# Facial Expression Awareness for Driver Distraction Detection


Minh-Trieu Tran
Department of Artificial Intelligence Convergence, Chonnam National University
Gwangju, South Korea
tmtvaa@gmail.com

Irfan Haider
Department of Artificial Intelligence Convergence, Chonnam National University
Gwangju, South Korea
irfan_haider99@hotmail.com

Guee-Sang Lee
Department of Artificial Intelligence Convergence, Chonnam National University
Gwangju, South Korea
gslee@jnu.ac.kr

Hyung-Jeong Yang
Department of Artificial Intelligence Convergence, Chonnam National University
Gwangju, South Korea
hjyang@jnu.ac.kr

Soo-Hyung Kim
Department of Artificial Intelligence Convergence, Chonnam National University
Gwangju, South Korea
shkim@jnu.ac.kr



## ABSTRACT

In recent years, there have been many road accidents in result of driver distraction. Following the report of World Health Organization, road accidents belong to the top ten highest causes of death around the world. The one most popular reason for accidents is distracted driving. A lot of research has been done so far to resolve the distracted driving issue under a classification task by applying the machine learning approach and deep learning techniques. However, most studies only focus on using image-based features without complementary information such as the emotion of the driver. Furthermore, emotions have been proved that not only affect people mentally and physically, but they also have correlation with behavior. Therefore, the driver's emotion can be one meaningful complementary information feature for driver distraction detection tasks. In this paper, we proposed a driver distraction detection framework based on facial expression awareness. We got an accuracy of 97% on the State Farm Distracted Drivers dataset (SFDDD). This approach achieves promising results compared to other state-of-the-art methods.



## KEYWORDS

Driver Distraction Detection, Distraction Classification, Facial Expression Recognition, Deep Learning, Neural Network


## 1 INTRODUCTION

Driver distraction can cause serious accidents or can be life threaten for other people on the road. Every year large numbers of accidents occur because of distraction of drivers [1,2,3]. Drivers can be distracted by different reasons while driving such as using mobile phones, talking with passengers, drinking, or eating something, looking around other than the road etc. To overcome this main issue of accidents, researchers started research on this a few years ago. To ensure safety while driving initially they determined the level of distraction and the types of distractions. Some researchers developed warning or alarm systems to reduce the distraction while driving [4]. In this regard, vehicle manufacturer companies researched more to understand and measure the causes of driver distraction and inattention. Some vehicle manufacturer companies developed the automation of vehicles to overcome accidents by automating driving functionalities [5,6]. Some vehicle companies launched modern vehicles with different automation functionality to assist drivers and reduce road accidents [6]. Some modern vehicles can detect various types of driver inattentions, such as driver's discomfort [7] and the vehicle system warns the driver immediately. Such kinds of modern vehicles also assist the driver in changing lanes and keeping a safe distance [8]. Recently researchers have focused more on the distraction of drivers and on the automation of vehicles to save lives. With the advancement of automation of driving functions and to achieve completely automated, advanced systems will be placed into automobiles [5]. It seems to be a revolution in automobile research and studies on the issues of autonomous driving and driver attention detection.

**a. A sample image of the "safe driving" class. The emotional state of this man looks to be neutral.**

**b. A sample image of the "talking to passenger" class. The emotional state of this woman looks to be happy.**

**Figure 1: Illustration of relationship between facial expression with driver distraction state.**

Researchers studied about drivers' distraction detection and found that machine learning plays a vital role in detecting distracted drivers. We can see the driver's activities that distract the driver while driving using machine learning. In this way, we can be aware and stop or notify them to do irrelevant activities and ultimately minimize road accidents. Machine learning, particularly deep learning, is highly concerned with constructing various intelligent models using multiple methods. It also enables the system to obtain information based on prior experiencing datasets. Monitoring the distracted drivers, analyzing the distracted driver's behavior, and facing the other problems using deep learning has been widespread and emerging research that attracts different researchers nowadays. Wearable technologies, such as camera systems on the road, are used to collect data from distracted drivers, which is used to train other models including support vector machines (SVM), Convolutional Neural Networks (NN), and Deep Neural Networks (DNN) [9,10,11]. Using these methods we can easily extract the features[35] by image.

