A REVIEW OF SEAT BELT NON-COMPLIANCE DETECTION IN DRIVERS

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Abstract
Traffic accident fatalities are still a severe problem in the world, and one of the contributing factors remains the failure of drivers to adhere to essential traffic regulations, exemplified by their non-compliance with seat belt usage. Previous research has developed systems for detecting drivers not wearing seat belts, consisting of three subsystems: car detection, windshield detection, and seat belt detection. Several reviews for car detection have been done, but a review focusing on seat belt detection has never been carried out. Therefore, this paper aims to review seat belt detection. The initial section outlines general steps to detect drivers not wearing a seat belt. The following section compares the methods used for seat belt detection. The research concludes by describing potential methods to improve accuracy and speed.

***Keywords*: Seat belt non-compliance detection; driver; traffic regulation.**

1. Introduction

Traffic accident fatalities are still a severe problem in the world, with one of the contributing factors being the failure of drivers to comply with traffic regulations, particularly regarding the usage of seat belts. Wearing a seat belt while driving a car on the highway is very important as it significantly improves driving safety and reduces the risk of severe injury or death in traffic accidents. Therefore, it is imperative to enhance the supervision and enforcement of seat belt usage rules related to using it on the road.

The current supervision of vehicle drivers concerning seat belt usage on the police highway relies solely on direct observation, which is not carried out for 24 hours due to officer limitations. This method has weaknesses, leading to the detection of only a fraction of drivers violating seat belt regulations. Therefore, a viable solution involves the deployment of CCTV (Closed-Circuit Television) cameras for highway surveillance, coupled with an automatic detection process targeting non-compliant drivers who violate not wearing seat belts.

The detection system for car drivers not wearing seat belts comprises car detection, windshield detection, and seat belt detection. Previous research has extensively reviewed car detection methods, with Arora and Kumar examining various vehicle detection techniques for the day and night [Arora and Kumar, (2022)]. In addition, the research explored the various challenges encountered when recognizing different types of vehicles. Berwo et al. surveyed vehicle detection and classification, primarily focusing on deep learning methods [Berwo et al., (2023)]. This technique is presented by comparing several datasets, loss, and activation functions. Gholamhosseinian and Seits also researched vehicle classification methods comprehensively [Gholamhosseinian and Seitz, (2021)], proposing a taxonomy of vehicle classification and reviewing soft computing solutions. Although a review of vehicle detection and classification, including cars, has been conducted, the same attention has not been given to seat belt detection. Therefore, this paper aims to review seat belt detection. The contribution of this paper is to provide recommendations for potential methods that can be applied to detect drivers and passengers who are not wearing seat belts in real time.

The following sections are organized: Section 2 outlines the general steps involved in detecting unbelted drivers and an overview of the methods utilized in seat belt detection. Subsequently, Section 3 presents the results and discussion on the methods used in the seat belt detection methods employed. Section 4 describes the conclusions and provides recommendations for future methodological advancements.

2. General Step

Detection of drivers not wearing seat belts involved three subsystems: car detection, windshield detection, and seat belt detection, as illustrated in Figure 1. Car detection aimed to identify the car object within the video frame, while windshield detection sought to locate the position of the car windshield. On the other hand, seat belt detection focuses on identifying the area of the driver and classifying whether they used a seat belt.

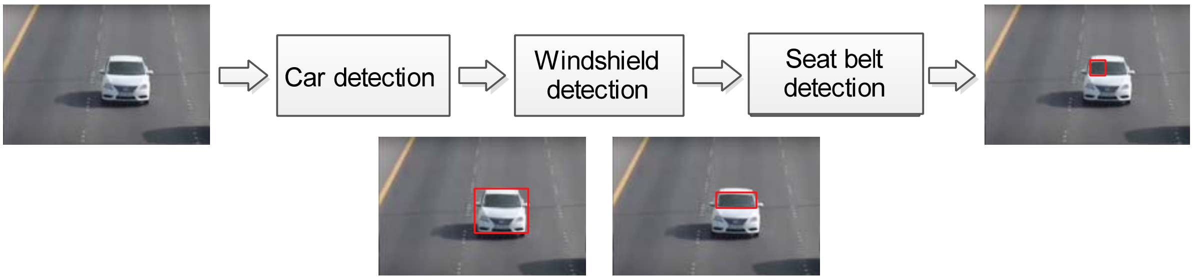

Fig. 1. General step for detecting the driver without a seat belt.

