Behaviour Detection of Driver using Convolutional Neural Networks

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Abstract:- With the emergence of technology and social media, people are getting careless and driver inattention is on the rise. This harms the safety of people on the roads. In this paper we address the issue of automated classification of driver practices leading to interruptions and driver inattention by utilizing Deep Learning and CNN(Convolutional Neural Networks). For an effective solution, the proposed work puts forth a model implementing CNN to detect the distracted driver and classify the cause of his/her distraction by processing the images sourced from a camera pre-installed in the vehicle.

Keywords:- *Machine Learning, Convolutional Neural Network, Deep Learning, Vgg16, Distracted Driver, Image Classification.*

I. INTRODUCTION

The safety of people on the road, pedestrians or drivers, is a serious concern, worldwide. The study of driver activity recognition has been gradually attracting attention over the last decade because of its different number of uses, including those for improving the well-being of drivers and passengers, giving driving aid, providing data to insurance agencies and even for self-driving automobiles in circumstances when there may ge requirement for a human to assume control of the vehicle.

Due to growing habit of multitasking among people in this fast-paced world, driver inattention is on the rise. Inattentions can be caused due to two common reasons – fatigue or distraction. Drowsiness amongst drivers is an important factor to be considered. In the same way, the person driving should avoid engaging in other activities. Referring to the report published by the National Highway Traffic Safety Administration (NHTSA), in 2015, in the United States of America, 391,000 people were injured in motor vehicle crashes involving distracted drivers. A shocking number of 3477 were killed [11]. As per NHTSA's report driver's inattention is the sole cause for 94% of car mishaps, with mechanical issues or environmental conditions constituting for less than 5%. In India itself, 130,000 deaths were registered due to road accidents [7]. Out of which one-fifth took place when the driver was distracted [8]. Further ahead, the report states that 37% of the drivers confess to use their phones and reply to texts. 18% of these people do it regularly while driving. A shocking 86% of drivers admit to any of the following: eating, drinking, using the navigation system, watching videos, surfing the internet or prepping [11]. A majority of these incidents could have been avoided had the driver been alerted the instant he was distracted. All of these reasons, call for a solution to minimize the distraction of drivers while driving, effectively reducing the risks of car crashes and other accidents.

The emergence of self-driving cars has put this problem on the back burner. The simple matter of fact is that the recent models of such auto-driven cars (as well as those being employed in the private transportation sector) need the operator to be alert and awake at all times to take over in case of emergencies. According to Lyft's (a private transport company) FAQ site, the administrator of such cars might have to assume control if there are any hurdles on the vehicle's path, such as constructions, traffic redirections or whatever other uncommon circumstances where human mediation is required. Unfortunately, in recent times, certain doubts regarding this new technology's safety have been raised, as evidenced by an incident that occurred when a self-driving car killed an innocent pedestrian. Along these lines, so as to have more safety features incorporated, having the option to identify unusual conduct and inform the driver precisely and in time for the driver to make a move is a key factor. In this paper we propose and present a correlation of various deep learning-based strategies to classify driver's behavior using data from the StateFarm Dataset [9].

The proposed work in our paper utilises a classifier based on CNN(Convolutional Neural Networks). It detects common distractions of the driver and also identifies the cause of those distractions. The images present in the dataset are sourced from the dashcam of the vehicle. This image is sent to the neural network system and the distraction class is detected. We also make use of pre-trained weights obtained from training CNN models and the ImageNet data. By making use of this pre-trained model we try to minimize the training time of CNN(Convolutional Neural Networks).Furthermore, this system can be implemented to build a Driver State Detection System which could detect and classify the different states of a driver while driving.

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This paper is structured as follows: in section II we present a literature survey with past examinations and their methodologies, in section III we present our technique and our data, in section IV we take a look at the algorithms and in section V, we discuss the final contemplations of the work to be done and how the proposed framework can be made more increasingly effective for future use.

II. LITERATURE SURVEY

Much research has been done for the problem of driver behaviour detection using various different techniques. In this section we review a few of the relevant and significant work done to find solutions to the problem.

