International Journal of Advanced Smart Convergence Vol.13 No.4 210-221 (2024)
http://dx.doi.org/10.7236/IJASC.2024.13.4.210

IJASC 24-4-22

The Impact of Face Angle and Lighting Changes on Eye State Recognition Accuracy: A Comparative Evaluation of CNN, MediaPipe, and Dlib Performance

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Abstract

This study systematically analyzes the impact of face angle and lighting changes on eye state recognition technology and compares the performance of three technologies: CNN, MediaPipe, and Dlib. Specifically, the CNN-based approach utilizes a transfer learning model, Inception, to assess eye state recognition accuracy. With recent advancements in AI and computer vision technology, eye state recognition has become crucial in applications like driver drowsiness detection, user authentication, and medical monitoring. However, the performance of these technologies is greatly influenced by face angle and lighting conditions. This research evaluates the recognition accuracy of the three technologies under various face angles and lighting conditions, finding that CNN demonstrates robust performance against both lighting and angle variations. This study aims to provide fundamental data to improve the reliability of eye state recognition technology and to suggest future research directions.

Keywords: *Eye State Recognition, MediaPipe, Face Angle Variations, Lighting Conditions, Driver Drowsiness Detection*

1. Introduction

Recent advancements in artificial intelligence (AI) and computer vision technology have led to significant developments in face and eye state recognition, which play a critical role in various applications. These technologies are especially essential in real-time safety and healthcare applications such as driver drowsiness detection systems, user authentication systems, and medical monitoring. Eye state recognition can play an important role in accurately determining drowsiness or focus, which can greatly improve system reliability and safety [1].

However, the accuracy of eye state recognition is affected by external factors like face angle and lighting conditions [2]. When the face angle changes, features around the eyes may become distorted or occluded, and

Manuscript Received: October. 19, 2024 / Revised: October. 24, 2024 / Accepted: October. 29, 2024
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lighting variations may obscure visual features around the eyes, reducing recognition performance. In real-world applications, the face may tilt or rotate at various angles, and lighting conditions are not always constant. Thus, eye state recognition technology capable of stable performance across diverse situations is needed [3].

Currently, open-source libraries such as CNN, MediaPipe, and Dlib are widely used for eye state recognition. Each of these technologies recognizes eye states using different methods, which may result in performance differences in response to face angle or lighting variations. However, systematic comparative studies on the impact of face angle and lighting changes on the recognition performance of these technologies remain insufficient. Therefore, studies analyzing the influence of these environmental factors on eye state recognition performance are significant for developing more reliable eye state recognition systems that are applicable in real-world environments [4].

This study aims to analyze the impact of face angle and various lighting conditions on eye state recognition performance and to comparatively evaluate the performance of three technologies: CNN, MediaPipe, and Dlib. Through this, the study intends to derive the optimal algorithm for reliable eye state recognition in various environments and to suggest the most suitable recognition technology for real-world applications like drowsiness detection and user authentication [5].

2. Related studies

2.1 Overview of Eye State Recognition Technology

Eye state recognition technology uses computer vision and artificial intelligence to determine whether the eyes are open or closed, and it is applied in various fields such as drowsiness detection while driving, user authentication, and medical monitoring. This technology involves extracting facial features, detecting the eye region, and analyzing the state [6][7]. Typically, data-driven methods are used, leveraging machine learning and deep learning to predict eye states based on extensive data training. Since this technology is sensitive to environmental changes, performance evaluation is necessary [8][9].

2.2 Overview of CNN, MediaPipe, and Dlib

CNN (Convolutional Neural Network): CNN is a deep learning model that excels in image analysis due to its specialized structure for pattern recognition. It learns detailed features around the face and eyes, providing robustness against various angles and lighting changes. In our study, the Inception model, a type of CNN, was used with transfer learning, combining CNN's powerful feature extraction capabilities with the multi-scale processing structure of the Inception network [10]. The Inception model applies multiple filter sizes in parallel, enabling effective feature extraction at various image scales. In this study, we used a pre-trained Inception network for its advantages in recognizing eye states under different lighting conditions.

