Face Recognition-Based Attendance System for Village Officials Using YOLOv8n, ArcFace, and Web-Based Microservice Architecture

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Article Info

Article history:
Received Apr 29, 2026
Revised May 12, 2026
Accepted May 20, 2026

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ABSTRACT

The attendance system at Bencah Village has been conducted manually, creating vulnerability to data manipulation, recording errors, and lack of transparency in managing village official attendance data. This study aimed to design and develop a face recognition-based attendance system for Bencah Village officials using deep learning technology, implemented as a web-based platform. The system was developed using the Waterfall Software Development Life Cycle (SDLC) model with a layered microservice architecture, integrating face detection using the lightweight YOLOv8n model, face feature extraction using InsightFace buffalo_l with the ArcFace approach generating 512-dimensional embedding vectors, and identity matching using cosine similarity with a threshold of 0.5. The backend was built with Laravel 12 and Python Flask, containerized using Docker and communicating via REST API. Functional testing using the black-box testing method on 25 main system functions confirmed that all functions performed as expected. Face recognition performance evaluation on 30 test data yielded a Recognition Accuracy of 93.33%, a False Acceptance Rate (FAR) of 0%, and a False Rejection Rate (FRR) of 10%. The FAR of 0% confirmed the system successfully prevented unauthorized identity acceptance, which is critical for attendance data integrity. These results demonstrate the system is feasible as a biometric attendance solution for village government environments.

Keywords: Attendance system, ArcFace, deep learning, face recognition, YOLOv8n

1. INTRODUCTION

Indonesia has approximately 75,265 village government units (desa) nationwide, the majority of which continue to rely on manual paper-based attendance recording methods that are inherently susceptible to data manipulation, human error, and lack of administrative transparency (Badan Pusat Statistik, 2023). A national audit report by the Badan Pemeriksa Keuangan (BPK) identified attendance recording irregularities as one of the top five administrative weaknesses in village government financial management, with manual attendance systems contributing directly to accountability gaps in personnel expenditure reporting. Research by the American Payroll Association further estimated that time and attendance fraud, including proxy attendance, costs organizations up to 2.2% of annual gross payroll (Rahayu et al., 2026), a figure with significant implications for village budget integrity given that personnel costs constitute the largest single expenditure category in most village budgets. Bencah Village represents a typical case where attendance is recorded manually, creating vulnerabilities such as proxy attendance practices and unstructured data management Sinaga et al., (2024) demonstrated that manual attendance systems carry a high vulnerability to attendance data manipulation, while Terampe & Arif Pramudwiatmoko, (2025) confirmed that manual recording mechanisms fail to guarantee sustained accuracy and transparency. Jaini & Asri, (2021) further emphasized that manual attendance systems hinder structured and well-documented management of attendance data, which is fundamentally incompatible with accountable village governance.

Research by Chairul et al., (2025) at the Dungingi Sub-district Office in Gorontalo City found that employee attendance rates after implementing electronic attendance still fluctuated between 81.52% and 91.08% per month, demonstrating that basic digitalization without strong identity verification does not fully resolve discipline challenges. Studies on online attendance systems for civil servants showed that web-based systems can achieve attendance rates reaching 95% with a tardiness rate of only 8% (Muhammad Adzar Al Yaman et al., 2025) , indicating substantial potential when properly implemented. Wahyu Setiya Putra & Fadlil Adhim, 2025) confirmed that web-based attendance systems can significantly accelerate recording and reporting processes, while digital biometric attendance has been shown to enhance transparency and accountability of civil servants (Afni Johannes et al., 2025).

Preliminary observation at Bencah Village revealed that the local government had planned to implement fingerprint-based attendance as an initial digitalization step. However, fingerprint systems carry inherent technical limitations, including reading failures caused by skin condition variations, finger orientation, and humidity levels that affect identification accuracy (Adedoyin et al., 2024). Consequently, face recognition technology has been identified as a more adaptive and contactless biometric alternative (Nurhidayanti, 2025). Face biometrics offer advantages including non-contact acquisition, integration compatibility with computer vision systems, and unique individual characteristics enabling reliable identification (Amirgaliyev et al., 2025).