The work done by Céline Craye and Fakhri Karray data collection was performed by utilising a driving-simulator. A total of 8 hours of video of driving sequences was recorded with the help of 8 participants [1]. Active sensor Kinect was used for feature selection. Active sensor Kinect can process colour and depth-data for extracting features such as eye behaviour, head orientation, arm position, and facial expressions [1]. They tackled the problem by creating two classifiers, one for detecting the distracted driver and the second for distraction recognition. Models like AdaBoost along with Hidden Markov Models were trained for classification tasks. These two models gave similar results in detecting distraction. The accuracy for detecting the distraction was 90% and for the type of distraction was 85%.

Yulan Liang and their team [2] worked on driving performance data and eye movements of the driver. They instructed their participants to get involved in distracting activities. To collect this data, six drives, lasting approximately 15 minutes, took place wherein, in-vehicles-devices were installed in four. The other two were baseline drives. 90 minutes of video footage in total was recorded. The movement of the eyes and driver data was recorded by Seeing Machines faceLAB along with a simulator functioning at a rate of 60Hz, respectively. An accuracy of 80% was obtained in detecting cognitive distraction with the help of Bayesian networks.

Ralph Oyini Mbouna studied driver attentiveness by examining the eye state and the head position and [5]. Data was collected from a camera fixed on the dashboard of the car. A total of 75 minutes of footage was captured. Visual features like head position, eye index and eye pupils were utilized. This information was then pushed into Support vector machine (SVM) models for binary classification of alert and non-alert driver. Based on the values of true positives, true negatives, false positives and false negatives, an accuracy of 91% was achieved for classification.

Matti Kutila [12] took a shot at recognizing cognitive and visual distraction detection. The data was acquired from the driving performances of 3 car drivers and 12 truck drivers. Feature extraction was carried out by driver driving data like lane tracking and stereo vision. Support Vector Machines and Rule- based algorithms were utilized on the data. Reasonable outcomes were obtained, for example, 80% accuracy in distinguishing visual distraction and 68-86% in cognitive distraction recognition was achieved.

III. PROPOSED WORK

To train a model to detect distracted drivers, a dataset of images of both distracted and non-distracted drivers is required. This would only require a binary classifier model that would predict if a driver is distracted or not. A more interesting problem would be one where the drivers are distracted in different ways, like eating or fixing their hair for example. This kind of problem requires a multi classifier model and a more specific dataset. Kaggle is an online platform for data science tutorials and competitions. State Farm Distracted Driver Detection competition hosted by State Farm is one of the competitions on Kaggle [9].

The dataset consists of images of drivers performing one of 10 possible activities, one of which is safe driving. The rest of the images belong to classes where the driver can be considered distracted (e.g. texting). In these three examples, c0 represents safe driving, while c1 and c8 represent texting with their right hand and doing their hair and/or makeup, respectively. All the images are taken from the same angle, in the same environmental conditions, which is both good and bad in training the model. It could be considered a positive event because, if a subset of this data is used as the test set, then the model will most likely perform well since the test images have the same conditions. However, this poses an issue when the model is generalized to images that don’t necessarily meet the same conditions as the ones in the original dataset. The hypothesis is that a drastic change in angle, or incoming light will cause the model to perform very poorly. This hypothesis is hard to confirm without finding a new dataset of distracted drivers in varying conditions, which, to our knowledge, does not exist.

CLASS	DESCRIPTION
C0	Safe Driving
C1	Texting (right hand)
C2	Talking on the phone (right hand)
C3	Texting (left hand)
C4	Talking on the phone (left hand)
C5	Operating the radio
C6	Drinking
C7	Reaching behind
C8	Hair Makeup
C9	Talking to passengers

Table 1:- Different Classes and Description

In order to overcome the distracted driver detection problem, the Convolutional Neural Network (CNN) model is used. CNNs have proven to perform remarkably well on classifying images, and as such, are a great fit for this problem.

IV. ALGORITHMS

A. *Convolutional Neural Networks*

LeCun was the man behind the idea of Convolutional Neural Networks [13]. CNNs were big leaps forward in the fields of image classification, voice recognition, target detection, etc.

CNNs come with multiple hidden layers which in turn helps in minimizing the proportions of the image, effectively, allowing the model to extract scarce image features in lower dimensional spaces. CNNs are generally made up of two components – feature extraction and classification. The extraction module extracts only a set of predominant features based on the algorithm being used. The distinctive features are singled out by the classification component to classify these images. CNNs are made of multiple layers which help to extract the distinctive features and pass them on to the classification layer for the classified category data.

