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Integration of Fingerprint Attendance Systems and Iot-Based Computer Vision for Employee Presence Monitoring

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Abstract

The fingerprint-based attendance system at the Makassar Public Health Laboratory (BLKM Makassar) has limitations because it only records administrative attendance and cannot verify the physical presence of employees in the workplace. This study aims to design and implement an integrated fingerprint attendance and Internet of Things (IoT)-based computer vision system to support automated employee presence monitoring. The system uses two ESP32-CAM units installed in the lobby area and connected to a Flask Python server and MariaDB database. Image processing employs Histogram of Oriented Gradients (HOG) for face localization, dlib 68 facial landmarks for face alignment, and ResNet-34 to generate 128-dimensional face embeddings. Face identification is performed using Euclidean Distance with a threshold of 0.45 and a Time Window Buffer mechanism during monitoring cycles at 10:00 and 14:00 WITA. The results show that image transmission through HTTP POST operates with HTTP 200 OK and a latency of approximately 80 ms. Under normal walking conditions, the system achieved a 100% detection success rate. From 150 dynamic tests, the multi-camera system achieved an overall detection success rate of 63.33%, while Camera 1 and Camera 2 achieved 60.67% and 40.00%, respectively. The system achieved a 74% success rate under fast walking conditions, which decreased to 16% during running due to motion blur and lighting conditions. The integration of fingerprint attendance and computer vision provides supporting information for identifying discrepancies between administrative attendance records and the visual presence of employees within the monitored camera-covered area.
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Keywords— *IoT, ESP32-CAM, Computer Vision, Face Recognition, ResNet-34, Euclidean Distance, Attendance.*

1. Introduction

The Internet of Things (IoT) enables cameras, networks, servers, and applications to be interconnected for automated data transmission and processing. Meanwhile, computer vision can be used to obtain visual presence information based on facial images captured by cameras. Integrating these technologies with fingerprint data enables administrative attendance records to be compared with visual monitoring results over a specific period. This architecture is consistent with the integration of connected objects, communication networks, and information services described in the IoT literature (Atzori et al., 2010). Fingerprint and facial recognition are

established biometric approaches for recognizing individuals from physiological characteristics (Jain et al., 2004).

Previous studies have shown that IoT technology has been used to improve the accessibility and management of biometric attendance data. (Uçar & Özdemir, 2022) developed a biometric attendance system based on fingerprint, Arduino, and ThingsBoard that enables attendance data to be centrally processed and accessed in real time through an IoT platform. Another approach integrates IoT with facial recognition, such as the study by Zainuddin et al., which developed a smart attendance system using facial recognition and Raspberry Pi to automatically record attendance and transmit data in real time.(Zainuddin et al., 2024)(Zainuddin et al., 2024)

The use of ESP32-CAM has also been implemented in facial recognition-based attendance systems. Natbais et al. developed an attendance system using ESP32-CAM and the FaceNet model, while Hamidah et al. implemented ESP32-CAM for an employee attendance system based on face recognition. These studies demonstrate that ESP32-CAM can be used as an image acquisition device for facial recognition systems; however, their implementation and testing primarily focused on attendance recording or recognition based on facial images.(Natbais et al., 2024)(Hamidah et al., 2024a) Gharib and Abusamra also reported an ESP32-CAM attendance system that transmits recognized student data via HTTP to a MySQL database for attendance reporting (Gharib & Abusamra, 2024).

