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IMPLEMENTATION OF DEEP LEARNING-BASED FACE RECOGNITION FOR A WEB-BASED EMPLOYEE ATTENDANCE SYSTEM

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Abstract—*Employee attendance recording is a critical component of effective human resource management, yet conventional methods such as attendance cards and manual logging remain vulnerable to data manipulation and recording errors. Universitas Janabadra currently relies on a single fingerprint device, which is inconvenient for staff working far from the attendance point and limited in its reporting capability. This study aims to design and implement a face-recognition-based employee attendance system that leverages deep learning to improve the efficiency, security, and accuracy of attendance recording. The system was developed through five stages: problem identification, requirement analysis, design, implementation, and testing. Face detection and recognition were implemented using the FaceMatcher method from the Face-API.js library, which is based on pre-trained SSD MobileNetV1 and built on TensorFlow.js, while the web-based attendance application was developed using the Laravel framework. Testing was conducted through test cases and compatibility testing under various lighting conditions, distances, and facial accessories. The results show that all functional test scenarios performed successfully, and a quantitative evaluation using 200 recognition trials, comprising 150 attempts from 15 registered employees and 50 attempts from 5 unregistered individuals, achieved an overall accuracy of 79.00%, a precision of 98.21%, a recall of 73.33%, an F1-score of 83.97%, a false acceptance rate (FAR) of 4.00%, and a false rejection rate (FRR) of 26.67%. This system has the potential to become a practical solution for reducing human error and attendance data manipulation in work environments such as Universitas Janabadra, although the relatively high false rejection rate indicates room for improvement in recognition reliability.*

Keywords: *attendance system, deep learning, face recognition, FaceMatcher, Laravel.*

Abstrak—*Sistem pencatatan kehadiran karyawan merupakan komponen krusial dalam pengelolaan sumber daya manusia yang efektif, namun metode konvensional seperti kartu absen dan pencatatan manual masih rentan terhadap manipulasi data dan kesalahan pencatatan. Universitas Janabadra saat ini masih mengandalkan satu unit mesin sidik jari yang menyulitkan karyawan dengan lokasi kerja jauh dari titik presensi serta terbatas dalam pelaporan data. Penelitian ini bertujuan merancang dan mengimplementasikan sistem presensi kehadiran karyawan berbasis face recognition dengan memanfaatkan deep learning untuk meningkatkan efisiensi, keamanan, dan akurasi pencatatan kehadiran. Sistem dikembangkan melalui lima tahap, yaitu identifikasi masalah, analisis kebutuhan, perancangan, implementasi, dan pengujian. Deteksi dan pengenalan wajah diimplementasikan menggunakan metode FaceMatcher dari pustaka Face-API.js yang berbasis SSD MobileNetV1 yang telah dilatih sebelumnya dan dibangun di atas TensorFlow.js, sedangkan aplikasi presensi berbasis web dikembangkan menggunakan framework Laravel. Pengujian dilakukan melalui test case dan compatibility testing terhadap berbagai kondisi pencahayaan, jarak, dan aksesoris wajah. Hasil penelitian menunjukkan bahwa seluruh skenario pengujian fungsional berhasil dijalankan, dan evaluasi kuantitatif menggunakan 200 percobaan pengenalan (150 percobaan dari 15 karyawan*

terdaftar dan 50 percobaan dari 5 individu tidak terdaftar) menghasilkan akurasi keseluruhan sebesar 79,00%, presisi 98,21%, recall 73,33%, F1-score 83,97%, false acceptance rate (FAR) 4,00%, dan false rejection rate (FRR) 26,67%. Sistem ini berpotensi menjadi solusi praktis untuk mengurangi human-error serta manipulasi data presensi di lingkungan kerja seperti Universitas Janabadra, meskipun tingkat FRR yang relatif tinggi menunjukkan masih ada ruang perbaikan pada keandalan pengenalan.

***Kata Kunci**: sistem presensi, pembelajaran mendalam, pengenalan wajah, FaceMatcher, Laravel.*

INTRODUCTION

In the current era of digitalization, efficiency and accuracy in human resource management have become key factors for organizational success, and employee attendance recording is one of the most decisive aspects of that management (Tobing, Yulia, & Rahayuningsih, 2023; Utomo, Maulana, Firmansyah, & Purwaningtias, 2026). Traditional attendance systems, such as manual logging or attendance cards, still leave several difficult-to-avoid problems, including the potential for data manipulation, input errors, and inefficient processing time (Noor & Utami, 2026). This condition drives the need for an automated attendance system that is resistant to fraud while still providing accurate and accountable attendance records (Oktarino, Jamilah, Kristyawati, & Syukriah, 2025).

