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A Hybrid Image Processing Approach for Real-Time Face Recognition in Attendance Monitoring

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Abstract. In the era of digital transformation, institutions are increasingly adopting automation to enhance administrative efficiency, particularly in human resource management. At Tanggirejo Village Hall, a critically low employee attendance rate of 46.45% in January 2024 exposed the limitations of manual attendance systems, which are prone to errors and manipulation. This study proposes a face recognition-based attendance system utilizing OpenCV's Haar Cascade Classifier for face detection and the Local Binary Pattern Histogram (LBPH) for face recognition. A total of 500 grayscale facial images from 10 employees were collected and processed to train and test the system. Evaluation using a Confusion Matrix revealed an accuracy of 72%, precision of 93%, and recall of 75%. While a 27% error rate was observed—primarily due to lighting inconsistencies and limited training data—the system performed reliably in real-time scenarios. The integration of these lightweight algorithms allows for fast and accurate identification, suitable for resource-constrained environments. This solution not only addresses the local attendance challenges but also presents a scalable, automated model that can be adopted by similar institutions seeking to improve productivity and operational transparency through real-time employee monitoring.

Keywords: Face Recognition, Attendance Monitoring, OpenCV, Haar Cascade Classifier, LBPH

1. INTRODUCTION

Advancements in information technology (IT) have profoundly transformed human resource management (HRM) across modern institutions, enhancing operational efficiency in today's dynamic organizational environments. Innovations such as Human Resource Information Systems (HRIS), cloud computing, and artificial intelligence have evolved HR from a traditionally clerical role into a strategic organizational pillar automating administrative tasks, improving decision-making, and driving performance [1-6]. This transformation plays a critical role in managing key aspects like employee attendance and performance, which directly influence productivity and institutional effectiveness. In government institutions where accountability and optimal resource utilization are crucial employee attendance becomes a reflection of discipline and commitment, thereby significantly affecting performance evaluations and organizational outcomes. However, legacy monitoring systems are increasingly inadequate, highlighting a growing demand for smart, technology-driven solutions.

Conventional attendance tracking methods, such as manual logbooks or RFID-based systems, fall short in meeting the demands of large, modern organizations. These outdated tools are slow, error-prone, and susceptible to manipulation, leading to problems like proxy attendance and unreliable records [7], [8]. For instance, Tanggirejo Village Hall reported a concerning 46.45% attendance rate in January 2024—an alarming statistic that underscores the ineffectiveness of traditional systems in ensuring accountability and productivity. These inefficiencies highlight the need for more reliable, automated systems capable of real-time, accurate employee tracking. Among emerging technologies, face recognition stands out as a promising alternative, offering real-time monitoring with superior accuracy [9], [10].

Recent developments in facial recognition algorithms have yielded efficient, scalable solutions that replace traditional attendance tracking with more secure, automated methods. OpenCV, a robust open-source computer vision library, is especially effective in real-time image processing [11], [12]. Its Haar Cascade Classifier can detect faces swiftly—achieving approximately 85% accuracy with an average processing speed of 50 milliseconds per image, making it well-suited for real-time applications [11]. When paired with the Local Binary Pattern Histogram (LBPH) algorithm, which analyzes facial textures and shows resilience to occlusions and varying expressions, the system reaches a commendable 78% accuracy rate [13], [14]. Together, these methods provide a practical and reliable framework for real-time employee monitoring.

Although advanced Convolutional Neural Networks (CNN) such as FaceNet and MTCNN boast over 94% accuracy and handle complex facial variations well, their heavy computational requirements limit their deployment in resource-constrained environments like government offices [15], [16]. By contrast, integrating OpenCV's Haar Cascade and LBPH algorithms offers a well-balanced solution—delivering quick detection, precise recognition, and up to a 10% reduction in false positives, all while remaining lightweight and hardware-friendly [13], [14]. This study leverages that synergy to design a robust attendance monitoring system capable of real-time detection and recognition, addressing long-standing issues found in manual systems.

The hybrid Haar Cascade–LBPH approach proves superior to standalone techniques, as evidenced by field data. Research shows this combined method can achieve 92.56% accuracy even under challenging conditions such as facial occlusions (e.g., masks or glasses), and up to 99.67% accuracy with local datasets—maintaining a strong 92.67% accuracy in real-time video streams when recognizing multiple faces simultaneously [17], [18]. While the Haar Cascade's speed (averaging 50 milliseconds per image) benefits from efficient integral image computation, the addition of LBPH slightly increases the processing time to around 70 milliseconds—but significantly enhances recognition resilience [13], [17]. This trade-off is well justified in practical settings, where varying lighting and facial expressions often present major challenges.

