International Journal of Informatics and Computation (IJICOM)
Vol. 8, No. 1, 2026
ISSN: 2685-8711, E-ISSN: 2714-5263 DOI: 10.35842/ijicom

Enhancing Face-Based Detection of Attendance Validation System

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Abstract

Attendance systems are essential for organizational compliance but often rely on non-visual mechanisms, such as QR codes or location verification. These conventional methods remain vulnerable to invalid attendance records, such as proxy attendance. This study investigates the implementation of a face-based detection approach for a web-based attendance validation system. It integrates facial image capture with QR code interaction, location verification, and time-based logging. The system utilizes lightweight 1:1 facial verification to confirm the physical presence of users during attendance events. Each attendance attempt records a facial image, timestamp, geographic coordinates, and attendance type to ensure that validation occurs only when all constraints are satisfied. Experimental evaluation involves 100 attendance attempts under three validation scenarios: normal conditions, facial occlusion cases, and invalid location attempts. Under normal conditions, the system correctly validates 48 out of 50 legitimate attendance attempts, achieving 96.0% accuracy, with two false rejections caused by temporary lighting limitations during image capture. For invalid scenarios, the system successfully rejects all 30 attempts involving facial occlusions such as masks, hats, and glasses, achieving 100% rejection accuracy. Similarly, all 20 attempts conducted outside the authorized geographic radius are blocked, also achieving a 100% rejection rate. Overall, the integrated validation framework achieves a system-level accuracy of 98.0%. The results demonstrate that face-based presence detection can provide a reliable mechanism for attendance validation.

Keywords:
Detection, Face-Based Presence, Location, Time, Verification

1. Introduction

Face recognition technology has become an important component in modern biometric authentication systems, particularly in applications such as attendance validation, access control, and identity verification. Traditional attendance systems often rely on manual signatures, identification cards, or fingerprint scanners, which are prone to human error, time inefficiency, and fraudulent practices such as proxy attendance. Face-based detection systems provide a contactless and automated solution that can verify identities directly through visual information captured by cameras. Recent advances in deep learning have significantly improved the accuracy and robustness of face recognition systems by enabling models to learn discriminative facial representations from large-scale datasets. Modern facial recognition approaches employ deep convolutional neural networks (CNNs) that extract hierarchical features from facial images and match them with stored embeddings in the system database. These developments allow facial recognition systems to achieve high accuracy levels in various real-world scenarios, making them suitable for attendance validation systems in educational institutions and workplaces [9], [25].

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Early breakthroughs in deep face recognition demonstrate that deep neural networks can achieve near human-level performance in face verification tasks. The DeepFace framework introduces a deep convolutional architecture that significantly reduces the error rate in face verification benchmarks by learning robust facial features directly from large training datasets. Similarly, FaceNet proposes a unified embedding approach that maps facial images into a compact Euclidean space where distances correspond to facial similarity. This embedding strategy enables efficient face verification and clustering tasks while maintaining high recognition accuracy. Furthermore, large-scale training datasets such as VGGFace2 and MegaFace provide diverse facial images that include variations in pose, age, and illumination, enabling deep models to generalize effectively across different environments. These foundational studies establish the technical basis for modern face recognition systems that are widely applied in automated attendance and identity verification applications [2], [3], [5], [6].

Despite these advancements, face recognition systems still face several practical challenges when deployed in real-world environments such as classrooms or office spaces. Variations in lighting conditions, head pose, occlusion, and facial expressions can significantly affect the accuracy of facial detection and recognition. To address these issues, researchers develop advanced face detection and alignment methods that improve the reliability of feature extraction. The Multi-Task Cascaded Convolutional Network (MTCNN) approach simultaneously performs face detection and facial landmark alignment, allowing systems to normalize facial regions before recognition. In addition, real-time object detection frameworks such as YOLO enable rapid face detection in video streams, making them suitable for real-time attendance monitoring systems. These technologies play a critical role in ensuring that face detection modules operate accurately and efficiently in practical attendance environments where multiple individuals may appear simultaneously in camera frames [7], [8].