This need is clearly evident at Universitas Janabadra, which to this day still relies on a fingerprint-based attendance system with only a single unit of hardware. The limited number of devices makes the attendance process time- and effort-consuming, particularly because of its location, which is relatively far from some of the main working areas. In addition, the existing system is also limited in terms of attendance data reporting, making the recorded data difficult to leverage further for other human resource management purposes.

Deep-learning-based face recognition technology offers a relevant solution to these problems. Deep learning, as a branch of artificial intelligence, enables computers to recognize and classify human faces with a high degree of accuracy through convolutional neural network architectures (Wijaya, Samodra, & Suyoto, 2023). Face detection and recognition techniques have been implemented in Indonesia through a range of approaches, from the Haar Cascade Classifier for facial-area segmentation (Nugroho & Sela, 2023) to CNN-based face recognition within OpenCV (Sunardi, Fadlil, & Prayogi, 2022), and deep-learning CNN methods for restricted-access verification such as government employee identification (Putra & Imelda, 2022). This approach has also been widely adopted in Indonesian face-recognition-based attendance research, whether using the You Only Look Once (YOLO) algorithm to identify students or employees (Salamah, Said, & Soim, 2022; Sari & Mirza, 2022), or using OpenCV-based face recognition for lecture attendance (Ramdhani & Sela, 2023), and has consistently shown promising accuracy and efficiency gains over conventional biometric methods such as fingerprint sensors, which remain common in Indonesian institutions but still require dedicated hardware and physical contact with the device (Nurtjahjani, Pribadi, Batubulan, & Shoumi, 2022; Rakasiwi, Kusumo, & Pangestu, 2022).

Despite this progress, most prior Indonesian face-recognition attendance studies rely on custom-trained or server-side deep learning pipelines, for example YOLO detectors retrained on locally collected data or OpenCV/CNN classifiers requiring a dedicated processing backend, which increases development effort and server infrastructure requirements. Comparable international work has likewise moved toward rigorously validated but still resource-intensive architectures, such as hybrid MTCNN-ArcFace pipelines evaluated with full accuracy, precision, recall, and error-rate metrics (Widyani, Suroso, & Taqwa, 2026), or design-science attendance frameworks built around dedicated computer-vision backends (Nguyen-Tat, Bui, & Ngo, 2024). The specific gap this study addresses is therefore the lack of a lightweight, purely client-side (browser-based) face-recognition attendance pipeline for the Indonesian higher-education context that relies entirely on pre-trained, off-the-shelf deep learning models rather than custom training or a dedicated inference server, while still integrating attendance-specific workflow features, namely shift management, leave requests, overtime, and role-based access, within a single web application.

Based on these problems and opportunities, this study aims to design and implement a web-based employee attendance system that applies face detection with deep learning, specifically through the FaceMatcher method in the Face-API.js library, a browser-based library built on TensorFlow.js, a JavaScript machine learning platform that has also underpinned other Indonesian web-based object-detection research (Arnesia, Pratama, & Sjafrina, 2022; Maleh, Teguh, Sahay, Okta, & Pratama, 2023), so that it is able to detect and recognize employees' faces in real time and record attendance accurately in order to reduce the risk of fraud and recording errors. The system built is a website-based

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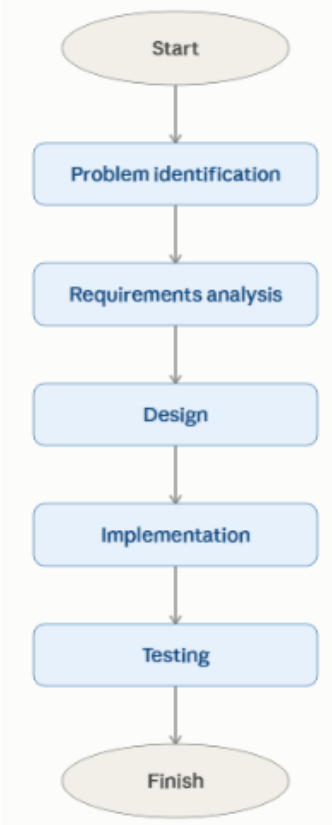
prototype using the Laravel framework, a PHP framework also applied in other Indonesian web-based information system studies (Susanto, 2023), and is not yet integrated with other information systems at Universitas Janabadra; the face dataset is limited to a specific sample of employees, and the image-capture conditions require that faces not be obstructed by accessories and that lighting not be too extreme.