Research on computer vision-based seat belt detection commenced around a decade ago. A summary of the methods and results of this research is presented in Table 1. Generally, this research was categorized into two types based on the features used: handcrafted features and non-handcrafted features. Handcrafted features involved manually designing and selecting features based on domain knowledge and expert experience. In contrast, non-handcrafted features relied on machine learning algorithms to extract features from image data automatically without human intervention. This method proved more adaptive and effective in handling complex and diverse data.

2.1. *Handcrafted feature*

Research focused on using handcrafted features to detect drivers not wearing seat belts. For example, Guo et al. determined the driver area and performed edge detection [Huiwen Guo et al., (2011)]. The left border of the driver area was determined based on the right border of the license plate area, while the upper border was derived from the upper border of the car windshield. The width of the driver area was calculated as 2/3 of the width of the license plate, and the height was determined as 2/3 of the windshield height. An illustration of the driver area determination process can be seen in Figure 2. Li et al. utilized the canny edge detection algorithm to detect the position of the seat belt. Also, they determined the driver area by cutting ½ of the left area of the windshield [Li et al., (2013)]. The position of the car windshield area was detected using a cascade Adaboost classifier. In another method, Zhou et al. proposed canny edge detection, a salient gradient map for feature extraction, and a learning-based algorithm for binary classification [Zhou et al., (2018)]. Yang et al. employed face detection techniques to determine the driver and used the connected area method for seat belt detection [Yang et al., (2019)]. Additionally, Wu et al. introduced driver area determination through semantic segmentation accelerated by pruning, with classification performed using the connected area method [Wu et al., (2019)].

Yongquan et al. introduced a driver detection system focused on reducing computation time by eliminating the need for seat belts [Yongquan et al., (2019)]. Specifically, the research was performed by designing a GPU acceleration method. The driver area was determined using Squeeze-YOLO, while seat belt usage was identified through a semantic segmentation algorithm and full convolution network pruning. Wang et al. used semantic segmentation, lightweight feature extraction, and the Squeeze-YOLO algorithm to detect the driver area [Wang, (2022)]. Meanwhile, Qiao and Qu proposed detection based on human joint points and seat belt endpoints [Qiao and Qu, (2021)].

