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Analysis of Illumination Invariant Method for Face Detection in Different Lighting Variations

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ABSTRACT

Lighting quality is a crucial factor that affects the performance of camera-based face detection systems, especially in CCTV surveillance systems that operate in low or uneven lighting conditions. This study aims to analyze the performance of illumination-invariant preprocessing methods in improving the accuracy of human face detection under various lighting conditions. Three preprocessing approaches were compared, namely Histogram Equalization (HE), Gamma Correction (GC), and a hybrid method that combines both (GC+HE). The dataset used consists of 1415 human face images taken using a webcam with variations in five lighting conditions, four face directions, and three shooting distances. All images were processed using the Haar Cascade Classifier algorithm as the face detection method. Performance evaluation was conducted using accuracy, precision, recall, and confusion matrix analysis metrics. The test results showed that the hybrid method provided the best performance with a precision of 92.79%, accuracy of 87.49%, and recall of 89.61%, compared to the HE and GC methods used individually. This improvement indicates that the combination of lighting normalization and contrast enhancement can produce more stable and informative facial images for the detection process. The findings of this study indicate that the hybrid-based illumination invariant approach is very effective for application in real-time visual surveillance systems, especially in environments with limited lighting.

I. Introduction

Video surveillance systems such as CCTV have become an important foundation in efforts to maintain security in both public and private spaces. However, the effectiveness of these systems is highly dependent on the visual quality of the recordings. One of the main challenges is the decline in image quality in low light conditions or when room lighting is inadequate. In many cases, conventional CCTV cameras often fail to capture important details such as human facial features, especially at night or in areas with uneven lighting. When the ambient luminance level falls below the optimal threshold of around 20 lux, image quality is compromised by visual disturbances such as noise, reduced contrast, and loss of important details from faces, which are key features for identifying perpetrators [1] [2]. Various studies support this statement, such as [3] emphasized that deep learning-based facial detection systems still face difficulties in processing low-light CCTV footage without digital compensation. The same applies to the research conducted by [4] which shows that CNN models experience a significant decline in performance when handling facial images with poor lighting. This is reinforced by a study which examined the use of Histogram Equalization on CCTV and found that this technique effectively improves contrast in dark conditions, but needs to be improved for real-time application.

These lighting quality issues not only affect visual quality, but also directly impact the performance of the automatic face detection system. Conventional methods such as Haar Cascade are very sensitive to shadows, light reflections, and bright backgrounds. This phenomenon makes it difficult for the system to distinguish faces from the background, especially in low lighting [5], [6]. In the context of workspaces or educational environments, the use of CCTV without additional lighting is considered suboptimal because it produces uninformative visuals and makes analysis difficult [7]. Empirical evidence also supports this, as the research conducted by [8] report that face detection quality can decrease by up to 30% in poor lighting conditions compared to ideal conditions. Error rates such as false positives and false negatives increase dramatically if lighting preprocessing is not applied. A study by [9] in the book "Digital Image Processing" explains that improving visual quality through image processing techniques is a key component in ensuring the reliability of camera-based security systems.

To address the decline in image quality caused by lighting conditions, as discussed earlier, an approach is needed that can normalize lighting intensity without losing important facial information. One commonly used approach is the illumination-invariant preprocessing technique. In this study, two commonly used techniques are Histogram Equalization (HE) and Gamma Correction. HE improves global contrast by spreading pixel intensity evenly, while Gamma Correction adjusts lighting intensity while maintaining facial texture details [10]. This approach is widely used in surveillance systems and face monitoring applications due to its lightweight nature and ease of implementation [11]. A hybrid approach that combines Gamma Correction and HE sequentially has been proven to provide more stable results. The study found that the combination of these techniques not only improves the contrast and visibility of human facial features, but also reduces background noise. The study a low-light room monitoring environment showed that enhancing contrast through preprocessing significantly contributes to improved face detection accuracy in low-light environments.

However, the use of these preprocessing methods still leaves room for further research, particularly with regard to systematic comparative evaluations under various lighting conditions in the context of CCTV-based security systems. The research conducted by [12] emphasize the importance of using evaluation metrics such as confusion matrix, accuracy, precision, recall, and F1-score to compare the effectiveness of each preprocessing method. With these parameters, the system can be optimized according to field requirements. The combination of Multiscale Retinex and HE has also been shown to improve face feature detection performance by up to 70% in low-light images. This improvement allows the system to accurately extract important facial features even in extreme conditions. The study shows that pixel-wise gamma mapping is also effective in stabilizing lighting without adding noise, which is very useful in real-time CCTV-based video.

In practical applications, especially in security systems such as smart CCTV or Internet of Things (IoT)-based monitoring systems, the ability to detect faces in low-light conditions is crucial. Many crimes occur in dark areas such as narrow alleys or underground parking lots, which are weak points for conventional CCTV cameras. The study shows that increasing contrast through preprocessing can significantly improve CCTV image results without the need to replace hardware. The application of Gamma Correction and Histogram Equalization also has high economic value because it does not require additional devices such as infrared cameras. The research conducted by [13] in the development of Low-FaceNet revealed that an efficient preprocessing system can improve real-time face recognition performance in systems with limited resources. The study also noted that lightweight visual systems developed with power-saving principles are suitable for application in IoT-based automatic surveillance systems.

Based on these practical implementation needs and previously identified research gaps, this study focuses on a comparative analysis of the performance of three illumination-invariant preprocessing methods, namely Histogram Equalization, Gamma Correction, and a combination of both, in detecting human faces under different lighting conditions. Unlike many previous studies that rely on a single preprocessing algorithm, this research proposes a hybrid illumination enhancement approach to improve system adaptability under dynamically changing lighting environments. The research was conducted experimentally by using a facial image dataset captured across multiple lighting scenarios, followed by systematic preprocessing and evaluation using precision, recall, and overall accuracy metrics. The scope of the study is limited to the preprocessing stage in human face detection, not to direct face classification or recognition, in order to explicitly quantify the contribution of illumination normalization to detection robustness. The novelty of this work lies in its structured comparative framework and adaptive hybrid strategy designed to enhance detection stability while maintaining computational efficiency for embedded and IoT-based surveillance systems. From a scholarly perspective, this study contributes empirical evidence demonstrating that combining contrast redistribution and luminance correction yields more consistent detection performance than single-method approaches. In terms of tangible societal benefits, the proposed method enables more reliable and cost-effective smart CCTV deployment without requiring additional hardware such as infrared cameras, thereby improving security monitoring in public spaces, industrial facilities, and transportation infrastructures operating under non-ideal lighting conditions.

II. METHODOLOGY

This section discusses matters related to the flow of research work, including datasets, data preprocessing, model training, model evaluation, implementation, and system testing.