According to a study [33], emotion effects the driver's behaviour or emotion distract the driver while driving. By detecting the emotion of the driver, it is very easy to predict whether the driver is distracted or not. Driver's emotion can be classified using different methods i.e. Convolutional Neural Network(CNN) and Deep Convolutional Neural Network(DNN). Therefore, in current study we construct a CNN which integrates the pretrained network for emotion recognition inside to identify the distracted driver behavior and to make it better. Figure 1 illustrates two examples of relationship between facial expression with driver distraction state.

Further papers consist of related work that describes the previous studies of distracted drivers and their behaviors, experiment details
describe our proposed method for this work, results are showing our performance of this work after applying the proposed method.

## 2 RELATED WORKS

Distraction and driver inattention is the core issue for road safety experts and stakeholders because of this road accidents have been increased for many years. According to National Highway Traffic Safety Administration(NHTSA) report [12], roughly 25% of accidents on the road reported to police involves some kind of driver distraction such as the driver is doing some irrelevant thing i.e drinking or eating fatigued or lost in thoughts while driving [13,14].

Due to increasing number of accidents day by day researchers focus on the transport and reasons behind the accidents of vehicles. According to a study [15] road accidents occurred due to the driver's distraction, when the driver's attention was diverted somewhere else because of some irrelevant activities. Distraction occurs when a driver focuses on other things instead of safely accomplishing the driving task because of some thoughts or something outside the car or sometimes something inside the car which distract the attention of driver and driver loses his/her concentration that results, a road accident [16]. In a reported study [17] Regan et. al. indicate four main elements of driver distraction: i) divert of concentration that takes the driver's attention away during driving, ii) involved in any relevant activity because of any object either outside or inside the vehicle iii) any thought or any activity that divert the mind of driver while driving iv) there are any implicit or obvious assumptions that may harm safe driving. Driver inattention and driver distraction have a significant relation. Distraction can be because of insufficient

