Driver Emotion Recognition for Safe Driving: A Comprehensive Survey

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Abstract*: Accidents on roads have been a serious issue for decades in the world. As a solution to this issue, driver emotion recognition has gained much attention where the affective states of the drivers are monitored. In the context of driver emotion recognition, both the physiological and non-physiological signals are utilised in identifying the emotional states of the drivers. Among the approaches taken by researchers in determining the driver emotional states facial emotions, speech emotions, Galvanic Skin Response (GSR), Electrocardiogram (ECG) signals, Electroencephalography (EEG) signals, etc., are much more prominent. Nevertheless, physiological signals are a valuable asset in identifying the emotional states since non- physiological signals such as facial emotion recognition, that is mainly used to detect driver affective states, can be misleading. This study aims to review the literature related to driver emotion recognition that aims on ensuring the safety of road users. Furthermore, the approaches taken by the researchers in the reviewed literature have been briefly discussed, and the challenges to these approaches have been further discussed to enhance the safety of road users and future research in the paradigm of driver emotion recognition.*

Keywords: *Affective Computing, Challenges, Driver Emotion Recognition, Road Safety, Safe Driving*

1. Introduction

Road accidents can be stated as a global challenge faced by almost all the countries in the world. This has resulted in many deaths, fatal injuries, and irreplaceable disabilities to individuals (Gamage et al., 2021). The World Health Organization (WHO) statistics indicate that road injuries are included in the top ten leading causes of death in low-income, lower-middle-income, and upper-middle-income countries (The top 10 causes of death, 2022). Therefore, it is proven that road accidents are a critical issue that must be considered.

Figure 1 depicts the road death statistics of the WHO, in WHO regions. It is apparent that except for two WHO regions with slight reductions in death rate, all the other WHO regions have increased road deaths since the year 2000. Nevertheless, the statistics also show that the global road death rate has been increasing within the past few years. Moreover, it must be stated that not only do the drivers and passengers get affected due to road accidents, but also almost all road users, including pedestrians have to suffer from road accidents.

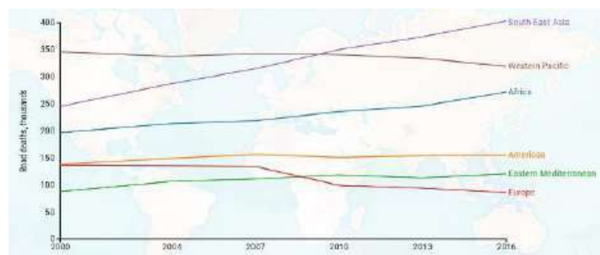

Figure 1. The road death rate in WHO regions
Source: (WHO | Death on the roads, 2022)

The above issue has led to the emergence of the driver emotion recognition paradigm where the emotional states of the drivers ought to be monitored for better road safety and thereby reduce the road accidents that cause due to the affective states of the drivers. Emotions are vital in decision-making and activating behavioural responses in individuals (Kazemitabar, Lajoie and Doleck, 2021). Therefore, the driver emotion recognition approach can be stated as a more appropriate approach for minimising road accidents since drivers are responsible for most road crashes where a slight change in the driver's affective state can cause a severe damage. Affective gaming concepts have also emerged (Kalansooriya, Ganepola and Thalagala, 2020), while incorporating biosignals in virtual reality systems are also noted (Kalansooriya et al., 2016) in the paradigm of affective computing.

Generally, two main approaches to driver emotion recognition exist: physiological and non-physiological signals. Physiological signals include the signals generated within the human body, while non-physiological signals include signals concerned with humans' external behaviour. EEG, ECG, and GSR are some physiological signals, while facial, voice, and gesture emotions fall under the non-physiological signals. This research aims to review the contemporary research in driver emotion recognition along with the challenges faced by the existing approaches and to add quality knowledge to enhance future research in this paradigm.

The rest of the paper is organised as follows. Section 2 includes the methodology that is followed while conducting this review work. Section 3 presents a critical literature review that discusses the contemporary literature on driver emotion recognition. Section 4 includes the discussion section that presents the challenges to emotion recognition approaches. The final section concludes the conducted research and provides further direction for future research in the field of driver emotion recognition for enhancing road safety.