Beyond detection, this integrated system revolutionizes attendance tracking through real-time identity verification, adaptable to multiple use cases—from educational institutions to secure administrative facilities [19]. It efficiently logs attendance in fluctuating lighting conditions and dramatically reduces false positives in face-based authentication systems [19], [20]. Its precision and flexibility have already proven effective in areas like criminal identification and automated attendance systems, significantly easing administrative burdens [17], [21]. By blending the speed of Haar Cascade with the accuracy of LBPH, this study introduces a powerful, cost-effective tool for employee

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monitoring that has the potential to redefine workforce management in public institutions.

2. METHODS

Figure 1 illustrates the overall research flow for the proposed face recognition-based attendance system, outlining each critical stage from data acquisition to system evaluation. This structured approach ensures a systematic development and performance assessment of the model.

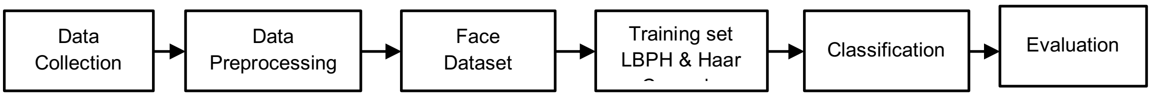

Figure 1. research stages

The research process, as illustrated in Figure 1, follows a systematic and structured flow that begins with data acquisition and culminates in performance evaluation. Each step is critical to building a reliable and efficient face recognition-based attendance system using LBPH and Haar Cascade methodologies.

2.1. Data Collection

Data collection is a critical initial stage in the face recognition system, as the quality of the data directly impacts the accuracy of facial identification. In this phase, a total of 50 facial images were captured from 10 employees using a webcam integrated with the system, taken from various angles to represent real-world conditions during the recognition process. The collected data is subsequently utilized to train the face recognition model.

Each employee's facial photo is processed by the recognition algorithm to match it with existing data. A unique ID serves as the identifier, while the facial image acts as the primary reference for the recognition process. Additional data, such as full name, age, gender, and job position, supports the verification process within the system. Examples of the collected data are presented in Table 1.

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Table 1. Sample Employee Facial Data and Identities

ID	Facial Photo	Full Name	Age	Gender	Position
1		Juli Asriyanto	32	Male	Head of Governance
2		Rusmiyanto	57	Male	Village Secretary
3		Adi Trinarno	47	Male	Head of Planning
4		Dedi Mugiyantoro	29	Male	Hamlet Head
5		Kastini	47	Female	Head of Admin & General

2.2. Data Preprocessing

Data preprocessing is a crucial step in preparing collected images for further processing. At this stage, the gathered facial images are refined to enhance quality and reduce noise. This process eliminates all color information, retaining only the light intensity per pixel [22]. One key technique involves converting colored images into grayscale format, followed by transforming the grayscale images into binary images. This ensures that only moving objects remain clearly defined, effectively minimizing variations in light intensity within the images [23]. The objective is to simplify the data and eliminate unnecessary color influences, thereby facilitating the subsequent face recognition process.

2.3. Face Dataset

After preprocessing the facial images, the next step is to store them in a dataset that serves as a data repository for face recognition. Each stored facial image is labeled with a User.ID.Number format to enable the system to efficiently match detected faces with stored images. This dataset is later used to compare detected faces with the stored images, allowing the system to identify employees based on their facial features.

2.4. Training Set with Haar Cascade Classifier and LBPH

The training set phase involves training the face recognition model using the preprocessed data. Two methods are employed in this stage: the Haar Cascade Classifier,

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which detects faces by identifying facial feature patterns such as eyes, nose, and mouth, and the Local Binary Pattern Histogram (LBPH), which recognizes faces by analyzing facial textures and comparing them to local binary histograms [19], [24]. The system trains both methods using the stored face dataset, enabling accurate detection and identification of employee identities, even with variations in facial expressions.

2.5. Classification

Classification is the stage where the system identifies detected faces by comparing them with the data in the dataset. Upon finding a match, the system classifies the face and displays the corresponding identity. This process ensures that detected faces are accurately recognized, providing automated identification results based on the preprocessed data.

2.6. Evaluation

The performance of the face recognition system is assessed using a Confusion Matrix by calculating accuracy, error rate, recall, and precision based on True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN) values. This evaluation provides insights into the system's accuracy and error levels while helping to pinpoint weaknesses in the face recognition process. Accuracy is a metric used to evaluate how effectively the system identifies faces by comparing the number of correct predictions to the total predictions made. A higher accuracy value indicates better system performance in correctly identifying faces. As a primary indicator of overall model performance, accuracy is critical in ensuring the system can classify employee faces with minimal errors. The accuracy calculation is presented in Equation 1.

$$Accuracy=\frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

The error rate measures the model's level of error in recognizing employee faces. It is calculated as the ratio of incorrect predictions to the total predictions made by the system. A lower error rate signifies a reduced likelihood of the system misidentifying faces, indicating optimal performance in distinguishing between recognized and unrecognized faces. In other words, a low error rate reflects the system's reliability. The error rate calculation is shown in Equation 2.