Ref.	Method	Result	Advantages	Disadvantages
[H Guo et al., (2011)]	Direction information measure and edge detection	CIR= 81.00%	Computation time is fast, relatively.	The camera position must be precise.
[Li et al., (2013)]	Gradient map computation, canny edge detection, and high-line extraction	Rec= 34.00%	Computation time is fast, relatively.	The testing needs are on busy highways, and the recall is still low.
[Zhou, Chen, and Wang, (2017)]	BN-AlexNet	CD= 92.51%	The accuracy is higher than traditional methods.	-
[Chen et al., (2018)]	CNN and SVM	CIR= 87.00%	This method significantly reduces false positives and undetected rates.	This method has only been tested on high-resolution image data.
[Zhou et al., (2018)]	Canny edge detection, salient gradient map, and machine learning	Acc= 84.30%	The performance is better than conventional methods.	Accuracy improvements are still needed to overcome low-quality images.
[Wu et al., (2019)]	Semantic segmentation and connected area	Acc= 94.87% Speed= 305 FPS	The speed is high, so it can potentially be applied to actual conditions.	-
[Yongquan et al., (2019)]	Squeeze-YOLO and semantic segmentation	-	This method can increase its speed.	-
[Elihos et al., (2019)]	SSD	Acc= 91.90% Prec= 94.50%	Produces relatively high accuracy for image data during the day and night.	There are still detection errors when someone wears clothes with lots of patterns.
[Chun et al., (2019)]	NADS-Net	F1-s= 63.55% Prec= 63.58%	Robust towards riders or passengers regarding gender, race, clothing, and illumination.	The precision value is still low.
[Yang, Zang, and Liu, (2020)]	Combination of texture extraction, SSD MobilNet V2, and particle filter tracking	Rec= 97.19% Prec= 95.21%	The detection speed is relatively high (21 FPS).	-
[Khalid and Hazela, (2021)]	YOLOv4 and Alexnet	Acc= 93.60%	Detection speed reaches 45 to 140 FPS, faster than R-CNN.	Fails to recognize close objects.
[Luo, Lu, and Yue, (2021)]	YOLOv3 and CNN	-	Robust to complex environments.	-
[Maduri et al., (2021)]	Deep learning	Acc= 90.00%	This method can be applied to real-time systems.	The accuracy still needs to be improved.
[Qiao and Qu, (2021)]	Human joint points	-	This method can detect seat belts that are partially blocked by other objects.	This method needs to be tested on low-resolution data.
[Ramakrishna, Venkatesulu, Rao, (2021)]	CNN	Acc= 91.40%	CNN Produces better accuracy than SVM.	CNN Produces low accuracy on non-standard datasets, namely 75.38%.
[Wang, (2022)]	Lightweight feature extraction, Squeeze-YOLO, and Semantic segmentation	Acc= 94.87% Speed= 305 FPS	The detection speed is relatively high.	-
[Feng, Yu, and Nan, (2022)]	A combination of YOLOv5 and Alexnet Network	DR (day)= 95.89% DR (night)= 95.12%	This method can be recognized well in non-complex road conditions.	The ability to recognize dark conditions needs to be improved.
[Wang and Ma, (2022)]	YOLOv3 and lightweight network structure.	Acc= 99.98% Speed= 69 FPS	The proposed method can improve the accuracy compared to only YOLOv3.	The time will increase when compared to YOLOv3.
[Kapdi et al., (2022)]	MobileNetV2	Prec= 89.00% Rec= 89.00%	The recall value for the negative class is high.	The recall value for the positive class is still low.
[Hosseini and Fathi, (2023)]	YOLOv5 and ResNet34	Acc= 99.70% Speed= 50 FPS	High accuracy and speed when applied on rare roads.	This method has not been tested on denser and more complex roads.
[Madake et al., (2023)]	Combination of Canny, FAST + BRIEF, and DT	Acc= 90.41%	The combination of multiple feature extractions can improve accuracy.	The combination of several features can reduce computing time.
[Zang, Yu, and Zhao, (2023)]	SlimSSDMV2 and LSD	Acc= 96.32%	This method can overcome the problem of low-quality images and can be applied to mobile terminals.	-
[Upadhyay, Sutrave, and Singh, (2023)]	YOLO v5	Prec-Rec= 99.50%	This method can be applied in real-time.	Low-quality data is untested.
Explanation: CIR= Correct Identification Ratio, CD= Correct Detection, IOU= Intersection Over Union, DR=Detection Rate, mAP= mean Average Precision, Rec= Recall, Acc= Accuracy, Prec= Precision, F1-s= F1-score.				

Table 1. Summary of research on seat belt detection.

Fig. 2. Example of determining driver area.