A. Related Work

Research on facial recognition in suboptimal lighting conditions has grown rapidly along with the increasing need for CCTV-based visual security systems. Illumination-invariant preprocessing techniques such as Histogram Equalization (HE) and Gamma Correction (GC) are widely used to stabilize image quality before face detection. The study developed a CCTV-based criminal investigation framework that utilizes dark image contrast enhancement, and the results show that visual quality enhancement methods are very helpful in the process of identifying perpetrators. This approach is important because unstable environmental lighting conditions can cause high noise and loss of important visual features on human faces. The research conducted by [14] also showed that an embedded system-based face recognition system that uses the illumination invariant method has more stable performance when faced with changes in light intensity, especially for door access control purposes. Similar findings were revealed by [15], who implemented a lighting-resistant facial recognition system for digital kiosk-based healthcare services and successfully maintained identification accuracy even under extreme lighting conditions. The results of this study reinforce that lighting preprocessing is a crucial stage in camera-based facial recognition systems under various lighting conditions.

In addition, other studies also emphasize the importance of combining methods to improve the resilience of facial detection systems against noise and excessive shadows. The research conducted by [16] proposed a campus security system based on automatic facial detection integrated with image processing to overcome the challenge of uneven lighting. By applying a hybrid technique that combines HE and GC, facial contour visibility is significantly improved, and false positives and false negatives in the detection process are reduced. The research conducted by [17] show that the lighting normalization method is very effective in reducing the effects of makeup and shadows on the face, making the system more adaptive to variations in user appearance. This study also found that the influence of lighting is more dominant in determining recognition performance than other parameters such as face position. Based on these studies, it can be concluded that illumination-invariant preprocessing is an important step in building a more reliable object detection system in the real world and is a strong foundation for this research

B. System Architecture Design

The system architecture used in this study is designed to support real-time human object detection through a combination of sensors, cameras, and integrated processing based on Raspberry Pi. When movement occurs, the PIR sensor detects changes in infrared radiation from the human body, then sends a signal to the Raspberry Pi as the system control center. Simultaneously, the LDR sensor and digital camera capture light intensity and visual images of objects to support the identification process. Data from the sensors and cameras is processed on the Raspberry Pi, which is then forwarded via a Wi-Fi network to a local server or cloud server. Several studies have shown that this approach is effective in increasing system response speed while enabling integration with IoT-based platforms to maximize monitoring performance [18][19]. In addition, this design also allows the system to efficiently detect, record, and store human movement data to support security investigations.

The next step is data processing on local and cloud servers, which allows for flexibility in analysis. Local servers serve as temporary storage that can be used to provide instant notifications, such as automatic alarms when objects are detected. Meanwhile, cloud servers are used to store data in the long term, perform artificial intelligence-based analysis, and provide remote access to users via internet-based devices. Previous research emphasizes the importance of cloud integration to support advanced analysis and real-time data availability [20], The implementation of this IoT-based architecture has also been proven effective in supporting various image processing and face detection methods, including the application of illumination invariant preprocessing techniques such as Histogram Equalization and Gamma Correction, which require higher computing power [21][22]. The design of this system architecture not only functions as a simple surveillance system, but also supports the application of advanced analytical methods to improve the accuracy of face detection in complex lighting conditions. The architectural design of this system can be seen in Figure 1.

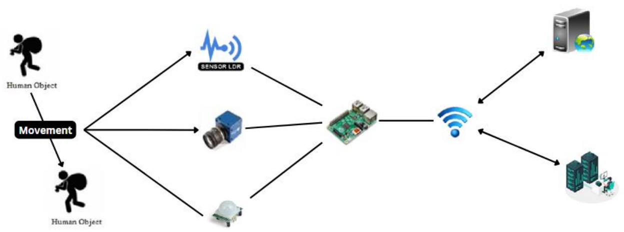

Figure 1. System Detection Architecture.

C. Human Face Detection Method

The face detection method used in this study employs the Haar Cascade Classifier, a popular algorithm in object detection systems due to its speed and efficiency on devices with limited resources. The detection process begins by capturing images from a camera or video, which are then converted to grayscale. This step is performed to simplify computation, as intensity-based detection does not require color information. Next, the grayscale image is processed using the Haar Cascade Classifier and Convolutional Neural Network (CNN). This algorithm works by scanning the image at various scales (multi-scale detection), so that faces can be recognized even if their size varies within the frame. If a face is detected, the system draws a bounding box around the face area, and the detection results are saved or displayed on the user's screen. However, if no face is detected, the system will output “No Face”.

Technically, the face detection system in this study employs two approaches like the Haar Cascade Classifier and the Convolutional Neural Network (CNN) to evaluate face detection performance under various lighting conditions. The Haar Cascade utilizes Haar-like features that represent differences in intensity between image regions and employs integral images to accelerate the computational process. This method is known for its low computational complexity and ability to operate in real-time on resource-constrained devices such as the Raspberry Pi in IoT-based surveillance systems [22][23][24]. In addition, this study employs a CNN-based approach as a modern benchmark due to its ability to handle variations in lighting conditions, poses, and backgrounds. CNN is used to compare detection performance with the Haar Cascade method and to evaluate the impact of lighting-invariant preprocessing on both approaches. However, CNN requires greater computational resources, whereas the Haar Cascade offers a faster and lighter solution suitable for real-time CCTV-based surveillance systems.

D. Illumination Invariant Model Concept

One of the biggest challenges in CCTV-based face detection systems is unstable lighting conditions, especially in environments with low light intensity or uneven lighting. To overcome this, this study uses an illumination invariant preprocessing model designed to stabilize lighting before the face detection stage is carried out. The system workflow begins with image capture via a camera, followed by a lighting condition check. If low lighting conditions are detected, lighting enhancement methods such as Histogram Equalization (HE), Gamma Correction (GC), or a combination of both in Hybrid form are applied. After this stage, the image is converted to grayscale to simplify computation, then forwarded to the face detection process using the Haar Cascade Classifier and Convolutional Neural Network (CNN). With this approach, the system can produce more stable facial images, thereby increasing accuracy and reducing the error rate in detection. A number of studies have confirmed that illumination enhancement is a crucial factor in improving the reliability of camera-based visual security systems [25].

The advantage of this illumination-invariant model is its flexibility in selecting lighting enhancement methods according to real conditions. Histogram Equalization provides a more even intensity distribution, making it suitable for images with low contrast, while Gamma Correction is more effective for improving images that are too dark or too bright. A hybrid approach that combines the two has even been proven to preserve facial texture details while improving contour visibility. Recent research shows that this combination of preprocessing can improve face detection performance by 20–30% compared to images without preprocessing [26][27]. Furthermore, integrating this method with IoT-based devices such as Raspberry Pi also enables real-time implementation without the need for expensive additional hardware. Therefore, illumination-invariant models are an important foundation for ensuring that face detection systems remain reliable in real-world environments, which are often full of lighting variations. This process is illustrated in the flowchart in Figure 2.