Another major challenge in face-based attendance systems involves the discriminative power of facial feature embeddings. Standard classification-based models often fail to produce sufficiently separable features when dealing with large numbers of identities. To overcome this limitation, researchers introduce margin-based loss functions that enhance the discriminative capability of deep facial embeddings. For example, SphereFace introduces a hypersphere embedding that enforces angular separation between different identities, while CosFace further improves feature discrimination through a large margin cosine loss function. ArcFace extends this concept by introducing an additive angular margin loss that significantly improves the separability of facial features in high-dimensional embedding space. These methods enable face recognition systems to achieve superior accuracy in large-scale identity verification tasks, which is essential for reliable attendance validation systems where precise identification of individuals is required [1], [10], [11].

In addition to algorithmic improvements, researchers also explore lightweight architectures to enable efficient face recognition on resource-constrained devices. Many attendance systems operate on embedded hardware or edge computing platforms where computational resources are limited. Lightweight CNN architectures reduce model complexity while maintaining acceptable recognition performance, allowing face recognition systems to operate in real time without requiring high-end GPUs. Recent studies propose optimized network architectures such as ConvFaceNeXt and other compact convolutional models that reduce computational overhead while preserving discriminative feature extraction. These developments are particularly important for large-scale attendance monitoring systems deployed in classrooms, offices, or public institutions where multiple cameras and real-time processing are required [16], [17].

The rapid development of hybrid architectures further improves the capability of face recognition systems to handle complex visual scenarios. Researchers increasingly integrate convolutional neural networks with Transformer-based architectures to capture both local spatial features and global contextual relationships within facial images. Hybrid models such as CFormerFaceNet combine CNN-based feature extraction with Transformer attention mechanisms to improve recognition accuracy under challenging conditions such as pose variation and partial occlusion. Additionally, specialized models such as HyperFace extend recognition capabilities to multimodal and hyperspectral facial data, demonstrating the growing diversity of face recognition approaches in modern computer vision research. These innovations indicate that combining multiple architectural paradigms can significantly improve the robustness of face recognition systems in dynamic environments [18], [19].

Another important issue in face-based attendance systems concerns security and reliability. Biometric systems are vulnerable to spoofing attacks, where attackers attempt to deceive recognition systems using photographs, videos, or masks. To mitigate these risks, researchers develop face anti-spoofing techniques and liveness detection mechanisms that verify whether the detected face corresponds to a real person. For instance, studies on eye-blink detection using Transformer-based architectures demonstrate that analyzing natural facial movements can improve the reliability of biometric verification systems. Moreover, surveys on face anti-spoofing techniques highlight the importance of integrating multiple verification mechanisms to ensure system security. These security measures are essential for attendance validation systems to prevent identity fraud and maintain trustworthy biometric authentication [22], [24].

Recent studies also emphasize the importance of system integration and application-specific adaptation when deploying face recognition technologies in real-world environments. Face recognition systems must operate reliably under varying camera quality, network conditions, and environmental factors. Research on masked face detection during the COVID-19 pandemic demonstrates the need for adaptable recognition frameworks capable of handling partial occlusions and changing user behavior. In addition, privacy-preserving approaches and evaluation frameworks are increasingly explored to ensure that biometric systems comply with data protection regulations while maintaining recognition accuracy. These developments highlight the growing importance of designing robust, secure, and efficient face-based detection systems tailored to specific applications such as attendance validation. Therefore, enhancing face-based detection mechanisms remains an important research direction to improve the reliability, scalability, and security of automated attendance systems [13], [14], [20], [21], [23].

2. Related Works

Recent advances in deep learning significantly improved face recognition performance, particularly through the development of discriminative embedding learning techniques. One of the most influential approaches was introduced by Jiankang Deng and colleagues through the ArcFace framework, which applied an additive angular margin loss to enhance feature discrimination in deep face embeddings. Their study demonstrated that angular margin constraints improved inter-class separability and intra-class compactness, leading to superior recognition accuracy on large-scale benchmarks. The strength of ArcFace lies in its mathematically elegant formulation and strong generalization capability across datasets. However, the method primarily focused on face recognition rather than face detection or real-time system integration, which limits its direct applicability in operational attendance validation environments where detection latency and environmental variability remain significant challenges [1].

