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Driver Distraction Detection and Classification using Machine Learning

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Abstract: One of the most critical problem overcome in India is death caused by the road accidents. Almost 80% of accidents are happen due to driver distraction. We attempt to develop robust system for detecting Driver distraction. There are some methods to detect it but that consumes more time. It is important to early detect the distraction, inform to the driver about the distraction. So, computer-based application needs to be developed to detect this distraction as early as possible and minimize the risk of accidents. The aim is to develop a simple and capable method to detect the distraction. There are some proposed methods that contain following stages, preprocessing, feature extraction and classification. To increase the accuracy of the result we use two layer neural network. ELM, softmax are used for feature extraction and SVM-ELM and method is used for classification. The accuracy of proposed method is 97.2% which shows its reliability.

***Index Terms* - Driver distraction, SVM , CNN, classification, machine learning.**

I. Introduction

One of the most critical factor in India is Distracted driving that causes severe car accidents. This was proposed as a potential contribution to the increase in accidents between 2013and 2018, and is a subject of increasing public concern[1]. Similar diversion behaviors are reported to have similar chance of causing accident[2]. Therefore it is important to properly identify and categorize distracting behaviors through images of drivers in their driving. The "distracted driving" is a persistent problem that attracts media, policy-makers and researchers' attention. The "distracted driving" is a persistent problem that attracts media, policy-makers and researchers' attention.

According to the World Health Organization, 1.3 million people have died in the last decade, and 3.3 million people have caused physical damage in India due to road accidents. Many of these incidents occur due to distracted drivers (for example, while driving using a mobile phone)[5].Road crashes have emerged among the most successful age groups from 18 to 25 as one of the top causes of death. As per the report of NCRB govt. of India. According to the study, the total number of deaths in 2015 was 1.45 lakes and driver distraction was the most common reason for these accidents[3].Above fig 1 shows that the causes of Distraction such as texting ,watching videos, using the GPS, looking in the mirror ,reading and using cell phone is the most common reason for distraction of driver.

Fig 1 : **Example of distraction**

There are three types of distraction which are most happen manual, cognitive, and visual distraction[6]. •Manual Distraction:-taking your hands off the wheel (for ex using cell phones like texting, talking. or doing any activity which diverts driver mind from safe driving)•Visual Distraction:-taking your eyes off the road(for ex adjust radio, texting on phone)•Cognitive Distraction:-taking your mind off of driving(for ex talking to a person).

II. LITERATURESURVEY

There are so many researchers who are working on driver distractiondetection using computer-based approach [13]. There are many researchers who work on driver distraction throughout the world. Most of the researchers uses machine leraning methods to improve the result, such as support vector machine , Naive Bayes, Decision Tree, softmax , convolution neural work (CNN)-basedmodels. Below is the table which summaries the different techniques used in different papers for detecting driver distraction.

TableI Related Work

Ref.no	Author	Name of paper	Description	Accuracy
[1]	M. Bayly, K. L. Young, and M. A. Regan	"Sources of distraction inside the vehicle and their effects on driving performance,"	A large number of activities performed while driving .so we developed IVIS system.	66%
[2]	S.G. Klauer et al	"Distracted driving and risk of road crashes among novice and experienced drivers,"	We develop the IVIS system, With the rapid development of IVISs that interact with drivers	78%
[3]	J. Engstörm and T. W. Victor	"Real-time distraction countermeasures,"	collision system adjustment when a potential collisions estimated	80%
[4]	H.Zhang, M. R. H. Smith, and G.J. Wit	"Identification of real-time diagnostic measures of visual distraction with an automatic eye-tracking system,	We identify the visual distraction using eye tracking in real time.	74%
[5]	N. Li and C.	"Predicting perceived visual and cognitive distractions of drivers with multimodal features,"	We identify the types of distraction using multi model feature.	84%
[6]	V. Garla, C. Taylor, and C. Brandt	"Semi-supervised classification and Laplacian SVMs: An application to cancer case management,"	This method used in this paper for text classification	87%
[7]	Y. Liang and J. D. Lee	"A hybrid Bayesian network approach to detect driver cognitive distraction,"	A naïve bayes method is used to find eye distraction	90%
[8]	W.Liu, J.Qian, Z. Yao, X. Jiao, and J. Pan	"Convolution Two-Stream Network Using Multi-Facial Feature Fusion for Driver Fatigue Detection"	CNN used to detect facial feature of driver distraction	94%
[9]	C. Agarwal, A. Sharma	"Image Understanding Using Decision Tree Based Machine Learning"	We use decision tree to classify the images	72%
[10]	Oyini Mbouna, R., Kong, S., Chun, M.-G	"Driver visual distraction detection using driving performance measures"	for driver alertness monitoring we develop system	86%

III. DATASET

The Dataset has been collected the training images from kaggle site[12]. Which consist the diverse set of images, with variations in different classes. State Farm provided the dataset used in this project through a Kaggle competition, which if a set of pictures of drivers taken inside a car capturing their activities such as texting, talking on the phone, eating, reaching behind, making up, etc[9].

