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Driver Driving Performance Analysis and Risk Detection Using Deep Learning

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ABSTRACT: Distracted driving is any activity that deviates an individual's attention from driving. Driver inattention and distraction are the main causes of road accidents, many of which result in fatalities. Driver distraction is a major cause of road accidents. Distracting activities while driving include text messaging and talking on the phone.Currently, distraction detection systems for road vehicles are notyet widely available or are limited to specific causes of driver inattention such as driver fatigue. Research efforts have been made to monitor drivers' attentional states and provide supportto drivers. Both invasive and non-invasive methods have been applied to track driver's attentional states, butmost of these methods either use exclusive equipment which are costly or use sensors that cause discomfort.The existing work of distracted driver detection is concerned with a limited set of distractions(Mainly cell phone usage).In this paper, a robust driver distraction detectionsystem that extracts the driver's state from the recordings of an onboard camera using Deep Learning based Faster Region Convolutional Neural Network (FRCNN).This project uses the state farm distracteddriver detection, which contains four classes: calling, texting, looking behind, and normal driving.The main feature of the proposed solution is the extraction ofthe driver's body parts, using deep learning-based segmentation, before performing the distraction detectionand classification task.Experimental results show that the segmentation module significantly improves theclassification performance. The average accuracy of the proposed solution exceeds 96% on our dataset.Theclass activation map (CAM) of our proposed method is subjectively more reasonable, which would enhancethe reliability and explain ability of the model.

I.INTRODUCTION

Overview

Distracted driving is any activity that diverts attention from driving, including talking or texting on your phone, eating and drinking, talking to people in your vehicle, fiddling with the stereo, entertainment or navigation system anything that takes your attention away from the task of safe driving.

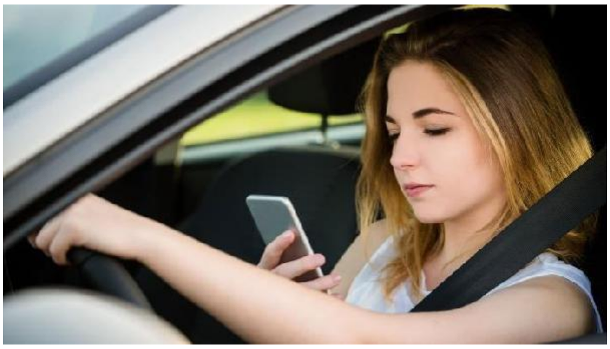

Figure 1.1. Distraction

Distracted driving occurs when a motorist is not giving their complete attention to the road, other vehicles, and signs along the roadway. According to the National Highway Traffic Safety Administration, three types of distracted driving exist:

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Figure 1.2. Distraction Type

1. Manual distraction: when a driver adjusts the radio, reaches for an item, pets their dog. etc. by removing their hands from the wheel.
2. Visual distraction: when a driver rubber necks by an accident, checks text message(s), looks at their kids in the back seat, etc. by taking their eyes off the road.
3. Cognitive distraction: when a driver daydreams, thinks about personal issues, considers their grocery list. etc. by taking their mind off of driving.

1.1.1. Distracted Driver Behaviours

Distracted driving comes in a variety of forms. These behaviours include instances when a driver is looking down or away from the road ahead for a period of time long enough to lose situational awareness of the forward driving scene like:

Daydreaming, using a cell phone, looking at something outside the vehicle, Activities of passengers, reaching for something on the dashboard, seat, or floor, Eating, drinking, or smoking, Changing the radio, climate control, or using a device in the car, Pets, insects, and objects moving inside the vehicle,Drowsy driving, talking on a cell phone, Texting, Smoking, using a tablet, reading paperwork, Programming an in-vehicle infotainment system.