Advances in deep learning, particularly Convolutional Neural Network (CNN) architectures, have substantially improved face recognition system accuracy. Minaee et al., (2021) showed that CNN-based approaches produce more stable and discriminative facial feature representations compared to conventional methods, while Sahu & Dash, (2021) confirmed that CNN enhances system robustness against lighting and pose variations. Sharma et al., (2025) established that deep learning has become the primary foundation for modern face recognition development. For the face detection stage, Terven et al., (2023) explained that the one-stage detector architecture of YOLO outperforms two-stage detectors in inference time efficiency, making it suitable for real-time applications. Specifically, YOLOv8n achieves a favorable balance between detection accuracy and computational efficiency (Alashrafi et al., 2025; Zhou & Liang, 2025), making it well-suited for resource-constrained environments such as village government offices.

Despite the growing body of research on face recognition-based attendance systems, several critical gaps remain unaddressed in existing literature. First, most implemented systems focus on corporate or university environments and have not been empirically validated in village government contexts, which present distinct operational constraints including limited hardware resources, small staff populations, and the absence of dedicated IT infrastructure (Marvelino Wijaya & Eric Samodra, 2023; Terampe & Arif Pramudwiatmoko, 2025). Second, existing systems commonly require model retraining when new users are enrolled, creating operational barriers in dynamic government settings where staffing changes occur periodically (Rahayu et al., 2026). Third, most face recognition attendance systems operate without location-bound verification, leaving them vulnerable to remote attendance fraud a particularly critical concern in government accountability contexts (Wahyu Setiya Putra & Fadlil Adhim, 2025).

To address these gaps, this study proposes a face recognition-based attendance system specifically designed for village government deployment. The selection of YOLOv8n for face detection is justified by its status as the lightest variant of the YOLOv8 family, achieving a favorable balance between detection accuracy and inference speed on CPU-only hardware without requiring GPU acceleration a critical constraint in village office environments (Alashrafi et al., 2025; Zhou & Liang, 2025). This differentiates the proposed approach from (Terampe & Arif Pramudwiatmoko, 2025), who employed the heavier YOLOv8m variant under GPU-assisted conditions, and from Rahayu et al., (2026), who used MTCNN a two-stage detector with higher computational overhead. The selection of ArcFace via the pre-trained InsightFace buffalo_l model is justified by its superior discriminative embedding properties derived from additive angular margin loss training (Deng et al., 2021), enabling reliable identity matching without task-specific retraining. Cosine similarity was chosen as the identity matching mechanism over classifier-based approaches such as SVM used by Rahayu et al., (2026); Terampe & Arif Pramudwiatmoko, (2025) because it supports dynamic employee enrollment without requiring model retraining, making it operationally superior for village government settings with occasional staff changes.

The novelty of this research is threefold: (1) it is the first empirical study implementing a deep learning face recognition attendance system in a village government context in Indonesia; (2) it integrates GPS-based location validation using the Haversine formula as a second security layer alongside face biometrics, addressing remote attendance fraud that purely biometric systems cannot prevent; and (3) it employs a containerized microservice architecture (Laravel 12 + Python Flask + Docker) enabling reproducible, scalable deployment without GPU dependency a combination not found in any of the compared related works. The system aims to improve identity verification reliability, attendance recording transparency, and data management efficiency for Bencah Village officials.

2. RESEARCH METHOD

Research Design and Development Methodology

This research was conducted at Bencah Village Office, Bangka Belitung Province, Indonesia, in 2026. The study adopted the Software Development Life Cycle (SDLC) Waterfall model as its development methodology, selected because system requirements were clearly defined from the outset, enabling systematic sequential completion of each phase before proceeding to the next (Hossain, 2023; Pargaonkar, 2023). The five development phases were: (1) requirements analysis, (2) system design, (3) implementation, (4) testing, and (5) maintenance.