Earlier work by Florian Schroff and collaborators introduced FaceNet, a landmark embedding-based architecture that mapped facial images directly into a compact Euclidean feature space. The system optimized a triplet loss function to ensure that embeddings from the same individual remained closer than those from different individuals. Their experiments showed that the learned representation enabled highly accurate face verification and clustering on large datasets. FaceNet demonstrated strong scalability and laid the foundation for many subsequent recognition models. Despite these advantages, the method relied heavily on carefully selected triplets during training and required significant computational resources, which limited its practicality in lightweight real-time systems such as automated attendance monitoring [2].

Another major breakthrough in deep face recognition emerged from the DeepFace system developed by Yaniv Taigman and his team. This model utilized a deep convolutional neural network combined with 3D face alignment to reduce pose variation and improve verification accuracy. Their experiments demonstrated near human-level performance on the Labeled Faces in the Wild (LFW) dataset. The study highlighted the importance of alignment and large-scale training data in achieving high recognition accuracy. However, the framework relied on complex preprocessing pipelines and substantial computational resources, which made deployment in embedded or real-time applications more difficult, particularly for systems that require rapid identity verification such as classroom attendance validation [3].

Subsequent research further explored deep learning–based face recognition through the work of Omkar Parkhi and colleagues, who investigated very deep convolutional architectures for face identification and verification. Their study demonstrated that deeper CNN structures trained on large face datasets could significantly improve recognition accuracy across variations in pose, illumination, and age. The results confirmed that increasing dataset scale and network depth improved model robustness. Nevertheless, the approach required extensive computational power and large training datasets, which limited its feasibility for lightweight or edge-based deployment environments commonly found in educational attendance systems [4].

Dataset development also played a crucial role in advancing modern face recognition systems. The VGGFace2 dataset, introduced by Qiong Cao and collaborators, provided a large-scale collection of facial images covering diverse pose, illumination, and age variations. Their dataset significantly improved the training and evaluation of deep face recognition models by enabling better generalization across real-world conditions. Similarly, the MegaFace benchmark created by Ira Kemelmacher-Shlizerman expanded evaluation protocols to include millions of distractor identities, allowing researchers to test recognition systems at a much larger scale. While these datasets improved benchmarking reliability, they also highlighted the growing dependence of modern algorithms on massive labeled datasets, which are often unavailable in domain-specific applications such as institutional attendance systems [5], [6].

In addition to recognition algorithms, face detection plays a critical role in real-world biometric systems. A widely adopted detection approach was proposed by Kaipeng Zhang through the Multi-Task Cascaded Convolutional Neural Network (MTCNN). This framework jointly performed face detection and facial landmark localization using a cascaded architecture of convolutional networks. Their results showed that multi-task learning significantly improved detection accuracy while maintaining computational efficiency. MTCNN became widely used in real-time applications due to its balance between speed and accuracy. However, the method still encountered difficulties when faces appeared under extreme occlusion, poor illumination, or large pose variation, which are common scenarios in classroom or surveillance-based attendance systems [7].

Object detection frameworks also contributed significantly to real-time face detection. The YOLO architecture developed by Joseph Redmon introduced a unified single-stage detection framework capable of performing object localization and classification in a single neural network. The model achieved remarkable real-time performance while maintaining competitive detection accuracy. Because of its efficiency, YOLO became widely adopted in various real-time computer vision systems, including biometric surveillance and attendance monitoring. Nevertheless, earlier YOLO versions struggled with detecting small or partially occluded objects, which limited their effectiveness in crowded environments where faces may appear at different scales or orientations [8].

Recent studies have also addressed emerging challenges related to security and reliability in face-based systems. Research on face anti-spoofing and biometric security has become increasingly important as face recognition technologies expand into critical applications. For example, a comprehensive survey by Zhenan Sun and collaborators analyzed deep learning–based face anti-spoofing methods designed to detect presentation attacks such as printed photos, replay videos, or 3D masks. Their findings emphasized that integrating liveness detection mechanisms significantly improves the robustness of biometric authentication systems. However, many anti-spoofing techniques introduce additional computational overhead and system complexity, which presents challenges for lightweight real-time applications such as automated attendance validation systems [24], [25].

