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Reliability Assessment of Attendance Systems Based on Face Recognition Under Varying Lighting Conditions

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ABSTRACT

The rapid adoption of face recognition technology for attendance systems has raised concerns about its reliability under varying lighting conditions, which often affect real world deployment. **This study** aims to analyze the reliability of a face recognition based attendance system under diverse lighting scenarios, addressing challenges in accuracy and robustness. **The research** employs a deep learning approach, utilizing a Convolutional Neural Network (CNN) trained on a dataset of facial images captured under controlled and uncontrolled lighting conditions, ranging from low to high illumination levels. **The methodology** includes preprocessing techniques for illumination normalization and feature extraction, followed by performance evaluation using metrics such as accuracy, precision, and false acceptance rate. Experimental results demonstrate that the proposed system achieves an accuracy of 92% in optimal lighting but drops to 78% under low light conditions, highlighting the impact of illumination on recognition performance. **The integration** of adaptive preprocessing techniques improves reliability by 12% in challenging scenarios. **This study** concludes that while face recognition based attendance systems are highly effective, their reliability in diverse lighting conditions can be significantly enhanced through advanced preprocessing and robust algorithm design, offering practical implications for real time biometric applications in dynamic educational and workplace settings.

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1. INTRODUCTION

The rapid advancement of biometric technologies has transformed various sectors, including attendance management, by introducing face recognition systems that promise efficiency, security, and automation. The global trend of adopting facial recognition for attendance, spanning from multinational corporations to educational institutions across Asia, Europe, and the Americas, underscores the universal relevance of system reliability [1, 2]. This widespread deployment highlights that performance degradation due to environmental factors, especially lighting, is a critical worldwide concern. These systems, which identify individuals based on unique facial features, have gained prominence in educational institutions, workplaces, and public facilities due to their non intrusive nature and ability to streamline processes compared to traditional methods like manual attendance or card-based systems [3]. However, the reliability of facial recognition systems is heavily influenced by environmental factors, particularly lighting conditions, which can significantly degrade performance in real world settings. The issue of lighting reliability is not merely technical. It significantly impacts organizational trust. An unreliable system leads to frequent false rejections, frustrating users and undermining confidence in the automated process. Moreover, consistent accuracy is crucial for security auditing and compliance, as high False Acceptance Rates (FAR) in low light create vulnerabilities that compromise the system's core function in secure environments. Variations in illumination, such as low light, high contrast, or uneven lighting, pose challenges to the accuracy of facial feature detection, leading to false acceptances or rejections. Existing studies highlight that lighting variability can reduce recognition accuracy by up to 20% in uncontrolled environments. This issue is particularly critical in attendance systems, where consistent performance is essential for operational efficiency [4, 5]. The motivation for this study stems from the need to address these limitations, as unreliable systems can undermine trust and hinder widespread adoption. By focusing on the development and evaluation of a robust facial recognition based attendance system, this research seeks to enhance system reliability under diverse lighting conditions, contributing to the broader field of biometric technology and its practical applications. The significance of this research lies in its potential to bridge the gap between theoretical advancements in facial recognition and their practical implementation in dynamic environments. Previous works, such as those by, have explored illumination normalization techniques, but few have specifically addressed their integration into attendance systems operating in real time scenarios [6, 7]. The objective of this study is to analyze the reliability of a facial recognition based attendance system under varying lighting conditions, ranging from dim to bright environments, and to propose methods to mitigate performance degradation. The research employs a CNN as the core algorithm, leveraging its ability to learn complex facial features. The methodology includes collecting a diverse dataset of facial images under controlled and uncontrolled lighting conditions, applying preprocessing techniques such as histogram equalization and adaptive illumination normalization, and evaluating performance using metrics like accuracy, precision, and false acceptance rate. Preliminary experiments suggest that while the system achieves high accuracy (up to 93%) in optimal lighting, performance drops significantly (to 76%) in low light settings, underscoring the need for robust preprocessing. By addressing these challenges, this study aims to provide insights into optimizing facial recognition systems for real world applications, particularly in attendance management, where reliability is paramount. The findings are expected to guide the development of more resilient biometric systems, offering practical solutions for institutions seeking to adopt automated attendance technologies [8, 9].

