INTEGRATION OF YOLOV5 FOR ENHANCED DRIVER SAFETY THROUGH FACIAL RECOGNITION AND DROWSINESS MONITORING

I Made Suartika[1]*, Thedicko Munawarsyah[2], Siti Shofiah[3], Eko Sediyono[4], Joko Siswanto[5], Tito Pinandita[6]
[1]Sarjana Terapan Transpotasi Darat, Politeknik Transportasi Darat Indonesia- STTD, Jl. Raya Setu No.89, Kabupaten Bekasi, Indonesia 17520, Indonesia
[2]Sarjana Terapan Teknologi Rekayasa Otomotif, Politeknik Keselamatan Transportasi Jalan, Jl. Semeru No. 03, Kota Tegal, Indonesia 52125, Indonesia
[3]Diploma 3 Teknologi Otomotif, Politeknik Keselamatan Transportasi Jalan, Jl. Semeru No. 03, Kota Tegal, Indonesia 52125, Indonesia
[4]Doktoral Ilmu Komputer, Universitas Kristen Satya Wacana, Jl. Diponegoro No.52-60, Kota Salatiga, Indonesia 50711, Indonesia
[5]Sarjana Terapan Rekayasa Sistem Transportasi Jalan, Politeknik Keselamatan Transportasi Jalan, Jl. Semeru No. 03, Kota Tegal, Indonesia 52125, Indonesia
[6]Faculty Of Information And Communications Technology, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, Durian Tunggal Melaka, Malaysia 76100, Indonesia
* made.suartika@pdtisttd.ac.id

ABSTRACT

Driver fatigue is a primary contributor to traffic accidents in various countries. To address this issue, the research developed a computer vision system using facial feature recognition and blink rate monitoring to promptly detect signs of driver fatigue. While facial recognition technology has proven effective in fatigue detection and mask compliance, it faces challenges in adapting to diverse environmental conditions and ensuring efficient device utilization. The study integrated YOLOv5 into machine learning to enhance fatigue detection using a Raspberry Pi 4, demonstrating significant improvements in driving safety through real-time object identification. The research documented significant outcomes from training the YOLOv5 model, with consistent reductions in bounding box prediction losses, object detection, and classification throughout the training process. Precision and recall metrics showed steady increases, while Mean Average Precision (mAP) scores indicated progressive gains, confirming the model's ability to accurately predict labels with minimal bounding box overlap. Precision-recall and recall-recall curves for "focused" and "microsleep" drivers illustrated how the YOLOv5 model adjusted its performance based on varying confidence levels in object recognition. In summary, this study underscores the effectiveness of YOLOv5 in enhancing driving safety by efficiently detecting and identifying potential signs of driver fatigue in real-time scenarios.

Keywords: driver fatigue detection; drowsiness monitoring; yolov5 model; machine learning

INTRODUCTION

The study investigates driver fatigue (Alkinani et al., 2020a; Biswal et al., 2021; Dey et al., 2019a; Shang et al., 2023; Sharma et al., 2022; Sun et al., 2020), consistently identified as a primary cause of traffic accidents (Akrout & Mahdi, 2023; Alkishri et al., 2022; Budiarti et al., 2023; Dey et al., 2019b; Junaedi & Akbar, 2018; T. Li et al., 2022; Wang et al., 2017) in various countries, including the United States, Australia, India, and Indonesia. In Indonesia, the complex and often irregular road conditions significantly impact driver vigilance, thereby increasing accident risks. Consequently, enhancing public awareness of safe driving practices and implementing effective technological solutions are crucial for mitigating accident rates (Chakraborty & Aoyon, 2014). One advanced technological solution under development is a computer vision (Chakraborty & Aoyon, 2014; Junaedi & Akbar, 2018; Reddy Chirra et al., 2019; Valsan A et al., 2021) system designed to detect signs of driver fatigue (Alkishri et al., 2022; Mangshor et al., 2020), such as facial feature recognition (Alkinani et al., 2020b; Ed-Doughmi et al., 2020; Elleuch et al., 2015; Gawande & Badotra, 2022; Hollósi et al., 2024; Wan et al., 2019) and blink rate monitoring (Gawande & Badotra, 2022; Hollósi et al., 2024; Reddy Chirra et al., 2019; Sowmyashree & Sangeetha, 2023). Its objective is to promptly identify potential distractions (Akrout & Mahdi, 2023; Alkinani et al., 2020b; Hollósi et al., 2024; Shariff et al., 2023) or drowsiness (Adochiei et al., 2020; Alkishri et al., 2022; Chakraborty & Aoyon, 2014; Junaedi & Akbar, 2018; Murthy et al., 2022; ÖZTÜRK et al., 2022; Reddy Chirra et al., 2019; Sowmyashree & Sangeetha, 2023; Valsan A et al., 2021) that may lead to decreased driver alertness (Akrout & Mahdi, 2023; Valsan A et al., 2021).

