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# ENHANCING OBJECT DETECTION ACCURACY IN LOW LIGHT ENVIRONMENTS THROUGH GDIP BASED ADAPTIVE IMAGE PROCESSING AND CONTRAST OPTIMIZATION TECHNIQUES

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**ABSTRACT**

Accurate object detection under low-light conditions remains a persistent challenge in computer vision due to poor visibility, high noise levels, and diminished edge clarity. This research addresses these limitations by introducing a structured image preprocessing framework that combines contrast enhancement, noise suppression, and Gradient Domain Image Processing (GDIP)-based adaptive edge amplification to improve detection performance. The enhancement pipeline is implemented using Python and OpenCV, while YOLOv5 serves as the detection backbone. Raw low-light images are sequentially processed through histogram equalization, bilateral filtering, and GDIP transformation before being passed to the detection network. Performance evaluation was conducted on the ExDark and LLVIP datasets. The proposed method achieved a precision of 81.3%, recall of 74.2%, and mAP@0.5 of 78.5%, representing significant gains over the baseline YOLOv5 model, which recorded 64.2% precision, 58.6% recall, and 61.0% mAP@0.5. Despite a modest increase in computational cost, with total inference time rising to 28.6 milliseconds per image, the system maintained 34.9 FPS, confirming its real-time applicability. This integrated enhancement approach not only boosts detection accuracy but also supports reliable deployment in low-light scenarios such as nighttime surveillance, autonomous navigation, and smart urban environments.

**Keywords:** *Low-Light Object Detection, GDIP Enhancement, Contrast Adjustment, Noise Reduction, YOLOv5, Image Preprocessing*

## 1. INTRODUCTION

Object detection under ideal lighting conditions has witnessed remarkable progress due to the development of advanced convolutional neural networks (CNNs) and large annotated datasets [1]. However, when deployed in real-world scenarios such as night-time surveillance, autonomous navigation, or low-light facial recognition, these models often suffer from significant accuracy degradation due to poor visibility, excessive image noise, reduced contrast, and loss of critical features [2][3][4]. The visual information captured in low-light images tends to be incomplete and noisy, complicating both feature extraction and object localization tasks [5]. Traditional image enhancement methods primarily focus on improving visual quality for human perception, often without considering the downstream impact on high-level vision tasks such as object detection [6]. Furthermore, conventional pipelines tend to decouple the enhancement and detection stages, leading to inefficiencies and sub-optimal performance. Recent works have attempted to integrate pre-processing with detection in an end-to-end manner. For instance, GDIP (Gated Differentiable Image Processing) introduced by Kalwar et al. [7] enables learnable combinations of enhancement operations within detection networks, achieving robust performance in challenging lighting environments. Similarly, IA-YOLO integrates adaptive filtering directly with YOLOv3, and PE-YOLO employs multi-scale enhancement strategies to improve feature clarity under poor illumination [8]. Despite these advancements, many of the existing methods still suffer from heavy computational loads, complex architectures, or lack generalizability across varied lighting conditions [9]. In response to these limitations, this study presents a lightweight yet effective framework that enhances object detection accuracy in low-light settings.

The proposed system combines histogram equalization, bilateral filtering [10], and GDIP-based adaptive enhancement with YOLOv5 as the detection backbone, implemented in Python using OpenCV. Unlike traditional pipelines, the model integrates image enhancement directly into the detection process, ensuring improved detection of obscured objects while maintaining computational efficiency. The framework is evaluated on benchmark datasets including ExDark and LLVIP [11] [12], which are specifically designed to represent low-light scenarios. Experimental results demonstrate substantial improvements in detection performance metrics such as mean Average Precision (mAP), precision, and recall when compared to baseline models without enhancement pre-processing. By bridging the gap between low-level enhancement and high-level object recognition, the proposed method supports practical applications in real-time surveillance, autonomous driving, and smart city infrastructure [13] [14]. Under low-light conditions, object detection faces severe challenges due to the degradation of image quality, including low contrast, heavy noise, and blurred textures. These factors directly affect the accuracy of both object classification and localization, particularly in real-world scenarios such as autonomous driving [15], pedestrian tracking [16], and emergency response systems [17]. While deep learning-based object detectors have seen significant advancements, their performance declines notably when images suffer from illumination deficiencies. This is because the models, often trained on well-lit datasets, struggle to generalize to complex lighting conditions present in practice [3].

