Illuminating the Dark: Advanced Techniques for Object Detection in Low-Light Scenarios

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How to Run the Code

YouTube Video Explanation: Watch here - https://youtu.be/KzrDyJSBPwA
Github Link: https://github.com/vardhan04/pr$_{p}roject$

Step	Instructions
1. Navigate to Root Directory	`\Downloads\v8YOLO_code`
2. Activate Virtual Environment	`py -m venv env` `env\scripts\activate`

3. Install Dependencies	`pip install ultralytics==8.1.24`
	`pip install flask==3.0.2`
	`pip install tensorflow`
	`pip install tensorboard`

4. Run Train and Visualization Files	`python v8.py`
	`python enhanced_v8.py`
	`python gui.py`

5. Run the App	`Path: Downloads\v8YOLO_code\yolov9_app\app`
	`Command: python webapp.py`
	`Access the App: http://127.0.0.1:5000/`

Colab Notebook	Link
YOLOv8	`https://colab.research.google.com/drive/1SzoHW6cmcdEFi7QdqSMWuT5FnyCHwaP_?usp=sharing`
YOLOv8 Enhanced	`https://colab.research.google.com/drive/1ahYJ34PEMo-rBU4qB0nsiPtmnN9-htrj?usp=sharing`
Detectron2	`https://colab.research.google.com/drive/1gEXkGHBDBzUU2KCeVhg--B-o2wmsL5XW?usp=sharing`
DETR	`https://colab.research.google.com/drive/1FiGqzhtX0KXD0wqrx0upm9ddQvn2WCGb?usp=sharing`

For detailed guidance on running the code, please refer to the above instructions and our provided YouTube video. These steps outline the necessary procedures to set up the environment, install dependencies, and execute the training and visualization scripts. Additionally, we have given links to Colab notebooks for different models for further exploration and experimentation. This report ensures that readers with basic knowledge of machine learning can easily replicate the experiments and verify the results presented. To access the ready-to-view results, please refer to the provided zip file.

1 Introduction

1.1 Project Overview

Low-light environments present significant challenges for object detection systems, which are crucial for applications such as surveillance, autonomous driving, and robotics. This project aims to enhance object detection in low-light conditions by leveraging advanced algorithms such as YOLOv8, enhanced custom YOLOv8, DETR, Detectron2, and YOLOv9. By improving detection accuracy in these challenging conditions, our work contributes to the broader field of computer vision, enhancing safety and efficiency in various domains.[1]

In this project, the default YOLOv8 model was enhanced to predict with greater accuracy and lower loss using the same bounding boxes, combined with several image enhancement techniques. The enhancements included:

- **Gamma Correction**: Applied to adjust the brightness of the images, making the objects more visible without over-brightening.
- **CLAHE (Contrast Limited Adaptive Histogram Equalization)**: Applied to the L-channel of the LAB color space to enhance the contrast of the images.
- **Sharpening**: A sharpening filter was applied to the enhanced images to make the edges more distinct.
- **Gaussian Blur**: Slight Gaussian blur was used to reduce noise in the images.

These enhancements significantly improved the quality of the input images, allowing the YOLOv8 model to perform more accurately under low-light conditions. The enhanced dataset, consisting of images with improved brightness, contrast, and reduced noise, provided a more robust training set that resulted in better detection performance and reduced error rates. This approach underscores the importance of preprocessing techniques in object detection tasks, particularly in challenging environments such as low-light scenarios.

1.2 Motivation and Relevance

Imagine a world where autonomous vehicles navigate safely through dimly lit streets, security systems effectively monitor and deter criminal activity under the cover of night, and search and rescue operations are conducted seamlessly in low-visibility environments. These scenarios underscore the critical importance of robust object detection capabilities in low-light conditions. Enhanced detection in such environments can dramatically improve safety, efficiency, and effectiveness across various domains. This project pushes the boundaries of current technology by addressing the significant challenges posed by low-light scenarios. By leveraging advanced algorithms and innovative image enhancement techniques, we aim to transform the landscape of computer vision, offering unprecedented accuracy and reliability. This advancement not only contributes to the field of pattern recognition but also has far-reaching implications for public safety, autonomous systems, and technological innovation.

