A NOVEL LOW COMPLEXITY ALGORITHM FOR OFFENCE GESTURE DETECTION IN LIVE VIDEO STREAM

ABID SIDDIQUE[1], MOHAMMED GHOUSUDDIN[2], REHNA V. J.[3]

[1]Research Scholar, Lincoln University College, Applied Science Department, Petaling Jaya, Malaysia

[2]Professor, Lincoln University College, Pharmacy & Applied Science Department, Petaling Jaya, Malaysia

[1]Sr. Lecturer, University of Technology & Applied Sciences, Engineering Department, Sultanate of Oman

E-mail: [1]abidsiddique@lincoln.edu.my, [2]md.gousuddin@lincoln.edu.my, [3]rehnavj@ibrict.edu.om

ABSTRACT

One of the major causes of road accidents is the use of mobile phones while driving. Calling or texting while driving, risking the life of the driver, passengers and other road users, is considered to be a traffic offence in most countries. The stringent measures taken by the authorities including increased penalties and jail terms, has made little effect, especially on the younger sections of the driving community, due to their addition to smartphone usage. The aim of this study is to provide a possible solution for this concern. A novel efficient gesture recognition algorithm for sensing specific gestures in real time while driving is presented in this paper. The offensive actions such as talking over cell phone or texting while driving are identified from real time live video streams captured in a non-smart environment using image processing algorithms, and the data is used to alert the user to refrain himself from improper driving conditions and/or send to concerned authorities for storage and subsequent action. The algorithm was tested using MATLAB 9.3 R2017b on over 60 sample videos. Experimental results demonstrate that the proposed algorithm is competent with successful detection rates approaching 98.3%. The time complexity of the algorithm is 1.5 times lower than its contemporaries and so is its computational complexity.

Keywords: *Image Processing, Texting-And-Driving, Offence Detection, Gesture Identification*

1. INTRODUCTION

The consequences of distracted driving are devastating especially when drivers are preoccupied with mobile phones while driving. Unfocused drivers talking over phone are about four times and drivers who are texting are twenty times more likely to be involved in crashes than non-distracted drivers [1]. Data collected by the NCSI (National Centre for Statistics and Information) and several other independent surveys shows the huge number of drivers who call or text while driving [2]. This crucial issue requires immediate attention and stringent steps, which the authorities are seriously contemplating, as the current measures including enlarged penalties and jail terms have little effect on deterring errant drivers. The main objective of the paper is to develop a suitable gesture identification algorithm for this particular application, to control cell phone related driver distractions, thereby preventing a larger proportion of road mishaps.

The study reveals a new algorithm to detect offensive gestures while driving. The proposed system is designed for a non-smart regular environment which do not require multiple sensors or actuators, but only a camera to capture the real time video of the driver. The main aim of the study is to understand gestures and track few particular motions (gestures of offence) of an individual in a sequence of video frames, that may be taken under various lighting conditions, having artifacts due to noisy circumstances, with partial or full occlusion and high background complexity. Focusing on one particular application of detecting the calling and texting gestures in the drive mode, helps the developed system to be capable of handling most of the challenges of computer vision based gesture recognition such as, high speed and spontaneity of movements, variety of human poses, unexpected appearance of objects, large number of degrees of freedom, unpredictability of 2D appearances based on the camera view-points, different spatial resolutions for temporal dimensions etc. The video frames are processed effectively to identify the gestures of offence and alert the driver and others concerned of the improper driving status. The algorithm is fast, secure, accurate and easily scalable.

Journal of Theoretical and Applied Information Technology
15th July 2023. Vol.101. No 13

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The paper is organized as follows: Section 2 discusses the background of the study, Section 3 reviews the literature and gives a summary of the current practices of gesture recognition in video streams, Section 4 conveys the methodology of implementation, Section 5 provides the experimental results followed by conclusion and future scope in Section 6.

2. BACKGROUND

The World Health Organization infers that preventable improper driver behaviors contribute to 80 to 90% of fatal road accidents compared to other causes such as harsh weather, vehicle failings or poor road conditions [3]. The most common objectionable driving behavior is the use of cell phones while driving. Drivers using mobile phones take their eyes off the road, their hands off the steering wheel, and their minds off the surroundings during driving, all of which are dangerous acts risking their own life and the lives of other road users. There are evidences that shows the impact of cell phone distractions on driving quality [3], like reduction in driving performance due to longer response times including braking reaction time, response time to traffic signals etc.; over or under speeding; inability to stay in the correct lane; shorter following distances etc. Text messaging likewise results in dangerous driving leading to fatal crashes, with young drivers particularly at risk.

