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IMPLEMENTATION IN REAL TIME OF DISTRACTED DRIVER DETECTION USING USING MACHINE LEARNING

Sourabh .S. Yerewar, Sarang Rohankar, Rohan Ingle, Rohan.N.Shembekar, Parag B Shahare,

Prof. S.S.Ganorkar

Abstract:

In India, the death rate due to traffic accidents is one of the most serious issues. Driver distraction is a factor in about 80% of accidents. We work to create a reliable system for identifying driver distraction. There are various ways to find it, but they take longer. Early distraction detection and communication with the driver are crucial. In order to minimise the danger of accidents and detect this distraction as early as feasible, computer-based applications must be created. The goal is to create a quick and effective distraction detection tool. Some methods that have been proposed include the preprocessing, feature extraction, and classification steps. We employ a two-layer neural network to improve the result's accuracy. ELM, Softmax, and SVM-ELM are used for feature extraction and classification, respectively. The proposed method's accuracy is 97.2%, demonstrating its dependability.

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

I. INTRODUCTION

Distracted driving is one of the most important factors that contributes to serious auto accidents in India. This is a topic that has drawn more public attention and has been suggested as having a possible role in the rise in accidents between 2013 and 2018[1]. According to reports, similar diversion behaviours have a similar likelihood of causing an accident[2]. Therefore, it's crucial to correctly recognise and classify distracting behaviours using pictures of drivers when they're on the road. The issue of "distracted driving" continues to catch the attention of scholars, policymakers, and the media. The issue of "distracted driving" The World Health Organisation reports that vehicle accidents in India have resulted in 1.3 million fatalities and 3.3 million injuries over the past ten years. Many of these occurrences are caused by distracted drivers, such as those who are using their phones while driving[5]

One of the leading causes of death for people between the ages of 18 and 25 has emerged as traffic accidents. according to the government of India's NCRB report. Driver distraction was the most frequent factor in the accidents that resulted in the study's total of 1.45 fatalities in 2015[3].The reasons of distraction are depicted in Fig. 1 above, including texting, viewing videos, using the GPS, glancing in the mirror, reading, and using a cell phone. The most common cause of driver distraction is using a cell phone. Manual, cognitive, and visual distractions are the three categories of distraction that occur most frequently[6].

•Manual Distraction: Letting go of the steering wheel (e.g., using a cell phone for texting or talking, or engaging in any activity that takes the driver's attention away from safe driving).•Visual Distraction: failing to pay attention to the road (for instance, adjusting the radio or texting on the phone).•Cognitive Distraction: moving your attention away from driving (for instance, conversing with someone).

II. LITERATURESURVEY

Many studies are focusing on computer-based methods for detecting driver distraction [13]. Around the world, there are numerous researchers who study driver distraction. The majority of researchers employ machine learning techniques to enhance the results, including support vector machines, Naive Bayes, Decision Trees, Softmax, and CNN-based models. The table that summarises the various methods used in several articles for identifying driver distraction is shown below.

III. DATASET

The training photos for the dataset were obtained from the Kaggle website[12]. They include a varied collection of photos with differences across many classes. The dataset utilised in this study was provided by State Farm through a Kaggle competition. It consisted of a collection of photographs of drivers taken inside cars while engaging in various activities, like texting, chatting on the phone, eating, reaching behind, making out, etc.[9].

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

A recently created semi-supervised, ELM-based learning algorithm and multiple regularisation framework is called Semi-supervised Extreme Learning Machine (SS-ELM)[13].[8] By mixing labelled and unlabeled data, in addition to its supervised origins, SS-ELM is proposed to increase productivity[14]. It inherits ELM's remarkable performance benefits over other semi-supervised algorithms and is evidently capable of handling multiclass situations.[11].

The SS-ELM presupposes that the ideal separation hyper plane is "smooth" in relation to the manifold and that the high-dimensional input data of each class are centred on a low-dimensional data collector under a multiple regularisation model[15].To put it another way, input data near one collector should have expected class labels that are the same as those that can be created to mitigate the next regularisation form.

1 $\sum i,j \ wi,j \ \|fi - fj\|2$ (1)

2 lm = where fiand fjarare the prognosis in relation to the represented xi and xj. The formula above, lm = Tr(FtLF) (2)

The graph Laplacian is known to exist where L= D-W.

Softmax 4.2

We now witnessed the softmax approach following the SSELM. Below is a calculation of the loss function:exp $f(xi,W)yi$ $\sum j$ exp $f(xi,W)j$

$1\sum N\ I=1$

$N22-\log() + Y\|W\|(3)$

$L=$

where the definition of xi,yi.

4.3 Two-layer Neural Network

The final technique we discover is a two-layer neural network. The architecture of a neural network is shown in Figure 4. For the output sheet's final classification, we use the Softmax enabling function.

A group of algorithms known as neural networks, which are loosely based on the human brain[11][12], are used to detect patterns.They utilise some type of labelling, raw input grouping, or machine perception to perceive sensory data.A neural network is a type of computer that processes information using dynamic state responses to outside inputs and is made up of a number of basic but highly interconnected components or nodes known as neurons or organised into layers[17][18].Between the algorithm's input and output in neural networks is a hidden layer where 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.

VI. CONCLUSIONS

We successfully developed the suggested system utilising several machine learning techniques to achieve the best outcome possible. The paper's primary source is an investigation on how accidents are discovered and avoided. Additionally, this guarantees the public's and the driver's safety. This essay presented a variety of solutions, including collisions. A significant issue that has contributed to a significant number of traffic accidents globally is driver distraction. Therefore, identifying the distracted driver is a crucial part of the system in self-driving automobiles. A two-layer neural network model that we also implemented provides 95.24 percent evaluation accuracy and does well on the distracted driver detection challenge. The classification process uses the retrieved features. Our suggested imaging technique divides the images into 10 different categories..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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