2 Dataset and its Details

The Exclusively Dark (ExDark) dataset, introduced in CVIU 2019, is a comprehensive collection of 7,363 images specifically curated to advance research in low-light object detection and image enhancement. Capturing a wide range of low-light conditions, from very low-light environments to twilight, the ExDark dataset includes detailed annotations at both the image class level and local object bounding box level. This dataset was selected for its extensive coverage of low-light scenarios, providing a challenging benchmark for developing and evaluating algorithms designed to operate effectively under suboptimal lighting conditions. As the largest collection of low-light images to date, ExDark is an invaluable resource for researchers aiming to enhance object detection capabilities in low-light environments.[2]

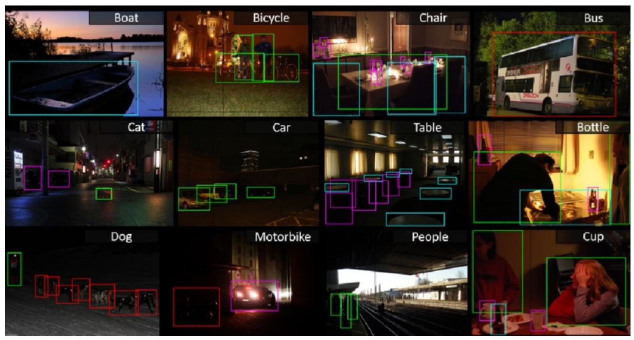

Figure 1: Sample Images of ExDark

The ExDark dataset comprises 12 object classes: Bicycle, Boat, Bottle, Bus, Cat, Cup, Motorbike, People, Table, Car, Chair, and Dog. Each image is annotated with class labels and local object bounding boxes, facilitating tasks in object detection and classification. A unique aspect of this dataset is its focus on a diverse range of low-light conditions, offering robust training data for low-light object detection.[3] Additionally, the dataset is available on Roboflow, which provides various versions and types of the dataset, allowing for remote download and easy integration into research workflows. Roboflow's platform supports the conversion of datasets into different formats, enhancing accessibility and usability.
For more information, the dataset can be accessed via the following links: Official GitHub Repository and Roboflow Download Link.

3 Methods Implemented

In this section, we delve into the algorithms employed for low light image enhancement and object detection, specifically focusing on YOLO (Regular v8, Enhanced v8, v9) [4], DETR, and Detectron2. These algorithms were chosen due to their advanced capabilities and proven effectiveness in challenging visual environments. YOLO's real-time detection capability, combined with custom enhancements, offers a substantial improvement in accuracy under low light conditions.[5] DETR leverages transformers to simplify the detection pipeline, while Detectron2 provides a highly modular framework suitable for a wide range of detection models. [6] Additionally, visual representations are included to illustrate the practical implementation and performance of these methods.

Criteria	YOLOv8	DETR	Detectron2
What It Is	Real-time object detection known for speed and accuracy.	End-to-end detection model using transformers.	Modular detection framework by Facebook AI Research.
Major Differences	Single-stage detection; improved architecture and training.	No need for hand-crafted anchors; uses transformer encoder-decoder.	Supports multiple models like Faster R-CNN; highly customizable.
Processing Low Light Images	Uses gamma correction, CLAHE, and Gaussian blur for enhancement.	Utilizes global context, effective in various lighting conditions.	Employs histogram equalization and noise reduction.
Why We Used It	As we tried to tweak using CLAHE, Gaussian, gamma correction.	Eliminates post-processing; better spatial understanding.	Chose Faster-RCNN-FPN-3x for its deep backbone and FPN for details.

