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A Two-Stage Framework for Object Detection in Low-Light Images Using Image Enhancement and Deep Learning Models

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Abstract: In low-lighting scenarios in object detection, a major challenge exists owing to reduced lighting, greater noise, lower contrast, and lighting changes. Thus, such scenarios have a significant effect on vision-based systems used in surveillance, path detection for autonomous vehicles, and security surveillance. A two-tier method using classical image processing and a deep learning platform for object detection in images is proposed and implemented in this work. The first stage uses a dedicated image processing chain aimed at increasing image brightness, contrast, and clarity while eliminating image noise. These processed images are then subjected to evaluation by two separate object detection models: YOLOv9 and Faster R-CNN. From ExDark dataset testing, the effectiveness of the method implemented has a mean Average Precision value of 96% at IOU= 0.50 for YOLOv9 and 88% mAP@50 for Faster R-CNN.

Keywords: Low-Light Images, Object Detection, Image Enhancement, Yolov9, Faster R-CNN, Deep Learning.

Introduction

Object detection in a low light setup is a challenging problem in modern computer vision research. There are various applications that require accurate results in perceptual tasks despite low lighting conditions or illumination changes. Digital images taken under such situations experience extreme deterioration of contrast with a highly noisy nature, presence of shadows, reflection artifacts, and unbalanced lighting, making it difficult for object identification and location (Guo et al, 2023) (Zuiderveld, 1994).

When compared to images acquired in normal illumination conditions, low-light images suffer from lower signal-to-noise ratios, blurred edges of objects, and lost texture information. The aforementioned problems directly affect the process of extracting features in object detection learning models, thus contributing to the rise in both false alarms and missed targets (Loh & Chan, 2019). The problem will continue to get worse due to the heterogeneity in low-light conditions, including nighttime and low light in indoor environments with unique patterns of illumination and noise. Hence, object detection models learned in well-illuminated images do not learn effectively in adverse conditions (Gao et al, 2022).

In order to overcome these issues, image enhancement has gained popularity and acceptance as the pre-processing technique for gaining better visibility and extracting structural details from dark images. Traditional image enhancement methodologies include Histogram Equalization (HE), Adaptive Histogram Equalization (AHE), and Contrast-Limited Adaptive Histogram Equalization (CLAHE), which are aimed at optimizing global and local contrasts and retaining key image details effectively (Vijayalakshmi et al, 2020) (Banik et al, 2018). The various Retinex image enhancement algorithms are designed for separating illuminance and reflectance layers of the image and hence obtain enhanced images according to the human vision perception model (Fu et al, 2023). However, these image enhancement techniques might generate noisy images and color distortions for very dark images.

In recent years, there have been significant improvements in the performance of object detection using deep learning approaches. Methods like Faster R-CNN and YOLO have shown considerable accuracy and reliability for complex scenarios of objects (Chen & Shah, 2021) (Ren et al, 2017). However, their efficiency relies heavily on the quality of the input image, and degradation of performance continues to exist for direct application of such models for low-light images (Vinoth et al, 2024). Some previous works have also suggested that combining image enhancement techniques with deep learning-based approaches for object detection could significantly enhance detection accuracy, but comparisons among different approaches of detection have not been explored in detail, especially for low-light realistic datasets such as ExDark (Loh & Chan, 2019) (Jiang et al, 2021). With the above-mentioned drawbacks in mind, this research aims to create a two-stage approach that integrates classical image enhancement and the latest deep-learning models for object detection. The first stage will aim to enhance image quality using adaptive image enhancement methods to boost brightness, contrast, and detail enhancement with a focus on noise reduction. The second stage will evaluate the effectiveness of image enhancement using a single-stage detector model called YOLOv9 and a two-stage detector model called Faster R-CNN. In this stage, a systematic comparison will be carried out between thetwo models in a fair low-light environment.

1. Related Work

Based on object detection in low-light conditions, existing studies can be divided into three major categories: methods for enhancing low-light images, object detection models using deep learning, and enhancement and detection framework models.