Traditionally, the prevailing approach has been to enhance the image first and then apply object detection. However, this two-step pipeline introduces three primary limitations. First, many enhancement techniques prioritize visual quality as perceived by humans, which does not necessarily align with the requirements of object detection models [6]. Second, the variability in lighting types ranging from extremely dim to backlit environments renders static enhancement techniques insufficient for comprehensive performance across all scenarios [12]. Third, noise suppression in low-light images may inadvertently smooth out fine object boundaries and textures, thereby impeding the detector's ability to localize and classify accurately [11]. To overcome these challenges, dynamic and adaptive methods are needed. Recent studies propose joint frameworks that integrate enhancement and detection into a single pipeline, enabling context-aware improvements that are optimized for detection rather than human perception [7]. For instance, sample-specific enhancement modules that apply different filters in parallel have shown promise. By assigning adaptive weights to each enhancement stream, such systems selectively reinforce features that are essential for accurate detection, mitigating the risk of over-smoothing or overexposure [8]. Moreover, the subtle differences between foreground objects and complex, dark backgrounds require detectors with stronger representation learning capabilities. One-stage deep learning-based detectors such as YOLOv7 are particularly suitable for this task due to their balance of speed and accuracy [18]. Histogram analysis of low-light images reveals that amplifying pixel intensity not only improves clarity but also enhances the semantic richness of the scene, supporting the feasibility of detection under poor lighting when appropriate pre-processing is applied [19]. In this context, the proposed work introduces a novel framework that combines GDIP-based adaptive image processing with YOLOv5 to enhance detection performance under diverse low-light conditions. This method dynamically adjusts contrast and noise levels in a context-aware manner and operates efficiently enough for real-time applications.

Although numerous studies have investigated low-light enhancement and object detection independently, relatively few have critically addressed the relationship between enhancement quality and downstream detection accuracy. Existing enhancement techniques frequently improve visual appearance without ensuring preservation of semantic features required for reliable object localization. Moreover, computational complexity and poor adaptability across diverse illumination conditions continue to restrict practical deployment. These research gaps motivate the development of the proposed GDIP-based adaptive enhancement framework, which jointly addresses image enhancement and detection accuracy within a computationally efficient pipeline.

**Problem Statement**

Although recent advances in low-light image enhancement and deep learning-based object detection have significantly improved computer vision performance, reliable object detection under adverse illumination remains a challenging problem. Existing enhancement techniques, including histogram equalization, Retinex-based algorithms, LLNet, MBLLEN, Zero-DCE, and other deep learning approaches, primarily focus on improving visual image quality rather than optimizing downstream object detection performance. Consequently, visually enhanced images do not always preserve the structural and semantic features required for accurate object localization and classification. Furthermore, many existing approaches employ computationally intensive architectures or separate enhancement and detection stages, thereby increasing inference time and limiting their applicability in real-time systems such as intelligent surveillance, autonomous vehicles, and smart city monitoring. These limitations identified in the literature demonstrate the need for an adaptive, computationally efficient enhancement framework that directly supports object detection under diverse low-light environments.

**Research Objectives**

Based on the identified research gap, this study aims to achieve the following objectives:

1. **To develop** a lightweight image enhancement framework that combines Histogram Equalization, Bilateral Filtering, and Gradient Domain Image Processing (GDIP) for low-light image enhancement.
2. **To improve** object detection accuracy by preserving discriminative edge and texture information required by the YOLOv5 detection framework.
3. **To evaluate** the effectiveness of the proposed enhancement pipeline using benchmark low-light datasets, namely ExDark and LLVIP, through Precision, Recall, and mean Average Precision (mAP) metrics.
4. **To analyze** the computational efficiency of the proposed framework and determine its suitability for real-time intelligent vision applications.
5. **To demonstrate** that adaptive gradient-domain enhancement provides superior detection performance compared with conventional preprocessing techniques while maintaining practical inference speed.

**Research Contributions**

The major contributions of this research are summarized as follows:

- A novel GDIP-based adaptive image enhancement framework is proposed to improve object detection performance under low-light conditions.
- Histogram Equalization, Bilateral Filtering, and Gradient Domain Image Processing are integrated into a unified preprocessing pipeline before YOLOv5 detection.
- Extensive experiments on the ExDark and LLVIP datasets demonstrate significant improvements in Precision, Recall, and mAP compared with the baseline detector.
- The proposed framework achieves a balance between detection accuracy and computational efficiency, making it suitable for real-time deployment in intelligent surveillance and autonomous systems.

## 2. LITERATURE REVIEW:

Object detection has evolved as a central task in computer vision, enabling applications across diverse real-world domains including autonomous vehicles, smart surveillance, and robotics. Detectors are broadly categorized into two-stage architectures, such as Faster R-CNN and Mask R-CNN, which use a region proposal mechanism followed by object classification, offering high accuracy at the cost of computational efficiency [20], [31]. In contrast, one-stage detectors like YOLOv3, YOLOv5, YOLOv7, and SSD achieve faster inference by predicting bounding boxes and class labels in a single forward pass, providing an efficient trade-off between accuracy and speed [21], [22], [33]. However, under low-light conditions, both detector types exhibit significant performance degradation. Factors such as loss of contrast, sensor noise, and blurred edges diminish the quality of features fed into the detection model, resulting in missed detections or incorrect classifications [23]. These challenges have prompted extensive research into image enhancement techniques aimed at improving visibility and boosting downstream detection accuracy.

Conventional enhancement techniques, including histogram equalization and Retinex-based models, aim to increase image brightness and contrast [10], [24]. While these methods succeed in improving the perceptual appearance of dark images, they often fail to deliver measurable gains in detection performance due to the lack of task-specific optimization. In response, several deep learning-based enhancement networks have been proposed to address the limitations of classical methods. Models like LLNet [25], MBLLEN [26], and KinD [27] utilize CNN architectures to restore visibility and structural detail in low-light scenes. Similarly, Deep Retinex Decomposition methods jointly estimate illumination and reflectance for improved enhancement [37]. The emergence of zero-reference learning methods, such as Zero-DCE and Zero-DCE++, introduced pixel-level adaptive adjustment of brightness and contrast without requiring paired training images [6]. Although these methods yield improved visual outputs, their primary focus remains aesthetic quality rather than optimizing detection or recognition tasks. To bridge this gap, task-aware enhancement frameworks have been explored, aiming to simultaneously improve visual clarity and object recognition.