Building on this gap, the contribution of this study is twofold: first, it provides empirical evidence on the feasibility of a fully client-side, pre-trained FaceMatcher pipeline for an attendance use case at the scale of an educational institution, distinguishing it from prior Indonesian work that trains or fine-tunes CNN/YOLO/OpenCV detectors specifically for this task; second, it provides a system prototype that can serve as a reference for further development, including addressing the limitations of two-dimensional object detection.

MATERIALS AND METHODS

Research Flow

This study was carried out through five systematically interrelated stages, as shown in Figure 1.

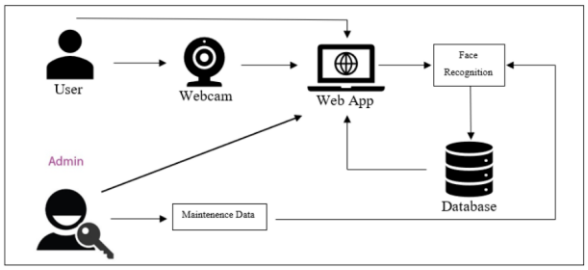


Source: (Research Result, 2026)
Figure 1. Research Flow

(1) problem identification, to formulate the overall attendance problem to be solved; (2) requirement analysis, to determine the software requirements and methods to be used; (3) design, covering the system architecture, use case diagram, system overview, and the application of the FaceMatcher method; (4) implementation, the process of transferring the design into program code; and (5) testing, to measure the conformity of the system's performance against the initial design targets.

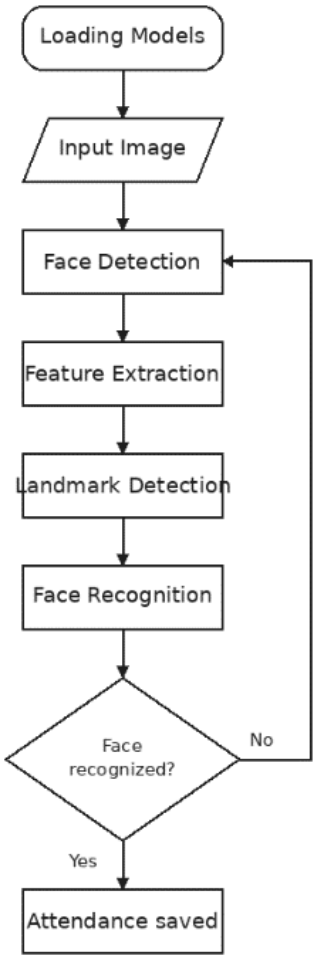
System Architecture and Overview

The architecture of the system built is shown in Figure 2. The user (employee) performs attendance through a webcam that sends the image to the web application (Web App). The image is then processed by the face recognition module, which matches the facial data against data stored in the database (Yasykur & Saputra, 2024). Employees can access the web application to view their own attendance history, while the admin manages employee data (data maintenance) so that the system can match facial images, arrange work schedules/shifts, and generate attendance reports for management.



Source: (Research Result, 2026)
Figure 2. System Architecture Design

The general workflow of the software, from model loading to the storage of attendance data, is shown in the flowchart in Figure 3. The system first loads the required Face-API.js models, then continuously captures image input from the webcam. Each frame is checked for the presence of a face (face detection); if no face is detected, the system returns to capturing the next frame. If a face is detected, the system performs feature extraction and facial landmark detection, followed by the face recognition process, which compares the detected face against the stored descriptors. If a match is found, the attendance record is saved to the database; if not, the system returns to the face detection stage for the next frame.



Source: (Research Result, 2026)

Figure 3. System Overview Flowchart

Use Case Diagram and Database

Following standard UML use case modeling practice, user interaction with the system is depicted through the use case diagram in Figure 4, which involves two main actors, namely the administrator and the user/employee. The administrator can access login, employee data management (CRUD), attendance recording along with the face detection module, and attendance recap. Employees can access pages to check in and check out, submit leave requests, log overtime attendance, and record off-site duty attendance. The system database consists of ten main tables, namely user, shift, mapping_shift, auto_shift, cuti (leave), reset_cuti, dinas_luar (off-site duty), biro (bureau), jabatan (position), and lembur (overtime), which are interrelated to support all attendance functions and employee shift management.



