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RESEARCH ARTICLE **Open Access**

Driver Drowsiness Detection Using Multi-Metric Modeling Based on Facial Landmarks

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Abstract: Drowsiness is a major factor contributing to traffic accidents, as it significantly reduces driver alertness, reaction time, and decision-making ability. This study aims to develop a real-time driver drowsiness detection system based on multi-metric modeling using facial landmarks. Three physiological indicators were employed: Eye Aspect Ratio (EAR) to measure eye openness, Mouth Aspect Ratio (MAR) to identify yawning activity, and Percentage of Eye Closure (PERCLOS) to assess prolonged eye closure patterns. These features were extracted using MediaPipe Face Landmarker, a lightweight and efficient facial landmark detection framework. A quantitative approach with a rule-based method was applied without requiring machine learning training, making the system computationally efficient and easily deployable. Sliding window smoothing was incorporated to reduce false detections and improve overall detection stability. The system was implemented as an Android mobile application and evaluated in real-time conditions using the device's front camera. Experimental results demonstrate that PERCLOS serves as the most stable and reliable drowsiness indicator, while the integration of all three metrics yields significantly more accurate detection compared to relying on a single indicator alone. This system offers a promising non-intrusive, accessible, and practical solution for real-time driver monitoring.

Keywords: Drowsiness Detection; Facial Landmark; Eye Aspect Ratio; Mouth Aspect Ratio; PERCLOS; Multi-Metric.

1. Introduction

The face is a part of the human body with unique characteristics that can be used to distinguish and recognize individuals objectively through visual observation (Sari *et al.*, 2023). Facial expressions play an important role in communication, as they can convey messages both verbally and nonverbally. In the communication process, the face contributes 55%, voice 38%, and language only 7% (Wefa & Mukhaiyar, 2024). Therefore, the face has become a widely studied object in the fields of computer vision and image processing, which aim to generate information or decisions about physical objects through sensor-based data acquisition. Beyond representing basic emotions, facial expressions also reflect physiological conditions such as fatigue and drowsiness, characterized by observable changes in the eyes and mouth.

Drowsiness is a physiological condition in which a person experiences an urge to sleep, which can occur at any time due to factors such as fatigue or lack of sleep (Maslikah *et al.*, 2020), and can be identified through changes in the eyelids that tend to close and feel heavy (U Nggiku & Rabi, 2022). The impact of this condition is significant, particularly in driving safety. Data from the North Sumatra Regional Police indicate that in 2025 there were 1,225 fatalities due to traffic accidents, with 1,448 serious injuries and 5,631 minor injuries (Pradilla, 2025). Furthermore, the National Transportation Safety Committee (KNKT) reported that approximately 60% of land transportation accidents are caused by driver fatigue, with drowsiness as the primary indicator (Mulianingsih, 2024). These figures highlight the urgency of developing accurate and effective drowsiness detection systems.

Computer vision-based approaches are widely adopted as they are non-intrusive and capable of real-time operation. One commonly used method is facial landmark detection, which identifies key points on the face to determine its structure and biological features (Aditiya *et al.*, 2022). These landmarks enable the extraction of various parameters as indicators of drowsiness. The most widely used indicator is PERCLOS (Percentage of Eye Closure), which measures the percentage of time the eyes are closed within a given interval and has been proven to be a stable predictor (Abe, 2023). The Eye Aspect Ratio (EAR) is used to detect changes in eye conditions such as blinking and gradual eye closure, offering high computational efficiency (Dwi Prasetyo *et al.*, 2025), while the Mouth Aspect Ratio (MAR) detects yawning activity as a physiological sign of drowsiness (Larasati, 2025). The combination of these indicators enables a more comprehensive assessment of driver condition.

However, previous studies still present several limitations. Most approaches rely on machine learning or deep learning methods that require large datasets and high computational resources (Telaumbanua *et al.*, 2023), and many use only a single indicator such as EAR, which is insufficient to fully represent drowsiness conditions. Safik Ritonga *et al.* (2024) showed that the Viola-Jones method outperformed YOLO in training efficiency, yet still depends on model training. Sugeng & Nizar (2023) achieved high accuracy using BlazeFace and EAR but did not integrate additional indicators such as MAR and PERCLOS. Hariesugama *et al.* (2023) used CNN with high accuracy, though performance decreased at certain distances. Asvin Mahersatillah Suradi *et al.* (2023) applied HOG and SVM with 68 landmark points but remained limited to driver scenarios, while Sitohang & Taufik (2018) focused only on face detection without analyzing physiological conditions.