Evaluations of facial recognition technology have demonstrated its efficacy across various applications, including surveillance, drowsiness detection, and mask compliance, emphasizing accuracy and operational efficiency. In addition to technological advancements, driver behavior influenced by driving style, experience, and emotional state also plays a pivotal role in road safety (Akrout & Mahdi, 2023; Alkinani et al., 2020b; Chakraborty & Aoyon, 2014; Hollósi et al., 2024; Yu et al., 2021; Zaman et al., 2023; Zhao et al., 2020). A significant challenge in implementing this technology lies in accurately detecting and interpreting human emotions, a critical aspect in the fields of computer vision and artificial intelligence. High accuracy in recognizing drivers' facial expressions is essential to effectively identifying fatigue or other impairments that could jeopardize road safety (Alkishri et al., 2022; Kim et al., 2019; Shang et al., 2023; Shofiah, Pradana, et al., 2024; Sun et al., 2020). However, the development of this technology faces challenges such as adapting to diverse environmental conditions (Z. Li et al., 2018; Shofiah, Sediyono, et al., 2024) and the necessity for cost-effective and efficient processing devices (Murthy et al., 2022). Real-time models employed for detecting driver drowsiness necessitate continuous monitoring of driver behavior to identify critical moments when vigilance levels decline (Adochiei et al., 2020; Alkishri et al., 2022; Cui et al., 2021; Ed-Doughmi et al., 2020; Hollósi et al., 2024; Junaedi & Akbar, 2018; Mangshor et al., 2020; Rudrusamy et al., 2023; Sharan et al., 2019; Sun et al., 2020; Valsan A et al., 2021; Zaman et al., 2023). With documented accuracies reaching up to 82% (Shen et al., 2018) indoors and a positive detection rate of 72.8% (Said et al., 2018) outdoors within a 1-2 meter range, this technology has demonstrated its efficacy in enhancing driver and road user safety. Ongoing efforts focus on developing detection systems that are affordable, portable, safe, fast, and accurate, aiming to significantly reduce accidents caused by driver fatigue under varying traffic conditions. Furthermore, current research integrates YOLOv5 in machine learning to enhance the accurate and efficient detection of fatigue signs, alongside exploring the implementation of vibrating cushions as a physical solution to awaken drowsy drivers, thereby improving responsiveness and safety on roadways.

METHOD

This study involved collecting data using cameras and sensors to monitor drivers, capturing facial expressions, eye movements, head positions, and other relevant details (See in Figure 1). The data underwent preprocessing steps including image normalization, face detection, and feature extraction during the model training on Roboflow. The YOLOv5 model, enhanced with techniques like mish activation, mosaic data augmentation, and self-adversarial training, was used to improve performance and efficiency. YOLO works by dividing an image into an S x S grid, with each grid cell responsible for detecting objects whose centers fall within it, predicting bounding boxes and confidence scores.