Source: (Research Result, 2026)

Figure 4. Use Case Diagram

Dataset Collection and Algorithm Development

The research dataset consists of facial photographs of Universitas Janabadra employees, entered directly through the face-dataset registration feature within the system. Fifteen employees were registered as the sample for this study, rather than the entire institutional population, and each employee was enrolled with five facial photographs captured during registration to build their labeled descriptor set. The development of the face detection and recognition algorithm makes use of Face-API.js: once the model is loaded, the system detects the face in the image, extracts a descriptor of 128 floating-point values per face in a labeled JSON format (the _label and _descriptors properties), and then constructs a faceapi.LabeledFaceDescriptors object for each label. These objects are used to build a faceapi.FaceMatcher with a tolerance threshold of 0.6. This threshold defines the maximum allowable Euclidean distance between two 128-dimensional face descriptors for them to be considered a match; it is a distance value, not a similarity percentage or confidence score, so a lower value indicates two faces are more alike. Consequently, a lower threshold enforces stricter matching (fewer accepted matches, at lower risk of false acceptance), while a higher threshold makes matching looser (more matches accepted, at higher risk of false acceptance). The value 0.6 follows the original validation of the underlying ResNet-34-like recognition network, which was reported by its developer to achieve 99.38% verification accuracy on the Labeled Faces in the Wild (LFW) benchmark specifically at a distance threshold of 0.6 (Iftekar & Zeeshan, 2024). This FaceMatcher is then invoked on the attendance page to find the best match between the face captured by the camera and the

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descriptors stored in the database, before the system automatically records attendance.

Face detection and face recognition are two distinct tasks performed by two separate pre-trained networks in this pipeline, and it is important to clarify which deep learning architecture is actually doing each part of the work under the hood, since Face-API.js does not train a new model for a specific deployment: SSD MobileNetV1 is solely responsible for face detection (locating a face in the frame and returning its bounding box), while FaceMatcher, built on the ResNet-34-like recognition network, is solely responsible for face recognition (deciding whose face it is). Face detection is performed by a pre-trained SSD (Single Shot Multibox Detector) built on a MobileNetV1 backbone, trained on the WIDERFACE dataset, which localizes each face in the input frame and returns its bounding box together with a confidence score. The 128-dimensional descriptor used by FaceMatcher is then produced by a separate pre-trained convolutional network with a ResNet-34-like architecture, adapted from the dlib face recognition model, which maps each detected face to a point in a 128-dimensional embedding space such that images of the same person lie close together. Both networks are used as-is, with their original pre-trained weights; this study does not train, fine-tune, or otherwise modify either network on the Universitas Janabadra employee data. Consequently, the deep learning contribution of this study lies in integrating and applying these existing pre-trained models within a working web-based attendance pipeline, including the dataset registration workflow, the FaceMatcher-based comparison logic, and the Laravel-based application around it, rather than in designing or training a new network architecture.

Quantitative Evaluation Protocol

To complement the functional and compatibility testing described below, a quantitative recognition trial was conducted on the deployed system. Each of the 15 registered employees attempted attendance 10 times under normal, consistent conditions (150 trials in total), and five individuals who were not registered in the system each attempted attendance 10 times (50 trials in total), for 200 trials overall. Each attempt was scored as a success only when the system displayed the correct registered identity with a descriptor distance below the 0.6 threshold; an attempt in which the system displayed no match at all, rather than an incorrect identity, was scored as a failure. Recognition time was not systematically instrumented in this trial; based on informal observation during testing, a typical attempt, from activating the camera to a recorded attendance entry, took approximately one minute, but this figure should be treated as an approximate indication rather than a precise measurement, and systematic timing is identified as a direction for future work.

From these trials, four outcome categories were tallied: a true positive (TP) is a trial in which a registered employee was correctly recognized; a false negative (FN) is a trial in which a registered employee was not recognized; a true negative (TN) is a trial in which an unregistered individual was correctly rejected; and a false positive (FP) is a trial in which an unregistered individual was incorrectly accepted as a registered employee. These values are used to perform calculations, following standard biometric evaluation practices as follows.

$$Accuracy = \frac{(TP + TN)}{(TP+FN+TN+FP)} \quad (1)$$

$$Precision = \frac{TP}{(TP+FP)} \quad (2)$$

$$Recall = \frac{TP}{(TP+FN)} \quad (3)$$

$$F1 - Score = 2\,x\,\frac{Precision\ x\ Recall}{Precision + Recall} \quad (4)$$

$$False\ Acceptance\ Rate\ (FAR) = \frac{FP}{(FP+TN)} \quad (5)$$

$$False\ Rejection\ Rate\ (FRR) = \frac{FN}{(FN+TP)} \quad (6)$$

(Amir & Nemer, 2025; Deng, Chiang, Kang, & Li, 2023; Fatima, Ghauri, Mohammad, Adeel, & Sarfraz, 2022; Omar, Rashedul, & Touhid, 2024; Wang & Xu, 2024)

Because the 10 trials per participant were repeated under broadly similar conditions rather than systematically varied lighting, distance, or accessory conditions, these metrics characterize overall recognition reliability rather than a condition-by-condition breakdown; condition-specific quantitative testing remains addressed only qualitatively in the compatibility testing reported below and is identified as a direction for future work.

