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Analysis of the Effect of RetinexNet-Based Image Preprocessing on Object Detection Performance Using YOLOv8 Under Low-Light Conditions.

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Abstract: The decline in performance in object detection systems based on deep learning is skewed to be meaningfully inclined when the system is used in low lighting conditions, especially due to the decrease in visual quality of the image. In this study, the focus is directed to evaluate the effect of the application of RetinexNet-based image preprocessing on object detection performance using YOLOv8 in low-light environments. The experimental process was carried out to compare the detection results between models that used preprocessing and those that did not use preprocessing, based on evaluation metrics such as precision, recall, and mean Average Precision (mAP). The results indicate that improving the visual quality of the sword image is always followed by an increase in detection accuracy, because these changes can cause a shift in the distribution of visual features that have an impact on the model's generalization ability. In addition, the phenomenon of domain shift resulting from image changes using RetinexNet was also found, which had an effect on the consistency of YOLOv8 performance. The main contribution of this study is to provide empirical evidence that preprocessing strategies for low-light conditions not only need to focus on improving visual quality, but also need to be adapted to the characteristics of the detection model in order to obtain a more adaptive pipeline under extreme lighting conditions.

Keywords: low-light image enhancement, RetinexNet, YOLOv8, object detection

1. Introduction

Developments in the field of computer vision have significantly expanded the application of object detection systems in various sectors such as security, intelligent transportation, industry, and autonomous systems. However, the performance of the object detection system is largely determined by the quality of the input images used. In low lighting conditions where the image quality generally decreases considerably by being characterized by reduced contrast, increased noise disturbance, color distortion, and loss of texture detail so that ultimately the detection accuracy decreases [1], [2]. In addition, conditions with low signal-to-noise ratios and uneven lighting distribution are the causes of the resulting visual features to be less than optimal for processing by deep learning models [3], [4]. Therefore, low light conditions are still considered as one of the main challenges faced in the development of computer vision-based object detection systems. Images obtained in low-light conditions generally indicate several distinctive characteristics, such as high noise levels, low contrast, and uneven distribution of exposure. In this condition, it is often encountered in night surveillance systems, indoor environments with limited lighting, with emergency situations [5], [6]. This decrease in quality not only affects subjective visual perception, but also interferes with the process of feature extraction by forming spatial representations at the stage of modern object detection by having a fairly good generalization ability, the performance still decreases significantly when extreme lighting conditions are used.

Within this framework, the pre-processing stage which focuses on improving image quality has a very important role in optimizing feature representation before the detection process is carried out. A number of studies have reported that improving image quality in low-light conditions can contribute to improving the performance of object detection systems, specifically in terms of precision and mean average precision (mAP) [4], [5], [9]. In addition, the quality improvement approach has been proven to be able to reconstruct reflectance and illumination components that are degraded due to noise disturbances and limited light intensity [10], [11]. Some of these findings are instructions for the integration of image enhancement techniques in the object detection pipeline is an important aspect and still needs to be further researched both from the conceptual side and the implementation side in it.

However, previous research indicates that there are still many research gaps regarding the integration between the image enhancement process and the object detection stage. Most existing approaches still separate the two processes in a two-stage pipeline framework, without adequately considering how changes in feature distribution can affect the performance of the detection model [5], [12]. In addition, conventional enhancement techniques such as histogram equalization and gamma correction often cause effects in excessive magnification and color distortion [1], [11]. Meanwhile, the more adaptive Retinex approach also has limitations because it relies heavily on sensitive illumination estimates under certain conditions [7], [13]. On the other hand, the method based on deep learning indicates the potential for superior performance, but its implementation has not been widely studied, especially in quantitative evaluation of its effect on object detection performance [2], [4].

Some previous studies on object detection in low-light conditions generally focused more on architectural innovations such as the application of attention mechanisms or changes to the network backbone without conducting a thorough study related to the relationship between the image quality improvement process and detection performance [6], [14]. Meanwhile, in an approach such as DRE-YOLO, which combines the principles of Retinex with a detection system in one end-to-end framework, it is still relatively limited and has not been extensively tested in various evaluation scenarios [7]. Therefore, there is still a large research gap, especially in empirical analysis to be able to find out whether improving the visual quality of images really contributes to improving the performance of object detection.