1.2. System Implementation Environment

The system was developed and tested on a hardware and software environment configured to reflect the resource-constrained conditions typical of village government offices in Indonesia. Table 1 summarizes the complete implementation environment specification.

Table 1. System Implementation Environment Specification

Category	Component	Specification
Hardware	Processor	Intel Core i5 (8th generation, 1.6 GHz base clock)
	RAM	8 GB DDR4
	GPU	None (CPU-only inference via CPUExecutionProvider)
	Camera	Built-in laptop webcam (720p, accessed via browser MediaDevices API)
OS & Runtime	Host OS	Windows 11 (64-bit)
	Containerization	Docker Desktop 4.x (Flask service containerized; Laravel served natively)
Backend	Laravel	Laravel 12 (PHP 8.2), Eloquent ORM, REST API
	Face Recognition Service	Python 3.10, Flask 2.x, ONNX Runtime (CPUExecutionProvider)
	Database	MySQL 8.0 (attendance records, user profiles, face embedding metadata)
Face Recognition Model	Face Detection	YOLOv8n (Ultralytics), input 640×640 px, confidence threshold 0.5
	Feature Extraction	InsightFace buffalo_l (ArcFace R100), pre-trained on MS1MV3, output: 512-dim L2-normalized vector

Category	Component	Specification
	Identity Matching	Cosine similarity; recognition threshold = 0.5; computed per-frame against stored reference embeddings
Frontend	UI Framework	Tailwind CSS 3.x, Alpine.js 3.x; camera via MediaDevices API (WebRTC), frame capture at 300 ms intervals
Face Registration	Photos per subject	6 photographs per official under controlled indoor conditions (ambient lighting ≥ 200 lux, camera distance 50–80 cm); orientations: frontal, left tilt 15°, right tilt 15°, upward tilt 10°, downward tilt 10°, slight rotation 20°

The face recognition service was intentionally designed for CPU-only inference to ensure deployability in village government environments where dedicated GPU hardware is unavailable. The InsightFace buffalo_l model was loaded using ONNX Runtime with CPUExecutionProvider, consistent with the deployment approach described by (Setiawan Fajar.M et al., 2025). Face frames captured from the browser were transmitted as base64-encoded JPEG images via REST API to the Flask service at the /recognize_frame endpoint. The YOLOv8n model was initialized at system startup and held in memory throughout the session to avoid repeated loading overhead. Frame capture intervals were set to 300 milliseconds on the client side, balancing responsiveness with server processing capacity under CPU-only conditions.

1.3. Face Recognition Pipeline

The face recognition pipeline consisted of three integrated sequential stages. In the first stage, face detection was performed using YOLOv8n, the lightest variant of the YOLOv8 architecture. YOLOv8 adopts an anchor-free detection approach with a modular backbone-neck-head structure enabling efficient multi-scale feature extraction (Yaseen, 2024). YOLOv8n was selected for its balance between detection accuracy and computational efficiency in real-time resource-constrained applications (Alashrafi et al., 2025; Zhou & Liang, 2025). Detected face frames were passed to the recognition service via the/recognize frame REST API endpoint. In the second stage, face feature extraction was performed using InsightFace buffalo_l, implementing the ArcFace approach. ArcFace employs additive angular margin loss during neural network training to enhance class separation and minimize intra-class variation, producing 512-dimensional embedding vectors that provide more discriminative facial representations compared to earlier methods (Deng et al., 2021). The pre-trained InsightFace framework enables efficient embedding extraction without training from scratch, supporting integration into web-based biometric applications (Setiawan Fajar.M et al., 2025).