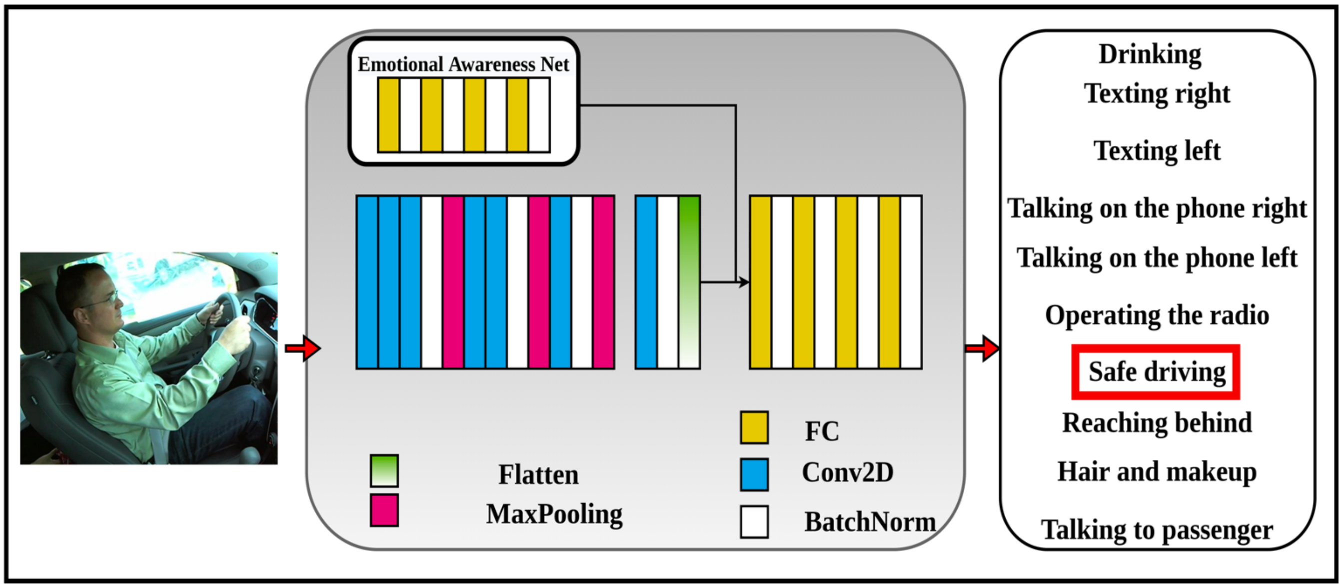


**Figure 2: The proposed framework for driver distraction detection.**

attention that driver results in unsafe driving [18]. Regan et al. [17] reviewed the definition of driver attention and driver distraction more deeply. According to their study, driver's inattention is lack of attention or no attention for doing the safe driving. Inattention of driver have different forms i.e. Driver Neglected Attention (DNA), Restricted attention (RA), Driver Diverted Attention (DDA), Driver, Driver Cursory Attention (DCA) and Mis prioritized Attention (DMA), these are directly related to driver inattention during driving a vehicle. Distracted driving is actually a kind of driver inattention. Some researchers have made considerable study in this area of distracted drivers and attention or inattention [10,17]. Vehicle manufacturers also include safety features in cars that monitor steering wheel motions, steering wheel turnaround rate, and driver head nodding to make sure the safe driving. Different techniques have been used in prior research to detect distracted drivers [6].

These days some machine learning algorithms are used to train on images to detect distracted drivers that are becoming very famous [19]. For detecting the distracted driver machine learning approaches are also used to build the data set of distracted drivers and train the model on data. Feng and Yue[23] reported a distracted driving dataset that has ten classes of ima ges. Different machine learning approaches are used i.e. linear SVM, naive bayes, softmax, decision trees and neural network also. Yuan Liao et al. [24] introduced a method for the detection task of distracted drivers by employing recursive feature reduction with the support vector machine (SVM-RFE). The result measured in this research as a correction rate is 95.8%. Tianchi Liu et al. [25] used a semi-supervised learning technique to detect the distracted driver and in this method, authors used unlabeled data and detected two major driver states of distraction however, drawback of their method is that it is only good for unlabeled data. Authors in another study [26], showed the CNN-based inception Resnet model on the collected images of distracted drivers to improve their performance. In the collected images it has six classes and each class has 1000 images. Firstly, the authors applied preprocessing on training and testing the images and then applied different othe methods of preprocessing on their data including adjustment, cropping, and flipping. Subsequently, they used Inception ResNet algorithm for training purposes. Authors used a pre-trained model on the ILSVRC 2012 dataset and achieved an accuracy of 83% on the test set. Authors in [27] reported a deep-learning-based structure that recognizes the laziness of drivers. In this study, they also incorporated a pre-trained VGG-19 and later fine-tuned them on a public dataset. By using this pre-trained model, authors achieved the highest test precision of 80% and 95%. They also claimed that their model didn't show overfitting even when they tested their own dataset. They also reported that their proposed model is better than XGBoost in terms of accuracy about 7%. In another study [28] on distracted drivers, the Park et. al. used SVM to fine-tune three CNNs models to the similar integrated features of such three networks in order to categorize every edge in four categories: alert, nodding, sleepy with blinking, and yawning. This approach was evaluated on simulated data, where the indicators of sleepiness were frequently easily noticeable, categorizing on the outward signs of tiredness. It was important to note that the analysis's exactness was 65.2%, which is less than the accuracy of 73%. In another study [29], Streiffier et. al. introduced the CNN model named as DarNet for distracted driver recognition. They collected the data for identifying the distraction of drivers. That dataset consists of six classes related to driver distraction. These classes are labeled as normal driving, talking, texting, reading, Makeup, and eating. In this reported study, the authors fine-tuned the inception v3 module. The inception v3 model was originally trained on the distracted driver's state from the Kaggle dataset. On the proposed approach, they attained 87.02% accuracy. Baheti et. al. [30] proposed a CNN-based architecture that used the VGG-16 network, the Leaky ReLU activation function rather than ReLU, and several regularization methods to avoid overfitting. They attained 96.31% accuracy on the AUC Distracted Driver dataset after using these approaches.