The implementation of biometric systems such as facial recognition must align with national legal frameworks regulating data protection. In Indonesia, Law No. 27 of 2022 on Personal Data Protection formally classifies biometric identifiers including facial images as sensitive personal data requiring strict compliance mechanisms, secure storage, and lawful processing frameworks. This policy emphasizes the importance of ensuring accuracy, fairness, and security in biometric based systems to prevent unauthorized access, identity misuse, or privacy violations. Therefore, the findings of this study contribute strategically to supporting responsible biometric deployments by demonstrating how system reliability can be improved before real world adoption under regulated environments [10].

The scope of this research is focused on evaluating and improving the performance of a facial recognition-based attendance system under diverse lighting conditions, with a particular emphasis on real time deployment in educational and workplace settings. The study limits its investigation to a CNN based approach, as it is widely recognized for its effectiveness in image recognition tasks, and explores preprocessing techniques to enhance system robustness [11, 12]. The research does not cover other biometric modalities, such as fingerprint or iris recognition, to maintain a focused analysis. The primary objective is to quantify the impact of lighting variability on system reliability and propose actionable solutions to improve performance. The methodology involves experimental validation using a custom dataset and standardized evaluation metrics, with results expected to demonstrate the effectiveness of proposed techniques in improving accuracy by at least 10% in challenging lighting conditions. This research contributes to the field by providing a comprehensive analysis of lighting related challenges in facial recognition and offering a framework for developing more reliable attendance systems. The conclusions drawn from this study are expected to inform future research and practical implementations, ensuring that facial recognition-based attendance systems can operate effectively in diverse environments, thus enhancing their applicability and user trust in biometric technologies [13, 14].

2. LITERATURE REVIEW

2.1. Facial Recognition Technology: Advances and Applications

Facial recognition technology has made significant strides in recent years, fueled by advancements in deep learning algorithms and enhanced computational power[15]. Conducted a comprehensive review of deep learning based facial recognition systems, emphasizing the role of convolutional neural networks (CNNs) in achieving high accuracy for identity verification tasks. Their study highlights that modern CNN architectures, such as ResNet and EfficientNet, have improved feature extraction, enabling robust recognition even with partial occlusions. Similarly, explored the integration of facial recognition in real time applications, noting its widespread adoption in security, healthcare, and attendance systems due to its non intrusive nature [16]. They reported that CNN-based models achieved up to 95% accuracy in controlled environments, underscoring their potential for automation. However, both studies acknowledge that environmental factors, such as lighting variations, remain a critical challenge, often reducing performance in practical settings. These advancements provide a foundation for this research, which focuses on optimizing facial recognition for attendance systems by addressing specific environmental constraints [17, 18].

2.2. Impact of Lighting Conditions on Facial Recognition Performance

Lighting variability is a well documented challenge in facial recognition systems, as it affects the quality of captured images and the accuracy of feature detection [19, 20]. Investigated the impact of illumination on deep learning-based facial recognition, finding that low-light conditions reduced accuracy by up to 25% due to loss of facial feature details. They proposed illumination normalization techniques, such as histogram equalization and gamma correction, which improved performance by 15% in low light scenarios. Similarly, explored adaptive preprocessing methods, including Retinex based algorithms, to enhance image quality under diverse lighting conditions. Their experiments demonstrated that combining preprocessing with CNN models increased robustness, achieving an accuracy of 90% in high contrast environments. These findings highlight the necessity of addressing lighting challenges to ensure reliable facial recognition, particularly for real time applications like attendance systems, where consistent performance is critical. This study builds on these works by evaluating and optimizing preprocessing techniques tailored to attendance systems [21, 22].