Despite these advances, several important limitations remain unresolved. Most enhancement networks are optimized using image quality metrics such as PSNR and SSIM rather than object detection metrics including Precision, Recall, and mAP. Consequently, visually enhanced images do not always translate into improved detection accuracy. Furthermore, many deep learning enhancement models introduce considerable computational overhead, making them unsuitable for real-time applications such as autonomous driving and intelligent surveillance. Existing approaches also exhibit limited robustness when illumination conditions vary significantly across scenes, often requiring extensive retraining or parameter tuning for different datasets. These limitations indicate that enhancement algorithms should be designed not only to improve image appearance but also to preserve discriminative features required by modern object detectors.

One direction involves integrated pipelines where enhancement is embedded into the detection architecture itself. For instance, Sasagawa et al. proposed a domain-adaptive detection strategy under low-light by modifying the YOLO backbone for better feature alignment [28]. Similarly, Hu et al. combined the MSRCR (Multi-Scale Retinex with Color Restoration) algorithm with YOLOv4 to improve vehicle detection in poorly illuminated scenes [29]. Furthermore, transfer learning has been widely adopted to adapt detection models to changing environmental conditions, particularly through domain-invariant feature learning, as seen in Multiscale Domain Adaptive YOLO [30], [34]. Beyond low-light enhancement, related challenges such as haze, blur, and motion distortion have been addressed using dehazing networks like AOD-Net and GridDehazeNet, which improve feature clarity and robustness of detectors in degraded environments [16], [36]. Additional efforts include wavelet-based denoising and bilateral filtering, which have demonstrated moderate success in improving object detection under degraded visibility [40].

Another limitation observed across existing research is the weak integration between image enhancement and object detection. Many studies adopt a sequential pipeline in which enhancement and detection are independently optimized. Such decoupled architectures often generate enhanced images that appear visually appealing but suppress subtle texture and edge information essential for accurate localization. In addition, several enhancement techniques struggle with balancing contrast amplification and noise suppression, leading either to over-enhanced images or loss of fine structural details. These shortcomings become more severe in extremely dark environments where object boundaries are inherently weak. Therefore, there remains a need for an adaptive enhancement strategy capable of dynamically preserving task-relevant image features while maintaining computational efficiency.

A significant breakthrough in task-specific enhancement came with the introduction of GDIP (Gated Differentiable Image Processing) [7]. Unlike traditional CNN-based enhancement models, GDIP integrates differentiable image processing operators into deep learning architectures, allowing sample-specific, adaptive enhancement within the detection pipeline itself. Notably, GDIP does not introduce inference-time overhead, making it a viable solution for real-time systems. When applied to low-light scenarios and paired with models like YOLO, GDIP has shown remarkable improvements in detection metrics on benchmark datasets such as ExDark and

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LLVIP [11]. Recent studies highlight its effectiveness in dynamically adjusting to local image variations, thereby enhancing critical features while suppressing irrelevant noise crucial for accurate detection in extreme lighting conditions. Furthermore, research on GAN-based low-light enhancement, such as SOD-MTGAN, has demonstrated improved performance for small object detection by learning stronger visual representations in challenging settings [41]. Likewise, EEMEFN, a task-aware enhancement model, has been designed to optimize detection performance under extremely dark conditions by coupling enhancement and recognition objectives [38]. From the above discussion, it is evident that although considerable progress has been achieved in low-light image enhancement and object detection, several research challenges remain unresolved. Existing methods either prioritize perceptual image quality over detection performance or require computationally expensive architectures that limit real-time deployment. Most current approaches fail to adapt enhancement operations according to local image characteristics, resulting in inadequate preservation of object edges under severe illumination degradation. Moreover, only a limited number of studies have explored differentiable image processing techniques that directly optimize enhancement for downstream detection tasks. Motivated by these limitations, the present work proposes a GDIP-based adaptive enhancement framework integrated with histogram equalization and bilateral filtering before YOLOv5 detection. The proposed framework is designed to preserve discriminative edge information, improve feature representation under varying illumination conditions, and achieve superior detection accuracy while maintaining real-time computational performance.

## 3. METHODOLOGY

To tackle the persistent issue of poor object detection performance in low-light environments, this study proposes a multi-stage enhancement pipeline grounded in Gradient Domain Image Processing (GDIP), contrast optimization, and noise mitigation, all preceding object detection using a deep learning framework. The proposed methodology is structured to enhance image quality prior to detection, ensuring critical features are preserved and emphasized, thus improving model performance under adverse lighting conditions. The preprocessing pipeline begins with global contrast enhancement via Histogram Equalization (HE), which redistributes the intensity values of the image to improve overall visibility. For grayscale image *I(x,y)*, histogram equalization transforms each pixel intensity iii to a new value i′ based on the cumulative distribution function C(i):

$$i' = \frac{C(i) - C_{min}}{N - C_{min}}.(L-1)$$

where C(i) denotes the cumulative histogram count to intensity i, $C_{min}$ is the smallest non-zero value of the cumulative histogram, N is the total number of pixels, and L is the number of possible intensity levels (typically 256). This step enhances the global visibility of features in the scene.