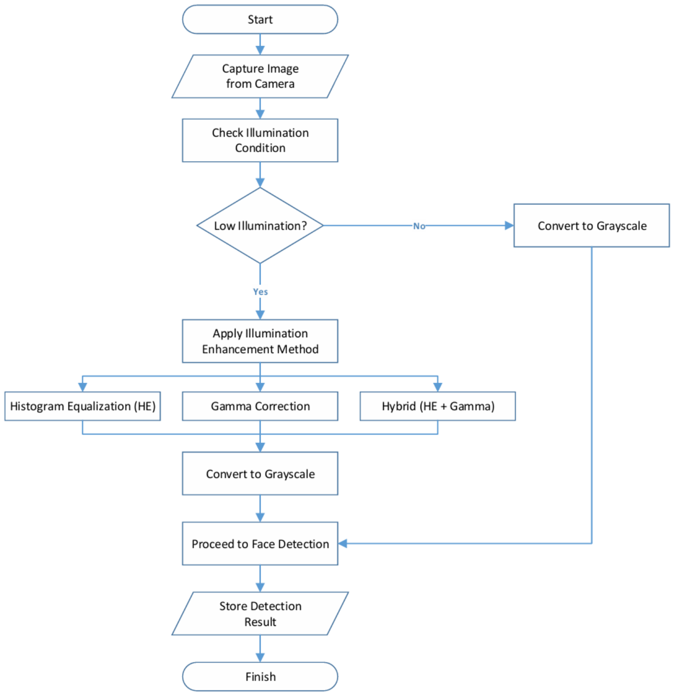

Figure 2. Flowchart of Illumination Invariant Implementation.

III. RESULTS AND DISCUSSION

In the context of face detection in CCTV-based surveillance systems, uneven lighting conditions often result in suboptimal image quality. Therefore, illumination invariant preprocessing methods are used to stabilize lighting and improve the clarity of facial features. The two most commonly applied methods are Histogram Equalization (HE) and Gamma Correction (GC). Histogram Equalization works by redistributing the pixel intensity values in the image so that the contrast distribution becomes more even. This technique is very effective for improving visibility in areas that are too dark or too bright [28]. Meanwhile, Gamma Correction is a non-linear method used to improve image brightness by adjusting the intensity value using an exponential function [29]. A gamma value of less than 1 is used to brighten the image, while a gamma value of more than 1 is used to darken it. The combination of the Gamma Correction and Histogram Equalization methods has been proven to increase the number of detected facial features while maintaining the natural structure of the face in the image [30]. In this study, the two methods were combined in a hybrid approach because the integration of contrast enhancement and brightness correction can produce more balanced lighting normalization and reduce the loss of important facial features in low-light conditions. Previous research has also shown that combining histogram equalization with adaptive gamma correction is effective in improving image quality in low-light conditions and enhancing visual information for computer vision applications [31].

The application of Gamma Correction (GC) and Histogram Equalization (HE) in CCTV-based surveillance systems plays a crucial role in improving image quality under uneven lighting conditions. GC is used to adjust overall brightness and preserve facial textures in dark images, while HE enhances the overall contrast distribution to make facial features more visible. In this study, both methods were applied sequentially as lighting-independent preprocessing steps prior to the face detection stage. To evaluate the effectiveness of the preprocessing methods, two face detection approaches like Haar Cascade and Convolutional Neural Networks (CNN) were used as comparison methods to determine whether faces could be successfully detected after image quality enhancement. Previous studies have reported that gamma- and histogram-based preprocessing can improve face detection performance by 15–30% on low-light CCTV images, indicating that preprocessing is a critical component in real-time video surveillance systems under challenging lighting conditions. The overall research design and processing stages applied can be seen in Figure 3.

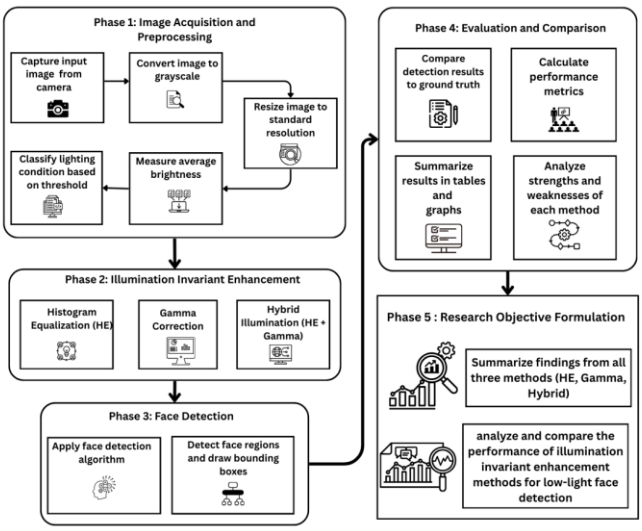

Figure 3. Research Design Plan.

A. *Phase 1: Image Acquisition and Reprocessing*

The initial stage in the face detection system is image acquisition and preprocessing. CCTV cameras are used to capture images of faces from real environments with varying lighting conditions. Each image captured is converted to grayscale format to reduce computational complexity, as color information does not significantly affect intensity-based face detection. The images are then converted to a standard size so that the comparison process between samples is more uniform. In addition, the system performs an average brightness analysis to classify lighting conditions such as bright, normal, low, and dark. At the stage of capturing input images from the camera, 1,415 images of human faces were taken using a webcam. Each image was grouped into five lighting conditions: normal lighting, low lighting, backlighting, direct lighting, and dark. In addition, each lighting category included variations in face direction (parallel, left, right, down) and shooting distance (close, medium, far). All data was structured in folders based on lighting category, face direction, and distance for easy processing in the next stage.

The next step involves converting the input image to grayscale and resizing it to a standard resolution before applying a preprocessing method that is not affected by lighting conditions. Conversion to grayscale is performed to reduce image complexity by retaining only luminance information, allowing the system to focus on important facial features such as texture, edges, and contours, while minimizing the impact of color variations caused by lighting changes. Grayscale conversion effectively preserves critical luminance information and reduces distortion caused by extreme lighting during face detection [32]. Afterward, the image is resized to ensure consistent dimensions across the dataset, which helps improve processing efficiency and maintain consistency during the detection process. These preprocessing steps are crucial for improving the stability and robustness of the face detection system under varying lighting conditions. Afterward, the image is resized to ensure consistent dimensions across the dataset, which helps improve processing efficiency and maintain consistency during the detection process. These preprocessing steps are crucial for improving the stability and robustness of the face detection system under varying lighting conditions. This is reinforced by [33], that brightness normalization can improve the consistency of facial feature representations by correcting uneven light intensity distributions

B. *Phase 2: Illumination Invariant Enhancement*

In this study, the illumination-invariant enhancement stage was performed after the initial detection of the face region (region of interest/ROI) from images captured in real time using a CCTV camera. Once the face area was successfully obtained, a lighting normalization process was performed to reduce the effects of low or uneven light intensity so that facial details could still be clearly recognized. Lighting conditions in this study were divided into five categories: Normal Lighting, Low Lighting, Backlighting, Direct Lighting, and Dark or Uneven Lighting, characterized by uneven light distribution due to shadows or a light source from a single direction.

