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DEEP LEARNING MECHANISM FOR DETECTING DISTRACTED DRIVING

BRIJESH PATIL
Lincoln University College, Malaysia.

Dr. DIVYA MIDHUN CHAKKARAVARTHY
Lincoln University College, Malaysia

ABSTRACT

It is a general trend in most of the countries to use electronic communication devices (Mobile Phones) while ridding/driving, be it on four-wheeler or two-wheeler. Most of the time it has become as part of the life style. Which further leads to distracted driving creating complications like road accidents and injuries. To control the situation, many roads safety rules have been implemented across the world to minimize or prevent distracted driving, such as “road safety enforcement policies” where floated across the Canada, in addition to this “Distracted driving enforcement techniques” were implemented which could monitor the drivers by keeping a watch by Live video cameras scopes. At some point of time when situation was still out of control many “distracted driving public awareness campaigns” where held. However, the situation is not better yet.

Index Terms: Neural Network, Deep learning, Distracted driving

1. INTRODUCTION

Based on the current situation of increasing cases of distracted driving, a deep analysis of various methods for detecting distracted driving is done along with proposed solution to overcome the intermediate loop holes to build up a stable system which prevent the user from falling into the situation of “Distracted driving”. In this paper various methods are highlighted which can effectively play a vital role in combining various Neural networks methods in addition of bio mechanical approach to handle the distracted driven concept.

[10] Driving is considered to be a skill which involves the use of cognitive functions of the brain. Cognitive functions can be seen as the natural conscience of a person. Ideally, this conscience should not let the driver get distracted from the task at hand. Unlike this ideal behavior, drivers of all age groups are involved in distracted driving practices and the relationship between the executive function performance and willingness to indulge in distracted driving is still a little mysterious. Hence, Caitlin Northcutt Pope et al, tried to investigate this relationship between cognitive executive functions and distracted driving indulgence via self-reported incidents from drivers. For this study, executive difficulties (assessed with BRIEF-A) and demographic features were considered as the factors for analysis.

2. Methodology

[6] The method involved for forming the dataset for this study was a demographic survey. A sample of 59 participants was chosen across age groups. These included 13 young adults (M_{age}=19.69 years), 21 middle-aged adults (M_{age}=43.93 years) and 25 older adults (M_{age}=71.66 years). All this people were properly recruited and it was made sure that they were active drivers who had driven within the past 12 months at

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the time of the research and had enough cognitive ability to drive as per requirement. Among these people, 25.4% (n=15) reported having met with a MVC within the past 3 years. These were topped by older adults, followed by young adults and middle-aged adults. The entire sample class reported as active users of cell phones, with varying ages of receiving their first cellphones.

Descriptive statistics by age group.

Characteristic	Total Sample ($n = 59$)	Young adult ($n = 13$)	Middle Adult ($n = 21$)	Older Adult ($n = 25$)
	n (%)	n	n	n
Race				
Caucasian	35 (59.3%)	8	11	16
African-American	19 (32.2%)	2	8	9
Other	5 (8.5%)	3	2	0
Gender				
Male	24 (40.7%)	8	7	9
Female	35 (59.3%)	5	14	16

Characteristic	M (SD)	M (SD)	Range	M (SD)	Range	M (SD)	Range
Age (years)	50.34 (21.29)	19.69 (0.28)	19.10–19.96	43.93 (5.75)	36.16–53.97	71.66 (7.02)	65.00–91.47
GEC	109.37 (23.16)	120.62 (26.44)	70.00–157.00	109.10 (24.51)	71.00–158.00	103.76 (18.57)	70.00–145.00
BRI	47.46 (11.07)	53.39 (13.94)	30.00–77.00	46.91 (11.54)	31.00–74.00	44.84 (7.86)	30.00–61.00
MI	61.91 (13.14)	67.23 (13.58)	40.00–83.00	62.19 (14.07)	40.00–87.00	58.92 (11.65)	40.00–84.00
Distracted Driving Behaviors†	17.92 (12.51)	29.77 (10.47)	11.00–51.00	22.00 (10.19)	6.00–52.00	8.34 (7.13)	0.00–25.00

Note. GEC = Global Executive Composite. BRI = Behavioral Regulation Index. MI = Metacognitive Index. BRIEF scales reflect raw scores. Raw score range for GEC is 70–210, for BRI is 30–90, and MI is 40–120.
† Raw sum of frequencies of distracted driving behaviors reported per week. Standardized scores were used for all analyses.