Driver's emotion is also one of the reason that may distract the driver while driving [33]. Chan et. al. [36] showed in their study that positive and negative emotion may directly affect the driver's behaviour. In reported [35] study they showed that billboards on the road effect the driver's behaviour which may cause the road accidents. The words written on the billboards effect on driving speed i.e. negative words on the board reduce the speed suddenly on the road and in one more study [37] negative word leads to poor steering control. While having the positive words keeps the driver neutral and it does not effect on driver's behaviour as compared to negative. In one study reported [38] that negative things around the driver leads to negative effect on the mind state that may results the worse driving behavior. However, other modalities may also distract the driver's behavior. Driver's behavior may be changed by listening to audio inside or outside the car. In some studies [39,40,41] they showed that audio modality also effect on driver's emotion and may also distract the driver while driving. Based on the correlation between emotion and the driver’s distraction that we discussed above, a framework that uses facial expression awareness knowledge is proposed for driver distraction detection. The detail of our method has been explained explicitly in the next section.

# 3 PROPOSED METHOD

## 3.1 Proposed Architecture

The proposed method included two steps: In the first step, we pre-train the classifier network for seven classes of emotion recognition (neutral, happy, angry, afraid, disgusted, sad, surprised) (KDEF dataset) using cross-entropy loss in advance. Once the emotion recognition network is trained. In the second step, the driver distraction detection framework will be trained over the SFDD dataset. Note that the emotion recognition network is integrated inside the driver distraction detection framework. Our proposed architecture is illustrated in Figure 2.

We proposed a lightweight pre-trained network for emotion classification. This network including six fully connected layers followed by batch normalization and the Relu activation layers. Figure 3 presents the proposed emotional awareness net, which is utilized in the proposed driver distraction detection network. Figure 4 indicates the accuracy and loss values of training and validation datasets during the training process.

## 3.2 Loss Function and Evaluation Metric

We employed a categorical cross-entropy loss function during training the model. For evaluation of the proposed method, we use the accuracy metric.

The equation of the loss function is shown below:

$$\text{Categorical Cross Entropy Loss} = -\sum_{i}^{C} x_i \log\left(\frac{e^{s_i}}{\sum_j^C e^{s_j}}\right)$$

The equation of accuracy metric is presented as:

$$\text{Accuracy} = \frac{\text{Correct classifications}}{\text{All classifications}}$$

# 4 EXPERIMENTAL RESULTS

In this study, we conduct experiments on the State Farm Distracted Drivers dataset (SFDDD) [34]. This dataset was collected under a 2D camera of dimension 640 ´ 480. There are 22,424 images in the dataset that have labels. For easy to compare with other research [31,32], we split multiple ratios such as 40%/30%/30%, and 15963/2769/3692 for training, validation, and testing set, respectively. Our experiments are implemented on a GPU 3090. The model is trained on 20 epochs. Table 1 presents the comparison results between the proposed method with other methods in the accuracy metric. Table 2 shows the effect of baseline convolution neural network, facial expression pre-trained