It is worth noting that CNNs typically suffer from overfitting, which occurs when a model adapts too well on trained data, but performs poorly on new data, and thus is said to generalize poorly. This is an issue that we try to reduce as much as possible throughout this work. CNNs depend on the idea that local understanding of an image is good enough, with the practical benefit of having fewer parameters, consequently reducing the computation time and data required to train the model rather than have a fully connected layer for every pixel, CNNs only have enough weights to look at small parts of the image at a time. The process consists of a convolution layer, a pooling and an activation function. It is not necessary for them to be in the same order. These three separate operations can be applied as separate layers to the original image multiple times. Finally, a fully connected layer (or several) are added at the end in order to classify an image accordingly. With the highly variable number of combinations and permutations, it can be difficult to find the exact one that gives the optimal performance. CNN designs are driven by the community and research who thankfully have made some successful results, and made their CNNs publicly available for others to use and improve upon.

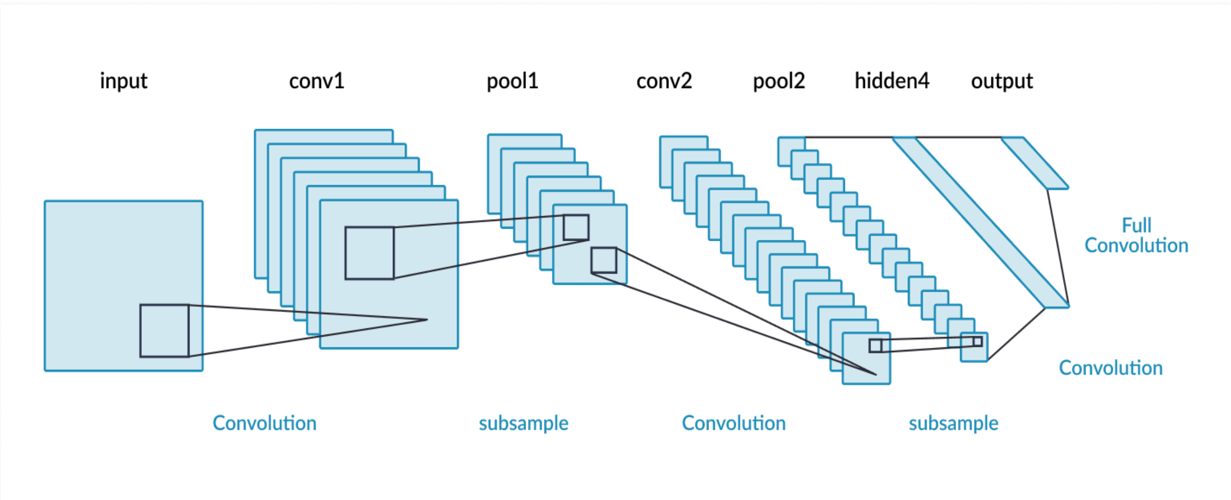

Fig 1:- Convoulutional Neural Network

B. *VGG16*

VGG is a CNN model proposed by Karen Simonyan, and Andrew Zisserman, in their paper "Very Deep Convolutional Networks for Large-Scale Image Recognition" [6]. VGG16 is named after the Visual Geometry Group at the University of Oxford. More specifically, VGG16 is a deep 16-layer Convolutional Neural Network, with 13 convolutional layers, and 3 fully connected ones at the top. A visual representation of the VGG16 architecture is shown in Figure 1. The model is able to achieve up to 92.7% top-5 accuracy on ImageNet4, which contains nearly 14 million images with over 1000 categories. The authors have not only made the model publicly available, but also its pre-trained ImageNet weights. This is something that is utilized in our work in order to not only decrease the computational cost, but also increase the accuracy of the model.