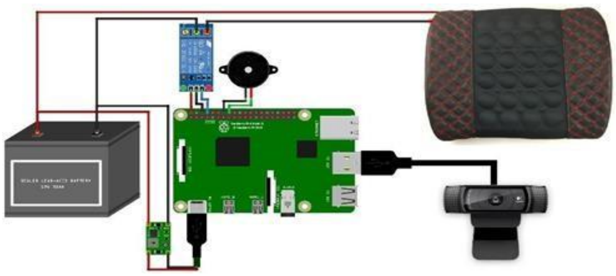


Figure 1. The circuit diagram for the Driver Detection System using Raspberry Pi 4 and USB Webcam with YOLOv5, featuring an added drowsiness alert pillow

The YOLOv5 project utilized an HP Pavilion Gaming 15-dk0000 laptop with specifications including Intel Core i5-10300H, AMD Ryzen 5 5600H, and Intel Core i5-9300H CPUs, 8 GB DDR4 RAM, and a 512 GB PCIe NVMe SSD. It featured a Full HD display and operated on Windows 10 Home, supported by an NVIDIA GeForce GTX 1650 GPU. These components were crucial for effectively training and deploying the YOLOv5 model for object detection tasks. Researchers developed a tool utilizing machine learning and a Raspberry Pi 4 as a mini-computer to alert drivers during microsleep events, employing YOLOv5 for object training and recognition. The Raspberry Pi 4, along with technologies like TensorFlow Lite or ONNX, is being considered for use in various projects. Various sample tests were conducted to evaluate differences in lighting conditions, device positioning, distinct objects, and time periods. The results showed that the YOLOv5-based detection tool was accurate in identifying microsleep. A qualitative research methodology, incorporating phenomenological research to understand drivers' experiences and behaviors and grounded theory to develop a framework for interpreting the data, was employed to measure the tool's accuracy.

RESULT AND DISCUSSION

Before training the model, preprocessing and augmentation were applied to the dataset. Suitable methods such as resizing, normalization, grayscale conversion, among others, were selected. A new version of the dataset was created by clicking on "Versions" in the Roboflow project sidebar.

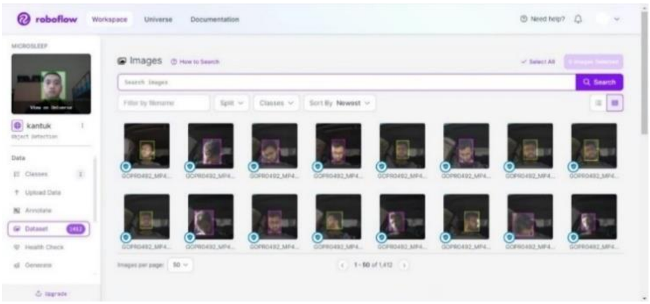


Figure 2. Dataset preparation for Roboflow project

The dataset (Figure 2) was then divided into train, validation, and test sets. The implementation of YOLOv5 in this research demonstrated strong capabilities in real-time object detection, particularly in detecting driver fatigue indicators such as "microsleep" and "focus". The training process involved using 2048-sized input images with a batch size of 16, trained for 100 epochs using the initial weights from yolov5s.pt. The training results indicated that YOLOv5 achieved commendable performance in recognizing critical object classes crucial for road safety. Utilizing Comet for visualizing training outcomes facilitated efficient monitoring and analysis of model performance. Thus, the use of YOLOv5 provided an effective solution in enhancing driving safety by accurately and real-time detecting and identifying potential driver fatigue indicators.

