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A Distracted Driving Detection Model Based on Driving Performance

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ABSTRACT: Driver distraction leads drivers toward accidents that affect lives, i.e., driver death or major injuries and causes of economic losses, globally. In the literature, several techniques have been introduced to detect driver distraction in an efficient way. However, their techniques are time-consuming, have a high false alarm rate and are difficult to deploy on edge devices due to the high number of parameters. To solve a certain problem, we proposed a novel framework for an efficient and effective driver distraction based on a CNNs with the integration of CAmechanism. Moreover, the proposed model contains three steps, such as training, testing and evaluation. Additionally, our proposed model is compared with various baseline CNNs where only the classification layers were fine-tuned while the rest of the models' layers were frozen. Moreover, the proposed model achieved optimal results in terms of testing accuracy and testing loss using two well-known datasets. The proposed model indicated 99.58% testing accuracy using the SFD3 dataset and 98.97% testing accuracy on the AUCD2 dataset. In other words, the proposed model can easily be deployed on resource constraints devices due to its size and less computational complexity. Further, due to the rapid increase in the developing technologies, the metaverse provides us a great opportunity for better contributions such as the implementation of our proposed work in metaverse-based 3D modeling.

KEYWORDS: convolutional neural network; driver distraction detection; driver behavior ANALYSIS

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.

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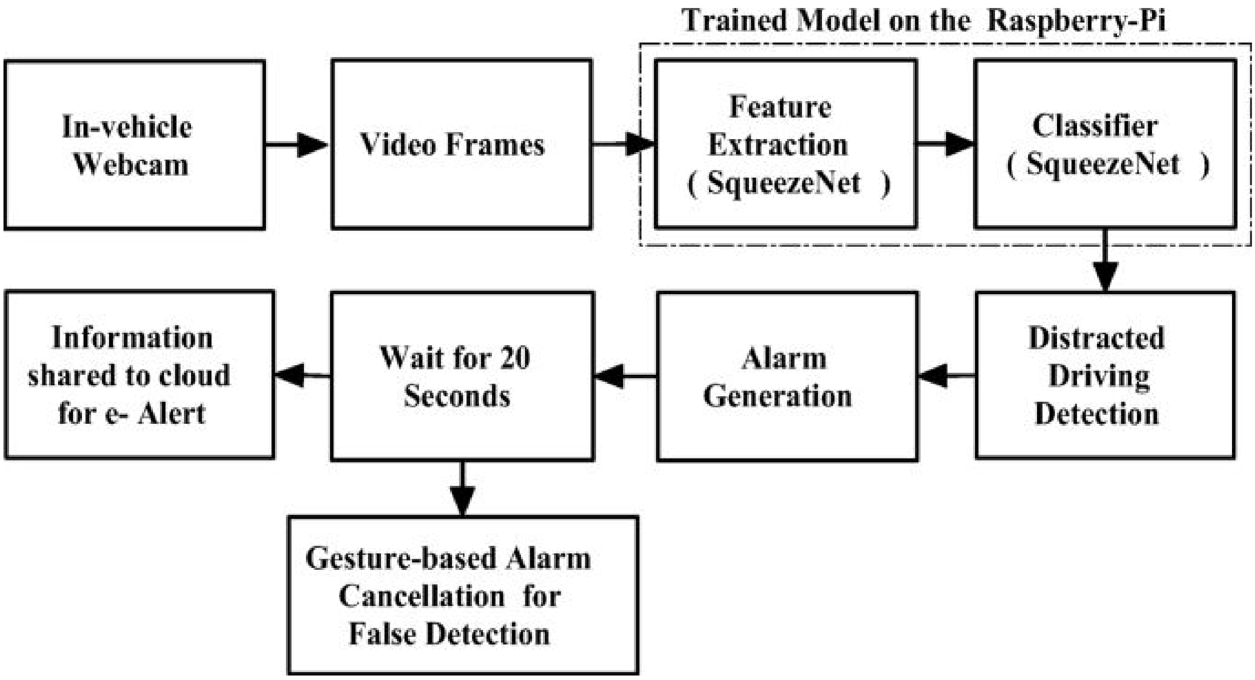