The researcher combined multiple descriptors for improved accuracy. For example, Qin et al. used a combination of haar-like features and Histograms of Oriented Gradients (HOG) with Adaboost learning as a classifier [Qin et al., (2014)]. The test results on five video datasets showed that this combination yielded a better miss rate than only haar-like or HOG. Madake et al. employed Canny, FAST (Features from accelerated segment test), and BRIEF (Binary Robust Independent Elementary Features) for feature extraction [Madake et al., (2023)]. In addition, the research compared five classification methods, namely Decision Tree (DT), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (KNN), and Gaussian Naïve Bayes (GNB). The results showed that the proposed feature extraction combination achieved better accuracy compared to other methods such as Scale-Invariant Feature Transform (SIFT), Oriented FAST, and Rotated BRIEF (ORB) + FAST, ORB+FAST+Canny+Hough Transform, as well as FAST and BRIEF. It should be noted that the DT method exhibited the highest accuracy at 90.41%.

2.2. *Non-handcrafted feature*

Convolutional Neural Network (CNN) has recently emerged as the primary method for seat belt detection. Sajja et al. compared this method with SVM and found that CNN achieved superior accuracy [Naik et al., (2021)]. Kapdi et al. used the MobileNetV2 model, which showed robustness to various weather conditions [Kapdi et al., (2022)]. Additionally, Chen et al. combined CNN and SVM, using CNN for feature extraction and SVM for classification. This method, involving multi-scale feature extraction and applied to images with complex road backgrounds, outperformed the Adaboost algorithm and CNN regarding detection averages [Chen et al., (2018)]. Kannadaguli proposed a detection method with Fully Connected One Shot (FCOS) and added a prediction elimination process using Non-Maximum Suppression (NMS) [Kannadaguli, (2020)]. Meanwhile, Elihos et al. compared several models, including the single shot multi-box object detector (SSD), VGG16 model, shallor CNN model, and Fisher vector model, concluding that the SSD model achieved the highest accuracy [Elihos et al., (2019)].

Some research used YOLO (You Only Look Once) to detect the driver area. For example, Luo et al. employed YOLOv3 to detect the driver area and CNN for classification [Luo et al., (2021)]. The test showed that the proposed method achieved high accuracy and remained robust even in complex environments. Similarly, Wang and Ma also utilized YOLOv3 and a lightweight network structure [Wang and Ma, (2022)]. The test results showed that increasing the number of lightweight templates improved accuracy from 80.57% to 99.98%, but it slightly reduced the speed from 78 to 69 FPS. Khalid and Hazela used YOLOv4 to determine the driver area and the Alexnet model for classification [Khalid and Hazela, (2021)].

Meanwhile, Feng et al. proposed YOLOv5 for driver area detection and AlexNet deep convolutional network for classification [Feng et al., (2022)]. This method saved memory and computation time compared to SVM. In addition, compared with traditional CNN such as LeNet and AlexNet, the proposed method showed better performance in overfitting problems. Hosseini and Fathi used YOLOv5 for car windshield detection and the ResNet32 model for classification [Hosseini and Fathi, (2023)]. The research determined the driver and passenger areas by halving the windshield area. The test results showed that the proposed method achieved better accuracy than previous research, such as the connected area method, FCOS, and Alexnet model.

Maduri et al. proposed a real-time detection method for drivers not wearing a seat belt, which utilized deep learning and was embedded in Raspberry Pi [Maduri et al., (2021)]. Upadhyay et al. also focused on this condition and applied the method in actual conditions using a camera installed in the cabin and YOLOv5 [Upadhyay et al., (2023)]. On the other hand, Zang et al. introduced the SlimSSDMV2 model and LSD (Line Segment Detector) for mobile devices [Zang et al., (2023)]. The proposed method produced 96.32% accuracy with a computation time of 358 ms.