Based on these gaps, this study comes with a new contribution with an overall investigation related to the effect of image preprocessing based on RetinexNet on the detection performance of objects using YOLOv8. This is different from previous research that tends to separate efforts to improve image quality with the development of detection architecture, this study specifically analyzes the direct relationship between the enhancement process and detection results with a comparative approach. This investigation is suitable because until now there is no clear agreement on whether the enhancement process always has a good impact on detection performance, especially in the context of shift dominance caused by changes in the distribution of visual features.

This study is a clear indication of the difference from previous research in the field of image enhancement and object detection by focusing on quantitative evaluation using standard metrics such as precision, recall, and mean Average Precision (mAP) which does not only rely on visual assessment or image quality improvement with subjective properties. This approach makes a scientific contribution by being a clue to improving visual quality is not always in line with improving object detection performance. Thus, this research enriches the treasures of science in the field of computer vision, especially related to the integration of image enhancement techniques in low-light conditions with object detection systems while creating practical implications for the development of more robust object detection systems in low-light conditions.

2. Methods

This study uses a quantitative method with an experimental approach with a comparative experimental study design to evaluate the effect of the implementation of RetinexNet-based image preprocessing techniques on the performance of the YOLOv8 object detection system under low lighting conditions. The research framework is arranged in two main stages, namely at the stage of improving image quality which is then continued in object detection, in line with the approach recommended in several studies on object detection in low-light environments using image enhancement techniques [5], [15].

A. Dataset

This study uses two main datasets that have different roles in the flow of experiments, namely LOLv2 and ExDark. The LOLv2 (Low-Light Dataset Version 2) dataset is specifically used to be able to train RetinexNet-based image improvement models. This dataset consists of a pair of images taken in low-light conditions along with a reference image (ground truth) with normal lighting so that it will allow the model to study illumination mapping through a supervised approach. Compared to the previous version, where LOLv2 provides a more diverse supply of lighting conditions, and a more complex noise distribution, it is considered more of a representation of real-world conditions [8].

The ExDark dataset (Exclusively Dark Dataset) is utilized in this study as a benchmark to evaluate the performance of object detection models. This dataset comprises thousands of images captured under low-light conditions, accompanied by object annotations across various categories, including humans, vehicles, and other common objects. The selection of ExDark is motivated by its characteristics, as it is specifically designed to assess the robustness of object detection algorithms in complex and challenging low-light environments. By employing two different datasets, the evaluation process between the image enhancement stage and the object detection stage can be conducted in a more systematic and objective manner [14].

Table 1. Characteristics Of The Lolv2 And Exdark Datasets

| Aspect | LOLv2 | ExDark |
|-----------------|--|---|
| Dataset Type | Image enhancement (paired dataset) | Object detection (unpaired dataset) |
| Main Objective | Enhancing the quality of low-light images | Object detection under low-light conditions |
| Data Structures | Paired (low-light & normal-light/ground truth) | Unpaired (low-light images only) |

- LOLv2 Dataset.** The LOLv2 dataset is a benchmark dataset for low-light image enhancement tasks that provides paired images captured under low-light conditions and corresponding normal-light images as ground truth. This dataset includes both real-world and synthetic images, encompassing a wide range of illumination levels and varying noise complexities [8]. In this study, the LOLv2 dataset is utilized as the primary data source for both training and evaluating the performance of the RetinexNet model in the image enhancement stage. The LOLv2 dataset (Low-Light dataset version 2) is an extension of the original LOL dataset, specifically designed to support deep learning-based research in low-light image enhancement. It offers paired low-light and normal-light (ground truth) images, enabling supervised model training.

LOLv2 consists of two main components, namely:

- **LOLv2-Synthetic:** synthetic low-light images generated from normal images.
- **LOLv2-Real:** low-light images captured in real-world conditions under insufficient illumination.

This dataset is widely utilized in enhancement research as it effectively represents diverse illumination conditions and provides paired data that are essential for model learning [8].



Figure 1. Comparison Between Low-Light Condition Images And Normal Images In The Lolv2 Dataset

- 2. ExDark Dataset.** ExDark merupakan kumpulan data yang secara khusus dikembangkan untuk keperluan The ExDark dataset is specifically developed for object detection tasks in environments with limited illumination conditions. This dataset comprises 7,363 images covering 12 distinct object categories, where each object is annotated with bounding boxes. The construction of this dataset is intended to evaluate and assess the performance of object detection methods across various illumination levels, including very low light, low light, and ambient light conditions [6], [14].

