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Detection of Abnormal Driving Behavior Detection Using ADBDConvolutional Neural Networks

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***Abstract*— Monitoring anomalous driving behaviours in real time is a critical component of increasing vehicle safety. To improve driver behaviour and driving practisesin order to avoid car accidents. The use of vision-based anomalous driving behaviour detection is growing in popularity because it is fundamental to the safety of drivers and passengers in cars and is a crucial step toward attaining automated driving at this level at this time. This difficult detection task can be greatly aided by recent advancements in deep learning approaches, such as advanced deep learning models' remarkable generalisation power and the large volumes of video clips required for completely training these data-driven deep learning models. To wrap off the research work, novel deep learning-based models, inspired by the newly developed and widely used fully connected convolutional network named the Abnormal Driving Behavior Detection (ADBD Net), are presented.**

***Keywords*— Abnormal Driving, Convolution Neural Networks,Monitoring Driving and Deep learning.**

I. Introduction

In accordance with World Health Organization (WHO) statistics, traffic accidents have risen to become one of the world's top ten leading causes of death[1]. In particular, traffic accidents claimed the lives of nearly 3500 people per day in 2014. According to studies, human factors, such as drivers' abnormal driving behaviours, are to blame for the majority of traffic accidents [2]. As a result, it is necessary to detect drivers' abnormal driving behaviours in order to alert them or report them to the Transportation Bureau so that they can be recorded.

In the evolution of society, transportation is critical. Demand for automobiles has risen considerably in recent decades as people's living conditions have improved and their disposable income has expanded. Generally driving is a difficult task on the road among the world. Several motor and cognitive talents will be acquired in order to drive. Inadequate human action is a primary contributor to traffic accidents. Imperfect perception, a lack of concentration, diverting attention to other tasks, and a low level of arousal have all been proposed as potential explanations of poor performance in various studies. A driver's ability to react effectively to critical events can be significantly impaired by driver tiredness induced by lengthy hours behind the wheel, as well as cognitive overload [3].

Understanding the causes of traffic accidents and the best ways to prevent them is crucial to improving traffic safety and driver well-being. At this time, high-resolution cameras are increasingly typically encountered in a wide range of visual applications. According to general consensus, anomalous driving conduct can be categorised into three categories. The first pertains to requirements such as smoking, drinking, eating, and adjusting the air conditioning, among others. The second category includes habits like as applying makeup, shaving, conversing, using cell phones or other distracting gadgets while driving, and so on. The third category includes distractions produced by the surroundings, such as caring for children, long-term unexpected events outside the vehicle, and so on. The usage of a cellphone has become a significant contributor to dangerous driving [5].

The rest of the research paper is organized as follows: The ease of use is reviewed in Section II. In Section III, we have detailed design and implementation of deep convolutional neural network techniques and classify the types of abnormal driving behaviors. We evaluate the performance and describe the experimental analysis of ADBD Net in Section IV. Finally, we give the conclusion and future enhancement remarks in Section V.

II. Ease of Use

Through Traffic Oscillation, Asymmetric Theory is Used to Identify Heterogeneous Driver Behavior Characteristics. To capture the driving characteristics of car-following behaviour during traffic oscillation [1,] the asymmetric driving theory is applied in this study [2–4]. The drawback is that it looks to be sophisticated due to the difficulty of machine learning algorithms and the demand for additional samples, which is a disadvantage. On the basis of Naturalistic Driving Study data, the researchers investigated the effects of various factors on right-turn distracted driving at intersections. The proposed technique detects the driver's behaviour while drowsy and issues an alarm. The drawback is that the deployment of ADAS indicators requires more precision. [3] A Review of Current Drowsiness Detection Techniques- This study provides a thorough examination of existing approaches for detecting driver drowsiness, as well as a detailed examination of commonly used classification algorithms. Thus, top supervised learning is used in this method, however the method appears to be inaccurate. [4] Deep learning fusions are used to detect abnormal driving behaviour in videos via video analysis. This work focuses on deep learning fusion techniques, and it is the first time that three new deep learning-based fusion models are given in this context [5]. Automated Driver Status Monitoring on a Small and Lightweight SBC Powered by a GPU. The system also uses PydMobileNet(PMN), which seems to have fewer number of parameters and FLOPs than MobileNetV2.As a result, this process is more efficient and resilient, and it takes less time; nevertheless, the cost is higher, and the accuracy is lower.