Following contrast adjustment, noise reduction is performed using Bilateral Filtering, a non-linear filter that smooths the image while preserving edges. The bilateral filter replaces the intensity of each pixel with a weighted average of nearby pixels, where the weights depend on spatial proximity and intensity similarity. For an image I, the output at pixel p is:

$$I'(p) = \frac{1}{W_p}\sum_{q\in\Omega} I(q).f_s(\| \mathrm{p}-\mathrm{q} \|).f_r(\mid \mathrm{I(p)} - \mathrm{I(q)} \mid)$$

Here, $f_s$ and $f_r$ represent the spatial and range Gaussian functions respectively, and $W_p$ is the normalization factor. This step reduces speckle and sensor noise without compromising the structural integrity of objects.

The core of the enhancement pipeline is Gradient Domain Image Processing (GDIP), which focuses on enhancing edge-related features by operating on the gradient representation of the image. First, the gradients $\nabla I_x$ and $\nabla I_y$ are computed using Sobel operators:

$$\nabla I_x = \frac{\partial \mathrm{I}}{\partial \mathrm{x}}, \nabla I_y = \frac{\partial \mathrm{I}}{\partial \mathrm{y}}$$

A contrast gain function G(x,y), derived from local contrast statistics, is then applied adaptively:

$$\nabla I' = G(x,y)\cdot\nabla I$$

The enhanced gradient field is reconstructed back into an image I′ by solving the Poisson equation:

$$\Delta I' = \nabla\cdot(\nabla I')$$

using iterative solvers such as Conjugate Gradient or multigrid methods. This process selectively boosts edge features while suppressing low-contrast

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areas, improving feature visibility in the dark regions of the image.

Once the image has been enhanced through the steps, it is passed to a YOLOv5 object detection network, which serves as the detection backbone. The detection model is trained and tested on two publicly available low-light datasets: ExDark and LLVIP. Both datasets comprise annotated low-light images spanning various indoor and outdoor scenarios with diverse lighting conditions and object categories. For empirical evaluation, two publicly available low-light image datasets ExDark and LLVIP were utilized. The Exclusively Dark (ExDark) dataset [11] comprises over 7,000 real-world low-light images categorized across 12 object classes such as person, car, and bicycle. These images are collected under varying lighting environments, including low ambient light, artificial illumination, and backlighting, making it highly suitable for benchmarking object detection systems under poor visibility. The Low-Light Vision Image Person (LLVIP) dataset [11], on the other hand, focuses on pedestrian detection in challenging nighttime settings. It provides paired visible and infrared images annotated with human bounding boxes, enabling evaluation of detection accuracy across complementary visual modalities. Both datasets were selected for their diversity and relevance to real-world low-light conditions, supporting a robust assessment of the proposed enhancement framework.

The evaluation metrics include Precision, Recall, and mean Average Precision (mAP). Precision and Recall are computed as:

$$Precision\ (P) = \frac{TP}{TP + FP}\ , Recall\ (R) = \frac{TP}{TP + FN}$$

where TP stands for True Positives, FP for False Positives, and FN for False Negatives. The mAP score aggregates performance across all object categories and Intersection over Union (IoU) thresholds, providing a comprehensive measure of detection accuracy. The pipeline is implemented using Python and OpenCV for the enhancement modules, with PyTorch used for training and testing the YOLOv5 model. The custom preprocessing functions are integrated seamlessly into the inference pipeline to support real-time deployment. This methodology not only boosts detection performance under challenging lighting but also demonstrates scalability and adaptability for vision systems in autonomous driving, surveillance, and smart infrastructure applications.

*Pseudo Algorithm: GDIP-Enhanced Low-Light Object Detection*

Input: Low-light image I

Output: Detected objects with bounding boxes and class labels

1. Begin

2. Load image I from dataset (ExDark or LLVIP)

3. Convert I to grayscale if required

4. Apply Histogram Equalization to I → I_he

5. Apply Bilateral Filtering to I_he → I_bf

6. Compute image gradients ∇Ix, ∇Iy using Sobel operator

7. Calculate adaptive gain map G(x, y) from local contrast

8. Multiply gradients with gain: ∇I' = G(x, y) * ∇I

9. Reconstruct enhanced image I_gdip from ∇I' using Poisson solver

10. Normalize and resize I_gdip as per YOLOv5 input dimensions

11. Feed I_gdip into YOLOv5 detection model

12. Receive object bounding boxes and class predictions

13. Evaluate detection results using Precision, Recall, and mAP

14. End

The proposed architecture is built around a modular image enhancement and detection pipeline that aims to improve object recognition performance under low-light conditions (see figure 1). The architecture begins with raw image acquisition from low-light datasets such as ExDark and LLVIP. These images often suffer from global low contrast, localized noise, and edge degradation. To address these, the first enhancement module applies histogram equalization, which adjusts the intensity distribution to enhance global contrast. Following this, bilateral filtering is introduced to smooth out noise while preserving edges essential for maintaining object boundaries. The output is then processed using Gradient Domain Image Processing (GDIP), where