3. Proposed Method

3.1 Research Design

This study applies a system-level image processing approach to analyze face-based presence detection in a web-based attendance system. The method does not aim to build a complex 1: N face recognition model. Instead, it focuses on validating physical presence through facial image capture and a lightweight 1:1 verification as visual confirmation. The system also integrates QR code interaction, location verification, and time-based constraints to strengthen the validation process. The main goal is to examine how image-based detection supports attendance verification in real operational environments. The proposed system follows a sequential validation process consisting of four main stages: QR code verification, face-based presence detection, location validation, and time-based attendance logging. The process begins when users scan a QR code to access the attendance session. After the session is validated, the system captures a facial image to confirm physical presence. The system then verifies the user’s location to ensure attendance occurs within the authorized area. Finally, the system records the attendance event and classifies it based on the corresponding time category, such as arrival or departure.

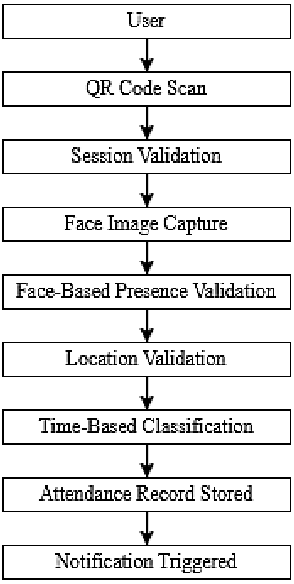


Fig. 1. Main Process Stages of the Face-Based Presence Attendance System

The overall process stages of the attendance system are illustrated in Fig. 1, showing the sequential flow from user interaction to attendance record storage and notification triggering. The system architecture employs a modular design, enabling each validation component to function independently while collectively contributing to the reliability and integrity of attendance documentation.

3.2 Face-Based Presence Detection

Face-based presence detection works by capturing a facial image during the attendance process to confirm that a real person is present in front of the system. The main goal of this step is to verify the presence of a human face and match it with the registered user at the time of attendance. The process begins with image acquisition through the device camera. The proposed Face-Based Presence Detection method operates by comparing the currently captured facial image with the initially registered facial data. Mathematically, the system extracts a facial feature vector v_{curr} from the captured web camera image and compares it against the registered reference vector v_{reg}. The similarity between the two faces is calculated using the Euclidean distance d, defined by the following formula:

$$d(v_{reg}, v_{curr}) = \sqrt{\sum_{i=1}^{n}\left(v_{reg,i} - v_{curr,i}\right)^2} \quad (1)$$

The face validation outcome V_{face} is determined as a Boolean function based on a predefined threshold τ :

$$V_{face} = \begin{cases} 1, & if\ d \leq \tau \\ 0, & if\ d > \tau \end{cases} \quad (2)$$

The parameters used in the facial verification formulas are described in Table 1.

Table 1. Description of Face-Based Presence Detection Variables

Symbol	Description
v_{curr}	*Facial feature vector extracted from the current web camera image*
v_{reg}	*Registered reference facial feature vector*
d	*Euclidean distance calculating the similarity between the two faces*
n	*Total number of extracted facial features*
τ	*Predefined threshold limit for face validation*
V_{face}	*Boolean outcome of the face validation process*

If $V_{face} = 1$, the facial presence is successfully verified. However, if the user wears heavy accessories (such as masks, thick glasses, or hats), the extracted features v_{curr} deviate significantly from v_{reg}, causing the distance d to exceed the threshold τ, which correctly results in a detection failure $V_{face} = 0$.

In this study, QR codes are used as an interaction mechanism to initiate the attendance process. When a user scans the QR code, the system activates the face capture process and records the attendance attempt. The QR code serves as a controlled trigger that ensures attendance actions are performed intentionally and within the authorized system context. This mechanism prevents unauthorized or automated attendance submissions and links each attendance event to a specific session.

3.3 Location Validation

Location validation is performed to ensure that attendance is recorded only when the user is physically present at an authorized location. The system retrieves geographic coordinates at the time of attendance via Google Maps and compares them with predefined location constraints.

