Journal of Embedded System Security and Intelligent Systems
E-ISSN: 2722-273X; P-ISSN: 2745-925X
https://journal.unm.ac.id/index.php/JESSI

Attendance System with Face Recognition Using K-Nearest Neighbor, Particle Swarm Optimization, and Histogram of Oriented Gradients

Mardi Hardjianto✉
Universitas Budi Luhur, Jakarta, Indonesia
Agnes Aryasanti
Universitas Budi Luhur, Jakarta, Indonesia
Putri Hayati
Universitas Budi Luhur, Jakarta, Indonesia

ARTICLE INFO

Keywords:
Attendance System; Face Recognition; HOG; K-NN; PSO.

Article History

Received: June 24, 2026
Revised : August 28, 2026
Accepted : Sept 12, 2026

This is an open access article under the CC BY-SA license

ABSTRACT

Purpose – This study evaluates a contactless employee-attendance prototype designed to recognize faces using a camera near an entrance and register attendance without requiring employees to stop at a conventional device.
Design/methods/approach – The prototype combined Histogram of Oriented Gradients (HOG) for facial feature representation, K-Nearest Neighbor (K-NN) for recognition, and Particle Swarm Optimization (PSO) for K-NN parameter optimization. The training set contained 180 facial images from 20 employees (nine images per employee). Evaluation used one image each from 27 participants, including 20 enrolled employees and seven individuals outside the enrollment set.
Findings – Of the 27 test images, 25 produced the expected outcome, corresponding to 92.6% accuracy (TP = 18, FP = 0, FN = 2, TN = 7). Two enrolled employees were classified as unknown, while all seven unregistered participants were rejected. Recognition may be sensitive to illumination, pose, camera angle and image sharpness; the present test did not isolate these effects.
Research implications/limitations – The small, single-image-per-participant test limits generalization, and the study does not report a direct K-NN versus PSO-optimized K-NN comparison. The prototype also responds to faces shown in photographs, indicating a presentation-attack vulnerability and a need for separate liveness evaluation.
Originality/value – The work investigates the integration of established HOG, K-NN and PSO methods into an entrance-based attendance workflow. Its contribution is a prototype implementation and a bounded account of recognition outcomes and practical limitations rather than evidence of superiority over alternative classifiers or deployment-ready security.

To cite this article : Hardjianto, M., Aryasanti, A., & Hayati, P. (2026). Attendance System with Face Recognition Using K-Nearest Neighbor, Particle Swarm Optimization, and Histogram of Oriented Gradients. *Journal of Embedded System Security and Intelligent Systems, 7*(4), 50-66. Doi. 10.59562/jessi.v7i4.15237

Correspondence Author: ✉ mardi.hardjianto@budiluhur.ac.id

INTRODUCTION

Employee attendance records support workplace administration because they link an individual to recorded times of arrival and departure. Manual registers can be misplaced, altered or incorrectly summarized, while device-assisted systems reduce some administrative work but still require an intentional action by the employee [1], [2]. In the institutional setting addressed by this study, an employee may pass an attendance station without completing that action, leaving an otherwise valid workday unrecorded. Facial-recognition attendance systems offer an alternative by connecting identity recognition with digital records [3], [16]. Their value, however, depends not only on identifying an enrolled face but also on registering the correct event consistently.

Contactless face recognition is relevant to attendance management because a camera can acquire facial images without fingerprints, cards or proximity to a terminal. Prior attendance prototypes have combined facial recognition with timestamped logs, monitoring components and

embedded hardware [2], [3], [16]. These systems also introduce operational questions about where the camera is installed, how an unknown person is handled and whether a repeated detection creates a duplicate record. Reviews of recognition algorithms stress that performance depends on the interaction between detection, facial representation and classification rather than on the classifier alone [21], [22], [23]. While the proposed entrance-based system integrates facial identification with automated attendance recording, the present evaluation focuses specifically on image-level recognition performance. The reliability of attendance-event recording, including missed detections, duplicate entries, and timestamp consistency, remains beyond the scope of the reported experimental assessment.

In the proposed workflow, employees pass a camera installed near an entrance, and the application attempts to match their faces to enrolled identities. The intended operation is to record arrival during the morning and departure during the afternoon without requiring a separate check-in action. This arrangement may expose facial images to variable distances, movement during capture and changes in viewing direction. Reviews of facial recognition identify pose, illumination, occlusion and resolution as recurrent sources of error [6], [20], [24]. Although a 4K-capable webcam was selected for image acquisition, camera resolution alone does not establish recognition reliability under changing entrance conditions.

A contactless attendance workflow must distinguish identity recognition from proof of physical presence. A classifier can match facial patterns without verifying that the image originates from a live person. Studies on presentation attacks identify risks associated with printed photographs and replayed media, alongside countermeasures designed to assess liveness [11], [17], [18], [19], [25], [26]. Person-specific detection and domain-adaptive methods provide additional approaches for resisting spoofing, although neither approach was evaluated in the current prototype [32], [33]. For attendance, this distinction is consequential because a correctly matched face displayed in a photograph does not establish that the employee is present.

Existing attendance studies have used dlib and K-NN for employee identification [7], while another has combined K-NN with geographical restrictions on attendance registration [8]. Viola-Jones with Local Binary Pattern Histograms and HOG-based approaches illustrate alternative recognition pipelines [4], [9], [10], [13]. HOG summarizes local gradient orientation; Euclidean-distance K-NN assigns a label through proximity to training representations [14], [15]. PSO provides a search procedure for selecting model parameters, and previous classification work has applied PSO with K-NN, including applications outside face recognition [12], [42]. These studies provide a methodological rationale for integrating HOG-based feature representation, K-NN classification, and PSO-assisted parameter selection within a unified facial-recognition framework. However, because computational efficiency and the incremental contribution of PSO were not independently evaluated, the proposed integration should be interpreted as an implementation strategy rather than evidence of superior recognition accuracy or computational performance.

A remaining empirical question concerns the ability of an integrated HOG–K-NN–PSO recognition pipeline to distinguish enrolled employees from unregistered individuals within a prototype designed for contactless attendance management. Although the system is intended to operate during routine entrance passages, the available evaluation is limited to individual facial images and therefore cannot establish recognition reliability during continuous movement or the accuracy of automatically recorded attendance events. Recent work has examined portable attendance with liveness detection and broader threats to recognition reliability, indicating that accuracy and anti-spoofing are distinct evaluation dimensions [16], [17], [18], [40]. HOG-based methods remain attractive for interpretable, structured descriptors, whereas recent reviews document the strengths and demands of alternative learned representations [20], [21], [22], [23]. The present study does not experimentally compare those alternatives or isolate the change

attributable to PSO. Its research gap is therefore framed narrowly as a prototype-level examination of the integrated workflow and its observed recognition limitations, not as a claim that the algorithmic combination has never been used elsewhere.

Accordingly, this study developed an employee attendance prototype combining HOG feature extraction, K-NN classification and a PSO-based K-NN parameter-search stage. The training set comprised 180 facial images from 20 employees, and recognition was assessed using 27 images from enrolled and unregistered individuals. The primary objective was to examine agreement between the system output and the expected identity or unknown label under the available test conditions. A related objective was to identify limitations relevant to passive entrance-based attendance, including the rejection of enrolled users and vulnerability to photographic presentations. The contribution lies in documenting the integrated workflow and its initial recognition outcomes, rather than establishing algorithmic superiority or production-level security.