Research also attempted to improve accuracy and speed by developing CNN models. Zhou et al. developed the Alexnet model by adding Batch Normalization (BN), producing BN-Alexnet [Zhou et al., (2017)]. The test results showed that this proposed method increased the average correct detection and reduced the training time compared to Alexnet, VGGNet-16, and GoogLeNet. Chun et al. proposed a CNN model named NADS-Net (A Nimble Architecture for Driver and Seat Belt Detection via Convolutional Neural Networks) using the feature pyramid network (FPN) backbone method and multiple detection heads [Chun et al., (2019)]. The method was applied under different demographics, appearances, and illumination. In addition, Yang et al. created a method that focused on CPU and real-time applications. The method combined traditional operators (texture extraction), SSD MobileNet V2, and the particle filter tracking algorithm. The test results showed that the proposed method improved precision [Yang et al., (2020)].

3. Result and discussion

The methods to locate the driver area, extract features, and classify data significantly impacted seat belt detection. It should be noted that previous research employed various handcrafted feature extraction methods. Combining these methods, such as Canny, FAST, and BRIEF [Madake et al., (2023)], showed improved accuracy. However, this led to increased computation time, which could be addressed by adding a feature selection process. This process involved a preprocessing technique for identifying key features, selecting relevant entities, and removing irrelevant and redundant ones [Remeseiro and Bolon-Canedo, (2019)]. Reducing the feature dimension enhanced performance, shortened training time, simplified the model, and sped up the classification process.

Several CNN models were widely used for seat belt detection, including SSD, VGG16, shallow CNN, and Fisher vector [Elihos et al., (2019)]. Among these models, SSD achieved the highest accuracy, and one of the CNN methods, namely Alexnet, was compared with the SVM classifier, which produced faster computation time.

YOLO for driver area detection produced high accuracy. Hence, various versions, such as YOLOv3, YOLOv4, and YOLOv5, were employed. Specifically, YOLOv5 showed better accuracy when compared to other methods, such as the connected area method, FCOS, and the Alexnet model [Hosseini and Fathi, (2023)]. Yung et al. compared YOLOv5, YOLOv6, and YOLOv7 to detect safety helmets [Yung et al., (2022)]. The test results showed that YOLOv7 achieved a better mAP than YOLOv5 and YOLOv6. In addition, YOLOv7 showed better accuracy and speed than the YOLOR, PP-YOLOE, YOLOX, Scaled-YOLOv4, and YOLOv5 algorithms. Therefore, it can be concluded that YOLOV7 has the potential to enhance seat belt detection by improving accuracy and speed.

4. Conclusions and future research

In conclusion, extensive research was done on detecting drivers not wearing seat belts. Some research has developed a system comprising car detection, windshield detection, and seat belt detection subsystems. However, the current research specifically focused on seat belt detection subsystems. When combining feature extraction methods with handcrafted features, accuracy tended to increase accuracy, but this also led to longer computation times. Therefore, a feature selection process could be implemented. Applying YOLOv5 to non-handcrafted features showed promising accuracy and speed, but further improvements were needed to make it suitable for real-time conditions. For enhanced accuracy, the implementation of YOLOv7 or YOLOv8 could be considered. Furthermore, recording data at the right angle and increasing image resolution can increase accuracy.

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Conflict of interest

The authors have no conflicts of interest to declare.

References

[1] Arora, N. and Kumar, Y. (2022): Automatic vehicle detection system in day and night mode: challenges, applications and panoramic review. Evolutionary Intelligence, pp. 1077–95.

[2] Berwo, M. A.; Khan, A.; Fang, Y.; Fahim, H.; Javaid, S.; Mahmood, J.; Abideen, Z. U.; and M.S, S. (2023): Deep learning techniques for vehicle detection and classification from images/videos: a survey. Sensors, **23**(10), pp. 1–35.

[3] Chen, Y.; Tao, G.; Ren, H.; Lin, X.; and Zhang, L. (2018): Accurate seat belt detection in road surveillance images based on CNN and SVM. Neurocomputing, **274**, pp. 80–87.

