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Prediction of Crash Risk based on Driving Behaviour

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Abstract: The major interest which is increasing for many kinds of applications includes human driver's characterisation. There are different promising approaches in order to characterise the drivers by means of control theoretic driver models. The driver state is monitored by applying features of driver model from survey till real road distraction experiment. The dataset for the experiment consists of driving behavior with visuomotor and even few secondary tasks like auditory and even driving reference. The individual estimation of model parameters uses data of driving of nearly eleven drivers for error prediction identification. Few hand gestures and head movements are gentle way of getting distracted by drivers which covers many states like eye closure either short or long term. This paper represents the distraction detection system with the help of attention strategy. By matching the scaled features, the transformation of frontal face of the driver, driver recognition can be made. The severity of accident zone is found in particular area based on dataset. Driver behavior at particular hotspot location is found which is considered as the accident hotspot in order to gain better accuracy. The results help in validation of robustness and effectiveness of the model. The solution is defined in this paper which helps in reduction of road accidents which is mainly caused by distraction of driver.
Index Terms: Distracted driving, Aggressive driving, Crash Risk, Driving Behaviors

I. INTRODUCTION

The dangerous behaviour found in day-to-day human activity is DRIVING. Many people get injured and even some get hospitalized even after so much of efforts. To reduce these kind of crashes governments and many different manufacturers have implemented networks for transportation and even to add many different assistance related things for the driver. Usually, the tracking of such kind of systems involves the camera and even radar in order to look over the surroundings of the vehicle and to mediate with the incident which may takes place. Many examples wrt this incident can be found which include driver alerting during signals, brake activation for vehicle collision. Obviously, crash systems have made contributions positively for the safety. These kind of systems gets activated during the errors which occurs seriously or when the error will occur. Majorly they aim to focus on the vehicle's position and the driver behavior which notes for complete crashes and this can be limited. So, it's better to prevent before the crash occurs.

The major habitual behavior of the driver is the distracted and the aggressive behavior of the driver, which is difficult to note down and even to fix it out. There's no good system in order to know these kinds of behaviours, if it is found the control for the driver couldn't be taken. So, based on the automation driving different levels of driving assistance can be expanded. Example, the vehicle with high condition and automation will persist for the repeated alerts and the vehicles with partial automation can detect for the dangerous behaviour. Similarly different kind of vehicles will be having different kind of behaviors to be detected.

So, here in these different methods and algorithms are used in order to predict the severity of the accidents and the hotspot for the accidents can be found which is caused by different driver distraction and even may be due to road interruptions.

But majorly, distraction is taken into consideration.

II. RELATED WORK

Work is directly attached for various sets of safety related to driving.

Driver monitoring comes as the first set of the data. The classification based on distraction of the driver. The main objective of monitoring the driving behavior is to find out the state such as psychophysiology which is very dangerous behavior of driving. Accordingly, the stress is the major question. The efforts of the stressed behavior are majorly classified based on different classes like, no driving, highway driving and even city driving. And few other researches are based on the surrounding like based on different road conditions. Even based on different elevated regions the stress can be defined.

The majority seen stress was found when the driver goes in elevated region or if some other vehicle overtakes. This kind of approach is seen in small datasets. Many experienced psychologists fail while analysing the people when they are looking at the videos.

The distraction notation comes from very accurate applications for different stressful actions of the driver in variety of phases while driving and for accounting on different factors.

These kinds of notations can be examined, as the distraction will be self-biased based on the environmental conditions. Upon that, the dataset also contains variety of stimuli which will induce the physical distractions, which provides different set of scenarios.

Other important feature of driving behavior is to use the data analytical method. many studies include different subjects, which can be tracked based on the recordings of it. Lets say for n number of subjects there are n seconds of sliding window for nearly 4n time in minutes which boosts the power of sampling. The importance of accuracy based on different subjects plays very important role because of variety of people who drives.

Curiously, the pre-processing and many other methods like feature extraction are used for detecting the driving behaviours. It includes many statistical metrics like heart rate and many other dermal activities, and the respiration, as well as the detection of conductance of skin.

The studies which deal with very few signals will focus mainly on the spectral features or may be the detection for peak points. The recurrence that are used for analysing the spectral features, but some are not still clear. Generally, there is no proof for many useful features which are being figured out. In order to address this, the physiological features must be taken into consideration. Evaluation process must be taken place based on many informative resources. The overall reduced feature acts as the dataset for this model.

