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OBJECT DETECTION FOR LOW-LIGHT ENVIRONMENT USING MULTISCALE RETINEX

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Abstract

Object detection is a critical task in computer vision, yet its performance degrades significantly under low-light conditions due to loss of detail and diminished features. This study proposes an image enhancement framework to improve detection robustness in challenging lighting. The methodology integrates Multiscale Retinex (MSR) for image enhancement and SSD MobileNet V2 for object detection. MSR was configured with optimal parameters (scale1:10, scale2:60, scale3:180, σ:100, β:30) to enhance brightness while preserving crucial image details. The experimental results demonstrate that Retinex correction is highly effective in extreme low-light scenarios. In 0 lux conditions, where objects were completely undetectable without processing, the proposed method enabled detection with confidence levels between 62% and 96%, yielding an average accuracy increase of 50%. In 15 lux conditions, accuracy improved by 6.6%. However, the system degraded at intensities above 25 lux, suggesting that the enhancement is most beneficial in near-dark environments. In conclusion, Multiscale Retinex significantly enhances the capability of SSD MobileNet V2 for object detection in environments with illumination below 77 lux. This approach provides a viable solution for improving the reliability of surveillance and automated systems operating in unpredictable lighting.

Keywords: ; Object Detection; Low-Light Enhancement; Multiscale Retinex; SSD MobileNet V2

Abstrak

Deteksi objek adalah tugas penting dalam visi komputer, namun kinerjanya menurun secara signifikan dalam kondisi cahaya rendah akibat hilangnya detail dan berkurangnya fitur. Studi ini mengusulkan kerangka peningkatan citra untuk meningkatkan ketahanan deteksi dalam pencahayaan yang menantang. Metodologi ini mengintegrasikan Multiscale Retinex (MSR) untuk peningkatan citra dan SSD MobileNet V2 untuk deteksi objek. MSR dikonfigurasi dengan parameter optimal (skala1:10, skala2:60, skala3:180, σ:100, β:30) untuk meningkatkan kecerahan sambil mempertahankan detail penting dalam citra. Hasil eksperimen menunjukkan bahwa koreksi Retinex sangat efektif dalam skenario cahaya sangat rendah. Pada kondisi 0 lux, di mana objek sama sekali tidak terdeteksi tanpa proses, metode yang diusulkan memungkinkan deteksi dengan tingkat kepercayaan antara 62% hingga 96%, meningkatkan akurasi rata-rata sebesar 50%. Pada kondisi 15 lux, akurasi meningkat sebesar 6,6%. Namun, sistem mengalami penurunan performa pada intensitas di atas 25 lux, menunjukkan bahwa peningkatan citra paling bermanfaat di lingkungan yang hampir gelap. Kesimpulannya, Multiscale Retinex secara signifikan meningkatkan kemampuan SSD MobileNet V2 dalam deteksi objek di lingkungan dengan pencahayaan di bawah 77 lux. Pendekatan ini menyediakan solusi yang layak untuk meningkatkan keandalan sistem pengawasan dan otomatisasi yang beroperasi dalam kondisi pencahayaan yang tidak menentu.

Kata kunci: Deteksi Objek; Peningkatan Cahaya Rendah; Retinex Multiskala; SSD MobileNet V2

INTRODUCTION

In the current situation, computer vision has many advantages for performing tasks that support human activity. Some of these include object detection on surveillance cameras and facial recognition systems. A camera is used to see an object, much like the human eye. Just as the human eye has limited vision, a camera also has limitations in seeing objects. One of the fundamental factors that affect vision is light. Light is necessary to form an image. Images captured in low-light conditions can cause details to be lost, so image enhancement is necessary. The purpose of image enhancement is to obtain finer details of an image(Hanumantharaju et al., 2011). Many methods have been developed to improve image quality and achieve high accuracy. In object detection, features cannot be detected at low light intensities, which prevents the camera from detecting the object. This affects the system's accuracy, which decreases as light intensity decreases.(Muhammad et al., 2024).

Object detection in computer vision is a central task in many applications, including autonomous surveillance, driving, and search and rescue. However, the performance of these systems degrades in low-light conditions. Recent work has focused on overcoming these challenges through low-light image enhancement and specialized detection methods(Al-refai et al., 2025). Low-light image enhancement is critical for improving the usability of visual data before high-level tasks such as object detection are applied. Techniques based on deep learning, such as those combining an attention mechanism with the Retinex model, have been shown to significantly enhance image quality by increasing brightness, improving contrast, and reducing noise(Huang et al., 2020).