Table 1. Comparison of Related Studies and the Proposed System

Study	Fingerprint	Face Recognition	ESP32/ESP32-CAM	IoT/Online Monitoring	Multi-Camera	Time Window Buffer
Ucar and ozemir (2022)	✓	–	Arduino	✓	–	–
Zainuddin et al. (2024)	–	✓	ESP32-S3/Raspberry Pi 5	✓	–	–
Natbais et al. (2024)	–	✓	ESP32-CAM	✓	–	–
Hamidah et al. (2024)	–	✓	ESP32-CAM	✓	–	–
Gharib & Abusamra (2024)	–	✓	ESP32-CAM	✓	–	–
Proposed system	✓	✓	✓	✓	✓	✓

The comparison indicates that previous studies have mainly focused on either fingerprint-based attendance management or facial recognition-based attendance systems. While these approaches demonstrate the feasibility of IoT-based biometric attendance monitoring, the reviewed studies do not combine administrative fingerprint records with visual presence information obtained from multiple cameras within a defined observation period. This creates a research gap in integrating administrative attendance records with visual monitoring to identify correspondence and discrepancies between the two information sources.

This study develops a system using two ESP32-CAM units as image acquisition nodes in the lobby area. Images are transmitted through a Wi-Fi network to a Flask Python-based server and processed using HOG, dlib 68 facial landmarks, face alignment, ResNet-34, 128-dimensional face embeddings, and Euclidean Distance (Belgibayev et al., 2025) . The system also employs a Time Window Buffer to provide tolerance for employee mobility, as employees are not necessarily present in the lobby at a single point in time.

The main contribution of this study is the integration of two information sources: fingerprint attendance as an indicator of administrative attendance and facial recognition as an indicator of

visual presence within the camera-covered area, supported by a two-camera redundancy mechanism and a Time Window Buffer. The system is not intended to determine employee presence throughout the entire office environment, but rather to provide an additional indicator within the monitored area.

2. Method

2.1 system design

This study employs a system development and experimental approach. The system is designed by integrating a fingerprint machine as the source of administrative attendance data and two ESP32-CAM units as image acquisition devices. The use of IoT in attendance systems enables attendance data to be transmitted and centrally managed through a network to support the monitoring process (Ahmad Raihan et al., n.d.-a) .

The ESP32-CAM captures employee facial images in the lobby area and then transmits the images through a Wi-Fi network to an Ubuntu-based virtual server using HTTP POST. The use of ESP32-CAM as an acquisition device in a face recognition-based attendance system has been implemented in previous research(Hamidah et al., 2024b) (Hamidah et al., 2024) On the server, the received images are processed using a computer vision pipeline consisting of face detection, facial landmarks, face alignment, face embedding extraction using ResNet-34, and face matching. The use of facial landmarks for face alignment has also been applied in facial image processing using dlib with 68 facial characteristic points (Jabberi et al., 2023) . The dlib library provides reusable machine learning components for research and application development (King, 2009).

The results of face matching, consisting of employee identity and detection time, are then stored in MariaDB. The approach of wirelessly transmitting facial recognition results to a database for attendance data management has also been implemented in an ESP32-CAM-based attendance system(Ghareeb & Abusamra, 2024a) . The data are subsequently integrated with fingerprint attendance data using a Time Window Buffer to obtain information on the correspondence between administrative attendance and visual presence in the monitored area. The integrated results are then displayed through a web dashboard as supporting information for attendance monitoring. A web-based interface for attendance monitoring has also been implemented in an IoT-based biometric attendance system (sitasi)The system architecture is shown in Figure 1.