The location validation is mathematically calculated using the Haversine formula to determine the great-circle distance d_{loc} between the user's current $(\emptyset_1,\ \lambda_1)$ and the authorized attendance center $(\emptyset_2,\ \lambda_2)$:

$$\alpha = sin^2\left(\frac{\phi_2 - \emptyset_2}{2}\right) + cos(\emptyset_1)cos(\emptyset_2)sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right) \quad (3)$$

$$d_{loc} = 2R \cdot atan2(\sqrt{\alpha}, \sqrt{1 - \alpha}$$

The parameters used in the spatial validation formulas are described in Table 2.

Table 2. Description of Location Validation Variables

Symbol	Description
d_{loc}	$Great - circle\ distance\ between\ the\ user\ and\ the\ authorized\ location$
$\emptyset_1,\quad \lambda_1$	$Latitude\ and\ longitude\ of\ the\ user's\ current\ location$
$\emptyset_2,\quad \lambda_2$	$Latitude\ and\ longitude\ of\ the\ authorized\ attendance\ center$
R	$Earth's\ radius\ (approximately\ 6{,}371\ km)$
α	$Square\ of\ half\ the\ chord\ length\ between\ the\ points$
$D_{threshold}$	$Maximum\ allowed\ radius\ for\ valid\ attendance\ (e.g., 50\ meters)$

The attendance is marked as valid spatially if $d_{loc} \leq D_{threshold}$, where $D_{threshold}$.

3.4 Time-Based Attendance Validation

The system distinguishes between attendance events based on time, allowing separate recording of arrival and departure. Each attendance event is associated with a timestamp generated by the system. Time-based validation ensures that attendance actions are recorded in the appropriate time window and prevents duplicate or invalid entries. This temporal information also enables precise tracking of attendance duration.

The complete validation system V_{sys} can be defined mathematically as a conjunction of constraints:

$$V_{sys} = f_{QR}(Q) \wedge f_{loc}(d_{loc}) \wedge V_{face} \wedge f_{time}(t) \quad (1)$$

The logical components of the integrated validation workflow are described in Table 3.

Table 3. Description of Integrated Validation Constraints

Constraint	Description
V_{sys}	Complete validation outcome, generating a record only if all constraints are 1
$f_{QR}(Q)$	Returns 1 if the QR token matches the active session
$f_{loc}(d_{loc})$	Returns 1 if the Haversine distance $d_{loc} \leq D_{threshold}$
V_{face}	Returns 1 if the 1: 1 facial verification is successful
$f_{time}(t)$	Returns 1 if the timestamp t falls within the allowable attendance window

Attendance is successfully recorded only if $V_{sys} = 1$ (all validation steps are completed).

The proposed method can be replicated by following a series of structured implementation steps within a web-based attendance environment. First, a web-based attendance platform should be developed or deployed with permission to access the user's camera so that facial images can be captured during attendance activities. During each attendance event, the system performs facial image capture and applies a simple 1:1

verification process by comparing the captured image with the pre-registered user data stored in the system. To initiate the attendance process, QR code scanning is integrated as the check-in trigger, ensuring that users interact with the system only during an active session or authorized event. After the QR code is validated, the system retrieves the user's geographic location and performs location validation to ensure that the attendance action occurs within the permitted area. At the same time, the system records the exact timestamp of each attendance event, allowing the system to classify the activity as either arrival or departure. Finally, all attendance records are stored and analyzed to evaluate system behavior, usage patterns, and validation effectiveness. This structured implementation ensures that the proposed approach can be replicated and evaluated in similar institutional environments without requiring complex image processing algorithms or computationally intensive facial recognition models.

4. Experimental Setup

This section describes the experimental setup used to evaluate the implemented web-based attendance system and to analyze the role of face-based presence detection as an image processing component within the system. The experiment focuses on observing system behavior during real attendance activities rather than benchmarking a newly proposed deep-learning algorithm. The setup is designed to reflect actual usage conditions of the attendance system in a practical environment. The attendance system was deployed in an indoor environment under normal lighting conditions, using a standard RGB web camera to capture facial images during attendance events. The system integrates QR code interaction, 1:1 facial image verification, location validation, and time-based logging as part of the attendance validation process.