1.1.2. Common Causes of Distraction

- **Mobile phones**

A substantial body of research shows that using a hand-held or hands-free mobile phone while driving is a significant distraction, and substantially increases the risk of the driver crashing.Mobile Phones and Driving Factsheet outlines the law relating to the use of mobile phones in a vehicle, concerns around the use of both hands-held and hands-free mobile phones while driving and issues around mobile phones that employers are advised to consider.

- **Headphones**

Although it has been noted that headphones can cause hearing damage, much less attention has been paid to the effects of headphones on the quality of driving. It is expected that drivers who are wearing headphones would need to shift their attention from what they hear in their headphones to external sound sources in certain situations, which could delay the speed of their response to external events. This is thought to be dangerous enough to form a risk in emergency situations. Headphones as a Driving Distraction Factsheet provides an overview of the evidence relating to headphones as a driving distraction.

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- **Satellite navigation (sat nav) devices**

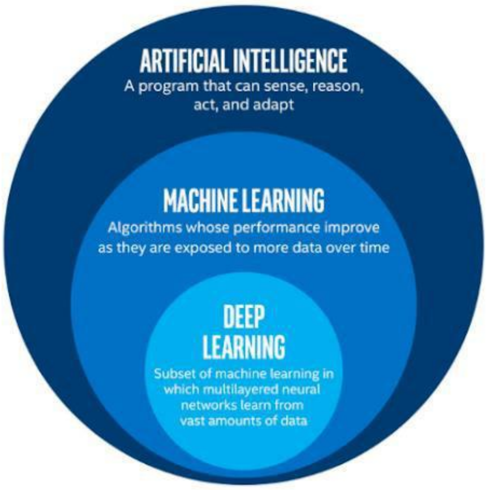
Several different types of Sat Navs are available to drivers, many of which are built into the vehicle itself.Used well, a Sat Nav can help drivers plan routes and prevent them from making last minute lane changes or hesitating because they are not sure of the directions. However, a badly used Sat Nav can distract the driver and increase the risk of an accident.

Infotainment Systems

Over the last ten years, there has been a huge increase in the digital technology available to motorists, allowing them to perform tasks that are unrelated to driving while they are behind the wheel. One of the biggest developments in this period has been the rise of infotainment systems. This refers to vehicle systems that combine entertainment and information delivery for drivers and passengers, often with the use of audio and touchscreens.

1.3. Deep Learning

Artificial intelligence is a set of algorithms and intelligence to try to mimic human intelligence. Machine learning is one of them, and deep learning is one of those machine learning techniques. Deep Learning is a subset of Machine Learning that uses mathematical functions to map the input to the output. These functions can extract non-redundant information or patterns from the data, which enables them to form a relationship between the input and the output. This is known as learning, and the process of learning is called training.



Deep learning can be used on a variety of input data types including audio, video, text, images, radio waves and machine signals to create applications such as natural language processing, audio recognition, computer vision and target recognition. At scale, these applications can comb through massive amounts of data that would be impossible for a team of humans to process.

1.3.1. Recurrent neural network (RNN)

Recurrent neural networks are a widely used artificial neural network. These networks save the output of a layer and feed it back to the input layer to help predict the layer's outcome. Recurrent neural networks have great learning abilities. They're widely used for complex tasks such as time series forecasting, learning handwriting, and recognizing language.

- **Convolutional neural network (CNN)**

A convolutional neural network is a particularly effective artificial neural network, and it presents a unique architecture. Layers are organized in three dimensions: width, height, and depth. The neurons in one layer connect not to all the neurons in the next layer, but only to a small region of the layer's neurons. The final output is reduced to a single vector of probability scores, organized along the depth dimension. Convolutional neural networks have been used in areas such as video recognition, image recognition, and recommender systems.

