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ABSTRACT

Wildlife detection in the night time is a critical computer vision problem that has applications in ecological monitoring, road safety surveillance, and conservation analysis. In real deployments, camera imaging systems are often found to be photon limited, which means that they are operating in an environment where the density of photons is low, and the noise level in the sensor as well as the object boundaries, motion blur, and infrared effects are also large.In real deployments, the density of photons, the noise level of the sensor, the boundaries of the objects, the motion blur, and the infrared effects are often large, causing the objects to be difficult to detect in a reliable manner. While the YOLO family of detectors can make fast inference in daylight images, they fail to perform well in dark, low-contrast night images with cluttered backgrounds and underexposed animals [1, 2, 37].

This thesis introduces a new unsupervised image-enhancement pipeline called **Progressive Dual-Branch Illumination-Contrast (PDIC)** specifically developed as an enhancement pre-processing step prior to a fixed YOLOv5 detector for night-time wildlife detection. In PDIC, the architecture of the detector is not changed, rather the visible evidence presented to the detector is enhanced. The framework is founded on the idea of decomposing image information based on the Retinex, and consists of two interconnected branches: an Illumination Compensation Branch for estimating and normalizing spatial illumination distribution, and a Contrast Enhancement Branch for enhancing the gradient of structures and mid-tone details and controlling the amplification of noise. The enhanced reflectance and illumination components are combined again in a learnable fusion module and progressive refinement allows the framework to process heavily underexposed images more than once [9, 8, 7, 4].

Training is completely unsupervised, that is, no paired low light and normal light images of wildlife are needed. The goal is to minimize smoothness of the illumination, gradient uniformity, exposure loss, color constancy loss, and total variation loss. These losses are chosen to maintain degradation of edges and contours relevant to the detectors and not just for human visual optimisation. The framework is applicable in practical camera trap use cases, where paired ground truth is challenging or even unfeasible [7, 15].

The pipeline is tested with wildlife data that has been recorded during the night on the NTLNP, which comprises 10,344 infrared images of 17 animal categories. Compared with the baseline evaluation (CLAHE+Retinex+YOLOv5) and night detection specific methods reported in the supporting research papers, PDIC+YOLOv5 achieves the highest mAP@50 (0.883) and Recall (0.868) when using the same downstream detector (YOLOv5). These results show that detector-agnostic enhancement can significantly boost the detection of wildlife at night, while keeping the detector and the pipelines unchanged [5, 6].

Keywords: Night-time Wildlife Detection, PDIC, YOLOv5, Unsupervised Image Enhancement, Retinex Theory, Camera Traps, Low-Light Imaging, Object Detection, Conservation Computer Vision.

CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AFPN	Asymptotic Feature Pyramid Network
AHE	Adaptive Histogram Equalisation
AUC	Area Under the Curve
CLAHE	Contrast-Limited Adaptive Histogram Equalisation
CNN	Convolutional Neural Network
CSPNet	Cross Stage Partial Network
DCE	Deep Curve Estimation
DETR	DEtection TRansformer
FPN	Feature Pyramid Network
FPS	Frames Per Second
GAN	Generative Adversarial Network
GeLU	Gaussian Error Linear Unit
GIoU	Generalized Intersection over Union
GPU	Graphics Processing Unit
HE	Histogram Equalisation
IoU	Intersection over Union
IR	Infrared
mAP	Mean Average Precision
NMS	Non-Maximum Suppression
NTLNP	Northeast Tiger and Leopard National Park
PANet	Path Aggregation Network
PDIC	Progressive Dual-Branch Illumination-Contrast
R-CNN	Region-based Convolutional Neural Network
ReLU	Rectified Linear Unit
RGB	Red, Green, Blue
SID	See-in-the-Dark
TV	Total Variation
UAV	Unmanned Aerial Vehicle
YOLO	You Only Look Once
Zero-DCE	Zero-Reference Deep Curve Estimation

CHAPTER 1

INTRODUCTION

1.1 Background and Motivation

Automated visual sensing systems like camera traps, roadside surveillance cameras, unmanned platforms and edge-AI devices are increasingly being used to monitor wildlife. The systems are used for biodiversity assessment, habitat management, anti-poaching and AV collision prevention purposes. In recent years, conservation-computer-vision research has demonstrated that deep learning can save time for manual image-review and allow for large-scale ecological inferences under the right conditions of reliable data and deployed methodology [1, 2].

Although great progress has been made, night time wildlife detection is still significantly more difficult than daytime detection. A significant proportion of the valuable observations are made in the dark, because many target species are nocturnal or crepuscular. Under these conditions, images have low photon count, limited dynamic range, high sensor noise, infrared illumination artifacts, low texture and lower color information. These alterations can cause animals to be lost from sight and can make it harder to discern whether small or camouflaged animals are present or are vegetation, shadows, soil or roadside detritus [37, 38].

