INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

ISSN: 2454-132X
Impact factor: 6.078
(Volume 6, Issue 5)
Available online at: www.ijariit.com

Abnormal driving behavior detection via Deep Learning Approaches

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ABSTRACT

During this period detection of abnormal driving is more important. It gives safety to passengers and drivers in vehicle. In our proposed method deep-learning methods used for abnormal driving behavior prediction. Deep learning classification methods are more applicable of various fields. The applications are computer vision, speech finding, language processing, audio identification, medical image analysis, bioinformatics and self-driving cars. Our simplified method we use three deep learning methods such as CNN, Deep Residual Network and Visualized Geometric Group16. The CNN extract high level features such as hidden object in an image and doesn't need hand-designed features. For the purpose we use one dataset that contain 22,424 color frames (images). In the existing system that use novel deep learning fusion methods to detect abnormal driving behavior and the accuracy of that dataset is 82%. Our proposed method revealed an accuracy 87.44%. So new method better than the existing method.

Keywords: *Driving behavior prediction, deep learning.*

1. INTRODUCTION

Driving is a complex task. For the driving will acquire several motor and cognitive abilities. Insufficient human action is a major cause of road traffic accidents. Imperfect perception, less concentration, focuses on other activities, and sub optimal arousal is mentioned as possible causes poor performance. For instance, driver drowsiness caused by extended hours of driving, as well as situations of cognitive overload, can significantly impair a driver's ability to react appropriately to relevant events. Understanding of these causes and the effective remedies is key importance to increase traffic safety and driver well-being. High-resolution cameras are more commonly seen with in a great number of visual applications at current situation. In video surveillance, multiple cameras are placed in various locations. They work together to identify, re-identify, and track the moving target [1].

Generally says that, detection of abnormal driving behavior can be mainly classified into three. The first one belongs to requirements such as smoking, drinking, eating, configuring the aircon,etc. The second include the distracted driving behaviors like makeup, shaving, chatting, use of mobile phones or other unnecessary devices, etc. The third contains distracted driving behavior caused by the surrounding environment, including caring for children, long –term unexpected events outside the vehicle, etc. The use of mobile phone has become a important factor in abnormal driving. Important things of this study can be summarized as follows. First, it is the first attempt to incorporate the recently proposed DenseNet into the challenging abnormal driving behavior detection task. Second including the important enhancement of width and cardinality in WGD, the sophisticated integration of ResNet and DenseNet in WGRD and AWGRD, are significant. Third, extensive experiments and comprehensive analyses further substantiate the superiority of newly introduced models in tackling the abnormal driving behavior problem of this study.

2. LITERATURE SURVEY

Abnormal driving behavior detection [2] mainly focus on safeties of drivers and passengers in the vehicle, and it mostly give automatic driving at the current situation. A heart rate variability method [3] is introduced in the year 2008, in that study new ECG- based techniques to detect drivers propensity to fall asleep at the wheel. The study that contain 3 steps: 1) searching for ECG-Based variables that change periodically with FA;2) determining a pattern changes occurring the time interval before FA; 3) defining possible thresholds used for early detection of FA in different subjects. A graph based method for detecting abnormal behavior starting from the analysis of vehicles trajectories. The scene is partitioned into zones and it is dynamically represented as a graph.

The majority of traffic accidents caused by inattentive or fatigue related to drowsiness [4].PERCLOS [5] is the most suitable method for this purpose. An intelligent driver assistance system [5] is introduced in 2016.For the detection k-means clustering algorithm is used.

A facial landmark detection [6][7] is used for the abnormal driving behavior detection. Logistic regression and FLD algorithm used for the purpose. Also a breaking behavior analysis [8] is used to understanding the driving. surface electromyography is based on the steering wheel [9] hiding positions. EMG signal is associated with the muscle metabolic process.

3. MATERIALS AND METHODS

3.1 Dataset

Use distracted driver detection database is available in kaggle. They contain various number of color frames (i.e., images) of drivers. Total 22,424 images. Each individual image has a pixel size of 640* 480. All images can be categorized into 10 classes, which indicate 10 different driving patterns. These driving patterns contain safe driving, texting (using right hand), talking on the phone (using right hand), texting (using left hand), talking on the phone (using left hand), operating the radio, drinking, reaching behind, hair and makeup, talking to passenger, etc.

Fig. 1: Different patterns of images

3.2 Feature Extraction

CNN extracts high level features [10] such as hidden objects in an image. Latent features or equivalently hidden features are features that we don't directly observe , here we extract those features .Compared with previous feature extraction techniques the Convolutional Neural Network can extract features from image automatically. The research shows CNN extracted features from middle layers, which improve the classification accuracy.

3.3 Algorithms

3.3.1 Convolutional Neural Network: Convolutional Networks is a biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Individual cortical neurons reply to stimuli only in a restricted region of the visual field known as the receptive field. The sensitive fields of different neurons partially overlap such that they cover the entire visual field. CNNs use comparatively little pre-processing compared to other image classification algorithms. This means that the network understand the filters that in traditional algorithms were hand-engineered. This independence from prior knowledge and human effort in feature design is a major advantage. When programming a CNN, the input is a tensor with shape

((no: of images)×(image width)×(image height)×(image depth))

Then a convolutional layer abstracted to a feature map, with shape.