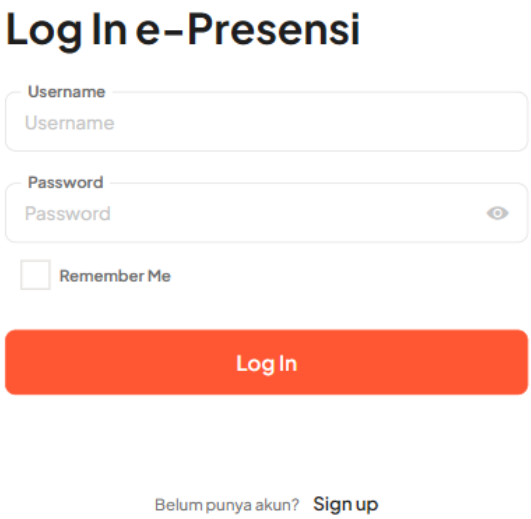
RESULTS AND DISCUSSION

System Interface Implementation

The attendance system was implemented as a web application using the Laravel framework, a PHP framework also used in other Indonesian web-based information system studies (Susanto, 2023) with three main groups of pages: the administrator pages (login, dashboard, employee data, face dataset registration, attendance history, and shift

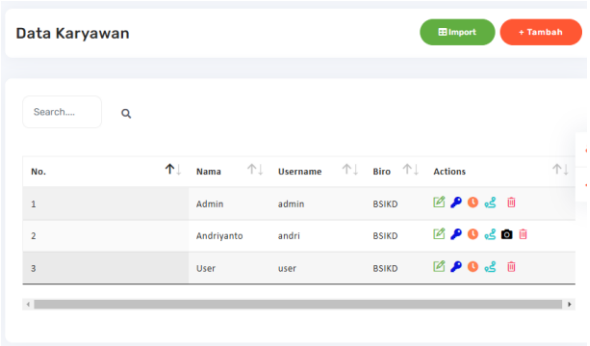
settings), the employee pages (login, dashboard, attendance, attendance history, leave requests, and overtime requests), and a login-free attendance page that allows employees to perform attendance directly using face recognition without entering account credentials.

Figure 5 shows the login page of the e-Presensi system, providing username and password fields for user authentication, along with a "Remember Me" option, password visibility control, and registration link.



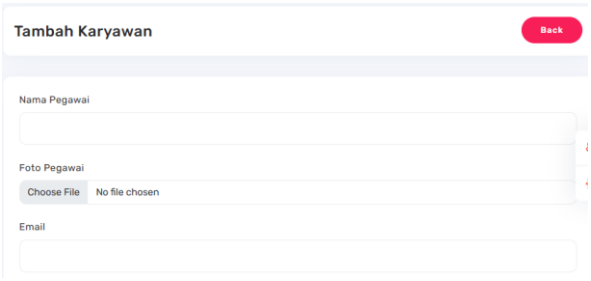
Source: (Research Result, 2026)
Figure 5. Login Page

Figure 6 shows the employee data management page of the e-Presensi system, which displays a list of registered employees along with their names, usernames, and assigned offices. The page also provides search functionality and action controls for managing employee records, including editing, viewing, and deleting data, as well as options to import and add new employee records.



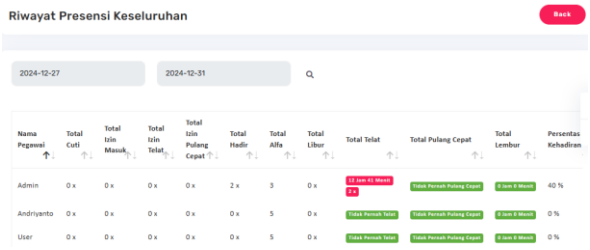
Source: (Research Result, 2026)
Figure 6. Employee Data Page

Figure 7 shows the employee registration page of the e-Presensi system, which provides a form for entering employee information, including employee name, photograph, and email address. The page also includes a navigation button to return to the previous page.



Source: (Research Result, 2026)
Figure 7. Add Employee Data Page

Figure 8 shows the attendance history page, where the system displays a recapitulation of each employee's attendance data including leave, absence, lateness, early departure, overtime, and attendance percentage within a user-selected date range.