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$$ErrorRate=\frac{FP+FN}{TP+TN+FP+FN} \tag{2}$$

Precision is a metric that assesses how accurately the system classifies detected faces as belonging to the correct employees. It is determined by comparing the number of true positive predictions to the total positive predictions made by the system. A high precision value indicates that the system rarely misidentifies faces not present in the dataset. Precision is particularly crucial in scenarios where false positives must be minimized, such as in access control systems relying on facial identification. The precision calculation is provided in Equation 3.

$$precision=\frac{TP}{TP+FP} \tag{3}$$

Recall measures the system's ability to identify all employee faces that should be detected. It is calculated by comparing the number of correctly recognized employee faces to the total number of actual employee faces in the dataset. A high recall value demonstrates that the system can detect nearly all present faces with minimal data loss. Recall is especially vital in situations where comprehensive detection is prioritized over precision per prediction, such as in security systems that must ensure no employee faces are missed. The recall calculation is detailed in Equation 4.

$$recall=\frac{TP}{TP+FN} \tag{4}$$

3. RESULTS AND DISCUSSION

3.1. Classification Methods

1) Haar Cascade Classifier

The Haar Cascade Classifier is employed for face detection due to its ability to recognize patterns quickly and efficiently. This algorithm operates by detecting specific facial features based on pixel intensity differences across various regions of an image. The detection process occurs incrementally through a series of Haar feature-based filters, enabling the system to identify faces with high accuracy. A simplified workflow of the face detection process using the Haar Cascade Classifier is illustrated in Figure 2.

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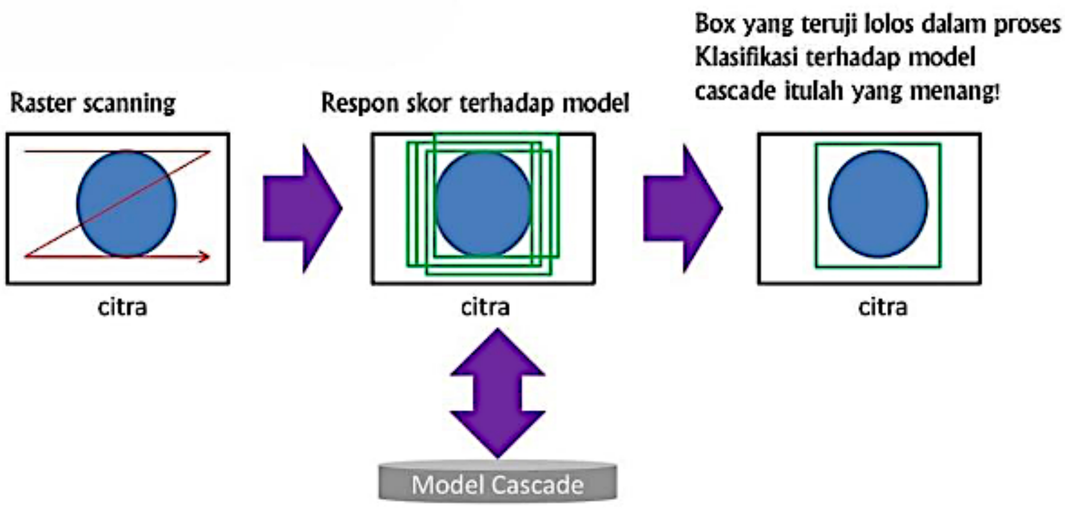

Figure 2. Haar Cascade Classifier Face Detection Process [25]

a) Raster Scanning: This process involves scanning the entire image using a sliding window method. At this stage, each region of the image is examined with detection windows of varying multi-scale sizes. The goal is to identify potential face locations across different positions and sizes within the image.
b) Response Scoring Against the Model: Each region of the image is evaluated based on pre-trained Haar features, which include pixel intensity differences between light and dark areas representing features like eyes, nose, and mouth. Regions meeting the cascade model's criteria (positive response) proceed to the next stage, while irrelevant regions are discarded to reduce computational load.
c) Classification Against the Cascade Model: At this stage, only regions passing the previous step undergo further testing through multiple classification layers. Each layer in the cascade model tightens the detection criteria, ensuring that only regions closely resembling a face advance to the final stage.
d) Final Output: After classification, regions that successfully pass all cascade layers are identified as detected faces. A bounding box is then displayed around each detected face in the image.