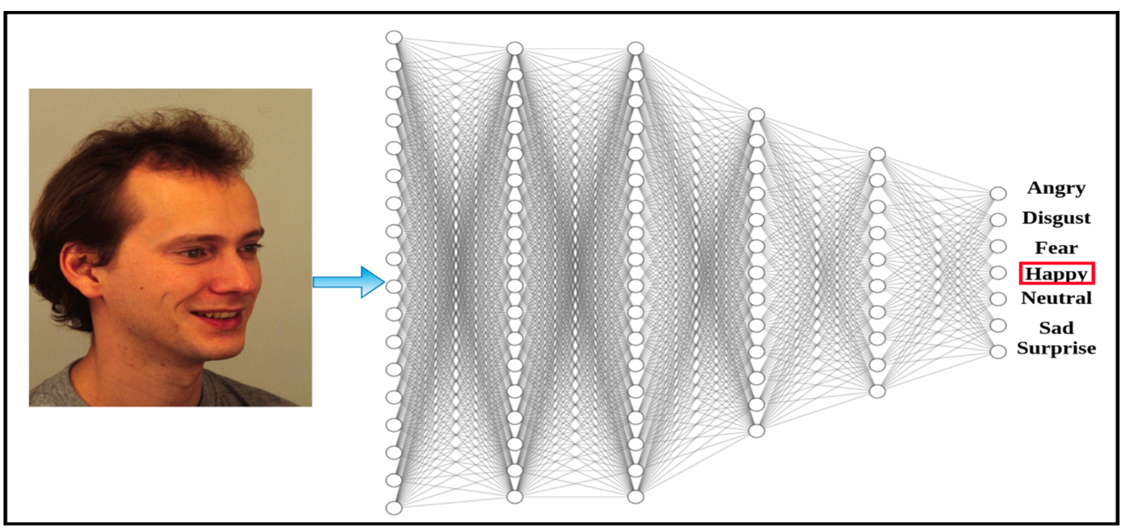


**Figure 3: The proposed framework for Emotional Awareness Net.**

net in our system.

## 5 CONCLUSIONS

In this paper, we present an efficacy network based on emotional awareness knowledge for driver distraction classification. Experiments show good of classification accuracy with 97%. Our proposed method presents the relationship between driver's emotion with their behavior. However, the limitation of this paper is only using one dataset for experiments. It is not optimal so in the future, we will evaluate our method in multiple datasets related to driver distraction and driver emotion.

**Table 1: The comparison results between proposed method with other methods in accuracy metric.**

| Ratio/number of samples of Test set | Method | Training set | Validation set | Test set |
|---|---|---|---|---|
| 30% | [32] | - | - | 94.00% |
| | Ours | 98.89% | 97.12% | 97.10% |
| 3692 | [33] | - | - | 92.00% |
| | Ours | 98.92% | 97.81% | 97.61% |