Ref: [1]

The demographic survey was conducted in the form a self-report questionnaire. Difficulty with executive functioning was assessed over 75 questions on a 3-point scale for common behavioural disruptions. This BRIEF comprised of two sections – Behavioural Regulation Index (BRI) and Metacognitive Index (MI). These were then used to get the Global Executive Composite (GEC) score. Since BRI and MI are highly correlated, GEC was an apt parameter to understand and assess executive functionality.

The next questionnaire was on different distracted driving behaviours. This was a 10-item self-reported questionnaire, in which the members of the sample class had to choose which of the given behaviors where they involved in and how often. The frequency was to be specified in the form of a whole number from 0 to 7 (days/week) based on how many days were they getting distracted by the specific cause. Eventually 2 of the items from the list, namely use of hands-free devices and GPS, were dropped. The responses on the basis of the remaining 8 items were then summed up to a composite score.

Correlations between measures of executive function, age, and distracted driving behaviors.

Measure	1	2	3	4	5
1. Age	—				
2. GEC	-0.27^{*}	—			
3. BRI	-0.28^{*}	$.95^{**}$	—		
4. MI	-0.23	$.96^{**}$	$.83^{**}$	—	
5. Distracted Driving Behaviors	-0.65^{**}	$.52^{**}$	$.47^{**}$	$.52^{**}$	—

Note. GEC = Global Executive Composite. BRI = Behavioral Regulation Index. MI = Metacognitive Index.
$^{*}p < 0.05$.
$^{**}p < 0.01$.

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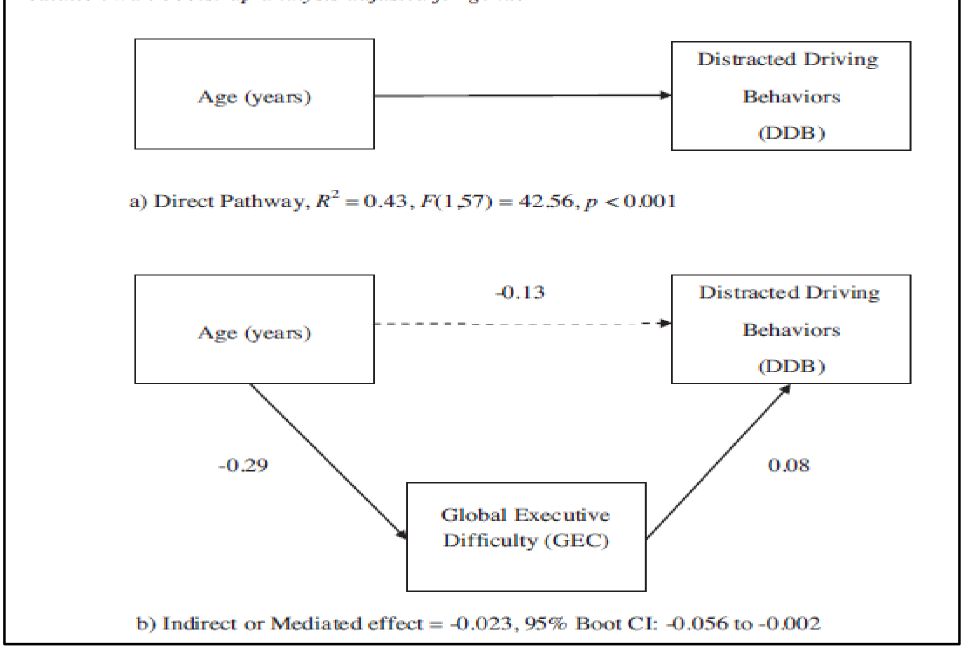
Linear regressions predicting distracted driving behaviors.