In the enhancement stage, this study tested three illumination-invariant preprocessing methods: Histogram Equalization (HE), Gamma Correction (GC), and a hybrid method (GC+HE). HE is used to improve the image's contrast distribution by evening out pixel intensity, while GC is used to adjust the image's brightness level non-linearly using a gamma parameter of 1.5 to preserve facial texture and detail in low-light conditions. In the hybrid method, the process is performed sequentially by first applying Gamma Correction to improve the image's global luminance, followed by Histogram Equalization to enhance local contrast and clarify facial contours [34]. This combination was chosen because GC can improve the visibility of dark areas without losing important details, while HE is capable of emphasizing facial patterns and structures, thereby producing more stable image quality for the face detection process using Haar Cascade and CNN in the subsequent stages. In addition, research conducted by [35] reports that gamma correction effectively improves the accuracy of face recognition under extreme lighting conditions. Therefore, the illumination-invariant method used in this study serves as a crucial step in enhancing image quality prior to the face detection evaluation process. The lighting category criteria used in this study are presented in Table I.

TABLE I
LIGHTING CATEGORY CRITERIA

No	Light Category	Lux Value (Lux)	Description
1	Normal Lighting	100 to 250	Image conditions with adequate lighting indoors
2	Low Lighting	30 to 75	An image in low light conditions, details are still clearly visible from a window with light sources such as sunlight.
3	Backlighting	75 to 100	A condition where the light source is behind the object
4	Direct Lighting	> 250	Lighting from multiple light sources and sufficiently bright
5	Dark	< 30	Dim lighting where image details are still visible from the room's light source

In low lighting conditions, the system has difficulty accurately detecting human facial features. As shown in Figure 4.

Figure 4. Original Image (a) and Gamma Correction (b).

To overcome this problem, the Gamma Correlation method was applied as part of the Illumination Invariant process to adjust the lighting intensity in the image. The results of processing using Gamma Correlation showed an improvement in the system's ability to detect all human objects in the image, as can be seen in Figure 4b. This test demonstrated the effectiveness of the method used in overcoming lighting constraints to support accurate object detection.

Figure 5. Histogram Equalization Combination.

Combination of Histogram Equalization After applying gamma correction to human facial images, this gamma correction is then combined with other lighting normalization methods within the framework of illumination-invariant preprocessing. Figure 5 shows the final result, where the facial image has undergone a combined pre-processing stage consisting of grayscale conversion, gamma correction, and Histogram Equalization (HE). After gamma correction produces an image with more stable lighting intensity in various areas, the histogram equalization stage is then applied to improve global contrast by distributing pixel intensity more evenly across the entire face area. This visual change is evident in the increased sharpness of facial details such as cheek contours, nose, eyes, and hair texture, which become clearer and more recognizable compared to the image before processing.

C. *Phase 3: Face Detection*

In the third stage, the system performs face detection using two approaches like the Haar Cascade Classifier and the Convolutional Neural Network (CNN) to compare detection performance after the image undergoes illumination-invariant preprocessing. The Haar Cascade was chosen because it offers high detection speed and low computational complexity, making it suitable for devices with limited resources such as the Raspberry Pi [36]. This method detects faces by analyzing pixel intensity differences using Haar-like features and the Integral Image mechanism, allowing the detection process to be performed quickly and efficiently [37]. Meanwhile, the CNN is used as a deep learning-based approach to evaluate face detection capabilities under more complex lighting conditions and as a benchmark against the conventional Haar Cascade method. The use of these two methods aims to analyze the impact of illumination-invariant preprocessing on the success of face detection, both in lightweight, low-computational-load methods and modern deep learning-based methods. Previous research has shown that the Haar Cascade remains effective when applied to Raspberry Pi-based systems [38]. whereas CNNs demonstrate superior capability in extracting facial features under diverse lighting conditions and backgrounds.

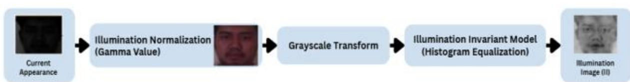

Figure 6. Illumination Invariant Face Detection Stages.

Figure 6 illustrates the preprocessing steps for facial images in response to changes in lighting, applied prior to the face detection process using the Haar Cascade and CNN. This process begins with the original face image (current appearance) captured under uneven lighting conditions, which can reduce the visibility of facial features. To address this issue, Gamma Correction with a specified gamma value is applied to normalize global brightness and stabilize the image’s luminance. The image is then converted to grayscale to simplify visual information and emphasize light intensity patterns rather than color information. Next, Histogram Equalization is performed to redistribute pixel intensity values and enhance image contrast, making facial contours and key features more distinct. The final result is an Illumination Image (II) with normalized brightness that is more stable against lighting variations and suitable for subsequent face detection stages. Based on these processing steps, Figure 7 shows that facial objects can be successfully detected after the process of improving resistance to lighting variations. This also confirms that the illumination invariant approach can improve the consistency and accuracy of the facial detection system under various lighting conditions.

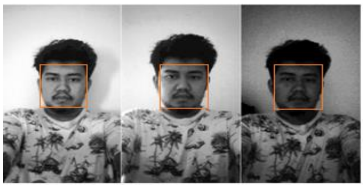

Figure 7. applying the Haar Cascade Method.

D. Phase 4: Evaluation And Comparison

In the evaluation phase, the performance of face detection using the Haar Cascade and CNN methods was compared to analyze the effectiveness of the proposed lighting-robust preprocessing approach in improving face detection under varying lighting conditions.

Figure 8. Normal (a) and Illumination Invariant (b) using Haar Cascade.