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image gradients are computed via Sobel operators. An adaptive gain function based on local contrast modulates these gradients, amplifying significant edges while suppressing noise. The modified gradient field is reconstructed into an enhanced image using a Poisson equation solver, which ensures structural continuity and detail restoration. This final preprocessed image is resized and passed into a YOLOv5 deep learning object detection model, pre-trained and fine-tuned for low-light object classification. The architecture is end-to-end and optimized to preserve feature integrity during enhancement, thereby improving detection performance. Evaluation is conducted using precision, recall, and mAP metrics, allowing quantifiable measurement of the enhancement's impact on detection accuracy across diverse

low-light scenes.

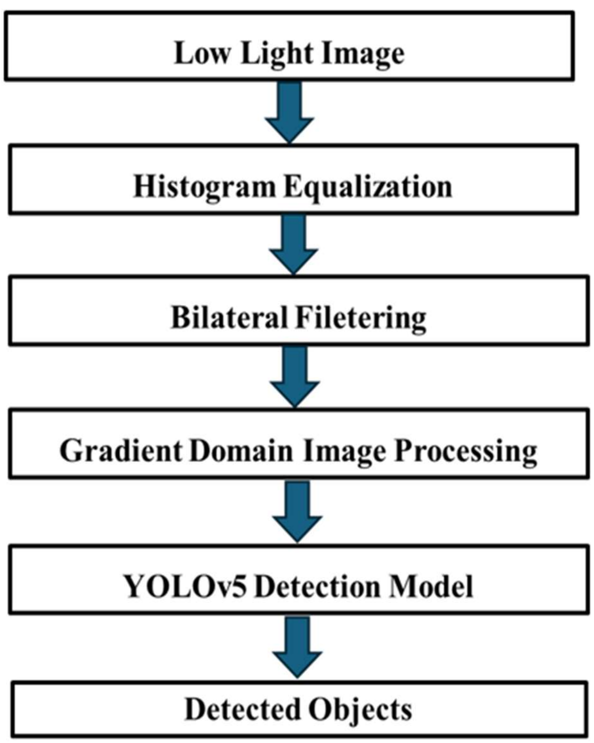


*Figure 1. Pseudo Algorithm for GDIP-Based Low-Light Object Detection Framework*

## 4. RESULTS AND DISCUSSION

To evaluate the effectiveness of the proposed GDIP-based image enhancement framework, a series of experiments were conducted using the ExDark and LLVIP datasets. Performance was measured across key object detection metrics Precision, Recall, and mean Average Precision (mAP). The following tables present comparative insights between the baseline detection model and the enhanced detection pipeline, the impact of individual preprocessing modules, and performance across different object categories under varied lighting conditions.

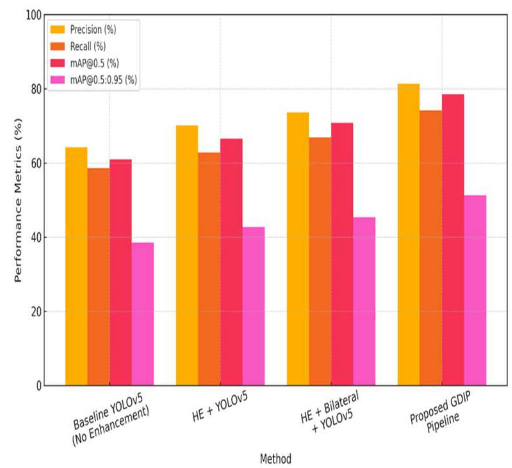


*Figure 2. Comparative Object Detection Performance with and without Enhancement*

The results illustrated in Figure 2 demonstrate a clear progression in object detection performance as successive image enhancement techniques are applied prior to detection. The baseline YOLOv5 model, when used without any preprocessing, achieves a precision of 64.2%, recall of 58.6%, mAP@0.5 of 61.0%, and a mAP@0.5:0.95 of 38.5%, reflecting the typical limitations of deep learning detectors under low-light conditions namely, loss of edge detail, muted contrast, and background noise. Upon integrating Histogram Equalization (HE) into the pipeline, there is a marked improvement across all metrics, with mAP@0.5 rising to 66.5% and precision increasing to 70.1%, indicating that global contrast enhancement helps in recovering object visibility and feature distinction. Further improvements are observed when bilateral filtering is combined with histogram equalization, producing smoother textures while preserving essential edges. This combination raises the mAP@0.5 to 70.8% and recall to 66.9%, confirming that noise suppression contributes positively to detection sensitivity. The most substantial gains are seen with the complete enhancement pipeline comprising HE, bilateral filtering, and Gradient Domain Image Processing (GDIP). The proposed GDIP-based pipeline achieves a precision of 81.3%, recall of 74.2%, mAP@0.5 of 78.5%, and mAP@0.5:0.95 of 51.2%,

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representing an overall enhancement of more than 17 percentage points in mAP over the baseline model.