- **Generative adversarial network (GAN)**

Generative adversarial networks are generative models trained to create realistic content such as images. It is made up of two networks known as generator and discriminator. Both networks are trained simultaneously. During training, the generator uses random noise to create new synthetic data that closely resembles real data. The discriminator takes the output from the generator as input and uses real data to determine whether the generated content is real or synthetic. Each network is competing with each other. The generator is trying to generate synthetic content that is

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indistinguishable from real content and the discriminator is trying to correctly classify inputs as real or synthetic. The output is then used to update the weights of both networks to help them better achieve their respective goals. Generative adversarial networks are used to solve problems like image to image translation and age progression.

- **Transformers**

Transformers are a model architecture that is suited for solving problems containing sequences such as text or time-series data. They consist of encoder and decoder layers. The encoder takes an input and maps it to a numerical representation containing information such as context. The decoder uses information from the encoder to produce an output such as translated text. What makes transformers different from other architectures containing encoders and decoders are the attention sub-layers. Attention is the idea of focusing on specific parts of an input based on the importance of their context in relation to other inputs in a sequence. For example, when summarizing a news article, not all sentences are relevant to describe the main idea. By focusing on key words throughout the article, summarization can be done in a single sentence, the headline.

1.4. Objective of the Project

The main objective of the project is to propose an end-to-end deep learning-based driver distraction detection system able to be used with any driver and in any environment.To propose a FRCNN-based model to detect distracted drivers and determine the reason for the distraction.

To propose using deep learning-based human body parts segmentation method to efficiently remove irrelevant objects and identify the driver's critical body parts (i.e., the image regions that contribute to the driver's distraction recognition).

III.LITERATURE SURVEY

A DEEP LEARNING BASED MODEL FOR DRIVING RISK ASSESSMENT Author – Chang Heon Lee, YiyangBian
Year – 2019

In this paper a novel multilayer model is proposed for assessing driving risk. Studying aggressive behavior via massive driving data is essential for protecting road traffic safety and reducing losses of human life and property in smart city context. In particular, identifying aggressive behavior and driving risk are multi-factors combined evaluation process, which must be processed with time and environment. For instance, improper time and environment may facilitate abnormal driving behavior. The proposed Dynamic Multilayer Model consists of identifying instant aggressive driving behavior that can be visited within specific time windows and calculating individual driving risk via Deep Neural Networks based classification algorithms. Validation results show that the proposed methods are particularly effective for identifying driving aggressiveness and risk level via real dataset of 2129 drivers' driving behavior.

A DRIVER DROWSINESS DETECTION FRAMEWORK USING DEEP LEARNING HEURISTIC Author – D. Mounika ,K. DivyaDeepika ,A.R.S.R. PuneethVarma
Year – 2021

On an average 1200 road accidents record daily in India out of which 400 leads to direct death and rest gets effected badly. The major reason of these accidents is drowsiness caused by both sleep and alcohol. Due to driving for long time or intoxication, drivers might feel sleepy which is the biggest distraction for them while driving. This distraction might cost death of driver and other passengers in the vehicle and at the same time it also causes death of people in the other vehicles and pedestrians too. This mistake of one person on road would take their own life and also takes lives of other and put respective families in sorrow and tough situations. To prevent such accidents we, team 5A propose a system which alerts the driver if he/she feels drowsy. To accomplish this, we implement the solution using computer-vision based machine learning model.

Drowsiness Detection System Utilizing Physiological Signals
Author -Trupti K. Dange, T. S. Yengatiwar. Year - 2013.

The Physiological parameters-based techniques detect drowsiness based on drivers' physical conditions such as heart rate, pulse rate, breathing rate, respiratory rate and body temperature, etc. These biological parameters are more reliable and accurate in drowsiness detection as they are concerned with what is happening with driver physically. Fatigue or drowsiness, change the physiological parameters such as a decrease in blood pressure, heart rate and body temperature, etc. Physiological parameters-based drowsiness detection systems detect these changes and alert the driver when he is in the state, near to sleep. A list of physiological condition-based drowsiness detection system. These measures are invasive, so require electrodes to be directly placed on the driver's body.