2. Methodology

The research conducted in this paper focuses on reviewing the published work on driver emotion state recognition for the safety of drivers. The methodology follows the general procedure for conducting a literature review as put forward by the researchers (Templier and Paré, 2015).

A. Formulating the research

The objectives of this study are based on investigating the affective states that are focused on by the researchers as the emotional states that cause the drivers to distract from their normal routine, and the approaches and techniques that researchers in driver emotion detection have utilised in order to ensure the safety on roads. Moreover, challenges to the driver emotion recognition approaches are to be investigated based on the emotion recognition approach being employed.

B. Searching the literature

IEEE Xplore, and Google Scholar databases were used to search the literature.

C. Screening for inclusion

In order to review the literature for this survey, the published work after the year 2015 was concerned to include the contemporary literature in the conducted research.

D. Assessing quality

The literature that matches this study's scope and the objective was identified after the initial screening.

E. Extracting Data

Data relevant to the research objectives were extracted from the chosen literature.

F. Analysing and synthesising data

A summary of the reviewed literature has been formulated by broadly discussing the approach and focused emotional states/affective states where a comparative approach has been undertaken. Furthermore, the challenges faced while detecting the driver's emotions in real-time while driving has also been discussed.

3. Literature Review

There have been multiple attempts by researchers in the paradigm of driver emotion recognition, and the approaches taken by these researchers fall under the physiological and non-physiological approaches. The focus of the researchers on the emotional states is also varying, and it is observed that some researchers focus on identifying just one emotional state while some researchers concern on identifying multiple emotional states.

Yan et al. (Yan, Wan, Qin and Zhu, 2018) have focused on the Angry emotional state, and three scenarios have been used to arouse the anger of the drivers, and these include frequent waiting for the traffic light, traffic blockage, and the intervention of encompassing vehicles on the road. Furthermore, these scenarios were practised in both the driver simulation environment and on road. The proposed angry driving detection model by these researchers has proven that this model has an accuracy of 85.0% to differentiate angry driving from normal driving. Driving anger that is also referred to as the 'road rage' has been the main concern of the researchers (Wan, Wu, Lin and Ma, 2019) when ensuring the safety of the drivers on roads. For the experimental study, thirty private car drivers on a congested path in Wuhan, China. From the results, the researchers have identified thirteen features that have a significant influence on the anger states of the drivers and these have been collected using multiple sensors concerning three data sets, namely, driver physiology, driving behaviours, and vehicle motions. Researchers (Naqvi et al., 2020) has concerned about driver aggressiveness, and the proposed system has employed facial features for driver emotion recognition, and the classification of emotions has been done as aggressive driving and normal driving. Further, the researchers (Hu, Zhu, Gao and Zheng, 2018) have incorporated biosignals, EEG and ECG in analysing the road rage of the drivers that they identify as a significant feature that influences the young drivers while driving.

Another emotional state that researchers try to address widely is drowsiness which is also termed as fatigue. According to the researchers Jan and Ahn (Jang and Ahn, 2020), driver drowsiness has been a major reason for the large-scale accidents that occur on roads, and facial and eye-blink recognition technologies have been used in the proposed system to detect the drowsiness. Further, a CO_2 sensor chip has also been utilised to ascertain further drowsiness and speech recognition has been used to convert speech to text so that the driver is able to request for the desired music or call someone in order to prevent the driver drowsiness while driving. Another group of researchers have identified that fatigue has been a vital cause of road accidents. These researchers have proposed a system with EEG signal analysis as the basis in a hypoxia plateau environment (Jing, Liu, Zhang and Guo, 2020).