2) Local Binary Pattern Histogram (LBPH)

The Local Binary Pattern Histogram (LBPH) is utilized for face recognition by analyzing texture based on local pixel patterns surrounding neighboring pixels (Ahsan). This algorithm converts facial images into numerical representations derived from pixel

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intensity differences, enabling more accurate face recognition. Feature extraction with LBPH involves comparing the intensity value of a central pixel with its neighbors, generating a binary pattern that is subsequently converted into a histogram representing unique facial characteristics. A simplified workflow of local feature extraction using LBPH is depicted in Figure 3.

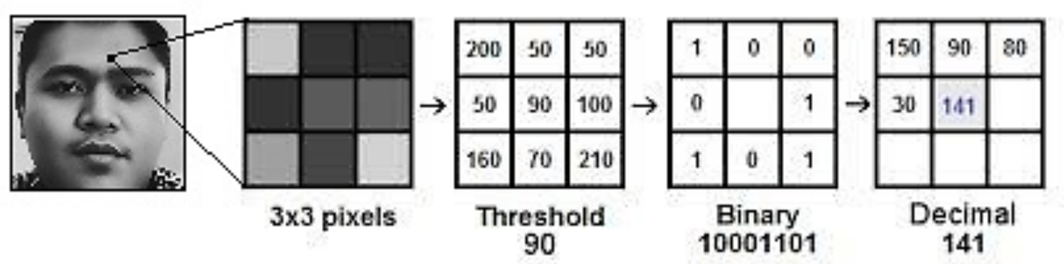

Figure 3. Local Feature Extraction with LBP

The facial image is first converted to grayscale to simplify processing. Each pixel is then analyzed based on the intensity values of its neighbors within a 3×3 block. Neighboring pixel values are compared to the central pixel: a value of 1 is assigned if the neighbor's intensity is greater, and 0 if it is less. The resulting binary pattern is converted into a decimal value to construct a histogram that captures the distinct features of the face. This process produces a feature vector used for face comparison and recognition [26].

3.2. Testing the Haar Cascade Classifier Model

The accuracy of the Haar Cascade Classifier model is evaluated using a Confusion Matrix and compared with the combined Haar Cascade Classifier and Local Binary Pattern Histogram (LBPH) method. Face detection accuracy is calculated by comparing the detection results with the Ground Truth (GT), which serves as a reference to determine the presence of faces in images. Accuracy is defined as the percentage of correct predictions relative to the total predictions, where GT is assigned a value of 1 if the image contains a face and 0 if it does not.

1) Model Predictions on Images Containing Faces

The Haar Cascade Classifier model's predictions were tested on 10 images, all of which contained faces (GT = 1). The model correctly identified faces in 6 images but failed to detect faces in 4 images. With a detection error rate of 40%, the model's accuracy limitations may stem from factors such as lighting conditions, face orientation, or image quality. Nevertheless, the model successfully detected faces in 60% of the tested images. The results of the Haar Cascade Classifier's performance on images containing faces are presented in Table 2.

Table 2. Prediction Results on Images Containing Faces

ID	Sentiment (Actual)	Prediction	Result
1	1	0	FN
2	1	1	TP
3	1	1	TP
4	1	0	FN
5	1	0	FN
6	1	1	TP
7	1	0	FN
8	1	1	TP
9	1	1	TP
10	1	1	TP

2) Model Predictions on Images Without Faces

The Haar Cascade Classifier model was also tested on 10 images that did not contain faces. The Ground Truth (GT) indicated that all images had no faces (GT = 0), and the model correctly identified all of them. No instances of False Positives (FP)—where the model incorrectly detects a face in an image without one—were observed. This demonstrates that the Haar Cascade Classifier achieved 100% accuracy in this scenario. The results of the model's performance on images without faces are shown in Table 3.

Table 3. Prediction Results on Images Without Faces

ID	Sentiment (Actual)	Prediction	Result
1	0	0	TN
2	0	0	TN
3	0	0	TN
4	0	0	TN
5	0	0	TN
6	0	0	TN
7	0	0	TN

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ID	Sentiment (Actual)	Prediction	Result
8	0	0	TN
9	0	0	TN
10	0	0	TN

3.3. Testing the Combined LBPH and Haar Cascade Classifier Method

The face recognition system's performance was tested at distances of 1 to 2 meters to evaluate the effectiveness of the combined method. At a 1-meter distance, the system identified employee faces based on registered data and classified them using a Confusion Matrix.

1) Testing at a 1-Meter Distance

The results showed that out of 10 tests, the system correctly recognized faces 8 times (True Positive) and failed in 2 cases (False Negative). This indicates a relatively high success rate in identifying employee faces at this distance. The test results at a 1-meter distance are presented in Table 4.