Besides, road accidents have recently led to wastage of resources and the capacities of the respective ministries being consumed, either in terms of financial resources or health issues. Among different types of driver distractions, the use of mobile phones while driving is of primary concern to policymakers. Evidences suggest that this trend is increasing rapidly as a result of the exponential growth in the use of mobile phones in society [3]. Reports indicate that the proportion of drivers using mobile phones while driving has increased from 1% to 11% over the past 5 years [3].

According to the U.S. Department of Transportation, National Highway Traffic Safety Administration (NHTSA), the number of fatal crashes due to distracted driving is alarmingly increasing. NHTSA collects data on distraction-affected crashes, which focus on distractions that are most likely to result in crashes such as dialing a cellphone, texting or being distracted by internal factors or an outside event. This anthropogenic activity can be curbed by adopting suitable measures to counter them.

The National Safety Council (NSC) has called for strict laws banning all cell phone use (including hands-free) along with installation and use of automated enforcement to have an effective roadway safety culture. The situation demands for innovative and automated mechanisms to reduce this practice [4].

A number of research works have been carried out by different research institutes and automobile manufacturers across the world on accident prevention and detection systems [5][6]. These systems range from wearable gadgets and sensors for employees in dangerous situations, to advanced driver assistance systems (ADAS) and accident avoidance technology for automobiles. While some studies investigate the integration of sensors and data analytics to identify and respond to accidents in real-time, some studies concentrate on applying artificial intelligence and machine learning approaches to anticipate and avoid accidents.

The overall goal of these researches is to lessen the frequency and severity of accidents while also enhancing safety in various contexts. However, the concept of built-in image acquisition and processing devices in cars to limit cell phone use is new, which is discussed in this paper. This work presents a novel, effective gesture recognition system for detecting offensive movements in real time, like talking on the phone or texting while driving. The data can then be used to alert the user to avoid engaging in these activities while driving and/or to send to the relevant authorities for storage and further action.

3. LITERATURE REVIEW

An important field of research in computer vision and machine learning is gesture identification via image processing. The purpose of gesture identification is to identify hand motions that users make when interacting with technology. Recent studies have offered a number of strategies for gesture identification utilizing image processing techniques. These techniques have produced encouraging results and have the potential to enhance how users engage with technology. Examining new studies on gesture recognition using image processing methods is the focus of this overview of the literature.

In 2020, Zhang et al. put forward an approach for gesture identification utilizing image processing techniques [7]. To recognize hand motions, the suggested method combines feature extraction methods with an SVM classifier. A 92.2% accuracy rate was attained by the suggested strategy for a

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

dataset of over 600 images. Another approach for gesture identification for human-robot interaction utilizing image processing was put forth by Zhang et al. in 2021 [8]. The suggested technique makes use of a CNN to identify hand motions. Around 1,500 images of hand motions in was used in the study. The accuracy of the suggested method was 92.8%. A recent study by N. Ahmed et al. (2021) reports an accuracy of 98.22% using a support vector machine (SVM) algorithm [9].

Convolutional neural networks (CNNs) were suggested by Yan et al. (2021) as a technique for classifying hand motions. One thousand hand gesture images were trained in the study. The accuracy of the suggested approach was 95.4% for the publicly available NVIDIA Multimodal Hand Gesture dataset [10].

A method for image processing-based sign language recognition was put forth by Li et al. in 2021. The suggested technique recognizes sign language gestures by combining CNN and LSTM [11]. 3,338 images of gestures in sign language make up the dataset for the study. The accuracy reached by the proposed method was 98.4%, which is greater than the accuracy attained by conventional methods. A hybrid Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) based gesture recognition algorithm was proposed by A. Singla et al. (2021) which reports an accuracy of 96.43% for the NVIDIA Multimodal Hand Gesture dataset [12].

Image processing techniques for gesture recognition have the potential to be used in the field of offence detection for security, social media content moderation, and law enforcement purposes. A method for offensive gesture recognition utilizing image processing was put forth by Luo et al. in 2019 [13]. To identify such gestures, the suggested method combines hand region segmentation, feature extraction, and SVM classifier. 1,200 images of hand gestures, both offensive and non-offensive, make up the dataset used in the study. The accuracy of the suggested strategy in detecting offensive gestures was 96.2% [13].