Low-Light Image Enhancement

Low-light image enhancement aims at increasing the visibility and contrast of images taken when the lighting is inadequate. Traditional solutions for image enhancement using insufficient lighting are based on conventional image processing techniques such as

Histogram Equalization (HE), and adaptive forms thereof including Adaptive Histogram Equalization (AHE), and Contrast-Limited Adaptive Histogram Equalization (CLAHE) (Gao et al, 2022) (Anil & Le, 2018). While these image enhancement algorithms are effective and computationally inexpensive, they also tend to increase the noise levels and image artifacts especially for images that are severely degraded by inadequate lighting.

The Retinex approach attempts to simulate human visual perception by analyzing an input image and extracting its illumination and reflection features. Traditional Retinex and multiscale Retinex contrast enhancement techniques have proved successful in retaining details and intensifying weak areas of an image (Ren et al, 2018). These schemes can, however, be sensitive to different parameters, and color distortion occurs in highly illuminated areas.

With the rise of deep learning techniques, there has been an increasing interest in data-driven enhancement techniques. Supervised enhancement techniques like LLNet and KinD learn the mapping between low-light and regular images to obtain satisfactory enhancement outputs (Hai et al, 2023) (Gonzales et al, 2009). Recently, unsupervised enhancement techniques like Zero-DCE and EnlightenGAN have overcome the training requirement for paired samples to enhance flexibility and generalization capabilities to some extent. However, it should also be noted that the mentioned supervised and unsupervised techniques often cause high computation complexity and generate additional artificial details that deteriorate detection performance.

Object Detection Models in Low-Light Conditions

Object detection using deep learning has achieved significant successes under typical lighting conditions. Two-stage object detectors, such as Faster R-CNN, propose potential regions prior to object classification and have shown high accuracy and robustness in challenging environments (Tarel & Hautiere, 2009). Single-stage object detectors, including YOLO and SSD, unify object localization and detection in one network and have the capability of real-time detection with high accuracy (Guo et al, 2020) (Hang et al, 2023).

Despite this, most of the detection models are learned under well-illuminated conditions using datasets such as COCO and PASCAL VOC, limiting their generalization capability for images captured under low illumination conditions. Experimental analysis has already shown a considerable reduction in performance of existing models when directly used on low illumination images, particularly due to a reduction in feature learning capabilities because of low contrast and noise in images (Wu et al, 2018). To overcome such problems, different approaches by several authors were proposed that focus on illumination during learning rather than during testing (Fraser et al, 1984).

The ExDark dataset is introduced to explore the limitation of existing detection algorithms in low-light conditions. Experiments conducted on the ExDark dataset prove that even the state-of-the-art detection algorithms suffer a significant decrease in accuracy in low-light conditions without any pre-processing or adaptation (Lee et al, 2012).

Enhancement-Aware Object Detection Frameworks

In order to fill this gap between enhancement and detection, current studies aim to investigate end-to-end pipelines where enhancement and detection are assembled and integrated together as a combination of low light image enhancement and object detection techniques. Evidence from various studies shows that pre-processing low light images by utilizing enhancement techniques can significantly contribute to enhancing the performance of object detection techniques (Bertalm et al, 2009) (Chaturvedi et al, 2016).

More sophisticated models include the optimization of the enhancement and detection processes within the scope of end-to-end learning models. The objective of these models is to optimize the enhancement networks for the sole purpose of improving detection tasks, as opposed to enhancing visualization capabilities (Nie et al, 2023). Even with the promising results of joint models, some might find their complexity and data demands to be detrimental to applicability in certain real-world contexts.

There is a scarcity of comparative studies that assess the performance of various detection solutions. Furthermore, the performance criteria have been outweighed in the literature that currently focuses on visual aesthetics in enhancements, rather than those relevant to the objectives of detection tasks. Thus, a need arises for a comprehensive framework that will evaluate classical image enhancements in combination with state-of-the-art approaches in practical low light conditions.