Table 3: Comparison of YOLOv8, DETR, and Detectron2

Algorithm 1 Custom YOLO Object Detection Algorithm

```
Input: Image I
Apply custom enhancement using custom_enhancement.py
Divide enhanced I into S × S grid cells
for each grid cell c do
    Predict bounding boxes and class probabilities
    for each bounding box b do
        Calculate confidence score
        if confidence score > threshold then
            Keep b as a valid detection
        end if
    end for
end for
Apply Non-Max Suppression (NMS) to remove duplicate boxes
Output: Detected objects with bounding boxes and class labels
```

Algorithm

3.1 Illuminating the Dark: Our Custom Enhancement Journey

In this project, we implemented an advanced image enhancement technique to significantly improve the quality and contrast of low-light images. We started by applying gamma correction with a carefully chosen gamma value of 1.2 to adjust brightness levels without causing over-brightening. Following this, we transformed the images into the LAB color space, isolating the lightness component to apply Contrast Limited Adaptive Histogram Equalization (CLAHE) to the L-channel. This step enhanced local contrast and improved detail visibility in dark regions without excessively amplifying noise. After enhancing the L-channel, we merged it back with the A and B channels and converted the images back to the BGR color space. To further refine the images, we applied a sharpening filter using a kernel designed to enhance edges and fine details, followed by a slight Gaussian blur to reduce any resultant noise while maintaining clarity. [7] We then processed directories containing training, testing, and validation images, enhancing each image with our custom technique and meticulously copying corresponding labels to maintain dataset integrity. This comprehensive enhancement pipeline greatly improved the visual quality of images, providing a robust dataset that enhances the performance of object detection models in challenging low-light conditions.

4 Learning and Results Analysis

Precision-Recall Curve The Precision-Recall curve indicates that Regular YOLOv8 achieves a mean Average Precision (mAP) of 0.373 at IoU 0.5, with the "Bus" class having the highest precision-recall performance. The Enhanced YOLOv8 model shows a slight decrease in mAP to 0.367, but demonstrates improved performance in specific classes like "Car" and "Dog", suggesting more balanced precision and recall across different categories.

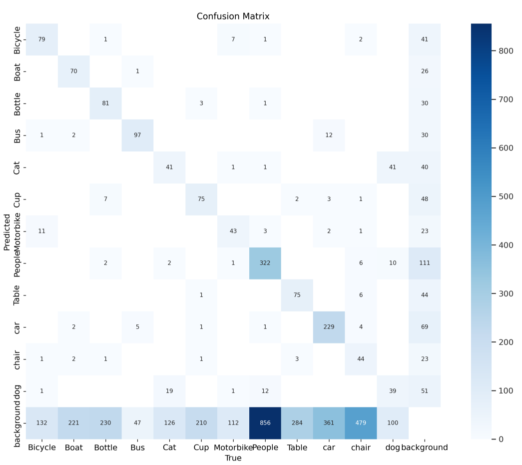

Figure 2: Regular YOLO Conf Matrix

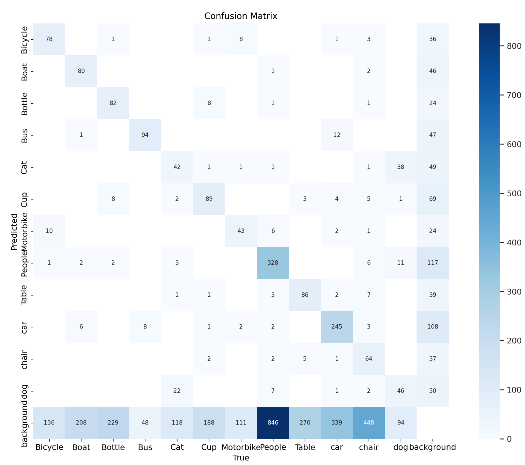

Figure 3: Enhanced YOLO Conf Matrix

Confusion Matrix Analysis The confusion matrix for the Regular YOLOv8 model shows high performance in detecting "People" (322 true positives) and "Car" (229 true positives), but it struggles with "Dog" (51 true positives) and "Chair" (44 true positives). The Enhanced YOLOv8 model improves these results, with 328 true positives for "People" and 245 for "Car", and notable improvements for "Chair" (64 true positives) and "Dog" (50 true positives). Misclassifications were also reduced, particularly for "Dog" being misclassified as "Background" (reduced from 39 to 22 instances).