In the third stage, identity matching was performed using cosine similarity, which measures the cosine of the angle between two embedding vectors in high-dimensional feature space. This metric focuses on vector orientation rather than magnitude, making it well-suited for comparing normalized ArcFace embeddings (Deng et al., 2021; Wang et al., 2018). The cosine similarity formula is:

$$\text{Cosine Similarity}(A,B) = (A \cdot B) / (\|A\| \times \|B\|)$$

where A is the face embedding vector of the detected face and B is the stored reference embedding. A threshold of 0.5 was applied: scores at or above the threshold indicated a recognized identity, while scores below resulted in rejection. This threshold value was determined based on two considerations. First, the discriminative embedding properties of ArcFace models trained with additive angular margin loss produce high intra-class cosine similarity (typically above 0.6 for same-identity pairs) and low inter-class similarity (typically below 0.4 for different-identity pairs), establishing a natural decision boundary around 0.5 (Deng et al., 2021). Second, this value is consistent with the threshold range employed in comparable ArcFace-based attendance system implementations, where Terampe & Arif Pramudwiatmoko, (2025) reported effective identity separation using a threshold of 0.5 in a YOLOv8-ArcFace-SVM pipeline operating under similar real-time constraints. A stricter threshold would increase FRR under occlusion conditions, while a more lenient threshold risks increasing FAR;

the 0.5 value prioritizes zero unauthorized access, which is the primary security requirement for government attendance systems. Each village official's face was registered using six photographs capturing varied head orientations to improve recognition robustness.

1.4. System Evaluation

System evaluation was conducted through two methods. First, functional testing used the black-box testing method on 25 main system functions covering the complete workflow from login to export and backup operations, with each test case defining specific input conditions and expected outputs. Second, face recognition performance evaluation was conducted on 30 test data comprising 20 registered face tests (10 subjects, 2 scenarios each) and 10 unregistered face tests. Test scenarios covered frontal pose, head tilts in multiple directions, closed eyes, glasses, mask usage, and inadequate lighting. Performance was quantified using Recognition Accuracy = (TP + TN) / Total × 100%, FAR = FP / (FP + TN) × 100%, and FRR = FN / (FN + TP) × 100%.

3. RESULT AND ANALYSIS

2.1. System Implementation

The face recognition-based attendance system was successfully implemented as a fully functional web-based platform. The village official interface enables attendance marking via real-time face recognition through the browser camera, absence request submission with document attachments, personal attendance history access, leave quota monitoring, and profile management. The administrator interface provides comprehensive management including real-time attendance monitoring for all village officials, absence request approval or rejection, working hour configuration, GPS location reference configuration, face recognition threshold configuration, face registration management, and Excel attendance report export with three sheets: detailed attendance, per-employee summary, and overall summary.

The system automatically detects and marks three attendance status conditions: tardiness, overtime, and early departure, computed from the difference between actual attendance time and configured working hours, displayed as color-coded badges in the administrator's attendance table. The GPS validation layer prevents out-of-area attendance recording, with GPS accuracy verification to prevent location spoofing via network-based positioning. This layered security approach combining face biometrics and GPS validation implements a defense-in-depth principle, ensuring neither mechanism alone can be bypassed without circumventing the other.

2.2. Learning Outcome Analysis

Functional testing using the black-box method was applied to 25 main system functions spanning the complete system workflow.

Table 2. Presents the categorized summary of testing results

No.	Test Category	Scenarios Covered	Result
1	Authentication & Login	Valid login, invalid credentials, empty field validation	All Pass (3/3)
2	Face Recognition Attendance	Recognized face with valid location, unrecognized face, out-of-area location, low GPS accuracy	All Pass (4/4)
3	Absence Management	Complete submission, incomplete submission, admin approval, admin rejection, real-time notification	All Pass (5/5)

4	Administrator Data Management	Face registration, data monitoring, employee management, announcements, report export	All Pass (8/8)
5	System Configuration	Working hours, GPS location, face recognition threshold, leave policy, backup & maintenance	All Pass (4/4)
6	Session Management	Logout functionality	All Pass (1/1)

All 25 tested functions produced outputs matching defined expectations, with no errors found across any test scenario. Testing covered both positive cases (valid inputs producing correct outputs) and negative cases (invalid inputs correctly triggering error responses or rejections). The successful integration between Laravel and Flask was confirmed across all scenarios, including cases where the face recognition service returned negative responses such as unrecognized faces or insufficiently detected faces. These results confirm the system has met all defined functional requirements.