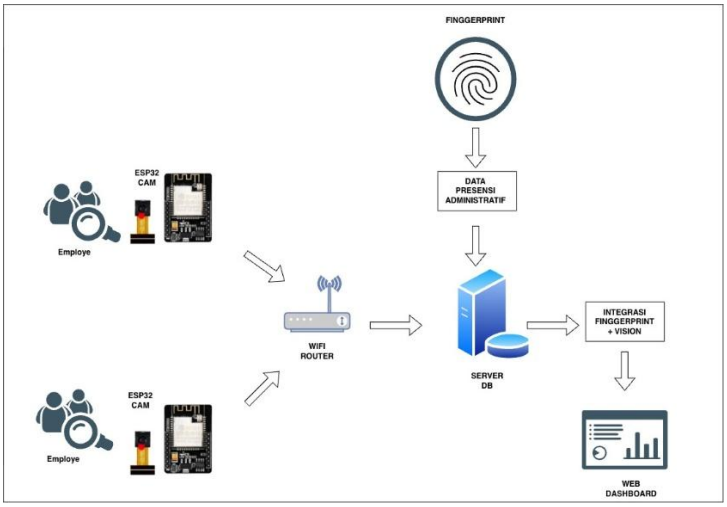


Figure 1. System Architecture

2.2 Hardware and configuration

The devices used in this study consist of image acquisition devices, network infrastructure, a processing server, an attendance device, and supporting software. Image acquisition uses two

ESP32-CAM units with OV2640 cameras connected through a 2.4 GHz Wi-Fi network. Data processing is performed on an Ubuntu-based virtual server using Python, Flask, OpenCV, and MariaDB. The device specifications and system configuration are presented in Table 1.

Table 2. Hardware and Spesification

Device / Componen	Spesification
Esp32-CAM	2 Unit OV2640
Image Resolution	640 x 480 Pixel
Network	Wifi 2.4 Ghz
Server	Virtual, Ubuntu, 2-core CPU, 4 GB RAM, 100 GB storage
Attandance Device	Fingerprint
Programming	Python
Framework	Flask
Image processing	OpenCV/face recognition, HOG, dlib, ResNet-34
Database	MariaDB
Interface	Web dashboard

2.3 Image Acquisition and Processing

The ESP32-CAM is used as an acquisition node to capture facial images at a resolution of 640 × 480 pixels. The images are then transmitted via HTTP POST to the server for processing using Histogram of Oriented Gradients (HOG) for face localization and region of interest (ROI) determination. The use of ESP32-CAM as an image acquisition device in a facial recognition system has been implemented in previous research (Hamidah et al., 2024b) . The HOG descriptor represents local image structure through distributions of gradient orientations and was originally evaluated for human detection (Dalal & Triggs, 2005).

Subsequently, dlib 68 facial landmarks are used as a reference for face alignment. The facial landmark approach is used to obtain characteristic facial points that serve as a reference for aligning the facial position before feature extraction (Jabberi et al., 2023). The aligned images are then processed using ResNet-34 to generate 128-dimensional face embeddings. The resulting facial embeddings are subsequently used for matching based on the distance between facial representations (Ghareeb & Abusamra, 2024a) A methodological foundation for facial landmark estimation is the ensemble of regression trees proposed for face alignment (Kazemi & Sullivan, 2014). The residual learning framework provides the architectural basis for ResNet networks by learning residual functions with respect to layer inputs (He et al., 2016).

The test images are then compared with the reference face embeddings using Euclidean Distance. A distance value ≤ 0.45 is classified as a match (MATCH), while a value > 0.45 is classified as unrecognized (UNKNOWN). The stages of facial image processing and feature extraction are shown in Figure 2.

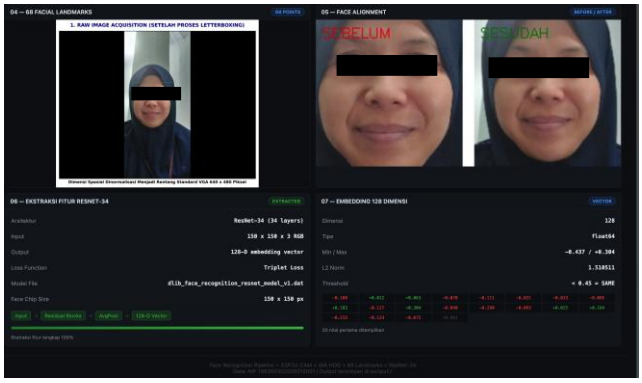


Figure 2. Image Processing and feature

2.4 face matching

Face matching is performed by calculating the Euclidean distance between the test face embedding and the reference face embedding. The use of Euclidean distance to compare numerical facial representations is one of the approaches used in face matching based on face embeddings (Ghareeb & Abusamra, 2024b).The distance between two embeddings is calculated using the following equation:

$$d(x, y)\sqrt{\sum_{i}(x_i - y_i)^2} \quad (1)$$

The smaller the distance value, the closer the numerical representation of the test face is to the reference face. This study sets a threshold of 0.45 as the decision boundary. A distance value ≤ 0.45 is categorized as a match (MATCH), while a value > 0.45 is categorized as unrecognized (UNKNOWN). The use of distances between learned face embeddings has a precedent in FaceNet, which maps facial images into a Euclidean space where distance represents facial similarity (Schroff et al., 2015).

2.5 Time Window Buffer and Data Integration

The Time Window Buffer is utilized to minimize the system's reliance on a single point of observation. The 10:00 WITA monitoring cycle employs a time frame spanning 09:00–11:00 WITA, whereas the 14:00 WITA cycle covers 13:00–15:00 WITA. If an employee is detected by either camera within the specified interval, they are recorded as visually detected within the monitoring area for that corresponding cycle.

Fingerprint data serves as the indicator for administrative attendance, while computer vision outputs represent visual presence. Instances where attendance is recorded administratively but no visual detection occurs during the time window are flagged as anomalous indications requiring further verification. Such conditions cannot be directly interpreted as conclusive evidence that the employee has departed from the office, given that camera coverage is restricted solely to the lobby area.

2.6 Testing Scenarios

Dynamic testing involved 10 registered employees. Each employee performed 5 trials under three movement scenarios: normal walking, brisk walking, and running. Thus, a total of 10 × 5 × 3 = 150 experiments were conducted. Camera 1 was positioned in front of the stairs, while Camera 2 was positioned at the lobby exit. The evaluation covered image transmission reliability, the influence of lighting conditions, face recognition success, and the contribution of multi-camera redundancy. The dynamic testing scenarios are presented in Table 2.

Table 3. Multi-camera testing scenario

Scenario	Speed	Trials/Employee	Number of Employees	Total
Normal walking	1.0–1.4 m/s	5	10	50
Brisk walking	1.5–2.0 m/s	5	10	50
Running	>2.5 m/s	5	10	50
Total				**150**

2.7 Experimental Procedure for Fingerprint and Visual Monitoring Integration

The integration evaluation compared administrative attendance records with visual detection outcomes obtained from the two-camera computer vision system. The dynamic experiment involved 150 trials involving 10 registered employees, with five repetitions per employee under three movement scenarios: normal walking, brisk walking, and running. Each trial was associated with an employee identifier, trial date, movement scenario, and observation time.

Fingerprint attendance records were retrieved from the attendance log, which contains employee identifiers and fingerprint transaction timestamps. Visual monitoring records were obtained from the face detection log stored in the MariaDB database, which contains recognized employee identifiers and detection timestamps. These records were used to compare administrative attendance and visual detection for the same employee and applicable observation period.

The Time Window Buffer (TWB) accommodated variations in the timing of employee movement and camera capture. Two observation cycles were defined: 09:00–11:00 WITA for the 10:00 cycle and 13:00–15:00 WITA for the 14:00 cycle. Within each applicable window, an employee was considered visually detected if at least one of the two cameras successfully recognized the employee. Recognition was considered successful when the Euclidean distance between the test and reference face embeddings was less than or equal to 0.45.

The integration outcomes were classified using two binary variables. Variable (A) represented the presence of a corresponding fingerprint attendance record, while variable (F) represented successful visual detection within the applicable TWB. The four mutually exclusive conditions were defined as follows:

1. Fingerprint and visual detected ((A=1, F=1)): a corresponding fingerprint attendance record was available, and the employee was successfully recognized by at least one camera within the applicable TWB.
2. Fingerprint only ((A=1, F=0)): a corresponding fingerprint attendance record was available, but neither camera successfully recognized the employee within the applicable TWB.
3. Visual only ((A=0, F=1)): the employee was successfully recognized by at least one camera within the applicable TWB, but no corresponding fingerprint attendance record was identified for the evaluated employee and attendance period.
4. Neither detected ((A=0, F=0)): neither a corresponding fingerprint attendance record nor a successful visual detection was identified for the evaluated employee and observation cycle.