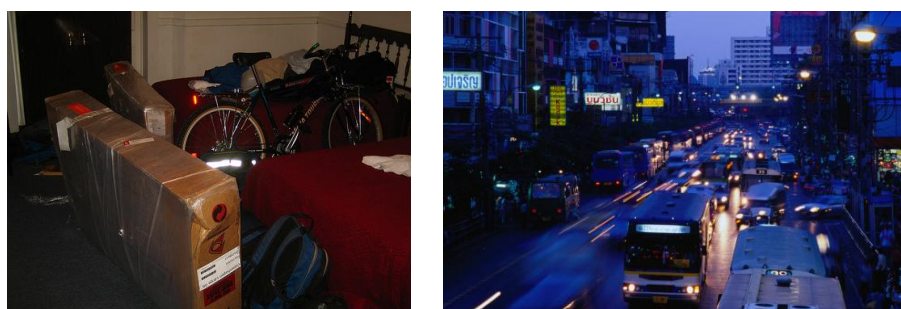


Figure 2. Example Of Exdark Images Under Low-Light Conditions

The dataset was partitioned using a stratified sampling approach, with 70% allocated for training, 20% for validation, and 10% for testing. This method was employed to ensure that the class distribution within each subset remained proportional and free from imbalance.

Table 2. Dataset Partitioning (Training, Validation, And Testing)

| Dataset | Train | Validation | Test |
|---------|-------|------------|------|
| LOLv2 | 70% | 20% | 10% |
| ExDark | 70% | 20% | 10% |

B. Research Stages

This research is carried out through several main stages that are interrelated as follows:

- 1. Data Acquisition and Preparation.** The dataset is obtained by downloading it from the official repository that has been provided. After the download process is completed, an inspection is carried out to ensure the consistency and accuracy of the annotations contained in the dataset. Furthermore, the annotation format used in the dataset was changed to match the annotation format required by the YOLO architecture so that its use can be optimized at the model training stage.
- 2. Initial Preprocessing.** At this stage, where all images are first resized, they are changed to 640 x 640 pixels to ensure uniformity of the input dimensions used by the model. In addition, the pixel value is normalized into the range [0-1] in an effort to improve the stability of the training process. To be able to enrich the variety of data and improve the generalization ability of the model, various data augmentation techniques are applied such as horizontal reversal, image rotation, and brightness level adjustment.
- 3. Image Enhancement Using RetinexNet.** RetinexNet works by modeling an image as a result of multiplication of two main components, namely reflectance (R) and illumination (L) as explained in Retinex theory [8], [15]. In the process, this model first decomposes the input image into two components. After that, the illumination component is then adjusted adaptively to improve lighting quality before the two components are combined again through the image reconstruction process.
- 4. Object Detection Using YOLOv8.** At this stage, the YOLOv8 model is used to carry out the object detection process. The image that has been improved in quality is used as input in the experimental scenario while the original image is used as a basis for comparison. Both types of images are then included in the model training process and used at the inference stage to be able to assess the detection performance of the resulting object.

C. Proposed Architecture

The system developed in this study provides the application of a two-stage pipeline by structurally separating the image improvement process from the detection process so that the two stages are carried out sequentially but still maintained as a different and independent process.

The system workflow can be analyzed with several main stages. The process begins by entering low-light images that become the initial data. Furthermore, the image is processed using the Retinex decomposition method to separate the two components, namely reflectance and illumination. After the two components were successfully obtained, a reconstruction process was carried out to produce an image enhancement with better lighting quality. The image of the enhancement result is then processed with the backbone of the YOLOv8 model to extract the suitable features. The extracted features are then used to predict the location of objects in the form of bounding boxes as well as in determining suitable object categories. In the final stage of this process, it is carried out by implementing the Non-Maximum Suppression (NMS) method to eliminate overlapping bounding box predictions so that the detection results become more accurate.

The architecture of the YOLOv8 model is made up of three main components that are closely integrated [14] [16]. The first component is the backbone which has a function to extract features from input images with the use of C2f modules so that the feature extraction process can be improved in efficiency. The second component is the neck which uses the PAN-FPN structure for the combination of feature information from various scales so that it can produce a richer representation of features. The third component is the head which is designed with a decoupled head approach where the object classification branch and the bounding box regression branch are separated in an effort to improve overall prediction performance.