METHOD

Review Design and Scope

This study followed a prototype-development and image-based evaluation design. The workflow comprised reviewing face-recognition approaches, specifying the imaging device, enrolling employee faces, extracting HOG descriptors, applying K-NN classification with a PSO-based parameter-search stage, and examining recognition outputs. The research sequence is presented in Figure 1. Outputs were compared with expected enrolled identities or the unknown class, and recognition accuracy was summarized descriptively. The reported evaluation concerns the integrated configuration; a paired evaluation of K-NN without PSO was not performed or documented.

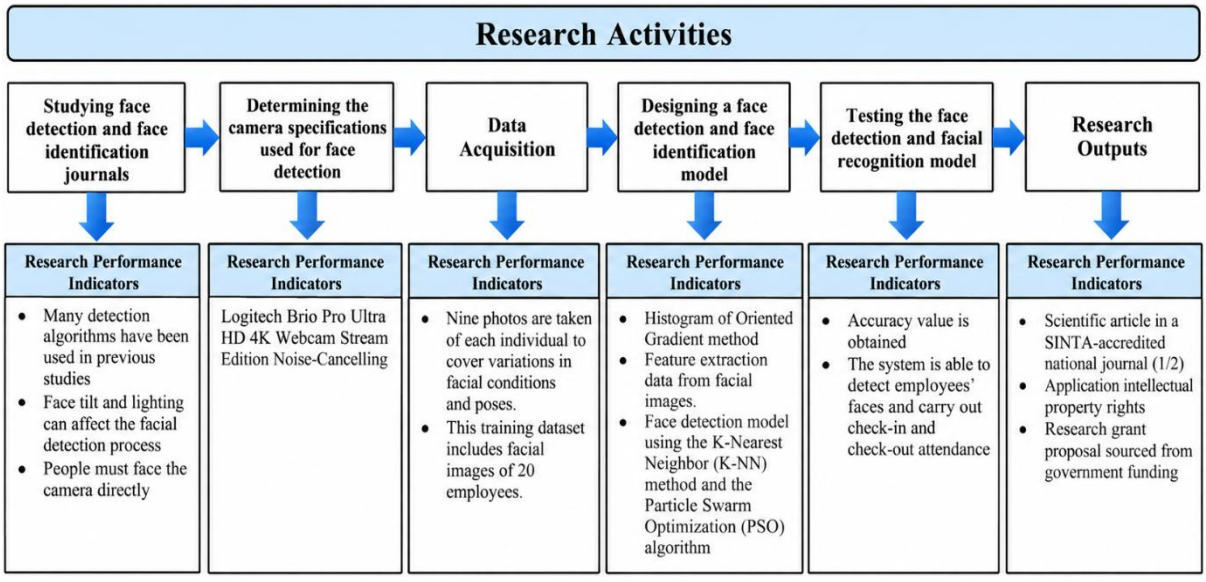


Figure 1. Overall Research Workflow

Participants, Setting, and Image Acquisition

The system was developed for employee attendance at a university, with an imaging device intended for placement near an entrance. A Logitech Brio Pro Ultra HD 4K Webcam Stream Edition with Noise-Canceling was used for facial-image acquisition. The enrollment set consisted of 20 employees, each represented by nine facial images captured with varied facial poses or conditions, yielding 180 training images. Nine representative orientations appear in Figure 2.

Employee names and identification numbers (NIP) were recorded in the database according to Table 1, and their images were stored in folders indexed by NIP. The available study record does not specify the collection period, sampling criteria or a standardized protocol for camera distance and illumination.

Table 1. Employee Table Specifications

Field	Type	Length	Information
ID	BigInteger	20	Employee ID
NIP	Varchar	6	Employee NIP
NAME	Varchar	45	Employee Name

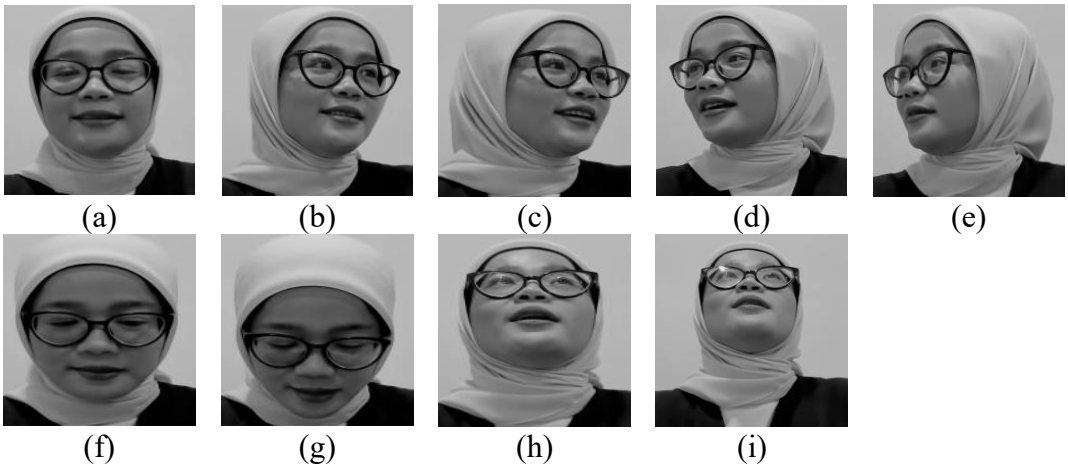


Figure 2. Employee Photos in Various Poses

Dataset Collection and Training

During enrollment, employee identification data were recorded before facial-image capture. Nine images per employee were stored in folders associated with the relevant identifier, as illustrated in Figure 3. For training, the system retrieved these images, located facial regions, generated HOG descriptors and applied the reported K-NN and PSO processing sequence (Figure 4). The resulting recognition information and employee labels were retained for subsequent attendance classification. The reported procedure does not specify a separate parameter-selection set, an independently documented validation protocol or the final optimized configuration.