Another crucial area of study involves identifying driving-related offense motions such as using a cell phone while driving. Detecting mobile phone use gestures while driving has been proposed by Al-Ali et al. (2019) [14]. To identify cell phone use gestures, the suggested method combines image segmentation, feature extraction, and SVM classifier. The study's dataset includes of 1,000 pictures of drivers engaged in a variety of activities, including both using and not using their cell phones. For cell phone use gesture detection, the suggested technique had a 93% accuracy rate.

Similar to this, Kaur et al. (2020) suggested another approach employing CNN to identify cell phone usage gestures [15]. The study's dataset comprises of 2,000 photos of drivers engaged in a variety of activities, including both mobile phone use and non-use activities. The accuracy of the suggested approach for detecting cell phone use gestures was 94.1%.

The use of decision trees and random forest classifiers for hand gesture detection is suggested in the research paper by A. Singla et al. [16] in 2019. The suggested method is based on training the classifiers on the extracted hand features after extracting hand features using the SIFT and SURF algorithms. For the NVIDIA Multimodal Hand Gesture dataset, the suggested technique had accuracy rates of 95.89% [16].

In highly specialized applications involving trained human experts and vital crime investigation, human motion detection and video processing have been deployed. However, there is a greater need to improve the accuracy in this area and explore the possibility of using it for real-time applications. A novel method is proposed in this paper for detecting cell phone use gestures while driving, in live video streams using frame comparison and segmentation techniques, which has shown higher accuracy for the NVIDIA Multimodal Hand Gesture dataset and with a significant reduction in computational and time complexity. The proposed design is motivated by the desire to curb road mishaps caused due to distracted drivers, and aims to provide a solution by making cars more intelligent and interactive which may notify or resist users under unacceptable driving circumstances.

4. METHODOLOGY

The four stages of the system architecture's operation are as follows: Using a high-resolution GoPro camera to record the live video stream, preprocessing the video signal, analyzing each frame to find the offensive gesture, and saving the frames with specific movements to memory. The video processing was tested on more than 60 sample videos in MATLAB 9.3 R2017b. Collecting the data set of videos to be examined for inappropriate gestures is the initial stage in the methodology. The video data set must include examples of both the offensive gesture—using a cell phone while driving—and the typical driving gesture. This data-set is stored in the database for comparison and recognition. The captured videos are then pre-processed, with the noise being removed and the brightness and contrast levels being adjusted. The system block diagram is shown in Figure 1.

The second step, frame extraction, involves breaking down the video into a series of frames, which are then separated out for processing. The region of interest (ROI), or the part of the frame where the offensive gesture is most likely to occur, is then found through analysis of the frames. When using a cell phone, the area of interest may be the vicinity of the driver's hand or ears because that is where the phone is usually held.

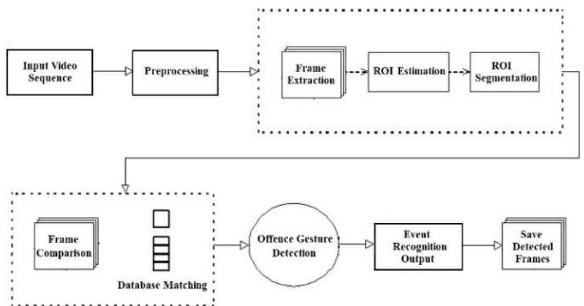

Figure 1: System Architecture

The next step is to segment the images, which is to separate the area of interest from the context. Standard picture segmentation methods like thresholding, edge detection, and clustering are used to accomplish this. The offensive gesture is subsequently extracted using an analysis of the segmented image's attributes. The features may take the form of statistical aspects of the image, a region's texture, or its geometry. The size, position, and form of the driver's hand may be among the features in this scenario of cell phone use. To detect the presence of a cell phone in the driver's hand or close to his ears, object detection is used. To increase the accuracy of detection, motion detection and temporal analysis of the video frames are also carried out.