Sarala et al. (Sarala, Yadav and Ansari, 2018) have worked on differentiating between positive and negative emotional states to enhance the safety of road users. An advanced driver assistance system has been developed by these researchers that work as an adaptive driver voice alert system using deep learning based on the emotions of the drivers. The emotional states of the drivers are determined using facial emotion recognition based on CNN, and Facial Emotion Recognition (FER) 2013 dataset is used in this regard. The voice alerts are produced intensively during the negative emotional states, while a moderate amount of voice alerts are generated in positive emotional states to assist the driver to focus on to driving. In another study (De Nadai et al., 2022), the researchers have not explicitly detected the emotional states of the drivers but have aimed to identify the Sympathetic Nervous System (SNS) and Parasympathetic Nervous System (PNS) responses where SNS responses are influenced by alarm situations such as struggle, drowsiness, stress, etc. while PNS responses deal with the absence of danger. In this research, ECG signals and driver position have been utilised in monitoring the emotions of drivers on line roads and two different drivers have been involved, and fifteen trips on two daily sessions were conducted in conducting the experiment. And with the ECG signals, Heart Rate Variability (HRV) signals are monitored to identify the emotional states of the drivers.

In the research conducted by (Lotz et al., 2022), the classification of emotional states is done concerning that all the positive emotions fall into the positive category while the negative emotions have been categorised into frustration/anger and anxiety/fear. This study has focused mainly on four emotional states, namely, neutral, positive, frustrated, and anxious. Further, neutral has been considered as the emotional state that mostly occurs in drivers. In order to collect data for the research, audio, video and physiological signal recordings in real-time and in-car have been used. Nevertheless, a limitation that was found in this study is that although ‘frustration and anger’, and ‘anxiety and fear’ have a difference in the psychological point of view, the authors have not taken that into consideration.

Furthermore, approaches taken by researchers in inducing the emotional states of the subjects are observed to be varying. Researchers (Zimasa, Jamson and Henson, 2019) have utilised music, and mental imagery in inducing the moods in their research and mind wandering theory has been used in order to identify the car following behaviour and driver glance patterns when influenced by neutral, happy, sad, and angry moods while car following.

The authors (Nisa' Minhad, Hamid Md Ali, Ooi Shi Khai and Anom Ahmad, 2016) have concerned on Skin Conductance Response (SCR) signals in human emotion classification for automotive drivers, and according to the authors, happiness, sadness, disgust, fear, and anger emotional states influence risky driving. Imagery, video, audio and video stimulus techniques have been used in this regard. According to the results obtained from the study, SCR processing is with more than 70% of accuracy than the previously stated methods in detecting the driver's emotions. Further, as stated by the authors, risky driving, speeding, and fatigue have been recognised as the major reasons for traffic accidents in Malaysia.

Research focusing on taxi drivers in Japan has been conducted to examine how emotions are associated with the driving speed of the drivers. The researchers have examined five affective states, namely, happy, angry, relaxed, sad, and neutral, using a biometric device. According to the results obtained, anger and sadness that are identified as negative emotions raise the speed of the drivers, while the neutral emotional state influence decreasing the speed of the drivers. Further, happy and relaxed affective states have not shown a notable influence on the speed of taxi drivers (Kadoya, Watanapongvanich and Khan, 2021).

According to the previous studies, it is also observed that researchers have proposed their own emotion models. The authors (Kowalczuk, Czubenko and Merta, 2019) have implemented an emotion monitoring system for drivers using the Plutchik’s paraboloid of emotions that the authors have identified as their own emotion model, and the recognition of the emotions identified in the above model has been done using facial emotion recognition and an external algorithm named ‘FER algorithm’. Then the Kalman filter is used to estimate the final emotional state of the driver, and the recognised emotion is treated as a measurement data. Further work of this research is to ascertain the influence of the mental state of the drivers on safe driving.

The system proposed by the authors (Bankar et al., 2018) makes use of EEG signals for emotion analysis for controlling the driver's emotional state. The authors of this research are concerned with a two-dimensional model of emotions, and the concern of the authors is for the four emotional states, excitement, stress, depression, and relaxation, where relaxation has been identified as the preferred emotion state for the driver. Further, the researchers propose to use music as a therapy to transform the emotional state of the driver into a relaxation state. El-Amin et al. (El-Amin et al., 2019) have utilised EEG signals of the drivers in recognising driver emotions, and the proposed system has demonstrated its capability to detect two states of emotions, sadness and happiness. The authors state that the extreme expression of these two emotional states must be discriminated against when ensuring the safety of the drivers.