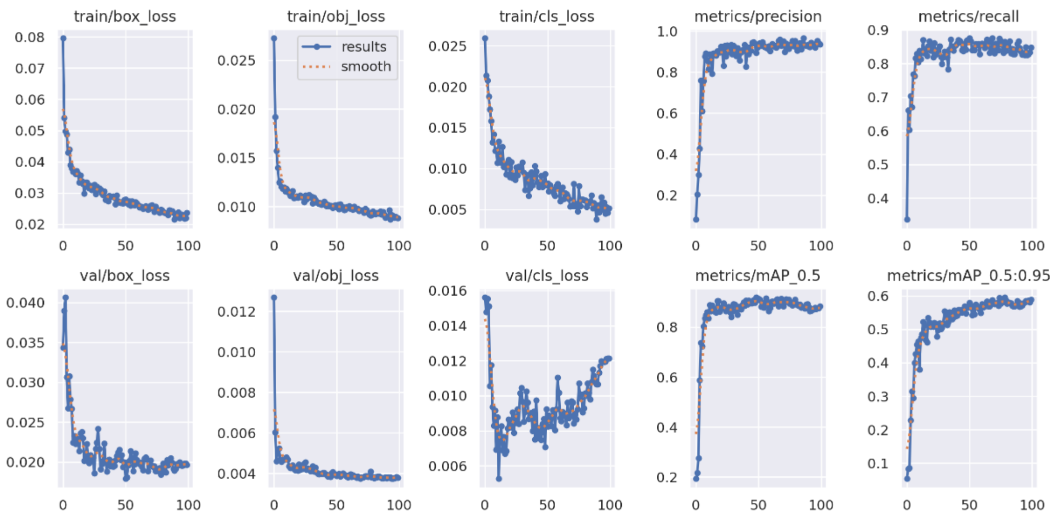
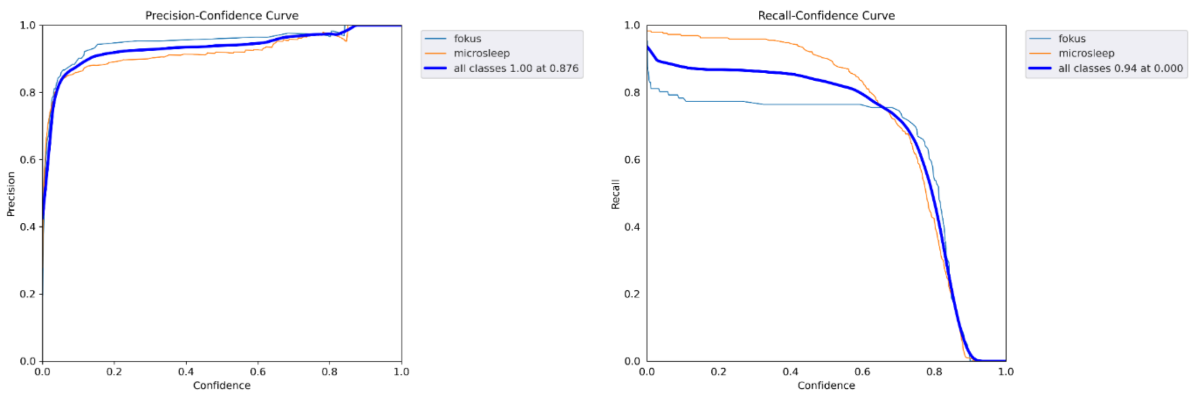


Figure 3. Visualizations of various training metrics for the YOLOv5 model

The training results of the YOLOv5 model (Figure 3) indicated significant improvements over time across various metrics. Losses in bounding box prediction, object detection irrespective of class, and object classification consistently decreased throughout the training epochs. This reflected the model's enhanced ability to accurately predict object boundaries, detect objects regardless of their class, and classify them into correct categories such as "microsleep" or "focused". Additionally, precision and recall metrics showed steady improvements, indicating the model's increasing accuracy in identifying objects with minimal overlap with actual bounding boxes. Validation data also exhibited similar trends to the training data, albeit with smaller fluctuations, demonstrating the model's robust performance across different datasets. Mean Average Precision (mAP) scores at IoU thresholds of 0.5 and across 0.5 to 0.95 also showed progressive increases, highlighting the model's consistent enhancement in predicting correct labels with minimal bounding box overlap. Overall, these training outcomes underscored the YOLOv5 model's effective progression in both object detection and classification tasks throughout the training process.



