Vol. 7, No. 4, December 2025

ISI Journal of Information Systems and Informatics

Published By Asosiasi Doktor Sistem Informasi Indonesia

Comparing Optical Flow and Haar Cascade for Head Movement Detection in Smart Wheelchair Control

Ni'Matul Ma'muriyah[1], Paerin[2], Andik Yulianto[3]

[1,2,3]Information System Department, Postgraduate Program, Batam International University, Batam Indonesia

Email: [1]nimatul@uib.ac.id, [2]2231048.paerin@uib.edu, [3]andik@uib.ac.id

Received: October 1, 2025
Revised: November 1, 2025
Accepted: Nove 17, 2025
Published: Dec 9, 2025

Corresponding Author:
Author Name*:
Paerin
Email*:
2231048.paerin@uib.edu

DOI: 10.63158/journalisi.v7i4.1302

Abstract. The development of Artificial Intelligence, particularly in Computer Vision, has enabled real-time recognition of human movements such as head gestures, which can be utilized in smart wheelchairs for users with limited mobility. This study compares two lightweight non-deep-learning methods Lucas–Kanade Optical Flow and Haar Cascade Classifier for real-time head movement detection. Both methods were implemented in Python using OpenCV and tested in four basic directions (left, right, up, and down) under three different lighting conditions: bright, normal, and dim. Each condition consisted of 16 trials per method, resulting in a total of 96 trials. The evaluation focused on detection accuracy and decision time. Under bright lighting, Optical Flow achieved 87.5% accuracy with a decision time of 0.338-1.41 s, while Haar Cascade reached 50% accuracy with 0.616–1.20 s. Under normal lighting, Optical Flow maintained 87.5% accuracy with 0.89–1.21 s, compared to Haar Cascade's 68.75% accuracy with 0.83–1.25 s. Under dim lighting, Optical Flow improved to 93.8% accuracy with 0.90–1.31 s, whereas Haar Cascade dropped to 62.5% accuracy with 0.89–1.58 s. These findings confirm that Optical Flow delivers more reliable and adaptive performance across varying illumination levels, making it more suitable for real-time smart wheelchair control. This study contributes to the development of affordable assistive technologies and highlights future directions for multi-user testing and hardware integration.

Keywords: Head movement, Smart Wheelchair, Optical Flow, Haar cascade Classifier, Real-time Detection

1. INTRODUCTION

The development of Artificial Intelligence (AI), particularly in the field of computer vision, has advanced rapidly. This technology enables the automation of digital image processing and supports a wide range of modern applications [1]–[5] . One of its key applications is biometrics identification systems based on human physical characteristics such as fingerprints, retinas, faces, and head movements [6]–[8]. Face and head detection are not only used for authentication purposes but also play an important role in assistive technologies, such as smart wheelchairs controlled through hand gestures or head movements [9]–[12].

Head-movement detection has become an important topic in computer vision due to its potential in Human Computer Interaction (HCI) and assistive systems [13] . In the context of smart wheelchairs, head gestures are considered a practical and non-invasive alternative input method for users with limited physical mobility [8], [14] . Studies have shown that head-based control systems can significantly improve the independence of people with disabilities, although challenges remain in terms of accuracy, stability, and responsiveness [7].

Lightweight non-deep learning methods such as the Lucas-Kanade Optical Flow and the Haar Cascade Classifier remain widely used. Optical Flow computes pixel displacement between consecutive video frames [15] and has been proven effective for detecting motion in dynamic scenes [16], [17]. However, it is sensitive to lighting variations and noise. Haar Cascade efficiently detects faces in real time; however, it heavily depends on pre-trained datasets and lacks adaptability to pose variations [14], [18], [19].

More recent research has focused on deep learning-based detection models such as YOLOv8, MobileNetV3, and GhostNet, which have achieved higher accuracy and robustness in complex environments [20]–[22]. Nevertheless, these models demand high-end hardware and large labeled datasets, limiting their practicality for lightweight assistive systems [18], [19]. Hence, traditional methods such as Optical Flow and Haar Cascade remain relevant for low-power, real-time implementations.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

In Masud et al [23], a vision-based autonomous wheelchair was developed using the Haar Cascade and Hough Transform algorithms for real-time eye-motion tracking on a Raspberry Pi platform. The system successfully demonstrated reliable eye-movement detection and wheelchair control in real time under controlled lighting conditions. This study illustrates that classical computer-vision algorithms can still provide effective performance for assistive systems without relying on GPU-based computation. However, the system also revealed the typical limitations of traditional methods sensitivity to illumination changes and restricted adaptability in dynamic environments.

Previous studies have explored these methods separately. Wahyuni et al. [12] implemented Optical Flow for human movement tracking using a multi-camera setup and achieved high accuracy under controlled lighting, but the system was sensitive to noise and brightness variations. Choi et al. [6] enhanced the Haar Cascade algorithm by calibrating vertical features to improve detection stability, yet it remained dependent on pre-trained datasets. Komang and Utaminingrum [24] applied Haar Cascade for head-gesture-based wheelchair control but limited their evaluation to overall accuracy. Meanwhile, Larasati and Utaminingrum [20], [25] used a modified YOLOv8 model that achieved superior accuracy and adaptability but required powerful GPU hardware.

From this body of research, it can be concluded that while Optical Flow and Haar Cascade are both efficient for lightweight motion-detection applications, there is still a lack of studies that directly compare their performance under real-time conditions and varied illumination environments. Previous works have generally evaluated these methods in isolation or under fixed lighting setups, without conducting a multi-metric analysis that includes both detection accuracy and decision time. Moreover, no prior research has specifically examined how these classical algorithms perform in the context of smart wheelchair control, where reliability under changing lighting conditions and rapid responsiveness are critical. This gap highlights the need for a focused comparative evaluation of both methods across multiple performance metrics and lighting scenarios to identify the most suitable approach for assistive mobility systems.

Therefore, this study aims to fill this research gap by developing a real-time head-movement detection prototype using the Lucas–Kanade Optical Flow method and conducting a comparative analysis with the Haar Cascade Classifier as a baseline. The evaluation involves 96 real-time trials across different lighting environments (bright, normal, and dim) and focuses on both detection accuracy and response speed. Through this comparative approach, the research provides empirical evidence on the trade-off between precision and computational efficiency in lightweight algorithms for human-motion detection.

Beyond its technical significance, this study also contributes to real-world applications, particularly in low-resource or developing environments, where deep-learning systems requiring high-end GPUs may not be feasible. The findings support the design of affordable assistive technologies for individuals with limited mobility, emphasizing practical accessibility without compromising performance.

The novelty of this research lies in presenting a complete multi-metric comparison between two non-deep-learning methods under real-time head-movement scenarios, focusing on accuracy, speed, and adaptability as critical factors for smart wheelchair navigation. These contributions are expected to strengthen the scientific understanding of classical computer-vision techniques and provide practical guidance for low-cost, real-time assistive control systems.

