International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Automated Detection of Driver Fatigue Using Deep Neural Networks in Vehicles

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DOI: https://doi.org/10.55248/gengpi.4.423.38499

ABSTRACT

Abstract— Traffic accidents caused by fatigue, exhaustion and distracted driving are a big problem on a global scale. In this study, we propose collective deep learning architecture for automatic driver drowsiness detection. While some earlier work suggested extracting lips and eyes movements to identify drowsiness, more modern systems based on computer vision worked only partially well. This is because they either use extremely large depth learning models with still poor performance or use hand-crafted features using traditional methods such as Naive Bayes and SVM. Our proposed deep learning architecture set evaluates the driver's condition using the integrated z functions mouth, eyes, and sub patterns important to the body in conjunction with a decision-making structure. Our proposed architecture delivers high accuracy in detecting driver drowsiness using the leverage effect strengths of many deep learning models. We conduct comprehensive experiments on real-world datasets that show the effectiveness of our methodology. Number of accidents brought drowsy driving can be drastically reduced with a proposed approach that would also increase traffic safety.

Keywords: automatic sleepiness detection, deep learning, computer vision, file architecture, road safety.

INTRODUCTION

Driver fatigue is a prime visitor component worldwide injuries and deaths. Researchers have created a series of drowsiness detection systems that use state-of-the-art tools like machine learning and computer vision to solve this problem. Approaches used to evaluate visual data, e.g such as facial expressions and eye movements and physiological signals such as EEG, EOG and EMG are highlighted here article reviews numerous recent studies on sleepiness detection systems. Driving safety thanks to intelligent driver drowsiness Detection based on Multi-CNN Deep Models and Face Under sampling suggests a sleepiness detection system that uses face subsampling and multi-convolutional neural network (CNN) to examine the driver's facial expressions and eye movements to assess their level of exhaustion. Electroencephalogram (EEG) signals are used for detection. Sleepiness and EEG-based robust and efficient Drowsiness detection systems using different machine Learning algorithms evaluate the effectiveness of different machine learning methods. Physiological indicators primarily based totally on gadget learning Sleepiness detection A technique for detecting the level of fatigue that uses physiological cues from several sources proposed singular and hybrid signalling approaches. Real-time fatigue diagnosis system described in Real-time sleepiness diagnosis system using OpenCV The algorithms analyse the visual data using the OpenCV computer vision library. The HAAR cascade algorithm is used as a driver drowsiness detection system to assess visual input and identify fatigue. An overview of the current state of the area is given in Trends and future prospects of sleepiness detection and Estimation Technology, which also looks at potential use for technology, The record additionally examines the prospective technological development and innovative sleepiness uses the detection method.

OBJECTIVE OF THE STUDY

1. Develop a system that can accurately and efficiently identify when a driver is becoming fatigued or drowsy while driving.
2. Monitor a driver's behaviour, such as eye movements, facial expressions, and other physiological signals, to detect signs of fatigue.
3. Use deep learning algorithms to analyse the collected data and identify patterns associated with driver fatigue.
4. Improve road safety by providing early warning of driver fatigue and alerting the driver to take a break or stop driving altogether.

SCOPE OF THE STUDY

- Data collection: Collecting data on driver behaviour and physiological signals, such as eye movements, facial expressions, and heart rate variability, while the driver is driving.

- ❖ Data pre-processing: Pre-processing the collected data to remove noise, normalize the data, and extract relevant features that can be used by the deep learning algorithm.
- ❖ Deep learning model development: Developing a deep learning model that can accurately classify driver behaviour as drowsy or alert based on the extracted features.

EXISTING SYSTEM

An existing problem with automatic sleepiness detection suggests removing the eyes and mouth movement to detect driver drowsiness, making these solutions less than ideal. The recent ones propose solutions based on computer vision, but they are limited performances because they either use hand-made elements with conventional techniques such as Naive Bayes and SVM or use overly bulky deep learning models that are still low at performances. To overcome this problem, the Inception V3 model isused.