2.3. Discussion: ECL Level and Design Implications

Face recognition performance was evaluated on 30 test data: 20 registered face tests covering 10 subjects under 2 condition scenarios each, and 10 unregistered face tests under standard frontal conditions. Test conditions spanned frontal pose, head tilts in four directions, closed eyes, glasses, mask usage, and inadequate lighting. Tables 3 and 4 present the evaluation results.

Table 3. Face Recognition Test Result Recapitulation

Code	Count	Description
TP (True Positive)	18	Registered face → correctly recognized by system
TN (True Negative)	10	Unregistered face → correctly rejected by system
FN (False Negative)	2	Registered face → not recognized by system
FP (False Positive)	0	Unregistered face → incorrectly accepted by system

Table 4. Face Recognition Performance Metrics

Metric	Formula	Calculation	Value
Recognition Accuracy	(TP + TN) / Total × 100%	(18 + 10) / 30 × 100%	93.33%
False Acceptance Rate (FAR)	FP / (FP + TN) × 100%	0 / (0 + 10) × 100%	0%
False Rejection Rate (FRR)	FN / (FN + TP) × 100%	2 / (2 + 18) × 100%	10%

The system achieved a Recognition Accuracy of 93.33%, an FAR of 0%, and an FRR of 10%. The FAR of 0% is the most critical security outcome, confirming that no unregistered face was incorrectly accepted as a valid identity throughout the entire evaluation. In attendance systems, false acceptance directly compromises data integrity by enabling fraudulent attendance recording. The cosine similarity threshold of 0.5 proved effective in maintaining this strict security boundary, consistent with the discriminative embedding properties established by (Deng et al., 2021) for ArcFace-based models.

The two False Negative cases contributing to the 10% FRR both stemmed from specific, technically explainable conditions. The first case involved a subject tested while wearing a mask, which covered the lower facial region including the nose and mouth areas providing critical discriminative features for the InsightFace buffalo_l model. The reduced available facial information caused the resulting embedding vector to diverge significantly from the registered reference embedding (captured without a mask), pushing the cosine similarity score below the 0.5 threshold. This finding is consistent with Sharma et al., (2025), who identified facial occlusion as a primary challenge for deep learning-based face recognition systems. The second case involved a subject tested under inadequate lighting conditions, where degraded frame quality prevented optimal facial texture detail extraction for accurate embedding generation.

Under standard operating conditions adequate lighting, no facial accessories, and unobstructed camera view the system demonstrated perfect recognition across all tested pose variations including head tilts in four directions, closed eyes, and glasses usage. These results align with findings by Minaee et al., (2021) and Sahu and Sahu & Dash, (2021) that CNN-based face recognition is robust against pose variations but faces challenges under significant occlusion. The YOLOv8n face detection stage performed consistently across all conditions, confirming its suitability for real-time village governance applications as established by Alashrafi et al., (2025); Zhou & Liang, (2025).

It is acknowledged that the evaluation dataset, comprising 30 test samples from 10 registered subjects, represents a limitation of this study in terms of generalizability. The subject count of 10 directly reflects the total active official staff of Bencah Village at the time of the study, meaning the evaluation covered 100% of the system's intended user population in its deployment context rather than a sample drawn from a larger pool. Face registration was conducted under controlled indoor conditions with ambient lighting of approximately 200–300 lux and a camera-to-subject distance of 50–80 cm, with each subject photographed across six head orientations (frontal, bilateral 15° tilts, 10° vertical tilts, and 20° rotation) to improve embedding robustness. Nevertheless, the small absolute subject count limits the statistical confidence of the reported FAR, FRR, and accuracy metrics, and caution should be exercised when generalizing these results to deployments with larger or more demographically diverse staff populations. Future evaluations should expand the test set to include a larger and more demographically varied subject pool to strengthen validity, consistent with recommendations from comparable early-stage deployment studies including Marvelino Wijaya & Eric Samodra, (2023).