Based on these limitations, there is a research gap in developing a lightweight drowsiness detection system that does not require model training and can integrate multiple indicators simultaneously. Therefore, this study proposes a multi-metric approach combining PERCLOS, EAR, and MAR using the pre-trained and optimized MediaPipe Face Landmarker, which reduces computational requirements while improving efficiency for mobile device implementation. A sliding window technique is also applied as a temporal processing mechanism to stabilize detection results and reduce frame-to-frame fluctuations. Accordingly, the objectives of this study are: (1) to implement MediaPipe Face Landmarker to extract facial features for calculating PERCLOS, EAR, and MAR; (2) to develop a multi-metric model for real-time drowsiness detection; and (3) to apply a sliding window technique to improve detection stability. This study is expected to contribute to the development of efficient, non-intrusive, and practical computer vision-based drowsiness detection systems for modern devices.

2. Literature Review

Drowsiness is a physiological condition characterized by a decrease in a person's level of consciousness, alertness, and cognitive ability. In the context of driving, this condition is a major risk factor for traffic accidents as it can cause delayed responses and even loss of vehicle control. One common phenomenon is microsleep, a brief episode of sleep lasting only a few seconds that is highly dangerous while driving (Wefa & Mukhaiyar, 2024). Several studies show that drowsiness-related accidents contribute to approximately 10–20% of total traffic accidents, with a relatively higher fatality rate compared to other factors (Quiles-Cucarella *et al.*, 2024). Therefore, the development of a drowsiness detection system is essential as a preventive measure to improve driving safety.

With the advancement of technology, various approaches have been developed to detect driver drowsiness. Generally, these methods can be classified into three main categories: vehicle-based behavior, physiological signal-based, and driver visual characteristic-based approaches (Quiles-Cucarella *et al.*, 2024). Among these, vision-based methods using computer vision are widely adopted because they are non-intrusive and applicable in real-time. In the visual-based approach, digital image processing plays an important role in extracting information from images or videos. The initial stage in this system is face detection, which identifies the presence and location of a face before further analysis is performed (Sari *et al.*, 2023). Classical methods such as Viola-Jones are still widely used due to their computational efficiency and real-time capability, although they have limitations in handling variations in lighting and facial pose. Methods such as Principal Component Analysis (PCA) and Eigenface are also used in face recognition but generally require more controlled image conditions. Recent developments show a shift toward deep learning-based methods such as Convolutional Neural Networks (CNN) and YOLO, which significantly improve detection accuracy; however, these approaches require higher computational resources and complex training processes (Safik Ritonga *et al.*, 2024).

To overcome these limitations, facial landmark-based approaches are widely used as they can represent the geometric structure of the face in greater detail. Facial landmarks are coordinate points used to identify important facial components such as the eyes, mouth, and head position (Sugeng & Nizar, 2023). Through this approach, various parameters can be extracted, including Eye Aspect Ratio (EAR) to measure eye openness, Mouth Aspect Ratio (MAR) to detect yawning activity, and head position analysis to support drowsiness identification. The EAR method has been proven effective in detecting eye closure in real-time (U Nggiku & Rabi, 2022), and the combination of these features can improve detection accuracy to more than 90% (Sugeng & Nizar, 2023). Another widely used indicator is PERCLOS (Percentage of Eye Closure), which measures the percentage of time the eyes are closed more than 80% within a certain period and has a strong correlation with drowsiness due to sleep deprivation and reduced alertness (Abe, 2023). However, no single indicator can optimally detect drowsiness under all conditions, as PERCLOS has limitations in detecting moderate or situational drowsiness (Abe, 2023). Therefore, a multi-metric approach combining EAR, MAR, PERCLOS, gaze direction, and head position has been developed and shown to improve system accuracy and robustness by considering various aspects of drowsiness behavior simultaneously (Quiles-Cucarella *et al.*, 2024).