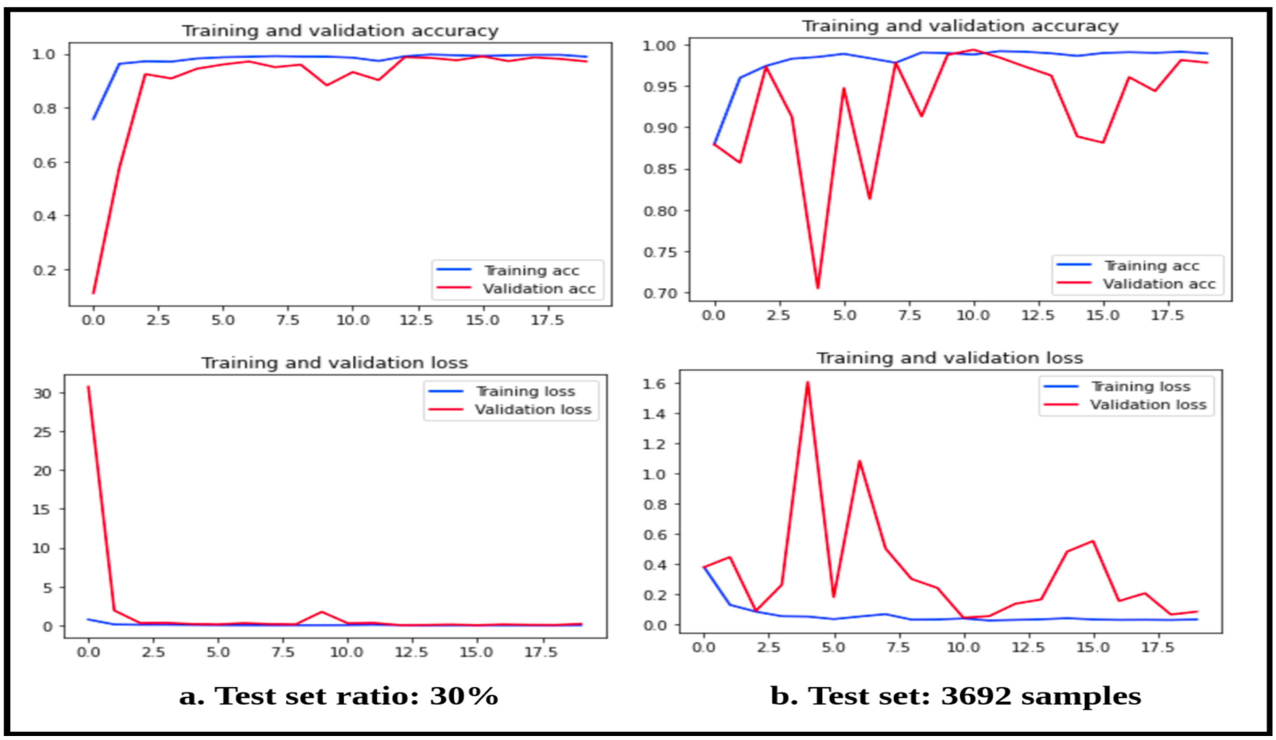


**Figure 4: The accuracy and loss values of training and validation datasets during training process.**

**Table 2: The effect of emotion recognition pretrained network in proposed method.**

| Ratio/number of samples of Test set | Method | Training set | Validation set | Test set |
|---|---|---|---|---|
| 30% | CNN | 98.49% | 88.38% | 86.70% |
| | CNN + EmoNet | 98.89% | 97.12% | 97.10% |
| 3692 | CNN | 99.24% | 94.25% | 94.43% |
| | CNN + EmoNet | 98.92% | 97.81% | 97.61% |

## ACKNOWLEDGMENTS

This research was supported by the Bio & Medical Technology Development Program of the National Research Foundation (NRF) & funded by the Korean government (MSIT) (NRF-2019M3E5D1A02067961) and by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF-2018R1D1A3B05049058 & NRF-2020R1A4A1019191).


## REFERENCES


[1] Olson, R. L., Hanowski, R. J., Hickman, J. S., & Bocanegra, J. 2009. Driver distraction in commercial vehicle operations, Federal Motor Carrier Safety Administration.

[2] Young, K., Regan, M., & Hammer, M. 2007. Driver distraction: A review of the literature. Distracted driving, 2007, 379-405.

[3] Regan, M. A., Lee, J. D., & Young, K. 2008. Driver distraction: Theory, effects, and mitigation. CRC press. Chicago.

[4] Koesdwiady, A., Soua, R., Karray, F., & Kamel, M. S. 2016. Recent trends in driver safety monitoring systems: State of the art and challenges. IEEE transactions on vehicular technology, 66(6), 4550-4563.

[5] Cunningham, M. L., Regan, M. A., & Imberger, K. 2017. Understanding driver distraction associated with specific behavioural interactions with in-vehicle and portable technologies. Journal of the Australasian College of Road Safety, 27-40.

[6] Kalayci, T. E., Kalayci, E. G., Lechner, G., Neuhuber, N., Spitzer, M., Westermeier, E., & Stocker, A. 2021. Triangulated investigation of trust in automated driving: Challenges and solution approaches for data integration. Journal of Industrial Information Integration, 21, 100186.