Object detection algorithms, such as the YOLO family or newer frameworks like GOI-YOLOv8, have been shown to experience performance degradation when exposed to non-uniform illumination(Mei et al., 2024). Incorporating Retinex-enhanced images into these pipelines helps mitigate such losses by reducing the variance introduced by environmental lighting changes. This preconditioning step enhances the robustness of detection systems when deployed in real-world applications where lighting conditions can be highly unpredictable(Mei et al., 2024). Li (W. Li, 2022) demonstrated that applying multi-scale Retinex with Color Restore (MSRCR) can improve vehicle detection in foggy or low-light settings by dehazing and clarifying image features. Similarly, combining Retinex-based image enhancement with object detection frameworks like YOLO has been explored to boost detection confidence and precision in challenging scenes(W. Li et al., 2022). Other experiment, Saputra(Saputra, 2016) conducted an experiment comparing face detection with MSRCR and AMSR at intensity levels of 439.75 lux, 273.25 lux, 150 lux, and 9 lux. The results showed a significant decrease in accuracy at 150 lux and 9 lux. Detection accuracy at 273.25 lux reached 90.56%, then at 150 lux it was 42.29%, and at 9 lux it was 0%. Accuracy decreased by 48.27% at 150 lux and by 42.29% at 9 lux.

With the presence of lighting problems, it can affect the accuracy of the model, such as in the case of object detection implementation. One of the challenges in the object detection process is the changing environmental conditions (Hanumantharaju et al., 2011).

Retinex is a method originally proposed by Edwin Land and John McCann in the early 1970s (Land & McCann, 1971), the challenge of detecting objects accurately in low-light images has stimulated the integration of image enhancement techniques with object detection frameworks. Retinex theory, which postulates that an observed image can be decomposed into illumination and reflectance components, has proven especially useful for such enhancement tasks. By leveraging Retinex-based methods, degradation due to insufficient illumination, noise, and color distortion can be mitigated before applying detection algorithms(M. Li et al., 2018). The iterative decomposition frameworks that refine illumination and reflectance estimates have also shown promise in tackling low-light challenges by iteratively restoring visibility and contrast(Gasparyan et al., 2023).

This paper proposes an image quality enhancement technique focused on lighting, aimed at improving object detection performance. The Multiscale Retinex method was selected because it enhances brightness while maintaining image details, ensuring that crucial details remain recognizable during detection. The object detection itself employs the SSD Mobile Net architecture. By the end of the study, images captured under different lighting conditions will be compared for object detection accuracy using the proposed enhancement method, and these results will be contrasted with those obtained without any image enhancement.

RESEARCH METHODS

In this study we tested the accuracy of hand detection at 7 different intensities in the range 0-133 lux by 3 subjects, measuring light intensity using lux meter. The processed data is in the form of video from real-time streaming. The data was captured using a Logitech C270 camera at 30 frames per second, with a recording duration of 10 seconds. Data was captured once at each intensity for each subject. Data collection was conducted by recording videos of each subject displaying their hand for 10 seconds at each light intensity. The video will be detected and compared for confidence accuracy before and after using Retinex. This study employed Multiscale Retinex to enhance image quality. The parameters S1, S2, S3, σ, and β were

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required for implementation. These parameters were determined by conducting tests on the images to identify the configuration that yielded the highest confidence value. The hand detection flowchart is depicted in figure 1.

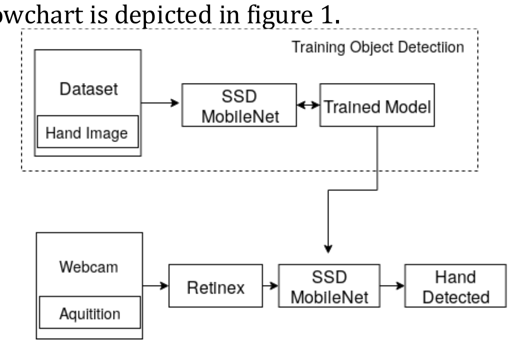

Figure 1 Retinex Hand Detection Flowchart

Retinex

Retinex is an algorithm that seeks to maintain color stability where an object is viewed in different lighting conditions . The computational strategy underlying Retinex aims to separate these components, thereby enabling image enhancement in challenging illumination conditions. According to Land, an image is formed as the product of reflectance and illumination (Land & McCann, 1971). Based on the Retinex theory, it can be written mathematically as in equation below(Lan & Guo, 2023).