In terms of implementation, drowsiness detection systems generally employ two main approaches: machine learning and rule-based systems. Machine learning-based approaches, particularly CNN, can achieve high classification accuracy exceeding 95% in several studies (Larasati, 2025), but require large datasets and complex training processes. In contrast, rule-based approaches apply threshold-based rules on parameters such as EAR, MAR, or PERCLOS, making them simpler and training-free. This makes rule-based methods more lightweight and suitable for real-time implementation on resource-constrained devices such as Raspberry Pi or mobile platforms (ADITIYA *et al.*, 2022).

Based on the literature review, most existing studies still rely on a single-metric approach, which is less robust in capturing variations in drowsiness behavior. Deep learning methods, while highly accurate, are often inefficient for mobile device implementation, and existing multi-metric approaches still face challenges in detection stability due to frame-to-frame value fluctuations. To address these issues, this study proposes a multi-metric approach using EAR, MAR, and PERCLOS parameters extracted from facial landmarks, combined with a temporal smoothing technique using a sliding window to improve detection stability. This approach is expected to produce a drowsiness detection system that is accurate, stable, and efficient for mobile device implementation.

3. Methodology

3.1 Research Type

This study employs a quantitative approach using a multi-metric method based on facial landmarks to detect drowsiness. The resulting data are numerical values derived from facial physiological parameters, namely Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), and Percentage of Eye Closure (PERCLOS). A quantitative approach is chosen as it enables systematic, structured, and measurable analysis based on numerical data obtained from drowsiness indicators (Syahroni, 2022).

3.2 Time and Location of the Study

This research is conducted from December 2025 to July 2026 in Medan, North Sumatra.

3.3 Research Procedure

The stages carried out in this study are as follows:

1) Literature Review — Reviewing national and international journals published within the last five years, particularly those related to PERCLOS, EAR, and MAR algorithms and their applications.
2) Proposed Workflow Framework — The proposed system workflow is illustrated in Figure 1.

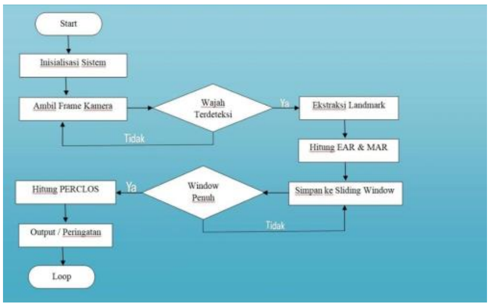

Figure 1. Workflow Framework

3.4 Tools and Materials

This study utilizes tools and materials that support the development, implementation, and testing of a facial landmark-based drowsiness detection system. Smartphones are used as the main device to run the application and capture facial images in real-time, while laptops are used for application development and testing. The hardware specifications are presented in Table 1.

Table 1. Hardware Specifications

No	Specification	Smartphone	Laptop
1	Type	Android	Laptop
2	Camera	Front Camera	—
3	RAM	≥ 4 GB	≥ 8 GB
4	Storage Media	Internal	SSD
5	Operating System	Android	Windows

The software used in this study includes Android Studio as the development environment, Kotlin as the primary programming language, Jetpack Compose for user interface design, and CameraX for real-time camera management. The materials used consist of data and parameters processed by the system, including real-time facial video captured from the smartphone front camera, facial landmark data extracted using MediaPipe Face Landmarker, and facial physiological parameters, namely EAR, MAR, and PERCLOS. All tools and materials are selected to support efficient implementation of the system on mobile devices without requiring additional deep learning model training.

3.5 Method

The method used in this study integrates Eye Aspect Ratio (EAR), Percentage of Eye Closure (PERCLOS), and Mouth Aspect Ratio (MAR) by utilizing facial landmark coordinates extracted using MediaPipe Face Landmarker. The multi-metric approach is selected to improve the reliability of drowsiness detection, as physiological indicators such as eye closure and yawning do not always occur simultaneously. The entire process is designed to operate in real-time, non-intrusively, and without requiring additional machine learning model training (Quiles-Cucarella *et al.*, 2024). Eye Aspect Ratio (EAR) measures the level of eye openness based on the geometric relationship between the vertical and horizontal distances of the eye, calculated from facial landmark points. The EAR value remains relatively stable when the eyes are open and decreases significantly when the eyes are closed. To improve stability and reduce noise, EAR is calculated for both the left and right eyes and then averaged to obtain the final value used by the system (Dwi Prasetyo *et al.*, 2025). Mathematically, EAR is defined as follows:

$$EAR = \frac{\| p_2 - p_6 \| + \| p_3 - p_5 \|}{2 \cdot \| p_1 - p_4 \|}$$

Where p_1 and p_4 represent the horizontal landmarks of the eye, while p_2, p_3, p_5, and p_6 represent the vertical landmarks of the eye (Dwi Prasetyo *et al.*, 2025). Because EAR values can be affected by small movements such as normal blinking, Percentage of Eye Closure (PERCLOS) is used as the main indicator of drowsiness over time. PERCLOS measures the percentage of time the eyes are closed during a certain observation period, providing a more stable result for assessing alertness. The eye-closed status is determined when the EAR value falls below a specific threshold and is processed using a sliding window method to reduce sudden frame-to-frame fluctuations, making PERCLOS more accurate in reflecting the user's actual drowsiness condition. A higher PERCLOS value indicates that the eyes are closed for a longer duration, corresponding to lower alertness (Wefa & Mukhaiyar, 2024). Mathematically, PERCLOS is defined as follows:

$$PERCLOS = \frac{\text{Duration of eye closure}}{\text{Total observation duration}} \times 100\%$$

Mouth Aspect Ratio (MAR) is used to measure the degree of mouth opening, which is associated with yawning as a physiological sign of drowsiness. MAR is calculated as the ratio between the vertical and horizontal distances of the mouth using several landmark points on the lips (Quiles-Cucarella *et al.*, 2024). Mathematically, MAR is defined as follows:

$$MAR = \frac{\| p_2 - p_8 \| + \| p_3 - p_7 \| + \| p_4 - p_6 \|}{2 \cdot \| p_1 - p_5 \|}$$

Where $p_1$and $p_5$are the horizontal landmark points of the mouth, while p_2, p_3, p_4, p_6, p_7,and $p_8$are the vertical landmark points of the mouth (Quiles-Cucarella *et al.*, 2024). In the developed system, the MAR value serves as a supporting indicator to detect yawning activity. A combination of an increase in MAR and a decrease in EAR is used to strengthen the system's decision in detecting drowsiness, particularly in situations where the eyes are not fully closed.

4. Result and Discussion

4.1 Results

4.1.1 Implementation of the Drowsiness Detection System

The proposed drowsiness detection system is implemented as an Android-based mobile application prototype to evaluate real-time performance in practical conditions. The system processes facial video input captured from the front camera and produces real-time drowsiness status displayed on the screen without requiring user interaction. The implementation consists of four main modules: video acquisition, facial landmark detection and extraction, computation of drowsiness indicators (EAR, MAR, and PERCLOS), and user state evaluation. All modules operate in an integrated pipeline executed on each video frame. The results show that the system runs stably on mobile devices and provides real-time analysis, demonstrating the feasibility of a multi-metric facial landmark approach for practical applications.

4.1.2 Face and Facial Landmark Detection Results

The system successfully detects faces and extracts facial landmarks in real-time for each video frame. Detection is indicated by the overlay of landmark points on the user's face without explicitly displaying bounding boxes. Landmarks remain consistently detected as long as the face is within the camera range and oriented toward the device. The system maintains stable performance under minor facial movements, expression changes, and moderate lighting variations.

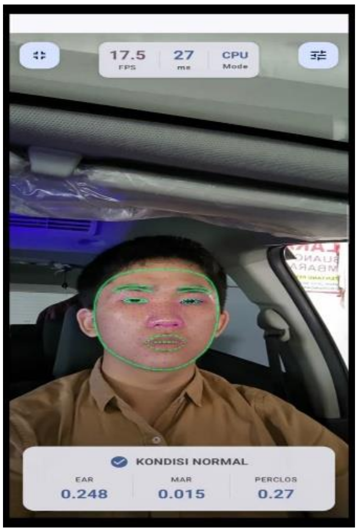

Figure 2. Results of facial landmark visualization

4.1.3 Eye Aspect Ratio (EAR) Behavior

Based on observations during testing, the Eye Aspect Ratio (EAR) exhibits a relatively stable pattern when the user's eyes are in an open condition. Under normal circumstances, EAR values range between 0.23 and 0.26, indicating that the eyes are fully open. In contrast, when the eyes are partially or fully closed for a certain duration, the EAR value decreases significantly and remains below the normal threshold. As shown in Figure 3, the system records an EAR value of 0.098 for the left eye and 0.104 for the right eye, resulting in the following average:

$$EAR_{avg} = \frac{0.098 + 0.104}{2} = 0.101$$

The EAR value of 0.101 falls below the defined threshold, indicating a closed-eye condition. This consistent decrease distinguishes drowsiness-related eye closure from brief normal blinking, confirming that EAR effectively captures changes in eye openness in real-time.