MediaPipe: Developed by Google, MediaPipe is a real-time machine learning framework particularly effective for detecting landmarks on the face, hands, and body. By detecting 468 key facial landmarks, it can analyze subtle facial movements, with GPU acceleration enabling real-time recognition even on mobile devices [11]. The Eye Aspect Ratio (EAR) calculation process in MediaPipe is useful for mathematically determining whether the eyes are open or closed. EAR is computed by using two vertical distances and one horizontal distance, and it is commonly applied in fatigue and blink detection.

First, we calculate the vertical distance using two landmarks for each eye, as used in MediaPipe. The expression below uses Euclidean distance to define the vertical distance for each eye.

$$\text{Left eye vertical distance: } \text{distance}_{v,left} = \sqrt{(x_{i1} - x_{i5})^2 + (y_{i1} - y_{i5})^2} \tag{1}$$

$$\text{Right eye vertical distance: } \text{distance}_{v,right} = \sqrt{(x_{j1} - x_{j5})^2 + (y_{j1} - y_{j5})^2} \tag{2}$$

$$\text{Left eye horizontal distance: } \text{distance}_{h,left} = \sqrt{(x_{i0} - x_{i3})^2 + (y_{i0} - y_{i3})^2} \tag{3}$$

$$\text{Right eye horizontal distance: } \text{distance}_{h,right} = \sqrt{(x_{j0} - x_{j3})^2 + (y_{j0} - y_{j3})^2} \tag{4}$$

$$\text{EAR} = \frac{\text{distance}_{v,left} + \text{distance}_{v,right}}{2\times(\text{distance}_{h,left} + \text{distance}_{h,right})} \tag{5}$$

The eye ratio (EAR) is calculated by dividing the sum of vertical distances by horizontal distances, with EAR magnitudes greater than or equal to 0.19 counted as open eyes and less than or equal to zero.

Dlib: Dlib is a robust library for facial landmark detection and analysis, capable of detecting 68 facial landmarks. Using a machine learning-based algorithm, Dlib is strong in recognizing eye states from various angles and demonstrates high resilience to lighting changes [12].

The "EAR (Eye Aspect Ratio)" formula is employed in Dlib code to assess whether the eyes are open or closed. EAR is an effective metric for detecting blinks, as it utilizes the ratio of vertical and horizontal distances of the eye landmarks.

In the code, the eye_aspect_ratio function calculates the EAR (Eye Aspect Ratio) for each eye as follows:

- Vertical Distance Calculation: To compute EAR, two pairs of vertical distances are measured.
  Vertical Distance A is the difference in the vertical coordinates between two points, eye[1] and eye[5].
  Vertical Distance B is the difference in the vertical coordinates between two points, eye[2] and eye[4].
- Horizontal Distance Calculation: The horizontal distance C is calculated as the difference in horizontal coordinates between the left and right boundaries of the eye, eye[0] and eye[3].
- EAR function works as follows:

$$\text{EAR} = \frac{|y_1 - y_5| + |y_2 - y_4|}{2\times|x_0 - x_3|} \tag{6}$$

The EAR is defined as the sum of the vertical distances divided by twice the horizontal distance. The EAR size was calculated as 0.25 or greater with an open eye and zero otherwise.

2.3 Impact of Face Angle and Lighting on Performance

Face angle and lighting conditions have a significant impact on eye state recognition performance. Landmarks around the eyes appear differently in frontal and side views of the face, which leads to significant differences in recognition accuracy. In addition, while recognition performance is high in bright and evenly distributed environments, it is difficult to make accurate judgments in dark environments because the features around the eyes are not distinct. The robustness of the algorithm to these lighting changes is crucial for real-world applications, so performance evaluation that takes into account face angles and lighting conditions is essential [13-15].

3. Research Methods and Performance Analysis

3.1 Overview of Eye State Recognition Technology

3.1.1 Experimental Design and Dataset

In this study, experiments were designed to evaluate eye state recognition accuracy under various face angles and lighting conditions. The dataset used in the experiments consists of 960 images, each labeled to indicate whether the eyes are open or closed.