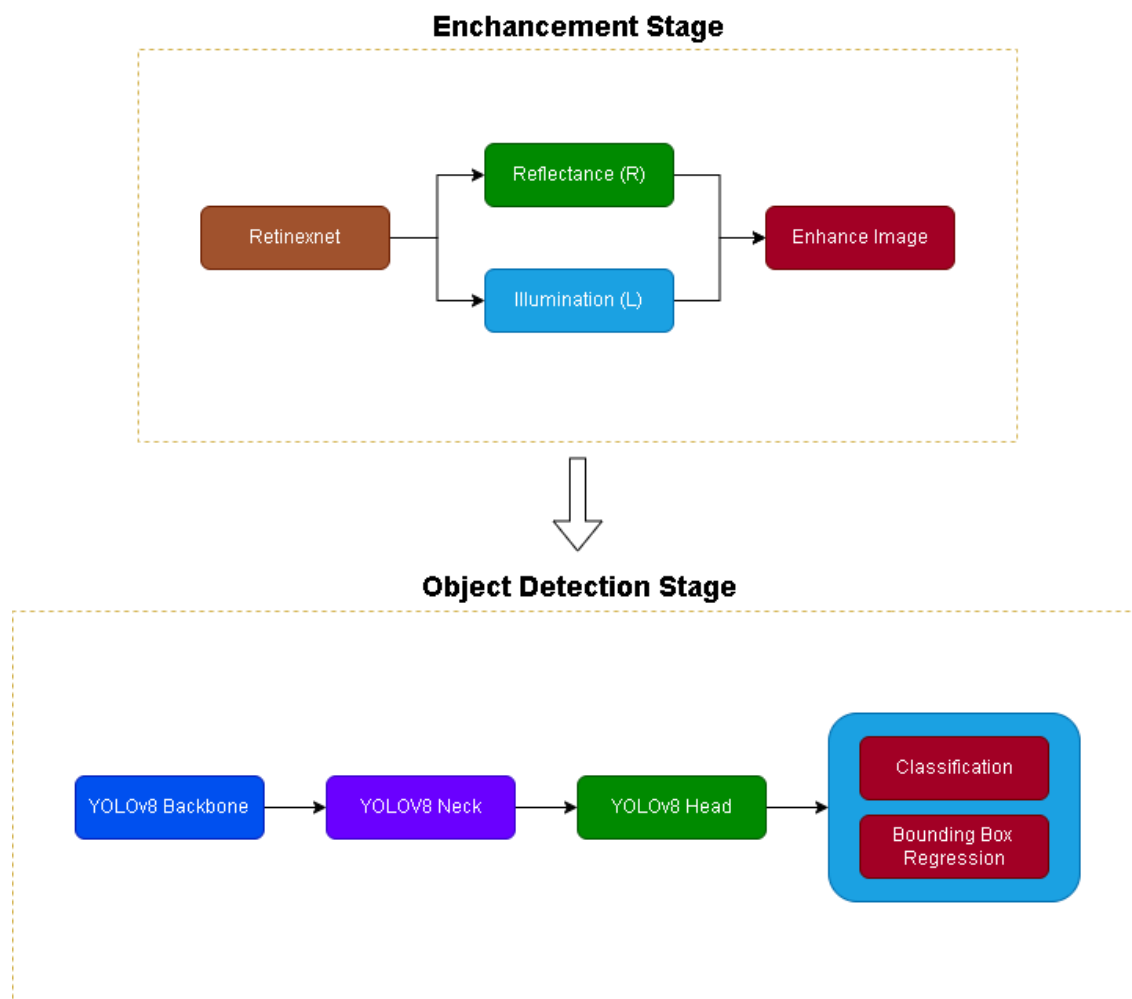


Figure 3. The Workflow Of Image Enhancement And Object Detection

This approach adopts the principle of integrating the image enhancement stage before the detection process in accordance with the methodological framework that has been introduced in previous research on object detection in low-light conditions [3], [5].

D. Experimental Scenario

This study applies two main testing schemes to ensure validity in the process of comparing experimental results:

1. **Baseline.** In this scenario, the YOLOv8 model is trained and evaluated directly using the ExDark dataset without going through the image quality improvement stage first.
2. **Eksperimen (RetinexNet + YOLOv8).** In the experimental setting, each image contained in the dataset is first processed using the RetinexNet method in an effort to improve the quality of lighting before being used in the training and testing stages of the YOLOv8 model.

All configurations and training parameters are maintained to remain the same in both scenarios so that any differences in observed performance can be directly attributed only to the influence of the preprocessing stage of image enhancement applied.

E. Implementation Details

1. **RetinexNet Configuration.** In this study, the image enhancement approach using RetinexNet is implemented through two main modules, namely Decomposition Network (DecomNet) and Relighting Network (RelightNet). DecomNet has a function to break down the input image into two basic components, namely reflection (R) and illumination

(I). The DecomNet architecture is composed of three convolutional layers, each of which uses a ReLU activation function, followed by sigmoid activation to ensure that the output value is within the normal range. Furthermore, the output of the network is separated, where the first three channels are the representation of the reflectance component while the last channel is the illumination component.