Figure 2 **: Driver distraction detection dataset**

These activities are classified into 10 classes as:

- +c0 : safe driving
- c1 : texting–right
- c2 : talking on the phone-right
- c3 : operating radio
- c4 : drinking
- c5 : reaching behind
- c6 : texting-left
- c7 : hair and makeup
- c8 : talking on the phone-left
- c9 : talking to a passenger

Figure 3 : **Classes of dataset**

IV. METHODOLOGY

We use different models for identification and classification in this paper. As we saw in above table no of different methods are used in different paper for classification of data and improve the result. In this paper we use following methods.

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4.1 The Semi-Supervised Extreme Learning Machine

Semi-supervised Extreme Learning Machine (SS-ELM) is a newly developed semi-supervised, ELM-based learning algorithm and multiple regularization framework[13][8] Compared to its supervised origins, SS-ELM is proposed to improve productivity by combining both labeled and unlabeled SS-ELM data inherits ELM's outstanding performance advantages as compared to other semi-supervised algorithms and obviously able to handle multiclass problems[14][11].

Under a multiple regularization model, SS-ELM assumes that the high-dimensional input data of each class is centered on a low-dimensional data collector, and that the ideal separation hyper plane is 'smooth' relative to the manifold[15].In other words, input data close to one collector should have expected class labels identical to those that can be formulated to mitigate the following regularization form

$$l_m = \frac{1}{2}\sum_{i,j} w_{i,j} \,||f_i - f_j||^2 \qquad (1)$$

where $fi$and $fj$are the forecast with respect to represented xi and xj. The above form

$$l_m = T_r(F^t LF) \qquad (2)$$

Where L= D–W is known as the graph Laplacian.

4.2 Softmax

After the SSELM we now saw the softmax method. The loss function is calculated as below:

$$L \;=\; \frac{1}{N}\sum_{I=1}^{N} -\log\left(\frac{\exp\ f(x_{i,W})y_i}{\sum_j \exp\ f(x_{i,W})j}\right) + Y||W||_2^2 \qquad (3)$$

where the definition of xi,yi.

4.3 Two-layer Neural Network

The final method we find is a neural network of 2 layers. Figure 4 demonstrates the Neural network architecture. We use softmax enabling feature for final classification for the output sheet

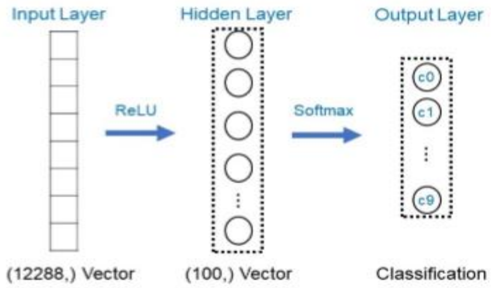

Fig 4 : Architecture of this two-layer neural network

Neural networks are a collection of algorithms designed to identify patterns, which are loosely modeled after the human mind[11][12].They perceive sensory data through some form of machine perception, marking, or rawinput clustering.A neural network is a computer system made up of a number of basic but highly interconnected components or nodes, known as neurons or organized into layers that process information using dynamic state responses to external inputs[17][18].Throughout neural networks, a hidden layer is located between the algorithm's input and output, in which the function applies weights to the inputs
and guides them as the output through an activation function[16]. In short, nonlinear transformations are carried out by the hidden layers of the inputs inserted into the network[19].

V. RESULTS AND DISCUSSION

All the experiments were performed in MATLAB. It gives average accuracy of 95.2% which is far better than referred work performed by using navie bayes, softmax and SVM classifier. The results are shown in Table II.

Table II: **Training and validation Set of Different models**

Classifires	Training Acc	Evalution Acc
Navie bayes	NA	56.48%
ELM	74%	76.63%
SVM ELM	78%	80.8%
Softmax	82.4%	83.4%
Two layer network	90.54%	**95.2%**

Table III: **Accuracy per class on Two Layer net**

Class	Acc
Safe driving	89.25
texting– right	96.66
talking on the phone- right	97.80
operating radio	88.68
drinking	95.72
reaching behind	97.34
texting- left	98.55
hair and makeup	**70.54**
talking on the phone- left	**78.46**
talking to a passenger	98.56

VI. CONCLUSIONS

In conclusion, we successfully implemented proposed system using different machine learning methods for best result among them. The paper is mainly based on a study of how accidents are detected and prevented. This also ensures the safety of both the driver and the public. In this paper discussed various solutions such as collisions. Driver distraction is a serious problem that has led to a large number of road crashes worldwide. Detection of the distracted driver is therefore an essential component of the system in self-driving cars. We have also implemented a two-layer Neural Network model that performs well on the distracted driver detection task and gives 95.24 percent accuracy in evaluation. Classification is performed on extracted features. Our proposed imaging system classifying the imagesinto10 different types of classes .The results are shown in the table III which provides 97.2%accuracy.
Future work would focus on creation of database that contains most basic reason for driver distraction. This would lead to evaluating the performance of various machine learning algorithms as regards the efficiency, accuracy of detection and classification of the various classes.

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