Fig 1: work flow of distracted driving

Coincidentally, India forms the largest portion of the worldwide fatality rates related to traffic accidents. Driver distraction, in its simplest form, is the act of operating an automobile while engrossed in another activity, most frequently using a smart phone or other devices, such as the stereo while driving or other related operations. 47% of respondents to a countrywide poll organised by TNS India Pvt Ltd reported taking calls while driving. The poll also infers that the dangers of using a phone while driving are viewed negatively by 94% of respondents. When a motorist is on the phone, 96% of occupants feel insecure, while 41% of drivers admitted to using their handsets for work or business related purposes. Furthermore, 60% of individuals are unwilling to pull over in a secure place and answer their phones, and 20% people have had close calls while operating on their cell phones. This goes to show that the advent of smartphones has worsened the already existing issue of drivers getting distracted and has led to the compromise of passenger safety as well. Moreover, distracted driving would go against the law in many jurisdictions and is subject to fines, licence revocation, and other sanctions.

II.LITERATURE SURVEY

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.

Distracted driver classification primarily incorporates two classical approaches. The first approach involves using wearable sensors that measure brain signals, heartbeat data and data from muscular activities. However, this approach could sometimes prove not to be cost effective or complex hardware with high involvement from users. The other approach involves using camera vision systems to detect and classify the type of distraction. They commonly make use of deep learning techniques to perform the feature extraction and classification tasks. While the first approach can detect cognitive distractions, the second one can detect manual and visual distractions. Hence, it makes sense that the two methods could be used in tandem to ensure efficient detection. In this paper, we discuss various methodologies that involve both the above mentioned approaches vividly.

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Ezzouhri et al. [1] propose using a segmentation module before performing the classification task to reduce noise in the image eg. background that could contribute to misclassification. In order to do this, they use a human body part segmentation technique called Cross Domain Complementary Learning (CDCL) on raw RGB images obtained from an onboard camera. This segmentation module outputs body part maps of the driver. The authors have designed their own dataset called the Driver Distraction Dataset to train the classification module that makes use of the VGG-19 network that is by itself, trained on the ImageNet dataset. The procedure followed to train the network is transfer learning, by unfreezing some multiperceptron layers for fine-tuning to match the dataset at hand. The authors have also experimented with the Inception V3 network and found it to output similar accuracy scores. Experimentation shows that segmenting the images appreciably boosts the accuracy rates of classification. The authors were able to obtain accuracy rates of 96% and 95% on their dataset and the AUC dataset respectively.

Shokoufeh, et al. [2] used driving data to identify driver distraction using a stacked LSTM network enhanced with an attention layer. To demonstrate the benefit of using an attention mechanism on the model's performance, they contrasted this model with stacked LSTM and MLP models. They tested eight different driving situations. Here is a quick summary of the steps involved: First, the original dataset was divided into training and test datasets, and an MLP model was employed to detect distracted driving (80:20 split). The system's intelligence was then increased using an LSTM network. The LSTM network was chosen because it uses driving data to recall the driver's prior behaviours to forecast the driver's behaviour, rather than simply using the driver's instantaneous actions. Additionally, LSTMs have the benefit of having both long-term and short-term memory. They also have the ability to forget irrelevant information that does not advance the system's intelligence. These LSTM characteristics contribute to a significant performance improvement over traditional RNN models. Third, by including an attention layer in the LSTM network, the model's performance has increased. The attention layer enables the model to take into account the weighted impact of each input sequence step on the output. It was discovered that the LSTM's train and test errors were 0.57 and 0.9, respectively. Over the MLP model, this demonstrated a substantial improvement. The train and test errors were lowered to 0.69 and 0.75 by the attention layer.

III.METHODS

We provided a brief discussion about the proposed model to solve the aforementioned problems in a satisfactory way. The proposed model is composed of two main steps such as (1) preprocessing, to prepare data for training and testing, and (2) training the traditional DL model for accurate driver distraction detection. Furthermore, we fine-tuned a pretrained DL model to enhance the driver distraction detection performance and minimize the false alarm rate. In the proposed work, we employed a CA module with several DL models and validated their performance against SOTA over the benchmark datasets.

Data preprocessing has a vital role in the ML and DL models and is considered as a fuel for their training. Data preprocessing is a technique for cleaning and organizing unusual data to make them well-known information. In simple words, data preprocessing is a task of data mining that prepares the raw data into an understandable form for model training [29]. Furthermore, the useful and error-free data provide optimal results at the time of evaluation. Additionally, there are several techniques of preprocessing, for instance, augmentation, enhancement, data transformation, and data reduction, among others.

