Comparative Analysis of the Yolo Method with the Ear and Mar Methods for Drowsiness Detection in the Driving Performance Index Evaluation Application

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***Abstract*— The development of computer vision technology currently allows early detection of a driver's physical condition to improve driving safety. This research aims to develop a mobile-based driver condition monitoring system using the integration of the Flutter framework and the Flask server. This system implements the YOLO (You Only Look Once) algorithm for real-time object detection and Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) analysis to detect symptoms of fatigue or drowsiness through facial images. Image data captured via an Android device is sent to a central server for processing, where the detection results are then stored in a database and displayed back to the user. Test results show that the system is able to classify driver conditions with a high level of accuracy and is able to manage travel sessions in a structured manner. This system is expected to be a preventive solution in reducing the number of traffic accidents caused by human error.**

***Keywords*— Computer Vision, Sleepiness Detection, EAR, Flutter, Flask, MAR, YOLO.**

I. INTRODUCTION

Driving performance evaluation is a vital element in transportation safety management, where the driver's physical and mental stability are key indicators in preventing accidents. A major issue that frequently arises is performance degradation due to fatigue and drowsiness, which directly slow reaction times and diminish visual focus. Therefore, a real-time driver monitoring system is needed that can function as a measuring instrument for safe driving thresholds to mitigate risks resulting from human error[1].

Currently, computer vision technology has developed geometry-based methods such as Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) to detect drowsiness symptoms through facial landmarks. While these methods boast lightweight computational capabilities, their real-world implementation is still limited by sensitivity to variations in camera position, distance, and low lighting conditions. This weakness often leads to facial detection failures or ratio miscalculations, especially when drivers are wearing accessories or are in a dynamic cabin environment[2].

As a solution, this study proposes the use of Deep Learning through the YOLOv8 algorithm, known to be more robust in recognizing comprehensive visual features with high accuracy. This system is implemented on Android devices using the YOLOv8n (nano) model to adaptively classify normal, drowsy, and sleep conditions[3]. In addition, the system is integrated with a web dashboard to monitor performance index (driving score) and location in real-time, thus enabling a more objective and responsive driver performance evaluation for fleet management[4].

To address the limitations of conventional methods, a more robust approach is required to handle the dynamic environment inside a vehicle cabin. Deep Learning technology, particularly the YOLO (You Only Look Once) algorithm, works by recognizing visual features (image patterns) holistically. Based on previous studies, YOLOv8 has demonstrated superior performance in terms of both accuracy and efficiency compared to other object detection models of similar class. YOLOv8 was selected because its variants are capable of achieving high mAP and F1-score values across various application domains such as agricultural pests detection (mAP 89.2%), seat-belt detection (mAP 94.5%), fruit detection (mAP 92.1%), and small-object detection (mAP 87.5%)[5].

This study does not merely compare two algorithms, but focuses on the implementation of an adaptive drowsiness detection system based on Android. The system is designed to process video input in real-time using a YOLOv8n (nano) model that has been specifically trained to classify normal, drowsy, and sleeping conditions. The EAR and MAR methods are still used in this study; however, their function is positioned as a baseline to validate the extent of performance and stability improvements offered by the proposed YOLO-based system, particularly across detection distance variations that simulate real-world usage on a vehicle dashboard[6].

In addition to detecting drowsiness, the system is integrated with a web dashboard to monitor the driver's performance

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index (driving score) and location in real time. This integration enables fleet companies or supervisors to objectively evaluate driver performance based on the frequency of drowsiness detected during the trip. Therefore, this research is expected to produce a prototype of a driving safety system that is more reliable, responsive, and ready to be implemented to reduce accident risks caused by human negligence[7].

II. METHOD

This research uses an experimental approach and the development of a software system designed to evaluate driving performance in real-time through computer vision. The system's development process follows a systematic flow to ensure accurate driving performance detection, starting with data acquisition through real-time video input capture using a camera pointed directly at the driver's face. Next, the system applies the You Only Look Once (YOLO) method in object detection to quickly and efficiently identify the presence of faces and key facial features[8]. Once facial features are identified, facial landmark extraction is performed to identify specific coordinate points, particularly in the eye and mouth areas. These coordinates are then used in the calculation of the Eye Aspect Ratio (EAR) algorithm to calculate the eye openness ratio to detect drowsiness, and the Mouth Aspect Ratio (MAR) algorithm to calculate the mouth openness ratio to detect yawning. As a final stage, a performance index evaluation is conducted where the integrated data from EAR and MAR are processed to determine an overall driving performance score or index[9]. This research was conducted through several main stages as shown in Figure 1.