Using physiological signals to track diver behavior using a machine learning algorithm that is ensemble and evolutionary[6]. The performance of the K- nearest neighbours, SVM, and naive Bayes algorithms is increased in the initiative using bagging, boosting, and voting ensemble learning methodologies. [7-11] Hybrid method enabled Manoeuvre classification and trajectory prediction using AI for vehicle behaviour prediction. The Long Short-Term Memory (LSTM) and Next Generation Simulation (NGSIM) public datasets provide real driving data in this paper, which is used to propose a hybrid approach to neural networks and trajectory prediction. The downside is the high implementation cost.

Researchers are using deep learning to change people's behaviour by detecting inattentive and aggressive human drivers, among other things. Driver Distraction (DD), Driver Fatigue (DF), and Drowsiness (D) are the three main categories of HIDB. The downside is that it is not very accurate in this case. Fuzzy-Clustering Analysis for Determining Drivers' Risk Perception in Road Safety A driver categorization discriminant model was created using Fisher discriminant analysis [9]. Identify the driver's dangers as soon as possible. The disadvantage of the paper is that it requires experiment reception in order to obtain accuracy. Based on on-road experiment driving data, a dynamic Bayesian network approach is used to assess vehicle driving risk [10]. They use a dynamic Bayesian network in this study to perform an inferential analysis of driving-related risks based on our research of real-world driving data. The downside is that the algorithms are complicated.

III. METHODOLOGY

Extraction of Features CNN retrieves high-level information from images, such as concealed objects [10]. Latent features, also known as hidden features, are features that we don't see immediately and which we extract here. Features extracted from images are automatically extracted by the Convolutional Neural Network (CNN). CNN gathered features from middle layers, which improved classification accuracy, according to the study.

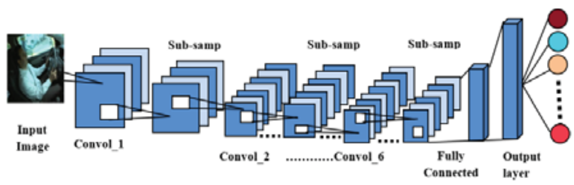


Fig. 1. CNN Model Architecture[2]

The Figure 1 explores the architecture of Convolutional Neural Network Model. CNNs are biological processes in which the network of connections between neurons has a structure similar to that of the visual cortex of an animal, as opposed to other neural networks. Unlike other neurons in the brain, individual cortical neurons can only respond to stimuli that are within their respective receptive fields, which are only a small portion of the visual field. In some cases, distinct neurons' sensitivity areas may partially overlap, allowing them to cover the whole field of vision. When compared to other image classification methods, CNNs require minimal pre-processing. This demonstrates that the network understands the filters that were previously hand-crafted in traditional algorithms, demonstrating that the network is intelligent. It is important to note that this feature design is completely independent of prior knowledge and human effort. A tensor with shape is used as the input while programming a CNN.

IV. EXPERIMENTAL ANALYSIS

Dataset in kaggle, you may use the distracted driver detection database. They contain a variety of colour frames (i.e., photos) of drivers in varying sizes. There are a total of 22,424 photos in this collection. Each image has a pixel size of 640*480 pixels. All of the photos can be divided into ten categories, each of which represents a particular driving pattern. The Figure 2 shows the drivingbehaviours which was listed in table 1as follows:

TABLE I. DATASET CLASSES

safe driving	operating the radio
texting using right hand	drinking,
talking phone usingright hand	reaching behind
texting using with left hand	hair and makeup
talking phone using left hand	talking to passengers

Fig. 2. Sample image for distracted driver detection database[3]

Data augmentation is used to increase the database's ability to handle advanced deep learning models. This stage involves performing a variety of image pre-processing operations on the image before it is saved, such as noise addition, intensity modifications and colour adjustments. At this point, the training and testing databases have been completed and all images in the database have been randomly and fairly separated into two half and then reconstructed. There are 32 batches, 10 training epochs, and a learning rate of 0.0001 per epoch in deep learning models. The above-mentioned parameters were pre-defined after extensive testing to guarantee the greatest possible detection performance. As a result, the three new deep learning-based fusion models have a higher training efficiency than traditional deep learning models, while having more parameters than the bulk of the conventional models. All training sessions are completed on a workstation with an Intel Core i3 processor, 4GB of RAM, and a Python Jupyter notebook.