Figure 8 shows a comparison of face detection results using the Haar Cascade method under normal conditions and after applying the illumination-invariant preprocessing method. In Figure 8a, which shows the detection results without the application of illumination-invariant preprocessing, the system was only able to correctly detect 7 out of a total of 21 tested face images. Several facial objects failed to be detected due to low lighting conditions and uneven light distribution, making facial details less visible. In addition, several detection errors (false positives) were found, indicated by the appearance of green boxes in areas that were not faces. These results show that the Haar Cascade method is highly sensitive to variations in lighting and background noise, especially when image contrast is low. Meanwhile, Figure 8b shows the detection results after the images underwent illumination-invariant preprocessing using a combination of Gamma Correction and Histogram Equalization. After the enhancement process was performed, all 21 facial images were successfully detected by the system, indicating that preprocessing is capable of improving the visibility and contrast of facial features under varying lighting conditions. However, although the detection success rate increased significantly, the system still produced several false positives, as indicated by the appearance of additional green boxes in non-facial areas in some images. This indicates that the illumination-invariant method successfully enhances the clarity of facial features, but simultaneously amplifies certain background patterns and noise that are mistakenly recognized as faces by the Haar Cascade classifier. Overall, these results demonstrate that the proposed preprocessing approach is effective in improving face detection success under low-light conditions, although detection accuracy still needs to be improved to reduce the occurrence of missed detections and false positives.

Figure 9. Normal (a) and Illumination Invariant (b) using CNN.

In addition, this study also conducted tests using the Convolutional Neural Network (CNN) method to compare face detection performance after applying illumination-invariant preprocessing. Figure 9a shows the results of face detection using CNN after applying Gamma Correction during the image preprocessing stage. Out of a total of 21 face images tested, the system successfully detected approximately 10 faces, marked with green boxes in the facial area. The application of Gamma Correction helped increase the image brightness, making some facial features that were previously dark more visible to the detection system. However, some faces were still not detected due to extreme lighting conditions such as low light and backlight. Furthermore, Figure 9b shows the detection results after applying a combination of Gamma Correction and Histogram Equalization. At this stage, the system successfully detected 19 out of 21 tested face images. The combination of these two methods improved the image’s lighting distribution and contrast, making facial features clearer and easier for the CNN to recognize.

The results show that the application of the illumination-invariant method can improve face detection performance under uneven lighting conditions. The combination of

Gamma Correction and Histogram Equalization has proven effective in improving image quality by enhancing the brightness and contrast of faces prior to the detection process [39][40]. Several previous studies have also stated that the combination of these two methods can reduce detection errors caused by low lighting and help preserve facial feature details [41][42]. Thus, the application of illumination-invariant-based preprocessing yields more stable and accurate detection results in the CNN method compared to without enhancement.

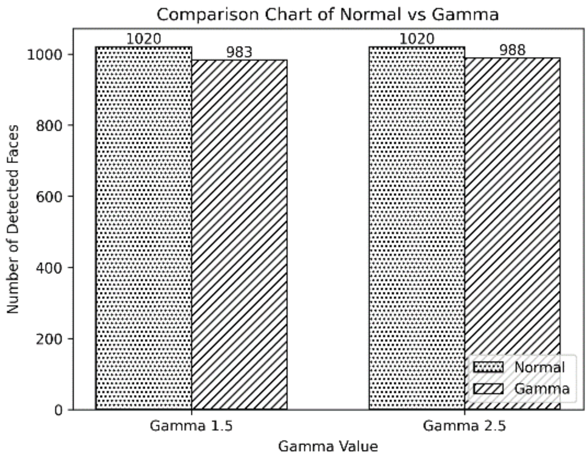

Figure 10. Comparison Chart of Normal vs Gamma.

In figure 10 shows a comparison of the number of faces successfully detected between images without lighting correction (Normal) and images that have been processed using Gamma Correction with two different gamma values, namely $\gamma = 1.5$ and $\gamma = 2.5$. Under normal lighting conditions, the system was able to detect 1020 faces from the entire dataset. After applying gamma correction with a value of $\gamma = 1.5$, the number of detections decreased to 983 faces, and at $\gamma = 2.5$, the number of detections decreased to 988 faces. These results show that the application of gamma correction does not improve overall face detection performance, and even causes a slight decrease compared to images without lighting correction. This decrease can be explained by the characteristics of gamma correction, which works non-linearly by modifying the distribution of pixel intensity. In some images, gamma correction does increase the brightness of dark areas, but in other images it can cause over-enhancement, i.e., an excessive increase in intensity that causes certain parts of the face to lose local detail.

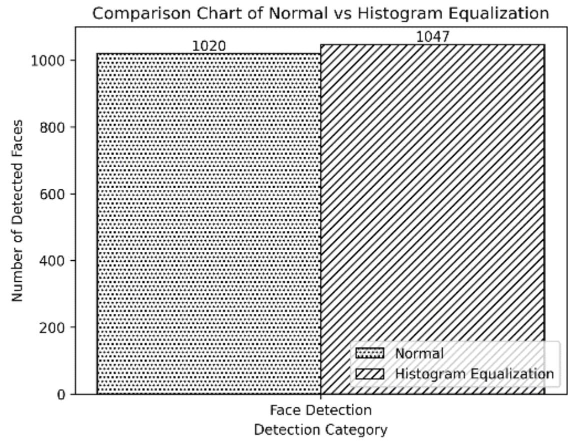

Figure 11. Comparison Chart of Normal vs Histogram Equalization.

In figure 11 shows a comparison of the number of faces successfully detected between Normal conditions (without increased lighting) and conditions after applying Histogram Equalization (HE) with a Gamma parameter of 1.5. Under Normal conditions, the face detection system detected 1020 faces. Meanwhile, in images that have undergone Histogram Equalization, the number of detections increased to 1087 faces, showing a performance improvement of 6.56%. This improvement illustrates that Histogram Equalization is able to improve the distribution of pixel intensity, making facial features easier to recognize by the detection algorithm. In addition, the increase in the number of detections from 1020 to 1087 faces also confirms that the use of HE as a preprocessing stage can improve the robustness of the face detection and recognition system against lighting variations, especially in low or uneven light conditions. Thus, methods such as Histogram Equalization can be considered an important component in the preprocessing pipeline to improve the performance of facial detection systems, both in Haar Cascade-based approaches and CNN-based methods.

E. Phase 5: Research Objective Formulation

The fifth stage involves formulating the final research objectives and interpreting the results based on the empirical findings obtained from all previous stages. In this phase, the experimental results are analyzed to evaluate the effectiveness of the illumination-invariant method on face detection performance using the Haar Cascade. The confusion matrix analysis indicates a significant difference in performance between the Gamma Correction (GC), Histogram Equalization (HE), and hybrid (GC+HE) methods. In the Gamma Correction method, the number of false positives and false negatives remains relatively high, indicating that the lighting normalization process has not yet been able to optimally improve image quality. This condition causes the system to still make errors in distinguishing between face and non-face areas, particularly under low and uneven lighting conditions. Meanwhile, the Histogram Equalization method shows better detection performance, particularly in the Face class, as evidenced by the increased number of true positives.