The system architecture is functionally divided into three main, interconnected modules: input, processing, and output. The input module acts as the primary sensor using a camera that captures visual images of the driver in various environmental conditions[10].

The visual data is then processed by the core processing unit, which consists of a YOLO layer to localize facial areas and landmarks (such as Dlib or Mediapipe) to map the coordinates of the eyelids and lips. Within the logic processor, the system applies strict thresholds to the EAR and MAR values; if the EAR value falls below the standard for a certain duration, the system automatically identifies drowsiness. The results of this processing are forwarded to the output module, which presents a visual interface in the form of performance status on the application and an audible warning via audio alarm if the driver's performance index is deemed below safety standards due to fatigue or loss of focus. The system block diagram is shown in Figure 2.

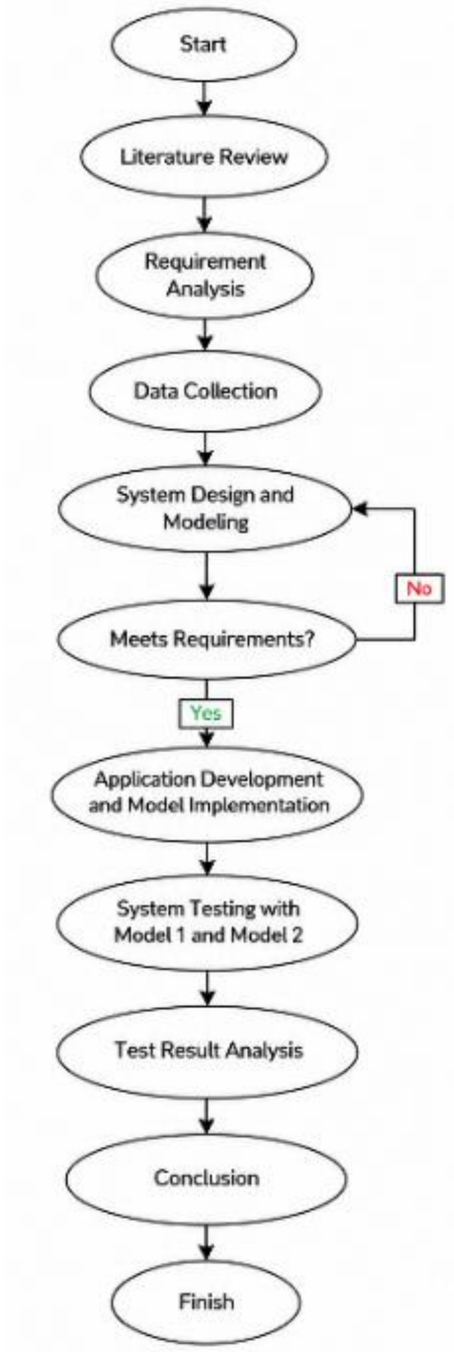


Figure 1. Research stages

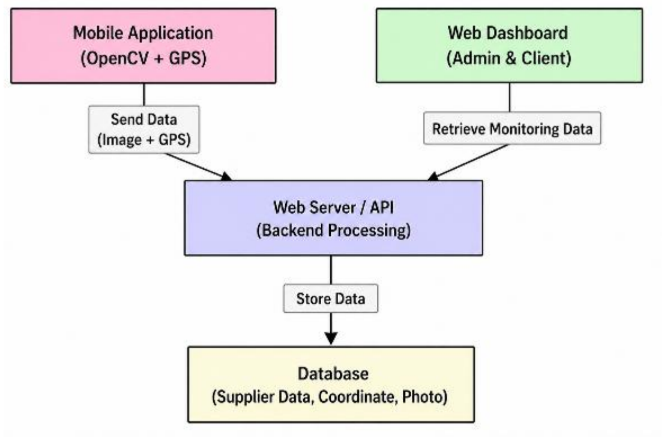


Figure 2. System Block Diagram

The advantage of this design lies in the synergy between the robustness of the YOLO method in object detection with the precision of the mathematical calculations of the EAR and MAR algorithms. This integration allows the system to monitor the frequency and duration of eye blinks through the EAR equation, while validating the level of fatigue through the detection of a wide open mouth or yawning through MAR calculations. To ensure its reliability, the system is tested through various operational scenarios that include variations in the driver's head position, the use of attributes such as glasses, to testing in dim lighting conditions[11]. This test procedure aims to measure the extent to which the facial feature coordinates generated by YOLO remain precise when processed by the EAR and MAR algorithms in producing an accurate driving evaluation index. The following is a figure showing the flowchart of the workflow between the YOLO method and the EAR/MAR method. The block diagram of the Yolo-based system is shown in Figure 3.