Model		Unstandardized Coefficients		Standardized Coefficients					
		b	*SE*	Beta	*t*	*F*	R^2	ΔR^2	*p*
Model 1						20.98	0.43		**<.001**
	Age	−0.15	0.02	−0.66	−6.45				**<.001**
	Gender	0.29	1.02	0.03	0.29				0.775
Model 2						23.13	0.53	0.13	**<.001**
	GEC	0.08	0.02	0.37	4.01				**<.001**
	Age	−0.13	0.02	−0.56	−5.93				**<.001**
	Gender	0.27	0.91	0.03	0.30				0.767

Note. Bold signifies $p < 0.05$. GEC = Global Executive Composite.

Ref:[1]

Correlation and Regression analyses were performed on the composite scores from the two questionnaires in order to know the unique effects of age, gender and other demographic factors on the instances of distracted driving.



Mediation with bootstrap analysis adjusted for gender

Ref: [1]

Conclusion

While it is well-known that young adults are the most common victims to distracted driving behaviours and MVCs, this study also established and proved that middle-aged adults are equally prone to distractions while driving. Understandably, older adults are least involved in equipment distraction but do find themselves stuck in executive functional limitations and thereby equally prone to MCVs. It can hance be understood that every age group and every gender across the world is equally prone to MCVs but young adults are most prone to technological distractions. This study had its limitations but was one of its kind in establishing a relationship between distracted driving behaviours and demographic/cognitive factors.

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Deep convolutional neural network [3][4][5][6]is a type of Artificial neural network that has shown considerable progress in tasks concerning image classification, object detection, action recognition, natural language processing and many more, making it a valuable asset used for obtaining datasets that can act as learning or trial sets. When using convolutional neural network to detect distracted driving, an attempt is made to explore the potential of training a system to detect inattention among drivers. Several such networks can be studied to build a detection system which can identify and predict distracted driving scenarios accurately.

CNN approach for detection implements a classifier based on CNN to detect a distraction and the cause for it. After identification, a distraction must then be labelled and categorized for risk assessment. Properly classifying a distraction is crucial as the subsequent safety measures to be taken depend on it. A study that used CNN to detect distracted driving used images captured using dashboard cameras of different drivers in many different countries, driving different type of vehicles that incorporated various drivers and driving conditions. Images pertaining to different lighting conditions caused by sunlight and shadows were also captured for every driver.

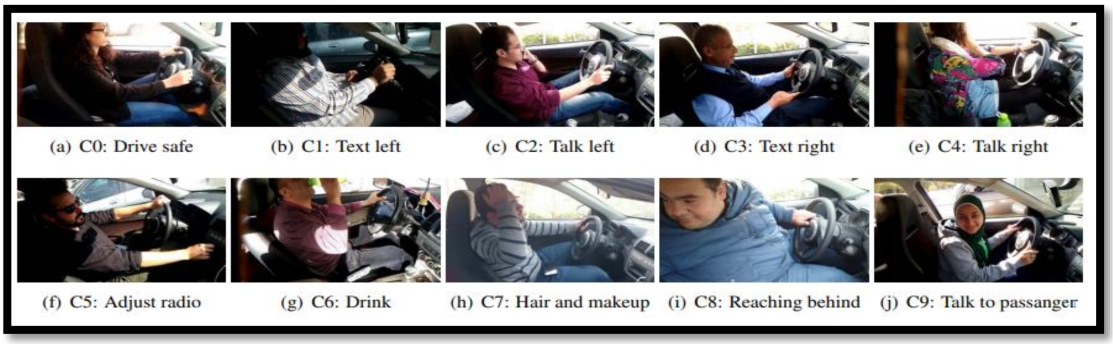

Figure: ten classes of driver postures from dataset [4]

Out of the data set 75% images are used for training, and the remaining 25% images are used for testing. VGG 16 and VGG 19 model CNNs then studied and classified the various images provided to them and predicted with good accuracy the type of distraction and the cause leading up to it.