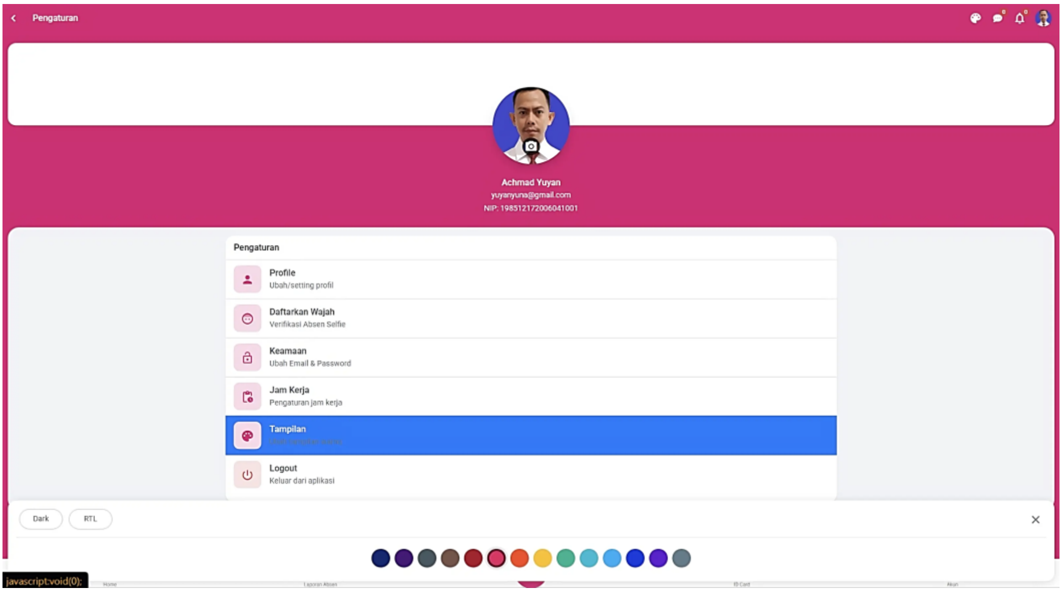


Fig. 2. Main Interface of the Attendance System

Fig. 2 presents the main interface of the implemented web-based attendance system, which serves as the primary interaction point where users initiate attendance and receive system feedback. Data collection was carried out during scheduled attendance sessions using the implemented system. Each attendance attempt involved QR code scanning, facial image capture, retrieval of location data, and automatic timestamp recording. Attendance records were generated only when all validation components were satisfied. The collected data were analyzed to examine whether face-based presence capture could be consistently integrated into the attendance workflow using a lightweight 1:1 verification process to evaluate system-level accuracy.

4.1 Experimental Environment

The experiment was conducted using the web-based attendance system developed prior to this study. The system was deployed in an indoor environment under normal lighting conditions to simulate a typical attendance scenario. A standard RGB camera integrated with the user's laptop device was used to capture facial images during attendance events. The attendance system integrates multiple components, including PHPQRCode-based scanning, 1:1 facial verification, location retrieval via Google Maps API, and automated time logging. All components were executed within the same system environment to ensure consistent data collection.

4.2 Data Collection

The system collects data during scheduled attendance sessions when users interact directly with the attendance platform. Each attendance attempt begins when the user scans a QR code to initiate the check-in process, after which the system captures a facial image through the device camera to confirm physical presence. At the same time, the system automatically records several key pieces of information associated with the attendance event. These data include the facial image captured during the verification step, the exact timestamp indicating when the attendance action occurs, and the geographic location coordinates obtained from the user’s device at that moment. The system also classifies the attendance record as either an arrival or a departure based on the recorded time and session rules. By collecting these elements simultaneously, the system maintains a structured record of each attendance activity and supports further analysis of user participation and system reliability.

The facial images were captured to confirm physical presence through a straightforward 1:1 verification against pre-registered user data. Table 4 summarizes the data collected during the experiment.