It is also observed that the researchers focus not only on the driver's emotional states but also on the passenger's emotional states in conducting research on road safety. The researchers (Alyuz et al., 2018) have focused on identifying the affective states of driver-passenger dyads while driving. They have involved 34 participants in 17 pairs in an indoor driving simulator environment to induce affective states during automated and manual driving. The main focus of the researchers has been on the two negative emotional states, namely, frustration and startle, while happiness and neutral emotional states are identified as preferred states. In further works, the researchers target on analysing data to identify gender-specific and scenario-related differences.

Wang et al. (2020) have worked on identifying driver emotions in a two-lane roads scenario with the use of real, virtual, and computer simulation experiments. Fifty-four subjects have been involved in the experimental process, and the emotions were induced using images, audio, etc. According to the authors, this research improves road traffic safety, and the authors seek to improve the system further concerning the extrinsic factors such as weather, road capacity, the personality of the driver, etc. The researchers (Patil and Veni, 2019) have utilised LBP and facial features in detecting the five emotional states, namely, anger, fear, happiness, neutral, and sadness, that they have identified as the affective states that must be detected to enhance the safety of the drivers. Support Vector Machine (SVM) is used as the classification algorithm for both of these researches (Wang et al., 2020) (Patil and Veni, 2019). However, Wang et al. have used an experimental procedure to collect the data for the research, while the Extended Cohn-Kande dataset has been used by Patil & Veni (2019).

4. Discussion

Among the approaches that are prominent in detecting driver emotional states, facial emotion recognition, speech-based emotion detection, GSR, ECG, and EEG signals are much more significant in state of the art. Nevertheless, multiple challenges are encountered when incorporating human emotion recognition for safe driving on roads. Figure 2 represents the challenges to facial emotion recognition as identified by the authors in the reviewed literature (Giannopoulos, Perikos, and Hatzilygeroudis, 2018) (Verma and Choudhary, 2018) (Bhattacharya and Gupta, 2019) (Theagarajan et al., 2017).

Figure 3 depicts the challenges to speech emotion recognition ((Basu, Chakraborty, Bag and Aftabuddin, 2017). The researchers (Vinola and Vimaladevi, 2015) state that audio features and facial and body gestures can improve emotion detection accuracy. Also, the authors emphasise that gender, age, and cultural differences of humans influence a person's mental state. Moreover, it must be stated that speech emotion recognition is not as appropriate as a driver emotion recognition approach since drivers' speech is not always available while driving. But when integrating other emotion detection approaches with speech emotion recognition, higher reliability can be achieved.

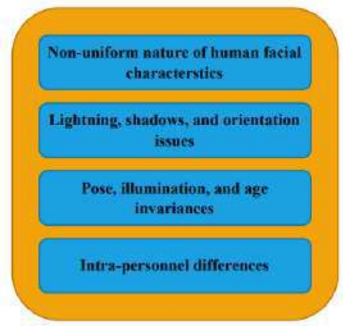

Figure 2. Challenges to facial emotion recognition
Source: The author designed

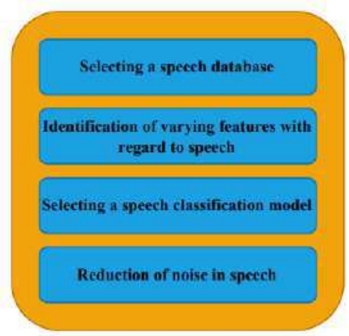

Figure 3. Challenges to speech emotion recognition
Source: The author designed

Physiological signals can be stated as a more reliable approach since internal emotional changes can be detected accurately through the biological signals rather than the physical characteristics that can be misleading. GSR is a low-cost approach for detecting the emotional states of the drivers, and GSR is sensitive only to the arousal dimension but not to the direction or valence (Ayata, et al., 2017). Nevertheless, in the context of driver emotion recognition, since air conditioning is available in almost all automobiles except for a few, this approach hinders the accurate emotion recognition of drivers.