Figure 3. Results of Drowsiness Detection with EAR and PERCLOS

4.1.4 Mouth Aspect Ratio (MAR) Behavior

The Mouth Aspect Ratio (MAR) remains low and stable when the mouth is closed or during light speech. Under yawning conditions, as shown in Figure 4.3, the MAR value reaches 0.776, indicating a significant increase in the vertical mouth distance. After the yawning activity ends, the MAR value returns to its normal range. This pattern confirms that MAR is effective as a supporting indicator for detecting drowsiness symptoms that are not always characterized by full eye closure.

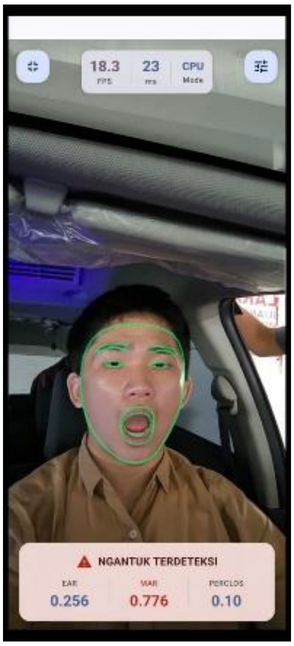

Figure 4. Results of Drowsiness Detection Using MARET

4.1.5 Effect of Sliding Window on Indicator Stability

EAR and MAR values fluctuate per frame due to noise, lighting changes, and facial movement, which may cause misinterpretation. To improve stability, a sliding window is applied by averaging values over recent frames. Table 2 presents an example of EAR values over a 3-frame window.

Table 2. Sliding Window Example

Frame	EAR Value
t	0.116
t−1	0.115
t−2	0.118

The smoothed EAR value is calculated as follows:

$$EAR_{smooth} = \frac{0.116 + 0.115 + 0.118}{3} = 0.116$$

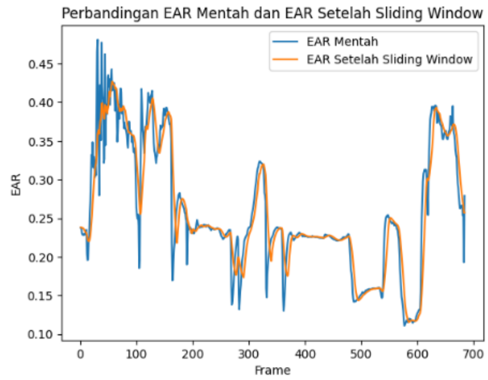

Figure 5. Comparison of raw EAR values per frame and EAR values after sliding window smoothing

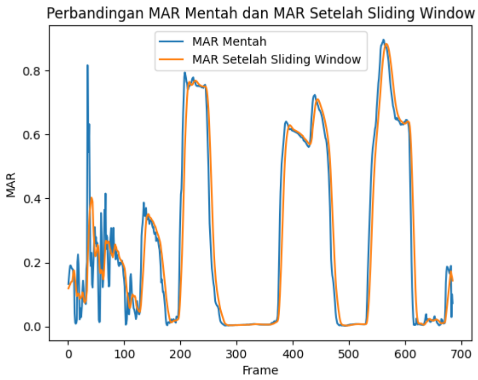

Figure 6. Comparison of raw MAR values per frame and MAR values after sliding window smoothing

The sliding window applied to MAR reduces spikes caused by minor lip movements or speech while preserving consistent increases during yawning, thereby improving reliability before PERCLOS calculation.

4.1.6 Percentage of Eye Closure (PERCLOS) Results

PERCLOS is used as the primary drowsiness indicator by measuring eye closure duration over a time window. Eye status is determined from EAR values processed with the sliding window. In a drowsy condition, all 10 frames in the observation window are classified as closed, resulting in the following PERCLOS value:

$$PERCLOS = \frac{10}{10} = 1.00$$

In drowsy conditions, PERCLOS reaches 0.87–1.00, while in normal conditions it remains low at approximately 0.27. Normal blinks have minimal impact due to their short duration. The integration of MAR further strengthens drowsiness detection, particularly when high PERCLOS coincides with yawning activity.