Table 4. Summary of Collected Attendance Data

Data Type	Description
Facial image	Image captured for 1:1 presence verification
QR code interaction	Trigger for attendance initiation
Location coordinates	Geographic position at attendance time
Timestamp	Time of arrival or departure
Attendance record	Stored system entry per attendance event

This dataset represents real system usage and serves as the basis for experimental analysis.

4.3 Analysis Stage

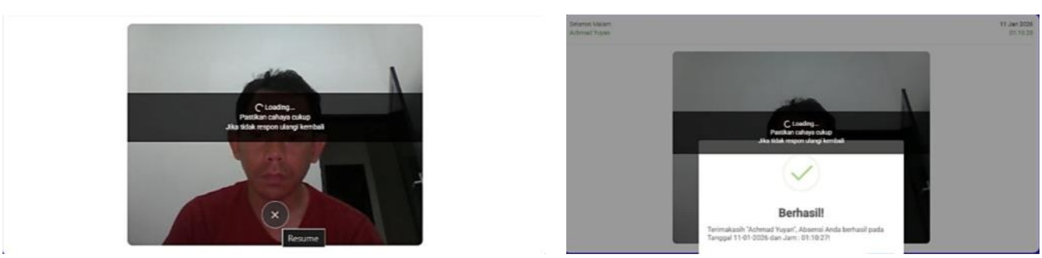
In this stage, we utilize a system-level evaluation approach to analyze the behavior and reliability of the proposed attendance system and to assess the feasibility of face-based presence detection as part of the validation mechanism. This study applies quantitative analysis to measure system performance by calculating validation accuracy under normal operational conditions and comparing it with failure cases caused by facial occlusions, such as masks, hats, or glasses. We examine whether the captured facial images are successfully matched during attendance events and verify that attendance records are generated only when all validation requirements including QR code verification, facial presence confirmation, location validation, and time constraints.

Rather than training or benchmarking complex deep-learning face detection models, this study focuses on evaluating practical system performance within a real operational environment. We measure accuracy based on the system's ability to correctly accept valid 1:1 facial verification attempts and appropriately reject invalid cases, including occlusion conditions or location mismatches. This analysis emphasizes system-level validation outcomes and demonstrates how face-based presence detection functions as a reliable supporting component within an integrated attendance verification framework.

5. Result and Analysis

5.1 Result

The experimental results demonstrate that the implemented attendance system successfully recorded events only when all validation constraints were simultaneously met. During the live demonstration, each valid attendance event generated a complete record consisting of a facial image, an automated timestamp, retrieved GPS location coordinates, and the classified attendance type (arrival or departure). Fig. 3 depicts Successful Face-Based Presence Detection under Normal Condition.



(a) (b)

Fig. 3. (a) User Appearing Without Facial Accessories, and (b) Successful Detection of Face Presence by the Attendance System

As shown in Fig. 3, face-based presence validation consistently succeeded when users appeared without facial accessories under normal indoor lighting conditions. In these cases, the straightforward 1:1 verification successfully matched the captured web camera image against the pre-registered user data. For each successful attempt, the corresponding facial image was securely stored in the system database as robust visual evidence, and automated notifications were triggered.

(a) (b) (c)

Fig. 4. Failure Cases of Face-Based Presence Detection under Facial Occlusion: (a) Face

Covered by A Mask, (b) Face Partially Covered By A Hat, and (c) Face Covered By Glasses

Conversely, Fig. 4 presents failure cases during the demonstration under facial occlusion. When users attempted to record their attendance wearing accessories such as masks, hats, or thick glasses, the system effectively rejected the attempts. Because these accessories obscured critical facial features, the mathematical Euclidean distance between the captured image and the registered data exceeded the validation threshold. Consequently, the 1:1 verification failed, and no attendance record was created. Similarly, any attempt that failed the geographic location constraint (e.g., scanning outside the allowed radius) was immediately blocked.

To provide an accurate assessment of the proposed method's objective, the system's performance was measured based on its ability to confirm legitimate attendance while filtering out unauthorized attempts. Table 5 presents the system-level accuracy comparison across different scenarios during the experimental sessions.