The algorithms of machine learning play a vital role in effectiveness for the model. Bayesian network are used for static or dynamic kind of data, many a times the discrete variables can be provided for the decision tree. The middle variable will always be binary to check whether the stresses of the driver. Remaining variables will be continuous such as road events. Bayesian network usually provides a good walk through for probabilistic framework. The rendering of the model is done to avoid the overfitting of the model. But finding out the prior probability is mandatory. For this reason, faster R-CNN, VGG-16, Inception-V3 are used in order to avoid the overfitting, and also to best train.

Totally, the method varies from previous studies till the different distractions and methods which are being used now a days. Only physical distraction will be found now a days which is monitored with the help of computer vision. For example, the blinking of eye, mouth movements and to check for the drowsiness. Similarly, many other different systems are used to differentiate between different distraction such as the changes in the radio stations or interacting with the maps and navigations. Many physical distractions may also be the reason for it.

Comparatively, this approach takes into picture for both physical as well as the mental distraction. And it also tries to mix out with physiological and behavioural, for short term prediction. The goal is to alert the driver about the predictable bad behaviors.

III. METHODS

A. Dataset

The two different kinds of datasets are used. One which contains the different distraction behavior of the humans while driving and the other which contains weather data, holiday data. So, that it helps to predict the severity of the accident in particular place. The unprecedented climatic changes affect the way of driving. Holidays dataset provides an insight of traffic congestion on the road on holidays as well as on regular days.

Different levels for consoling the electrification are being captured using different attributes present in the dataset. The dataset provides well defined parameters necessary to add the predictions based on behavioral information. Naturally the classification is based on the values provided by the dataset.

B. Pre-processing

The dataset present is being pre-processed like filtering away the boundaries of the distraction.

The pre-processing of grayscale conversion is to collapse the data, because processing raw kind of image is bit impossible. It actually helps to reduce the wok of the algorithm which we will use.

Image resizing is done in order to train the model faster on small sized images. So, this critical step is necessary for the vision of the computer.

Data augmentation is made to make the slight changes in order to increase the diversity without the collection of new data. This technique is also used to increase the size of the dataset. It helps in preventing the irrelevant features for better performance. Real time dataset requires online augmentation and the smaller dataset requires offline augmentation.

The shifting of image pixels, Rotation for specific degree, Increasing or decreasing the contrast of the image.

C. Feature Extraction

1) *Head Movements:* At regular intervals the change in the movement of head is captured for determining the consciousness while driving
2) *Hand Gestures:* During driving there exists both valid hand gestures such as changing the position of the palm on steering wheel, moving the hand for honking the horn, adjusting the mirror and invalid gestures such as operating the radio, mobile phones, music player, eating etc.
3) *Change in Body Posture:* It collectively includes the features of head movements and hand gestures. It also includes turning of body, deviating from the track site.

D. Algorithms

Customised CNN

Faster CNN is used to train the model which acts as a detector network from end-to-end. It saves time from other algorithms being compared. This algorithm or methodology is considered because the whole network can be accurately predicted from different objects and the computations from the model can happen parallelly.

1) *VGG* **-** 16 algorithm, as the name itself suggests that this takes 16 layers deep down the network. The pretrained data can be loaded from the database named as ImageNet database. It is used for object detection and even for classification with more accuracy. The very different thing about this algorithm is they don't use large number of hyperparameters instead they focus to work on having convolution layers of different strides.
2) *Inception* **-** V3 algorithm recognise the images from the ImageNet dataset. The pretrained version of the trained network helps in classification of the images. The optimisation is the network is easier and the network is deeper.

E. Multiscale Predictions

As this project takes multiple factors into consideration as the input for better accuracy, collecting the multiple factor information in the defined format is a slight complex task which has to be dealt for better processing. The main aim of this study is to maximize the accuracy in detecting driver cognitive distraction by using a new experiment design and method applied for the first time for this research issue.

IV. RESULTS

The accuracy of the model can be predicted with the help of the plots in which it alerts the driver who gets distracted. The model also provides the epoch results in order to find the total number of passes from the whole training dataset and this helps the model to represent the samples with much less errors.