However, this method still produces some detection errors in the No Face class due to increased global contrast, which causes some background areas to be detected as faces. The results of the confusion matrix comparison between the GC and HE methods using the Haar Cascade can be seen in Figure 12.

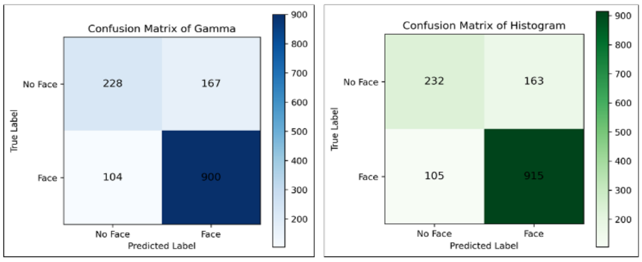

Figure 12. Confusion Matrix of GC and HE using Haar Cascade.

Figure 13 presents a comparison of the confusion matrix results between the Gamma Correction (GC) and Histogram Equalization (HE) methods using CNN-based face detection. In the Gamma Correction method, the system successfully detected 1,393 face images in the Face class; however, there were still 20 non-face images incorrectly classified as faces (false positives) and 2 non-face images correctly identified (true negatives). These results indicate that while Gamma Correction can enhance face visibility in low-light conditions, the enhancement process is not stable enough to accurately distinguish between face and non-face regions, leading to some background areas being detected as faces. Meanwhile, the Histogram Equalization method yields better performance, where all 1,393 face images were successfully detected, and the system correctly identified all 22 non-face images without producing any false negatives. The absence of detection errors in the HE method indicates that contrast enhancement via Histogram Equalization is more effective at clarifying facial structures and reducing detection ambiguity compared to Gamma Correction.

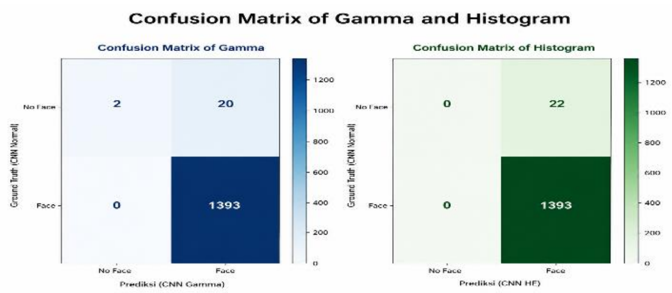

Figure 13. Confusion Matrix of GC and HE using CNN.

Figure 14 presents the confusion matrix results of the hybrid method that combines Gamma Correction (GC) and Histogram Equalization (HE) using CNN-based face detection. The results show that this hybrid approach achieves the best detection performance compared to previous methods. The system successfully detected all 1,393 face images in the Face class and correctly classified all 22 non-face images without producing any false negatives or false positives. This indicates that the combination of GC and HE is capable of normalizing lighting conditions more effectively and enhancing the visibility of facial features under varying lighting conditions. In the hybrid process, Gamma Correction is applied first to stabilize global brightness and clarify dark areas, followed by Histogram Equalization to enhance local contrast and clarify facial contours. This sequential combination allows the system to preserve important facial details while reducing the effects of uneven lighting and background noise. As a result, the CNN model is able to distinguish between facial and non-facial regions more accurately and consistently. These findings demonstrate that a lighting-invariant hybrid approach provides a more robust and stable preprocessing technique for facial detection systems, particularly in CCTV-based surveillance environments with challenging lighting conditions.

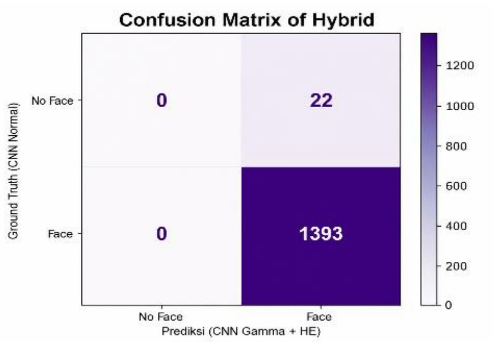

Figure 14. Confusion Matrix of Hybrid.

The test results show that each lighting preprocessing method yields different face detection performance. The evaluation was conducted using precision, accuracy, and recall metrics to measure detection effectiveness and system performance under various lighting conditions.

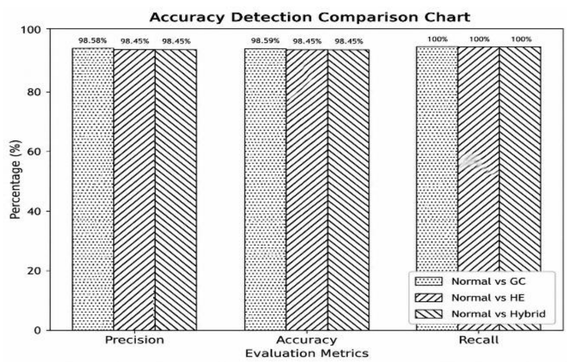

Figure 15. Accuracy Detection Comparison Chart.

Figure 15 presents a comparison of CNN-based face detection performance based on three evaluation metrics like precision, accuracy, and recall for the following methods: Normal vs. Gamma Correction (GC), Normal vs. Histogram Equalization (HE), and Normal vs. Hybrid (GC+HE). Based on the graph, the Gamma Correction method achieves the highest precision and accuracy values, at 98.58% and 98.59%, respectively, indicating that this method is slightly better at reducing false detections and maintaining overall classification performance. Meanwhile, the HE and Hybrid methods produce similar results, with precision and accuracy values of 98.45%. Although the differences between these methods are relatively small, the results show that all lighting-invariant preprocessing approaches are capable of delivering stable detection performance under varying lighting conditions. In terms of recall, all methods achieved a perfect score of 100%, indicating that the system successfully detected all face objects in the dataset without missing any actual faces. These results demonstrate that the application of lighting-invariant preprocessing significantly enhances the system's ability to maintain facial visibility under low and uneven lighting conditions. Overall, the hybrid method still offers significant advantages because it combines the brightness normalization of gamma correction with the contrast enhancement of histogram equalization, resulting in more balanced and consistent image quality.