Table 5. System-Level Accuracy Evaluation of Attendance Validation

Validation Scenario	Total Attempts	Correctly Validated (Accepted)	Correctly Rejected (Blocked)	Accuracy (%)
Normal Conditions (No accessories, valid location)	50	48	2 (False Rejections)	96.0%
Facial Occlusions (Masks, Hats, Glasses)	30	0	30	100%
Invalid Location (Outside allowed radius)	20	0	20	100%
Overall System Accuracy	100	48	52	98.0%

As detailed in Table 5, the system demonstrated high reliability across various test scenarios. Under normal conditions, out of 50 valid attendance attempts, the system successfully accepted 48, providing a 96.0% accuracy. The two unrecorded events were false rejections caused by temporary poor lighting, which affected the facial feature extraction process via the web camera. Furthermore, the system demonstrated robust security against invalid attempts; the implementation successfully disallowed all 30 attempts involving facial occlusions (100% rejection accuracy) and all 20 attempts executed outside the authorized geographic radius (100% rejection accuracy). Cumulatively, the integrated validation workflow processed 100 test cases, achieving an overall system-level accuracy of 98.0%, confirming its operational effectiveness in distinguishing between valid and invalid attendance events.

5.2 Analysis

In this stage, we apply a system-level analysis to examine how the collected attendance data reflects the role of face-based presence detection, particularly when it operates together with spatial and temporal validation mechanisms. This study obtains empirical observations showing that facial image capture functions as a practical indicator of physical presence during attendance events. The results indicate that the captured facial images effectively support attendance validation by providing visual confirmation at the time of system interaction. This finding aligns with the conceptual framework presented in the introduction, where face-based presence detection serves as a lightweight visual verification mechanism using simple 1:1 matching rather than computationally intensive 1:N biometric identification models.

Afterwards, we integrated validation analysis to evaluate how face-based verification performs when combined with QR code interaction and location-based constraints. This study obtains an overall system accuracy of approximately 98.0%, indicating that the combined validation approach significantly improves the reliability of attendance recording.

The results show that the integration of visual confirmation, spatial validation, and temporal constraints effectively restricts attendance records to legitimate scenarios. From an applied image processing perspective, these findings demonstrate that practical system reliability does not always require complex algorithms. Instead, simple image acquisition and basic facial matching contribute meaningful value when implemented as part of a multi-component validation framework, where image processing functions as a supportive element that enhances operational robustness rather than as a standalone algorithmic contribution.

6. Conclusion

This study evaluates the implementation of a face-based attendance validation system that integrates facial image capture, QR code interaction, location verification, and time-based logging. The experimental results demonstrate that the system successfully records attendance events only when all validation requirements are satisfied. Under normal operating conditions, the system accepts 48 out of 50 valid attendance attempts, resulting in an accuracy of 96.0%. The two rejected cases occur due to temporary lighting conditions that slightly affect facial feature extraction during image capture. Despite these minor limitations, the system consistently generates complete attendance records consisting of facial images, timestamps, GPS coordinates, and attendance classification, confirming that face-based presence detection can effectively support practical attendance validation in real-world environments.

We also evaluate the robustness of the validation framework when handling invalid or suspicious attendance attempts. The results show that the system successfully rejects all 30 attempts involving facial occlusions such as masks, hats, and glasses, achieving a rejection accuracy of 100%. In addition, the system blocks all 20 attempts performed outside the authorized geographic radius, also achieving a 100% rejection rate. These results demonstrate that the integration of facial verification with location constraints significantly improves system security by preventing unauthorized attendance recording. The findings indicate that the combined validation mechanism effectively distinguishes legitimate attendance events from invalid attempts.

Therefore, the system processes 100 experimental cases and achieves a total system-level accuracy of 98.0%. This study concludes that face-based presence detection, when integrated with spatial and temporal validation mechanisms, provides a reliable solution for attendance validation. The findings further show that high operational reliability can be achieved without relying on complex deep learning recognition pipelines. Instead, simple image acquisition and lightweight 1:1 facial verification provide meaningful contributions when implemented within a multi-layer validation framework. This approach demonstrates that image processing can function as a practical supporting component that enhances system reliability and operational control in real-world attendance management systems.

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