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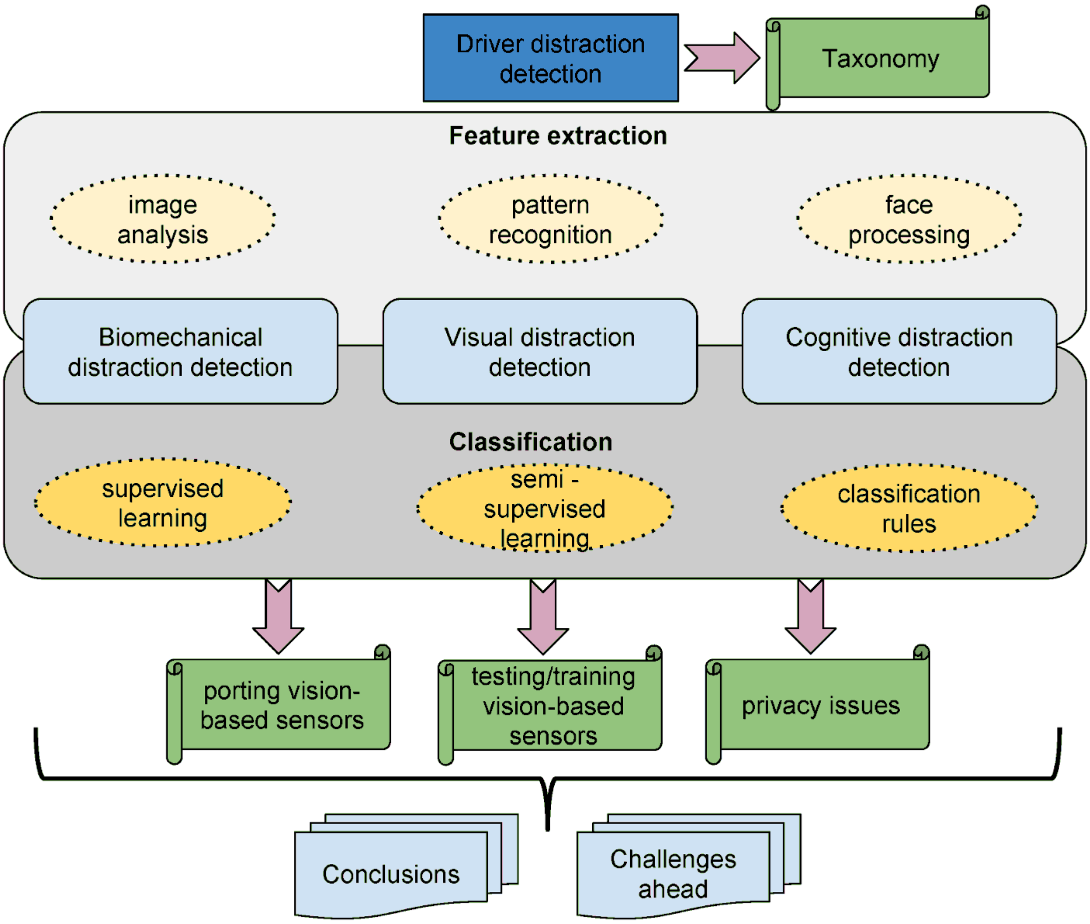

Fig 2 : Driver Distraction Using Visual-Based Sensors

Data augmentation is a technique that prevents ML and DL models from acquiring irrelevant information. In addition, ML and DL models require a huge amount of data (which are not available easily) for predicting accurate results. In some cases, the available datasets are expanded artificially by applying augmentation techniques [30]. After applying the augmentation technique, the network learns the same object located in the picture with a different view, which enhances the performance of the model. Furthermore, there are different steps available in geometric augmentation, for instance, resizing, cropping, rotating, flipping, scaling, and so on. These transformations expand the available dataset and bring the network toward optimal results.