The dataset was collected to include diverse lighting conditions and face angles, enabling a comprehensive evaluation of recognition performance across different scenarios.

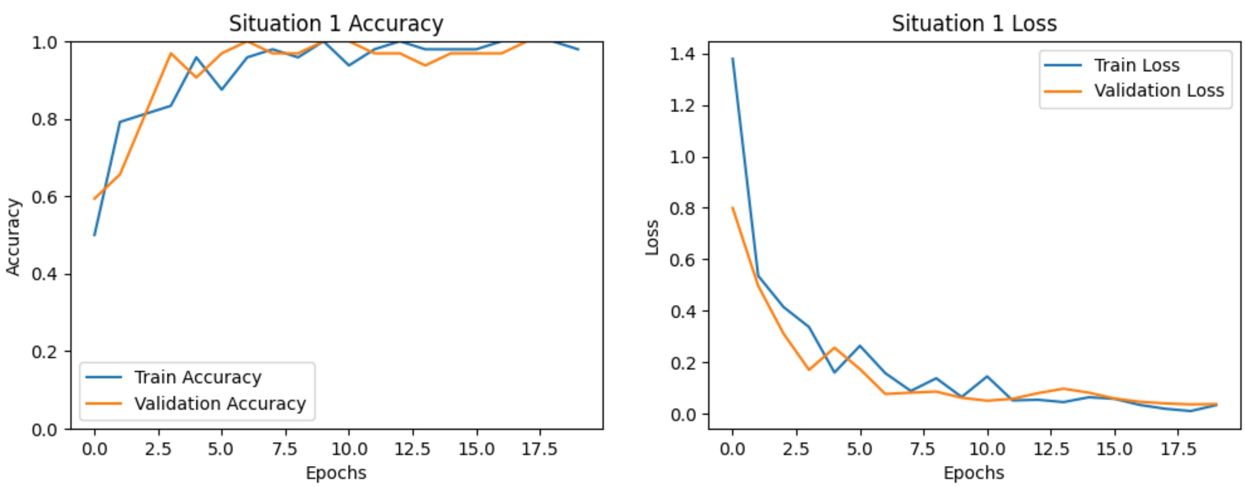

Figure 1. Example of learning graph of CNN Inception model

Figure 1 is an example of a graph of the accuracy and loss values of the result of learning to classify eye closure and eye opening in general lighting using CNN's Inception model.

3.1.2 Lighting Conditions

The lighting conditions were set to general lighting, very bright lighting, and very dark lighting. Images under each lighting condition were collected with various face angles. This method provided an opportunity to analyze how changes in lighting affect the performance of eye state recognition models.

3.1.3 Face Angle Conditions

For face angle conditions, yaw, pitch, and roll angles were set. Images were captured with the face rotated at 45-degree angles for each of these directions. This allowed for the evaluation of the robustness and accuracy of eye state recognition models under various scenarios. These conditions contributed to a thorough assessment of eye state recognition performance across diverse settings.

3.2 Performance analysis

3.2.1 Performance Comparison Based on Lighting Changes

To evaluate the impact of lighting changes on the performance of eye state recognition models, performance was analyzed under six different lighting conditions using an alpha blending technique. The alpha blending technique adjusts the transparency of original and background images for composition. In this study, for bright lighting conditions, a white overlay with 20% transparency was applied, while for dark lighting conditions, a black overlay with 20% transparency was used. Table 1 presents the results of the analysis of the images in Figure 2.

Table 1. Accuracy performance under different lighting conditions (in %)

Performance Metric		CNN	MediaPipe	Dlib
Eyes closed	Accuracy in normal light	100.0	99.4	91.9
	Accuracy in bright light	98.2	91.2	62.5
	Accuracy in low light	100.0	93.1	60.6
Eyes open	Accuracy in normal light	93.7	93.8	73.8
	Accuracy in bright light	87.3	92.5	59.4
	Accuracy in low light	87.3	93.7	59.4

Figure 2. Different lighting conditions

1) Analysis of Eye Closure Recognition Accuracy

CNN: In eye closure recognition, CNN demonstrated stable performance with over 90% accuracy across all lighting conditions, achieving 100% accuracy in general lighting, 98.2% in bright lighting, and 100% in dark lighting. This indicates that CNN is robust to lighting changes.