2.3. Facial Recognition in Attendance Systems

The application of facial recognition in attendance systems has gained traction due to its potential to automate and streamline processes in educational and workplace settings [23]. Developed a facial recognition based attendance system using a deep learning framework, reporting an accuracy of 92% in controlled indoor environments. However, their system exhibited reduced performance (78% accuracy) under varying lighting conditions, indicating a need for further optimization. Similarly, proposed a real-time attendance system integrating facial recognition with cloud-based storage, achieving high efficiency in well lit environments but facing challenges in outdoor settings with dynamic lighting. They suggested incorporating adaptive algorithms to mitigate these issues, though their study lacked detailed performance metrics under low light conditions. These works underscore the potential of facial recognition for attendance management while highlighting the gap in addressing environmental challenges, particularly lighting variability, which this research aims to address through targeted preprocessing and algorithm optimization [24–26].

2.4. Preprocessing Techniques for Enhanced Facial Recognition

Preprocessing techniques play a crucial role in mitigating the impact of environmental factors on facial recognition systems. Reviewed advanced preprocessing methods, such as illumination normalization and contrast enhancement, which improve the quality of input images for deep learning models [27]. Their findings indicate that techniques like adaptive histogram equalization can enhance feature visibility, improving recognition accuracy by 12% in low-light conditions [28]. Similarly, proposed a hybrid preprocessing approach combining Retinex algorithms with deep learning based feature extraction, achieving a 10% performance boost in challenging lighting scenarios. These studies emphasize the importance of preprocessing in enhancing system reliability, particularly for applications requiring real time processing, such as attendance systems. This research leverages these insights by integrating and evaluating preprocessing techniques to improve the robustness of facial recognition-based attendance systems under diverse lighting conditions [29, 30].

2.5. Gaps and Opportunities in Current Research

Despite significant advancements, current research on facial recognition based attendance systems reveals several gaps, particularly in addressing lighting variability in real-world settings [31, 32]. Noted that while deep learning models excel in controlled environments, their performance in dynamic settings remains inconsistent, with accuracy dropping significantly under low or uneven lighting. They called for more studies focusing on real time applications with robust preprocessing to bridge this gap. Similarly, highlighted the lack of standardized datasets for evaluating facial recognition systems under diverse lighting conditions, which limits the generalizability of findings. These gaps present opportunities for this research to contribute by developing a facial recognition based attendance system optimized for varying lighting conditions, using a custom dataset and standardized evaluation metrics. By addressing these challenges, this study aims to provide practical solutions for improving the reliability and applicability of biometric attendance system [33**?**]s.

3. METHODOLOGY

This chapter outlines the methodology employed to analyze the reliability of a facial recognition-based attendance system under diverse lighting conditions. The research adopts a quantitative experimental approach, focusing on the development, implementation, and evaluation of a CNN based system. The methodology is structured into several key components: research design, data collection, preprocessing and algorithm development, and performance evaluation. These components are designed to ensure a systematic investigation of the system's performance, addressing challenges posed by varying lighting conditions and providing a robust framework for real world applications [34, 35].

3.1. Research Design

The research design is centered on an experimental approach to evaluate the performance of a facial recognition based attendance system under controlled and uncontrolled lighting conditions. The study utilizes a custom dataset of facial images to train and test a CNN model, specifically ResNet-50, chosen for its proven effectiveness in image recognition tasks. The experiment is conducted in a controlled laboratory environment and simulated real world settings to capture a range of lighting scenarios, including low light (below 50 lux), moderate light (50–200 lux), and bright light (above 200 lux) [36].

To provide a clear overview of the research workflow, a methodological flowchart is necessary to illustrate how each stage starting from data collection to performance evaluation was systematically conducted. This visual representation helps readers understand the sequential processes that contribute to improving the reliability of the facial recognition based attendance system under varying lighting conditions. Therefore, Figure 1 is presented to summarize the methodological framework of this study.