PROPOSED SYSTEM

There are certain concepts to overcome these mentioned limitations or restrictions. Drowsiness detection systems can detect signs of tiredness and alert drivers, which reduces the risk of accidents caused by drowsy driving. With an estimated 100,000 accidents caused drowsy driving every year in the US alone can be helped by drowsiness detection systems lessen the wide variety of fatigue-associated accidents. Drowsiness detection systems provide drivers with early warning before they get too tired, giving them time to take the necessary action. Drowsiness detection systems can adapt the cabin environment to increase driver comfort, for example by increasing ventilation or temperature. It may have a sleepiness detection system installed in it.

LITERATURE SURVEY

Islam A. Fouad , Road accidents on long routes around the world are often caused by drowsy drivers. This is primarily because there is no system that measures vigilance. If an accurate and robust fatigue detection system is available, the driver will be alerted to interrupt his journey. Dealing with this method will assist the driving force to keep away from injuries and make the proper decisions. This paper aims to detect driver drowsiness using a powerful software tool. It was originally developed by capturing electroencephalography (EEG) signals and processing them. In this research, special device studying algorithms had been carried out to the EEG alerts of twelve topics to determine their performance. In a first step, all recorded data for all subjects were segmented into second epochs. Brain signals were labelled as awake or sleepy for each epoch. By capturing signals from only three electrodes, it was found that using more than one classifier resulted in the highest accuracy of 100% for all subjects considered in this study. In general, this developed EEG-based system detects driver drowsiness and inattention in real-time with high accuracy, making it a practical and reliable option for real-time applications.

Md Mahmudul Hasanab, Christopher N. Watlingab and Grégoire S. Larue, Drowsiness is one of the major contributors to traffic accidents and fatality worldwide. To solve this urgent global problem, researchers continue to develop the driving force behind sleepiness detection structures that use a whole range of measures. However, most research uses singular metric approaches to detect sleepiness and fails as a result to achieve satisfactory reliability and validity to be implemented in vehicles. Method: This study examines sleepiness detection software primarily based entirely on singular and hybrid approaches, the technique considered a range of metrics from 3 physiological signals – electroencephalography (EEG), electrooculography (EOG) and electrocardiography (ECG) – and used subjective indices of sleepiness (assessed via the Karolinska Sleepiness Scale) as the floor truth. The methodology consisted in recording the signal using psychomotor vigilance test (PVT), pre-processing, extraction and determination of important features from physiological alerts to sleepiness detection. Finally, four guarded machine learning models were developed based on subjective sleepiness responses using extracted physiological features to detect sleepiness levels. Using a hybrid approach, it appears that the vehicle driver drowsiness detection system needs to be improved. Practical applications will need to consider factors such as intrusiveness, ergonomics, cost-effectiveness and user orientation

Deeksha Phayde, Pratima Shanbhag and Subramanya G. Bhagwath, Facts show that numerous traffic accidents worldwide occur due to fatigue, drowsiness and distraction while driving. Few people work on automatic sleepiness detection problems, the extraction of driver's physiological signals including ECG, EEG, cardiac variability, blood pressure, etc. That make those answers much less than ideal. While the latest ones propose solutions based on computer vision but show limited performance either use hand-crafted elements with conventional techniques such as Naïve Bayes and SVM or use overly bulky deep learning models that are still underpowered. Therefore, in this work, we propose a comprehensive deep learning architecture that works again incorporated eye and mouth subsample features along with decision structure determine driver eligibility. The proposed file model consists of only two InceptionV3 modules that help with the contents of the network parameter space. These two modules only perform eye and mouth extraction subsamples extracted with Fast MTCNN from face images. The output of this gadget will decide whether the driving force is drowsy or not. The benchmark NTHU DDD video dataset is used for efficient training and evaluation of the proposed model. The model established train and validation accuracy of 99.65% and 98.5%, respectively. Accuracy of 97.1% on the evaluation data set, which is significantly higher achieved models proposed in recent works on this data set

MODULE AND DESCRIPTION

DATA COLLECTION:

The NTHU-DDD dataset contains about 5,000 photos of motorists in varying degrees of drowsiness, from fully awake to fully asleep. With the use of an infrared camera that records both visible and infrared light, the dataset was compiled in order to pick up on even the slightest variations in the driver's facial expressions.