MediaPipe: MediaPipe achieved accuracies of 99.4% and 93.1% in normal and dark lighting, respectively, but showed a slight decrease to 91.2% in bright lighting. Although slightly lower than CNN, it maintained high recognition performance overall.

Dlib: Dlib achieved 91.9% accuracy in normal lighting but showed a significant drop in accuracy to 62.5% in bright lighting and 60.6% in dark lighting, indicating that Dlib is sensitive to changes in lighting.

2) Analysis of Eye Opening Recognition Accuracy

CNN: For eye opening recognition, CNN achieved 93.7% accuracy in normal lighting and maintained 87.3% accuracy in both bright and dark lighting conditions, demonstrating robustness to changes in lighting.

MediaPipe: MediaPipe recorded 93.8% accuracy in normal lighting and showed stable performance with 92.5% and 93.7% accuracy in bright and dark lighting, respectively.

Dlib: Dlib achieved 73.8% accuracy in normal lighting and experienced a drop to 59.4% accuracy in both bright and dark lighting, indicating a notable sensitivity to lighting changes.

Overall, CNN and MediaPipe demonstrated stable performance under varying lighting conditions, with CNN delivering the best performance across all lighting conditions. Dlib, however, showed a higher sensitivity to lighting changes, suggesting it may experience performance degradation in environments with inconsistent lighting.

3.2.2 Face Angle Conditions (Yaw, Pitch, Roll)

1) When the Face Angle is Frontal (0°)

Table 2. Accuracy performance under Front Angel 0° (in %)

Performance Metric	CNN	MediaPipe	Dlib
Eye Closure, Frontal Angle 0°	100.0	100.0	100.0
Eye Opening, Frontal Angle 0°	93.7	100.0	100.0

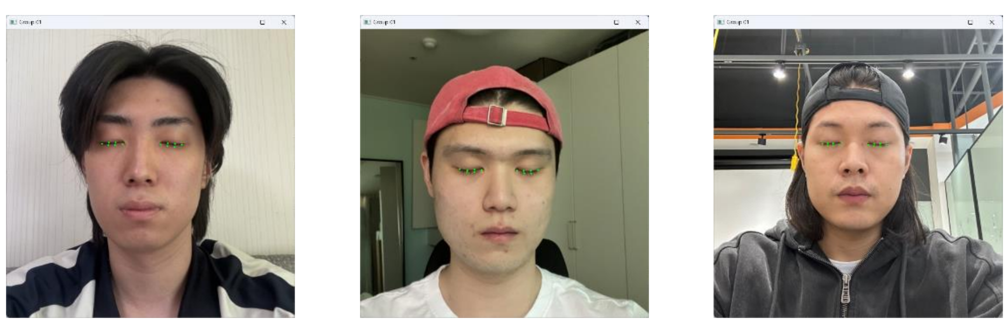

Figure 3. Front Angel 0°

Table 2 presents the results of the analysis of the images in Figure 3.

① Eye Closure Recognition Accuracy(Frontal Angle 0°)

CNN: Achieved 100% accuracy for eye closure recognition, indicating that CNN effectively learns diverse facial features to accurately recognize eye closure in a frontal view. This high accuracy reflects CNN's deep network structure, which captures fine details around the eyes.

MediaPipe: Also recorded 100% accuracy for eye closure in a frontal view, showing excellent performance due to its real-time capability and fast processing speed. MediaPipe provides high accuracy in facial landmark detection, ensuring stable recognition in various lighting environments.

Dlib: Similarly, Dlib achieved 100% accuracy for eye closure recognition, utilizing 68 facial landmark points to detect eye closure accurately in frontal views and demonstrating stable performance.

② Eye Opening Recognition Accuracy(Frontal Angle 0°)

CNN: Recorded 93.7% accuracy for eye opening recognition, demonstrating its capacity to learn various facial features and recognize eye opening accurately in a frontal view. This success indicates CNN’s ability to precisely extract detailed features around the eyes.