(a) (b)

Figure 4. (a) precision-recall (precision-confidence curve) and (b) recall-recall (recall-confidence curve) in the context of focus drivers and microsleep drivers

The precision-recall and recall-recall curves for "focus" and "microsleep" drivers (Figure 4) depicted the model's behavior based on varying confidence levels in object recognition. For "focus" drivers, the model exhibited high recall at low confidence levels but experienced a gradual decline as confidence increased, indicating proficient identification under lower certainty conditions. Conversely, the "microsleep" curve followed a similar trend, albeit with slightly lower recall performance at comparable confidence levels. At a confidence level of 0.000, the model achieved a recall of 0.94 across all classes, demonstrating its ability to accurately detect all positive instances even at minimal confidence. Overall, these graphs provided insights into how the YOLOv5 model adapted its performance relative to confidence levels in distinguishing between focused and microsleeping drivers (Figure 5).

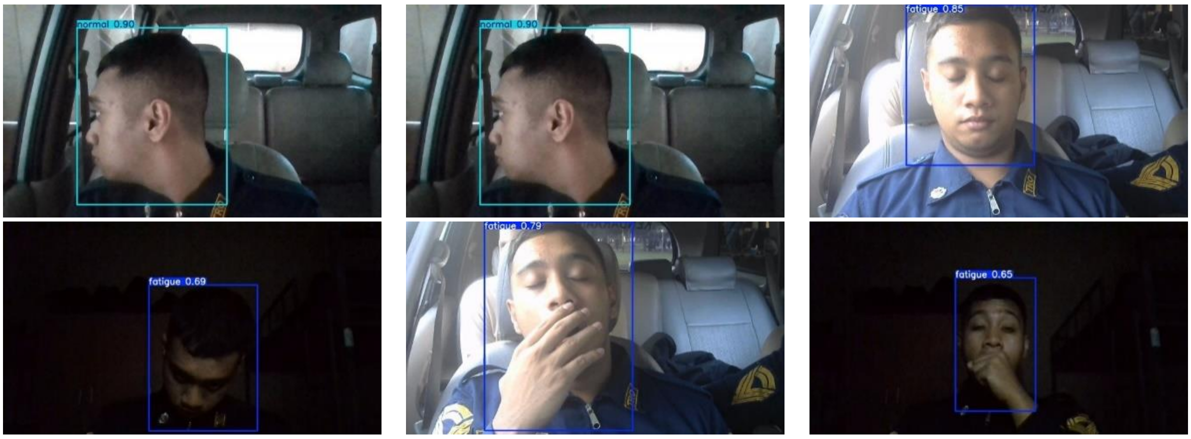


Figure 5. Capture focused and microsleeping drivers by YOLOv5

The implementation of the YOLOv5 model in this research has proven to be a powerful solution for real-time detection of driver fatigue indicators, such as "microsleep" and "focus," offering significant potential to enhance road safety. Throughout the training process, the model exhibited consistent improvements in key performance metrics, including precision, recall, and loss reduction. This reflects its growing accuracy in detecting objects, predicting bounding boxes, and classifying them into the correct categories. Precision-recall curve analysis further revealed that YOLOv5 performs effectively at various confidence levels, with impressive recall even at low confidence thresholds, making it highly reliable for critical detection tasks. The findings affirm the model’s suitability for real-time driver monitoring systems, capable of providing timely alerts and interventions to prevent accidents caused by driver fatigue. Future research could further optimize the model's performance, test its robustness in real-world conditions, and explore ethical considerations regarding privacy, paving the way for safer, more responsive vehicle systems.

CONCLUSION

This research demonstrates the efficacy of the YOLOv5 model in detecting driver fatigue indicators in real-time. Through comprehensive training and evaluation of performance metrics, the model consistently improved its detection and classification capabilities. The precision-recall curves revealed that the model balances precision and recall effectively across various confidence levels, with particularly strong performance at low confidence thresholds. These findings affirm YOLOv5's potential application in real-time driver monitoring systems to enhance road safety. However, future research should focus on optimizing the model, testing its performance in diverse real-world conditions, and exploring its integration with existing vehicle safety systems. Additionally, ethical considerations surrounding driver privacy must be addressed to ensure responsible deployment of such technologies.