Class	Total Samples	Correct Predictions	Incorrect Predictions	Accuracy (%)
Safe Driving	922	863	59	93.60
Texting Using Left Hand	326	315	11	96.63
Talking on Phone Using Left Hand	341	329	12	96.48
Texting Using Right Hand	494	471	23	95.34
Talking on Phone Using Right Hand	306	291	15	95.09
Adjusting Radio	305	297	8	97.38
Drinking	403	392	11	97.27
Hair and Makeup	301	284	17	94.35
Reaching Behind	290	273	17	94.14
Talking to Passanger	643	623	20	96.89

Table: Class-wise Accuracy using Modified VGG-16 Architecture [4]

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[9] Another method of detecting distracted driving is through the fusion of block chaining and deep learning CNN. Initially blockchain is utilized in relevance to economics and finance fields, but due to the immunity and probity of the digital data provided by blockchain, transmission of the multimedia content is gaining popularity among the researchers. A video is recorded and timestamped at fixed intervals then split and extracted into hashes which are transmitted. The entire technique of data acquisition is done in two steps, first being deep learning that recognizes driver behavior and the second, block chaining that transmits the captured data. This data is provided to the CNN which gives prediction by analyzing the chunk of frames, whether the driver involved in distracted behavior or not depending upon the pre-defined categories.

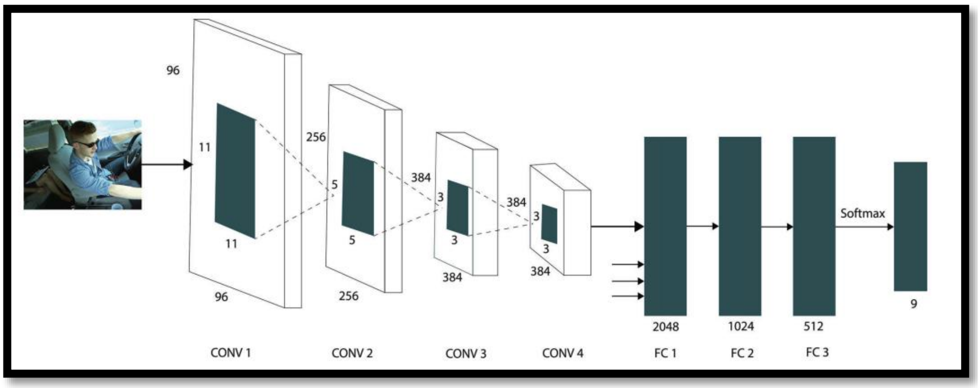

Figure: convolutional neural network [9]

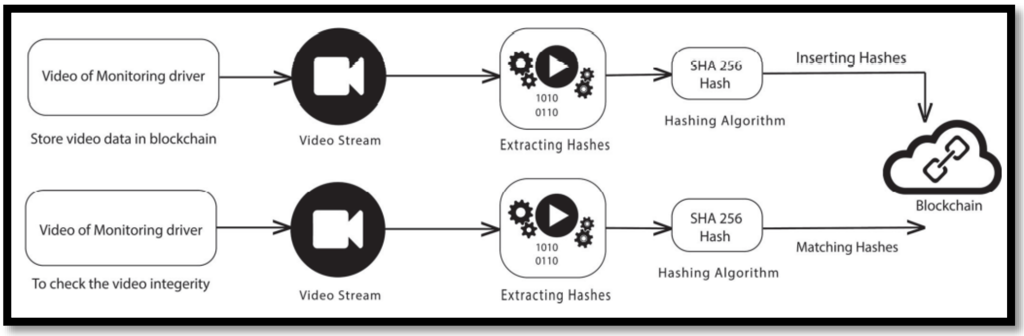

Figure: blockchain [9]

[11][12][13] Deep learning can also be implemented to allow for **real time detection of distracted driving**. This method has been explored and studies using various CNN systems like VGG-16, GoogleNet, AlexNet and ResNet. as tests on a real driver could prove dangerous, a test bed was constructed to simulate a driving experience.