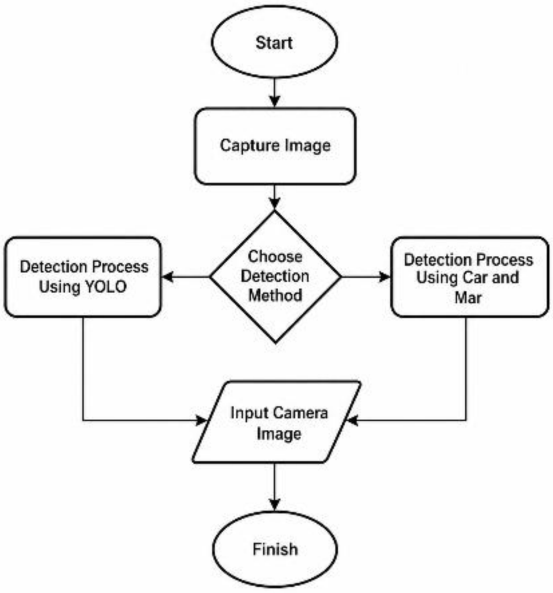


Figure 3. Block diagram of the yolo method system and the ear and mar method

A. Android Application Design

The workflow design of this Android application is systematically designed to ensure that driving performance monitoring runs automatically and in a structured manner. The application operation begins with the Destination Input stage, where the user is asked to specify a travel destination as part of the initialization of the driving session[12]. Once the destination is set, the user can press the Start button to activate the monitoring system. In the operational stage, the application automatically performs visual data acquisition by capturing a picture of the driver's face every second. This periodic image capture aims to ensure monitoring consistency without overloading the device's memory[13]. Each captured image is then processed in real-time by the YOLO algorithm to detect facial features, followed by the calculation of EAR and MAR values. All coordinate data and performance evaluation results from each second of image capture are managed by the application to provide instant warnings if any indication of drowsiness or fatigue is detected[14]. The following is a flowchart of the Android application design in Figure 4.

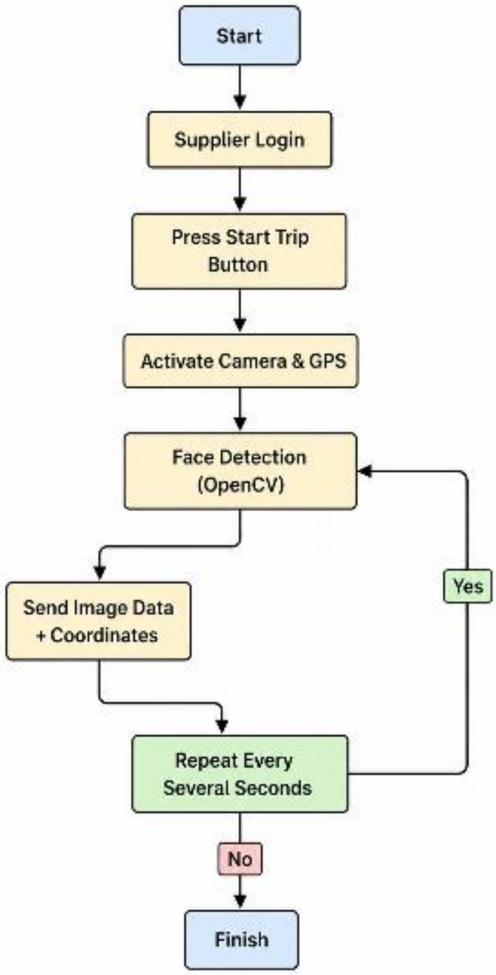


Figure 4. Application design flow diagram

B. Web Server Design

The web server implementation in this study is designed to centrally manage the traffic of driving performance evaluation data. Based on the system architecture, the web server functions as an intermediary that receives facial coordinate data packets, EAR values, and MAR values sent by the Android application via internet communication protocols[15]. The incoming data is then processed and stored in the Firebase Realtime Database[16]. Firebase was selected based on its ability to synchronize data instantly, so that changes in performance indexes detected on the driver's side can be immediately updated and accessed by the system without significant latency[17]. In addition to functioning as data storage, this web server design also supports reporting and history monitoring features. The database structure is arranged hierarchically to store user IDs, trip destinations, and timestamps for each detected drowsiness or fatigue event[18]. The following is a flowchart of the web server design in Figure 5.