2. METHODS

This research employs an experimental quantitative approach by developing a prototype of a camera-based head-movement detection system. The main focus of this study is to compare two lightweight non-deep learning methods, namely Lucas-Kanade Optical Flow as the primary method and the Haar Cascade Classifier as the baseline. The scope of this research is limited to the software-level implementation of the input module without including physical integration with a smart wheelchair system.

The implementation was carried out on an ASUS Vivobook 14 ProX OLED N7400 equipped with an Intel Core i7-11370H (3.3 GHz) processor, NVIDIA GeForce RTX 3050 GPU, 16 GB RAM, and an internal 720p (30 fps) webcam. The software environment consisted of Python 3.10, OpenCV 4.9.0, NumPy 1.26, and Tkinter for the graphical user interface, developed within Visual Studio Code (VS Code) as the integrated development environment (IDE).

The built-in 720p (30 fps) webcam was selected as the image acquisition device to maintain a balance between processing speed and visual clarity. Higher-resolution cameras such as 1080p or 4K increase computational demands and delay frame processing, which can reduce real-time responsiveness. Conversely, resolutions below 720p may cause pixel loss and motion blur, affecting the precision of Optical Flow tracking. The 720p configuration thus provides optimal performance for real-time motion detection on consumer-grade hardware, aligning with the study's goal of developing a lightweight and affordable assistive system. Additionally, 720p webcams are widely available and cost-effective, making them a practical standard for low-cost assistive prototypes. This choice ensures that the system design remains replicable and scalable for future real-world implementations. The performance analysis was conducted descriptively using multiple evaluation metrics, including accuracy and decision time. These metrics were used to assess and compare the system's ability to detect head movements in real time under various lighting conditions.

2.1. Research Flow

The overall research flow of this study is illustrated in Figure 1, outlining the major stages conducted from the identification of the research problem to the conclusion. This structure ensures that each stage of the research aligns with the study objectives—namely, comparing the performance of the Lucas–Kanade Optical Flow and Haar Cascade Classifier for head-movement detection in smart wheelchair control. The research process consists of the following steps:

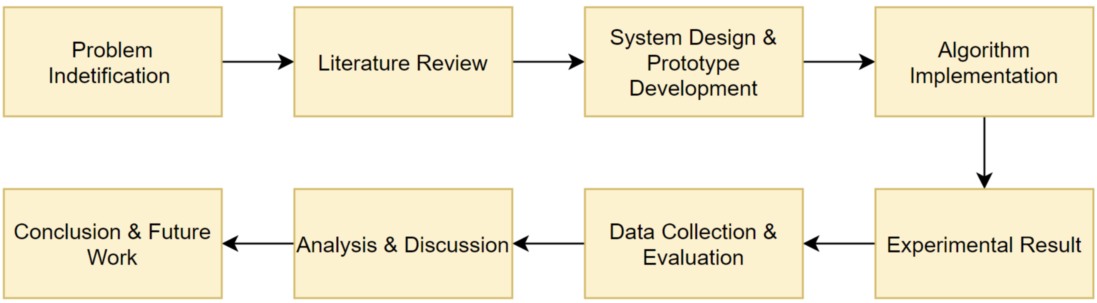


Figure 1. Research Flow

1) **Problem Identification:** The study began by identifying the main problem—developing an accurate yet lightweight vision-based input system for smart

wheelchairs. Existing approaches often rely on costly sensors or complex deep-learning models, creating a need for a simpler alternative based on classical computer-vision methods.

2) **Literature Review:** A review of prior works was conducted to understand the strengths and weaknesses of Optical Flow, Haar Cascade, and other recent models such as YOLOv8 and MobileNet. This stage helped define the research gap and justify the need for a comparative evaluation of the two lightweight methods under various lighting conditions.
3) **System Design and Prototype Development:** The system architecture was designed to include image acquisition using a 720p webcam, preprocessing, motion detection modules (Optical Flow and Haar Cascade), and a Tkinter-based GUI. The design aimed to ensure real-time operation on standard laptop hardware.
4) **Algorithm Implementation:** Both methods were implemented using Python 3.10 and OpenCV 4.9.0 with identical testing parameters to ensure fairness in comparison. The Optical Flow method tracks pixel motion between consecutive frames, while the Haar Cascade method detects facial positions using pre-trained features.
5) **Experimental Result:** Experiments were performed using a single participant who executed four head-movement directions (left, right, up, and down) under three lighting conditions (bright, normal, dim). Each condition consisted of 16 trials per method, resulting in 96 total trials. Data such as decision time, FPS, and prediction accuracy were automatically logged.
6) **Data Collection and Evaluation:** The recorded data were processed to compute accuracy and average decision time for each method under different illumination levels. These metrics served to evaluate robustness and efficiency in real-time performance.
7) **Analysis and Discussion:** Comparative results were analyzed to interpret why Optical Flow performed more consistently in dim environments, while Haar Cascade suffered from illumination sensitivity. This stage also discussed system limitations, including the single-participant setup.
8) **Conclusion and Future Work:** The research was concluded by summarizing key findings and recommending Optical Flow as a more adaptive method for low-resource smart-wheelchair systems. Future work was proposed to expand testing

to multiple users, integrate hardware-level control, and explore hybrid deep-learning solutions.

2.2. System Workflow

Research methods may include the theories which are used in the literature review which are obtained in the literature and should be accompanied by reference. Inform briefly about the research methods which are used and explain how its stages. The proposed system consists of several main components, namely a camera as the input device, an image processing module utilizing the Optical Flow method, a motion direction classification process, and an output interface that displays the detected head-movement direction. The overall workflow of the head-movement detection system is illustrated in Figure 2, which presents the main stages from user motion capture to the final detection output.

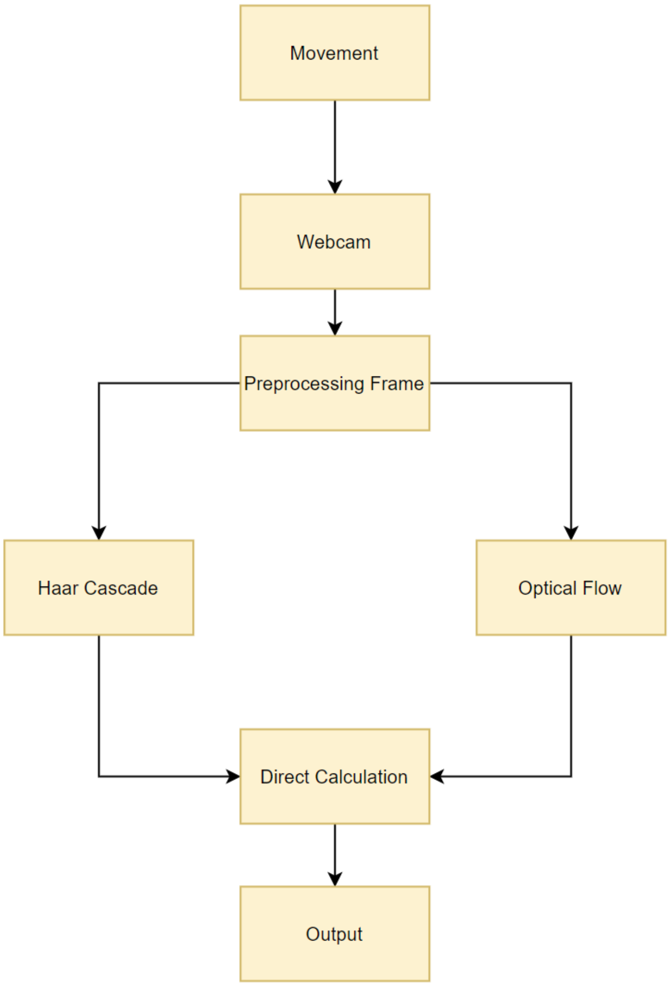


Figure 2. System workflow of the real-time head-movement detection prototype.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