4.1.7 Rule-Based Decision System and Threshold Determination

Drowsiness detection is determined using a rule-based system that evaluates temporally smoothed EAR, MAR, and PERCLOS against predefined thresholds. This approach is chosen due to the clear physiological meaning of each indicator and its deterministic, transparent decision-making without requiring machine learning training. The threshold values used in the system are presented in Table 3.

Table 3. Threshold Parameters

Parameter	Threshold Value	Description
Eye Aspect Ratio (EAR)	0.18	Eyes are considered closed if EAR falls below this threshold consecutively across several frames, indicating decreased alertness.
Mouth Aspect Ratio (MAR)	0.60	The mouth is considered wide open (yawning) if MAR exceeds this threshold for a certain duration.
Percentage of Eye Closure (PERCLOS)	0.40	The user is categorized as drowsy if the percentage of eye closure reaches or exceeds 40% of the total observation window.

The decision rules applied by the system are as follows:
1) Normal: PERCLOS is below the threshold and EAR is within the normal range.
2) Drowsy: PERCLOS exceeds the threshold and/or EAR is consistently low, supported by high MAR indicating yawning.

4.2 Discussion

Observations show that changes in EAR and MAR do not always occur simultaneously. In some cases, MAR increases significantly due to yawning without a notable decrease in EAR. In other cases, EAR decreases due to eye closure without an increase in MAR. Figure 4.4 illustrates an example of normal conditions, where the EAR value is within the normal range, the MAR value is low, and the PERCLOS value is relatively small. This finding confirms that relying on a single indicator is insufficient to comprehensively represent drowsiness conditions, and that a multi-metric approach provides more robust detection. Based on the results, PERCLOS demonstrates the highest stability as a drowsiness indicator, as it reflects cumulative eye closure behavior over time rather than instantaneous frame values. EAR effectively captures real-time changes in eye openness and serves as the basis for PERCLOS calculation, while MAR provides complementary information by detecting yawning activity that may occur independently of eye closure. The integration of these three indicators enables the system to detect a wider range of drowsiness manifestations, improving overall detection reliability compared to single-indicator approaches. The rule-based system consistently distinguishes between normal and drowsy conditions in real-time testing. In normal conditions, EAR remains above 0.18, MAR is relatively low, and PERCLOS stays below 0.4, leading to a non-drowsy classification. Conversely, in drowsy conditions, EAR consistently falls below the threshold, PERCLOS exceeds 0.4, and is sometimes reinforced by increased MAR indicating yawning. This combination enables the system to reliably detect drowsiness without relying on a single indicator, while the rule-based design ensures transparent, computationally efficient, and stable real-time implementation on mobile devices.

5. Conclusion and Recommendations

The facial landmark-based drowsiness detection system was successfully implemented on an Android mobile device, operating in real-time using the smartphone's front camera. MediaPipe Face Landmarker is capable of extracting facial landmark points in a stable and consistent manner, provided that the face remains within camera range and lighting conditions are adequate. The Eye Aspect Ratio (EAR) effectively detects changes in eye openness, while the Mouth Aspect Ratio (MAR) serves as a supporting indicator for yawning detection. Percentage of Eye Closure (PERCLOS) proves to be the most stable primary indicator of drowsiness, as it accounts for the cumulative duration of eye closure over a specific time interval. The integration of EAR, MAR, and PERCLOS within a multi-metric model results in more reliable detection compared to relying on a single indicator alone. The application of a sliding window technique further reduces fluctuations caused by normal blinking, facial movements, and image noise, improving overall detection stability. Finally, the rule-based decision system enables transparent, deterministic, and easily interpretable decision-making without requiring machine learning model training, making the system computationally efficient and suitable for deployment on resource-constrained mobile devices.

Future improvements may include incorporating additional facial-based indicators, such as head tilt and gaze direction, to further enhance detection accuracy. A hybrid approach combining rule-based methods with lightweight machine learning could also be explored to improve adaptability to individual user characteristics. Furthermore, the system can be extended by integrating early warning features, such as audio alerts or vibration feedback, to provide immediate response upon drowsiness detection.

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