Regarding real-time processing performance, the system operated at an estimated end-to-end latency of 2–4 seconds per recognition cycle under CPU-only inference conditions, encompassing frame capture, base64 encoding and transmission via REST API, YOLOv8n face detection, InsightFace ArcFace embedding extraction, and cosine similarity matching. The YOLOv8n detection stage alone required approximately 80–150 ms per frame on the test hardware, consistent with benchmarks reported by Alashrafi et al., (2025) for lightweight YOLO variants on CPU. This latency profile is acceptable for attendance recording use cases, where recognition is triggered once per attendance event rather than continuously. For reference, Rahayu et al. (2026) reported 10–15 FPS on comparable CPU hardware using a similar MTCNN-ArcFace pipeline, while Terampe & Arif Pramudwiatmoko, (2025) achieved 7.2 FPS using YOLOv8m-ArcFace-SVM under GPU-assisted conditions. Formal FPS benchmarking using dedicated profiling tools is identified as a direction for future work to provide more precise performance characterization.

Three operational limitations of the present system warrant quantification for practical deployment guidance. First, regarding recognition distance, the system was evaluated at a camera-to-subject distance of 50–80 cm through a browser-based webcam interface. At distances exceeding approximately 100 cm, the YOLOv8n face detection confidence dropped below the 0.5 threshold under standard indoor lighting, resulting in failed detections. This constrains the system to close-proximity attendance scenarios rather than walk-by or wide-angle configurations. Second, regarding lighting conditions, recognition performance was maintained under ambient lighting of approximately 200 lux and above, corresponding to typical indoor office illumination. Under the inadequate lighting condition tested (estimated below 100 lux), embedding quality degraded sufficiently to produce a false negative, as reported in the FRR analysis above. Deployments in poorly lit environments should supplement ambient lighting or implement frame quality checks prior to recognition attempts. Third, regarding anti-spoofing, the current implementation does not include liveness detection; consequently, the system does not distinguish between a live face and a static photograph, which represents a security vulnerability that should be addressed in future iterations through mechanisms such as blink detection as demonstrated by Rahayu et al., (2026).

2.4. Comparison with Related Work

To assess the contribution and positioning of the proposed system, a structured comparison with four related studies is presented in Table 5. The studies were selected based on their relevance to face recognition-based attendance systems and overlapping technological components.

Table 5. Comparison with Related Studies

Aspect	Marvelino Wijaya & Eric Samodra (2023)	Wahyu Setiya Putra & Fadlil Adhim (2025)	Terampe & Arif Pramudwiatmoko (2025)	Rahayu et al. (2026)	Proposed Study	Key Advantage
Face Detection	CNN (custom)	Not specified	YOLOv8m	MTCNN	YOLOv8n (lightest)	Real-time efficiency on low-resource hardware
Feature Extraction	CNN embedding	Not ArcFace	ArcFace 512-dim	ArcFace 512-dim	ArcFace 512-dim (InsightFace buffalo_l)	Pre-trained; no retraining for new employees
Identity Matching	Softmax classifier	Not specified	SVM (Polynomial)	SVM (Sigmoid)	Cosine Similarity (threshold 0.5)	Dynamic enrollment; no retraining required
Anti-Spoofing	None	None	None	Blink Detection (EAR, MediaPipe, threshold 0.27)	Planned (Future Work)	Rahayu et al. (2026) confirms EAR-based liveness effectiveness
GPS Location Validation	No	Yes	No	No	Yes (Haversine formula)	Prevents remote/out-of-area fraud; defense-in-depth
System Architecture	Monolithic	Web-based	Desktop / CCTV	Desktop real-time	Layered microservice (Laravel + Flask + Docker)	Containerized; reproducible; scalable
Performance Metrics	Not reported	Not reported	93.7% acc; 7.2 FPS	95% acc; 10–15 FPS; Precision 95.86%	93.33% acc; FAR 0%; FRR 10%	FAR 0% = zero unauthorized access; critical for government integrity
Deployment Context	Government office	Civil servants	Corporate (CCTV, 3m height)	Corporate (25 employee classes)	Village governance (Bencah Village, Indonesia)	First empirical study in village government biometric attendance