The system begins with the user's head movement (left, right, up, or down), which serves as the primary input signal. This movement is captured in real time by the laptop's built-in webcam, which continuously records video frames at 30 frames per second (FPS). The captured frames are then processed through two different detection methods: Haar Cascade Classifier and Lucas-Kanade Optical Flow. The Haar Cascade method is responsible for detecting the position of the user's face within each frame, while the Optical Flow method calculates pixel displacement between consecutive frames to estimate the direction of motion. Next, a direct calculation process determines the direction of the user's head movement by comparing the displacement vectors or positional changes with predefined threshold values. This process classifies the movement into one of four categories: *Moving Left (Turn Left Side)*, *Moving Right (Turn Right Side)*, *Moving Up (Go Straight)*, or *Moving Down (Go Down)*. Finally, the output module displays the detected head-movement direction on the graphical user interface (GUI) in real time, both as text and as an overlay on the video feed. In addition, all detection results are automatically logged in a CSV file for subsequent evaluation of system accuracy and decision time.

2.3. Optical Flow Method

Optical Flow is used to estimate motion by tracking pixel intensity changes between consecutive frames in a video sequence. In this study, the Lucas-Kanade variant of Optical Flow is applied, which assumes that the motion of pixels is constant within a small local neighborhood (window). The basic Optical Flow formula as shown in Equation 1.

$$I_x u + I_y v + I_t = 0 \tag{1}$$

where I_x and I_y are the spatial intensity gradients along the horizontal and vertical directions, respectively; I_t is the temporal intensity gradient representing the change in brightness over time; and u and v are the velocity components of the Optical Flow vector in the horizontal and vertical directions.

2.4. Haar Cascade Method

The Haar Cascade is a feature-based detection algorithm popularized by Viola and Jones, which utilizes Haar-like features and an AdaBoost classifier for rapid object detection. In this study, the Haar Cascade method is employed to detect the user's face in each video

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

frame captured by the webcam. Once the face is successfully detected, the centroid point of the detected region is computed, and the displacement between consecutive frames ($\Delta x, \Delta y$) is analyzed to determine the direction of head movement. Threshold values for Δx and Δy are defined to classify the head-movement direction into four categories: left, right, up, and down. These parameter values were selected empirically to ensure stable detection at an average distance of approximately ±50 cm between the user and the camera, which aligns with the experimental setup and common practices reported in related literature [5], [11].

2.5. Data Collection and Analysis

The experimental testing was conducted in real time using the laptop's built-in 720p camera. Four head-movement directions were tested left, right, up, and down each performed four times under three different lighting conditions: normal, bright, and dim. This resulted in 48 trials per method and a total of 96 trials for both the Optical Flow and Haar Cascade systems combined.

Lighting conditions were arranged to represent typical indoor variations that could affect camera-based detection. Normal lighting used the room's overhead lamp as the main illumination source, providing standard ambient light like everyday indoor environments. Bright lighting used the same overhead lamp with additional light from a smartphone flashlight directed toward the participant's face to increase brightness. Dim lighting relied only on the laptop screen's glow, with the overhead lamp and other lights turned off, creating a low-illumination condition. These settings were chosen to simulate realistic scenarios in which smart wheelchair users may operate under different indoor lighting conditions.

All experiments were performed using a single participant positioned at an average distance of ±50 cm from the camera. The use of one participant ensured consistent head-movement patterns, posture, and lighting alignment across all trials, allowing a controlled comparison between the two algorithms. However, this approach also limits the generalizability of the results, as it does not account for variations in facial structure, skin tone, or motion behavior among different individuals. The experimental design was therefore considered an initial proof-of-concept stage, focusing primarily on system implementation and comparative evaluation between the two methods. The limitations

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

of this study, including the use of a single participant and fixed environmental conditions, are further discussed in the Discussion section. Future development will involve multi-user testing (considering variations in age, gender, and facial accessories) as well as different camera distances and illumination settings to strengthen generalizability. System performance was evaluated using two complementary approaches.

1) Per-trial accuracy: A movement was considered correctly detected if most frames in that trial matched the actual head-movement direction.
2) Decision time: The time required for the system to transition from the initial (center) position to the new direction.

Additionally, the system recorded the frames per second (FPS) as an indicator of real-time processing efficiency. Overall performance was analyzed descriptively using accuracy, confusion matrix, decision time, and FPS. Given the limited sample size, inferential statistical tests such as t-test or ANOVA were not applied in this phase. These analyses are planned for future research with larger datasets to enhance the statistical validity and generalization of the findings.

3. RESULTS AND DISCUSSION

3.1 System Implementation

The head-movement detection system was implemented using the Python programming language, with the OpenCV library for video image processing and Tkinter for the Graphical User Interface (GUI). The system architecture consists of three main components, namely image acquisition, motion detection processing, and user interface display.

1) Image Acquisition: The laptop's built-in camera captures real-time video input. Each frame is converted into grayscale format to simplify computation and reduce noise during processing.
2) Motion Detection Process: The system independently applies two methods for comparison: the Lucas–Kanade Optical Flow and the Haar Cascade Classifier. Both methods analyze frame-by-frame motion to detect and classify head movements in four directions (left, right, up, and down).

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

3) Graphical User Interface (GUI): The GUI was developed using Tkinter, designed to be lightweight and easy to operate. The interface displays the detected head-movement direction in real time, along with live video visualization. The implementation result of the GUI is shown in Figure 3.