Table 4. Testing at a 1-Meter Distance

ID	Distance	Sentiment (Actual)	Prediction	Result
1	1	Juli Asriyanto	Juli Asriyanto	TP
2	1	Rusmiyanto	Rusmiyanto	TP
3	1	Adi Trinarno	Adi Trinarno	TP
4	1	Dedi Mugiyantoro	Juli Asriyanto	FN
5	1	Kastini	Kastini	TP
6	1	Ira Intan Permatasari	Ira Intan Permatasari	TP
7	1	Yaumil Reno Sofian	Juli Asriyanto	FN
8	1	Sundowo	Sundowo	TP
9	1	Sugondo	Sugondo	TP
10	1	Sutamto	Sutamto	TP

2) Testing at a 2-Meter Distance

The face recognition system was tested at a 2-meter distance to assess its ability to identify employee identities based on registered data. Out of 10 tests, the system correctly identified faces 7 times (True Positive), while 3 errors occurred (False Negative), where employee faces were either misidentified or not detected accurately. These results suggest a slight decline in performance compared to the 1-meter distance, indicating that distance impacts recognition accuracy. The test results at a 2-meter distance are shown in Table 5.

Table 5. Testing at a 2-Meter Distance

ID	Distance	Sentiment (Actual)	Prediction	Result
1	2	Juli Asriyanto	Juli Asriyanto	TP
2	2	Rusmiyanto	Rusmiyanto	TP
3	2	Adi Trinarno	Adi Trinarno	TP
4	2	Dedi Mugiyantoro	Juli Asriyanto	FN
5	2	Kastini	Kastini	TP
6	2	Ira Intan Permatasari	Ira Intan Permatasari	TP
7	2	Yaumil Reno Sofian	Juli Asriyanto	FN
8	2	Sundowo	Sundowo	TP
9	2	Sugondo	Sugondo	TP
10	2	Sutamto	Sundowo	FN

3) Testing with Unregistered Identities

Testing the face recognition system with unregistered data revealed that at a 1-meter distance, the system incorrectly identified the face, while at a 2-meter distance, it successfully classified the unregistered face correctly. These findings suggest that the system remains susceptible to identification errors at certain distances. The results of testing with unregistered faces and identities are detailed in Table 6.

Table 6. Testing with Unregistered Identities

ID	Distance	Sentiment (Actual)	Prediction	Result
1	1	Davit – Unregistered	Juli Asriyanto	FP
2	2	Davit – Unregistered	Random	TN

3.4. Test Result Graphs

1) Haar Cascade Classifier Model Evaluation

Based on the evaluation results of the Haar Cascade Classifier model displayed in the graph, the model achieves an accuracy of 80% with an error rate of 20%. The precision reaches 100%, indicating that the model does not misclassify detected faces. However,

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the recall is only 60%, suggesting that the model struggles to detect all present faces. The evaluation results of the Haar Cascade Classifier model will be compared with those of the combined method integrating Local Binary Pattern Histogram (LBPH) and Haar Cascade Classifier. This combined approach is expected to enhance the system's face recognition capabilities. The evaluation graph for the Haar Cascade Classifier model is presented in Figure 4.