ECG signals are another approach that many researchers in driver emotion recognition have utilised. Among the challenges with regard to the ECG-based emotion detection systems, the increase in heart rate occurs on fear, excitement, or arousal. Another challenge is that there should be a correct selection between subject-dependent and subject-independent classification procedures (Nikolova., Mihaylova, Manolova, and Georgieva, 2019). Researchers (Zhong, Wang and Miao, 2020) have identified three challenges in EEG-based emotion analysis, namely, ineffective exploitation of the topological structure of EEG channels to identify varying EEG representations, changing nature of EEG signals across different subjects thereby hindering the generalizability of the already trained classifiers, and not producing the required emotions when emotion eliciting stimuli are being watched. Ethical issues such as the privacy of the individuals may also be affected by the use of these signals; therefore, this should be a significant concern in these systems (Hu, Chen, Wang and Zhang, 2019).

The above-discussed approaches fall under the two general approaches to driver emotion recognition: physiological and non-physiological. Facial and voice emotion recognition fall under the non-physiological approaches, while GSR, ECG, and EEG fall under the physiological signals. Both the facial and voice emotion recognition approaches have the issue of misleading since the way individuals react to particular situations varies from individual to individual. Moreover, the GSR approach has the issue of being inefficient when used in air-conditioned automobiles. ECG and EEG can be stated as more effective physiological signals in the paradigm of driver emotion recognition, although there are some issues that arise from them. Nevertheless, it is also identified that considering the accuracy issues, researchers utilising physiological signals in emotion recognition tend to focus on few emotions in their studies.

Nonetheless, at the same where the authors emphasise the need to address all the emotional states that affect drivers to get into accidents, it must also be stated that human emotions cannot be limited to a few adjectives (Goonewardena and Kalansooriya, 2020) since the emotion classifications are based on how the individuals involved in emotion classification define the emotional states and the main concerns in classifying the emotions. According to the authors (Chunawale and Bedekar, 2020), laboratory-based environmental simulations are not very reliable since the emotions are artificially induced in humans, and even the emotional state felt by an individual in a particular instance differ from another. Reaction time (Saini, Eksambekar, Zahoor and Bedekar, 2016) has also been identified as a significant challenge since the time taken to perceive and react to a situation like an accident consumes a greater time.

5. Conclusion

The findings suggest that multiple researchers have focused on varying emotional states and approaches when the emotion detection of drivers is concerned. Furthermore, some researchers seem to focus on only one emotional state in their studies, while some researchers focus on multiple emotional states that can lead the drivers to get distracted from regular driving routines. It must be stated that the concern must be on the negative emotional states as a whole but not only on a specific set of emotional states since any external or internal influence that arises in the cognitive domain of the driver may result in a fatal accident that is irreplaceable. Furthermore, when the emotion detection approaches are concerned, both the physical features and physiological signals have been affected by researchers in detecting the driver's emotional states. Nevertheless, it must be stated that it is the physiological signals that are more reliable when determining the driver's emotional states since the physical appearance in terms of facial, speech, gestures, etc. can be misleading since the above factors may depend on the social, cultural, and behavioural aspect of the individuals. Therefore, it is the physiological signals that remain the same for individuals mostly, and authors emphasise the significance of the physiological approach in detecting driver emotional states in real-time by minimising the challenges that arise from them. Accordingly, if a driver emotion recognition system is to be implemented universally, the utilisation of the physiological signals is the most appropriate. Moreover, the knowledge of challenges to emotion detection approaches is also vital in developing such a system.

References

Alyuz, N., Aslan, S., Healey, J., Alvarez, I. and Esme, A., 2018. Towards Understanding Emotional Reactions of Driver-Passenger Dyads in Automated Driving. In: *2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018)*. IEEE, pp.585-592.

Ayata, D., Yaslan, Y. & Kamaşak, M., 2017. Emotion Recognition via Galvanic Skin Response: Comparison of Machine Learning Algorithms and Feature Extraction Methods. IU-Journal of Electrical & Electronics Engineering, Istanbul University - Journal of Electrical & Electronics Engineering, pp. 3147-3156.

Bankar, C., Bhide, A., Kulkarni, A., Ghube, C. and Bedekar, M., 2018. Driving Control Using Emotion Analysis Via EEG. In: *2018 IEEE Punecon*. IEEE, pp.1-7.

Basu, S., Chakraborty, J., Bag, A. and Aftabuddin, M., 2017. A review on emotion recognition using speech. In: *2017 International Conference on Inventive Communication and Computational Technologies (ICICCT)*. IEEE, pp.109-114.