The primary step after extracting the features is to categorize them as offensive or non-offensive gestures. This is accomplished by comparing succeeding video frames to one another and to the image data set, i.e., the image database that comprises both offensive and non-offensive gestures. Even slight variations seen in subsequent frames can predict the possibility of a defined gesture, and they are confirmed by comparisons to similar gestures in the database images. The data was verified using classification algorithms like the support vector machine. Once the offensive event is detected, the corresponding frames are saved in memory so that the user or authorities can view them later. This aids the authorities in presenting legal evidence of any driving offence. The flow diagram for offence gesture identification in live video frames using histogram comparison is shown in Figure 2.

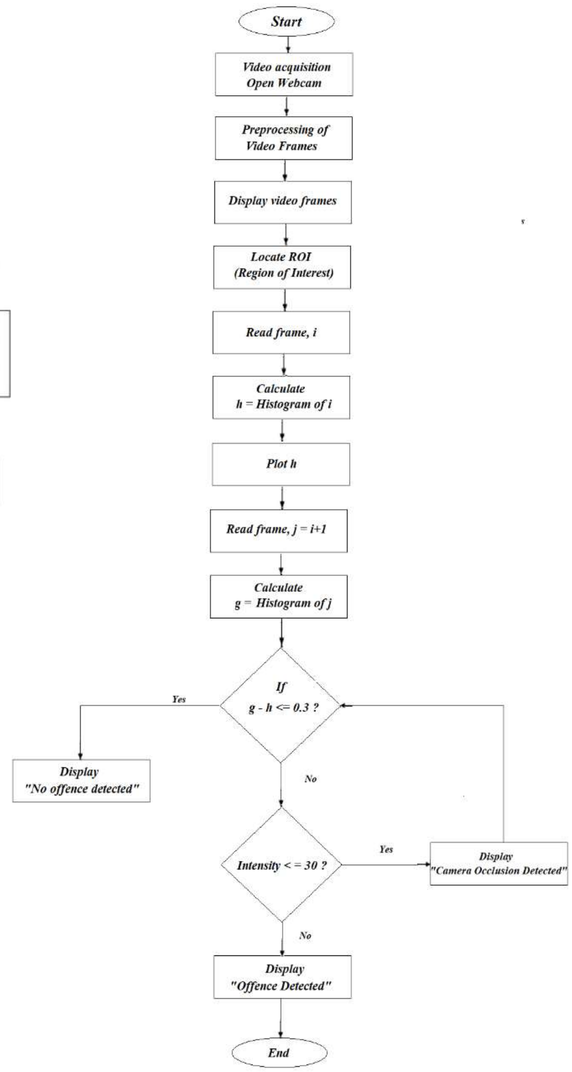

Figure 2: Flow Diagram for Offence Detection by Histogram Comparison

3.1 Evaluation of Algorithm's Performance

A variety of parameters, including accuracy, precision, recall, F1 score, and computing efficiency, can be used to evaluate, compare, and optimize the effectiveness of various gesture recognition algorithms. The parameters indicate the algorithm's positive and negative aspects and can be used to suggest changes to the design and implementation of the algorithm, and therefore these metrics are crucial in evaluating the algorithm's performance.

The primary parameter for assessing the effectiveness of gesture recognition systems is typically the accuracy. This is the frequency with which the system properly recognizes the gesture. It is often expressed as a percentage. This statistic, however, might not be sufficient on its own because it does not account for false positives and false negatives. Other frequently used metrics that offer a more thorough assessment of algorithm effectiveness are recall and precision. The percentage of times the computer successfully recognizes the gesture when it is actually present is known as precision. Recall is a percentage-based measure of how frequently the algorithm correctly recognizes the gesture when it is present.

The algorithm's overall performance is gauged by the F1 Score, which considers both precision and recall. It is a performance statistic that offers a balanced measure of both recall and precision and is calculated as:

$$F1\ Score = 2 * [\frac{(Precision*Recall)}{(Precision+Recal\ )}] \quad (1)$$

Also, it's crucial to take computing efficiency into account, especially in real-time applications. The processing resources needed by the algorithm to recognize a gesture are measured by the algorithm's computational complexity. A range of factors, such as the particular application, the kind of gestures being identified, and the available hardware resources, will overall affect how well gesture recognition algorithms function. The goal of ongoing research in this field is to create new uses for this technology while also enhancing the precision and effectiveness of gesture recognition algorithms.