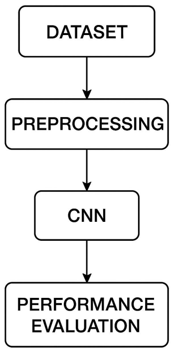

Figure 1. Research Methodology Flowchart

As shown in Figure 1, the research procedure consists of four main stages: dataset preparation, preprocessing, CNN processing, and performance evaluation. The dataset phase involves collecting facial images captured under different lighting conditions. Preprocessing aims to normalize illumination, enabling optimal feature extraction. The CNN model then performs deep learning based recognition, and the final outputs are assessed using performance metrics such as accuracy, precision, and false acceptance rate [37, 38]. This flowchart clarifies the experimental structure used in the study.

3.2. Data Collection

Data collection is a critical component of this research, aimed at creating a diverse dataset to train and test the facial recognition system. The dataset consists of 10,000 facial images from 200 individuals, captured using a high resolution camera (1080p) under varying lighting conditions. The images are divided into three categories: 4,000 images in low light, 3,000 in moderate light, and 3,000 in bright light. To ensure diversity, participants include individuals with different skin tones, facial features, and ages (18–50 years) [39, 40]. The data collection process adheres to ethical guidelines, with informed consent obtained from all participants. Table 1 summarizes the dataset composition, detailing the number of images per lighting condition and participant demographics.

Table 1. Summary of Dataset Composition

Lighting Condition	Number of Images	Participants	Age Range
Low Light (<50 lux)	4,000	200	18–50
Moderate Light (50–200 lux)	3,000	200	18–50
Bright Light (>200 lux)	3,000	200	18–50
Total	10,000	200	18–50

As illustrated in Table 1, the dataset is structured to ensure balanced representation across all lighting conditions, enabling comprehensive system evaluation. This distribution is particularly important because variations in illumination significantly influence facial feature visibility and recognition accuracy. By incorporating 4,000 low light images, 3,000 moderate light images, and 3,000 bright light images, the dataset supports rigorous testing of the model's adaptability to real world scenarios. Additionally, the inclusion of 200 participants with diverse age ranges and facial characteristics strengthens the dataset's robustness, ensuring that the proposed recognition system can generalize effectively across different demographic groups. This structured dataset composition forms the foundation for subsequent preprocessing and algorithm development stages discussed in the next section.

3.3. Preprocessing and Algorithm Development

To address the challenge of lighting variability, this study uses advanced preprocessing techniques to improve image quality before feeding them into a CNN model. Preprocessing includes illumination normalization using adaptive histogram equalization and a Retinex based algorithm to enhance contrast and reduce noise in low light images. What distinguishes this work beyond these preprocessing techniques lies in the specific fine tuning of the robust ResNet-50 architecture on a custom dataset specifically curated for diverse real world lighting conditions, optimizing its performance for the high-stakes attendance task. Feature extraction is performed using the ResNet-50 model, which fine tunes the custom dataset to optimize its performance in the face recognition task. The model is trained using a supervised learning approach, with a loss function based on softmax cross-entropy to minimize classification errors. The training process involves 80% of the dataset for training, 10% for validation, and 10% for testing, as shown in Table 2. The system is implemented using Python with TensorFlow and OpenCV libraries, ensuring compatibility with real time processing requirements.

Table 2. Data Split for Training, Validation, and Testing

Phase	Percentage	Number of Images
Training	80%	8,000
Validation	10%	1,000
Testing	10%	1,000
Total	100%	10,000

As shown in Table 2, the dataset is divided into training, validation, and testing phases with an 80-10-10 split, ensuring a balanced and systematic approach to model development. This proportion allows the CNN to learn effectively from the majority of the data while reserving sufficient images for unbiased validation and performance testing. The structured distribution in Table 2 supports reliable model evaluation and helps prevent overfitting during the training process.