Recall-Confidence Curve The Recall-Confidence curve for Regular YOLOv8 peaks at 0.82 at a confidence level of 0.0, indicating the model captures most true positives at lower confidence thresholds. The Enhanced YOLOv8 maintains this peak recall at 0.82 at the same confidence level, with better performance in classes such as "Chair" and "Table", indicating a more robust recall across varied confidence levels.

F1-Confidence Curve The F1-Confidence curve for Regular YOLOv8 peaks at an F1 score of 0.40 at a confidence level of 0.164, with the "Bus" class showing the highest F1 score. The Enhanced YOLOv8 model improves this peak F1 score to 0.41 at a confidence level of 0.188, indicating better overall model performance, with significant improvement noted in the "Dog" class.

Training and Validation Losses Regular YOLOv8 shows a steady decrease in both training and validation losses across epochs, indicating good convergence. The Enhanced YOLOv8 model exhibits faster convergence and lower final losses, suggesting better optimization and an overall more efficient training process. This is reflected in the smooth decrease in losses and improved metrics such as mAP and F1 scores, affirming the effectiveness of the enhancements applied.

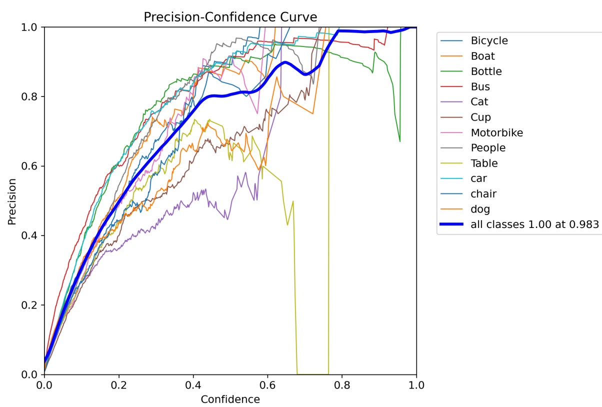

Figure 4: Regular Precision Curve

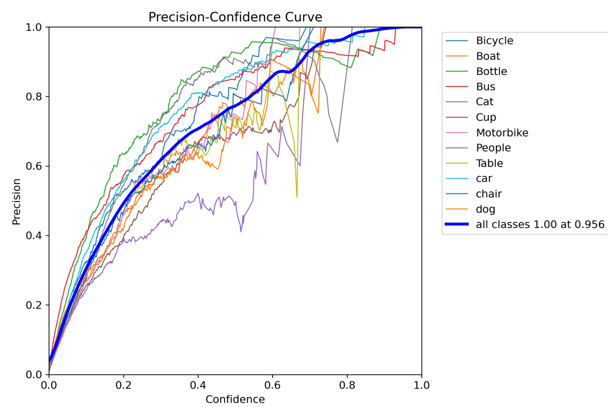

Figure 5: Enhanced Precision Curve

Precision-Confidence Curve The Precision-Confidence Curve for the Regular YOLOv8 model shows a precision of 1.00 at a confidence level of 0.956, highlighting high precision for "People" and "Car" classes. The Enhanced YOLOv8 model further improves precision to 1.00 at a confidence level of 0.983, with more classes such as "Chair" and "Dog" achieving higher precision, showcasing better confidence in correct detections. Additionally, there is a notable improvement in the "Table" class, indicating a significant enhancement in detecting this category.