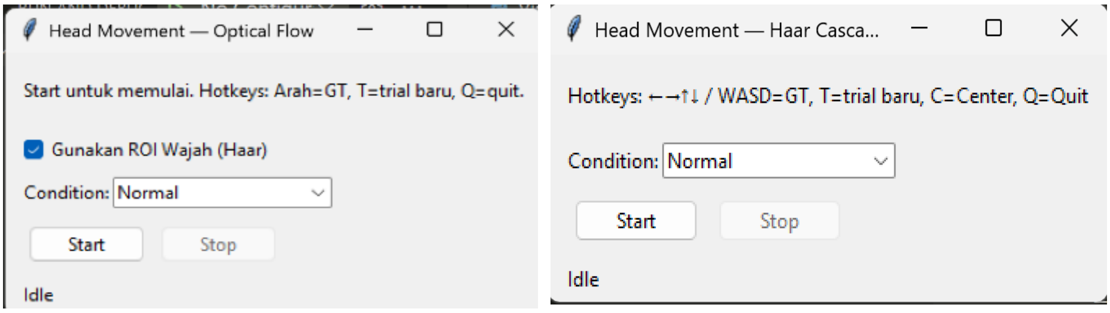
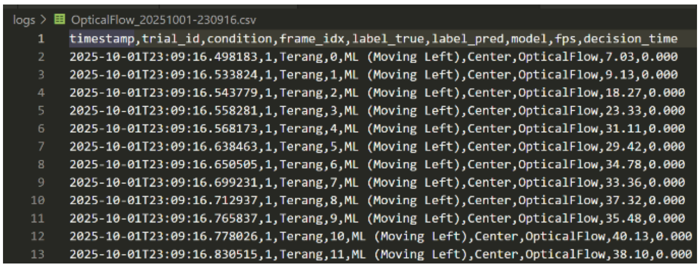


Figure 3. GUI of the Head-Movement Detection System

In addition to visual output on the GUI, the system automatically records detection logs in CSV format. The log file contains essential information such as timestamp, ground truth, predicted direction, Frames Per Second (FPS), and decision time. A snippet of the recorded CSV log is presented in Figure 4.


```
logs > OpticalFlow_20251001-230916.csv
timestamp,trial_id,condition,frame_idx,label_true,label_pred,model,fps,decision_time
2025-10-01T23:09:16.498183,1,Terang,0,ML (Moving Left),Center,OpticalFlow,7.03,0.000
2025-10-01T23:09:16.533824,1,Terang,1,ML (Moving Left),Center,OpticalFlow,9.13,0.000
2025-10-01T23:09:16.543779,1,Terang,2,ML (Moving Left),Center,OpticalFlow,18.27,0.000
2025-10-01T23:09:16.558281,1,Terang,3,ML (Moving Left),Center,OpticalFlow,23.33,0.000
2025-10-01T23:09:16.568173,1,Terang,4,ML (Moving Left),Center,OpticalFlow,31.11,0.000
2025-10-01T23:09:16.638463,1,Terang,5,ML (Moving Left),Center,OpticalFlow,29.42,0.000
2025-10-01T23:09:16.650505,1,Terang,6,ML (Moving Left),Center,OpticalFlow,34.78,0.000
2025-10-01T23:09:16.699231,1,Terang,7,ML (Moving Left),Center,OpticalFlow,33.36,0.000
2025-10-01T23:09:16.712937,1,Terang,8,ML (Moving Left),Center,OpticalFlow,37.32,0.000
2025-10-01T23:09:16.765837,1,Terang,9,ML (Moving Left),Center,OpticalFlow,35.48,0.000
2025-10-01T23:09:16.778026,1,Terang,10,ML (Moving Left),Center,OpticalFlow,40.13,0.000
2025-10-01T23:09:16.830515,1,Terang,11,ML (Moving Left),Center,OpticalFlow,38.10,0.000
```
Figure 4. CSV log file generated during real-time head-movement detection

3.2 Performance Under Bright Lighting Conditions

The first set of experiments was conducted under bright lighting conditions, where light intensity was high and the user's face was clearly visible to the camera. This setting represents an ideal environment for visual detection systems, as pixel contrast is high and image noise is minimal.

Based on the results shown in Table 1 and 2, the Lucas-Kanade Optical Flow method demonstrated the best performance compared to the Haar Cascade Classifier. Optical Flow was able to detect head-movement directions with both high speed and accuracy.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

The sharp difference in pixel intensity between frames made it easier for the system to calculate motion vectors, allowing each direction especially left and right to be identified precisely. The average accuracy reached 87.5%, with the fastest decision time of 0.0209 seconds when detecting downward movement. These results indicate that Optical Flow performs very efficiently under optimal lighting conditions.

In contrast, the Haar Cascade method showed fewer stable results, despite the face being clearly visible. Strong light reflections on the skin, nose, or eyeglass areas caused inconsistencies in centroid detection across frames. The average accuracy reached 50%, with the fastest decision times of 0.0307 seconds when detecting rightward. This suggests that Haar Cascade is highly sensitive to bright light reflections and extreme contrast on facial features. Overall, under bright lighting conditions, Optical Flow outperformed Haar Cascade in both accuracy and detection speed. Haar Cascade exhibited instability due to excessive light reflections, whereas Optical Flow proved more suitable for environments with strong or natural illumination.

Table 1 Results for each head-movement direction under bright lighting using the Optical Flow method

Movement	Trial 1	Trial 2	Trial 3	Trial 4	Accuracy
Left	Left	Left	Left	Left	100%
Right	Center	Right	Right	Right	75%
Down	Down	Down	Down	Down	100%
Up	Up	Up	Up	Center	75%
Average Accuracy					87.5%

Table 2 Results for each head-movement direction under bright lighting using the Haar Cascade method

Movement	Trial 1	Trial 2	Trial 3	Trial 4	Accuracy
Left	Center	Left	Down	Left	50%
Right	Center	Left	Right	Right	50%
Down	Center	Down	Center	Down	50%
Up	Up	Up	Down	Center	50%
Average Accuracy					**50%**

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

As illustrated in Figures 5 and 6, both Optical Flow and Haar Cascade exhibited distinct per-direction performance under bright lighting. Optical Flow achieved balanced precision and recall across all four head-movement directions, while Haar Cascade showed reduced recall for vertical (up–down) motions, likely due to reflection sensitivity and feature misdetection. These per-class metrics further confirm the superior consistency of Optical Flow when illumination is high.

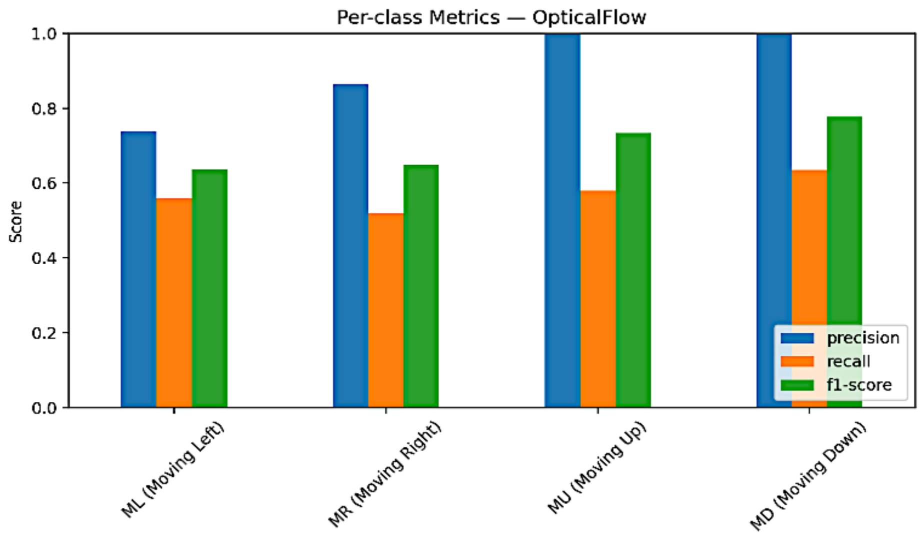


Figure 5. Per-class precision, recall, and F1-score of the Optical Flow method under bright lighting conditions.