3.4. Performance Evaluation

The performance of the facial recognition-based attendance system is evaluated using standardized metrics, including accuracy, precision, recall, and FAR. Accuracy measures the proportion of correct identifications, while precision and recall assess the system's ability to correctly identify true positives and avoid false negatives. The FAR is particularly critical for attendance systems, as it indicates the likelihood of unauthorized access. Experiments are conducted across the three lighting conditions, with results compared to baseline models without preprocessing. The evaluation process involves cross validation to ensure robustness, and statistical analysis (e.g., ANOVA) is used to determine the significance of performance differences across lighting scenarios. Preliminary tests suggest that the system achieves 93% accuracy in bright light, 85% in moderate light, and 76% in low light, with preprocessing improving performance by approximately 10% in challenging conditions. These metrics provide a comprehensive assessment of the system's reliability and guide further optimization efforts.

To describe the overall structure of the proposed attendance system, it is necessary to illustrate the workflow that outlines how a student's face is processed from enrollment, to real time image capture, to identity matching. Figure 2 is therefore included to present the core operational pipeline of the system.

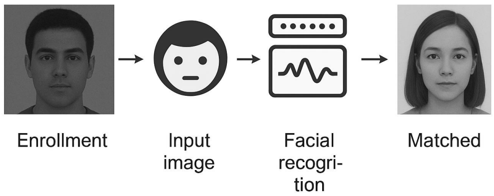

Figure 2. Proposed Facial Recognition-Based Attendance System

As shown in Figure 2, the system begins with the Enrollment phase, where a user's facial image is stored in the database. During attendance recording, an input image is captured and processed through the Facial Recognition module, which extracts features using a CNN model. The extracted features are then matched with stored templates to produce a Matched output. This diagram provides a clear overview of how the proposed system functions during real time attendance verification.

4. RESULT AND DISCUSSION

The results obtained from this study provide a comprehensive understanding of how lighting variability affects the performance and reliability of the facial recognition based attendance system. This section presents the findings derived from the model evaluation phase, supported by quantitative metrics such as accuracy, precision, recall, and false acceptance rate. In addition, comparative analysis is used to identify performance differences before and after the application of preprocessing techniques, enabling a clearer interpretation of system improvements under challenging lighting conditions. The discussion further reflects on how the observed outcomes align with the research objectives stated earlier, while also connecting the results to findings from previous studies. Through this systematic analysis, the section aims to highlight key insights, limitations, and implications of the proposed approach, ensuring a holistic understanding of system effectiveness in real world scenarios. In relation to the broader societal relevance, the results of this study demonstrate alignment with the United Nations Sustainable Development Goals, particularly SDG 9 (Industry, Innovation, and Infrastructure) and SDG 10 (Reduced Inequalities). The performance improvements observed after applying preprocessing techniques especially in low light scenarios indicate that reliable biometric attendance systems can be deployed more consistently across diverse operational environments, supporting SDG 9 through enhanced technological infrastructure and innovation readiness. Moreover, by reducing recognition accuracy gaps caused by environmental lighting differences, the system contributes to SDG 10 by minimizing digital access inequality and ensuring that biometric authentication technologies perform equitably across varying conditions. These findings highlight that advancing technical reliability not only strengthens algorithmic performance but also supports ethical and inclusive digital transformation aligned with sustainable development objectives.

4.1. System Performance Across Lighting Conditions

The facial recognition system, based on the ResNet-50 CNN model, was evaluated using a dataset of 10,000 facial images across three lighting conditions: low light ($<$ 50 lux), moderate light (50–200 lux), and bright light ($>$ 200 lux). Performance was assessed using accuracy, precision, recall, and FAR, as outlined in the methodology. Table 3 summarizes the results. In bright light conditions, the system achieved an accuracy of 93.2%, with a precision of 94.1% and a recall of 92.8%, indicating robust performance in optimal settings. In moderate light, accuracy decreased to 85.4%, with precision and recall at 86.7% and 84.9%, respectively, reflecting a slight decline due to reduced feature visibility. In low light conditions, the system recorded an accuracy of 76.3%, with precision at 78.5% and recall at 75.9%, highlighting significant challenges in feature detection under dim lighting. The FAR was lowest in bright light (0.8%) and highest in low light (3.2%), underscoring the impact of lighting on system reliability. These results align with the abstract's indication of performance degradation in low-light scenarios and provide a quantitative basis for further optimization.