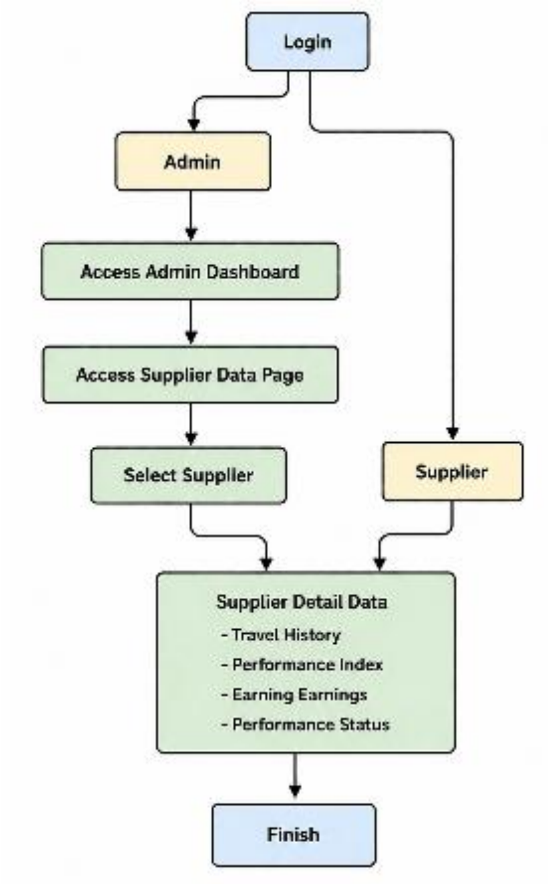


Figure 5. Web and server flow diagram

III. RESULTS AND DISCUSSION

System testing was conducted to determine the performance of driver drowsiness detection methods using the YOLO method and the YOLO method integrated with Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR). This testing aimed to compare the performance of the two methods in detecting drowsiness based on accuracy, distance testing, and lighting testing.

A. Light Test Results

Light intensity testing was conducted to determine the reliability of the server-side algorithm in detecting driver condition through images transmitted by Android devices under different environmental conditions. This is crucial because changes in lighting can affect the visibility of facial landmarks, which are key parameters in calculating EAR and MAR.

Based on a series of experiments, Table I presents the comprehensive results of the light intensity testing:

TABLE 1
LIGHT INTENSITY TEST RESULTS

Testing Scenario	Total Sample (Image)	Successfully Detected (Image)	Failed (Image)	Accuracy (%)	explanation
Bright Light (Daylight)	40	40	0	100%	Very Good (Optimal)
Dim Light (Afternoon)	41	30	11	73,17%	passably
Dark Light (Night)	40	21	19	52,5%	Not enough (Need Additional Light)

Bright Light (Daylight/Outdoor): In this condition, the camera sensor on the Android device can capture facial details very clearly. The server can perform precise facial point extraction because the contrast between the eyelids and facial skin looks sharp. Detection accuracy in this condition reaches the highest level. The image capture display when the light is bright is shown in Figure 6 below:

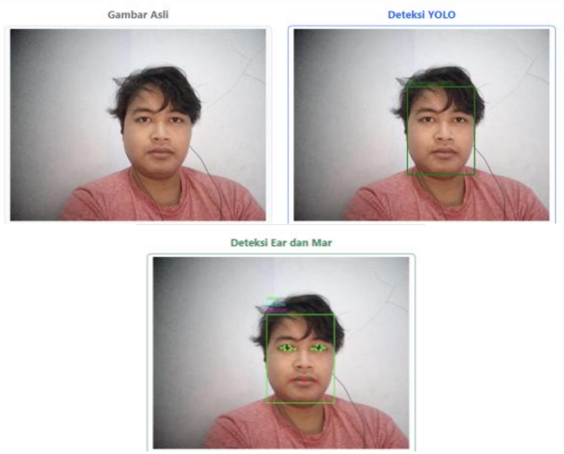


Figure 6. Image Capture Display When the Light is Bright

Low Light (Indoor/Evening): When the light intensity decreases, there is a slight decrease in detail in the image (noise appears). However, thanks to optimizations in the YOLO and Dlib models used on the server, the system is still able to detect faces and calculate EAR/MAR values stably as long as the eyes and mouth features are still captured by the camera sensor. The image capture display when the light is low is shown in Figure 7 below:

Figure 7. Low Light Image Capture Display

Dark Light (Night/Low Light): Testing in dark conditions aims to see the tolerance limits of the cellphone camera sensor and server algorithm. If the Android device is not equipped with a night mode feature or sufficient cabin lights, the detection accuracy will decrease drastically because facial landmarks points cannot be mapped accurately on a pitch-black image. The image capture display when the light is low is shown in Figure 8 below:

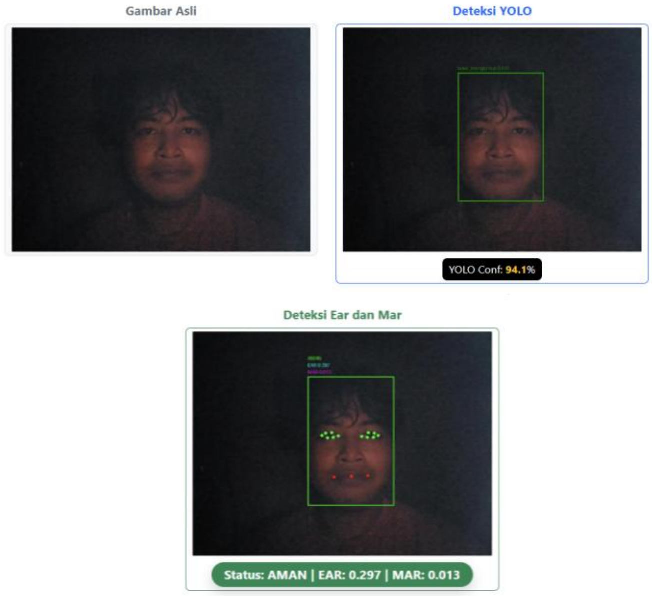


Figure 8. Low Light Image Capture Display

B. Distance Test Results

Detection distance testing was conducted to determine the system's sensitivity in recognizing facial objects and eye conditions at various distances. Data collection was carried out in stages at three predetermined measurement points: 30 cm, 60 cm, and 90 cm. These distance variations were tested to analyze the impact of changes in object distance on the system's detection and classification success.

Based on the series of experiments conducted, Table II presents the comprehensive results of the distance testing:

TABLE 2
DISTANCE TEST RESULTS

No	Test Distance	Method	Amount of Data	Correct Prediction	Wrong Prediction	Accuracy
1	30 cm	YOLOv8	33	33	0	100%
		EAR & MAR	33	6	27	18.18%
2	60 cm	YOLOv8	31	31	0	100%
		EAR & MAR	31	6	25	19.35%
3	90 cm	YOLOv8	33	12	21	36.36%
		EAR & MAR	33	0	33	0%

In close-range testing (30 cm), a very extreme difference in performance was seen. The proposed YOLOv8-based method was able to achieve perfect accuracy (100%), successfully identifying all 33 test samples in normal, drowsy, and sleeping conditions. The 30 cm distance tester display is shown in Figure 9 below:

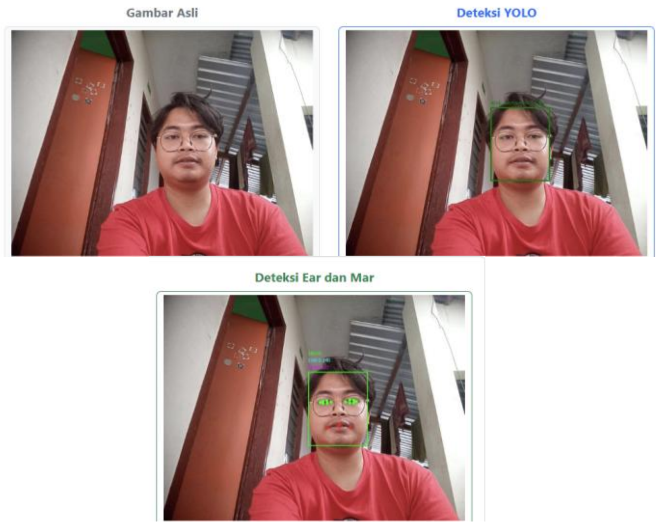
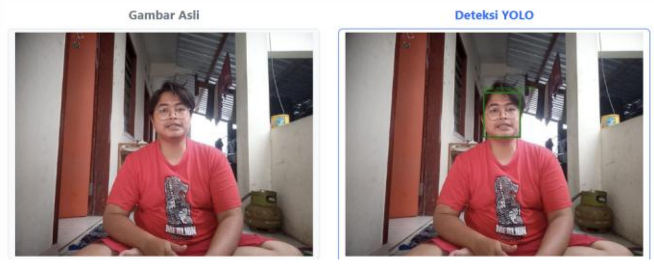


Figure 9. 30cm Distance Tester Display

In contrast, the comparison methods (EAR & MAR) experienced significant failure, achieving only 18.18% accuracy. The low accuracy of the geometric method at very close range is due to the algorithm's inability to handle disproportionate facial landmarks when the face fills the camera frame. This demonstrates that the YOLO method is much more adaptive to close-range camera positions than conventional methods.