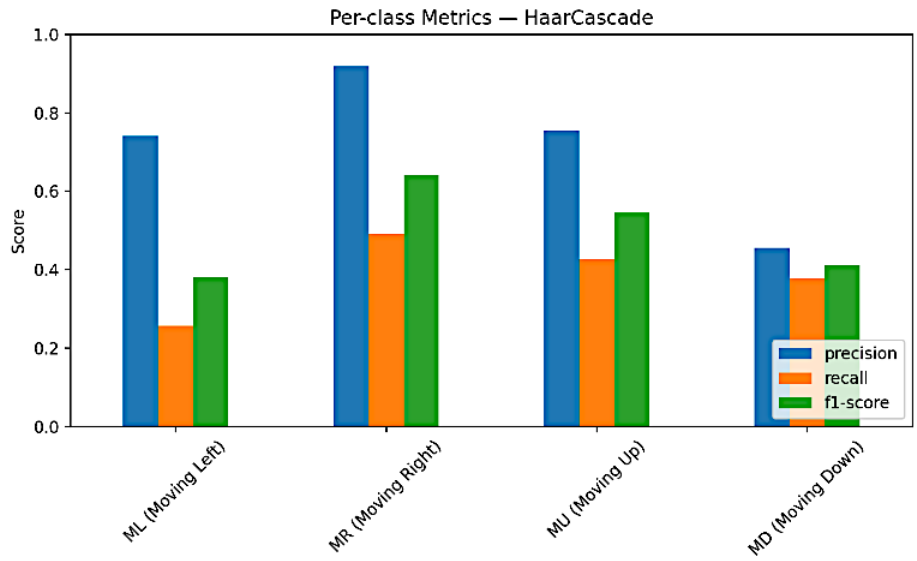


Figure 6. Per-class precision, recall, and F1-score of the Haar Cascade method under bright lighting conditions.

3.3 Performance under Normal Lighting Conditions

The second test was conducted under normal lighting, which corresponds to standard indoor illumination without additional external lighting. This condition represents typical real-world usage. Based on the results in Table 3 and 4, both methods performed adequately; however, Optical Flow consistently delivered superior performance. Under this condition, Optical Flow maintained stable detection with an average accuracy of 87.5%. The system accurately recognized horizontal movements (left and right), while vertical movements (up and down) showed slightly lower precision due to smaller contrast differences. The fastest decision while detecting rightward movement was 0.0173 seconds, indicating that Optical Flow remained efficient and responsive even when illumination decreased from ideal conditions.

Meanwhile, the Haar Cascade Classifier experienced a more significant performance drop. The reduced light intensity made key facial features such as the eyes and mouth less distinguishable for the pre-trained model. The average accuracy decreased to around 68.75%, and the fastest decision time was 0.0142 seconds for rightward movement. This suggests that Haar Cascade relies heavily on sufficient lighting to detect facial features accurately. Overall, in normal lighting, Optical Flow proved more adaptable to moderate lighting variations and continued to deliver fast and consistent results. Conversely, Haar Cascade showed reduced accuracy and stability, particularly in vertical movements, demonstrating that pixel-based motion detection methods are more robust to illumination changes than feature-based ones.

Table 3 Results for each head-movement direction under normal lighting using the Optical Flow method

Movement	Trial 1	Trial 2	Trial 3	Trial 4	Accuracy
Left	Left	Center	Left	Left	75%
Right	Right	Right	Right	Right	100%
Down	Down	Down	Down	Center	75%
Up	Up	Up	Up	Up	100%
Average Accuracy					87.5%

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

Table 4 Results for each head-movement direction under normal lighting using the Haar Cascade method

Movement	Trial 1	Trial 2	Trial 3	Trial 4	Accuracy
Left	Right	Center	Center	Left	25%
Right	Right	Right	Right	Right	100%
Down	Down	Center	Down	Down	75%
Up	Center	Up	Up	Up	75%
Average Accuracy					68.75%

As illustrated in Figure 7 and 8, the Lucas–Kanade Optical Flow method achieved more balanced precision and recall scores across all four head-movement directions compared to the Haar Cascade Classifier. Optical Flow remained highly consistent under normal lighting, while Haar Cascade showed slightly lower recall on vertical motions due to limited illumination contrast.

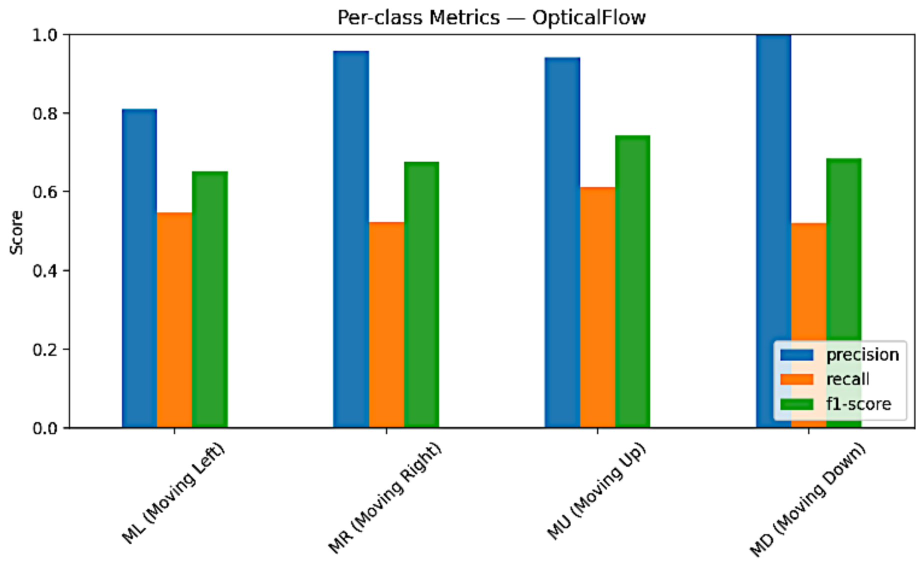


Figure 7. Per-class precision, recall, and F1-score of the Optical Flow method under normal lighting conditions.

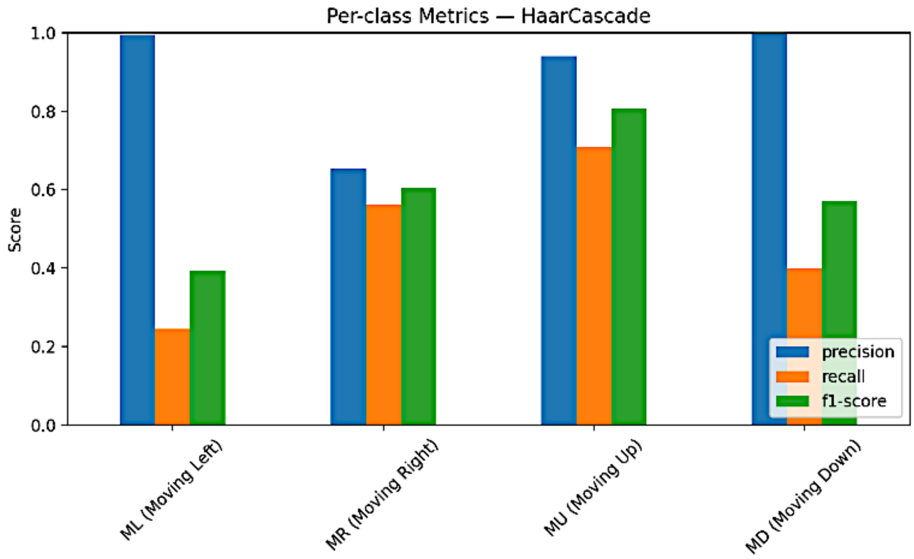


Figure 8. Per-class precision, recall, and F1-score of the Haar Cascade method under normal lighting conditions.