2. Proposed Two-Stage Framework

The primary intention of conducting this research work is to design an efficient mechanism for object detection in dark images. This chapter explains the proposed approach in great detail. There are two major components of this proposed approach. The initial stage includes image enhancement using conventional methods. The secondary stage includes object detection using deep learning models. Both components explain how the proposed mechanism tackles the issues that occur during dark images and help ensure the achievement of correct object detection results.

Proposed Methods

Low light image object detection using two-stage approach that combines image enhancement processes and object detection methods.

1) Proposed approaches to improve low light images and dark images are used to increase the visibility of images, highlighting edge features. It deals with the problems of low contrast, noise, and brightness.
2) The method adopts Faster R-CNN with a region-based convolutional neural network and ResNet-50 as its backbone, and YOLOv9c, a one-stage detector, as depicted in Figure 1.

Figure 1. The Overall Two-Stage Framework

Dataset

The ExDark dataset [3] consists of 7,363 images with 12 classes, taken both indoors and outdoors with diverse low light conditions. Image resolutions vary greatly, ranging from 130×130 pixels to 4000×4000 pixels, with bounding box annotations in the bbGt format. ExDark includes challenging lighting conditions, which involve low contrast, low light, bright lights, and local bright light sources, making it a relevant basis for assessing the effectiveness of low-light techniques of object detection. However, the ExDark dataset contains some realistic drawbacks like missing annotations, varying resolutions, imbalance in classes, as well as heavy illumination effects due to strong light reflection.

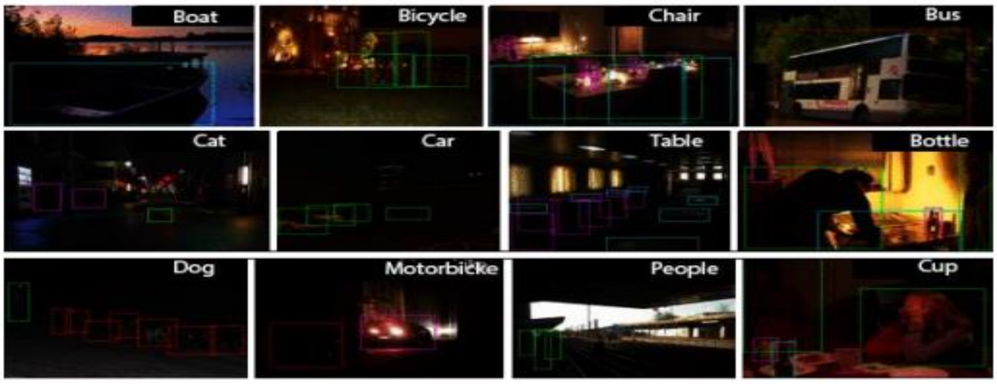

Figure 2. The Classes in The Exdark Dataset

Pre-Processing

After filtering, the images were divided into a set of 4,273 training images, 1,487 validation images, and 240 testing images. Images not annotated with a bounding box were removed, since negative supervision is required in a system performing supervised learning. In light of reorganizing the images according to object class, a major issue is presented by the multi-object property of ExDark images, where images of a primary category often include objects of other categories. As a result, a skewed distribution of object frequency, where some objects appear in larger-than-proportional numbers of images in the training set, is presented.