MediaPipe: Also achieved 100% accuracy for eye opening recognition. MediaPipe excels in facial recognition and landmark detection, delivering outstanding performance in eye opening recognition in frontal views due to its real-time processing capability and high accuracy.

Dlib: Recorded 100% accuracy in eye opening recognition, showing strong performance in frontal views by analyzing facial features accurately and maintaining a high recognition rate.

In summary, all three models (CNN, MediaPipe, Dlib) demonstrated perfect accuracy for both eye closure and eye opening recognition in frontal views (0°). Particularly, CNN exhibited strengths in detailed feature analysis through its deep network structure.

2) Performance Comparison for Yaw Angle (45° Rotation)

The impact of changes in the yaw angle of the face on model performance was analyzed. Table 3 presents the results of the analysis of the images in Figure 4.

Table 3. Accuracy performance under Yaw Angle 45° Rotation (in %)

Performance Metric	CNN	MediaPipe	Dlib
Eye Closure, Yaw Angle 45° Rotation	100.0	97.5	77.5
Eye Opening, Yaw Angle 45° Rotation	93.7	100.0	95.0

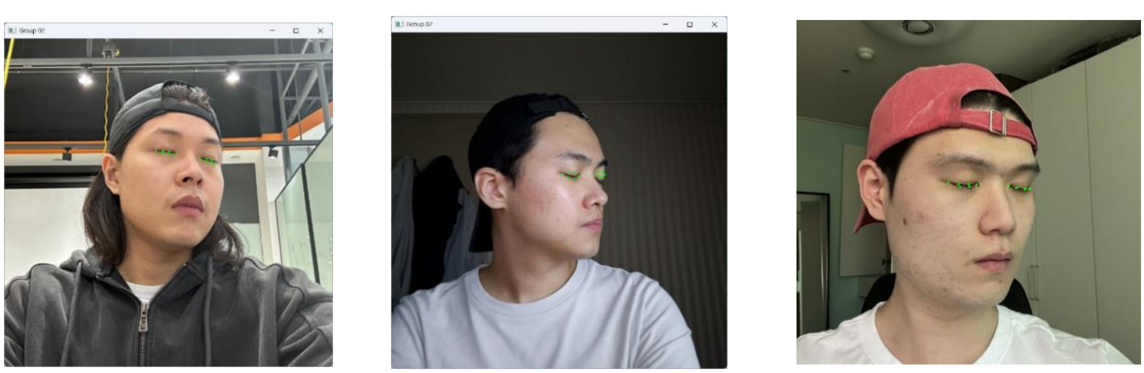

Figure 4. Yaw Angle 45° Rotation

① Eye Closure Recognition Accuracy (Yaw 45°)

CNN: Maintained 100% accuracy in recognizing eye closure with a 45° rotation, showing high robustness to angle variations. This indicates that CNN is trained to detect eye features accurately across diverse facial angles.

MediaPipe: Achieved 97.5% accuracy for eye closure with a strong level of robustness to angle variations, though with a slight performance drop. Nonetheless, it maintains practical levels of accuracy.

Dlib: Accuracy dropped to 77.5% for eye closure recognition with a 45° rotation, indicating that Dlib may struggle to maintain stable performance when the face is rotated.

② Eye Opening Recognition Accuracy (Yaw 45°)

CNN: Recorded 93.7% accuracy for eye opening recognition with a 45° rotation, demonstrating excellent performance despite the angle variation.

MediaPipe: Achieved 100% accuracy for eye opening recognition, showing very strong resistance to yaw angle changes, likely due to its combination of real-time processing and high accuracy.

Dlib: Achieved 95.0% accuracy for eye opening recognition, showing relatively better performance than for eye closure but still somewhat less stable than CNN and MediaPipe.

From this analysis, CNN and MediaPipe showed strong performance for a 45° rotation in the yaw angle, with MediaPipe demonstrating high resilience in recognizing both eye closure and eye opening. Dlib performed relatively well for eye opening recognition but experienced accuracy declines in eye closure recognition.