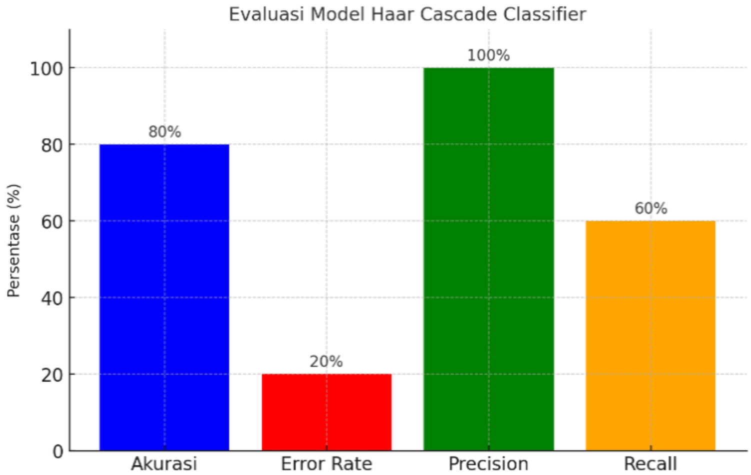

Figure 4. Evaluation Graph of the Haar Cascade Classifier Model

2) Combined Haar Cascade Classifier and LBPH Method Evaluation

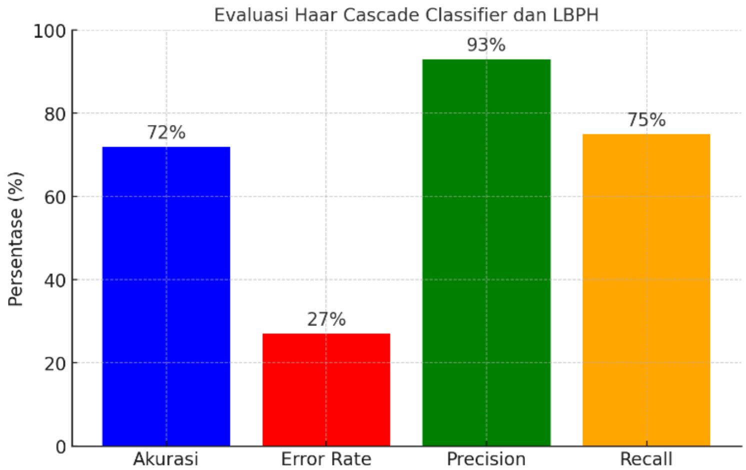

Figure 5. Evaluation Graph of the Haar Cascade and LBPH Method

Based on the evaluation results of the combined LBPH and Haar Cascade method displayed in the graph, the system's performance is reflected across four key metrics: an accuracy of 72%, an error rate of 27%, a precision of 93%, and a recall of 75%. The relatively high accuracy indicates that the majority of the system's predictions are

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correct, while the error rate reveals a persistent level of inaccuracy. The high precision underscores the system's effectiveness in producing correct positive predictions, whereas the recall demonstrates its ability to detect most positive cases overall. The evaluation graph for the combined LBPH and Haar Cascade method is shown in Figure 5.

3.5. Implementation

1) Real-Time Face Recognition System Testing

The real-time face recognition system was tested and successfully detected two employee faces simultaneously, accurately displaying each employee's identity. The system consistently detected faces despite movement, as long as they remained within the camera's range, and recognized them based on identity data registered in the dataset. This recognition process utilized image processing algorithms, where each detected face underwent stages of detection, recognition, and matching with dataset records. Additionally, the system demonstrated its capability to provide supplementary information—such as name, age, gender, and job position—displayed in real-time on the user interface. The results of simultaneous testing are presented in Figure 6.

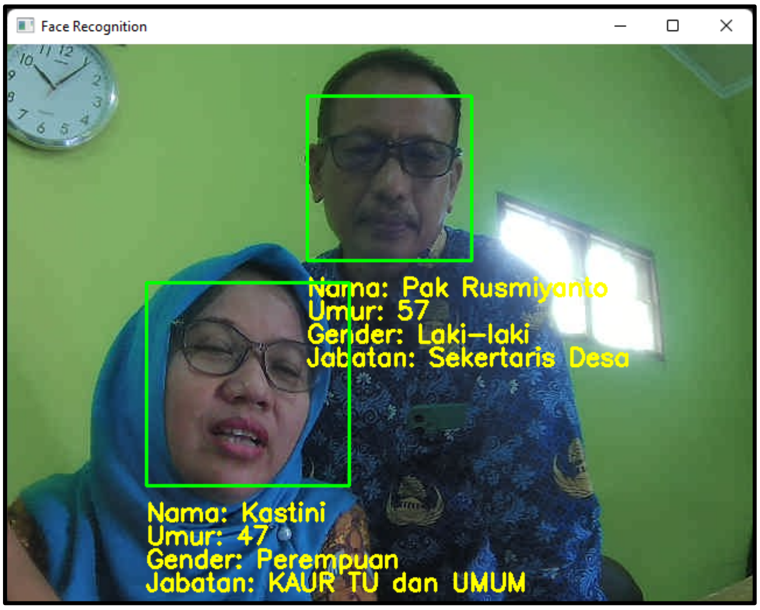

Figure 6. Simultaneous Testing on Village Secretary and Head of Administration and General Affairs Employees

2) Face Recognition System Testing at a 1-Meter Distance

Real-time face recognition testing at a 1-meter distance showed that the system accurately detected and identified faces, displaying identity details such as name, age, gender, and job position based on dataset records. Successful detection relied on adequate lighting and the face being oriented toward the camera, while background variations and additional objects had no significant impact on the recognition process. These results confirm the algorithm's effectiveness in rapidly processing data. Consequently, the system holds potential for applications in employee attendance monitoring, access management, and other scenarios requiring employee face recognition. The test results at a 1-meter distance are shown in Figure 7.