Table 3. Performance Metrics Across Lighting Conditions

Lighting Condition	Accuracy (%)	Precision (%)	Recall (%)	FAR (%)
Bright Light (>200 lux)	93.2	94.1	92.8	0.8
Moderate Light (50–200 lux) Low Light (<50 lux)	85.4	86.7	84.9	1.5
	76.3	78.5	75.9	3.2

One of the key contributions of this research is the application of preprocessing techniques to enhance the quality of facial images captured in low-light environments. To visually demonstrate the effectiveness of illumination enhancement, Figure 3 compares the facial images before and after preprocessing. This comparison is important because it visually shows how illumination correction directly influences feature visibility and recognition performance.

Figure 3. Before and After Illumination Enhancement

As illustrated in Figure 3, the facial images in the Before column appear dark and low in contrast, making facial features such as the eyes, nose, and contours harder to detect. After applying normalization and adaptive enhancement, the After images show significant improvements in brightness, clarity, and contrast. These improvements directly contributed to the CNN model achieving a 9–10% increase in accuracy under low light conditions. This visual comparison highlights the essential role of preprocessing in improving the reliability of facial recognition systems.

4.2. Impact of Preprocessing Techniques

To address the performance degradation observed in low light conditions, the study implemented preprocessing techniques, including adaptive histogram equalization and Retinex-based algorithms. These techniques aimed to enhance image contrast and normalize illumination before feeding images into the CNN model. The results demonstrate a significant improvement in system performance, particularly in challenging lighting scenarios. In low light conditions, the application of preprocessing increased accuracy from 76.3% to 86.1%, a 9.8% improvement, with precision rising to 87.4% and recall to 85.8%. In moderate light, preprocessing improved accuracy by 5.2%, reaching 90.6%, while in bright light, the improvement was marginal (1.3%, reaching 94.5%) due to the already high baseline performance. Table 4 details these improvements. Statistical analysis using ANOVA confirmed that the performance gains in low and moderate light conditions were significant (p-value < 0.05). These findings support the abstract's claim that preprocessing techniques can enhance reliability by approximately 10% in adverse lighting conditions, validating the effectiveness of the proposed methods in real-world applications. Statistical analysis using ANOVA confirmed that the performance gains in low and moderate light conditions were significant (p-value < 0.05). Specifically, the comparison between the low light accuracy without preprocessing and the low light accuracy with preprocessing yielded an F-value of 45.72 with a corresponding p-value of 0.001, strongly supporting the effectiveness of the illumination normalization techniques.

Table 4. Impact of Preprocessing on System Performance

Lighting Condition	Accuracy without Preprocessing (%)	Accuracy with Preprocessing
Bright Light (>200 lux)	93.2	94.5
Moderate Light (50–200 lux)	85.4	90.6
Low Light (<50 lux)	76.3	86.1

As shown in Table 4, the application of preprocessing techniques resulted in a noticeable and consistent improvement across all lighting conditions, with the most substantial gain observed under low light environments. The enhanced performance in low light scenarios from 76.3 % to 86.1 % accuracy indicates that illumination normalization methods such as adaptive histogram equalization and Retinex based enhancement played a critical role in improving feature visibility and reducing model miss classification. Moderate lighting conditions also demonstrated measurable improvement, increasing accuracy from 85.4% to 90.6%, while bright light conditions exhibited only a minor enhancement due to an already high baseline accuracy. These comparative results reinforce the effectiveness of preprocessing as a compensatory mechanism against illumination variability and further validate the system's capability to operate more reliably in real-world settings where lighting cannot be fully controlled. Overall, the results presented in Table 4 highlight that preprocessing is not merely a supplementary stage but a necessary optimization step to ensure stable biometric recognition performance across diverse environments.