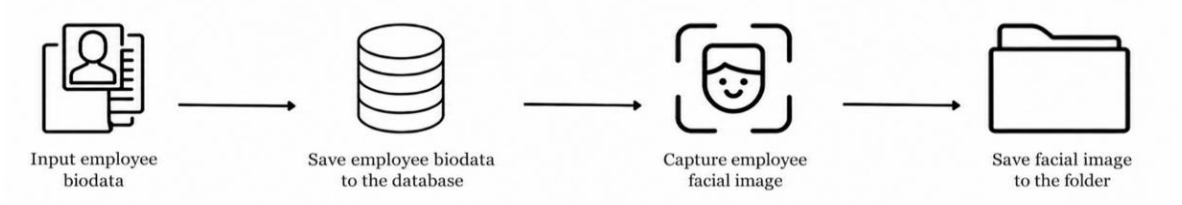


Figure 3. Dataset Collection Flow

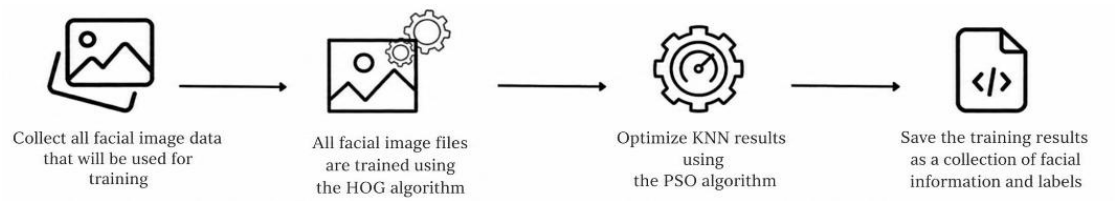


Figure 4. Dataset Training Stages Flow

Attendance Process

The prototype was intended to acquire a facial image while an employee passed through the camera field of view, without requiring a deliberate check-in action. After face detection, a facial descriptor was processed and compared with registered identities. A recognized identity could then be associated with the attendance database, using morning and afternoon rules to distinguish arrival from departure (Figure 5). The detailed flowcharts also depict a check for an attendance event previously recorded on the same day (Figures 9 and 10). However, the reported recognition test used individual facial images; it did not measure repeated passage detection, recording latency or duplicate-event frequency in routine operation.

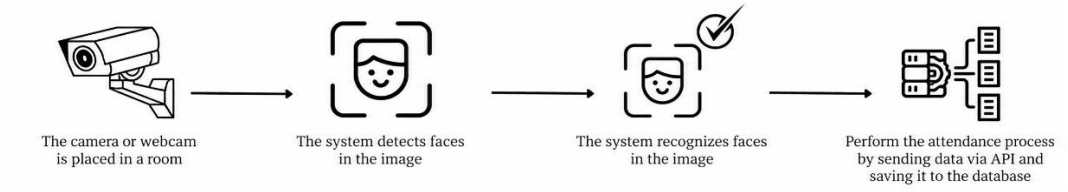


Figure 5. Attendance Process Stages Flow

Histogram of Oriented Gradients

Histogram of Oriented Gradients (HOG) represents facial texture and shape using the distribution of local intensity-gradient directions. In the described implementation, RGB images were converted to grayscale using the following weighted combination:

$$\text{Gray} = 0.2989R + 0.5870G + 0.1140B$$

Horizontal and vertical gradients were calculated from neighboring image intensities and combined into magnitude and orientation estimates. The described HOG pipeline uses 8 × 8-pixel cells with nine orientation bins followed by block normalization to construct a feature vector [14]. Equations (1)–(4) reproduce the derivative kernels and calculations reported for this procedure. Face alignment, descriptor dimensionality, block configuration and handling of undefined orientation ratios are not specified in the available implementation description. These details are relevant because feature consistency between enrollment and test images depends on preprocessing and descriptor construction.

$$d_x = [\,-1 \quad 0 \quad 1\,] \tag{1}$$

$$d_y = [\,-1 \quad 0 \quad 1\,]^T \tag{2}$$

$$m(x,y) = \sqrt{(G_x^2 + G_y^2)} \tag{3}$$

$$\theta = \arctan(G_y / G_x) \tag{4}$$

A 4 × 4 matrix example illustrates intermediate gradient computations and orientation accumulation; its visual outputs are preserved in Figures 6 and 7. The illustration explains the descriptor computation but is not an additional experiment on the employee dataset. Figure 8 shows how gradient information is represented in the final HOG descriptor.

$$Gx = \begin{bmatrix} 3 & 2 & 0 & -4 \\ 2 & 2 & 2 & -3 \\ 5 & 4 & 1 & -6 \\ 4 & 3 & 3 & -6 \end{bmatrix} \qquad Gy = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 0 & 2 & 2 & 4 \\ 2 & 2 & 3 & 3 \\ -2 & -5 & -6 & -7 \end{bmatrix}$$

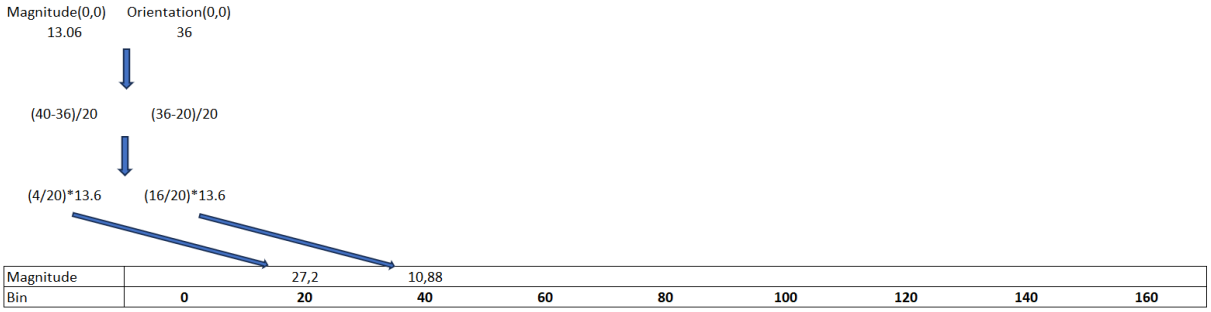


Figure 6. Histogram Creation Process

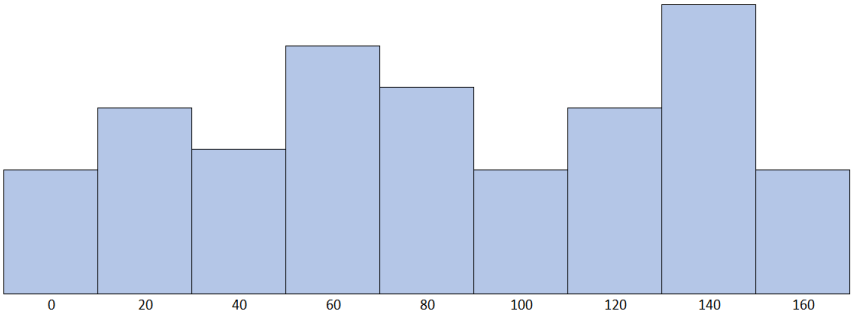


Figure 7. Histogram Creation Results

The normalized histograms were combined into the feature representation used for similarity-based classification.

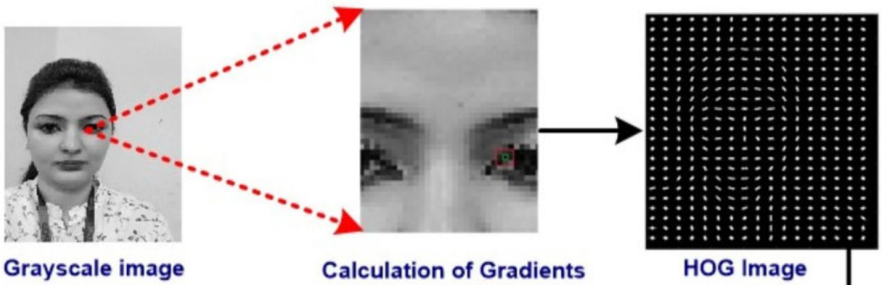


Figure 8. Process and Results of the HOG Method

K-Nearest Neighbor Classification

K-NN compared the HOG descriptor of a test image with descriptors from enrolled faces. Euclidean distance provided the similarity measure, and neighboring training samples were used to assign an employee class, following Equation (5) [15]. An unknown-class outcome is also reported in the evaluation, but the study does not specify its distance threshold, decision rule or final value of K. These implementation details are necessary to replicate the balance between correctly rejecting unregistered people and recognizing legitimate employees.

$$d(x,y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \qquad (5)$$

In Equation (5), d(x,y) represents the Euclidean distance between feature vectors x and y across indexed coordinates. The accompanying grayscale-image example illustrates a distance calculation but does not supply the actual neighbor distances or an acceptance threshold for any of the 27 test participants.

