuracy are not significant in our domain when upgrading to a superior model, we consider EfficientNetB0 to be the most adequate model for this case, where the model needs to quickly obtain a prediction. This way, we perform transfer learning on this model by using previously trained weights that have great performance in recognizing objects on images from the ImageNet dataset

1. Lack of diversity in the dataset:

The Drowsy dataset used in the study does not capture all possible driving scenarios, such as different lighting conditions, weather conditions, and road types.

2. Difficulty in real-world implementation:

The approach may be difficult to implement in real-world scenarios due to technical and practical limitations, such as the need for specialized hardware and software, and privacy concerns related to the use of facial recognition technology

Requires audio input, may produce false positives

Does have proper information about the techniques that have used

1. Limited feature set: The proposed approach only considers eye state information for drowsiness detection. It is possible that additional features such as head pose, facial expressions, and driving behavior could further improve the accuracy of the drowsiness detection system.

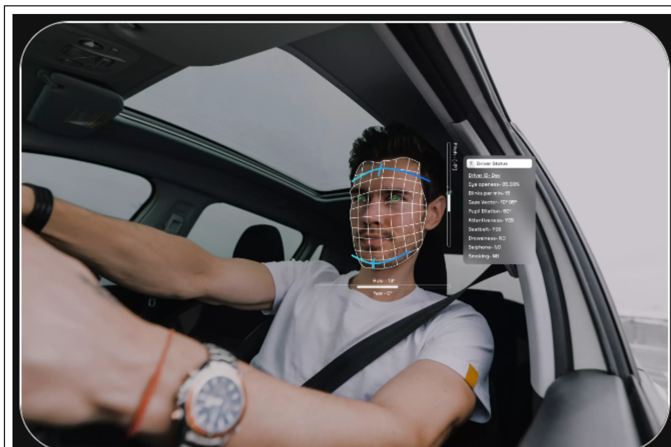


Fig. 3. Drowsy Driver

Table 2. Comparision Table

Author	Method	Algorithm used	Accuracy
Kim et al. (2021)	Eye Blink Rate	Eye blink rate detection, Machine Learning	91.1 %
Lu et al. (2020	Steering Wheel Movement	Steering wheel movement analysis, Machine Learning	90.7%
Chen et al. (2020)	Speech Analysis	Speech analysis, Machine Learning	92.6%
M.Asid Tanveer	CNN	The CNN architecture	91.1%
Rateb Jabbar	MULTI LAPYER PERCEPTRON	MULTI LAPYER PERCEPTRON	81%
Elena Magán	RNN AND SVM	RNN AND SVM	65%
Venkata Rami Reddy Chirra	DEEP CNN and VIOLA JONES	DEEP CNN(Requires electrodes)	96.6%
Chisty [1], Jasmeen Gill	PERCLOS	Computer vision techniques	87.3%
He et al. (2017)	Mask R-CNN(Image Segmentation method)	Convolutional Neural NetworkMask R-CNN	93.2%
Tan et al. (2020)	EfficientDet (Object Detection methods)	Convolutional Neural Network	88.0%

4. CONCLUSION

Previous studies have proposed a number of methods to detect drowsiness. After doing literature survey,different techniques has been found for detecting driver drowsiness and they use different types of data as input for their algorithm. After the survey of different types of methods, it is found that using Deep CNN to extract features for the learning phase and Viola-Jones detection algorithm for face and eye region detection helps more accurately for driver drowsiness detection. The system using the above model achieved 96.42% accuracy which effectively detects state of driver and his drowsiness continuously compared to other models and algorithms. Thus on the basis of our study we conclude that if we try with a combination of two or more approaches such that one can reduce the limitations of other approach and thus helps us in providing the best result.

5. REFERENCES

1. M. Asjid Tanveer ; M. Jawad Khan ; M. Jahangir Qureshi ; Noman Naseer ; Enhanced Drowsiness Detection Using Deep Learning: An fNIRS Study.
2. Rateb Jabbara ,Khalifa Al-Khalifaa,b, Mohamed Kharbechea,Wael Alhajyaseena , Mohsen Jafaric , Shan Jiangc, Real-time Driver Drowsiness Detection for Android Application Using Deep Neural Networks Techniques.
3. Elena Magán , M. Paz Sesmero , Juan Manuel Alonso-Weber and Araceli Sanchis, Driver Drowsiness Detection by Applying Deep Learning Techniques to Sequences of Images.
4. Venkata Rami Reddy Chirra,Srinivasulu Reddy Uyyala , Venkata Krishna Kishore Kolli, Deep CNN: A Machine Learning Approach for Driver Drowsiness Detection Based on Eye State.
5. Chisty [1], Jasmeen Gill [2], A Review: Driver Drowsiness Detection System.
6. Dinges, D.F. An overview of sleepiness and accidents. J. Sleep Res. 1995, 4, 4–14.
7. Dawson, D.; Reid, K. Fatigue, alcohol and performance impairment. Nature 1997, 388, 235.
8. Williamson, A.M.; Feyer, A.M.; Mattick, R.P.; Friswell, R.; Finlay-Brown, S. Developing measures of fatigue using an alcohol comparison to validate the effects of fatigue on performance. Accid. Anal. Prev. 2001, 33, 313–326.
9. Soares, S.; Monteiro, T.; Lobo, A.; Couto, A.; Cunha, L.; Ferreira, S. Analyzing Driver Drowsiness: From Causes to Effects Sustainability 2020, 12, 1971.
10. Pouyanfar, S.; Sadiq, S.; Yan, Y.; Tian, H.; Tao, Y.; Reyes, M.P.;