Bhattacharya, S. and Gupta, M., 2019. A Survey on: Facial Emotion Recognition Invariant to Pose, Illumination and Age. In: *2019 Second International Conference on Advanced Computational and Communication Paradigms (ICACCP)*. IEEE, pp.1-6.

Chunawale, A. and Bedekar, M., 2020. Human Emotion Recognition using Physiological Signals: A Survey. In: *2nd*

International Conference on Communication & Information Processing (ICCIP) 2020.

El-Amin, A., Attia, A., Hammad, O., Nasr, O., Ghozlan, O., Raouf, R., Hamed, A., Eldawlatly, H., El-Moursy, M. and Eldawlatly, S., 2019. Brain-in-Car: A Brain Activity-based Emotion Recognition Embedded System for Automotive. In: *2019 IEEE International Conference on Vehicular Electronics and Safety (ICVES)*. IEEE, pp.1-5.

Extranet.who.int. 2022. *WHO | Death on the roads*. [online] Available at: <https://extranet.who.int/roadsafety/death-on-the- roads/#trends> [Accessed 23 June 2022].

Gamage, T., Dabarera, W., Ekanayake, E., Jayasinghe, P., Chathuranga, A., Jayawardhana, R. and Kalansooriya, P., 2021. An Approach to Design a Smart Helmet Using Kansei Engineering. In: *14th International Research Conference of General Sir John Kotelawala Defence University*. [online] pp.106-113. Available at: <http://ir.kdu.ac.lk/handle/345/5206> [Accessed 23 June 2022].

Giannopoulos, P., Perikos, I., Hatzilygeroudis, I. (2018). Deep Learning Approaches for Facial Emotion Recognition: A Case Study on FER-2013. In: Hatzilygeroudis, I., Palade, V. (eds) Advances in Hybridisation of Intelligent Methods. Smart Innovation, Systems and Technologies, vol 85. Springer, Cham. https://doi.org/10.1007/978-3-319-66790-4_1

Goonewardena, I. and Kalansooriya, P., 2020. Analysis on emotion classification methods. In: *13th International Research Conference of General Sir John Kotelawala Defence University*. pp.493-505.

Hu, H., Zhu, Z., Gao, Z. and Zheng, R., 2018. Analysis on Biosignal Characteristics to Evaluate Road Rage of Younger Drivers: A Driving Simulator Study. In: *2018 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, pp.156-161.

Hu, X., Chen, J., Wang, F. and Zhang, D., 2019. Ten challenges for EEG-based affective computing. *Brain Science Advances*, 5(1), pp.1-20.

Jang, S. and Ahn, B., 2020. Implementation of Detection System for Drowsy Driving Prevention Using Image Recognition and IoT. *Sustainability*, 12(7), p.3037.

Jing, D., Liu, D., Zhang, S. and Guo, Z., 2020. Fatigue driving detection method based on EEG analysis in low-voltage and hypoxia plateau environment. *International Journal of Transportation Science and Technology*, 9(4), pp.366-376.

Kadoya, Y., Watanapongvanich, S. and Khan, M., 2021. How is emotion associated with driving speed? A study on taxi drivers in Japan. *Transportation Research Part F: Traffic Psychology and Behaviour*, 79, pp.205-216.

Kalansooriya, P., Ganepola, G. and Thalagala, T., 2020. Affective gaming in real-time emotion detection and music emotion recognition: Implementation approach with electroencephalogram. In: *2020 International Research Conference on Smart Computing and Systems Engineering (SCSE)*. IEEE, pp.111-116.

Kalansooriya, P., Mitsui, Y., Takaki, S., Kinefuchi, M., Takahashi, A. and Nomura, S., 2016. The Effect of a Bio-signal Interactive Virtual Reality on Subjective Impression - A Preliminary Study. *International Journal of Affective Engineering*, 15(3), pp.317-323.

Kazemitabar, M., Lajoie, S. and Doleck, T., 2021. Analysis of emotion regulation using posture, voice, and attention: A qualitative case study. *Computers and Education Open*, 2, p.100030.

Kowalczuk, Z., Czubenko, M. and Merta, T., 2019. Emotion monitoring system for drivers. *IFAC-PapersOnLine*, 52(8), pp.200-205.