Particle Swarm Optimization

PSO was described as a search procedure for K-NN parameter selection [12]. Candidate particles were initialized and evaluated according to a fitness function, while particle-specific best positions (Pbest) and the swarm-wide best position (Gbest) guided successive updates. Equations (6) and (7) preserve the reported velocity and position rules. Applications of PSO-K-NN in other prediction domains demonstrate the rationale for exploring this combination but do not establish its benefit for the attendance data evaluated here [42]. The available implementation report does not state the search ranges, swarm size, fitness criterion, stopping conditions or optimized parameter values.

$$v_i^t = v_i^{t-1} + c_1 r_1 (x_i^L - x_i^{t-1}) + c_2 r_2 (x^G - x_i^{t-1}) \quad (6)$$

$$x_i^t = v_i^t + x_i^{t-1} \quad (7)$$

Here, x_i^L indicates a particle's best recorded position, x^G the swarm-wide best position, c_1 and c_2 learning coefficients, and r_1 and r_2 random values between zero and one. Because no corresponding unoptimized K-NN output is presented, the effect of the parameter-search stage on recognition accuracy cannot be isolated from the reported results.

Detailed Algorithm Flowcharts

Figures 9–11 present the detailed enrollment, training, attendance-decision, HOG feature-extraction and K-NN classification sequences. They complement the broader workflow by describing the intended processing logic. These flowcharts document system organization but do not substitute for numerical configuration details or independent comparative experiments.