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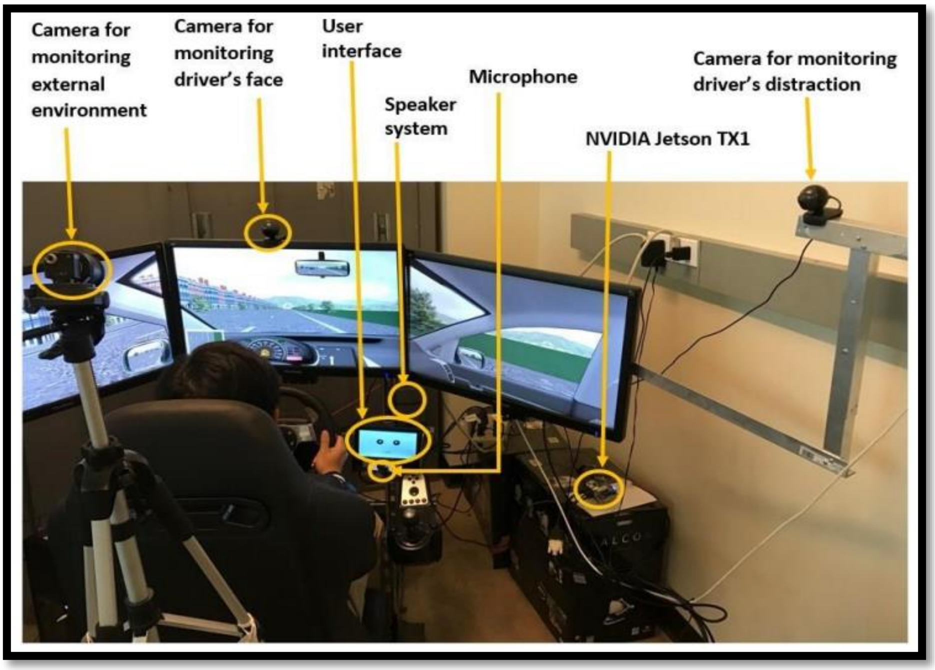

Figure: assisted driving test bed [12]

Figure: screenshots from the four monitors of the setup [12]

A group of people were then asked to use to simulator and perform various activities over the course of five minutes as the camera recorded it. The video was then fed for processing to different CNN models. The models could then identify various actions that it could classify as distracted driving based on information provided to it. However, there were instances where the CNN got confused between actions that had similar hand and face movements.

[7] Another cause of traffic accidents is **driver fatigue and drowsiness.** The task of driving needs the driver to be aware and attentive. However, fatigue and drowsiness cause nodding of head, yawning and blurred vision which all cause the driver to be distracted. A tired driver can be identified using brain computer interface (BCI), which would create a direct interface between the human brain and an external device. Among different types of BCI systems, the EP (evoked potential) system is best suited for this. Among different type of EPs, the steady state visual evoked potential (SSVEP)

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is used in various BCI applications. SSVEP is used to detect the state of driver's sleepiness using a setup of 4 LEDs.

The bio- mechanical distracted driver recognition model based on stacked autoencoder and CNN involves the use of consecutive integration of two sub models: hand and face localizer which is used to localize hand and face, and reserves silent features of an input image. The second sub-model is convolutional neural network which is used to recognize each class of biomechanical distraction.

Using these as inputs, a new distracted driver posture recognition based on stacked auto encoder and CNN was proposed. In this model, changing illumination condition and different skin color tone was not considered and it consisted offhand and face localization and modified conventional network-based classification. At hand and face localization point they applied the stacked auto encoder for segmenting hand and face in the presence of illumination and different skin color tones effects, then these both modules were sequentially instructed to recognize each class of distracted posture with the efficiency of 98.68%. The proposed system outperforms earlier approaches of distracted driver detection models. The improvement that can be made to this model in incorporation of detection based on the silent features on or off road that can distract the driver.