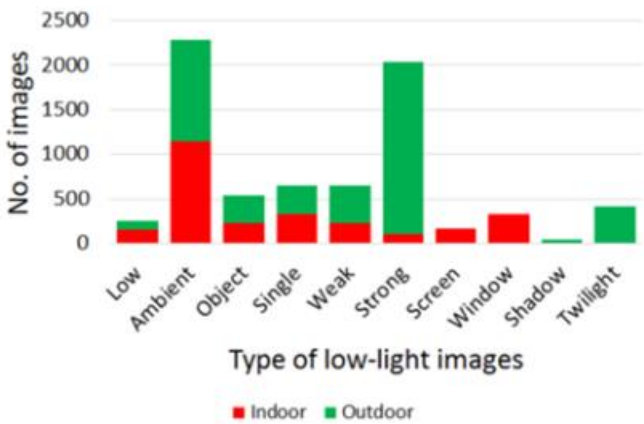

Figure 3. The Type of Low-Light Images in The Exdark Dataset

3. Experimental Setting

The system being tested was installed in an MSI Sword laptop that has an 11th-generation Core i7 CPU, an NVIDIA RTX 3050 GPU, 8 GB of RAM, and an operating system of Windows 11. In terms of programming environments, Python 3.9.12 was used through Anaconda. In an effort to speed up the processing of tasks such as training andtesting, GoogleColab was also used, taking advantage of its A100 GPU.

Dataset

The reason for choosing the ExDark dataset lies in its extensive coverage of night conditions, which made it suited for testing enhancement and detection capabilities in night lighting conditions. ExDark consists of training, validation, and test splits, with a total of 85% for training and the validation data points totaling 1,487, with the remaining 15% for testing. ExDark also covers varying lighting conditions, from very dark lighting up to highly reflecting lighting conditions, including direct headlight exposure, making detection even more difficult.

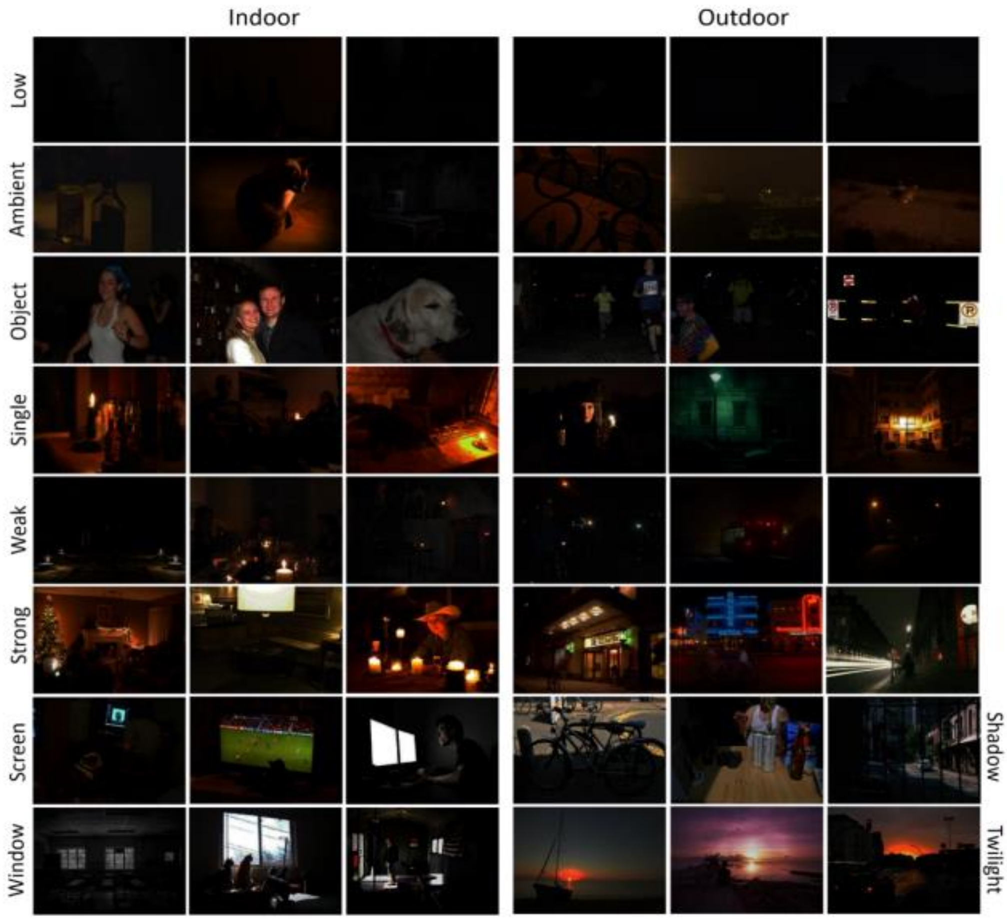

Figure 4. Types of Images That the Exdark Dataset Includes

4.2 Pre-Processing Result

This pre-processing phase was used on the ExDark image dataset. It aimed to improve the quality of the dataset, making it ready for other tasks like object detection. This phase included various image enhancement techniques that aimed to compensate for the negative effects associated with lighting, noise, and lack of edge sharpness in the images. This method used to enhance the images worked perfectly by controlling lighting, contrast, and edge sharpness.