The next stage is carried out using RelightNet to improve the illumination component so that better optimization can be obtained based on the combined output of reflectance and initial illumination. This model works by receiving inputs in the form of R and I mergers which are then processed through five convolutional layers in a sequential arrangement using the ReLU activation function. At the end where the sigmoid function is applied, it is applied to produce a new illumination map that is closer to natural lighting conditions. Through this strategy, the improvement of image quality can be done adaptively without any reduction or sacrifice of the structural details of the objects contained in a scene. In general, this research created the development of RetinexNet by using a lightweight architectural approach and not including a pooling layer so that the spatial resolution of the image can be maintained. This approach is considered important because it will allow the details of the object to be optimally maintained before the image enters the detection stage.

Table 3. The Architecture And Parameters Of Retinexnet

| Component | Layer | Parameter | Activation |
|------------|--------|------------------------------|------------|
| DecomNet | Conv2D | 3 → 64, kernel 3×3 | ReLU |
| | Conv2D | 64 → 64, kernel 3×3 | ReLU |
| | Conv2D | 64 → 4, kernel 3×3 | Sigmoid |
| Output | Split | 3 channel (R), 1 channel (I) | - |
| RelightNet | Conv2D | 4 → 64, kernel 3×3 | ReLU |
| | Conv2D | 64 → 64, kernel 3×3 | ReLU |
| | Conv2D | 64 → 64, kernel 3×3 | ReLU |
| | Conv2D | 64 → 32, kernel 3×3 | ReLU |
| | Conv2D | 64 → 32, kernel 3×3 | Sigmoid |

2. YOLOv8 Configuration. The object detection model employed in this study is YOLOv8, implemented using the Ultralytics framework. The selected variant is YOLOv8n (nano), chosen for its computational efficiency while maintaining competitive detection performance. The training process was conducted using a preconfigured dataset, including an input image size of 512×512 pixels and a total of 50 training epochs. The training configuration was designed by considering a trade-off between computational efficiency and optimal model performance. The initial learning rate was set to 0.003, accompanied by the implementation of automatic mixed precision (AMP) to accelerate the training process. Meanwhile, the batch size was kept relatively small (batch size = 4) to accommodate the limitations of the available GPU memory capacity. The entire training process was executed on a single GPU (device = 0), with the number of workers minimized to ensure stability throughout the training procedure.

Table 4. YOLOv8 Configuration

| Parameter | Value |
|---------------|----------------------------|
| Model | YOLOv8n |
| Epoch | 50 |
| Image Size | 512 |
| Batch Size | 4 |
| Learning Rate | 0.003 |
| Optimizer | Default (Adam Ultralytics) |

It should be emphasized that this study does not involve retraining the YOLOv8 model using images that have undergone enhancement. The same model is consistently applied to both the original low-light images and the images processed using RetinexNet. This strategy is implemented to ensure that every difference in detection performance observed correctly shows the influence of the preprocessing stage, without being influenced by other factors, for example the retraining process or model adaptation to differences in data distribution.

3. **Hardware and Environment.** The entire experimental procedure in this study was carried out using a computing system that was specifically formed to support the deep learning process based on GPU. With the availability of hardware that has been equipped with GPU acceleration, it has an important role in improving the efficiency of training time or inference processes, especially in the application of convolutional neural network models such as RetinexNet and YOLOv8.

Overall, the hardware specifications used in this study are the use of GPUs from the NVIDIA RTX series that support CUDA-based parallel computing, thus making computing performance optimization more efficient. In addition, the system is supported by a multi-core processor architecture that has a role in facilitating the data preprocessing stage and the management of the experimental flow. The availability of supporting memory capacity (RAM) is also an important aspect in ensuring that dataset loading processes with model training can run smoothly without bottlenecks, especially when handling high-resolution images.

The determination of system specifications is carried out by considering the need for experiments that connect two deep learning models, namely RetinexNet as a method to improve image quality with YOLOv8 for object detection purposes. Through this configuration, all stages from training to evaluation can be conducted consistently while also ensuring optimal efficiency in terms of computational time.