3) Performance Comparison for Pitch Angle (45° Rotation)

The impact of the pitch angle of the face on model performance was compared. Table 4 presents the results of the analysis of the images in Figure 5.

Table 4. Accuracy performance under Pitch Angle 45° Rotation (in %)

Performance Metric	CNN	MediaPipe	Dlib
Eye Closure, Pitch Angle 45° Rotation	93.7	100.0	100.0
Eye Opening, Pitch Angle 45° Rotation	81.2	75.0	10.0

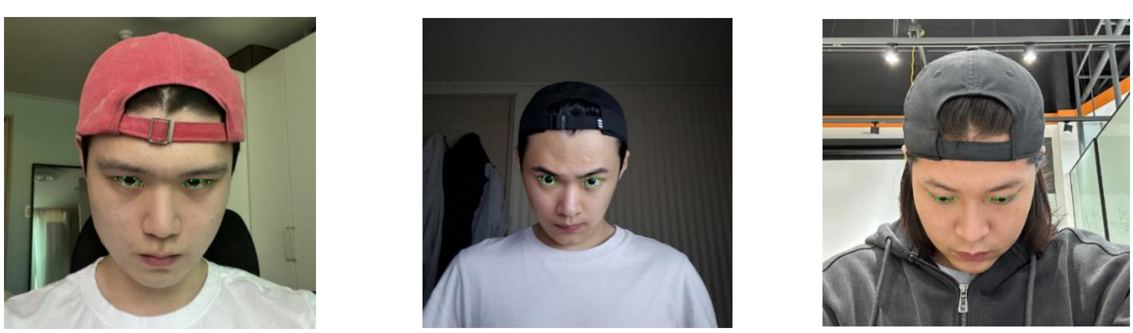

Figure 5. Pitch Angle 45° Rotation

① Eye Closure Recognition Accuracy (Pitch 45°)

CNN: Achieved 93.7% accuracy for eye closure with a 45° pitch rotation, maintaining robust performance despite the angle variation.

MediaPipe and Dlib: Both technologies achieved 100% accuracy in eye closure recognition, demonstrating high stability under pitch angle changes, suggesting their capability to recognize eye closure accurately even when the head is tilted.

② Eye Opening Recognition Accuracy (Pitch 45°)

CNN: Achieved 81.2% accuracy for eye opening recognition, outperforming the other technologies and showing relative robustness to pitch angle changes.

MediaPipe: Recorded 75.0% accuracy, which shows a slight decrease in performance, indicating some vulnerability in recognizing eye opening under pitch angle changes.

Dlib: Achieved only 10.0% accuracy for eye opening recognition, showing high sensitivity to pitch angle changes and significant performance degradation, suggesting limited adaptability for eye opening recognition when the face is tilted.

This analysis shows that MediaPipe and Dlib maintained high recognition accuracy for eye closure under pitch angle changes but performed less effectively in eye opening recognition. CNN showed comparatively stable performance in both conditions under pitch angle variations.

4) Performance Comparison for Roll Angle (45° Rotation)

The impact of changes in the roll angle of the face on performance was analyzed. Table 5 presents the results of the analysis of the images in Figure 6.

Table 5. Accuracy performance under Roll Angle 45° Rotation (in %)

Performance Metric	CNN	MediaPipe	Dlib
Eye Closure, Roll Angle 45° Rotation	87.5	100.0	90.0
Eye Opening, Roll Angle 45° Rotation	87.5	100.0	90.0