To ensure that the class imbalance problem in the ExDark dataset is addressed, a data balancing technique was employed. Some classes like Bicycle and Dog that had many occurrences were decreased randomly to a fixed number of 500 occurrences for each class. This helped in attaining greater balance. Additionally, it ensured that no class had precedence or priority due to larger occurrence counts.

Table 1. Data Balancing for Exdark Dataset Classes

Before Balancing		After Balancing	
Bicycle	651	Bicycle	٥٠٠
Boat	679	Boat	٥٠٠
Bottle	547	Bottle	٥٠٠
Bus	637	Bus	٥٠٠
Car	735	Car	٥٠٠
Cat	735	Cat	٥٠٠
Chair	648	Chair	٥٠٠
Cup	519	Cup	٥٠٠
Dog	801	Dog	٥٠٠
Motorbike	503	Motorbike	٥٠٠
People	609	People	٥٠٠
Table	504	Bicycle	٥٠٠

Results of the Proposed Image Enhancement Method

The proposed image enhancement scheme was evaluated on the ExDark database to evaluate its effectiveness compared to classical image enhancement schemes and compared to schemes utilizing deep learning. The experimental results show that the proposed scheme has improved the image quality in the low-light and dark environments compared to other schemes, including the classic schemes: Retinex and Adaptive Histogram Equalization. The proposed scheme outperforms many other schemes utilizing deep learning in the scenarios where the illumination degradation is more apparent.

A threshold level of 55 was used in the thresholding process for classifying the images into dark or low-light images, hence allowing the adaptation of the image enhancement technique based on the lighting conditions of each image individually. This adaptability was responsible for the observed improvements in the images. Additionally, the image quality metrics applied to measure the resulting images from the proposed approach of the Contrast-to-Noise Ratio and the Natural Image Quality Evaluator metric validate the improvements seen.

Results and Comparative Analysis of Image Enhancement Techniques

The quality assessment metrics, particularly NIQE and CNR, acted as an objective measure for assessing the quality improvements brought forth by the newly proposed image enhancement approach in this thesis. From the comparative analysis set forth in Table

4.2, it can be seen that the suboptimal or imbalanced enhancements brought forth by prior methods of image enhancement, such as Histogram Equalization (HE), Adaptive Histogram Equalization (AHE), CLAHE, and Retinex image enhancement, occurred when they were applied to benchmark images having strong low illumination effects. It has been evidenced from this analysis that though partial improvements from CLAHE and Gamma correction brought forth satisfactory advances, they were not consistent. Indeed, it has also been noticed that the prevalent image enhancement algorithms share certain prominent limitations. In this context, it can be seen that this newly proposed image enhancement approach outlaid improved performances compared to other image quality improvement methods. Additionally, it has also outperformed both existing traditional algorithms for image enhancement and an image enhancement method utilizing deep learning. Additionally, it should be pointed out that this threshold adaptation technique using an adaptational threshold of 55 helped in modulating the total image enhancement process based on illumination intensity.