[7] Neuhuber, N., Lechner, G., Kalayci, T. E., Stocker, A., & Kubicek, B. 2020. Age-related differences in the interaction with advanced driver assistance systems-a field study. In International Conference on Human-Computer Interaction (pp. 363-378). Springer, Cham.

[8] Agrawal, U., Mase, J. M., Figueredo, G. P., Wagner, C., Mesgarpour, M., & John, R. I. 2019. Towards real-time heavy goods vehicle driving behaviour classification in the united kingdom. In 2019 IEEE Intelligent Transportation Systems Conference (ITSC) (pp. 2330-2336).

[9] Eraqi, H. M., Abouelnaga, Y., Saad, M. H., & Moustafa, M. N. 2019. Driver distraction identification with an ensemble of convolutional neural networks. Journal of Advanced Transportation.

[10] Kouchak, S. M., & Gaffar, A. 2019. Using bidirectional long short term memory with attention layer to estimate driver behavior. In 2019 18th IEEE International Conference On Machine Learning And Applications (ICMLA) (pp. 315-320).

[11] Alvarez, A. D., Garcia, F. S., Naranjo, J. E., Anaya, J. J., & Jimenez, F. 2014. Modeling the driving behavior of electric vehicles using smartphones and neural networks. IEEE Intelligent Transportation Systems Magazine, 6(3), 44-53.

[12] National Highway Traffic Safety Administration. 2013. Preliminary statement of policy concerning automated vehicles. Washington, DC, 1, 14.

[13] Stutts, J. C., Reinfurt, D. W., & Rodgman, E. A. 2001. The role of driver distraction in crashes: an analysis of 1995-1999 Crashworthiness Data System Data. In Annual proceedings. Association for the Advancement of Automotive Medicine Vol. 45, pp. 287-301.

[14] Hatoyama, K., Nishioka, M., Kitajima, M., Nakahira, K., & Sano, K. 2019. Perception of time in traffic congestion and drivers′ stress. In International Conference on Transportation and Development 2019: Smarter and Safer Mobility and Cities (pp. 165-174).

[15] Lee, J. D. 2014. Dynamics of driver distraction: The process of engaging and disengaging. Annals of advances in automotive medicine, 58, 24.

[16] Stutts, J. C., Reinfurt, D. W., & Rodgman, E. A. 2001. The role of driver distraction in crashes: an analysis of 1995-1999 Crashworthiness Data System Data. In Annual proceedings. Association for the Advancement of Automotive Medicine Vol. 45, pp. 287-301.

[17] Regan, M. A., Hallett, C., & Gordon, C. P. 2011. Driver distraction and driver inattention: Definition, relationship and taxonomy. Accident Analysis & Prevention, 43(5), 1771-1781.

[18] Horberry, T., Anderson, J., Regan, M. A., Triggs, T. J., & Brown, J. 2006. Driver distraction: The effects of concurrent in-vehicle tasks, road environment complexity and age on driving performance. Accident Analysis & Prevention, 38(1), 185-191.

[19] Pisharody, D. M., Chacko, B. P., & Basheer, K. M. 2022. Driver distraction detection using machine learning techniques. Materials Today: Proceedings, 58, 251-255.

[20] Islam, M. M., Uddin, M. A., Islam, L., Akter, A., Sharmin, S., & Acharjee, U. K. 2020. Cyberbullying detection on social networks using machine learning approaches. In 2020 IEEE Asia-Pacific Conference on Computer Science and Data Engineering (CSDE) pp. 1-6.

[21] Ahmed, N., Ahammed, R., Islam, M. M., Uddin, M. A., Akhter, A., Talukder, M. A. A., & Paul, B. K. 2021. Machine learning based diabetes prediction and development of smart web application. International Journal of Cognitive Computing in Engineering, 2, 229-241.

[22] Ahamed, K. U., Islam, M., Uddin, A., Akhter, A., Paul, B. K., Yousuf, M. A., ... & Moni, M. A. 2021. A deep learning approach using effective preprocessing techniques to detect COVID-19 from chest CT-scan and X-ray images. Computers in biology and medicine, 139, 105014.