(no: of imgaes)×(map width)×(map height)×(map channels)

3.3.2 Visualized Geometric Group16: VGG16 is a convolutional neural network model. The model achieves 92.7 percent top-5 test accuracy in ImageNet, it is a dataset of over 14 million images belonging to 1000 classes. Also construct on the enhancement over AlexNet by restore large kernel-sized filters (11 and 5 in the first and second convolutional layer, respectively) with multiple 33 kernel-sized filters one after other. What is most important about the model, besides the capability of classifying objects in photographs, is that the model weights are freely available and can loaded and applied in your own models and applications.

3.3.3 Deep Residual Network: Deep Neural Networks are more difficult to train. Residual learning framework to simplify the training of networks that are deeper than compared with previously used. We explicitly reformulate the layers as learning residual function switch reference to the layer inputs, instead of learning un-referenced functions. We give comprehensive empirical evidence showing that these residual networks are very easy to optimize, and gain accuracy from considerably increased depth.

3.3 Method

The process begins with preparing a plan for the implementation of the system. According to this plan, the activities are carried out, discussions based on resources and the additional equipment has to be required to implement the new system. Implementation is the final and important phase. It is the most important stage in achieving a new system and also giving the users confidence that new system will work more effective.

3.4 Evaluation

The overall prediction accuracy and loss value are used to measure performance of the prediction of the work. It provides an interface to keep track of the performance during the validation of classifier on the dataset. TP(True positive) represents the positive events that are correctly predicted; TN(True Negative) represents number of negative events that are correctly predicted; FP(False positive) represents number of negative events that are incorrectly predicted; false negatives (FN) is the number of negative events that despite positive.

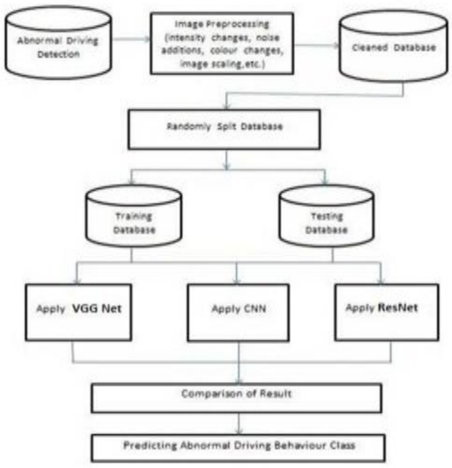


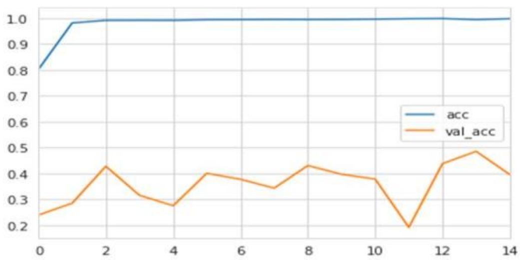
Chart 1: Methodology of abnormal detection

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

4. RESULTS AND DISCUSSION

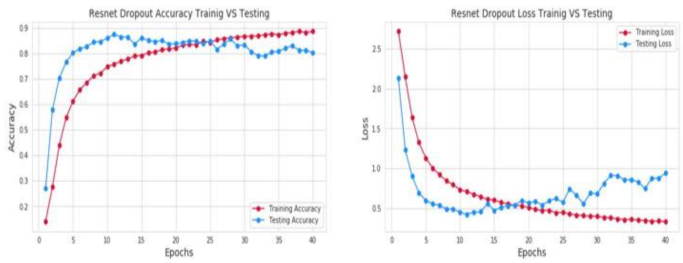
4.1 Training

Training accuracy and validation accuracy of the three models are shown below In the Figure 5.3 shows the training accuracy and validation accuracy of CNN. The number of training epoch is 15 and validation accuracy maximum achieved by CNN is 48.44 % and loss value 2.0584 on epoch 14.



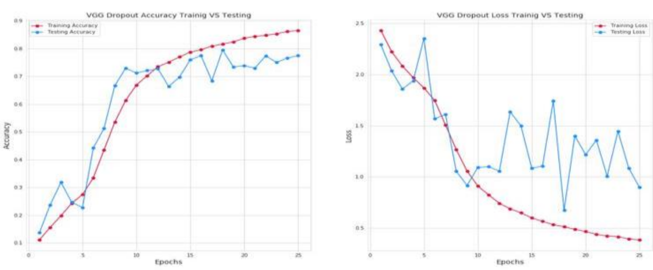
Graph 1: Training and validation accuracy of CNN

In the training and validation accuracy and training and validation loss of ResNet model. The number of training epoch is 40 and achieved maximum validation accuracy of 87.44 % and loss value 0.4245 on epoch 11.



Graph 2: Training and validation accuracy of ResNet

After the training accuracy and validation accuracy and training loss and validation loss of VGG16 Net model. The number of training epoch is 25 and achieved maximum validation accuracy of 79.51% and loss value 0.6737 on epoch 18.



Graph 3: Training and validation accuracy of VGG16

5. CONCLUSION

During this period detection of abnormal driving is more important also ensure safeties for drivers. Also receives vast popularity as it is an important step to realize fully automatic driving. In this study a deep learning based model introduced to fulfill the video based abnormal driver detection. Here we trained and tested the three deep learning models and measured the accuracy by each dataset known as Distracted driver dataset which is provided by Kaggle. Experiment based on distracted driver detection dataset.

6. ACKNOWLEDGEMENT

We take this opportunity to express our sincere gratitude to all those without whom this project would not have been a success. First of all, we owe our thanks to the Almighty for providing us the strength and courage to complete the project. We express our deep and sincere gratitude to our guide Prof. Roy TP (Department of CSE, Younus College of Engineering & technology) providing valuable advice and timely instructions, without which we could never have been able to complete the work in time.

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