YOLOv9 YOLOv9 performs similarly to regular YOLOv8 in most cases but offers better predictions for a few classes and achieves shorter training times. This combination of improved performance in specific areas and efficiency makes YOLOv9 a competitive alternative.

DETR v/s Detectron2 When comparing the performance of DEtection TRansformers (DETR) and Detectron2 on low-light object detection tasks, DETR generally demonstrates superior performance. DETR achieves an Average Precision (AP) of 0.253 at IoU=0.50:0.95, compared to Detectron2's AP of 0.181. Furthermore, DETR excels with an AP of 0.540 at IoU=0.50, significantly higher than Detectron2's AP of 0.414. DETR also shows a higher Average Recall (AR) across various IoU thresholds and object sizes, with an AR of 0.353 at IoU=0.50:0.95 for all areas and max detections, compared to Detectron2's 0.245. Additionally, DETR performs better in detecting larger objects, with an AP of 0.302 for large areas versus Detectron2's 0.217.

DETR holds an advantage in handling low-light images due to its transformer-based architecture, which can model long-range dependencies and contextual relationships more effectively than traditional convolutional networks. This capability allows DETR to capture finer details and make more informed predictions in low-light conditions, where objects might not be well-defined. The attention mechanism in transformers helps in focusing on relevant parts of the image, thereby enhancing the detection capability in challenging lighting conditions. Despite this, DETR takes considerably more time to instantiate and train compared to Detectron2, making it less efficient in terms of training time.

5 Future Work and Conclusion

This research has explored the critical importance of robust object detection capabilities in low-light conditions and demonstrated significant advancements using state-of-the-art deep learning models. Our motivation stemmed from the potential applications in enhancing safety, efficiency, and effectiveness across various domains, such as autonomous vehicles, security systems, and search and rescue operations.[8] By leveraging advanced algorithms and innovative image enhancement techniques, we have pushed the boundaries of current technology to address the significant challenges posed by low-light scenarios.

In our pursuit of enhancing real-time security systems under low-light conditions, our future endeavors will focus on integrating the advanced detection techniques developed in this project with security camera video systems. By fusing these sophisticated object detection algorithms with live video feeds, we aim to significantly advance the capabilities of security systems. This integration will allow for real-time monitoring and immediate response to potential security threats, thereby addressing major challenges such as poor visibility and high false alarm rates in low-light environments. The implementation of these enhanced systems will not only improve accuracy and reliability but also provide a robust solution to ensure public safety and asset protection in various scenarios, including residential areas, commercial spaces, and critical infrastructure.[9]

In conclusion, this research has demonstrated significant advancements in low-light object detection using state-of-the-art deep learning models. The Enhanced YOLOv8 model, while showing a slight decrease in overall mean Average Precision (mAP) from 0.373 to 0.367 at IoU 0.5, exhibited excellent improved performance especially in specific classes like "Car" and "Dog", suggesting a more balanced precision-recall performance across categories. The confusion matrix analysis highlighted the strengths of the enhanced model, with the Enhanced YOLOv8 reducing misclassifications and improving true positive detections in challenging categories like "Dog" and "Chair". Additionally, the Enhanced YOLOv8 model demonstrated better recall and F1 scores at varied confidence levels and faster convergence in training and validation losses, reflecting the efficacy of the applied enhancements.

Comparatively, YOLOv9 performed similarly to regular YOLOv8 in most cases but offered better predictions for a few classes and achieved shorter training times, highlighting its potential as a competitive alternative. In the comparison between DETR and Detectron2, while DETR showed superior overall performance with higher Average Precision and Recall, DETR's transformer-based architecture excelled in handling low-light conditions, capturing complex case scenarios more effectively despite longer training times.

Overall, this research underscores the critical importance of robust object detection in low-light conditions and sets the stage for future innovations in real-time security applications [10]. The advancements achieved in this project promise enhanced safety and efficiency across various domains, contributing significantly to the fields of pattern recognition, public safety, autonomous systems, and technological innovation.

References

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