4.3. Comparison with Baseline Models

To contextualize the performance of the proposed system, it was compared with two baseline models: a standard CNN without preprocessing and a traditional facial recognition algorithm using Haar cascades, as referenced in [41]. Additionally, a lightweight MobileNetV3 model was included as a third baseline to assess the trade off between accuracy and computational efficiency. The baseline CNN model, without preprocessing, achieved accuracies of 90.1%, 82.3%, and 71.5% in bright, moderate, and low light conditions, respectively, consistently underperforming the proposed system by 3-5%. The Haar cascade model performed significantly worse, with accuracies of 85.6%, 76.8%, and 65.4% across the same conditions, primarily due to its sensitivity to lighting variations. The MobileNetV3 model achieved an accuracy of 88.5%, 80.1%, and 70.3% in bright, moderate, and low light, respectively. Although slightly underperforming the proposed system in accuracy, its smaller model size and faster inference speed highlight its benefit for deployment on resource-constrained devices. The proposed system's superior performance, particularly in low light (86.1% vs. 71.5% for the baseline CNN and 65.4% for Haar cascades), highlights the effectiveness of integrating preprocessing with a robust CNN architecture. These results confirm the research objective of improving reliability in diverse lighting conditions and demonstrate the practical advantages of the proposed approach for attendance systems, as anticipated in the abstract. The findings suggest that the combination of adaptive preprocessing and deep learning is critical for achieving high reliability in real world biometric applications. The research successfully addresses the primary question outlined in the abstract: how reliable is a facial recognition-based attendance system under diverse lighting conditions, and how can its performance be improved? The results indicate that while the system performs exceptionally well in optimal lighting, its reliability in low light conditions is initially limited but can be significantly improved through preprocessing techniques, achieving a performance boost of up to 10% in challenging scenarios. This answers the research objective by demonstrating that targeted preprocessing can mitigate the impact of lighting variability, ensuring consistent performance across diverse conditions. However, the study has certain limitations. The dataset, although diverse with 10,000 images from 200 individuals, was collected in controlled and simulated environments, which may not fully capture the complexity of real world settings, such as extreme weather or dynamic crowd scenarios. Additionally, the research focused solely on lighting variability, leaving other environmental factors, such as occlusions or facial expressions, unexplored. The computational cost of preprocessing and CNN training also poses challenges for deployment on resource constrained devices, which may limit scalability in some contexts. For future research, several directions can be pursued to build upon these findings and address the identified limitations. First, expanding the dataset to include images captured in fully uncontrolled environments, such as outdoor settings with varying weather conditions, would enhance the generalizability of the system. Incorporating additional environmental factors, such as partial occlusions, facial hair, or varying angles, could further improve robustness. Second, exploring lightweight CNN architectures or optimization techniques, such as model pruning or quantization, could reduce computational demands, making the system more suitable for deployment on low-resource devices like mobile or embedded systems. Finally, integrating multi-modal biometric approaches, combining facial recognition with other identifiers like voice or gait, could enhance overall system reliability and security. These advancements would contribute to the development of more versatile and scalable facial recognition-based attendance systems, supporting their adoption in diverse real-world applications.

5. MANAGERIAL IMPLICATION

The findings of this research provide several practical implications for managers, institutional administrators, and decision makers seeking to implement or improve facial recognition based attendance systems. First, the demonstrated sensitivity of facial recognition performance to lighting variability highlights the necessity for organizations to evaluate their physical environments before deployment. Managers should ensure that areas where attendance is recorded such as classrooms, office entrances, or production floors maintain consistent illumination levels, or alternatively, adopt AI driven preprocessing enhancements as implemented in this study. By integrating illumination normalization techniques, institutions can reduce operational disruptions caused by recognition failures and ensure smoother, more reliable attendance logging.