Table 5. Hardware Specifications

| Component | Specifications |
|----------------|-----------------------------|
| GPU | NVIDIA RTX 4050 |
| CPU | Intel Core i5 |
| RAM | 16 GB |
| Storage | SSD 512 GB |
| FrameworkRate | PyTorch, Ultralytics YOLOv8 |
| Sistem Operasi | Windows 11 |

3. Results and Discussion

A. RetinexNet Enhancement Results

The evaluation at the enhancement stage was conducted through visual inspection and intensity distribution analysis to assess changes in image quality before and after processing using RetinexNet. In general, low-light images in their initial condition exhibit low illumination levels, limited contrast, and a noticeable dominance of noise in darker regions. After undergoing the enhancement process, the images demonstrate improvements in overall brightness and contrast, accompanied by a more uniform illumination distribution. Furthermore, object details that were previously difficult to discern become more visible, particularly in areas that were formerly obscured by shadows.

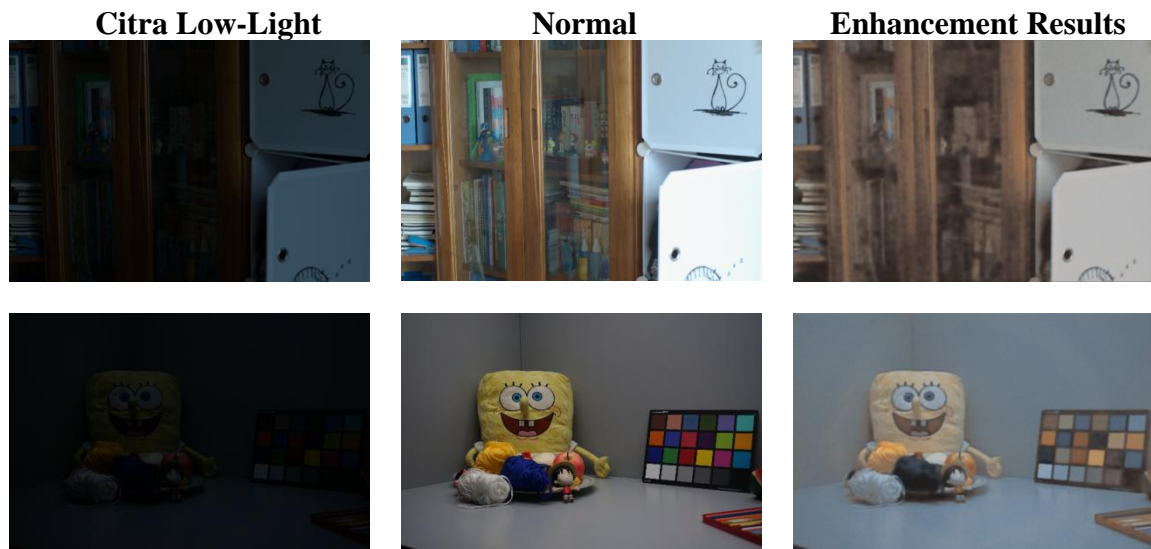


Figure 4. Visual Comparison Of Low-Light Images, Normal Images, And Enhancement Results

B. YOLOv8 Object Detection Results

- Overall Performance Analysis.** The evaluation of object detection performance was conducted under two experimental conditions. The first condition employed the baseline YOLOv8 model without incorporating any image enhancement techniques, whereas the second condition implemented the integration of RetinexNet as a preprocessing stage prior to the detection process. A comparative performance analysis of these two approaches was carried out using several evaluation metrics, namely precision, recall, and mean Average Precision at an IoU threshold of 0.5 (mAP@0.5).



Figure 5. Comparison Of Object Detection Results Between The Baseline And After Enhancement

Visually, the baseline model remains capable of identifying the primary objects with a relatively consistent level of confidence. Under conditions where brightness enhancement is applied, certain objects indeed become more distinguishable; however, this is accompanied by the emergence of additional predictions that exhibit comparatively low confidence scores.

Table 6. Comparison Of The Performance Between The Yolov8 Baseline And Retinexnet + Yolov8

| Metrik | YOLOv8 (Baseline) | RetinexNet + YOLOv8 | Alterations |
|-----------|-------------------|---------------------|-------------|
| Precision | 0.7721 | 0.7394 | - 0.0327 |
| Recall | 0.6502 | 0.5855 | - 0.0647 |
| mAP@0.5 | 0.7359 | 0.6596 | - 0.0763 |

2. Per-Class Performance Analysis. The class-wise evaluation results indicate that the application of enhancement-based scenarios instead led to a decline in performance across all evaluation metrics. The most significant reduction was observed in the mAP@0.5 metric, suggesting that the level of alignment and consistency between the predicted bounding boxes generated by the model and the ground truth data has degraded.