At a medium distance (60 cm), which represents the average distance between the driver and the car dashboard. Based on 31 test samples, the YOLOv8 method again demonstrated very stable performance by maintaining perfect accuracy (100%). The system was able to detect faces and classify normal, drowsy, and sleeping conditions without the slightest error. The 60 cm distance tester display is shown in Figure 10 below:



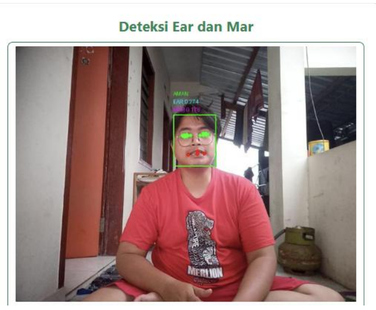


Figure 10. 60cm Distance Tester View

On the other hand, the comparison methods (EAR and MAR) only recorded a slight increase in accuracy to 19.35% (6 correct predictions out of 31 data points). Although this distance provides a better Field of View than the 30 cm distance, the geometric method still often fails to maintain consistent facial landmark detection, especially in dynamic conditions. This confirms that the YOLOv8 method has a significant advantage in terms of reliability over conventional methods at vehicle operational distances.

At a long distance (90 cm). The results show a significant performance decrease in both methods, indicating the effective operational limits of the system. The proposed method (YOLOv8) experienced a decrease in accuracy to 36.36%. Although it is still able to recognize some facial samples, the image resolution is too low at this distance makes it difficult for the model to extract detailed features in the eye and mouth areas. The Tester View at a distance of 90 cm is shown in Figure 11 below:

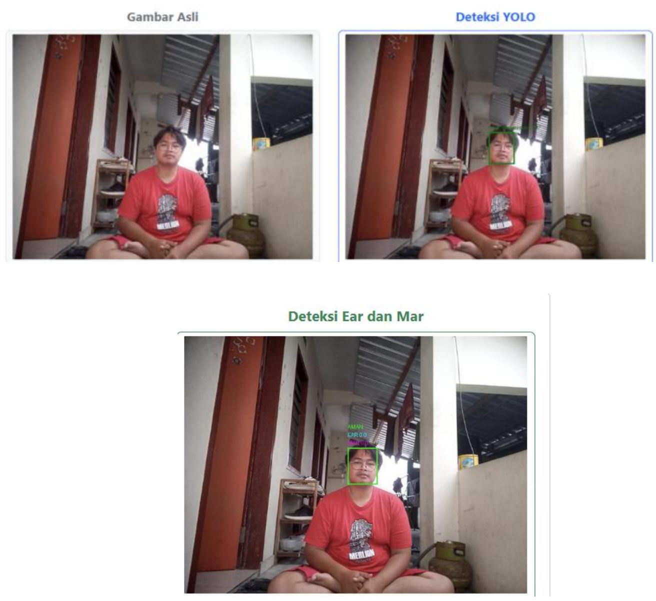


Figure 11. 90cm Distance Tester View

Meanwhile, the comparison methods (EAR and MAR) failed completely with 0% accuracy. At a distance of 90 cm, the algorithm failed to map facial landmarks, making it impossible to calculate the eye ratio. These results highlight the optical limitations of standard smartphone cameras, with a maximum effective distance for driver monitoring being 60-70 cm. Beyond this distance, facial features become too small to analyze in real time without the aid of an external zoom lens.

C. *Yolo Method Accuracy Test Results*

The YOLO method is used to detect and classify driver drowsiness based on live facial images. This method works by extracting visual features from the face and eyes without additional ratio calculations.

Based on a series of experiments that have been carried out, the following is Table III which presents the results of the Yolo method testing as a whole:

TABLE III
RESULTS OF YOLO METHOD ACCURACY TESTING

Driver Condition	Amount of Data	Correct Detection	CALCULATION FORMULA	Accuracy (%)
Normal	184	182	(182/184)×100%	98.91%
drowse	63	63	(63/63)×100%	100%
Sleep	125	109	(109/125)×100%	87.20%
		Average		95.37%

D. *Accuracy Test Results of EAR and MAR Methods*

Further testing was conducted using conventional geometry-based methods, namely Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) calculations. This method works by detecting 68 facial landmark points using the Dlib library, then calculating the Euclidean distance between the eyelids and lips to determine whether the eyes are closed or the mouth is yawning based on a predetermined threshold value.