The number of observations assigned to each condition was counted, and the percentage was calculated relative to the total of 150 evaluated observations. The resulting counts and percentages are presented in Table 6. Any discrepancy between fingerprint attendance and visual detection was treated as an indication requiring further verification, rather than conclusive evidence of employee absence, because the cameras covered only the lobby area.

3 Results And Discussion

3.1 Implementation Results

The two ESP32-CAM units were successfully integrated with the local network and processing server. The devices were able to capture facial images at a resolution of 640 × 480 pixels and transmit them to the server via Wi-Fi using HTTP POST. The images received by the server were then processed through the computer vision stages, and the recognition results were recorded in the MariaDB database. Facial recognition processing was performed on a virtual

server so that the computational workload was not placed on the ESP32-CAM devices. The system design can be seen in Figure 3.

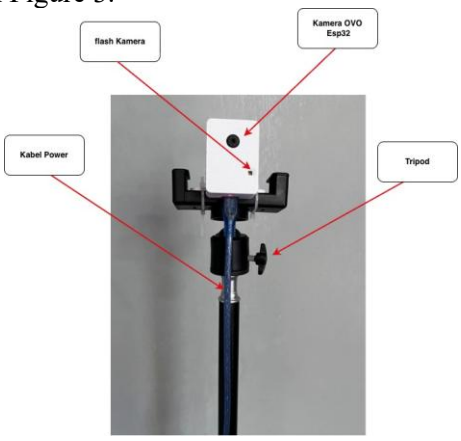


Figure 3. Hardware Design

3.2 HTTP POST Transmission Testing

Transmission testing showed that communication between the ESP32-CAM and the server operated using the HTTP POST method. Several failure conditions were identified during testing: an unregistered endpoint generated a 404 Not Found response, a full internal buffer could cause a connection lost or buffer fail condition, while an empty payload generated a 400 Bad Request response. Under normal operating conditions, image transmission through the /upload endpoint returned an HTTP 200 OK response with a latency of approximately 80 ms. These results indicate that the image transmission mechanism from the ESP32-CAM to the server can operate over the Wi-Fi network in the lobby area.

Table 4. Hardware testing

Testing Condition	Response/Result
Unregistered endpoint	404 Not Found
Full internal buffer	Connection lost / buffer fail
Empty payload	400 Bad Request
Valid image transmission	200 OK
Normal transmission latency	±80 ms

3.3 Multi-Camera Dynamic Testing Results

Dynamic testing was conducted with 10 employees under three movement scenarios: normal walking, brisk walking, and running. Each scenario consisted of 50 trials, resulting in a total of 150 trials. The tests were performed using the two cameras separately, and the detection results from both cameras were then integrated as a multi-camera system.

Table 5. Table Testing Result

Scenario	Trials	Camera1	Camera2	Simultan	C1%	C2%	System%
Normal walking	50	50	50	50	100	100	100
Brisk walking	50	35	8	6	70	16	74
Running	50	6	2	0	12	4	16
Total	150	91	60	56	60,67	40,00	63,33

Under the normal walking scenario, with a speed range of 1.0–1.4 m/s, both cameras achieved a 100% success rate. This result indicates that relatively stable subject movement enables face detection and recognition to operate effectively at both camera positions.

Under the brisk walking scenario, at approximately 1.5–2.0 m/s, Camera 1 achieved a success rate of 70%, while Camera 2 achieved 16%. The difference between the two cameras was related to camera positioning and lighting conditions in the test area, particularly backlight interference near the exit door. By combining the detection results from both cameras through the redundancy principle, the system success rate reached 74%.