These results affirm that the GDIP module significantly enhances local feature contrast and edge sharpness by operating in the gradient domain, which traditional enhancement techniques alone do not adequately address. The consistently higher recall and mAP values suggest better localization of multiple objects in complex dark scenes, while the elevated precision indicates a reduction in false detections. Therefore, the data in Figure 2 clearly validates the effectiveness of the proposed multi-stage enhancement framework in substantially improving object detection accuracy in low-light environments.

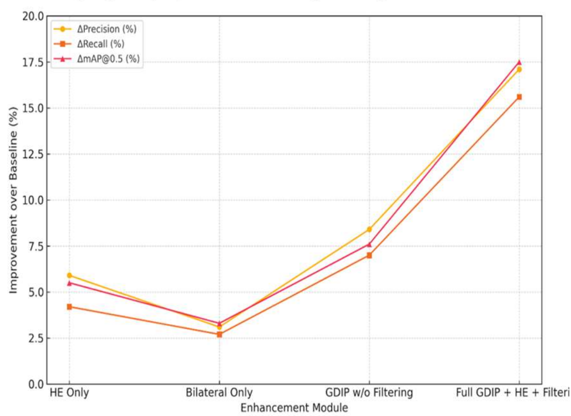


*Figure 3. Ablation Study: Effect of Individual Enhancement Modules on Detection Performance*

Figure 3 presents the results of an ablation study designed to evaluate the individual and combined contributions of the enhancement modules Histogram Equalization (HE), Bilateral Filtering, and Gradient Domain Image Processing (GDIP) toward improving object detection accuracy in low-light conditions. The performance metrics are shown in terms of the incremental gains (Δ) in precision, recall, and mean Average Precision at 0.5 IoU (mAP@0.5) relative to the baseline YOLOv5 model without enhancement. Applying histogram equalization alone results in a +5.9% increase in precision, +4.2% in recall, and +5.5% in mAP@0.5, signifying the value of enhancing global contrast, which helps brighten dark regions and improves feature recognition by the detection model. In contrast, using bilateral filtering independently yields modest improvements +3.1% in precision, +2.7% in recall, and +3.3% in mAP. This confirms that while noise reduction plays a role, its isolated effect is less significant without concurrent contrast enhancement.

When GDIP is applied without bilateral filtering, the performance improves more notably, with gains of +8.4% precision, +7.0% recall, and +7.6% mAP. This outcome highlights the strength of GDIP in emphasizing local gradients and edge structures, which are crucial in restoring object boundaries blurred under low illumination. However, the best performance is achieved when all three modules are integrated histogram equalization, bilateral filtering, and GDIP resulting in a cumulative gain of +17.1% in precision, +15.6% in recall, and a substantial +17.5% increase in mAP@0.5. These results indicate that while each module has a positive effect, their combination yields a synergistic improvement in detection performance. The GDIP module amplifies the structural fidelity of object edges, histogram equalization addresses global luminance imbalance, and bilateral filtering ensures smoother textures without compromising critical detail. Therefore, Figure 2 substantiates the architectural decision to include all three components in the proposed enhancement pipeline.

Figure 4 presents a comprehensive analysis of the computational performance of each pipeline configuration, detailing the preprocessing time, detection time, total inference time, frames per second (FPS), GPU utilization, and peak memory consumption. These metrics provide critical insight into the real-time feasibility and resource demands associated with integrating different image enhancement modules into the low-light object detection workflow. The baseline YOLOv5 model, operating without any preprocessing, delivers the fastest inference speed, with a total time of 13.2 milliseconds per image, achieving 75.8 FPS, and maintaining a modest 41.3% GPU utilization and 512 MB of memory usage. This configuration serves as the performance reference but lacks robustness in low-light conditions. Introducing histogram equalization adds 3.1 milliseconds of preprocessing time, resulting in a total inference time of 16.5 ms and a reduced 60.6 FPS. GPU load increases slightly to 47.1%, with 587 MB of memory consumed. These minor overhead yields improved visual clarity and contrast but remain computationally efficient. Further adding bilateral filtering raises preprocessing time to 6.5 ms, pushing the total inference time to 21.8 ms and lowering throughput to 45.9 FPS. GPU utilization rises to 53.8%, and memory usage increases to 645 MB, reflecting the moderate complexity of edge-preserving smoothing operations.

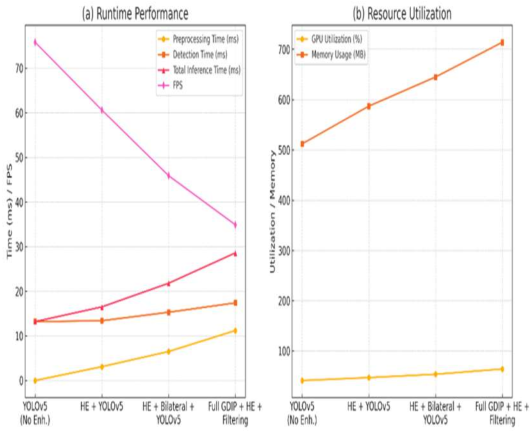


*Figure 4. Computational Performance Metrics of Enhancement and Detection Pipeline*