Based on a series of experiments that have been carried out, the following is Table IV which presents the results of the detection tests using the ear and mar methods as a whole:

TABLE 4 RESULTS OF ACCURACY TESTING OF EAR AND MAR METHODS

Driver Condition	Amount of Data	Correct Detection	CALCULATION FORMULA	Accuracy (%)
Normal	184	147	(147/184)×100%	79.89%
drowse	63	17	(17/63)×100%	26.98%
Sleep	125	120	(120/125)×100%	96.00%
		Average		67.62%

and numbering with Arabic numerals. Image captions in one line are positioned in the center (e.g. Figure 2), while image captions that are more than one line must be left aligned (e.g. Figure 1). Captions with figure numbers must be placed in accordance with the relevant points, as shown in Fig. 1 and 2.

IV. CONCLUSION

This study demonstrates that the YOLOv8 method outperforms the conventional EAR and MAR methods for driver drowsiness detection, achieving an average accuracy of 95.37% compared to 67.62%, with an improvement of 27.75%. YOLOv8 provides more reliable and robust performance by directly classifying overall facial conditions, including eye closure, yawning, facial expressions, and head pose, while remaining less sensitive to visual noise, lighting variations, facial occlusions, and changes in viewing angles. In contrast, the EAR and MAR methods offer more detailed physiological measurements of eye and mouth movements but are highly dependent on accurate facial landmark detection, making them more susceptible to environmental disturbances and resulting in fluctuating detection performance. The proposed client-server architecture, which utilizes an Android application for image acquisition and a server for model inference, was successfully implemented, enabling efficient real-time drowsiness detection while minimizing computational load, battery consumption, and overheating on mobile devices. Furthermore, the system effectively calculates a driving performance index based on the average level of detected drowsiness during driving sessions, providing objective evaluations and timely early warning notifications. Although the developed system demonstrated high accuracy, stability, and practical feasibility, its performance remains dependent on image quality, camera specifications, lighting conditions, facial orientation, and testing scenarios. Therefore, future research should focus on expanding the dataset, optimizing the detection model, and evaluating the system under more diverse real-world conditions, including nighttime driving, mask usage, severe vehicle vibrations, and varying smartphone camera qualities, to further improve system adaptability and deployment readiness.

ACKNOWLEDGEMENTS

The authors would like to express their sincere gratitude to Politeknik Negeri Malang for providing the facilities, resources, and institutional support throughout the entire research process. The availability of laboratories, equipment, and academic guidance greatly contributed to the successful completion of this study. The authors also extend their deepest appreciation to the lecturers and supervisors for their valuable insights, constructive feedback, and continuous guidance during the planning, implementation, and evaluation stages of this research. In addition, special thanks are addressed to colleagues and team members who offered meaningful discussions, technical assistance, and moral support that helped overcome various challenges encountered during the development of the system. Finally, the authors would like to thank their families for their patience, encouragement, and unwavering support, which provided motivation and strength to complete this research successfully.

REFERENCES

[1] A. Professsor and C. Engineering, "DRIVER DROWSINESSS DETECTION USING YOLO I . INTRODUCTION II . LITERATURE REVIEW," *ALOCHANA J.*, vol. 13, no. 2231, pp. 744–751, 2024.

[2] M. Hadid, "Sistem Klasifikasi Dan Deteksi Kendaraan Otomatis Dengan Custom Dataset YOLOv8 (Studi Kasus: Kota Balikpapan)," *Int. Sci. J. Eng. Agric.*, vol. 23, no. 3, p. 219, 2025, doi: 10.12962/j2579-891x.v23i3.19632.

[3] H. Zhang, D. Ni, N. Ding, Y. Sun, Q. Zhang, and X. Li, "Transportation Research Interdisciplinary Perspectives Structural analysis of driver fatigue behavior : A systematic review," *Transp. Res. Interdiscip. Perspect.*, vol. 21, no. July, p. 100865, 2023, doi: 10.1016/j.trip.2023.100865.

[4] L. Youwei, "Real-time eye blink detection using general cameras: a facial landmarks approach," *Int. Sci. J. Eng. Agric.*, vol. 2, no. 5, pp. 1–8, 2023, doi: 10.46299/j.isjea.20230205.01.

[5] E. D. Udayanti, E. Kartikadarma, and F. Firdausillah, "Convolutional Neural Network and LSTM for Seat Belt Detection in Vehicles using YOLO3," *J. RESTI*, vol. 8, no. 3, pp. 355–360, 2024, doi: 10.29207/resti.v8i3.5784.