Under the running scenario, at speeds above 2.5 m/s, the success rate of Camera 1 decreased to 12%, while Camera 2 achieved 4%. The multi-camera system produced a success rate of 16%. This decrease indicates that increased movement speed affects the success of face recognition. This condition may be related to motion blur, faster changes in facial position, and limitations in the frame capture process of the OV2640 camera. Previous work found that pose differences between test and reference images influence the effects of illumination, motion blur, and resolution on recognition performance (Dutta et al., 2012). This supports evaluating image quality as a possible contributing factor, although the present movement trials do not isolate its causal effect.

Overall, out of 150 trials, the system successfully detected or recognized the subject in 95 trials, corresponding to 63.33%. These results indicate that the system performs optimally during normal movement, but its success decreases as movement speed increases. The use of two cameras provides observation redundancy, allowing the system to obtain a detection when one camera experiences a failure.

3.4 Multi-Camera Redundancy Analysis

The test results indicate that deploying two distinct camera perspectives provides substantial benefits, particularly when one camera fails to capture the face. During brisk walking, the contribution of Camera 2 effectively complemented Camera 1, and vice versa. Nonetheless, redundancy does not completely mitigate detection failures under extreme movement, as both cameras encounter degraded image quality stemming from motion blur.

Overall, across the 150 trials, 95 successful detections were recorded, yielding an overall rate of 63.33%. This 63.33% figure reflects the end-to-end functional success rate across dynamic scenarios rather than the isolated classification accuracy of ResNet-34. This distinction is critical because final system performance is governed by the entire processing pipeline—from image acquisition, localization, and alignment to feature extraction, matching, camera positioning, illumination, and subject velocity.

3.5 Time Window Buffer Analysis

The test results show that using two camera viewpoints provides benefits by increasing the probability of detection when one camera fails to capture a face. In the brisk walking scenario, differences in camera position and observation conditions allowed the detection result from one camera to complement the other. However, multi-camera redundancy does not completely overcome failures during extreme movement. Under the running condition, both cameras experienced reduced success rates, indicating that image quality limitations caused by motion blur remain a factor affecting face recognition.

Overall, 95 successful detections, or 63.33%, were obtained from 150 tests. This value represents the functional success rate of the system across all dynamic scenarios and is not the accuracy of ResNet-34 considered separately. The final system performance is influenced by the entire processing chain, from image acquisition, face localization, face alignment, and feature extraction to face matching, camera positioning, lighting conditions, and subject movement speed.

The Time Window Buffer provides tolerance for employee mobility during the observation period. Employees who are not present in the lobby at the nominal observation time still have an opportunity to be detected within the same time range. The 10:00 WITA observation cycle uses the 09:00–11:00 WITA range, while the 14:00 WITA cycle uses the 13:00–15:00 WITA range. This mechanism reduces dependence on a single frame or a single observation point in time, allowing the detection results to represent the visual presence of employees during the observation period.

Nevertheless, the Time Window Buffer cannot be used to determine employee location comprehensively. An undetected status only indicates that no visual detection occurred within the camera-covered area during the time window. Employees may still be in their workspaces or other areas outside the camera coverage. Therefore, the computer vision results in this study are positioned as an indicator of visual presence within the monitored area, rather than evidence of employee presence or absence throughout the entire workplace.

3.6 Integration of Attendance and Visual Monitoring

Integrating the two data sources provides more complete information than using fingerprint data alone. When administrative attendance is recorded and an employee is visually detected within the time window, the condition can be recorded as a correspondence between attendance indicators based on the system data. Conversely, when attendance is recorded but no visual detection occurs within the monitored area during the time window, the system generates an anomaly indication that can be used for further verification.