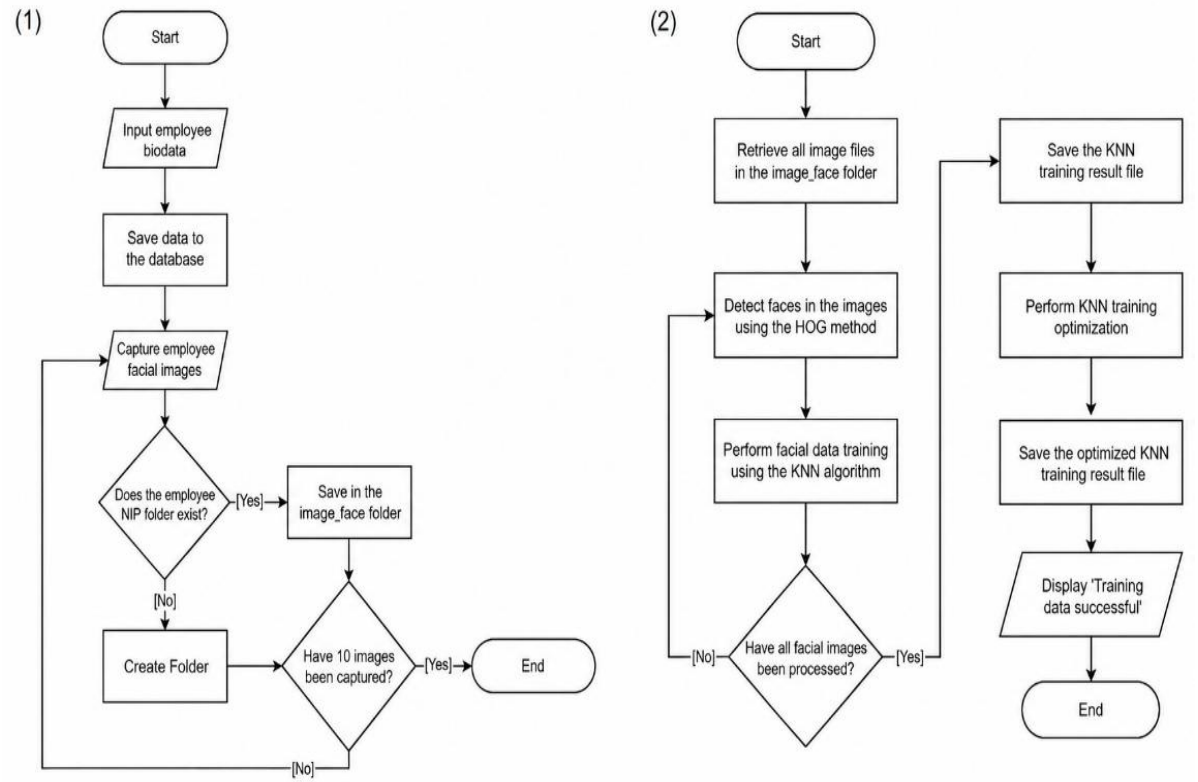


Figure 9. (1) Dataset Collection Flowchart, (2) Dataset Training Flowchart

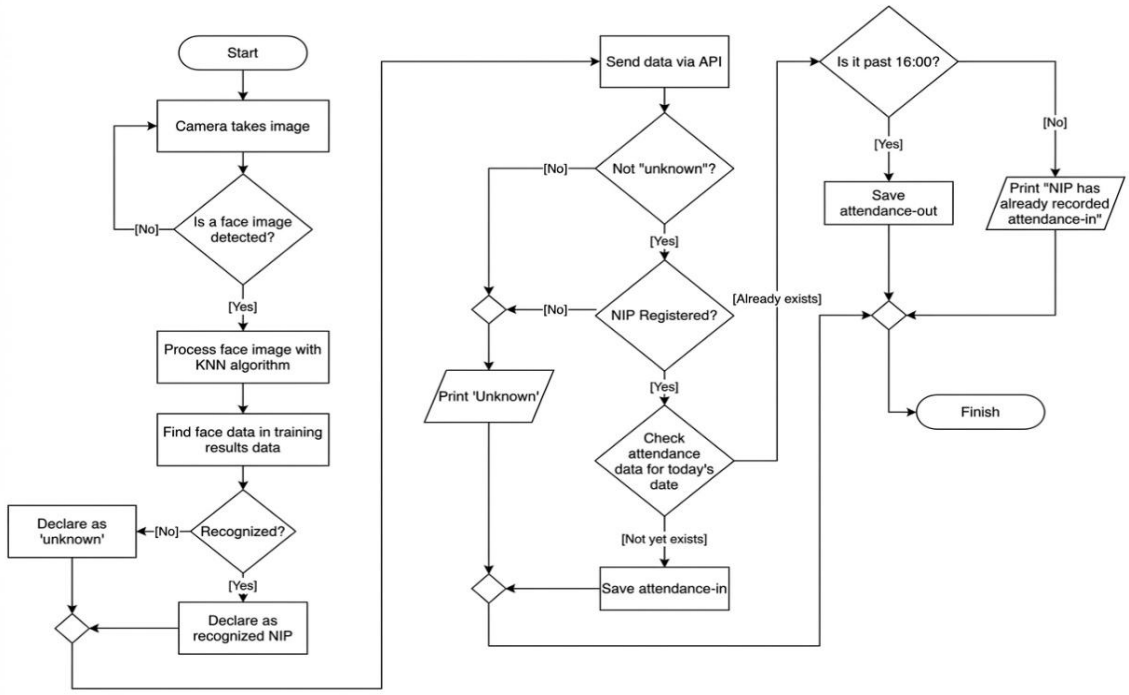


Figure 10. Attendance Process Flowchart

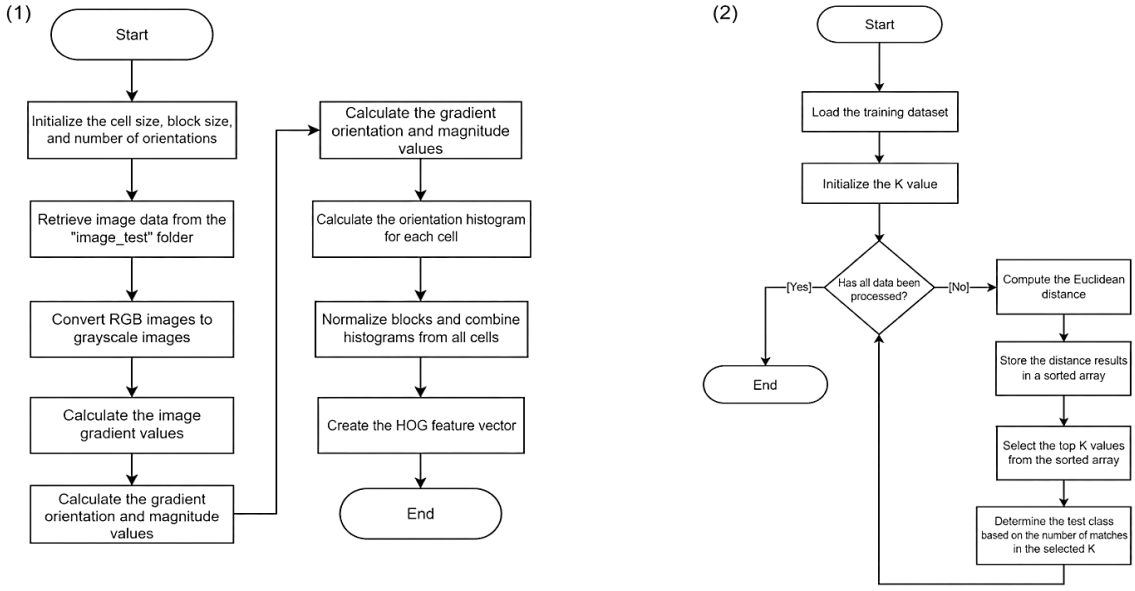


Figure 11. (1) Histogram of Oriented Gradients Flowchart, (2) K-NN Method Flowchart

Testing Procedure

The evaluation included 27 facial images, one image from each of 27 people: 20 enrolled employees and seven individuals not represented in the enrollment set. Each image was processed by the reported HOG and K-NN with PSO pipeline and compared with the expected employee identifier or the unknown label. Table 2 provides the image-level outcomes and Table 3 presents the corresponding registered-versus-unregistered confusion matrix. The reported values were 18 true positives, zero false positives, two false negatives and seven true negatives, giving 92.6% accuracy. Repeated measurements per participant, a matched K-NN-only comparison and a standardized live-versus-photograph test were not part of the reported quantitative evaluation.

RESULTS

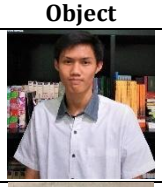
Program Testing

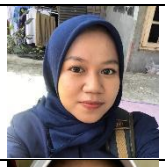
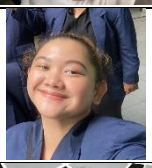
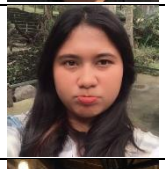
The image-based test examined whether the prototype assigned each image to the expected enrolled identity or to the unknown class. Twenty-seven images from distinct participants were evaluated, and the individual outcomes appear in Table 2. Although the system was designed to record attendance automatically, the accuracy test primarily documents facial recognition rather than continuous entrance-event performance.

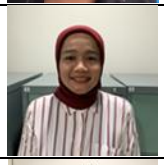
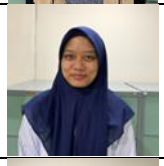
1. Accuracy Test Results

Table 2 presents the expected and system-generated outcomes for all 27 test participants. Correct agreement was observed in 25 cases, while the two mismatches were enrolled people assigned to the unknown class.

Table 2. Accuracy Test Results

No.	Object	Name	Expected results	Detection Results	Test Results
1		Participant 1	240101	240101	In accordance
2		Participant 2	240102	240102	In accordance
3		Participant 3	240111	240111	In accordance
4		Participant 4	unknown	unknown	In accordance
5		Participant 5	240106	240106	In accordance
6		Participant 6	240112	240112	In accordance
7		Participant 7	240107	Unknown	It is not in accordance with
8		Participant 8	240109	240109	In accordance

9		Participant 9	240113	240113	In accordance
10		Participant 10	240115	240115	In accordance
11		Participant 11	240114	240114	In accordance
12		Participant 12	240104	240104	In accordance
13		Participant 13	240110	240110	In accordance
14		Participant 14	240103	240103	In accordance
15		Participant 15	unknown	unknown	In accordance
16		Participant 16	unknown	unknown	In accordance
17		Participant 17	unknown	unknown	In accordance
18		Participant 18	unknown	unknown	In accordance
19		Participant 19	unknown	unknown	In accordance

20		Participant 20	unknown	unknown	In accordance
21		Participant 21	240088	unknown	It is not in accordance with
22		Participant 22	250002	250002	In accordance
23		Participant 23	250017	250017	In accordance
24		Participant 24	250015	250015	In accordance
25		Participant 25	250023	250023	In accordance
26		Participant 26	250027	250027	In accordance
27		Participant 27	250025	250025	In accordance

The resulting recognition-versus-unknown confusion matrix contains 18 true positives, 0 false positives, 2 false negatives and 7 true negatives (N = 27).

Table 3. Confusion Matrix

N = 27		**Actual Value**	
		Positive	**Negative**
Prediction	**Positive**	18 (TP)	0 (FP)
	Negative	2 (FN)	7 (TN)

The resulting accuracy was (18 + 7) / 27 = 92.6% after rounding. This value summarizes agreement with expected outcomes among the 27 evaluated images; it does not represent a validated estimate of continuous attendance-event reliability or resistance to spoofing.

$$Accuracy = \frac{(TP + TN)}{(TP + FP + FN + TN)} = \frac{18 + 7}{18 + 0 + 2 + 7}$$

$$Accuracy = \frac{25}{27} \times 100\% = 92.6\%$$

Discussion

The experimental evaluation achieved an overall image-level accuracy of 92.6%, with 25 correct outcomes among 27 test images. Specifically, 18 of the 20 enrolled employees were correctly recognized, corresponding to a recognition rate of 90.0%, while all seven unregistered individuals were correctly classified as unknown. Although these findings indicate encouraging preliminary recognition performance, the two false rejections highlight the possibility of attendance omissions among legitimate employees. Furthermore, the limited number of test images, particularly those representing unregistered individuals, restricts the generalizability of the observed recognition and rejection rates to broader operational environments. This error pattern is relevant to attendance because a false rejection may require an employee to verify or correct a missing record. It is not equivalent to reliable end-to-end attendance performance, since the reported test did not measure repeated camera passages or database-event timing. Previous attendance implementations show how recognition can be connected to logged events, but use different system configurations and evaluation protocols [3], [16]. The present result therefore supports prototype feasibility under the tested conditions, not superiority over those systems.