The overall prediction accuracy and loss value are used to evaluate the work prediction's performance. It gives you a way to maintain track of your classifier's performance while it's being validated on a dataset. T_P, T_N, F_P, and F_N are all denoted in Table 2 as the number of positive events correctly predicted, the number of negative events correctly predicted, the number of positive events incorrectly predicted, and the number of negative events that occurred despite being positive (False Negative).

TABLE II.CONFUSION MATRIX

Predicted_Class \ Actual_Class		
	True_Positive	False_Positive
	False_Negative	True_Negative

Recall, Specificity, F-Score, Accuracy and Precision which are used to evaluate the proposed ADBD_Net Model performance. The total number of true predictions made by the ADBD_Net model over all types of predictions made is called accuracy in classification problems, and it may be determined using equation 1-5.

$$Acc = \frac{t\_p+t\_n}{t\_n+f\_p+t\_p+f\_n} \tag{1}$$

$$Re = \frac{t\_p}{t\_p+f\_n} \tag{2}$$

$$F-Score = 2\frac{Precision\ X\ Recall}{Precision+Recall} \tag{3}$$

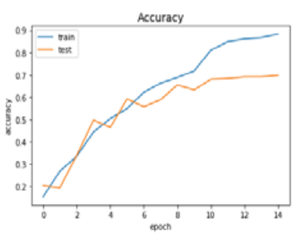
$$Specificity = \frac{t\_n}{t\_n+f\_p} \tag{4}$$

$$Pr = \frac{t\_p}{t\_p+f\_p} \tag{5}$$

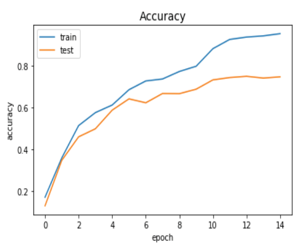
TABLE III. CONFUSION MATRIX OF DISTRACTED DRIVER DETECTION DATABASE

	SD	TRH	TPRH	TLH	TPLH	OR	D	RB	HM	TP
SD	91.4	1	0.8	0.5	1.1	0	0.2	0	0	0
TRH	0	91.6	1.4	1.1	0.9	0	0	0	0	0
TPRH	2.3	0.7	90.2	1.6	0	0	0.2	0	0	0
TLH	2.3	0	1.4	90.6	0.7	0	0	0	0	0
TPLH	0.7	0.2	0	1.1	92.8	0	0	0	0	0
OR	0	0	0	0	0	89.2	0	0	1	1.6
D	0	0	0	0	0	0	93.7	6.6	0.4	1.7
RB	0	0	0	0	0	0	0	90.6	2.6	1.9
HM	0	0	0	0	0	0	0	9.6	89.7	0.7
TP	0	0	0	0	0	0	0	3.3	0.7	89.5

The figure 3 (a) and (b) shows the proposed model accuracy for Elu and ReLU activation function.



(a) Accuracy for 'ELU'



(b) Accuracy for 'ReLU'

Fig. 3. (a) and (b) Accuracy of proposed model for different activation function

V. CONCLUSION

The exploration of video-based aberrant driving behaviour identification is critical today because it is a dependable and automatic approach of assuring driver safety that can be deployed. At this time of year, it is especially important to detect unusual driving patterns, as is ensuring river safety. It is also quite popular because it represents a significant step toward the eventual implementation of fully automated driving. Using video footage, a deep learning-based model was developed to identify potentially dangerous drivers in this study. For the training and testing of the three deep learning models, as well as for measuring their accuracy, we used the Distracted driver dataset provided by Kaggle. Use a dataset of distracted drivers to conduct your experiment.

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