[4] Chun, S.; Ghalehjegh, N. H.; Choi, J.; Schwarz, C.; Gaspar, J.; McGehee, D.; and Baek, S. (2019): NADS-net: a nimble architecture for driver and seat belt detection via convolutional neural networks. in *17th IEEE/CVF International Conference on Computer Vision Workshop, ICCVW 2019*. Department of Industrial and Systems Engineering, University of Iowa, Iowa City, IA 52242, United States: Institute of Electrical and Electronics Engineers Inc.

[5] Elihos, A.; Alkan, B.; Balci, B.; and Artan, Y. (2019): Comparison of image classification and object detection for passenger seat belt violation detection using NIR RGB surveillance camera images. in *15th IEEE International Conference on Advanced Video and Signal-Based Surveillance, AVSS 2018*. Havelsan Inc., Ankara, Turkey: Institute of Electrical and Electronics Engineers Inc.

[6] Feng, W.; Yu, W.; and Nan, R. (2022): Deep learning based vehicle seat belt detection algorithm for driver and passenger seat occupants. Pp. 306–10 in *7th International Conference on Intelligent Informatics and Biomedical Sciences, ICIIBMS 2022*. Shanghai Institute of Technology, Shanghai, China: Institute of Electrical and Electronics Engineers Inc.

[7] Gholamhosseinian, A. and Seitz, J. (2021): Vehicle classification in intelligent transport systems: an overview, methods and software perspective. IEEE Open Journal of Intelligent Transportation Systems, **2**(July), pp. 173–94.

[8] Guo, Huiwen; Lin, H.; Zhang, S.; and Li, S. (2011): Image-based seat belt detection. in *Proceedings of 2011 IEEE International Conference on Vehicular Electronics and Safety, ICVES 2011*. Beijing, China: IEEE.

[9] Guo, H; Lin, H.; Zhang, S.; and Li, S. (2011): Image-based seat belt detection. in *2011 IEEE International Conference on Vehicular Electronics and Safety, ICVES 2011*. College of Electrical and Information Engineering, Hunan University, Changsha, China.

[10] Hosseini, S. and Fathi, A. (2023): Automatic detection of vehicle occupancy and driver's seat belt status using deep learning. Signal, Image and Video Processing, **17**(2), pp. 491–99.

[11] Kannadaguli, P. (2020): FCOS based seatbelt detection system using thermal imaging for monitoring traffic rule violations. in *2020 4th International Conference on Electronics, Materials Engineering and Nano-Technology, IEMENTech 2020*. Kolkata, India.

[12] Kapdi, R. A.; Khanpara, P.; Modi, R.; and Gupta, M. (2022): Image-based seat belt fastness detection using deep learning. Scalable Computing, **23**(4), pp. 441–55.

[13] Khalid, S. Bin and Hazela, B. (2021): Employing real-time object detection for traffic monitoring. in *Proceedings of the International Conference on Innovative Computing & Communication (ICICC) 2021*.

[14] Li, W.; Lu, J.; Li, Y.; Zhang, Y.; Wang, J.; and Li, H. (2013): Seatbelt detection based on cascade adaboost classifier. in *Proceedings of the 2013 6th International Congress on Image and Signal Processing (CISP 2013)*. Vol. 2. IEEE.

[15] Luo, J.; Lu, J.; and Yue, G. (2021): Seatbelt detection in road surveillance images based on improved dense residual network with two-level attention mechanism. Journal of Electronic Imaging, **30**(3),.

[16] Madake, J.; Yadav, S.; Singh, S.; Bhatlawande, S.; and Shilaskar, S. (2023): Vision-based driver's seat belt detection. in *2023 International Conference for Advancement in Technology*. Goa, India: IEEE.

[17] Maduri, P. K.; Singh, G.; Sharma, S.; Mishra, R. K.; and Mishra, N. K. (2021): Seat belt and helmet detection using deep learning. in *3rd International Conference on Advances in Computing, Communication Control and Networking*. Galgotias College of Engineering and Technology (AKTU), Electronics and Instrumentation Engineering, Greater Noida, India: Institute of Electrical and Electronics Engineers Inc.