IV. CONCLUSION

This study successfully analyzed the performance of preprocessing methods that are robust to lighting variations namely Gamma Correction (GC), Histogram Equalization (HE), and a hybrid method (GC+HE) in improving face detection performance under varying lighting conditions. Experimental results show that lighting preprocessing significantly improves face visibility and detection consistency in environments with low and uneven lighting. A comparison using Haar Cascade and Convolutional Neural Networks (CNN) indicates that CNN provides more stable detection performance, while Haar Cascade remains effective for lightweight real-time systems with limited computational resources. Based on confusion matrices and evaluation metrics, the hybrid method achieves the most balanced and robust performance by combining global brightness normalization from Gamma Correction with local contrast enhancement from Histogram Equalization, thereby enabling the system to detect facial features more accurately and consistently. This study also confirms that lighting-invariant preprocessing is a critical step for reducing detection errors such as false positives and missed detections in CCTV-based surveillance systems. However, this study has limitations due to its relatively small dataset and testing scenarios that primarily focus on lighting variations. Future research should utilize a larger and more diverse dataset, incorporate real-world conditions such as noise and blurring, and implement this system in IoT-based smart surveillance and indoor security monitoring applications to evaluate its performance in practical environments.

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REFERENCES

[1] T. W. Yin and A. S. B. Shibghatullah, "Enhancement of Low-Light Image using Homomorphic Filtering, Unsharp Masking and Gamma Correction," 2022. [Online]. Available: https://www.researchgate.net/publication/363304851

[2] S. Saluky, Y. Marine, and N. Bahiyah, "Penerapan Normalisasi Histogram untuk Peningkatan Kontras Pencahayaan pada Pengamatan Visual CCTV," *J. Teknol. dan Inform. Poltekharber*, vol. 8, no. 3, 2023, [Online]. Available: http://ejournal.poltekharber.ac.id/index.php/informatika/article/view/4929

[3] S. S. Priya and R. I. Minu, "Augmenting Face Detection in Extremely Low-Light CCTV Footage Using the EDCE Enhancement Model," *Trait. du Signal*, vol. 40, no. 6, pp. 2741–2750, 2023, doi: 10.18280/ts.400634.

[4] L. N. Soni and A. A. Waoo, "Face Detection Under Low-Light and Low-Resolution Conditions Using Contrast-Limited Adaptive Histogram Equalization and a Modified Convolutional Neural Network," *J. Neonatal Surg.*, vol. 14, no. 32s, pp. 2620–2631, 2025, doi: 10.63682/jns.v14i32S.7793.

[5] B. Sandhiya, S. Surya, and S. Pramod, "Crime Investigation System using CCTV Footage: A Novel Framework for Contrast Enhancement of Dark Images," in *2024 4th International Conference on Pervasive Computing and Social Networking (ICPCSN)*, Salem, India: IEEE, 2024, pp. 462–467. doi: 10.1109/ICPCSN62568.2024.00078.

[6] X. Li, M. Liu, and Q. Ling, "Pixel-Wise Gamma Correction Mapping for Low-Light Image Enhancement," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 34, no. 2, pp. 681–694, 2024, doi: 10.1109/TCSVT.2023.3286802.

[7] A. Yuliati, C. Machbub, and P. H. Rusmin, "Kajian Singkat Tentang: Pengendalian dan Penjejakan Objek Berbasis Visual," *Al-Jazari J. Ilm. Tek. Elektro, Inform. dan Tek. Mesin*, vol. 3, no. 2, 2018, [Online]. Available: https://journal.umtas.ac.id/aljazari/article/view/341

[8] S. Tommandru and D. Sandanam, "Low-Illumination Image Contrast Enhancement Using Adaptive Gamma Correction and Deep Learning Model for Person Identification and Verification," *J. Electron. Imaging*, vol. 32, no. 5, p. 53018, 2023, doi: 10.1117/1.JEI.32.5.053018.

[9] S. Mustakim, M. Kom, and S. Agustin, *Pengolahan Citra Digital*. Yogyakarta: Cendikia Mulia Mandiri, 2025.

[10] A. H. Alsaeedi, S. M. Hadi, and Y. Alazzawi, "Adaptive Gamma and Color Correction for Enhancing Low-Light Images," *Int. J. Intell. Eng. Syst.*, vol. 17, no. 1, pp. 105–113, 2024, [Online]. Available: https://inass.org/wp-content/uploads/2024/02/2024083115-1.pdf

[11] W. Setiawan, "Perbaikan Citra Menggunakan Anti-Aliasing (AA) untuk Mengetahui Akurasi Face Recognition pada Aplikasi Monitoring Ruangan Berbasis Webcam," Universitas Islam Negeri Maulana Malik Ibrahim Malang, Malang, 2015. [Online]. Available: http://etheses.uin-malang.ac.id/8761/

[12] C. K. Kumar, G. Sethi, and K. Rawal, "Adapting to the Dark: A Novel Adaptive Low Light Illumination Correction Algorithm for Video Sequences in Wireless Communications," *Int. J. Emerg. Eng. Res.*, vol. 11, 2023, doi: 10.37391/ijeer.11ngwcn01.

[13] Y. Fan and [et al.], "Low-FaceNet: Face Recognition-Driven Low-Light Image Enhancement," *IEEE Trans. Instrum. Meas.*, vol. 73, pp. 1–13, 2024, doi: 10.1109/TIM.2024.3372230.

[14] B. S. B. Dewantara, M. M. Bachtiar, and S. E. Lantang, "Door Access Control based on Illumination Invariant Face Recognition in Embedded System," in *2020 Electrical Power, Electronics, Communications, Controls and Informatics Seminar (EECCIS)*,

IEEE, 2020, pp. 291–296. doi: 10.1109/EECCIS49483.2020.9263427.

[15] F. Muhammad, B. S. B. Dewantara, and R. Sigit, “Implementation of Illumination Invariant Face Recognition for Accessing User Record in Healthcare Kiosk,” in *2020 International Electronics Symposium (IES)*, IEEE, 2020. doi: 10.1109/IES50839.2020.9231644.

[16] Y. Bourdima, “Enhancing Campus Security: Face Detection and Automatic Recognition System for Guelma University,” University of Guelma, Guelma, Algeria, 2024. [Online]. Available: https://dspace.univ-guelma.dz/xmlui/handle/123456789/16476

[17] U. Saeed, K. Masood, and H. Dawood, “Illumination normalization techniques for makeup-invariant face recognition,” *Comput. Electr. Eng.*, vol. 91, 2021, doi: 10.1016/j.compeleceng.2020.107048.