Source: (Research Result, 2026)
Figure 8. Attendance Summary Page

Figure 9 shows the result of face detection on the attendance ("Presensi Masuk") page. The system successfully recognizes the user's identity in real time, displaying the predicted label together with the Euclidean distance between the captured descriptor and the closest registered descriptor (e.g., "admin (0.58)", where 0.58 is the distance value itself, not a similarity percentage or confidence score) inside a bounding box drawn around the detected facial region. Because 0.58 is below the 0.6 tolerance threshold described in the Materials and Methods section, the system accepts this as a positive match before the attendance record is submitted.

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Source: (Research Result, 2026)

Figure 9. Attendance Page with Face Detection

Functional Testing Results

Following the black-box, equivalence-partitioning testing approach commonly applied in Indonesian information-system research (Wulandari et al., 2022), test case testing was carried out on the system's main workflow, covering the login process, employee face registration, user data management, attendance management, face detection, and attendance status monitoring. A summary of the test results is presented in Table 1. All test scenarios were declared successful, noting that the face detection process displays the employee's name along with an attendance-success notification as soon as the face is recognized by the system.

Table 1. Test Case Results of the System

No	Concept	Result	Action	Notes
1	Login	Administrator and employees use a username and password to log in to the system	Passed	Must already have a registered account
2	Face registration	Employee registers their face with the web-based system	Passed	-
3	User management	Employee data can be added and edited by the admin	Passed	-
4	Attendance management	Admin can add employees and attendance remarks	Passed	-
5	Face detection	System detects the employee's face from the webcam using Face-API.js	Passed	Employee name and attendance-success notification appear
6	Attendance status	Employee can view their attendance status in attendance history	Passed	Displays attendance time status

Source: (Research Result, 2026)

Compatibility Testing Results

Compatibility testing was carried out by employees attempting attendance under various device and environmental conditions, as summarized in Table 2. Lighting and the distance of the face from the webcam proved to be the factors most affecting the speed and success of detection, while the use of accessories such as hats and glasses had little effect. In contrast, wearing a mask hindered detection because it covers the mouth and nose area, which is an important part of the facial features extracted by the system.

Table 2. Compatibility Test Results

Stage	Test Condition	Notes
Web system	Different browsers, browser versions, computers, and webcams	A current browser, a capable computer, and a high-quality webcam speed up system performance
Attendance	Dark, bright, and dim lighting	Optimal lighting improves the system's ability to recognize faces
Attendance	Face-to-webcam distance of 1 meter and 2 meters	The closer the face is to the webcam, the faster the system detects the face
Attendance	Use of glasses, hats, and masks	Glasses and hats have no significant effect; masks hinder detection because they cover the mouth and nose
Attendance	Attendance performed simultaneously by several employees	The system can still read and record attendance automatically for each employee

Source: (Research Result, 2026)

Quantitative Recognition Performance

Table 3 summarizes the outcome of the 200-trial quantitative evaluation described in the Materials and Methods section. Of the 150 attempts by the 15 registered employees, 110 were correctly recognized (true positives) and 40 were not recognized at all (false negatives). Of the 50 attempts by the 5 unregistered individuals, 48 were correctly rejected (true negatives) and 2 were incorrectly accepted as a registered employee (false positives).

Table 3. Confusion Matrix of the Quantitative Recognition Trial

Outcome	Count	Description
True Positive (TP)	110	Registered employee correctly recognized
False Negative (FN)	40	Registered employee not recognized
True Negative (TN)	48	Unregistered individual correctly rejected
False Positive (FP)	2	Unregistered individual incorrectly accepted

Source: (Research Result, 2026)

Based on this confusion matrix, the system achieved an overall accuracy of 79.00%, a precision of 98.21%, a recall of 73.33%, and an F1-score of 83.97%; the false acceptance rate (FAR) was 4.00% and the false rejection rate (FRR) was 26.67%, as summarized in Table 4. Per-employee success rates over the 10 trials ranged from 60% to 90%, with a mean of 73.33%, indicating that recognition reliability, while generally functional, varied noticeably across individuals.