$I_{(x,y)} = L_{(x,y)} \cdot R_{(x,y)}$ ……………………………………………(1)
$\log\ I_{(x,y)} = log\ L_{(x,y)} + log\ R_{(x,y)}$ ……………………..(2)
$\log R_{(x,y)} = log\ I_{(x,y)} + log\ L_{(x,y)}$ ……………………...(3)
$\log\ R_{(x,y)} = log\ I_{(x,y)} - \log\ [F_{(x,y)} * I_{(x,y)}]$ …………(4)

Where $R_{(x,y)}$represents the reflectance component, $L_{(x,y)}$ denotes the illumination component, $I_{(x,y)}$represents digital image representation and $F_{(x,y)}$is gaussian function. This model is central to many Retinex implementations, where the aim is to estimate both R and L from the observed image. This formulation underlies many low-light image enhancement and color constancy algorithms.

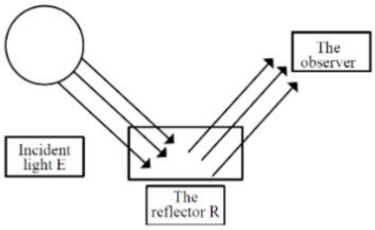

Figure 2 Ilustration Retinex Algorithm

The image that will be subject must be separated between the reflectance and luminance components by using a logarithmic form as shown in Figure 2. The separation will result in Single scale Retinex at i channel below.

$$R_{SSRi(x,y)} = log\ I_{(x,y)} - \log\ [F_{(x,y)} * I_{(x,y)}]$$

Single scale Retinex(SSR) can provide dynamic range compression and color rendition, but both cannot be done simultaneously using a single scale(Khammar, 2024). Using a small x can increase the detail in dark areas and have σ dynamic compression is good but with bad color distortion, the opposite applies when using a larger σ. Therefore, by combining the various scales, we get Multiscale Retinex. The result of the addition of the channel is called Multiscale Retinex (MSR). Single scale Retinex applies the Retinex concept using a single convolution operation with a Gaussian filter to estimate the illumination component, while MSR employs multiple scales of Gaussian filters to capture both local and global illumination variations(Xie et al., 2023). it can be written mathematically as in equation below. $R_{MSRi(x,y)}$ stands for Multiscale Retinex and $\omega_n$represent weight on scale n.

$$R_{MSRi(x,y)} = \sum_{n=1}^{N} \omega_n\ R_{SSRi(x,y)} \ldots\ldots\ldots\ldots\ldots\ldots\ (5)$$
$$= \omega_n\big[log\ I_{(x,y)} - \log\big[F_{(x,y)} * I_{(x,y)}\big]\big]$$

Unlike single-scale Retinex (SSR), MSR processes the image at multiple scales using Gaussian filters with different standard deviations, thereby capturing both fine details and global illumination variations(Meng et al., 2022). This multiscale strategy provides a balanced trade-off between noise suppression and detail preservation. At smaller scales, fine textures are preserved; at larger scales, overall brightness and gradual variations are better represented(Kim et al., 2024).

SSD Mobilenet

The object detection process in this study employs the SSD (Single Shot Detector) architecture with the MobileNet architecture. The SSD is an object detection framework that achieves real-time speed by performing object localization and classification in a single forward pass through the network. The approach is particularly effective when combined with lightweight feature extractors such as MobileNet. MobileNet is a convolutional neural network designed specifically for mobile and embedded applications, emphasizing low

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computational cost and high efficiency. Together, the SSD MobileNet combination provides an optimal balance between detection speed and accuracy(Kee et al., 2024). SSD training process requires input image with ground truth. This method can produce 3x fast processing time of Faster R-CNN. SSD architecture consists of input image, base architecture, extra feature layer and non-maximum suppression. In this research, the base architecture used is MobileNet. MobileNet stands out for employing depthwise separable convolutions, which significantly cut down the number of parameters and computational demands relative to traditional convolutional networks. Its lightweight structure is optimal for mobile or embedded systems, thereby lending itself well to integration with SSD for scenarios that require speed and resource efficiency(Estrada et al., 2022). The advantage of using MobileNet in the convolution process is that it costs much less than standard convolution. The convolution process on this MobileNet uses depth-wise convolution and point-wise convolution. The cost generated from the convolution process is shown in the equation below(Howard et al., 2017).