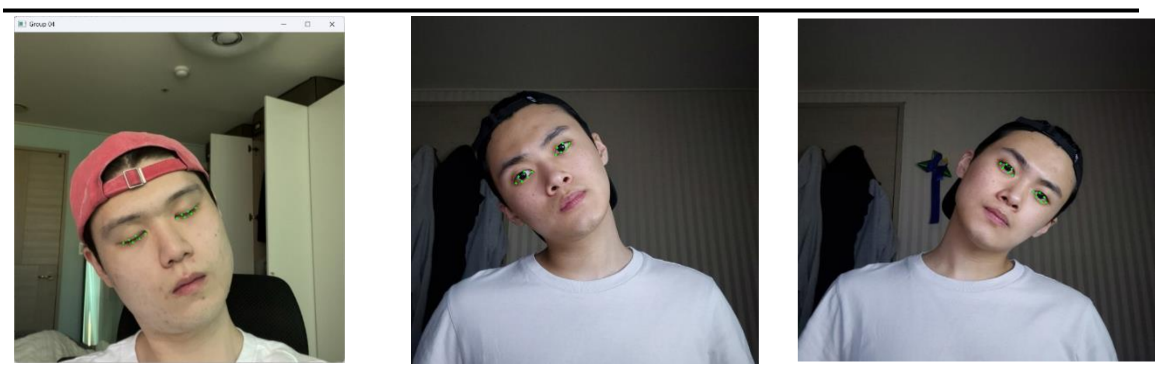

Figure 6. Roll Angle 45° Rotation

① Eye Closure Recognition Accuracy (Roll 45°)

CNN: Achieved 87.5% accuracy for eye closure recognition, showing strong but slightly reduced performance under roll angle changes.

MediaPipe: Maintained 100% accuracy, demonstrating high stability and robustness despite the face's tilt.

Dlib: Achieved 90.0% accuracy for eye closure recognition, with a slight performance decline due to roll angle changes, suggesting potential limitations in eye closure recognition when the face is tilted.

② Eye Opening Recognition Accuracy (Roll 45°)

. CNN: Achieved 87.5% accuracy for eye opening recognition, showing strong but slightly reduced performance under roll angle changes.

MediaPipe: Maintained 100% accuracy, demonstrating high stability and robustness despite the face's tilt.

Dlib: Achieved 90.0% accuracy for eye opening recognition, with a slight performance decline due to roll angle changes, suggesting potential limitations in eye closure recognition when the face is tilted.

Overall, MediaPipe demonstrated the strongest performance under roll angle variations, while CNN and Dlib showed a slight decrease in performance..

4. Comparative Analysis

MediaPipe maintained very high performance under most conditions, especially showing excellent performance under roll angle variations, as shown in Table 6. CNN exhibited high accuracy in the frontal and 45° pitch rotation angles, demonstrating stable performance even with some variations. D lib showed relatively lower performance in most conditions, with the greatest performance drop obse rved under yaw rotations

Table 6. Performance Comparison of Eye State Recognition Across Different Face Angles

Recognition State	Angle Condition	CNN	MediaPipe	Dlib
Eye Closure Recognition Accuracy	Frontal Angle	Very High	Very High	Very High
	Yaw 45° Rotation	Very High	Moderately High	Low
	Pitch 45° Rotation	High	Very High	Very High
	Roll 45° Rotation	High	Very High	High
Eye Opening Recognition Accuracy	Frontal Angle	High	Very High	Very High
	Yaw 45° Rotation	High	Very High	Moderately High
	Pitch 45° Rotation	High	Low	Low
	Roll 45° Rotation	High	Very High	High

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5. Conclusion

This study analyzed the effects of face angle and lighting changes on the performance of eye state recognition technologies (CNN, MediaPipe, Dlib) through experiments. The results showed that CNN maintained high recognition accuracy across all angles and lighting conditions, demonstrating particularly robust performance under face rotation and lighting variations, likely due to CNN's ability to effectively learn diverse facial features and adapt to environmental changes. MediaPipe generally exhibited stable results, showing real-time performance and high accuracy; however, a slight decrease in accuracy was observed in eye opening recognition at a 45° pitch angle. Dlib showed excellent recognition rates in the frontal position but was sensitive to yaw and pitch angle changes, resulting in lower accuracy under certain conditions.

This study contributes by identifying the strengths and limitations of each technology across various face angles and lighting conditions, providing valuable insights for selecting appropriate technologies for real-world applications involving face recognition and behavior analysis systems. Future research should aim to improve recognition accuracy and develop solutions that can effectively handle diverse facial features and environmental variations.

Acknowledgement

This research was supported by the Kyungbok University innovation support project funded by the Ministry of Education(MOE, Korea) and National Research Foundation of Korea(NRF)(2024).

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