IV.RESULTS AND DISCUSSIONS

Many frozen CNNs with CA mechanism were used in this study. All the models obtained optimal performance based on a variety of metrics such as testing accuracy, testing loss, F1-score, precision, and recall. True positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) are the confusion matrix instances, through which we determined the performance of a specific network. Accuracy is a confusion matrix term that indicates the performance of the model for all classes. In simple words, it can measure the number of accurate samples to the total number of samples. The recall is also called sensitivity or True Positive Rate (TPR). This instance evaluates the model to detect driver's distraction in positive image samples. The specificity of a confusion matrix is determined by the ability to correctly classify negative samples in all true negative cases. Confusion matrix can manage the model that keeps away the model from misidentifying the driver's distraction. F1-score manages the stability between recall and precision.

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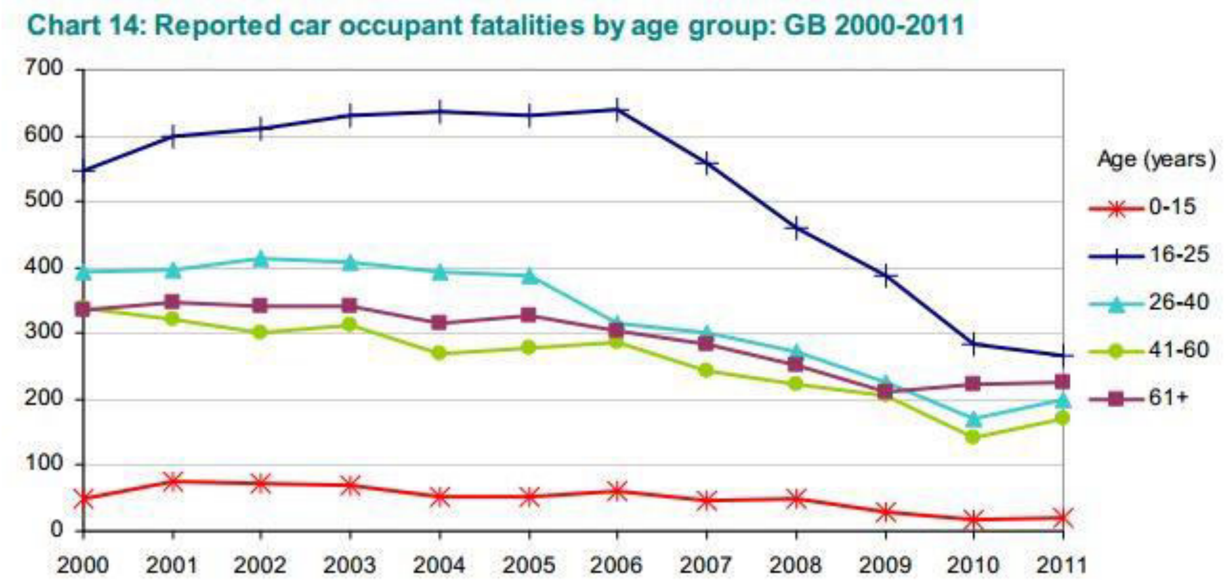

Fig 3: Result analysis

This section provides the discussion and results over several DL-based models with and without CA mechanism. The comparison of proposed model with other DL-based models using evaluation metrics such as, F1-score, precision, recall, testing accuracy, and testing loss over SFD3 and AUCD2 datasets are briefly explained in the following subsequent sections. The proposed model and other baselines were trained for 50 epochs with 32 batch size using a low learning rate of 0.001. Further, we set Stochastic Gradient Descent (SGD) with a momentum of 0.9 to ensure that the network retains most of the previously learned information. In these experiments, the proposed model was used to update the learning parameters moderately, which resulted in optimal performance on the target dataset. Additionally, we used the default input size (224 × 224) for each network.

V.CONCLUSION

Compared with driver physical measures, using driving performance measures to detect driver cognitive distraction is more effective, simple, and of real time, so it is used to detect driver state in this paper. NCD, LCD, and HCD were defined as three different cognitive distraction states using different secondary tasks. Twelve drivers were recruited to take part in the experiment. For every participator, 7 original data about driving performance were obtained from the driving simulator directly, and 14 characteristic parameters were extracted as SVM models input. In order to improve real-time performance of the developed models, window size used in this research was 1?s. At last, different SVM models (NLModel, NHModel, LHModel, and NLHModel) were developed by using the same training instances from two of the three distraction states (NCD, LCD, and HCD) to compare the accuracy of this detection system when the driver was in different cognitive distraction states.

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