3.4 Performance under Dim Lighting Conditions

The final test was conducted under dim lighting, where light intensity was very low, and only minimal illumination surrounded the user. This scenario poses a challenge for computer vision systems because noise increases and facial features become less visible. As shown in Table 5 and 6, the Optical Flow method once again outperformed the Haar Cascade Classifier. Under low illumination, Optical Flow could still detect head-movement directions reliably, particularly for horizontal directions (left and right). This robustness is attributed to its reliance on relative pixel displacement rather than static facial features, allowing motion vectors to be computed even in darker frames. The results showed an average accuracy of 93.8%, with fastest decision times of 0.026 seconds when detecting upward movement. Although slightly slower than in bright conditions, the method remained stable and efficient.

In contrast, the Haar Cascade suffered a substantial performance degradation. Low light made facial features such as the eyes, nose, and mouth difficult to detect, leading to inconsistent face localization across frames. As a result, the system often failed to identify head movement, especially for vertical directions. The average accuracy dropped to 62.5%, with fastest decision times reaching 0.0381 seconds. These variations indicate that Haar Cascade is highly sensitive to lighting changes and tends to become unstable under poor illumination. Overall, the results under dim lighting demonstrate that Optical

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

Flow is more resilient to variations in light intensity and maintains consistent head-movement detection performance. In contrast, Haar Cascade strongly depends on adequate illumination to detect facial features effectively. Therefore, it can be concluded that Optical Flow is more adaptive and suitable for real-time head-movement detection systems in smart wheelchairs operating under diverse lighting conditions.

Table 5 Results for each head-movement direction under dim lighting using the Optical Flow method

Movement	Trial 1	Trial 2	Trial 3	Trial 4	Accuracy
Left	Left	Left	Left	Left	100%
Right	Right	Right	Right	Right	100%
Down	Down	Down	Center	Down	75%
Up	Up	Up	Up	Up	100%
Average Accuracy					93.75%

Table 6 Results for each head-movement direction under dim lighting using the Haar Cascade method

Movement	Trial 1	Trial 2	Trial 3	Trial 4	Accuracy
Left	Left	Left	Left	Left	100%
Right	Right	Center	Center	Center	25%
Down	Down	Down	Center	Center	50%
Up	Center	Up	Up	Up	75%
Average Accuracy					62.5%

As shown in Figures 9 and 10, the Lucas–Kanade Optical Flow method maintained higher precision, recall, and F1-scores across all four head-movement directions compared to the Haar Cascade Classifier. Optical Flow exhibited strong adaptability in dim conditions, where motion-based pixel tracking allowed stable detection despite the limited brightness. In contrast, Haar Cascade showed a significant decline in recall for upward and downward movements, caused by reduced facial feature visibility and insufficient contrast.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

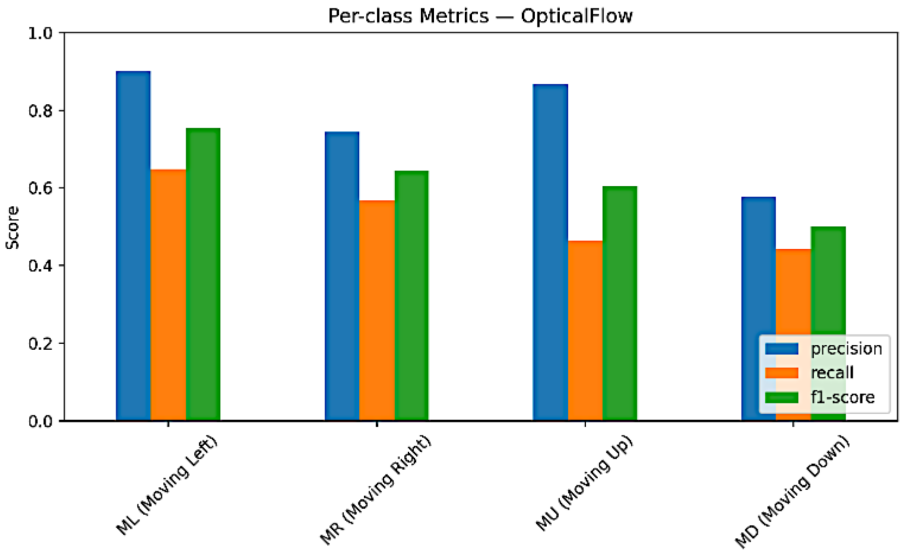


Figure 9. Per-class precision, recall, and F1-score of the Optical Flow method under dim lighting conditions.

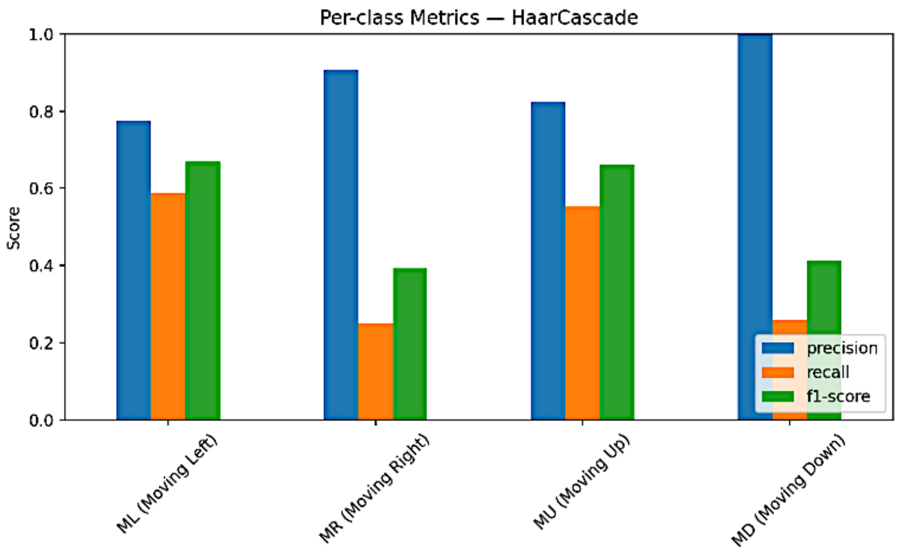


Figure 10. Per-class precision, recall, and F1-score of the Haar Cascade method under dim lighting conditions.