[23] Feng, D., & Yue, Y. 2019. Machine Learning Techniques for Distracted Driver Detection.

[24] Liao, Y., Li, S. E., Wang, W., Wang, Y., Li, G., & Cheng, B. 2016. Detection of driver cognitive distraction: A comparison study of stop-controlled intersection and speed-limited highway. IEEE

Transactions on Intelligent Transportation Systems, 17(6), 1628-1637.

[25] Liu, T., Yang, Y., Huang, G. B., Yeo, Y. K., & Lin, Z. 2015. Driver distraction detection using semi-supervised machine learning. IEEE transactions on intelligent transportation systems, 17(4), 1108-1120.

[26] Kim, W., Choi, H. K., Jang, B. T., & Lim, J. 2017. Driver distraction detection using single convolutional neural network. In 2017 international conference on information and communication technology convergence (ICTC) pp. 1203-1205.

[27] Koesdwiady, A., Bedawi, S. M., Ou, C., & Karray, F. 2017. End-to-end deep learning for driver distraction recognition. In International Conference Image Analysis and Recognition . Springer, Cham. pp. 11-18.

[28] S. Park, F. Pan, S. Kang and C. D. Yoo. 2016. Driver Drowsiness Detection System based on Feature Representation Learning using Various Deep Networks. Proc. Asian Conf. Comput. Vis., 154-164.

[29] C. Streiffer, R. Raghavendra, T. Benson and M. Srivatsa. 2017. A Deep Learning Solution for Distracted Driving Detection. Proc. 18th ACM/IFIP/USENIX Middleware Conf., 22-28.

[30] B. Baheti, S. Gajre and S. Talbar. 2018. Detection of Distracted Driver using Convolutional Neural Network. Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit. Workshops (CVPRW), 1032-1038.

[31] M. S. H. S. Bahari and L. Mazalan. 2022. Distracted Driver Detection Using Deep Learning. In 2022 IEEE 18th International Colloquium on Signal Processing & Applications (CSPA), 198-203.

[32] M. Aljasim and R. Kashef. 2022. E2DR: A Deep Learning Ensemble-based Driver Distraction Detection with Recommendations Model. Sensors, 1858.

[33] Steinhauser, Klara, F. Leist, K. Maier, V. Michel, N. Pärsch, P. Rigley, F. Wurm, and M. Steinhauser. 2018. Effects of emotions on driving behavior. Transportation research part F: traffic psychology and behaviour, 150-163.

[34] State Farm Distracted Driver Detection. Available online: https://www.kaggle.com/c/state-farm-distracted-driver-detection (accessed on 20th August 2022)

[35] Behav. Cogn. Neurosci. 2003. The interface between emotion and attention: A review of evidence from psychology and neuroscience Rev., 2 (2003), pp. 115-129

[36] Chan, M., & Singhal, A. 2015. Emotion matters: Implications for distracted driving. Safety science, 72, 302-309

[37] L.M. Trick, S. Brandigampola, J.T. Enns 2012 How fleeting emotions affect hazard perception and steering while driving: the impact of image arousal and valence Accid. Anal. Prev., 45 (2012), pp. 222-229

[38] F. Pratto, O.P. John 1991 Automatic vigilance: the attention-grabbing power of negative social informationJ. Pers. Soc. Psychol., 61 (1991), pp. 380-391

[39] W. Brodsky 2002 The effects of music tempo on simulated driving performance and vehicular control Transport. Res. F: Traffic Psychol. Behav, pp. 219-241

[40] W. Brodsky, Z. Slor, 2013; Background music as a risk factor for distraction among young-novice drivers Accid. Anal. Prev., 59 (2013), pp. 382-393

[41] C. Pêcher, C. Lemercier, J. Cellier; 2009 Emotions drive attention: effects on driver's behaviour Saf. pp. 1254-1259