Classfiication	Type of environment	No. of samples extracted in Region of Interest
Drowsy	"bareface"	100736
	"glasses"	101021
	"night_bareface"	50843
	"night_glasses"	49417
	"sunglasses"	101630
	Total	**403647**
Non-Drowsy	"bareface"	74479
	"glasses"	74062
	"night_bareface"	31733
	"night_glasses"	32372
	"sunglasses"	69762
	Total	**282408**

PRE-PROCESSING:

The photos of the dataset were cleaned to remove noise and irregularities. It also includes the use of normalization techniques such as Z-score normalization, which scales the data to have a mean of 0 and a standard deviation of 1, then subtracts the mean from each value in the data set, as well as filters to remove artifacts such as highlights and shadows. The values in the dataset are scaled to a range between 0 and 1 and the minimum value is then subtracted from each value in the dataset and then divided by the range of the dataset.

INITIAL ENSEMBLE NETWORK:

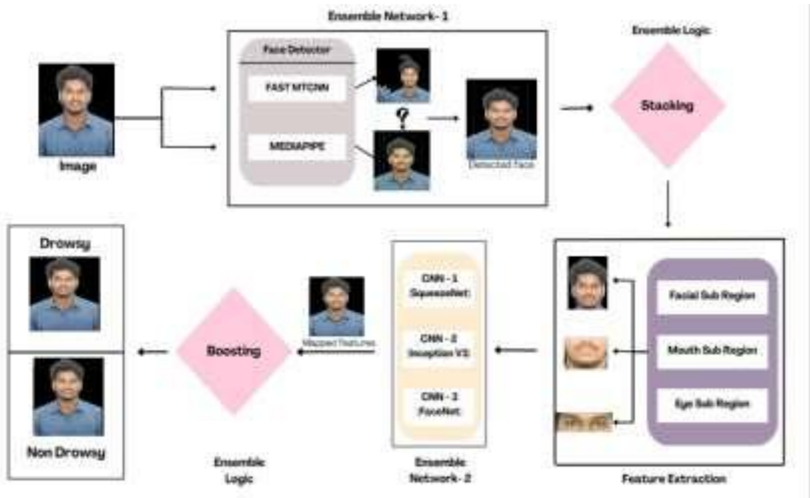
Fast MTCNN and MediaPipe components form the first Ensemble network. The driver's face is in each frame using the Fast MTCNN face detection algorithm. A collection of computer vision algorithms called MediaPipe is used to extract facial landmarks from each image, including the areas around the eyes and mouth.

FINAL ENSEMBLE NETWORK:

Based on the features extrapolated from the first Ensemble network, the second Ensemble network is used to categorize the driver state. Three CNN models are included in this network: SqueezeNet, Inception V3, and Face Net. A large dataset of images was used to train the SqueezeNet and Inception V3 image classification algorithms. FaceNet is a face reputation version that has discovered to understand the exceptional capabilities of every face.

SYSTEM ARCHITECTURE:

This section describes the proposed ensemble architecture for drowsiness detection systems to operate in various real-world driving environment scenarios. The three steps of the built model are face region extraction/segmentation, CNN training, and ensemble network training.