REFERENCES

Adochiei, I. R., Tirbu, O. I., Adochiei, N. I., Pericle-Gabriel, M., Larco, C. M., Mustata, S. M., & Costin, D. (2020). Drivers' drowsiness detection and warning systems for critical infrastructures. 2020 8th E-Health and Bioengineering Conference, EHB 2020, 14–17. https://doi.org/10.1109/EHB50910.2020.9280165

Akrout, B., & Mahdi, W. (2023). A novel approach for driver fatigue detection based on visual characteristics analysis. Journal of Ambient Intelligence and Humanized Computing, 14(1), 527–552. https://doi.org/10.1007/s12652-021-03311-9

Alkinani, M. H., Khan, W. Z., & Arshad, Q. (2020a). Detecting Human Driver Inattentive and Aggressive Driving Behavior Using Deep Learning: Recent Advances, Requirements and Open Challenges. IEEE Access, 8, 105008–105030. https://doi.org/10.1109/ACCESS.2020.2999829

Alkinani, M. H., Khan, W. Z., & Arshad, Q. (2020b). Detecting Human Driver Inattentive and Aggressive Driving Behavior Using Deep Learning: Recent Advances, Requirements and Open Challenges. IEEE Access, 8, 105008–105030. https://doi.org/10.1109/ACCESS.2020.2999829

Alkishri, W., Abualkishik, A., & Al-Bahri, M. (2022). Enhanced Image Processing and Fuzzy Logic Approach for Optimizing Driver Drowsiness Detection. Applied Computational Intelligence and Soft Computing, 2022. https://doi.org/10.1155/2022/9551203

Biswal, A. K., Singh, D., Pattanayak, B. K., Samanta, D., & Yang, M. H. (2021). IoT-based smart alert system for drowsy driver detection. Wireless Communications and Mobile Computing, 2021. https://doi.org/10.1155/2021/6627217

Budiarti, R. P. N., Nugroho, B. W., Ayunda, N., & Sukaridhoto, S. (2023). Drowsy Eyes and Face Mask Detection for Car Drivers using the Embedded System. Register: Jurnal Ilmiah Teknologi Sistem Informasi, 9(1), 86–94. https://doi.org/10.26594/register.v9i1.2612

Chakraborty, M., & Aoyon, A. N. H. (2014). Implementation of Computer Vision to detect driver fatigue or drowsiness to reduce the chances of vehicle accident. 1st International Conference on Electrical Engineering and Information and Communication Technology, ICEEICT 2014. https://doi.org/10.1109/ICEEICT.2014.6919054

Cui, Z., Sun, H. M., Yin, R. N., Gao, L., Sun, H. Bin, & Jia, R. S. (2021). Real-time detection method of driver fatigue state based on deep learning of face video. Multimedia Tools and Applications, 80(17), 25495–25515. https://doi.org/10.1007/s11042-021-10930-z

Dey, S., Chowdhury, S. A., Sultana, S., Hossain, M. A., Dey, M., & Das, S. K. (2019a). Real Time Driver Fatigue Detection Based on Facial Behaviour along with Machine Learning Approaches. 2019 IEEE International Conference on Signal Processing, Information, Communication and Systems, SPICSCON 2019, 135–140. https://doi.org/10.1109/SPICSCON48833.2019.9065120

Dey, S., Chowdhury, S. A., Sultana, S., Hossain, M. A., Dey, M., & Das, S. K. (2019b). Real Time Driver Fatigue Detection Based on Facial Behaviour along with Machine Learning Approaches. 2019 IEEE International Conference on Signal Processing, Information, Communication and Systems, SPICSCON 2019, 135–140. https://doi.org/10.1109/SPICSCON48833.2019.9065120

Ed-Doughmi, Y., Idrissi, N., & Hbali, Y. (2020). Real-time system for driver fatigue detection based on a recurrent neuronal network. Journal of Imaging, 6(3). https://doi.org/10.3390/jimaging6030008

Elleuch, H., Wali, A., & Alimi, A. M. (2015). Smart tablet monitoring by a real-time head movement and eye gestures recognition system. International Journal of Computing and Digital Systems, 4(3), 183–192. https://doi.org/10.12785/IJCDS/040305