A few benchmark dataset that have been created to assess the effectiveness of gesture recognition systems include the ChaLearn Gesture Challenge [17][18], the NVIDIA Hand Gesture Recognition Dataset [19][20], and the NTU Hand Gesture Dataset [21]. These datasets offer a thorough assessment of algorithm performance because they cover a wide range of gesture types, lighting setups, and camera angles. This study reports the above mentioned parameters for hand gesture recognition on the publicly available NVIDIA Multimodal Hand Gesture dataset using the proposed method. The particular values of accuracy, precision, recall, and F1 score for gesture identification algorithms rely on the datasets and algorithms used for evaluation, including the data's quality, the algorithm's use, and the gesture identification system's intended use.

5. RESULTS AND DISCUSSION

The majority of camera-based gesture recognition systems only function in limited environments due to the impact of illumination and complex backgrounds. A quick and easy motion history image-based approach to categorize dynamic hand movements and object detection is implemented in this work. The results of the study are detailed in this section. The detection rates, computational complexity and time complexity of the algorithm is compared with its contemporaries as well. In the algorithm implementation, a real-time live video of the driver captured using a high resolution camera, is given as input to the system. The outputs obtained for the gesture recognition algorithm for detecting offensive gestures while driving such as texting and calling while driving, programmed in MATLAB are shown below.

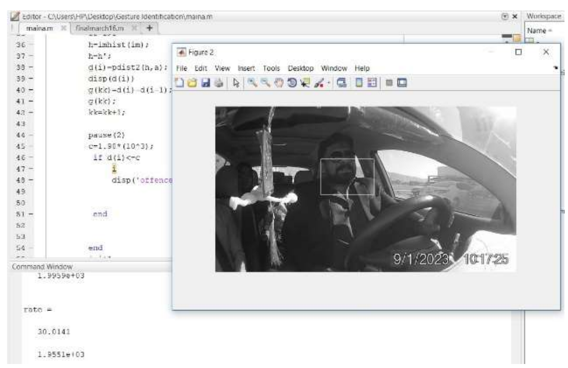

Figure 3: Gesture not identified - No offence detected

In Figure 3, the driver is not involved in the targeted activities of using mobile phone while driving. Therefore, the system does not detect any offensive gesture.

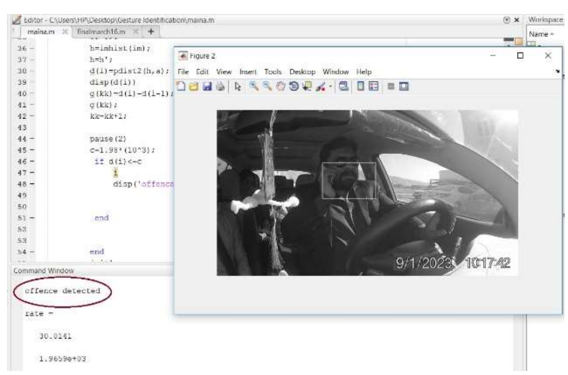

Figure 4: Calling Gesture Detected

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

When the driver makes or receives a call and talks over phone while driving, the system detects the offensive gesture. The result of this event is shown in Figure 4. In Figure 5, the driver looks at his phone during drive, for texting or reading messages. This gesture is also identified as offensive which is detected and alerted.

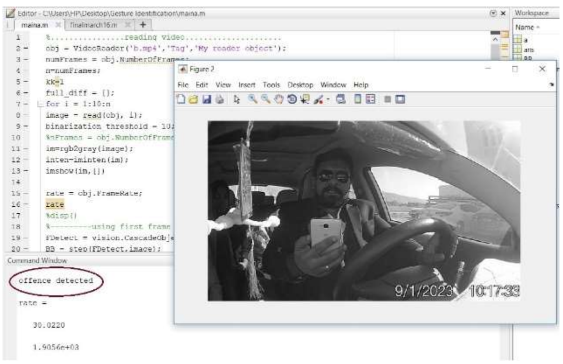

Figure 5: Texting Gesture Identified

In terms of comparison, there are numerous other ways for gesture recognition, including rule-based systems, template matching, and deep learning-based techniques. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been particularly effective deep learning-based techniques in recent years. However, in certain instances, template matching and rule-based systems can also be useful. Performance measurements are provided here along with details on how to utilize them to assess classification algorithms.