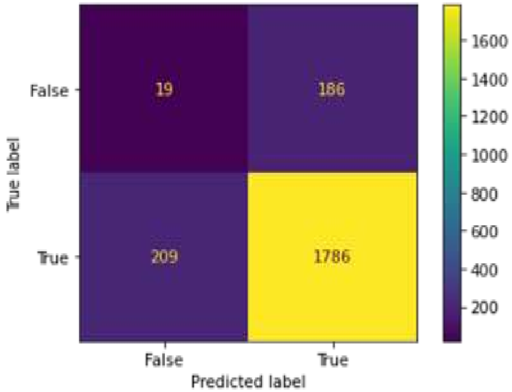


System Architecture

EQUATIONS:

Precision = TP + (TP + FP)

Precision should ideally be 1 (high) for a good classifier. Precision becomes 1 only when the numerator and denominator are equal i.e., TP = TP +FP, this also means FP is zero. As FP increases the value of denominator becomes greater than the numerator and precision value decreases.



Accuracy = (TP + TN) / (TP + TN + FP + FN).

where TP, TN, FP, FN, and FP represent the number of true positives, true negatives, true negatives, and false positives, respectively. In a good classifier, accuracy and recall should both be one, which also means that FP and FN should be zero. Hence, a metric that considers both precision and recall is necessary.

F1 score = 2 * ((Precision*Recall)/ (Precision + Recall))

Only when precision and recall are both 1 does the F1 Score become 1. Only when precision and recall are both strong can the F1 score rise. A more useful metric than accuracy is the F1 score, which is the harmonic mean of recall and precision.

TABLE:

TABLE SHOWING THE ACCURACY PERCENTAGE

PERSPECTIVE ANGLE	ACCURACY %
FACE WITH MASK	90-91
FACE WITH SPECS	92
ACTUAL FACE	94

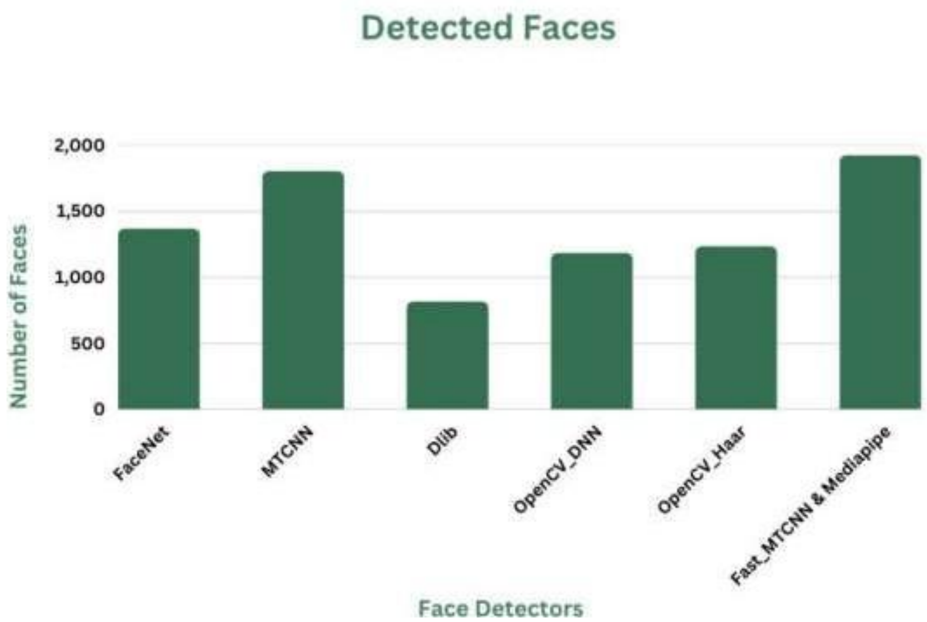
MODEL PARAMETERS IN DIFFERENT DATASET

S. No.	Dataset	Face Detection Model	Mask Recognition Model	Voice Message	Framework	Optimization	Deployment
1	Kaggle	YOLO-v3		No	*	No	*
2	WIDER FACE,MAFA ,RMFD	YOLO-v3		No	TensorFlow	Yes (NCNN)	Web-based
3	SMFD, LFW, RMFD	ResNet-50	Decision Tree, Ensemble Algo, SVM	No	*	No	*
4	WIDER, FACE, SMFD, LFW	FFDMask	Slim CNN	No	Keras, PyTorch	No	Edge-based (Jetson Nano)
5	Kaggle	MTCNN	Ensemble Algo	Yes, (PyAudio)	TensorFlow, Keras	Yes, (TEnsorRT)	Edge-based (Jetson Xavier NX)
6	NTHU-DDD	Fast-MTCNN + MediaPipe	Ensemble Algo	Yes, (pyttsx3)	MediaPipe	Yes, (TEnsonRT)	Docker

RESULT:

Based on the driver's face expressions, the system is finite output classifies their mental State. There are four classes yawning, looking left, right and with closed eyes. First Ensemble Network's characteristic and the other Ensemble Network Predictions serve as a basis for its classification

The Bar Graph below shows us the deep learning algorithm (face detectors) used in this system and their ability to detect the number of faces



Accuracy = (TP + TN) / (TP + TN + FP + FN).

where TP, TN, FP, FN, and FP represent the number of true positives, true negatives, true negatives, and false positives, respectively. In a good classifier, accuracy and recall should both be one, which also means that FP and FN should be zero. Hence, a metric that considers both precision and recall is necessary.

Precision = TP + (TP + FP)

Precision should ideally be 1 (high) for a good classifier. Precision becomes 1 only when the numerator and denominator are equal i.e., TP = TP +FP, this also means FP is zero. As FP increases the value of denominator becomes greater than the numerator and precision value decreases.

Recall = TP + (TP + FN)

A proper classifier must don't forget a price of 1 (high). Appeal will only increase to 1 when the numerator and denominator are the same equals, or when TP = TP + FN, which also means that FN is zero. The recall value decreases as FN increases because the value of the denominator is now greater than the numerator

F1 score = 2 * ((Precision*Recall)/ (Precision + Recall))

Only when precision and recall are both 1 does the F1 Score become 1. Only when precision and recall are both strong can the F1 score rise. A more useful metric than accuracy is the F1 score, which is the harmonic mean of recall and precision

TABLE FOR PERFORMANCE ANALYSIS

Performance Analysis				
	Accuracy	Precision	Recall	F1 Score
RestNet 50	90.23 %	0.897	0.901	0.899
InceptionNet - V3	87.89 %	0.820	0.842	0.830
VGG16	81.45 %	0.791	0.802	0.812
MobileNet - V3	91.20 %	0.891	0.901	0.911
MTCNN	93.40 %	0.921	0.899	0.929
Fast MTCNN + Mediapipe (our CNN)	**94.28 %**	**0.939**	**0.901**	**0.923**

The Above Table is Calculated Based on the Formulas in the Previous Page

CONCLUSION:

In this paper, a stacking-based ensemble architecture has been proposed that integrates the weighted contributions of two Inception V3 CNNs—which separately learn mouth and eye features on samples collected from the NTHU-DDD reference dataset. Unlike earlier research, this work is credible because it detects fatigue by simply moving a dashboard camera rather than by monitoring the driver's EEG, EKG or any other physiological signs. To extract the coordinates of regions of interest (mouth and eyes) before processing by two CNNs, Fast MTCNN was used in the proposed model. The weights of each ensemble are trained on a perceptron network using the outputs of the other two CNNs as its input. We show that the ensemble architecture performs better than individual CNNs when trained on eye and mouth subsamples. The results showed a faster image extraction speed after using Fast MTCNN, indicating that this end-to-end model is also robust to changes in position and lighting conditions. The proposed model outperformed other recently proposed non-invasive solutions on this dataset, according to results that showed very accurate detection capability over a large valuation dataset.

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