Table 4. Quantitative Recognition Performance Metrics

Metric	Value
Accuracy	79.00%
Precision	98.21%
Recall	73.33%
F1-score	83.97%
False Acceptance Rate (FAR)	4.00%
False Rejection Rate (FRR)	26.67%

Source: (Research Result, 2026)

Because these metrics are estimated from a limited number of trials, 95% Wilson score confidence intervals were also computed to indicate their statistical precision: accuracy 79.00% (72.8-84.1%, n=200), precision 98.21% (93.7-99.5%, n=112), recall 73.33% (65.7-79.8%, n=150), FAR 4.00% (1.1-13.5%, n=50), and FRR 26.67% (20.2-34.3%, n=150). The FAR interval is particularly wide because it is estimated from only 50 unregistered-user trials containing 2 false acceptances; a single additional or fewer false acceptance would shift the point estimate to 6.00% or 2.00% respectively, so the 4.00% figure should be read as an approximate indication of a low but non-zero false acceptance risk rather than a precise value, and testing with a substantially larger and more diverse set of unregistered individuals is recommended to narrow this interval in future work.

Quantitative Compatibility Testing

To quantify two of the conditions summarized qualitatively in Table 2, an additional trial was conducted in which the same five registered employees from the main quantitative evaluation each attempted attendance 10 times under low lighting, 10 times using a laptop webcam, and 10 times using a smartphone camera, for 150 newly collected trials. These are compared in Table 5 against a bright-lighting baseline of 50 trials; because the main quantitative evaluation reported in Table 3 was itself conducted under bright, normal office lighting using a laptop webcam, that same set of 50 trials for Employees 1 to 5 is reused here as the bright-lighting reference rather than being re-collected. Distance and facial-accessory conditions were not tested quantitatively in this trial and remain reported only qualitatively in Table 2; quantifying them is identified as a direction for future work.

Table 5. Success Rate by Lighting Condition and Capture Device

Condition	Successful	Failed	Success Rate
Bright lighting (baseline, reused from Table 3)	37	13	74.00%
Low lighting	30	20	60.00%
Laptop webcam	31	19	62.00%
Smartphone camera	38	12	76.00%

Source: (Research Result, 2026)

The results show that recognition success dropped from 74.00% under bright lighting to 60.00% under low lighting, a 14 percentage-point decrease, confirming the qualitative observation in Table 2 with a concrete figure. Unexpectedly, the smartphone camera achieved a higher success rate than the laptop webcam (76.00% versus 62.00%, also a 14 percentage-point difference), which is plausibly attributable to the smartphone's higher image resolution and better low-light sensor performance; this suggests that capture device quality is at least as influential as ambient lighting for this system's recognition reliability, an aspect not considered in earlier qualitative testing.

Discussion

The quantitative trial reported above shows that the FaceMatcher method in Face-API.js achieved an overall accuracy of 79.00%, a precision of 98.21%, a recall of 73.33%, an F1-score of 83.97%, a false acceptance rate of 4.00%, and a false rejection rate of 26.67% across 200 trials, while all functional and compatibility test scenarios also ran according to the design. These figures can now be compared, at least indicatively, with other Indonesian face-recognition attendance systems, although differences in sample size, testing protocol, and dataset composition mean the comparison should be read as approximate rather than a controlled benchmark: YOLO-based student and employee attendance systems (Salamah et al.,

2022; Sari & Mirza, 2022) and OpenCV-based lecture attendance systems (Ramdhani & Sela, 2023) have generally reported effective real-time identification without disclosing comparable precision, recall, or error-rate figures, so a fully like-for-like comparison is still not possible. Against the more rigorously benchmarked centroid-based MTCNN-ArcFace attendance framework (Widyani et al., 2026), which reported 92.86% accuracy, a 4.76% FAR, and a 2.38% FRR, the system evaluated here shows a markedly lower accuracy and a substantially higher FRR (26.67% versus 2.38%), though a comparable, and notably slightly lower, FAR (4.00% versus 4.76%; however, as noted above, the 95% confidence interval for this study's FAR spans roughly 1% to 14%, so this comparison should be treated as indicative rather than a confirmed advantage). This pattern suggests that the FaceMatcher pipeline in this study is conservative in accepting unfamiliar faces but correspondingly prone to failing on legitimate registered employees, an asymmetry consistent with using only five enrollment photographs per employee, which likely provides limited coverage of pose, lighting, and expression variation compared to the larger enrollment sets typically used in more accuracy-focused pipelines.