As shown in Table 5, the proposed system occupies a distinct position among related works through the combination of several differentiating characteristics. First, regarding face detection, the use of YOLOv8n the lightest variant of the YOLOv8 family provides computational efficiency advantages over the YOLOv8m employed by Terampe & Arif Pramudwiatmoko, (2025) and the non-standard CNN architecture used by Marvelino Wijaya & Eric Samodra, (2023), making the proposed system better suited for resource-constrained environments. Second, by employing cosine similarity with a pre-trained InsightFace buffalo_l model rather than a trained SVM classifier as Terampe & Arif Pramudwiatmoko, (2025) and Rahayu et al., (2026), the proposed system eliminates the need for model retraining when new employees are enrolled, reducing onboarding time significantly. Third, the integration of GPS-based location validation using the Haversine formula shared only with Wahyu Setiya Putra & Fadlil Adhim, (2025) among the compared studies introduces a defense-in-depth security layer that prevents out-of-area attendance recording, a critical concern in government accountability settings. Fourth, the containerized microservice architecture (Laravel 12 + Python Flask + Docker) distinguishes the proposed system from all compared studies in terms of deployment reproducibility and scalability. Finally, the present study contributes empirical evaluation specifically targeting the village government context in Indonesia, a deployment domain not addressed by any of the compared works.

A notable limitation acknowledged in the Future Work section is the absence of an anti-spoofing mechanism. Rahayu et al., (2026) demonstrated that blink detection using Eye Aspect Ratio (EAR) with a threshold of 0.27 via MediaPipe Face Mesh effectively prevented print attacks in a comparable attendance context, achieving 10–15 FPS with 95% recognition accuracy across 25 employee classes. This finding provides direct empirical support for integrating liveness detection as a priority enhancement to the present system. Furthermore, while (Terampe & Arif Pramudwiatmoko, 2025) reported 93.7% accuracy with 7.2 FPS using a YOLOv8m-ArcFace-SVM pipeline, the present study achieves a comparable recognition accuracy of 93.33% while attaining a FAR of 0%, indicating a stronger prioritization of attendance security integrity through strict threshold enforcement a more critical criterion in government attendance management than raw accuracy alone.

3. CONCLUSION

This study successfully designed, developed, and evaluated a face recognition-based attendance system for Bencah Village officials as a web-based platform. The system integrated real-time face detection using YOLOv8n, 512-dimensional face embedding extraction via InsightFace buffalo_l with ArcFace, and cosine similarity-based identity matching within a microservice architecture using Laravel 12 and containerized Python Flask. Black-box functional testing on 25 main functions confirmed all features operate correctly. Face recognition performance evaluation on 30 test data yielded a Recognition Accuracy of 93.33%, an FAR of 0%, and an FRR of 10%. The FAR of 0% demonstrates effective prevention of unauthorized identity acceptance, confirming the system's suitability as a biometric attendance solution for village governance environments previously relying on manual methods.

Future work should focus on: (1) enriching face registration data with varied lighting conditions to reduce FRR; (2) exploring adaptive per-individual cosine similarity thresholds; (3) implementing liveness detection to prevent photo/video spoofing attacks; (4) integrating automated attendance event notifications; and (5) extending the system toward a multi-tenant architecture capable of serving multiple village government units simultaneously.

ACKNOWLEDGEMENTS

The author gratefully acknowledges the guidance of supervisors Zikri Wahyuzi, S.T., M.Kom and Arvi Pramudyantoro, M.Kom, and the leadership of Yudistira Bagus Pratama, M.Kom as Head of the Computer Science Study Program, Universitas Muhammadiyah Bangka Belitung. The author also thanks the Bencah Village Office administration for their cooperation and support during data collection and system deployment.

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