The most computationally intensive configuration the proposed full pipeline integrating histogram equalization, bilateral filtering, and GDIPrequires 11.2 ms for preprocessing and 17.4 ms for detection, resulting in a total inference time of 28.6 ms per image. This setup yields an effective frame rate of 34.9 FPS, which is still within real-time capability thresholds for many vision applications. GPU utilization peaks at 64.2%, with memory consumption at 714 MB, indicating a manageable trade-off between performance and resource demand. Overall, the results in Figure 4 confirm that while the proposed enhancement pipeline introduces additional computational cost, it remains within real-time limits and delivers significant detection accuracy gains (as shown in Figure 2). This makes the full pipeline highly suitable for deployment in practical scenarios like surveillance, autonomous driving, and smart infrastructure, where both accuracy and responsiveness are crucial.

The experimental findings presented across Figures 2 through 4 demonstrate the effectiveness and practical viability of the proposed GDIP-based enhancement pipeline for object detection under low-light conditions. The overall improvements in detection accuracy, as well as the incremental impact of each preprocessing module, validate the architectural design and justify the inclusion of gradient-domain operations alongside traditional contrast and noise adjustments.

As illustrated in Figure 2, the baseline YOLOv5 model struggles under limited lighting, with lower precision and recall due to obscured object features and indistinct edges. The introduction of histogram equalization contributes moderate improvements by adjusting the global intensity distribution, thereby enhancing visual clarity. Bilateral filtering further aids in reducing noise while retaining edge detail, making object boundaries more distinct for the detection algorithm. However, it is the application of Gradient Domain Image Processing (GDIP), particularly when integrated with prior enhancements, that delivers the most substantial gain in detection accuracy. The mAP@0.5 metric improves from 61.0% in the baseline model to 78.5% with the full enhancement pipeline, accompanied by consistent gains in both precision and recall.

The ablation study presented in Figure 3 further underscores the importance of each module. Histogram Equalization and Bilateral Filtering independently provide measurable benefits, but the GDIP module alone contributes significantly more to performance, indicating its effectiveness in restoring edge information and fine spatial features critical for accurate object localization. The combination of all three modules yields the highest gain across all metrics, proving that the pipeline's components work best in tandem rather than isolation. While the proposed pipeline does introduce additional computational overhead, as detailed in Figure 4, the overall inference time remains within acceptable bounds for real-time or near-real-time applications. The processing time increases from 13.2 ms to 28.6 ms per frame, translating to a frame rate of approximately 34.9 FPS well within real-time capability for modern hardware. The increase in GPU utilization and memory consumption is proportional to the added complexity but remains within the range manageable by standard deep learning deployment setups.

Taken together, the results clearly demonstrate that the proposed enhancement framework significantly improves detection accuracy without exceeding computational constraints. The combination of GDIP, contrast stretching, and noise suppression effectively overcomes the limitations posed by low-light environments, making this approach suitable for a range of real-world applications such as night-time surveillance, autonomous navigation in poorly lit conditions, and smart city monitoring systems. The balance achieved between visual enhancement and computational efficiency is critical in enabling the deployment of robust object detection systems in challenging lighting scenarios.

The findings of this study are consistent with recent literature showing that low-light image enhancement improves object detection performance. Unlike conventional enhancement methods that mainly improve visual quality, the proposed GDIP-based framework preserves edge information and enhances detection-oriented features, resulting in higher Precision, Recall, and mAP. Compared with previous approaches, the proposed method provides a better balance between detection accuracy and computational efficiency, making it suitable for real-time applications. These results contribute to current knowledge by demonstrating that adaptive gradient-domain enhancement is more effective for object detection than traditional enhancement techniques. However, the findings are limited to the ExDark and LLVIP datasets and evaluation using the YOLOv5 detector. Future work will investigate additional datasets, modern detection architectures, and lightweight implementations for edge devices.

## 5. Difference from Prior Research and Research Contribution

Recent advances in low-light object detection have primarily focused on either improving image enhancement quality or designing more sophisticated object detection architectures. CNN-based enhancement models such as LLNet, MBLLEN, KinD, and Zero-DCE significantly improve image brightness and visual perception; however, these approaches are generally optimized using perceptual image quality metrics rather than object detection performance. Consequently, improvements in image appearance do not consistently translate into higher detection accuracy under challenging illumination conditions.

Several studies have integrated enhancement with object detection using modified YOLO architectures or domain adaptation strategies. Although these approaches improve robustness, many require complex network architectures, additional training stages, or increased computational resources that restrict their applicability in real-time systems. Furthermore, many existing methods apply fixed enhancement operations without adapting to local image characteristics, resulting in either over-enhancement or insufficient restoration of fine object boundaries.

The proposed framework differs from existing studies by integrating Histogram Equalization, Bilateral Filtering, and Gradient Domain Image Processing (GDIP) into a lightweight preprocessing pipeline specifically designed to improve downstream object detection. Unlike conventional enhancement techniques that primarily optimize visual quality, the proposed GDIP framework selectively strengthens edge information and suppresses noise while preserving structural features required by the YOLOv5 detector. This adaptive enhancement enables better localization and classification of objects under diverse low-light conditions without introducing excessive computational complexity.