Table 7. Per-Class Object Detection Evaluation Results

| Class | Precision | Recall | mAP50 |
|-----------|-----------|--------|-------|
| People | 0.778 | 0.586 | 0.701 |
| Bicycle | 0.804 | 0.675 | 0.729 |
| Car | 0.814 | 0.602 | 0.722 |
| Motorbike | 0.795 | 0.619 | 0.731 |
| Bus | 0.860 | 0.810 | 0.854 |
| Boat | 0.773 | 0.547 | 0.668 |
| Cat | 0.690 | 0.592 | 0.628 |
| Dog | 0.646 | 0.676 | 0.708 |
| Bottle | 0.638 | 0.464 | 0.524 |
| Cup | 0.731 | 0.473 | 0.552 |
| Chair | 0.719 | 0.490 | 0.578 |
| Table | 0.625 | 0.492 | 0.519 |

Overall, object categories with larger spatial dimensions and more distinctive visual characteristics, such as Bus, tend to achieve the most optimal detection performance (mAP50 = 0.854). In contrast, objects with relatively smaller sizes and more complex visual patterns, such as Bottle, Cup, and Table, exhibit comparatively lower performance levels.

Some of the observed detection failures include:

- **Missed detection:** objects are not detected at all, particularly in the case of small objects.
- **False positive:** objects are detected in regions that do not correspond to the actual target due to noise or enhancement artifacts.
- **Localization error:** The bounding boxes become inaccurate due to extreme contrast variations.

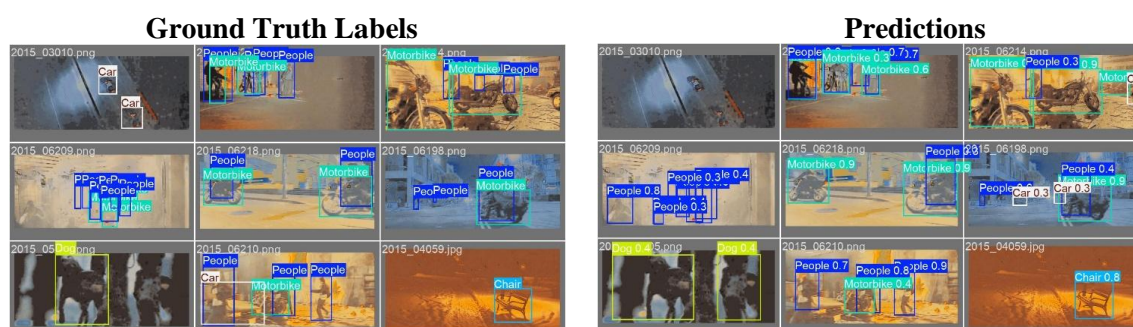


Figure 6. Comparison Between Ground Truth Labels And Predictions In Detection Failure Cases

C. Discussion

The experimental results indicate that improvements in the visual quality of images are not always directly proportional to enhancements in object detection performance. Although RetinexNet is capable of improving illumination and image contrast, alterations in color distribution and pixel intensity instead introduce a domain shift between the data used during training and the data processed during the inference stage. The convolutional backbone in YOLOv8 has previously learned feature representation patterns from original low-light images; therefore, when the visual

distribution changes due to the enhancement process, the feature extraction performed by the model becomes less optimal than before.

A decrease in precision indicates an increase in incorrect positive predictions (false positives), while a decline in recall reflects a reduced capability of the model to identify all objects that should be detected. In addition, the image enhancement process may amplify noise in certain regions of the image, which can ultimately affect the stability of bounding box localization as well as the object filtering process during the Non-Maximum Suppression (NMS) stage.

In general, the findings of this study emphasize that the application of deep learning-based image preprocessing techniques cannot be assessed solely based on subjective visual quality improvements, but must be quantitatively evaluated using object detection performance metrics. The primary contribution of this study is to provide empirical evidence that, within the experimental configuration employed, the baseline YOLOv8 model executed without an enhancement stage demonstrates more consistent performance compared to approaches that integrate RetinexNet as part of the image preprocessing pipeline.

4. Conclusions

The findings of this study indicate that the application of image enhancement techniques does not consistently yield stable positive effects on object detection performance. Consequently, their effectiveness is highly influenced by the characteristics of the dataset as well as the type of model employed. Therefore, further research is recommended to reassess the model training process using more representative datasets, while also designing an end-to-end integrated pipeline to improve the overall system performance.