$$D_k x D_k x\ M\ x\ N\ x\ D_f x D_f\ + M\ x\ N\ x\ D_f x D_f$$

The above equation is the cost of depth-wise and point-wise convolution, where D_k is kernel dimensions, M input channels,N number of channels and D_f feature map dimensions. In point-wise convolution, the kernel used (D_k) is 1x1. While the standard convolution cost produced is more expensive, as shown in the equation below(Howard et al., 2017).

$$D_k x D_k x\ M\ x\ N\ x\ D_f x D_f$$

The output of the base network will produce a feature map. The map feature will be evaluated using default boxes with different aspect ratios and generate a confidence value along with the detected location box. The candidate object must have an IOU above the threshold. List of candidates will be sorted by non-maximum suppression block. An overview of the SSD process is shown figure 3 (Liu et al., 2016).

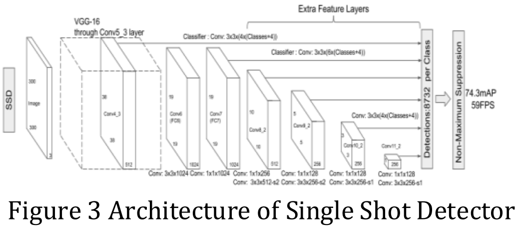

Figure 3 Architecture of Single Shot Detector

SSD Mobilenet V2

The MobileNetV2 model is an improvement over MobileNet V1. It incorporates shortcut (residual) connections and uses depthwise separable convolutions, enabling MobileNetV2 to reduce the number of weights and biases more effectively and to enhance operational speed. The architecture of the SSD MobileNetV2 object detection algorithm combines the SSD and MobileNetV2 models, as shown in figure 4.

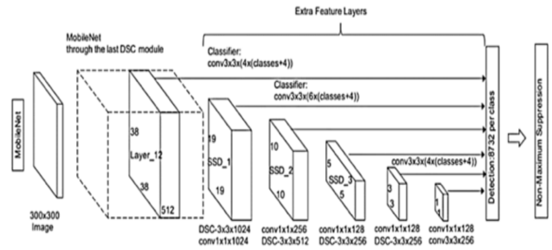

Figure 4 Architecture of MobileNet V2

In this setup, MobileNetV2 serves as the base network, functioning as the feature extractor, while SSD acts as the object localizer. The MobileNet feature extractor captures image features and produces a feature map that highlights essential characteristics for classification or detection tasks. SSD's detection model then uses these feature maps to determine the class and bounding box of an object (Saadoon & Koyuncu, 2023).

In this integrated model, MobileNet extracts robust and semantically rich features from input images using its efficient convolutional layers. These features are subsequently fed to the SSD detection head, which employs a series of convolutional filters to predict object classes and refine bounding box coordinates across multiple feature maps(Saadoon & Koyuncu, 2023). SSD is able to simultaneously evaluate object presence and predict precise locations with minimal computational overhead. This efficiency makes the SSD a popular choice for real-time applications where latency is a critical factor(Lavanya, 2025). The combination of Mobile Net and SSD represents an optimal blend of efficiency and accuracy. In the MobileNet-SSD framework, MobileNet serves as a lightweight feature extractor, providing robust feature maps at minimal computational cost. These feature maps are then passed to the SSD detection head, which applies convolutional filters over different layers to generate predictions for object classes and their corresponding bounding boxes(Howard et al., 2017).

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RESULTS AND DISCUSSION

There are three parameters of Multiscale Retinex were tested refer to table 1. Parameter 1 was obtained from research by (Bel et al., 2014), and other parameters were determined by the researcher. Parameter 1 serves as the reference point. The other two input parameters assume the value below Parameter 1 for each s1, s2, s3, σ and β as specified in Parameter 2, and the value above Parameter 1 for each s1, s2, s3, σ and β as specified in Parameter 3.Parameter testing is used to determine the value to be used in system testing. The results of each parameter combination were tested by object detection process with 3 images. These parameters represent the lowest intensity condition, the middle condition, and the higher condition at 3 variation intensity conditions which was 0 lux, 20 lux and 77 lux as shown figure 5.