A multi-modal dataset for various forms of distracteddriving [14] was used to test how various stresses affected the driver. From surveys reporting the causes of traffic crashes, one could identify three major factors: cognitive, emotional, and sensorimotor stressors that overtax the driver's physiological resources, thus opening the car-driver feedback loop. In fact, it has been documented that even when these stressors do not result in a crash, they degrade traffic efficiency. Another crash causing factor that has gained attention in recent years, is startle. Startling events are often the result of car malfunction, such as the case of unintended acceleration. It has been postulated that the ability of the driver to handle such events is compromised by the presence of stressors.

Experiments were conducted on volunteers who have a license and drove on a regular basis. The subjects also belonged to various age groups to see how the stress-based distractions varied with age. The experimental setup involved a driving simulator was subjects accompanied by facial and thermal cameras along with sensors that detected the state of the drivers' palm, heartbeat and breathing rate. Test then observed the status of the driver during four different type of driving conditions. A practice drive for the user to get familiar with equipment, relaxed drive to collect data during ideal driving scenarios and different loaded drives that put cognitive and emotional stress on the driver while driving along an equally long highway. A separate loaded drive was also conducted where the software produced startling errors randomly during the drive. The data procured during these experiments is used to create a dataset that gives us a general idea about how stress and various other randomizing factors affect the driver and cause momentary distractions that could prove perilous in day-to-day situations.

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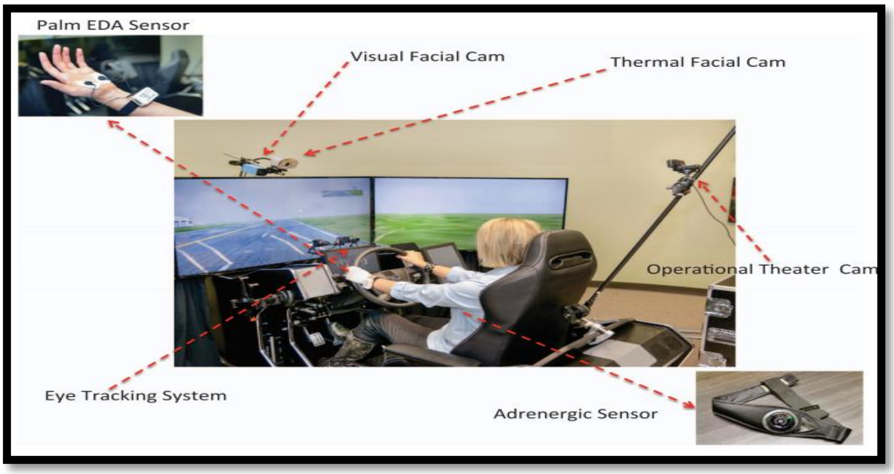

Figure: experimental setup [14]

3. CONCLUSION

We see many issues related to driving every day on a global scale. It is imperative that we come up with a system that would groom safety discipline at the individual level. Some research suggests the use of deep learning and neural networks [17] that would understand and capture the drivers' position and identify distracted driving. There are also proposals that bend toward the concept of vehicle that would take control away from the drivers when it detects distracted driving, thereby notifying the driver of the issue and prevent accidents. Such a safety control system [18] can have some control over the engine speed and brakes allowing it to slow down, speed up and stop the vehicle whenever necessary. Considering all the points, a mechanism could be developed which would control the speed of vehicle to a certain extent depending on the level the distraction the driver is facing. This would vary for each driver. The system would first alert the drivers about the situation making them aware. This approach could be tested out using a simulator to determine the accuracy and identify problems and then rolled out into vehicles. A system such as this could prevent mishaps at an early stage saving human life and preventing damage to public and property.

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