[18] Naik, D. S. B.; Lakshmi, G. S.; Sajja, V. R.; Venkatesulu, D.; and Rao, J. N. (2021): Driver's seat belt detection using CNN. Turkish Journal of Computer and Mathematics Education (TURCOMAT), **12**(5), pp. 776–85.

[19] Qiao, Y. and Qu, Y. (2021): Safety belt wearing detection algorithm based on human joint points. in *2021 IEEE International Conference on Consumer Electronics and Computer Engineering (CCECE 2021)*. IEEE.

[20] Qin, X. H.; Cheng, C.; Li, G.; and Zhou, X. (2014): Efficient seat belt detection in a vehicle surveillance application. in *Proceedings of the 2014 9th IEEE Conference on Industrial Electronics and Applications, ICIEA 2014*. Hangzhou, China: IEEE.

[21] Remeseiro, B. and Bolon-Canedo, V. (2019): A review of feature selection methods in medical applications. Computers in Biology and Medicine, **112**, pp. 103375 (1-9).

[22] Upadhyay, A.; Sutrave, B.; and Singh, A. (2023): Real time seatbelt detection using yolo deep learning model. in *2023 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS)*. Bropal, India: IEEE.

[23] Wang, D. (2022): Intelligent detection of vehicle driving safety based on deep learning. Wireless Communications and Mobile Computing, **2022**, pp. 1–11.

[24] Wang, Z. and Ma, Y. (2022): Detection and recognition of stationary vehicles and seat belts in intelligent internet of things traffic management system. Neural Computing and Applications, **34**(5), pp. 3513–22.

[25] Wu, T.; Zhang, Z.; Liu, Y.; Guo, W.; and Wang, Z. (2019): Driver seat belt detection based on YOLO detection and semantic segmentation. Journal of Computer-Aided Design and Computer Graphics, **31**(1), pp. 126–31.

[26] Yang, D.; Zang, Y.; and Liu, Q. (2020): Study of detection method on real-time and high precision driver seatbelt. in *Proceedings of the 32nd Chinese Control and Decision Conference (CCDC 2020)*. IEEE.

[27] Yang, Z.; Xiong, H.; Cai, Z.; and Peng, Y. (2019): A new method of vision-based seat belt detection. International Journal of Embedded Systems, **11**(6), pp. 755–63.

[28] Yongquan, J.; Tianshu, W.; Jin, L.; Zhijia, Z.; and Chao, G. (2019): GPU acceleration design method for driver's seatbelt detection. in *2019 14th IEEE International Conference on Electronic Measurement and Instruments, ICEMI 2019*. Changsha, China: IEEE.

[29] Yung, N. D. T.; Wong, W. K.; Juwono, F. H.; and Sim, Z. A. (2022): Safety helmet detection using deep learning: implementation and comparative study using YOLOv5, YOLOv6, and YOLOv7. in *2022 International Conference on Green Energy, Computing and Sustainable Technology, GECOST 2022*. Miri Sarawak, Malaysia: IEEE.

[30] Zang, Y.; Yu, B.; and Zhao, S. (2023): Lightweight seatbelt detection algorithm for mobile device. Multimedia Tools and Applications, **82**, pp. 24505–19.

[31] Zhou, B.; Chen, D.; and Wang, X. (2017): Seat belt detection using convolutional neural network BN-Alexnet. in 13th International Conference on Intelligent Computing, ICIC 2017, pp. 384–95.

[32] Zhou, B.; Chen, L.; Tian, J.; and Peng, Z. (2018): Learning-based seat belt detection in image using salient gradient. in *12th IEEE Conference on Industrial Electronics and Applications, ICIEA 2017*. Vols. 2018-Febru. College of Computer Science and Technology, Wuhan University of Science and Technology, Wuhan, China: Institute of Electrical and Electronics Engineers Inc.

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