Gawande, R., & Badotra, S. (2022). Deep-Learning Approach for Efficient Eye-blink Detection with Hybrid Optimization Concept. International Journal of Advanced Computer Science and Applications, 13(6), 782–795. https://doi.org/10.14569/IJACSA.2022.0130693

Hollósi, J., Ballagi, Á., Kovács, G., Fischer, S., & Nagy, V. (2024). Bus Driver Head Position Detection Using Capsule Networks under Dynamic Driving Conditions. Computers, 13(3). https://doi.org/10.3390/computers13030066

Junaedi, S., & Akbar, H. (2018). Driver Drowsiness Detection Based on Face Feature and PERCLOS. Journal of Physics: Conference Series, 1090(1). https://doi.org/10.1088/1742-6596/1090/1/012037

Kim, W., Jung, W. S., & Choi, H. K. (2019). Lightweight driver monitoring system based on multi-task mobilenets. Sensors (Switzerland), 19(14). https://doi.org/10.3390/s19143200

Li, T., Zhang, T., & Li, Q. (2022). Train Driver Fatigue Detection Using Eye Feature Vector and Support Vector Machine. International Journal of Circuits, Systems and Signal Processing, 16, 1007–1017. https://doi.org/10.46300/9106.2022.16.123

Li, Z., Chen, C., Ci, Y., Zhang, G., Wu, Q., Liu, C., & Qian, Z. (Sean). (2018). Examining driver injury severity in intersection-related crashes using cluster analysis and hierarchical Bayesian models. Accident Analysis and Prevention, 120, 139–151. https://doi.org/10.1016/j.aap.2018.08.009

Mangshor, N. N. A., Majid, I. A. A., Ibrahim, S., & Sabri, N. (2020). A real-time drowsiness and fatigue recognition using support vector machine. IAES International Journal of Artificial Intelligence, 9(4), 584–590. https://doi.org/10.11591/ijai.v9.i4.pp584-590

Murthy, K. S. R., Siddineni, B., Kompella, V. K., Aashritha, K., Sri Sai, B. H., & Manikandan, V. M. (2022). An Efficient Drowsiness Detection Scheme using Video Analysis. International Journal of Computing and Digital Systems, 11(1), 573–581. https://doi.org/10.12785/ijcds/110146

ÖZTÜRK, M., KÜÇÜKMANİSA, A., & URHAN, O. (2022). Drowsiness Detection System Based on Machine Learning Using Eye State. Balkan Journal of Electrical and Computer Engineering, 10(3), 258–263. https://doi.org/10.17694/bajece.1028110

Reddy Chirra, V. R., Uyyala, S. R., & Kishore Kolli, V. K. (2019). Deep CNN: A machine learning approach for driver drowsiness detection based on eye state. Revue d'Intelligence Artificielle, 33(6), 461–466. https://doi.org/10.18280/ria.330609

Rudrusamy, B., Teoh, H. C., Pang, J. Y., Lee, T. H., & Chai, S. C. (2023). IoT-Based Vehicle Monitoring and Driver Assistance System Framework for Safety and Smart Fleet Management. International Journal of Integrated Engineering, 15(1), 391–403. https://doi.org/10.30880/ijie.2023.15.01.035

Said, S., AlKork, S., Beyrouthy, T., Hassan, M., Abdellatif, O. E., & Fayek Abdraboo, M. (2018). Real time eye tracking and detection- A driving assistance system. Advances in Science, Technology and Engineering Systems, 3(6), 446–454. https://doi.org/10.25046/aj030653

Shang, Y., Yang, M., Cui, J., Cui, L., Huang, Z., & Li, X. (2023). Driver Emotion and Fatigue State Detection Based on Time Series Fusion. Electronics (Switzerland), 12(1). https://doi.org/10.3390/electronics12010026