Table 2. The Performance Metrics for Enhancement Images Methods

Method	**NIQE↓**	**CNR↑**
HE (Histogram Equalization)	4.3	0.9
AHE (Adaptive HE)	3.8	1.1
CLAHE	3.7	1.2
SSR (Single-Scale Retinex)	3.4	1.7
MSR (Multi-Scale Retinex)	3.2	1.8
MSRCR (Multi-Scale Retinex with Color Restoration)	2.9	2.0
CLAHE + Gamma	2.6	2.4
Proposed Method	**2.١**	**3.4**

Figure 5. Results and Comparative Analysis of Image Enhancement Techniques

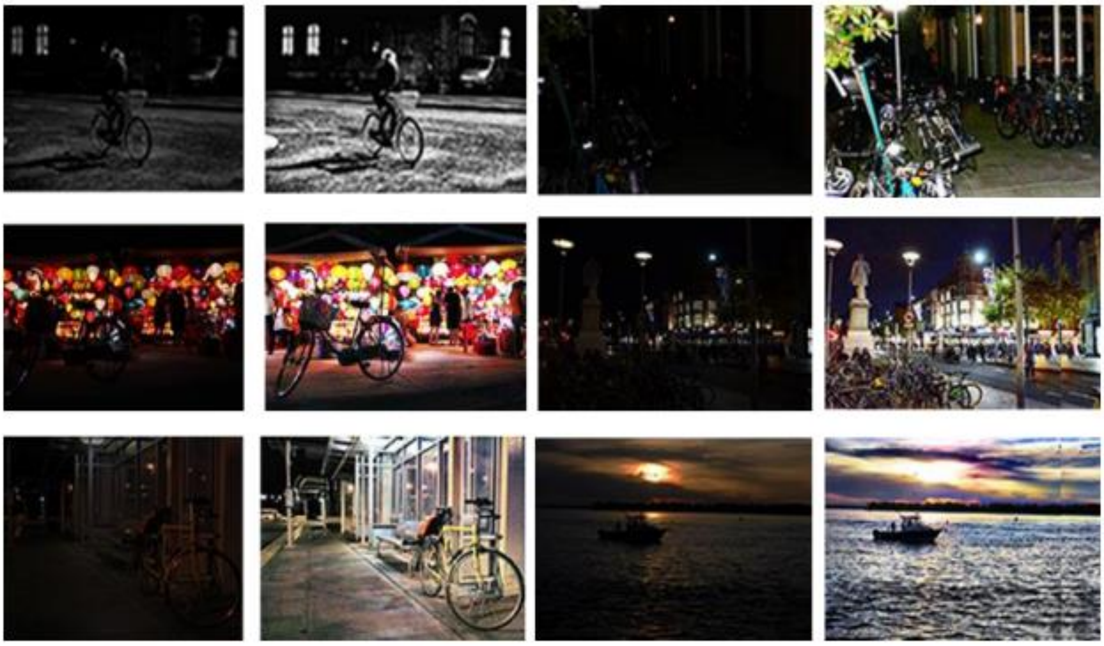

Figure 6. Samples of Images from The Exdark Dataset after Applying the Proposed Method

Results of Using Faster R-CNN

Faster R-CNN was also tested using the modified ExDark dataset. From the results, it was clear that there was an improvement in terms of mean Average Precision (mAP) for Faster R-CNN when using modified pictures, hence verifying that the processing step of image modification was correctly implemented. Though it was demonstrated that the network was capable of performing precise identification of objects as well as more defined boundary detection, it was performing below that of the YOLO network. Additionally, its Precision and Recall were improved from before when using the original pictures. There was improvement in terms of accuracy for Faster R-CNN when using modified pictures, hence verifying that image modification was correctly done.

Figure 7. Samples of Object Detection Images using Faster RCNN after Applying The Proposed Method

Conclusion

This work successfully demonstrates a two-stage approach that seeks to enhance object detection results under low-light conditions using a combination of traditional image enhancement methods and modern deep learning-based object detection models. Experimental results carried out using the ExDark dataset have shown significant improvement in detection precision for both single-stage and two-stage models. The superiority of the proposed image enhancement technique has been well validated for dealing with light exposure issues. Moreover, optimal results have been observed with the YOLOv9 object detection model.

As for future studies, there are several aspects that will be explored, which include integrating learning and adaptive enhancement modules into the framework for optimal performance and generalization. Another promising approach is extending the proposed framework into video sequences and embedded systems for low-light detection.

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