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Robust Deep Learning Based Driver Distraction Detection and Classification
Author: Amal Ezzouhri , Zakaria Charouh , Mounir Ghogho , Zouhair Guennoun
Year: 2021
Problem identified

The main component of the proposed framework is the human body parts segmentation. It is applied to the raw RGB image in order to efficiently remove the irrelevant objects and identify the driver's critical body parts. The resulting image is then fed into the classification model. In this section, we first discuss the human body parts segmentation step, and then we describe the classification models and training methods used to classify the segmented image.

HCF: A Hybrid CNN Framework for Behaviour Detection of Distracted Drivers
Author: Chen Huang, Xiaochen Wang, Jiannong Cao, Shihui Wang, Yan Zhang.
Year: 2020
Doi: 10.1109/ACCESS.2020.3001159
Problem identified

The author finds there is loss function to evaluate the performance of the HCF during training. The loss function evaluates the error between the output of the HCF and the given target value. Meanwhile, to speed up HCF training, The author propose a new momentum-based training rate optimization (MTRO) algorithm based on the Adam algorithm.

IV. PROJECT DESCRIPTION

EXISTING SYSTEM

The existing system used Support Vector Machine (SVM) for classifying the face (if the eyes ae closed or not) as drowsy or not drowsy. To separate the two classes of data points, there are many possible hyperplanes that could be chosen. The objective of SVM is to find a plane that has the maximum margin, i.e., the maximum distance between data points of both classes.

DISADVANTAGE

- Lack of accuracy and robustness
- Expensive or limited to special high-end car models.
- Computational overhead
- Take long time to predict

V. PROPOSED SYSTEM

In this system, instead of Support Vector Machine (SVM) we use a Classification Model based on Convolutional Neural Networks (CNN). Deep Learning is concerned with algorithms inspired by the structure and function of the brain called artificial neural networks. Convolutional Neural Networks are a type of Artificial Neural Networks which are widely used for image classification and even Multi-Class classification of images. Convolution layers in a CNN consist of a set of learnable filters. During forward propagation, we slide each filter across the whole input step by step where each step is called stride. We propose CNN since the accuracy of the system is improved by using a CNN. The driver's face is continuously captured using a camera. The image frames are extracted and by face detection, the face of the driver is detected.

ADVANTAGES

- Faster detection of driver distraction and a higher success rate.
- Good balance between affordability and functionality.
- Accurate and efficient.
- No computational overhead

VI. RESULT

Our models were assessed using a variety of performance measures as well as execution time. Tus, we could assess how well and quickly our structures performed in comparison to other cutting-edge approaches. AUC, F1, and Cohen kappa scores were among the performance indicators. Te k-fold cross-validation test was also utilized as an evaluation