3.5 Performance Based on Decision Time

Table 7 presents the average decision time of the system for each head-movement direction across the two tested methods Optical Flow and Haar Cascade under three different lighting conditions: normal, dim, and bright. Decision time represents the duration required by the system to recognize a head movement stably, measured from the start of motion until the final predicted direction is locked.

ISI Journal of Information Systems and Informatics

Published By Asosiasi Doktor Sistem Informasi Indonesia

Based on the data in Table 7, the Optical Flow method generally demonstrates faster and more consistent decision times than the Haar Cascade. Under normal lighting, the longest decision time occurred for leftward movement 1.213 s, while the shortest was for rightward movement 0.890 s. In dim conditions, decision times slightly increased but remained stable, ranging between 0.906–1.313 seconds. The bright condition produced the fastest detection time of 0.338 seconds for leftward movement, indicating that optimal illumination allows Optical Flow to interpret motion vectors more quickly and precisely.

Table 7. Decision time (in seconds) for each head-movement direction under different lighting conditions

No	Direction	Optical Flow (s)			Haar Cascade(s)		
		Normal	Dim	Bright	Normal	Dim	Bright
1	Left	1.213	1.179	0.338	0.795	1.181	1.205
2	Up	1.135	1.059	1.41	0.602	0.8	0.616
3	Right	0.89	1.313	0.399	0.829	1.583	0.795
4	Down	1.085	0.906	0.993	1.25	0.894	1.93

In contrast, the Haar Cascade Classifier exhibited longer and more variable decision times across lighting conditions. Under normal lighting, the shortest response occurred for rightward movement 0.829 s, while the longest was for downward movement 1.25 s. Under dim lighting, detection time increased significantly to 1.583 seconds for rightward movement, suggesting that Haar Cascade's response slows when facial features become less detectable due to low illumination. Under bright conditions, the results were inconsistent, with the fastest detection at 0.616 seconds (upward) but also the slowest at 1.93 seconds (downward) reflecting instability caused by light reflections and contrast variations. Overall, these findings confirm that Optical Flow outperforms Haar Cascade in terms of both detection speed and consistency across all lighting conditions. Because Optical Flow relies on direct pixel vector changes between consecutive frames, it is inherently more robust to illumination differences. Conversely, Haar Cascade depends heavily on the successful detection of facial features, making its performance more

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

susceptible to lighting variation and image contrast. Therefore, it can be concluded that Optical Flow is more efficient and adaptive to changes in lighting conditions, making it more suitable for real-time head-movement detection in computer vision–based smart wheelchair control systems.

3.6 Discussion

While both the Lucas–Kanade Optical Flow and Haar Cascade Classifier methods demonstrated reliable performance in controlled experimental settings, several limitations must be considered when applying these approaches in real-world assistive systems. First, the experiment involved a single participant with consistent facial features, distance, and camera orientation. This limits generalizability, as detection performance may vary with users of different ages, face shapes, and skin tones. Future implementations should include a more diverse group of participants to capture variability in human appearance and motion patterns. Second, facial accessories such as eyeglasses, masks, or headscarves can significantly affect detection reliability. Haar Cascade, which depends heavily on pre-trained facial features, tends to fail when such accessories obscure the eyes or nose. In contrast, Optical Flow, which tracks relative pixel movement rather than static features, may still operate effectively, although excessive occlusion or motion blur can degrade performance.

Third, camera positioning and angle play a crucial role in system robustness. Both methods were tested using a fixed frontal camera angle, whereas real-world wheelchair use often involves slight head rotations, tilts, or dynamic backgrounds. Optical Flow is moderately tolerant to small camera shifts, but Haar Cascade's feature matching rapidly deteriorates with non-frontal faces. Incorporating adaptive region tracking or multi-angle calibration could mitigate this limitation. Finally, the current system functions purely at the software simulation level, without integration into an actual wheelchair platform. In practical use, additional factors such as latency, vibration, and lighting inconsistency could further influence performance. Real-world testing with embedded systems and external sensors (e.g., infrared or depth cameras) is essential to validate overall usability and safety.

Despite these limitations, the findings highlight that classical computer-vision techniques still provide a feasible foundation for low-cost, real-time assistive technologies.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

Addressing these challenges through user diversity, environmental variation, and hardware integration will be vital for developing reliable head-controlled wheelchair systems.

4. CONCLUSION

This study compared the Lucas–Kanade Optical Flow and Haar Cascade Classifier methods for real-time head-movement detection in a smart wheelchair control context. The experimental results under three lighting conditions—bright, normal, and dim—showed that Optical Flow consistently outperformed Haar Cascade in both accuracy and decision speed. Optical Flow achieved up to 93.8% accuracy in dim environments and maintained stable detection across all lighting levels, demonstrating strong adaptability to illumination changes. In contrast, Haar Cascade exhibited lower accuracy (50–68.75%) and greater sensitivity to lighting variations due to its dependence on contrast-based facial features.

Based on these findings, Optical Flow is recommended for lightweight, real-time assistive systems, especially in environments with variable or low lighting. Its robustness and computational efficiency make it suitable for practical smart wheelchair applications where high-end hardware is not available. Haar Cascade may still be useful in controlled lighting or as a supplementary feature detector, but it is less stable for direct motion tracking. This research has several limitations. The prototype was evaluated using a single participant, which limits the generalizability of the findings. Moreover, the study was conducted entirely in a software-based environment without integration into a physical wheelchair system. These limitations restrict the scope of the results to proof-of-concept validation.

Future research should involve multi-user testing to evaluate performance across diverse facial features, head shapes, and accessories such as glasses or masks. The detection module should also be integrated with a real wheelchair platform to validate its control responsiveness and safety in real environments. Additionally, exploring deep learning or hybrid motion-detection models could further enhance accuracy and robustness under challenging conditions. Overall, this comparative study demonstrates that classical computer-vision methods, particularly Optical Flow, remain viable for

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

affordable and real-time assistive technologies, paving the way for further innovations in smart wheelchair design.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to the supervising lecturers for their continuous guidance and valuable feedback throughout this research. Appreciation is also extended to fellow students and colleagues for their collaboration and constructive discussions during the development of the system. Finally, the authors wish to thank their families and parents for their unwavering support, encouragement, and motivation that made the completion of this study possible.

REFERENCES

[1] M. A. Gunawan, H. S. Purba, N. A. B. Saputra, N. Wiranda, and M. H. Adini, "Perancangan Pendeteksi Wajah dengan Metode Haar Cascade dan Local Binary Pattern Berbasis OpenCV," *Comput. Educ. Technol. J.*, vol. 4, no. 1, p. 7, 2024, doi: 10.20527/cetj.v4i1.12332.

[2] N. Ma Muriyah, J. H. Sim, and A. Yulianto, "Evaluating YOLOv5 and YOLOv8: Advancements in Human Detection," *J. Inf. Syst. Informatics*, vol. 6, no. 4, pp. 2999–3015, 2024, doi: 10.51519/journalisi.v6i4.944.