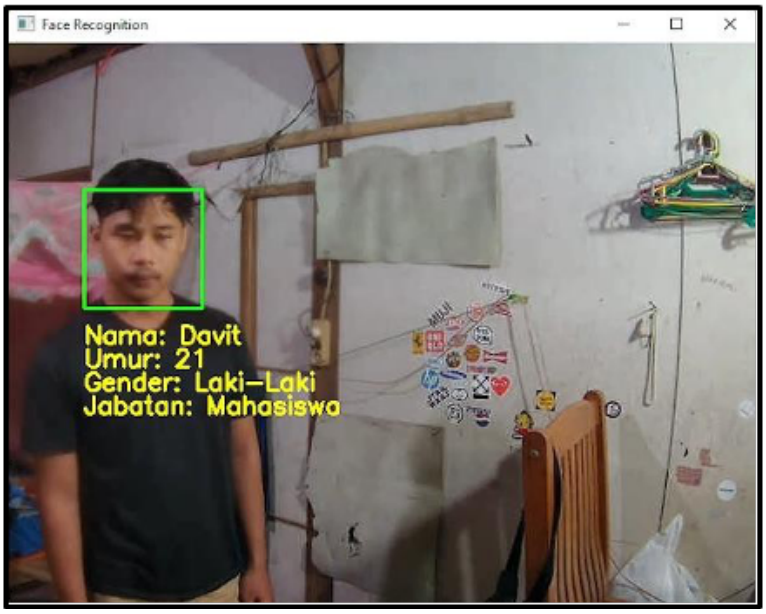

Figure 7. Testing at a 1-Meter Distance

3) Face Recognition System Testing at a 2-Meter Distance

The face recognition system was tested in real-time at a 2-meter distance. The system accurately detected faces and displayed identity information—including name, age, gender, and job position—consistent with the data stored in the dataset. This test demonstrated that the system remains effective even as the distance between the camera and the face increases. Furthermore, the results indicate that the employed algorithm is sufficiently robust to recognize faces at greater distances, provided lighting conditions and camera angles are supportive. The test results at a 2-meter distance are presented in Figure 8.

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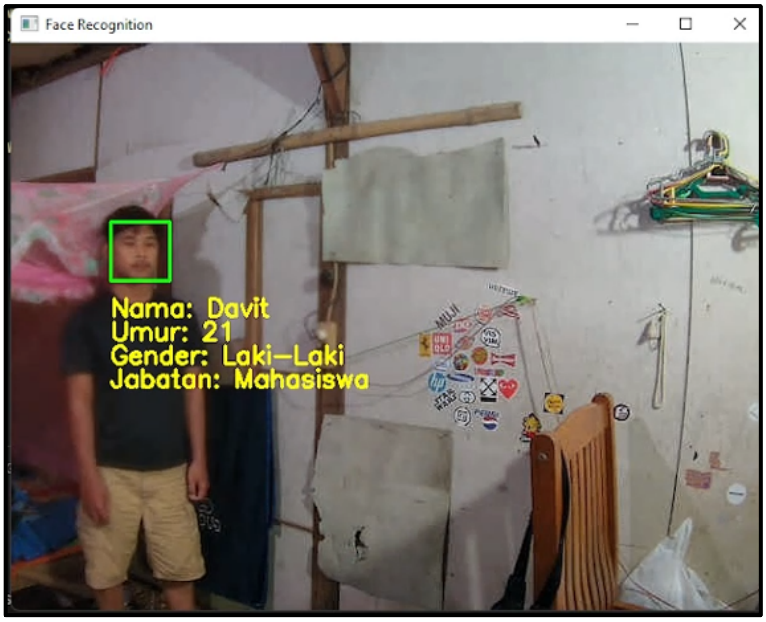

Figure 8. Testing at a 2-Meter Distance

3.6. Discussion

This study presents a critical evaluation of two face recognition techniques—Haar Cascade Classifier and the Local Binary Pattern Histogram (LBPH)—applied independently and in combination to develop a real-time attendance monitoring system. Through detailed classification, testing, and implementation phases, the system's strengths and limitations are illuminated, allowing for a deeper analytical understanding of their practical implications in institutional environments.

The Haar Cascade Classifier, traditionally lauded for its speed and simplicity, demonstrated strong performance in detecting the absence of faces, with a 100% accuracy rate for non-face images. This suggests a high degree of specificity, where the classifier excels at minimizing false positives. However, its 60% detection rate for face-present images reveals a crucial limitation—insufficient sensitivity, or low recall, in real-world conditions. The classifier frequently fails to detect actual faces, especially under suboptimal lighting, partial occlusions, or non-frontal angles. This raises concerns about its applicability as a standalone tool for critical identity-based systems like attendance logging.

Contrastingly, LBPH, when paired with Haar Cascade, offers a significantly improved performance, particularly in recognizing registered faces. The hybrid model's recall increased to 75%, with a precision of 93%, revealing a more balanced capability to detect true faces while limiting incorrect identifications. This synthesis is particularly notable in real-time scenarios, where rapid detection must be coupled with accurate recognition. The analytical strength of LBPH lies in its texture-based approach, allowing it to generalize well across facial expressions, lighting conditions, and partial obstructions—factors that frequently compromise Haar-only systems.