References

- [1] M. T. Rasheed, G. Guo, D. Shi, H. Khan, and X. Cheng, "An Empirical Study on Retinex Methods for Low-Light Image Enhancement," *Remote Sens.*, vol. 14, no. 18, p. 4608, Sep. 2022, doi: 10.3390/rs14184608.
- [2] M. M. Tatana, M. S. Tsoeu, and R. C. Maswanganyi, "Low-Light Image and Video Enhancement for More Robust Computer Vision Tasks: A Review," *J. Imaging*, vol. 11, no. 4, p. 125, Apr. 2025, doi: 10.3390/jimaging11040125.
- [3] S. Fu, Q. Zhao, H. Liu, Q. Tao, and D. Liu, "Low-light object detection via adaptive enhancement and dynamic feature fusion," *Alex. Eng. J.*, vol. 126, pp. 60–69, Jul. 2025, doi: 10.1016/j.aej.2025.04.047.
- [4] R. Al Sobhahi and J. Tekli, "Comparing deep learning models for low-light natural scene image enhancement and their impact on object detection and classification: Overview, empirical evaluation, and challenges," *Signal Process. Image Commun.*, vol. 109, p. 116848, Nov. 2022, doi: 10.1016/j.image.2022.116848.
- [5] G. Al-refai, H. Elmoaqet, A. Al-Refai, A. Alzu'bi, T. Al-Hadhrami, and A. Alkhateeb, "Two-stage object detection in low-light environments using deep learning image enhancement," *PeerJ Comput. Sci.*, vol. 11, p. e2799, Apr. 2025, doi: 10.7717/peerj-cs.2799.
- [6] Y. Liu, S. Li, L. Zhou, H. Liu, and Z. Li, "Dark-Yolo: A Low-Light Object Detection Algorithm Integrating Multiple Attention Mechanisms," 2024, *SSRN*. doi: 10.2139/ssrn.5074245.
- [7] J. Wu, B. Ding, B. Zhang, and J. Ding, "A Retinex-based network for image enhancement in low-light environments," *PLOS ONE*, vol. 19, no. 5, p. e0303696, May 2024, doi: 10.1371/journal.pone.0303696.

- [8] M. Yin and J. Yang, "ILR-Net: Low-light image enhancement network based on the combination of iterative learning mechanism and Retinex theory," *PLOS ONE*, vol. 20, no. 2, p. e0314541, Feb. 2025, doi: 10.1371/journal.pone.0314541.
- [9] Y. Zhang *et al.*, "Low-light image enhancement method based on retinex theory and dual-tree complex wavelet transform," *J. King Saud Univ. Comput. Inf. Sci.*, vol. 37, no. 5, p. 83, Jul. 2025, doi: 10.1007/s44443-025-00102-6.
- [10] Y. Ruan, H. Ma, D. Ma, W. Li, and X. Wang, "Low-light image enhancement using dual cross attention," *Eng. Appl. Artif. Intell.*, vol. 159, p. 111501, Nov. 2025, doi: 10.1016/j.engappai.2025.111501.
- [11] R. Weng, Y. Zhang, H. Wu, W. Wang, and D. Wang, "The Retinex enhancement algorithm for low-light intensity image based on improved illumination map," *IET Image Process.*, vol. 18, no. 12, pp. 3381–3392, Oct. 2024, doi: 10.1049/ipr2.13180.
- [12] M. J. C. S. Reis, "Low-Light Image Enhancement Using Deep Learning: A Lightweight Network with Synthetic and Benchmark Dataset Evaluation," *Appl. Sci.*, vol. 15, no. 11, p. 6330, Jun. 2025, doi: 10.3390/app15116330.
- [13] T. Chen and D. Liu, "Low Light Image Enhancement Based on Retinex Theory and Diffusion Model," in *Proceedings of the 2024 8th International Conference on Digital Signal Processing*, Hangzhou China: ACM, Feb. 2024, pp. 21–26. doi: 10.1145/3653876.3653908.
- [14] Z. Han, Z. Yue, and L. Liu, "3L-YOLO: A Lightweight Low-Light Object Detection Algorithm," *Appl. Sci.*, vol. 15, no. 1, p. 90, Dec. 2024, doi: 10.3390/app15010090.
- [15] Y. Wu and Y. Liu, "DRE-YOLO: A dual-path retinex enhancement network for low-light object detection".
- [16] C. Joshua and G. Martins, "Low-Light Image Enhancement as a Preprocessing Step for Object Detection," Feb. 2022.