Table 1 Multiscale Retinex Parameters

No	S1	S2	S3	σ	β
1	15	80	250	125	46
2	10	60	180	100	30
3	30	100	210	140	60

Figure 5 Parameter 2 Multiscale Retinex

Based on the best confidence score, parameter 1 will be used as the Retinex parameter. The result detection shown in table 2, the resuls indicate that parameter1 demonstrates superior performance compared to the other parameters based on confidence level.

Table 2 Confidence Score using Variation Parameters Table 1

Data	Parameter 1	Parameter 2	Parameter 3
	Confidence	Confidence	Confidence
Image 1	98%	97%	98%
Image 2	100%	100%	100%
Image 3	32%	0%	0%

The object detection experiment was carried out by 3 subjects who had different skin tones and 7 different light conditions. The input from this research is a video, which will be detected using Retinex and without Retinex. The detection success rate is determined by the confidence level value obtained during hand detection for each subject under varying lux conditions.

Table 3 Comparison Test Results with Retinex

Lux	Subject 1		Subject 2		Subject 3	
	Original	Retinex	Original	Retinex	Original	Retinex
0	40%	70%	0%	70%	50%	100%
15	100%	100%	100%	100%	80%	100%
20	100%	100%	100%	70%	100%	90%
25	100%	100%	100%	90%	100%	90%
33	90%	100%	100%	100%	100%	90%
77	100%	90%	100%	80%	100%	100%
133	90%	70%	100%	100%	90%	70%

Table 3 is the result of the test, where Original is the original data and Retinex is the data that has been subjected to Retinex. The object detection performance is depicted in the graph in figure 6 below.

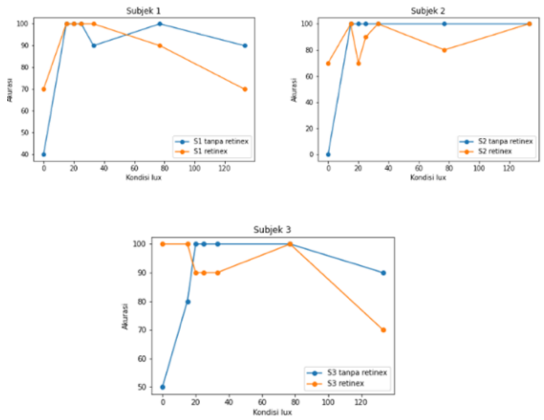

Figure 6 Confidence Level Graph Against Light Intensity

As shown in Figure 6, under 0 lux conditions, subject 1 achieved a confidence level of 40%. When the Retinex method was applied, the confidence increased to 70%, indicating a 30% improvement. The data in the figure represent the difference in confidence levels at specific lux conditions. This difference was calculated for each lux condition and for every subject. The graph in figure 6 shows a significant increase in the 0 lux condition for all subjects. The condition of 15 lux is only in image 3 which has increased by 20%, for other subjects, there is no change in value. Under conditions of 25 lux onwards, the system is degraded when using Retinex. The percentage increase in Retinex for the three subjects is shown in Table 4 below. The score is obtained from the difference in confidence scores by measuring the average confidence level of each frame when using Retinex and not using Retinex, referring to the image in Figure 6. The reduction in confidence level is attributed to the sufficiently bright lighting conditions. Application of Retinex under these conditions can further decrease the confidence level, as demonstrated in Table 4.

Table 4 percentage decrease and increase per lux

Lux (lux)	Subject 1	Subject 2	Subject 3
0	30%	70%	50%
15	0%	0%	20%
20	0%	-30%	-10%
25	0%	-10%	-10%
33	10%	0%	-10%
77	-10%	-20%	0%
133	-20%	0%	-20%

Based on table 4 the increase occurred in conditions of 0 lux and conditions of 15 lux without a decrease. Other conditions experienced more decrease in accuracy than increase. The higher the intensity causes the results of the Retinex image to experience instability which changes the color tone, this causes changes in the pixel value in the image. An image that has enough light will be brighter which causes a higher pixel value. Features of an image will be difficult to identify for the detection process. Figure 7 shows the histogram of the image before and after being subjected to Retinex operation.