The two observed mismatches involved enrolled identifiers 240107 and 240088, both labeled unknown. Enrollment therefore did not guarantee later recognition under the conditions in which the test images were acquired. Pose, illumination, camera angle, facial sharpness and alignment may change HOG representations and K-NN distances, although the study did not determine which factor caused either mismatch. Previous research has described the effects of imaging conditions, masking and degraded image quality on facial recognition [4], [5], [6], [20], [24], [29]. The nine enrollment images per employee included varied poses, but their incremental contribution was not isolated experimentally. The appropriate inference is that recognition of enrolled people remained imperfect in this small test, with acquisition conditions representing plausible rather than established causes.

HOG contributes a fixed, gradient-based feature representation to the recognition pipeline. Its local edge histograms can support comparisons when the crop, orientation and scale of input images are sufficiently consistent, and HOG has been used in camera-based face recognition [10], [13]. Nevertheless, handcrafted descriptors do not automatically accommodate major changes in view angle, occlusion or facial alignment. Surveys of both traditional and learned features describe these trade-offs and the importance of testing algorithms on comparable datasets [21], [22], [23]. The present study reports one HOG configuration but does not vary its cell dimensions, block settings or preprocessing stages. It is therefore reasonable to interpret HOG as an implemented feature-extraction choice, not as an experimentally identified best descriptor.

K-NN assigned labels by comparing HOG descriptors with nearby enrollment samples. This choice is straightforward for a modest enrollment set, but results depend on the distance metric, neighbor count and rule used to reject unfamiliar faces [7], [8], [15]. In the reported tests, every unregistered input was rejected, while two registered faces were also labeled unknown. Broader methodological reviews note that descriptor choice and evaluation protocols can affect comparison between face-recognition methods [21], [22], [23]. The absence of the final

neighborhood parameter (K), the unknown-class rejection threshold, and the corresponding parameter-selection procedure represents an important limitation for methodological reproducibility. These unspecified settings prevent an independent examination of how the classifier balances the recognition of enrolled employees against the rejection of unfamiliar faces. Although two enrolled employees were incorrectly classified as unknown, the available evidence does not establish whether these errors resulted from parameter configuration, descriptor variability, or image-acquisition conditions. Future evaluations should therefore document the complete classification settings and examine individual recognition distances to clarify the mechanisms underlying false rejection.

PSO formed part of the reported K-NN parameter-selection process, but the evaluation presented outcomes for the integrated pipeline only. Without a matched K-NN-only result on the same training and test data, no improvement attributable specifically to PSO can be calculated. PSO-K-NN has been studied in other classification and prediction contexts [12], [42], yet results from those domains are not direct evidence for face-recognition performance. The unspecified fitness function, search bounds and selected parameter values also limit methodological reproducibility. The integration of PSO into the K-NN parameter-selection process demonstrates the implementation of an optimization-oriented recognition framework; however, its independent contribution to classification performance remains empirically undetermined. Because the evaluation did not include a conventional K-NN baseline tested under identical conditions, the reported accuracy cannot be attributed specifically to the optimization stage. A controlled comparative evaluation involving optimized and non-optimized K-NN configurations, identical training and testing partitions, and consistent performance metrics would be necessary to determine whether PSO improves recognition accuracy, reduces classification errors, or changes computational requirements. Accordingly, the present findings establish the implementation feasibility of the integrated framework rather than the demonstrated superiority of PSO-assisted classification.

All seven unregistered participants were classified as unknown, with no acceptance of an unregistered identity in this limited image test. This outcome does not establish resistance to attacks in which an enrolled person's face is shown on a photograph or screen. The reported response of the prototype to facial images presented through photographs raises an important concern regarding its vulnerability to presentation attacks. Although this observation suggests that the current recognition pipeline does not independently establish whether an observed face belongs to a physically present individual, the available evidence does not determine whether photographic inputs successfully generated accepted employee identities or attendance records. Consequently, the observed recognition accuracy should not be interpreted as evidence of biometric security or effective spoofing resistance. Future development should incorporate a dedicated liveness-verification mechanism and evaluate its effectiveness through controlled experiments involving genuine facial presentations, printed photographs, and digital replay attacks before the system is considered suitable for security-sensitive attendance applications. Research on face presentation-attack detection distinguishes live faces from print and replay attacks [11], [17], [25], [26]. Proposed countermeasures include person-specific verification, domain-adaptive models, feature-fusion architectures and texture-sensitive spoofing detection [28], [32], [33], [41], while synthetic-image and wider biometric-spoofing studies describe additional threats [27], [36], [37]. These approaches were not implemented or tested in this prototype, so the zero false positives for unenrolled individuals must not be interpreted as a security-performance measure.

The passive entrance design is intended to reduce attendance omissions associated with failing to interact with a conventional terminal. The same design may increase variation in face orientation, movement and camera distance when employees pass without stopping. Comparable

contactless and portable attendance systems emphasize the need to consider processing time and log reliability in addition to recognition correctness [2], [3], [16]. The presented system flowcharts connect identification to morning and afternoon rules and contain a duplicate-record check, but the reported experiment did not quantify these functions over repeated attendance events. Thus, it cannot establish missed-passage frequency, event latency, duplicate-record incidence or stable operation with a larger employee population. These operational measures remain separate from the image-classification result reported here.

The use of employee identifiers, stored face photographs and an attendance database also raises questions about biometric information handling. Technical work on privacy-preserving recognition and synthetic biometric data highlights approaches to reducing exposure or reliance on identifiable facial information [30], [31], [38]. However, this study does not report access-control testing, retention periods, a formal privacy assessment or a security audit of the stored data. Consequently, successful recognition should not be equated with secure biometric-data management. Prior to broader deployment, institutional procedures for collection, image publication consent, storage and authorized access would need to be established and documented.

Taken together, the results provide a preliminary functional assessment of a HOG-K-NN-PSO attendance prototype, not a controlled validation of the improvement attributable to the algorithmic combination. The observed 92.6% accuracy applies to 27 test images and cannot be extrapolated directly to movement, different cameras or more varied facial presentations. Reviews of face recognition, face forgery and anti-spoofing recommend broader conditions and explicit attack protocols for evaluating reliability and security [17], [18], [19], [20], [21], [22], [23], [34], [35], [39], [40]. The present study contributes a concrete prototype workflow and documents two false rejections together with a qualitative photo-presentation vulnerability. It does not establish improved K-NN accuracy from PSO, quantify anti-spoofing performance or measure attendance events under sustained operation. Those questions require further experiments and implementation records rather than stronger wording of the present findings.