Few patterns which were predicted for distraction is also used for many other aggressiveness of the driver. So, according to the dataset the findings of distractions based on the gestures and postures of the driver is monitored and even the weather condition and the holiday condition is also considered to predict the severity of the accident at different locations.

The model also draws different functions from different variables i.e., from imaging and even by driving behaviour variable. So, the overall combination outperforms the whole individual dataset which supports the result during driving.

As a whole, python application helps in visualising the predictions based on experimental analysis.

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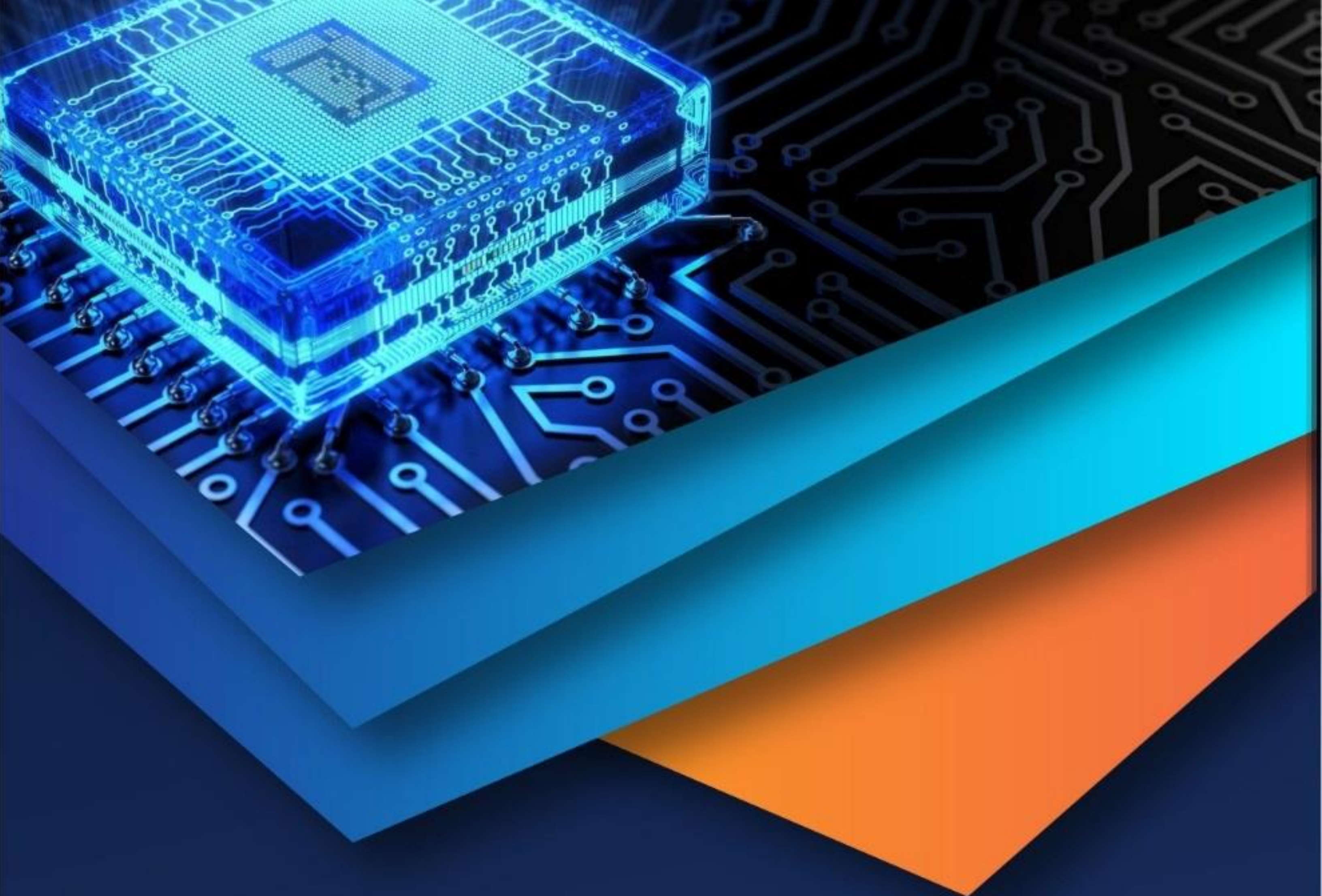

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