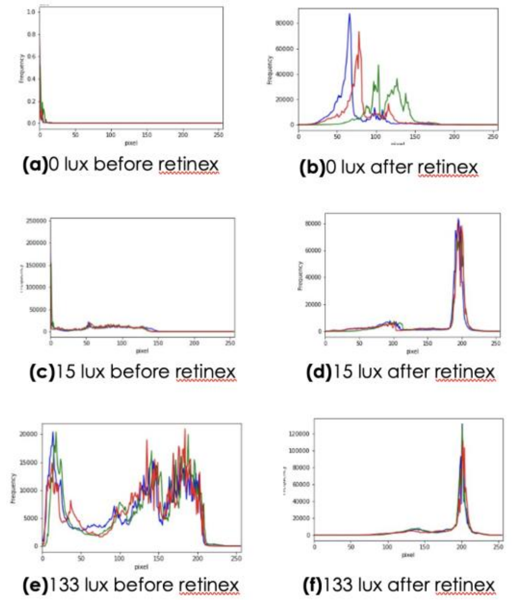

Figure 7 Histogram Image (left:without retinex, right:using retinex)

Based on Figure 7, it is known that after Retinex there are shifting values of the pixels to be lighter. An image with insufficient lighting will damage the pixels' values after Retinex's operation. At 0 lux, the pixel distribution is concentrated in the 0-25 range when the image does not use Retinex, and the histogram shows a dark image. Applying retinex shifts the distribution toward a more even spread within the 0 to 170 pixel range. Similar effects are observed at other lux values. However, at 133 lux, which represents the brightest lighting condition, the histogram before retinex application already exhibits a uniform distribution. In this scenario, applying Retinex under bright conditions can reduce image contrast and increase pixel saturation. This disruption shifts pixel values toward higher intensities, causing object details to appear pale or disappear. Figure 7(e) shows that pixels spread evenly. Table 4 shows that the accuracy of the experiment without using Retinex is higher than using Retinex. In that case there is the biggest accuracy decreasing. It is shown in Table 4 with the lux value is 133 lux. As shown in Table 4, higher lighting levels cause Retinex to negatively affect detection performance, likely because of excessive brightening that harms image features.

In the lux 133 condition, the detection process becomes chaotic, resulting in incorrect detection. In conditions with high lighting, this study found that at lighting levels from 77 lux to 133 lux, retinex is not necessary. This can be seen in the image displayed figure 8 below.

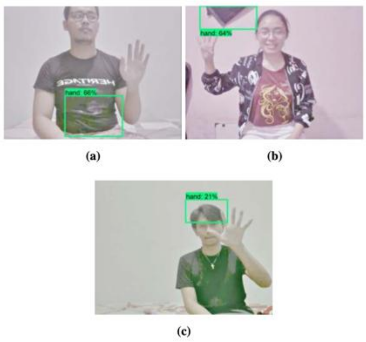

Figure 8 (a)133lux, (b)77lux, (c)133lux

Under the 0 lux condition, the retinex correction is highly effective. Although no objects are detected at 0 lux without retinex, retinex enables detection with confidence levels of 62% and 96%. The supporting argument is presented in figure 9 below.

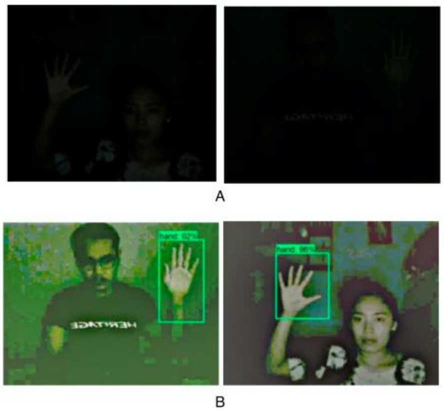

Figure 9 (A) 0lux Without Retinex, (B)0Lux With Retinex

CONCLUSIONS AND SUGGESTIONS

Conclusion

In this experiment, hand detection has been carried out at 7 different intensities from 0 – 133 lux. The results from Retinex have maximum performance in conditions of 0-15 lux. The average increase of the three subjects in the 0 lux condition had an increase of 50% and the 15 lux condition had an increase of 6.6%. The same can be used to complement features on systems that have light limitations. In addition, it can be concluded that Retinex works very effectively for object detection under conditions with less than 77 lux.

Suggestion

For future work, Retinex can be improved to make it more stability when increasing contrast and to minimize discoloration. Especially at high lux conditions, Retinex can interfere with the detection process, so it is recommended not to use it in high lux conditions.

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