This study developed an employee-attendance prototype integrating HOG-based facial descriptors, K-NN classification and a PSO-based parameter-search stage. From 180 enrollment images of 20 employees, the system was evaluated using 27 test images, including seven individuals not present in the training set. The reported outcomes were 18 true positives, seven true negatives, two false negatives and no false positives, corresponding to 92.6% accuracy. These findings support image-level recognition feasibility under the tested conditions but do not demonstrate sustained attendance recording as employees move past the camera. In particular, the limited test set, absent PSO parameter details and missing matched K-NN baseline preclude a reproducible assessment of the optimization stage's separate contribution. The reported ability to respond to faces displayed in photographs also indicates a presentation-attack vulnerability not addressed by the recognition metric. Further research should document the complete parameter configuration, evaluate optimized and unoptimized models on identical data, repeat recognition under different acquisition conditions and separately test attendance-event logging and liveness protection.

AKNOWLEDGMENT

The authors gratefully acknowledge the institutional support, facilities, and access provided during the research process. The authors also thank the employees who participated in the facial image data collection and system testing activities, which contributed to the successful completion of this study.

AUTHOR CONTRIBUTION STATEMENT

MH contributed to the conceptualization of the study, research design, methodology development, supervision, system development planning, interpretation of the results, and preparation of the original manuscript draft. AA contributed to data collection, implementation of the facial-recognition attendance system, experimental testing, data analysis, and interpretation of the research findings. PH contributed to data processing, validation of the experimental results, research documentation, manuscript preparation, and critical revision of the manuscript for clarity and academic quality. All authors reviewed and approved the final version of the manuscript.

AI DISCLOSURE STATEMENT

The authors used ChatGPT during the preparation of this manuscript to assist with English language refinement, sentence clarity, and manuscript organization. The AI tool was not used to generate or modify the research data, experimental results, or statistical findings. After using the tool, the authors thoroughly reviewed and edited the manuscript and take full responsibility for the accuracy and integrity of the published content.

REFERENCES

[1] S. Mus and M. Mustafa, "Aplikasi sistem presensi dosen dan mahasiswa Fakultas Ilmu Pendidikan UNM," EDUSTUDENT: Jurnal Ilmiah Pendidikan dan Pembelajaran, vol. 1, no. 1, pp. 1–7, 2021, doi: 10.26858/edustudent.v1i1.19974.

[2] N. C. Basjaruddin, E. Rakhman, Y. Sudarsa, M. B. Z. Asyikin, and S. Permana, "Attendance system with face recognition, body temperature, and use of mask using Multi-Task Cascaded Convolutional Neural Network (MTCNN) method," Green Intelligent Systems and Applications, vol. 2, no. 2, pp. 71–83, 2022, doi: 10.53623/gisa.v2i2.109.

[3] L. J. Satria, I. F. Kamsin, and N. K. Zainal, "Face-Nest, facial recognition attendance system with timestamp logs: An information system security approach," International Journal of Information and Education Technology, vol. 13, no. 8, pp. 1304–1312, 2023, doi: 10.18178/ijiet.2023.13.8.1932.

[4] I. K. S. Buana, "Penerapan pengenalan wajah untuk aplikasi absensi dengan metode Viola Jones dan algoritam LBPH," Jurnal Media Informatika Budidarma, vol. 5, no. 3, pp. 1008–1017, 2021, doi: 10.30865/mib.v5i3.3008.

[5] F. Tabassum, M. I. Islam, R. T. Khan, and M. R. Amin, "Human face recognition with combination of DWT and machine learning," Journal of King Saud University - Computer and Information Sciences, vol. 34, no. 3, pp. 546–556, 2022, doi: 10.1016/j.jksuci.2020.02.002.

[6] M. Wang and W. Deng, "Deep face recognition: A survey," Neurocomputing, vol. 429, pp. 215–244, 2021, doi: 10.1016/j.neucom.2020.10.081.

[7] S. Sugeng and A. Mulyana, "Sistem absensi menggunakan pengenalan wajah (face recognition) berbasis Web LAN," Jurnal Sisfokom (Sistem Informasi dan Komputer), vol. 11, no. 1, pp. 127–135, 2022, doi: 10.32736/sisfokom.v11i1.1371.

[8] M. M. D. Noya and M. Hardjianto, "Pengenalan citra wajah pada sistem presensi karyawan menggunakan metode K-Nearest Neighbor dan Haversine Formula," Jurnal Telematika MKOM, vol. 15, no. 2, pp. 57–64, 2023.

[9] D. Setiyadi, F. Atabiq, and S. Aisyah, "Sistem presensi karyawan berbasis pengenalan wajah dengan metode Support Vector Machine," Journal of Applied Electrical Engineering, vol. 5, no. 2, pp. 55–62, 2021, doi: 10.30871/jaee.v5i2.3147.

[10] R. Andrea, N. Ikhsan, and Z. Sudirman, "Face recognition using Histogram of Oriented Gradients with TensorFlow in surveillance camera on Raspberry Pi," International Journal of Information Engineering and Electronic Business, vol. 14, no. 1, pp. 46–52, 2022, doi: 10.5815/ijieeb.2022.01.05.