Table 1: Comparison of Performance Parameters

Parameter / Model	Accuracy	Precision	Recall	F1 Score
MHMM [11]	94.68%	94.69%.	94.68%	94.68%
ANN & CNN [12]	96.43%	96.43%	96.43%	96.43%
SVM [9]	98.22%	98.22%	98.21%	98.22%
MDT [23]	95.89%	95.81%	95.89%	95.85%
Proposed Model	98.31%	98.31%	98.33%	98.31%

Here, the suggested model for the four parameters is contrasted with the gesture recognition techniques employing Modified Hidden Markov Models (MHMM) [22], Artificial Neural Networks (ANN) & Convolutional Neural Networks (CNN) [12], Support Vector Machines (SVM) [9], and Modified Decision Trees (MDT) [23] as indicated in Table 1. These measures could, however, differ based on the specific dataset, algorithm, and evaluation standards that were employed.

Results show that the suggested method is capable, with effective detection rates close to 98.31%. The algorithm's computational complexity and time complexity are both 1.5 times lower than those of its contemporaries. The SVM and Random Forest classifiers have a computational complexity of $O(n^2)$, where n is the number of training samples [9]. The Decision Tree classifier has a computational complexity of $O(nmlog(m))$, where n is the number of training samples and m is the number of features [23]. The Artificial Neural Network (ANN) and Convolutional Neural Network (CNN) classifiers have computational complexities of $O(pq)$, where p is the number of input features and q is the number of neurons in the hidden layer for ANN [12], and $O(w^{2n}2d^2)$ for CNN, where w, n, and d are the width, height, and depth of the input image, respectively [10]. However, the algorithm complexity is not analyzed for the Hand Gesture Recognition using a Modified Hidden Markov Model.

However, it is important to note that the precise values of these metrics can vary significantly based on the dataset and evaluation methodology used, as well as other factors like the precise features used for the recognition of gestures, the training procedure, the complexity of the algorithm, and the particular application of the gesture identification system. As a result, the outcomes may not be directly comparable.

6. CONCLUSION

Overall, the research work has opened up a new avenue for developing safer and more efficient driver assistance systems that can detect and prevent distracted driving caused by cell phone use. The proposed method for detecting cell phone use gestures while driving using frame comparison and segmentation techniques, have shown promising results with increased accuracy of 98.3% and a significant reduction in computational and time complexity by 1.5 times. However, depending on the dataset and evaluation methodology used, as well as additional factors like the precise features used for gesture recognition, the training process, the algorithm's complexity, and the specific application of the gesture identification system, the precise values of these metrics can vary significantly. Consequently, the results might not be exactly identical.

There is a great scope for fusrther research in this area to improve the accuracy of the proposed method

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

and to explore the possibility of using it for real-time applications. Detecting cell phone use gestures during driving using image processing can be applied in various fields, such as law enforcement and insurance. For example, cell phone use gesture detection can be used by law enforcement agencies to identify drivers who are using their cell phones while driving and issue fines accordingly. In addition, insurance companies can use cell phone use gesture detection to identify high-risk drivers and adjust their insurance premiums accordingly. The integration of machine learning algorithms and neural networks can be explored to enhance the accuracy and reliability of the system. The use of more advanced hardware and sensors could also improve the efficiency of the system. The design suggested has the potential to help reduce the number of distracted driving accidents caused by cell phone use, which is a major concern for public safety.

ACKNOWLEDGEMENT

The authors thank the management and staff of University of Technology and Applied Sciences - Ibri, Oman for providing the inspiration and support to conduct the research work. The contribution of the reviewers in improving the paper quality is also acknowledged.

REFERENCES:

[1] US Department of Transportation, "Distracted Driving Global Fact Sheet", (https://usdotblog. typepad. com/ files/6983_distracteddrivingfs_5- 17_ v2.pdf, accessed 27 July 2021).

[2] National Center for Statistics and Analysis, "Overview of motor vehicle crashes in 2019", Traffic Safety Facts Research Note. Report No. DOT HS 813 060, National Highway Traffic Safety Administration, December, 2020.

[3] "Mobile phone use: a growing problem of driver distraction", Geneva, Switzerland, World Health Organization, 14 February 2011.

[4] Abid Siddique, Mohammed Ghousuddin and Rehna V. J, "A Contemporary Approach Towards Curbing Cell Phone Use Related Road Mishaps," *IECON 2021 – 47th Annual Conference of the IEEE Industrial Electronics Society*, 2021, pp. 1-5.