From an implementation standpoint, LBPH complements Haar's rapid detection, effectively reducing the error rates associated with isolated pixel-intensity comparisons. However, this integration comes at the cost of increased computational demand and slight processing delays (from 50 ms to ~70 ms per frame). While this trade-off is acceptable in low to moderate load environments, it may become a bottleneck in high-density, multi-face recognition scenarios without further optimization.

A critical analysis of distance-based testing reveals the inherent spatial sensitivity of the system. At a 1-meter distance, the hybrid method achieved an 80% success rate, while performance dropped to 70% at 2 meters. This decline, while moderate, highlights a key operational constraint—facial resolution degrades with distance, affecting the texture extraction accuracy of LBPH and the feature detection strength of Haar. The degradation suggests that although the system can function effectively in proximity-based attendance points (e.g., door checkpoints), its reliability decreases in open or large-area environments without camera resolution compensation.

Additionally, testing with unregistered identities exposed a potential vulnerability to false positives, particularly at closer ranges. At 1 meter, the system incorrectly matched an unregistered face to a known identity—a security risk in applications requiring strict verification. However, at 2 meters, the system correctly rejected the unregistered face. This variance suggests that facial feature generalization in LBPH may increase at closer proximity, possibly due to shared texture patterns across different individuals. Therefore, further refinement of recognition thresholds or inclusion of additional classifiers (e.g., Support Vector Machines or CNNs) may help mitigate identity overlap in closely ranged encounters.

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The evaluation graphs underscore a strategic design tension between precision and recall—an unavoidable trade-off in pattern recognition systems. While Haar Cascade boasts high precision (100%) in avoiding false positives, its low recall (60%) implies many genuine faces go undetected. Conversely, the combined method slightly reduces precision (93%) but meaningfully increases recall (75%), making it a more holistically balanced solution for attendance tracking. From a deployment perspective, especially in administrative or institutional settings, missing a real employee (false negative) is often more problematic than mistakenly identifying an unknown person—especially if subsequent layers of verification exist. This analysis supports the argument that recall-centric optimization is preferable in attendance systems, where false absences can impact employee records, payroll, or institutional compliance. In this regard, the LBPH-enhanced system's marginally lower precision is a tolerable trade-off, particularly when weighed against its significantly better capacity to detect and confirm identities.

The system's real-time testing further validates its operational feasibility. It successfully detected and recognized multiple employees in dynamic conditions, maintaining accuracy despite motion and slight changes in position. The seamless UI integration, displaying metadata such as name, age, gender, and job title, enhances usability and administrative efficiency. These results affirm the system's scalability for real-world environments like village offices or classrooms, where identification must occur quickly and accurately. However, performance remains contingent upon lighting conditions, frontal face orientation, and camera stability. While background complexity and environmental noise had minimal effect, any deviation from a frontal view or adequate lighting led to decreased detection success. This suggests the system remains geometry-sensitive, and further research should explore the incorporation of deep learning-based alignment or pose correction modules to improve detection under varied orientations.

The findings present compelling evidence that a hybrid approach—combining traditional and texture-based techniques—offers a practical compromise between speed, accuracy, and computational efficiency. However, the system's susceptibility to false negatives at increased distances, and occasional false positives with unregistered individuals, indicates that contextual use is crucial. For high-security environments, further enhancements or integration with biometric modalities (e.g., voice or iris) may be necessary.

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Future research should investigate adaptive thresholding, more resilient facial feature extraction using CNN-lite models (e.g., MobileNetV2), and continuous learning algorithms that can update the recognition database dynamically. Moreover, deploying the system in varied real-world institutions will allow for longitudinal evaluation and model refinement under uncontrolled settings.

4. CONCLUSION

This study successfully developed a face recognition-based attendance system using OpenCV, integrating the Haar Cascade Classifier for face detection and the Local Binary Pattern Histogram (LBPH) for face recognition. The hybrid approach proved effective in automating employee attendance, offering real-time identification with a reasonable balance of speed and accuracy. Evaluation results—72% accuracy, 93% precision, and 75% recall—indicate that the system performs reliably under controlled conditions, although challenges such as poor lighting and limited training data affect consistency. These findings suggest that further improvements, such as expanding the dataset and applying data augmentation, could enhance overall performance. The combined Haar-LBPH system demonstrates strong potential for real-world applications in attendance monitoring, access control, and administrative automation. Its lightweight design and efficient performance make it a practical solution for institutions seeking scalable and intelligent employee tracking systems.

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