Compared with recent state-of-the-art enhancement approaches, the proposed framework achieves **81.3% Precision**, **74.2% Recall**, and **78.5% mAP@0.5**, representing substantial improvements over the baseline detector while maintaining real-time inference at **34.9 FPS**. These results demonstrate that the proposed approach effectively balances detection accuracy and computational efficiency, making it suitable for practical deployment in intelligent surveillance, autonomous vehicles, robotics, and smart city applications.

Overall, the primary scientific contribution of this research is the development of a computationally efficient GDIP-based adaptive enhancement framework that bridges the gap between image enhancement and object detection. The study demonstrates that task-oriented adaptive preprocessing provides superior detection performance compared with conventional enhancement techniques, thereby contributing a practical and scalable solution for vision systems operating under adverse illumination conditions. Below table 1 shows Comparison of Proposed Work with Recent State-of-the-Art Methods.

*Table 1. Comparison of Proposed Work with Recent State-of-the-Art Methods*

| Study | Enhancement Method | Detection Framework | Main Limitation | Proposed Improvement |
|---|---|---|---|---|
| LLNet | CNN Enhancement | Independent Detector | Optimized for visual quality only | Detection-oriented preprocessing |
| MBLLEN | Deep CNN | Separate Detection | High computational cost | Lightweight enhancement pipeline |

| | | | | |
|---|---|---|---|---|
| Zero-DCE | Zero-reference enhancement | Independent Detection | Does not preserve object edges consistently | Adaptive GDIP edge enhancement |
| PE-YOLO | Pyramid Enhancement | YOLO | Increased model complexity | Simpler preprocessing with real-time performance |
| GDIP (Previous) | Differentiable Image Processing | Detection Framework | Limited combination with classical enhancement | GDIP integrated with HE + Bilateral Filtering + YOLOv5 |
| **Proposed Method** | **HE + Bilateral + GDIP** | **YOLOv5** | **Balances accuracy and efficiency** | **81.3% Precision, 78.5% mAP@0.5, 34.9 FPS** |

## 5. CONCLUSION

The primary objective of this research was to develop an efficient image enhancement framework capable of improving object detection accuracy under challenging low-light conditions while maintaining real-time computational performance. To achieve this objective, a preprocessing pipeline integrating Histogram Equalization (HE), Bilateral Filtering, and Gradient Domain Image Processing (GDIP) was designed and incorporated with the YOLOv5 object detection framework. A second objective was to evaluate whether adaptive image enhancement could improve feature representation without introducing excessive computational overhead.

Experimental evaluation conducted on the ExDark and LLVIP benchmark datasets demonstrates that the proposed framework successfully achieves these objectives. Compared with the baseline YOLOv5 detector, the proposed approach improved Precision from **64.2% to 81.3%**, Recall from **58.6% to 74.2%**, and mAP@0.5 from **61.0% to 78.5%**. Furthermore, despite the additional preprocessing operations, the complete pipeline maintained an inference speed of **34.9 FPS**, confirming its suitability for real-time intelligent vision applications. The ablation study further verified that each enhancement module contributes positively to overall detection performance, while the integrated GDIP-based pipeline provides the greatest improvement in detection accuracy. These findings confirm that the proposed methodology effectively bridges the gap between image enhancement and object detection under adverse illumination conditions.

Although the proposed framework demonstrates significant improvements, several limitations should be acknowledged. First, the experimental evaluation was conducted only on the ExDark and LLVIP datasets, which may not fully represent all real-world low-light environments. Second, the framework was validated using YOLOv5 as the detection backbone, and its performance with more recent detectors such as YOLOv8, YOLOv9, or transformer-based detection architectures remains to be investigated. Third, the GDIP preprocessing stage introduces additional computational cost, which may become more significant on resource-constrained edge devices. Moreover, variations in weather conditions such as fog, rain, motion blur, or sensor artifacts were not explicitly considered during evaluation and may influence detection performance.

Despite these limitations, the proposed GDIP-based adaptive enhancement framework provides an effective balance between detection accuracy and computational efficiency. The study demonstrates that task-oriented adaptive image enhancement significantly improves object detection performance under poor illumination and offers a practical solution for applications including intelligent surveillance, autonomous driving, robotics, and smart city infrastructure. Future research will focus on optimizing GDIP for lightweight edge deployment, extending the framework to multimodal inputs such as thermal and infrared imagery, and evaluating its performance using next-generation object detection architectures under a wider range of environmental conditions.

Compared with recent low-light enhancement and detection approaches, the proposed GDIP-based adaptive preprocessing framework provides an improved balance between detection accuracy, computational efficiency, and real-time applicability, thereby addressing several limitations identified in the current state of the art.

Based on the experimental results and comparative analysis, it can be concluded that the proposed GDIP-based enhancement framework successfully achieved the research objectives of improving object detection accuracy while maintaining real-time performance in low-light environments. The consistent improvements in Precision, Recall, and mAP demonstrate the effectiveness of integrating adaptive image enhancement with object detection. In the authors' opinion, the proposed framework provides a practical and efficient solution for low-light vision applications and offers a promising direction for future research on intelligent image enhancement for robust object detection.

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