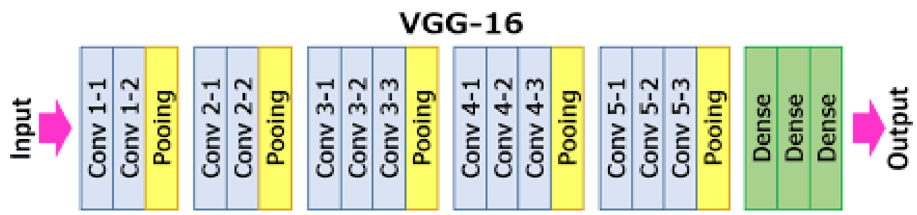

Fig 2:- VGG16

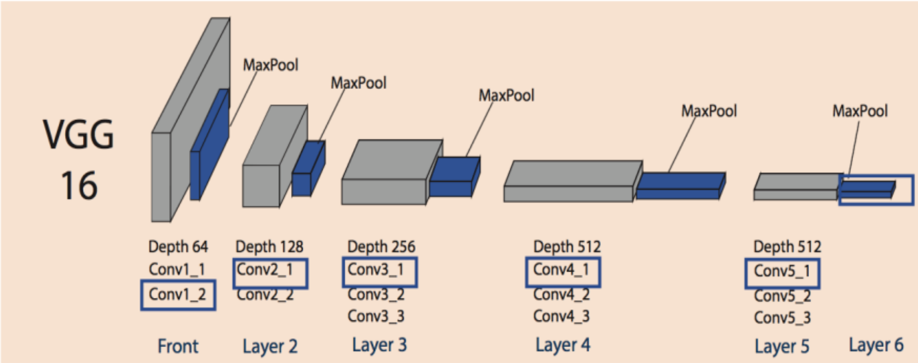

Fig 3:- VGG16

V. CONCLUSION AND FUTURE WORK

Deep Learning using Convolutional Neural Networks is used widely in image classification, voice recognition, etc. In our proposed work we have used the same for detecting distractions and their causes by making use of VGG16.

Our proposed work suggests developing a system which can detect distraction among drivers while driving. The proposed model can identify the driver behaviour amongst the given 10 classes of distraction.

Such trained model can be implemented in a Driver State Monitoring System which help to monitor the state of the driver while driving. The automobile industry can benefit from this system as it helps in preventing accidents. A model can be created which raises warning or notifications when it detects the driver being distracted which ultimately helps in avoiding accidents due to driver distraction.

The system can be expanded by adding in some more distraction classes to the existing ones. To make the system more efficient. A drowsiness detection module could also be added which would help in expanding the scale of work.

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REFERENCES

[1]. Craye, Céline, and Fakhri Karray. "Driver distraction detection and recognition using RGB-D sensor."(2015).

[2]. Liang, Yulan, John Lee, and Michelle Reyes. "Nonintrusive detection of driver cognitive distraction in real time using Bayesian networks." (2007)

[3]. Sarfaraz Masood, Abhinav Rai, Aakash Aggarwal, M.N. Doja & Musheer Ahmad “Detecting Distraction of drivers using Convolutional Neural Network.” (2017)

[4]. Valeriano, Napoletano & Schettini “Recognition of driver distractions using deep learning” (2018)

[5]. Mbouna et al. 2013, "Visual analysis of eye state and head pose for driver alertness monitoring." IEEE transactions on intelligent transportation systems

[6]. Simonyan, Karen, and Andrew Zisserman, 2014 "Very deep convolutional networks for large-scale image recognition.

[7]. Mobiles phone use and increasing road accidents - Raghvan Guruswami, accessed September 10, 2016, http://blogs.siliconindia.com/guru_raghavan/Technology/Mobile-phones-use-and-increasing-road-accidents-bidrhF4230a61127033.html

[8]. Distracted Driving, Centres for Disease Control and Prevention, accessed September 8, 2016,http://www.cdc.gov/motorvehiclesafety/distracted_driving.

[9]. State Farm Distracted Drivers Dataset, accessed on June 15 2017, https://www.kaggle.com/c/state-farm-distracteddriver-detection/data

[10]. Chollet, François. "Keras." (2015). Accessed on June 15 2017, https://github.com/fchollet/keras.

[11]. “Distracted driving,” - NHTSA, https://www.nhtsa.gov/risky-driving/ distracted-driving/, 2015, accessed: 2018-05-17.

[12]. Kutila, et al, 2007, "Driver distraction detection with a camera vision system." In 2007 IEEE International Conference on Image Processing, vol. 6, pp. VI-201. IEEE.

[13]. LeCun et al. 1998, "Gradient-based learning applied to document recognition." Proceedings of the IEEE 86, no. 11 2278-2324