[6] A. Y. Iin Fatimah Hanis, "Mapping Global Research Trends on Noise-Induced Hearing Loss in Fishermen: A Bibliometric Analysis from aBehavioral Perspective," *Asian J. Heal. Sci.*, vol. 4, no. 12, p. 9, 2025, [Online]. Available: https://ajhsjournal.ph/index.php/gp/article/view/269/287

[7] I. M. G. S. Kadek Priyogi Giri Hartawan, "Tinjauan Sistematis Literatur Tentang Sistem Deteksi Penyakit Berbasis Deep Learning," *Digit. Transform. Technol.*, vol. 6, no. 1, p. 12, 2026, [Online]. Available: https://itscience-indexing.com/jurnal/index.php/digitech/article/view/7503/5625

[8] A. M. I. Dimas Tubagus Hanggar Kesuma, Mila Kusumawardani, "5.pdf," *J. Telecommun. Netw. (JurnalJaringan Telekomun.*, vol. 15, no. 2, p. 11, 2025, [Online]. Available: https://jurnal.polinema.ac.id/index.php/jartel/article/view/6184/5243

[9] I. M. Mutiara Putri Adrini, Martono Dwi Atmadja, Ahmad WildaYulianto, Rachmad Saptono, "6.pdf," *J. Telecommun. Network(Jurnal JaringanTelekomunikasi*, vol. 15, no. 2, p. 10, 2025, [Online]. Available: https://jurnal.polinema.ac.id/index.php/jartel/article/view/6859/5238

[10] L. D. M. Fenny Fitriani, Waluyo Waluyo, Abdul Rasyid, Adzikirani Adzikirani, "7.pdf," *J. Telecommun. Netw. (Jurnal Jar. Telekomun.*, vol. 14, no. 4, p. 8, 2024, [Online]. Available: https://jurnal.polinema.ac.id/index.php/jartel/article/view/5282/5191

[11] N. M. Sarosa, Moechammad, "8.pdf," *J. Teknol. Inf. dan Ilmu Komput.*, vol. 8, no. 4, p. 6, 2021, [Online]. Available: https://jtiik.ub.ac.id/index.php/jtiik/article/view/4407/pdf

[12] R. T. Puteri and F. Utaminingrum, "Deteksi Kantuk Menggunakan Kombinasi Haar Cascade dan Convolutional Neural Network," *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 4, no. 3, pp. 816–821, 2020, [Online]. Available: http://j-ptiik.ub.ac.id

[13] N. Nuryani, K. Nisak, and A. Dwijo Sutomo, "Pengembangan Sistem Deteksi Kantuk Menggunakan Pengklasifikasi Random Forest pada Sinyal Elektrokardiogram (Development of Drowsiness Detection System Using Random Forest Classifier on Electrocardiogram Signals)," *J. Nas. Tek. Elektro dan Teknol. Inf.* |, vol. 10, no. 3, pp. 265–271, 2021.

[14] N. M. Surbakti *et al.*, "Penggunaan Bahasa Pemrograman Python dalam Pembelajaran Kalkulus Fungsi Dua Variabel," *Algoritm. J. Mat. Ilmu Pengetah. Alam, Kebumian dan Angkasa*, vol. 2, no. 3, pp. 98–107, 2024, doi: 10.62383/algoritma.v2i3.67.

[15] C. Wijayanto and Y. A. Susetyo, "JIPI (Jurnal Ilmiah Penelitian dan Pembelajaran Informatika) Volume 07, Nomor 03 : IMPLEMENTASI FLASK FRAMEWORK PADA PEMBANGUNAN APLIKASI SISTEM INFORMASI HELPDESK (SIH)," *J. Ilm. Penelit. dan Pembelajaran Inform.*, vol. 07, no. September, pp. 858–868, 2022.

[16] N. S. Rafael Jonathan, "14.pdf," *J. Inform.*, vol. 23, no. 01, p. 11, 2023, [Online]. Available: https://jurnal.darmajaya.ac.id/index.php/JurnalInformatika/article/view/3637/pdf

[17] Panji Rachmat Setiawan, Rizdqi Akbar Ramadhan, and Ause Labellapansa, "Pelatihan Pemrograman Flutter," *J. Pengabdi. Masy. dan Penerapan Ilmu Pengetah.*, vol. 3, no. 1, pp. 22–27, 2022, doi: 10.25299/jpmpip.2022.10699.

[18] J. A. J. Kansil, "Implementasi Framework Flutter Untuk Membangun Aplikasi E-commerce Pada Toko Sayur Garvita Fresh," no. 25, 2024, [Online]. Available: https://repository.wicida.ac.id/5470/