Lotz, A., Ihme, K., Charnoz, A., Maroudis, P., Dmitriev, I. and Wendemuth, A., 2022. Recognising Behavioral Factors while Driving: A Real-World Multimodal Corpus to Monitor the Driver's Affective State. In: *Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018)*. pp.1589-1596.

Naqvi, R., Arsalan, M., Rehman, A., Rehman, A., Loh, W. and Paul, A., 2020. Deep Learning-Based Drivers Emotion Classification System in Time Series Data for Remote Applications. *Remote Sensing*, 12(3), p.587.

Nikolova, D., Mihaylova, P., Manolova, A., Georgieva, P., 2019. ECG-Based Human Emotion Recognition Across Multiple Subjects. In: Poulkov, V. (eds) Future Access Enablers for Ubiquitous and Intelligent Infrastructures. FABULOUS 2019. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, 283, pp 25-36.

Nisa' Minhad, K., Hamid Md Ali, S., Ooi Shi Khai, J. and Anom Ahmad, S., 2016. Human emotion classifications for automotive driver using skin conductance response signal. In: *2016 International Conference on Advances in Electrical, Electronic and Systems Engineering (ICAEES)*. IEEE, pp.371-375.

Saini, T., Eksambekar, R., Zahoor, S. and Bedekar, M., 2016. Automobile driver profiling: Infering emotions through actions for safe driving. In: *2016 2nd International Conference on Contemporary Computing and Informatics (IC3I)*. IEEE, pp.494- 498.

Sarala, S., Yadav, D. and Ansari, A., 2018. Emotionally Adaptive Driver Voice Alert System for Advanced Driver Assistance System (ADAS) Applications. In: *2018 International Conference on Smart Systems and Inventive Technology (ICSSIT)*. [online] IEEE, pp.509-512.

Templier, M. and Paré, G., 2015. A Framework for Guiding and Evaluating Literature Reviews. *Communications of the Association for Information Systems*, 37.

Theagarajan, R., Bhanu, B., Cruz, A., Le, B. and Tambo, A., 2017. Novel representation for driver emotion recognition in motor vehicle videos. In: *2017 IEEE International Conference on Image Processing (ICIP)*. IEEE, pp.810-814.

Verma, B. and Choudhary, A., 2018. Deep Learning Based Real-Time Driver Emotion Monitoring. In: *2018 IEEE International Conference on Vehicular Electronics and Safety (ICVES)*. IEEE, pp.1-6.

Vinola, C. and Vimaladevi, K., 2015. A Survey on Human Emotion Recognition Approaches, Databases and Applications. *ELCVIA Electronic Letters on Computer Vision and Image Analysis*, 14(2), p.24.

Wan, P., Wu, C., Lin, Y. and Ma, X., 2019. Driving Anger States Detection Based on Incremental Association Markov Blanket and Least Square Support Vector Machine. *Discrete Dynamics in Nature and Society*, 2019, pp.1-17.

Wang, X., Guo, Y., Bai, C., Yuan, Q., Liu, S. and Han, J., 2021. Driver's Intention Identification With the Involvement of Emotional Factors in Two-Lane Roads. *IEEE Transactions on Intelligent Transportation Systems*, 22(11), pp.6866-6874.

Who.int. 2022. *The top 10 causes of death*. [online] Available at: <https://www.who.int/news-room/fact-sheets/detail/the-top-10- causes-of-death> [Accessed 23 June 2022].

Yan, L., Wan, P., Qin, L. and Zhu, D., 2018. The Induction and Detection Method of Angry Driving: Evidences from EEG and Physiological Signals. *Discrete Dynamics in Nature and Society*, 2018, pp.1-16.

Zhong, P., Wang, D. and Miao, C., 2020. EEG-Based Emotion Recognition Using Regularized Graph Neural Networks. *IEEE Transactions on Affective Computing*, pp.1-12.

Zimasa, T., Jamson, S. and Henson, B., 2019. The influence of driver's mood on car following and glance behaviour: Using cognitive load as an intervention. *Transportation Research Part F: Traffic Psychology and Behaviour*, 66, pp.87-100.

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