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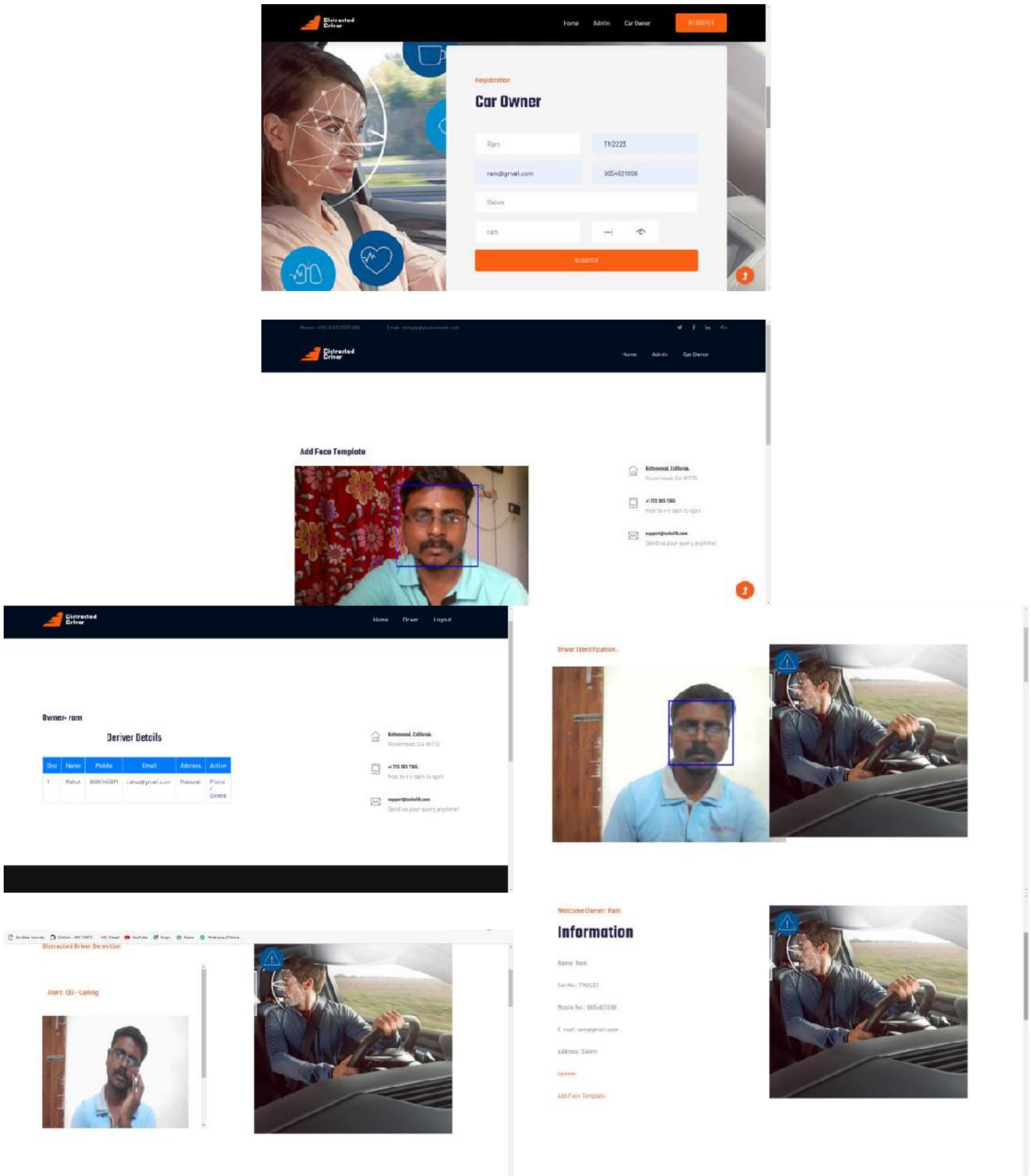
approach. While training and prediction time was the focus of the execution speed measures, the performance measures are calculated using International Transactions on Electrical Energy Systems.



VII. CONCLUSION

In this paper, a research project to develop a non-intrusive driver's drowsiness system based on Computer Vision and Artificial Intelligence has been presented. This system uses advanced technologies for analyzing and monitoring drivers eye state in real-time and in real driving conditions. Based on the results presented on Tables 1, 2 and 3, the proposed algorithm for face tracking, eye detection and eye tracking is robust and accurate under varying light, external illuminations interference, vibrations, changing background and facial orientations. To acquire data to use while developing and testing the algorithms, several drivers were recruited; they were exposed to a variety of difficult situations commonly encountered on the roadway. This guarantees and confirms that these experiments have proven robustness and efficiency in real traffic scenes.

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VIII. FUTURE ENHANCEMENT

This model will be embedded in a program run on multiple smartphone operating systems in the following phases. Because the suggested AI model can identify the driver's behavioural driving behaviour every three minutes, the information is synced every three minutes with the server system situated in the cloud. This device will function with any cellphone that permits access to GPS, regardless of the type of vehicle and whether the vehicle is a self-driving or conventional type.

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