Compared to fingerprint-based biometric attendance systems that remain common in Indonesian institutions (Nurtjahjani et al., 2022), a face-recognition approach removes the need for physical contact with a sensor device and allows attendance to be captured from an ordinary webcam, though the 4.00% FAR observed here confirms that this convenience carries a small but non-zero risk of misidentification that a fingerprint sensor would not typically exhibit, reinforcing the case for the anti-spoofing and liveness-detection safeguards discussed above. In addition, this study observed qualitatively that classification time increases with the amount of facial data that must be processed, and recognition was informally observed to take roughly one minute per attempt during testing, though this was not timed systematically; instrumenting recognition time precisely is identified as a direction for future work. Lighting, distance, and face coverings such as masks were observed to be the environmental variables most affecting detection success, a pattern consistent with the general limitations of two-dimensional, image-based face detection systems. The supplementary quantitative trial reported in Table 5 confirms this for two of these variables: success dropped by 14 percentage points under low lighting compared to bright lighting (60.00% versus 74.00%), and, notably, capture device quality proved at least as influential, with a smartphone camera outperforming a laptop webcam by the same 14-point margin (76.00% versus 62.00%). Distance and facial-accessory conditions, by contrast, were only assessed qualitatively in this study, so confirming their effect on FRR and FAR with equivalent quantitative rigor is left for future work.

Beyond recognition accuracy, the current system also has unaddressed security and privacy limitations that should be considered before wider deployment. Because the FaceMatcher pipeline relies solely on two-dimensional RGB frames from a webcam and includes no liveness detection, it remains susceptible to presentation attacks in which a printed photograph or a displayed image of a registered employee's face is presented to the camera instead of a live face; combining recognition with anti-spoofing or challenge-response liveness checks, as explored in recent presentation-attack-resistant biometric verification research (Micheletto & Marcialis, 2024), would be necessary to mitigate this risk. In addition, the facial descriptors and photographs stored for each employee constitute sensitive biometric data under Indonesia's Personal Data Protection Law (Undang-Undang No. 27/2022), so production deployment would require encryption of stored descriptors, strict access control to the employee database, and a documented data-retention and consent policy, none of which were implemented or evaluated in this prototype.

The choice of FaceMatcher also entails trade-offs relative to alternative recognition architectures beyond the accuracy figures compared above. Because the underlying SSD MobileNetV1 detector and ResNet-34-like recognition network run entirely client-side in the browser via TensorFlow.js, the system avoids the need for a GPU-backed inference server, which lowers deployment cost and simplifies integration into a standard web application; this is the primary advantage FaceMatcher offers over heavier, server-side pipelines such as the MTCNN-ArcFace framework discussed above, or lightweight FaceNet-derived models that have achieved competitive accuracy at model sizes as small as 3.5 MB while still requiring a dedicated inference step (Deng et al., 2023; Zhalgas, Amirgaliyev, & Sovet, 2025). Narrowing the accuracy gap identified above without abandoning this client-side deployment model would likely require enrolling each employee with a substantially larger and more varied set of reference photographs than the five used in this study, rather than switching to a heavier recognition architecture, and is identified as a priority for future work.

CONCLUSION

This study successfully designed and implemented a web-based employee attendance system that applies face detection with deep learning through the FaceMatcher method in the Face-API.js library, specifically a pre-trained SSD MobileNetV1-based detector combined with a ResNet-34-like recognition network, both used without additional training, integrated with a Laravel application. The test case and compatibility testing produced results consistent with the initial design, and a quantitative evaluation of 200 recognition trials, comprising 150 attempts from 15 registered employees enrolled with five photographs each and 50 attempts from 5 unregistered individuals, showed an overall accuracy of 79.00%, a precision of 98.21%, a recall of 73.33%, an F1-score of 83.97%, a false acceptance rate of 4.00%, and a false rejection rate of 26.67%. These results indicate that the system reliably avoids accepting unregistered individuals but still fails to recognize legitimate employees in roughly one out of every four attempts, so that while it has the potential to reduce the risk of fraud and attendance recording errors compared to conventional methods, its recognition reliability for registered employees requires improvement before full deployment. In addition, classification time was informally observed to take roughly one minute per attempt, though this was not measured systematically, and face recognition is still limited to two-dimensional, front-facing images.

Based on these findings, further research is recommended to narrow the false rejection rate observed in this study, for example by enrolling each employee with a substantially larger and more varied set of reference photographs than the five used here, and by instrumenting recognition time systematically rather than relying on informal observation. The non-zero false acceptance rate also indicates that anti-spoofing or liveness-detection safeguards, as discussed above, should be prioritized before wider deployment. Beyond that, face image capture should not be limited to the frontal view only; developing three-dimensional object detection capability so that the system can distinguish a real face from a static image or replica would further improve the security of attendance recording. Given that capture device quality was found to affect recognition success as much as lighting, deploying the system with higher-resolution cameras, or applying image pre-processing to compensate for lower-quality webcams, is recommended alongside further quantifying the effect of distance and facial accessories, which remained only qualitatively assessed in this study. Integrating the system with a broader employee database and testing it on a larger and more diverse employee population are also recommended as follow-up steps before the system is fully implemented in a real work environment.

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