[11] M. A. Hosen, S. H. Moz, M. M. H. Khalid, S. S. Kabir, and S. M. Galib, "Face recognition-based attendance system with anti-spoofing, system alert, and email automation," Radioelectronic and Computer Systems, vol. 2023, no. 2, pp. 119–128, 2023, doi: 10.32620/reks.2023.2.10.
[12] L. Suhartini, M. B. Sulthan, and I. Wahyudi, "Optimasi K-Nearest Neighbor dengan Particle Swarm Optimization untuk memprediksi harga tembakau," Jurnal Aplikasi Teknologi Informasi dan Manajemen (JATIM), vol. 2, no. 2, pp. 82–91, 2021, doi: 10.31102/jatim.v2i2.1293.
[13] A. Gunadarma and K. R. R. Wardani, "Penerapan Histogram of Oriented Gradients, Principal Component Analysis dan AdaBoost untuk sistem pengenalan wajah," Jurnal Telematika, vol. 13, no. 2, pp. 93–98, 2018, doi: 10.61769/telematika.v13i2.225.
[14] Y. Yohannes, M. E. Al Rivan, S. Devella, and M. Meiriyama, "Klasifikasi motif Songket Palembang menggunakan Support Vector Machine berdasarkan Histogram of Oriented Gradients," Jurnal Teknologi Terpadu, vol. 9, no. 2, pp. 143–149, 2023, doi: 10.54914/jtt.v9i2.1032.
[15] A. Yudhana, S. Sunardi, and A. J. S. Hartanta, "Algoritma K-NN dengan Euclidean Distance untuk prediksi hasil penggergajian kayu sengon," Transmisi: Jurnal Ilmiah Teknik Elektro, vol. 22, no. 4, pp. 123–129, 2020, doi: 10.14710/transmisi.22.4.123-129.
[16] Surantha, N., and Sugijakko, B., "Lightweight face recognition-based portable attendance system with liveness detection," Internet of Things, vol. 25, art. 101089, 2024, doi: 10.1016/j.iot.2024.101089.
[17] Sharma, D., and Selwal, A., "A survey on face presentation attack detection mechanisms: Hitherto and future perspectives," Multimedia Systems, vol. 29, no. 3, pp. 1527–1577, 2023, doi: 10.1007/s00530-023-01070-5.
[18] Ham, H., Saptawijaya, A., and Arymurthy, A. M., "Domain generalization and domain adaptation approaches for face anti-spoofing: A survey," IEEE Access, vol. 13, pp. 149390–149408, 2025, doi: 10.1109/ACCESS.2025.3592034.
[19] Xing, H., Tan, S. Y., Qamar, F., and Jiao, Y., "Face anti-spoofing based on deep learning: A comprehensive survey," Applied Sciences, vol. 15, no. 12, art. 6891, 2025, doi: 10.3390/app15126891.
[20] Zhalgas, A., Amirgaliyev, B., and Sovet, A., "Robust face recognition under challenging conditions: A comprehensive review of deep learning methods and challenges," Applied Sciences, vol. 15, no. 17, art. 9390, 2025, doi: 10.3390/app15179390.
[21] Gururaj, H. L., Soundarya, B. C., Priya, S., Shreyas, J., and Flammini, F., "A comprehensive review of face recognition techniques, trends, and challenges," IEEE Access, vol. 12, pp. 107903–107926, 2024, doi: 10.1109/ACCESS.2024.3424933.
[22] EL Fadel, N., "Facial recognition algorithms: A systematic literature review," Journal of Imaging, vol. 11, no. 2, art. 58, 2025, doi: 10.3390/jimaging11020058.
[23] Nemavhola, A., Chibaya, C., and Viriri, S., "A systematic review of CNN architectures, databases, performance metrics, and applications in face recognition," Information, vol. 16, no. 2, art. 107, 2025, doi: 10.3390/info16020107.
[24] Mahmoud, M., Kasem, M. S., and Kang, H.-S., "A comprehensive survey of masked faces: Recognition, detection, and unmasking," Applied Sciences, vol. 14, no. 19, art. 8781, 2024, doi: 10.3390/app14198781.
[25] Kim, S.-H., Jeon, S.-M., and Lee, E. C., "Face biometric spoof detection method using a remote photoplethysmography signal," Sensors, vol. 22, no. 8, art. 3070, 2022, doi: 10.3390/s22083070.
[26] Kong, Y., Li, X., Hao, G., and Liu, C., "Face anti-spoofing method based on residual network with channel attention mechanism," Electronics, vol. 11, no. 19, art. 3056, 2022, doi: 10.3390/electronics11193056.
[27] Li, S., Dutta, V., He, X., and Matsumaru, T., "Deep learning based one-class detection system for fake faces generated by GAN network," Sensors, vol. 22, no. 20, art. 7767, 2022, doi: 10.3390/s22207767.

[28] Li, J., and Sun, W., "A neural network based on supervised multi-view contrastive learning and two-stage feature fusion for face anti-spoofing," Electronics, vol. 13, no. 24, art. 4865, 2024, doi: 10.3390/electronics13244865.
[29] Yang, M., Li, S., and Zeng, J., "The effects of AI-driven face restoration on forensic face recognition," Applied Sciences, vol. 14, no. 9, art. 3783, 2024, doi: 10.3390/app14093783.
[30] Yang, W., Wang, S., Cui, H., Tang, Z., and Li, Y., "A review of homomorphic encryption for privacy-preserving biometrics," Sensors, vol. 23, no. 7, art. 3566, 2023, doi: 10.3390/s23073566.
[31] Hu, W., Zhou, D., Zhu, Z., Qiao, T., Yao, Y., and Hassaballah, M., "Privacy-preserving face recognition method based on extensible feature extraction," Journal of Visual Communication and Image Representation, vol. 100, art. 104140, 2024, doi: 10.1016/j.jvcir.2024.104140.
[32] Pei, M., Yan, B., Hao, H., and Zhao, M., "Person-specific face spoofing detection based on a Siamese network," Pattern Recognition, vol. 135, art. 109148, 2023, doi: 10.1016/j.patcog.2022.109148.
[33] Lin, J.-D., Han, Y.-H., Huang, P.-H., Tan, J., Chen, J.-C., Tanveer, M., and Hua, K.-L., "DEFAEK: Domain effective fast adaptive network for face anti-spoofing," Neural Networks, vol. 161, pp. 83–91, 2023, doi: 10.1016/j.neunet.2023.01.018.
[34] Madi, M., Khammari, M., and Larabi, M.-C., "An overview of face anti-spoofing methods for face recognition systems," Journal of Visual Communication and Image Representation, 2026, art. 104952, doi: 10.1016/j.jvcir.2026.104952.
[35] Thakur, B., Selwal, A., and Sabha, A., "Interpreting face spoofing vulnerabilities and their countermeasures: State-of-the-art and future perspectives," Computer Vision and Image Understanding, vol. 270, art. 104861, 2026, doi: 10.1016/j.cviu.2026.104861.
[36] Ma, L., Yang, P., Xu, Y., Yang, Z., Li, P., and Huang, H., "Deep learning technology for face forgery detection: A survey," Neurocomputing, vol. 618, art. 129055, 2025, doi: 10.1016/j.neucom.2024.129055.
[37] Kumar, S., Rani, S., Jain, A., Verma, C., Raboaca, M. S., Illés, Z., and Neagu, B. C., "Face spoofing, age, gender and facial expression recognition using advance neural network architecture-based biometric system," Sensors, vol. 22, no. 14, art. 5160, 2022, doi: 10.3390/s22145160.
[38] Blümel, F. E., Schulz, M., Breithaupt, R., Jung, N., and Lange, R., "Enhancing resilience in biometric research: Generation of 3D synthetic face data using advanced 3D character creation techniques from high-fidelity video games and animation," Sensors, vol. 24, no. 9, art. 2750, 2024, doi: 10.3390/s24092750.
[39] Antil, A., and Dhiman, C., "Unmasking deception: A comprehensive survey on the evolution of face anti-spoofing methods," Neurocomputing, vol. 617, art. 128992, 2025, doi: 10.1016/j.neucom.2024.128992.
[40] Firc, A., Malinka, K., and Hanáček, P., "Deepfakes as a threat to a speaker and facial recognition: An overview of tools and attack vectors," Heliyon, vol. 9, no. 4, art. e15090, 2023, doi: 10.1016/j.heliyon.2023.e15090.
[41] Jaswanth, P., Chowdary, P. Y., and Ramprasad, M. V. S., "Deep learning based intelligent system for robust face spoofing detection using texture feature measurement," Measurement: Sensors, vol. 29, art. 100868, 2023, doi: 10.1016/j.measen.2023.100868.
[42] Zhu, M., Lin, J., Cao, G., Zhang, J., Zhang, X., Zhou, J., and Gao, Y., "Prediction of constitutive model for basalt fiber reinforced concrete based on PSO-KNN," Heliyon, vol. 10, no. 11, art. e32240, 2024, doi: 10.1016/j.heliyon.2024.e32240.