Sharan, S. S., Viji, R., Pradeep, R., & Sajith, V. (2019). Driver Fatigue Detection Based on Eye State Recognition Using Convolutional Neural Network. Proceedings of the 4th International Conference on Communication and Electronics Systems, ICCES 2019, Icces, 2057–2063. https://doi.org/10.1109/ICCES45898.2019.9002215

Shariff, W., Dilmaghani, M. S., Kielty, P., Lemley, J., Farooq, M. A., Khan, F., & Corcoran, P. (2023). Neuromorphic Driver Monitoring Systems: A Computationally Efficient Proof-of-Concept for Driver Distraction Detection. IEEE Open Journal of Vehicular Technology, 4(October), 836–848. https://doi.org/10.1109/OJVT.2023.3325656

Sharma, V. P., Yadav, J. S., & Sharma, V. (2022). Deep convolutional network based real time fatigue detection and drowsiness alertness system. International Journal of Electrical and Computer Engineering, 12(5), 5493–5500. https://doi.org/10.11591/ijece.v12i5.pp5493-5500

Shen, J., Li, G., Yan, W., Tao, W., Xu, G., Diao, D., & Green, P. (2018). Nighttime driving safety improvement via image enhancement for driver face detection. IEEE Access, 6, 45625–45634. https://doi.org/10.1109/ACCESS.2018.2864629

Shofiah, S., Pradana, B., Bunga, S., & Ayu, R. (2024). Pengenalan Wajah dengan Viola Jones. 3(4).

Shofiah, S., Sediyono, E., Hasibuan, Z. A., Kristianto, B., Setiawan, S., Pratindy, R., Hakim, M. I. N., & Humami, F. (2024). Driver Facial Detection Across Diverse Road Conditions. ILKOM Jurnal Ilmiah, 16(2), 108–114.

Sowmyashree, P., & Sangeetha, J. (2023). Multistage End-to-End Driver Drowsiness Alerting System. International Journal of Advanced Computer Science and Applications, 14(4), 464–473. https://doi.org/10.14569/IJACSA.2023.0140452

Sun, Y., Yan, P., Li, Z., Zou, J., & Hong, D. (2020). Driver fatigue detection system based on colored and infrared eye features fusion. Computers, Materials and Continua, 63(3), 1563–1574. https://doi.org/10.32604/CMC.2020.09763

Valsan A, V., Mathai, P. P., & Babu, I. (2021). Monitoring driver’s drowsiness status at night based on computer vision. Proceedings - IEEE 2021 International Conference on Computing, Communication, and Intelligent Systems, ICCCIS 2021, 989–993. https://doi.org/10.1109/ICCCIS51004.2021.9397180

Wan, Y., Liu, M., Fan, J., Zhao, Y., Jiang, J., & Yao, L. (2019). Multi-feature analysis fatigue driving based on Conditional Local Neural Fields algorithm detection method. Journal of Physics: Conference Series, 1237(2). https://doi.org/10.1088/1742-6596/1237/2/022157

Wang, F., Chen, X., Wang, D., & Yang, B. (2017). An improved image-based iris-tracking for driver fatigue detection system. Chinese Control Conference, CCC, 11521–11526. https://doi.org/10.23919/ChiCC.2017.8029198

Yu, B., Bao, S., Zhang, Y., Sullivan, J., & Flannagan, M. (2021). Measurement and prediction of driver trust in automated vehicle technologies: An application of hand position transition probability matrix. Transportation Research Part C: Emerging Technologies, 124. https://doi.org/10.1016/j.trc.2020.102957

Zaman, K., Zhaoyun, S., Shah, B., Hussain, T., Shah, S. M., Ali, F., & Khan, U. S. (2023). A novel driver emotion recognition system based on deep ensemble classification. Complex and Intelligent Systems, 9(6), 6927–6952. https://doi.org/10.1007/s40747-023-01100-9

Zhao, X., Zhao, X., Yu, Q., Ye, Y., & Yu, M. (2020). Development of a representative urban driving cycle construction methodology for electric vehicles: A case study in Xi’an. Transportation Research Part D: Transport and Environment, 81. https://doi.org/10.1016/j.trd.2020.102279