[5] Toyota. (n.d.). Pre-Collision System. Retrieved from https://www.toyota-global.com/innovation/safety_technology/safety_technology/pre-collision_system/

[6] Volvo. (n.d.). Collision Avoidance. Retrieved from https://www.volvotrucks.us/innovations/collision-avoidance /

[7] Zhang, X., Jiang, Y., Hu, L., & Sun, H, "Gesture Recognition Based on Image Processing and Support Vector Machine". In *Proceedings of the 3rd International Conference on Artificial Intelligence and Industrial Engineering*, 2020, pp. 92–97.

[8] Zhang, L., Zhao, Z., Liu, Y., & Chen, L, "Human-Robot Interaction Based on Gesture Recognition with Convolutional Neural Network", In *2021 5th International Conference on Intelligent Information Processing*, 2021, pp. 117–122.

[9] Ahmed, N., Rahman, M. T., Hasan, M. R., & Nahar, J, "A Comparative Study of SVM and Random Forest for Hand Gesture Recognition", In *2021 2nd International Conference on Electrical, Communication and Computer Engineering (ICECCE)*, 2021, pp. 1-6.

[10] Yan, X., Liu, Q., Zhang, B., & Hu, X, "Hand Gesture Recognition with Convolutional Neural Networks", *Applied Sciences,* 11(7), 2021, 3191.

[11] Li, R., Li, H., Zhang, H., & Wu, X, "A Sign Language Recognition Method Based on Deep Learning", In *2021 3rd International Conference on Frontiers of Educational Technologies,* 2021, pp. 178–182.

[12] Singla, A, Sharma, N, & Girdhar, R., "Gesture Recognition using Artificial Neural Network and Convolutional Neural Network" *In 2021 International Conference on Inventive Research in Computing Applications*, 2021, pp. 168-173.

[13] Luo, Y., Zhu, H., Li, S., & Hu, X, "Offensive gesture recognition based on image processing", *Multimedia Tools and Applications*, 2019, 78(21), 30587-30603.

[14] Al-Ali, A. R., Alam, M. M., Al-Turjman, F., & Al-Fahdawi, S, "Detection of mobile phone usage while driving using image processing techniques", In 2019 *IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT)*, 2019, pp. 441–446.

[15] Kaur R., Sharma A., & Kumar M, "A novel approach for the detection of mobile phone

usage while driving using convolutional neural networks", *International Journal of Advanced Intelligence Paradigms*, 2020, 15(1/2), 103–118.

[16] Singla, A., Sharma, N., & Girdhar, R, "Gesture Recognition using Decision Tree and Random Forest Classifiers", *In 2019 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE)*, 2019, pp. 7-11.

[17] Escalera, S., León, D., Madadi, M., & Ponce-López, V, "ChaLearn Gesture Challenge: A competition on Multimodal Gesture Recognition", In *Proceedings of the International Conference on Computer Vision Workshops (ICCVW),* 2013, pp. 117-122.

[18] Escalera, S., Baró, X., Valveny, E., & Escalante, H. J. "The 2020 ChaLearn Gesture Challenge: Open-Set Gesture Recognition", In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, 2021, pp. 3854-3859.

[19] Keskin, C., Kirillov, A., & Koltun, V, "Deep Learning of Biomimetic Sensorimotor Transformations", In *Advances in Neural Information Processing Systems (NIPS),* 2016, pp. 437-445.

[20] NVIDIA, "NVIDIA Hand Gesture Recognition Dataset", 2022. Retrieved from https://developer.nvidia.com/gameworksdownload#?dn=nvidia-hand-gesture-recognition-dataset

[21] Wan, C., Li, Y., & Xia, S., "NTU Hand Gesture Dataset", 2019. Retrieved from https://www.yunliangyu.com/publications/NTU_Hand_Gesture_Dataset.html

[22] Nair, N.B., & Kumar, N.S, "Real-time Hand Gesture Recognition using a Modified Hidden Markov Model", *IEEE Access*, 9, 2121, pp. 15751-15762.

[23] Khan, M. M, Rahman, M.M, Al Mamun, S.A, & Khalil, M. I, "Real-time Hand Gesture Recognition System based on Modified Decision Tree Algorithm. Journal of Ambient Intelligence and Humanized Computing", 12, 2021, pp. 4771-4786.