An anomaly indication cannot be treated as conclusive evidence that an employee has left the office. An undetected condition may occur for several reasons, including the employee being outside the camera coverage or limitations in visual detection, such as motion blur. Therefore, the results of integrating fingerprint and computer vision are more appropriately used as supporting information for attendance verification and attendance-discipline evaluation, rather than as the sole basis for determining employee absence.

Based on the integration results, 95 of 150 trials (63.33%) showed correspondence between fingerprint attendance and visual detection. Meanwhile, 35 trials (23.33%) recorded fingerprint attendance without visual detection, and 10 trials (6.67%) showed visual detection without a corresponding fingerprint record. A further 10 trials (6.67%) showed neither fingerprint attendance nor visual detection. Overall, 45 trials (30.00%) showed a discrepancy between the two sources of information. These results indicate that integrating fingerprint and computer vision can provide additional information for identifying discrepancies between administrative attendance records and visual presence in the monitored area.

Table 6. Quantitative Results of Fingerprint and Visual Monitoring Integration

Logical Condition	Test Count	Percentage	System Status and Interpretation
Fingerprint and visual detected $(\boldsymbol{A \wedge F = 1})$	95	63,33 %	**Correspondence:** Fingerprint attendance was recorded and the employee was visually detected within the monitored area.
Fingerprint recorded, visual not detected $(\boldsymbol{A \wedge \neg F = 1})$	35	23,33 %	**Attendance anomaly indication:** Fingerprint attendance was recorded, but no visual detection was obtained within the monitored area during the *time window*.
Visual detected, fingerprint not recorded $(\boldsymbol{\neg A \wedge F = 1})$	10	6,67 %	**Administrative anomaly indication:** The employee was visually detected within the monitored area, but no

			corresponding fingerprint attendance record was found
Neither detected **($\neg A \wedge \neg F = 1$)**	10	6,67 %	**No detection:** No fingerprint attendance record and no visual detection were obtained during the observation period.
Total	150	100 %	**150 dynamic experimental trials** (normal walking, brisk walking, and running)

3.7 System Limitations

The developed system still has several limitations. Camera coverage is limited to the lobby area, so the system cannot yet monitor employee presence throughout the entire workplace. Recognition performance is also affected by subject movement speed and lighting conditions, particularly backlight. Testing of variations in facial orientation remains limited, while faces covered by masks or veils may cause recognition to fail. In addition, the limited RAM of the ESP32-CAM and Wi-Fi network stability may affect image acquisition and transmission to the server.

This study also does not yet include comprehensive testing of system security and biometric data protection. These aspects need to be considered in future system development, particularly with regard to transmission security, storage of facial data, and access control for recognition results. Future development should also evaluate biometric template protection, considering security, revocability, and the impact of protection methods on matching accuracy (Jain et al., 2008).

4 Conclusions

This study successfully designed and implemented the integration of fingerprint and IoT-based computer vision to support employee presence monitoring in the lobby area of BLKM Makassar. The two ESP32-CAM units were able to transmit 640 × 480 pixel images via HTTP POST to the server with an HTTP 200 OK response and a latency of approximately 80 ms under normal conditions.

The combination of Histogram of Oriented Gradients (HOG), dlib 68 facial landmarks, face alignment, ResNet-34, 128-dimensional face embeddings, and Euclidean Distance with a threshold of 0.45 can be used as a facial identification pipeline. Dynamic testing showed a system success rate of 100% under the normal walking scenario, 74% during brisk walking, and 16% during running. From 150 tests, the cumulative success rate of the multi-camera system reached 63.33%, with Camera 1 achieving 60.67% and Camera 2 achieving 40.00%.

The implementation of the Time Window Buffer during the 10:00 and 14:00 WITA observation cycles provides tolerance for employee mobility and enables comparison between administrative attendance data and visual presence within the monitored area. Integrating the two data sources can produce an anomaly indication when fingerprint attendance is recorded but no visual detection occurs during the time window. However, this indication cannot be used as the sole evidence of employee absence because camera coverage is limited to the lobby area.

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