[18] S. K. Panda and S. K. Sahu, “Design of IoT-based real-time video surveillance system using Raspberry Pi and sensor network,” in *Springer*, 2020. [Online]. Available: https://link.springer.com/chapter/10.1007/978-981-33-6081-5_11

[19] Z. Balogh, M. Magdin, and G. Molnár, “Motion detection and face recognition using Raspberry Pi, as a part of the Internet of Things,” *Acta Polytech. Hungarica*, vol. 16, no. 3, pp. 167–185, 2019, [Online]. Available: http://epa.niif.hu/02400/02461/00088/pdf/EPA02461_acta_polytechnica_2019_03_167-185.pdf

[20] B. A. Sassani, A. David, and X. Li, “AgentPi: An IoT Enabled Motion CCTV Surveillance System,” in *Proceedings of the IEEE Conference*, 2019. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/8890256/

[21] B. N. Rao, R. Sudheer, and M. A. Sadhanala, “Movable surveillance camera using IoT and Raspberry Pi,” in *Proceedings of the IEEE Conference*, 2020. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9225491/

[22] J. A. Mohammed, A. Paul, and A. Kumar, “Implementation of human detection on Raspberry Pi for smart surveillance,” in *Proceedings of the IEEE Conference*, 2020. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9298383/

[23] H. Meddeb, Z. Abdellaoui, and F. Houaidi, “Development of surveillance robot based on face recognition using Raspberry-PI and IoT,” *Comput. Electr. Eng.*, vol. 107, 2023, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0141933122002575

[24] T. Prathaban, W. Thean, and M. S. Sazali, “A vision-based home security system using OpenCV on Raspberry Pi 3,” in *AIP Conference Proceedings*, 2019. [Online]. Available: https://pubs.aip.org/aip/acp/article-abstract/2173/1/020013/746630

[25] R. Ullah, H. Hayat, and A. A. Siddiqui, “A real-time framework for human face detection and recognition in CCTV images,” *J. Electr. Comput. Eng.*, vol. 2022, 2022, [Online]. Available: https://doi.org/10.1155/2022/3276704

[26] A. I. Awodeyi, O. A. Ibok, I. Omokaro, and J. U. Ekwemuka, “Effective preprocessing techniques for improved facial recognition under variable conditions,” *Digit. Signal Process. Lett.*, 2025, [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2773186325000155

[27] A. K. M. Baareh, “Facial Recognition and Discovery Using Convolution Deep Learning Neural Network,” *J. Comput. Sci.*, vol. 20, no. 11, pp. 1559–1568, 2024, doi: 10.3844/jcssp.2024.1559.1568.

[28] S. Anila and N. Devarajan, “Preprocessing technique for face recognition applications under varying illumination conditions,” *ResearchGate*, 2012, [Online]. Available: https://www.researchgate.net/publication/284602698

[29] I. Chatisa, Y. A. Syahbana, and A. U. A. Wibowo, “Object Detection and Monitor System for Building Security Based on Internet of Things (IoT) Using Illumination Invariant Face Recognition,” *Kinet. Game Technol. Inf. Syst. Comput. Network, Comput. Electron. Control*, 2023, doi: 10.22219/kinetik.v8i1.1622.

[30] R. D. Putra, T. W. Purboyo, and L. A. Prasasti, “A Review of Image Enhancement Methods,” *ResearchGate*, 2019, [Online]. Available: https://www.researchgate.net/publication/335420759

[31] Y. Chang, C. Jung, P. Ke, H. Song, and J. Hwang, “Automatic Contrast-Limited Adaptive Histogram Equalization With Dual Gamma Correction,” *IEEE Access*, vol. 6, pp. 11782–11792, 2018, doi: 10.1109/ACCESS.2018.2797872.

[32] H. T. Ho, L. V Nguyen, T. H. T. Le, and O. J. Lee, “Face detection using eigenfaces: A comprehensive review,” *IEEE Access*, 2024, [Online]. Available: https://ieeexplore.ieee.org/abstract/document/10614584/

[33] S. A. Iliukhin, T. S. Chernov, and D. V Polevoy, “A method for spatially weighted image brightness normalization for face verification,” in *Proceedings of SPIE 11041, Eleventh International Conference on Machine Vision (ICMV 2018)*, 2019, pp. 1–6. [Online]. Available: https://www.researchgate.net/publication/331806793_A_method_for_spatially_weighted_image_brightness_normalization_for_face_verification

[34] B. Nugroho and E. Y. Puspaningrum, “Performance of Contrast Adjustment in Face Recognition with Training Image under Various Lighting Conditions,” *IJCONSIST Journals*, vol. 3, no. 2, pp. 25–29, 2022, doi: 10.33005/ijconsist.v3i2.63.

[35] E. Y. Puspaningrum, B. Nugroho, and A. Istifariyanto, “Preprocessing with Symmetrical Face and Gamma Correction for Face Recognition under Varying Illumination with Robust Regression Classification,” *Kursor J.*, vol. 9, no. 2, 2017, doi: 10.28961/kursor.v9i2.142.

[36] R. F. Hasani and M. Yusuf, “Penerapan Haar Cascade Classifier Berbasis Raspberry Pi untuk Sistem Keamanan Gerbang Otomatis di Wilayah Perumahan,” *Spektral*, vol. 5, no. 2, pp. 281–289, 2024, [Online]. Available: https://jurnal.pnj.ac.id/index.php/spektral/article/view/7566

[37] D. R. Rochmawati, “Deteksi Wajah dengan Metode Haar Cascade Menggunakan OpenCV,” *J. Teknol. Komput. dan Inform.*, vol. 3, no. 1, 2024, doi: 10.59820/tekomin.v3i1.293.

[38] D. Kurnia, S. A. Putri, and E. A. Nugroho, “Implementasi Face Recognition untuk Sistem Absensi Karyawan dengan Pendeteksi Suhu Berbasis Raspberry,” *Ramatekno J. Res. Technol.*, vol. 1, no. 2, 2021, doi: 10.61713/jrt.v1i2.18.

[39] M. Leszczynski, “Image Preprocessing for Illumination Invariant Face Verification,” *J. Telecommun. Inf. Technol.*, vol. 42, no. 4, pp. 19–25, 2010, [Online]. Available: https://www.jtit.pl/jtit/article/view/1092

[40] S. Ashor and H. M. Ahmed, “Applying Gamma and Histogram Equalization Algorithms for Improving System-performance of Face Recognition-based CNN,” *Iraqi J. Comput. Commun. Control Syst. Eng.*, 2022, [Online]. Available: https://iasj.rdd.edu.iq/journals/uploads/2024/12/12/732ef3f1f412f611c01967333a6c6fe1.pdf

[41] A. Salman, M. Hayaty, and I. N. Fajri, “Facial Images Improvement in the LBPH Algorithm Using the Histogram Equalization Method,” *JUITA J. Inform.*, vol. 10, no. 2, pp. 217–223, 2022, [Online]. Available: https://jurnalnasional.ump.ac.id/index.php/JUITA/article/view/13223

[42] M. Veluchamy and B. Subramani, “Image Contrast and Color Enhancement using Adaptive Gamma Correction and Histogram Equalization,” *Opt.*, vol. 183, pp. 329–337, 2019, [Online]. Available: https://dept-info.labri.fr/~achille/ti/Activites/Note-de-lecture/Articles/image_contrast_and_color_enhancement_using_adaptative_gamma_correction_and_histogram_equalization_2019.pdf