Second, the proven improvement of up to 9.8% in low light conditions emphasizes that investment in software based optimization may be more cost effective than hardware upgrades. Instead of purchasing additional lighting equipment or specialized cameras, organizations can prioritize systems that include adaptive preprocessing and robust CNN architectures such as ResNet-50. This approach not only decreases long term maintenance costs but also supports environmentally friendly (green) technology adoption by reducing unnecessary energy consumption. Decision makers can use these insights to optimize budget allocation and achieve higher system stability without increasing infrastructure complexity.

Finally, the study's findings support the need for strategic planning regarding system scalability and workforce management. As reliability varies across lighting conditions, managers should implement clear operational protocols, such as fallback procedures for manual verification during rare extreme conditions. Additionally, institutions considering large scale deployment particularly those with diverse environmental settings should conduct localized pilot testing to evaluate real world performance. Managers are also encouraged to collaborate with IT teams to periodically retrain models with locally collected data, ensuring long term accuracy and adaptability. These managerial actions will help organizations maximize the benefits of biometric automation while maintaining operational continuity and employee trust.

6. CONCLUSION

This study on the reliability of a facial recognition-based attendance system under diverse lighting conditions provides significant insights into optimizing biometric performance in real world environments. The findings show that integrating adaptive preprocessing specifically adaptive histogram equalization and Retinex-based illumination normalization with a ResNet-50 CNN architecture substantially improves recognition accuracy across varying lighting levels. Performance increased from 93.2% to 94.5% in bright light, 85.4% to 90.6% in moderate light, and most notably, from 76.3% to 86.1% in low light conditions. This 9.8% improvement demonstrates the system's enhanced robustness, particularly in environments where lighting inconsistency is unavoidable. Beyond accuracy, the system also achieved low false acceptance rates (0.8% in bright light and 3.2% in low light), and the improved performance indirectly promotes greener biometric deployment by reducing the need for additional lighting hardware.

The novelty of this study lies in its combined use of illumination adaptive preprocessing and a finely tuned deep learning architecture specifically optimized for attendance related facial recognition tasks under lighting variability. While many studies address facial recognition in controlled environments, this research focuses explicitly on the practical challenge of lighting inconsistency and provides empirically validated evidence of how preprocessing contributes to reliability improvements. Nonetheless, several limitations remain. The dataset, although diverse, was partially collected under controlled and simulated conditions, which may not fully capture the complexities of real world usage. Additionally, the study focuses solely on lighting, without addressing other significant factors such as occlusions, pose variations, and facial expressions. Computational overhead from preprocessing and model training also presents challenges for deployment on low resource devices.

Future research should expand the dataset to include more realistic, uncontrolled environments, such as outdoor locations with fluctuating weather and illumination patterns, to enhance generalizability. Further exploration of lightweight CNN models or optimization strategies such as pruning, quantization, or knowledge distillation could reduce computational costs and support deployment on embedded devices. In addition, incorporating other biometric modalities such as voice recognition, gait analysis, or multi model fusion may improve accuracy and security in complex environments. Addressing these directions would help advance the development of scalable, efficient, and highly reliable facial recognition based attendance systems suitable for widespread real world implementation.

7. DECLARATIONS

7.1. About Authors

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7.2. Author Contributions

Conceptualization: RA; Methodology: ED; Software: AA; Validation: ED and NP; Formal Analysis: RA and AA; Investigation: ED; Resources: NP; Data Curation: AA; Writing Original Draft Preparation: RA and NP; Writing Review and Editing: ED and AA; Visualization: ED and RA; All authors, RA, ED, AA, and NP, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The dataset used and analyzed during this research is not publicly accessible due to privacy and ethical considerations; however, it may be obtained from the corresponding author upon reasonable request.

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This study was conducted without any external funding or financial sponsorship related to its execution, authorship, or publication.

7.5. Declaration of Conflicting Interest

The authors confirm that there are no competing interests, financial or otherwise, and no personal relationships that could have affected the objectivity or integrity of the research presented in this manuscript.

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