[3] A. Yulianto, W. Andreas, and S. Sabariman, "Perancangan Prototype Brankas Menggunakan Sistem Pengenalan Wajah Dengan Metode Convolutional Neural Network (CNN)," *Telcomatics*, vol. 8, no. 1, p. 10, 2023, doi: 10.37253/telcomatics.v8i1.7852.

[4] H. Haeruddin, H. Herman, and P. P. Hendri, "Pengembangan Aplikasi Emoticon Recognition dan Facial Recognition menggunakan Algoritma Local Binary Pattern Histogram (LBPH) dan Convolutional Neural Network (CNN)," *J. Teknol. Terpadu*, vol. 9, no. 1, pp. 49–55, 2023, doi: 10.54914/jtt.v9i1.613.

[5] M. Salehi, N. Javadpour, B. Beisner, M. Sanaei, and S. B. Gilbert, "Cybersickness Detection Through Head Movement Patterns: A Promising Approach," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 14735 LNAI, pp. 239–254, 2024, doi: 10.1007/978-3-031-60611-3_18.

ISI Journal of Information Systems and Informatics

Published By Asosiasi Doktor Sistem Informasi Indonesia

[6] C. H. Choi, J. Kim, J. Hyun, Y. Kim, and B. Moon, "Face Detection Using Haar Cascade Classifiers Based on Vertical Component Calibration," *Human-centric Comput. Inf. Sci.*, vol. 12, 2022, doi: 10.22967/HCIS.2022.12.011.

[7] I. Print, F. L. Ramadini, and E. Haryatmi, "Penggunaan Metode Haar Cascade Classifier dan LBPH Untuk Pengenalan Wajah Secara Realtime," *InfoTekJar*, vol. 6, no. 2, 2022.

[8] V. Pradeep, "Fuzzy based Computing for Disabled using 3D Head Movement," *Inform.*, vol. 49, no. 15, pp. 1–14, 2025, doi: 10.31449/inf.v49i15.5399.

[9] T. K. T. Zizi, S. Ramli, M. Wook, and M. A. M. Shukran, "Optical Flow-Based Algorithm Analysis to Detect Human Emotion from Eye Movement-Image Data," *J. Image Graph. Kingdom)*, vol. 11, no. 1, pp. 53–60, 2023, doi: 10.18178/joig.11.1.53-60.

[10] J. Xie, C. Yang, W. Xie, and A. Zisserman, "Moving Object Segmentation: All You Need is SAM (and Flow)," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)* , vol. 15481 LNCS, no. i, pp. 291–308, 2025, doi: 10.1007/978-981-96-0972-7_17.

[11] Y. Fang, W. Liu, and S. Zhang, "Wi-Senser: Contactless Head Movement Detection during Sleep Utilizing WiFi Signals," *Appl. Sci.*, vol. 13, no. 13, 2023, doi: 10.3390/app13137572.

[12] E. S. Wahyuni, Z. Iqbal, and D. Farahiya, "Detection of Human Movement Direction Using Optical Flow Analisys on Multiple Camera Angles," *J. Nas. Tek. ELEKTRO*, vol. 10, no. 2, Jul. 2021, doi: 10.25077/jnte.v10n2.924.2021.

[13] H. Hameed *et al.*, "Wi-Fi and Radar Fusion for Head Movement Sensing Through Walls Leveraging Deep Learning," pp. 1–14.

[14] O. A. Naser, S. Mumtazah, K. Samsudin, M. Hanafi, S. M. B. Shafie, and N. Z. Zamri, "Comparative Analysis of MTCNN and Haar Cascades for Face Detection in Images with Variation in Yaw Poses and Facial Occlusions," *J. Commun. Softw. Syst.*, vol. 21, no. 1, pp. 109–119, 2025, doi: 10.24138/jcomss-2024-0084.

[15] H. Guo and Y. Wang, "Enhanced Optical Flow Estimation via Multiscale Kernel Selection and Super-Resolution Integration," *Res. Sq.*, pp. 0–23, 2025.

[16] M. Gehrig, M. Muglikar, and D. Scaramuzza, "Dense Continuous-Time Optical Flow From Event Cameras," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 46, no. 7, pp. 4736–4746, 2024, doi: 10.1109/TPAMI.2024.3361671.

[17] C. Murui, Z. Zheng, T. Wenkai, and L. Junlin, "Research on Largemouth Bass Target Recognition and Tracking Utilizing the Optical Flow Approach," *Adv. Comput. Signals Syst.*, vol. 8, no. 1, pp. 142–152, 2024, doi: 10.23977/acss.2024.080117.

ISI Journal of Information Systems and Informatics
Published By Asosiasi Doktor Sistem Informasi Indonesia

[18] Jamal Rosid, "Face Recognition Dengan Metode Haar Cascade dan Facenet," *Indones. J. Data Sci.*, vol. 3, no. 1, pp. 30–34, 2022, doi: 10.56705/ijodas.v3i1.38.

[19] N. A. Mohd Ariffin, U. A. Gimba, and A. Musa, "Face Detection based on Haar Cascade and Convolution Neural Network (CNN)," *J. Adv. Res. Comput. Appl.*, vol. 38, no. 1, pp. 1–11, 2025, doi: 10.37934/arca.38.1.111.

[20] A. Z. Larasati and F. Utaminingrum, "Sistem Kendali Pengikut Terarah Smart Wheelchair pada Pencahayaan Beragam Menggunakan Gamma Correction dan YOLOv8n Termodifikasi," *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 9, no. 2, pp. 2–6, 2025.

[21] J. Zhong, T. Chen, and L. Yi, "Face expression recognition based on NGO-BILSTM model," *Front. Neurorobot.*, vol. 17, no. 2, pp. 212–218, 2023, doi: 10.3389/fnbot.2023.1155038.

[22] A. Riza Mufita and F. Utaminingrum, "Deteksi Arah Pergerakan Kepala untuk Navigasi pada Kursi Roda Pintar Menggunakan Kombinasi Metode Berbasis YOLOv8N," *J. Pengemb. Teknol. Inf. dan Ilmu Komput.*, vol. 9, no. 2, pp. 2548–964, 2025.

[23] U. Masud, N. Abdualaziz Almolhis, A. Alhazmi, J. Ramakrishnan, F. Ul Islam, and A. Razzaq Farooqi, "Smart Wheelchair Controlled Through a Vision-Based Autonomous System," *IEEE Access*, vol. 12, no. March, pp. 65099–65116, 2024, doi: 10.1109/ACCESS.2024.3395656.

[24] I. Komang Somawirata and F. Utaminingrum, "Smart wheelchair controlled by head gesture based on vision," *J. Phys. Conf. Ser.*, vol. 2497, no. 1, 2023, doi: 10.1088/1742-6596/2497/1/012011.

[25] W. Krisna Wijaya, I. Komang Somawirata, and R. Putra Muhammad Davi Labib, "Deteksi Objek Menggunakan YOLO V3 Untuk Keamanan Pada Pergerakan Kursi Roda Elektrik," *Nucl. J.*, vol. 1, no. 2, pp. 94–98, 2022, doi: 10.32492/nucleus.v1i2.49.