Modern object detectors, particularly one-stage YOLO-family models, are widely used due to their practicality, with respect to speed and accuracy [3, 4]. But these detectors are extremely local and require the presence of stable local gradients, textures and multi-scale feature activations. If they are suppressed during night-time imaging, they can result in missed detections or false positive detections in shadow areas, or in a poor bounding box localization. This thesis thesis' primary research question is thus not only how best to improve image appearance, but how best to enhance night-time images for improving downstream wildlife detection [5, 31].

1.2 Problem Statement

The issue discussed in this thesis is degradation of wildlife detection with YOLOv5 based on night-time low light imaging. The existing solutions normally take one of two routes. The first path adapts the detector architecture to match detection conditions at night to make it suitable for night time detection, which is similar to that of YOLO variants developed for night time detection [5]. These techniques can enhance accuracy, but would necessitate redirection of the detector, retraining of the detector, and careful application to a limited platform. The second approach is implemented by first applying classical image preprocessing techniques like CLAHE, gamma correction, or Retinex filtering, followed by a detection step [6]. They are simple but make use of static transformations and do not work well if there is a significant inter-species, inter-habitat, and/or camera-position variation in illumination.

For a practical wildlife-monitoring system, an approach must be adaptive, detector-compatible and trainable without paired low-light and well-lit ground truth. In camera-trap conditions paired data is uncommon since the same animal and scene can not be recorded simultaneously under both poor and ideal light conditions. This encourages an unsupervised enhancement approach to enhance the detection cues while maintaining the original YOLOv5 inference pipeline [7, 8].

1.3 Proposed Approach

In this thesis, the Progressive Dual-Branch Illumination-Contrast (PDIC) framework is developed. The purpose of PDIC is to serve as a preprocessing module that is put in front of YOLOv5. It will not change the YOLOv5 weights, anchors, losses, or detection heads. Rather it enhances the input image to provide more distinct object boundaries and more discriminative animal features to the fixed detector [4].

The framework is based on three principles. First, enhancement must be physically interpretable, and PDIC takes the Retinex-inspired perspective of decomposing an observed image into illumination and reflectance. Second, enhancement should be detection-aware, that is, not only aesthetically pleasing but also highlighting structural gradients and reducing noise.

Third, enhancement should be deployable, so training is based on no-reference losses that are used in unsupervised low-light enhancement algorithms like Zero-DCE and Retinex-based deep enhancement (DE) in [7, 8].

1.4 Research Objectives

The goals of this thesis are:

1. To investigate how image degradation in low-light conditions affects YOLO-family wildlife detection.
2. To develop a dual-branch illumination normalization and contrast/structure enhancement approach inspired by Retinex.
3. To train the enhancement pipeline without paired low-light/normal-light ground truth using no-reference losses.
4. To test the proposed PDIC–YOLOv5 pipeline on the NTLNP night-time wildlife dataset using Precision, Recall, F1-score, mAP@50, and mAP@50:95.
5. To compare the proposed system with classical preprocessing and night-time detection systems using the same downstream detector where possible.

1.5 Scope and Contributions

This work focuses on night-time wildlife detection based on RGB or infrared camera-trap images. The thesis is concerned not with the design of a new detector, but with a pre-processing and enhancement. Intentionally this scope is chosen as many field systems already use the known YOLO pipelines, and the switching of the detector may raise annotation, retraining and deployment costs [1, 18].

The most significant contributions have been:

1. A detector-agnostic PDIC enhancement framework for night-time wildlife imagery.
2. A dual-branch architecture to separately model illumination compensation and contrast enhancement.

3. A progressive refinement algorithm for severely underexposed images.

4. An unsupervised loss function combining illumination smoothness, gradient consistency, exposure, color constancy, and total variation regularization.

5. A structured experimental comparison of mAP@50 and Recall on the NTLNP dataset using a fixed YOLOv5 detector.

1.6 Thesis Organisation

This thesis is written as a standard empirical thesis, where the introduction motivates the problem, the literature survey is where the research gap is presented, the methodology is used to explain the proposed system, and the results chapter presents and interprets the experimental results. Chapter 2 introduces the theory of low-light imaging, object detection and Retinex enhancement. Related works are introduced in Chapter 3 to detect wild animals, detect night scenes using YOLO, transformer and hybrid approach, sensor modalities and low-light enhancement. Subsequent, the PDIC architecture and the unsupervised objective of training is described in Chapter 4. The experimental setup, results, ablation studies and discussion are presented in Chapter 5. The thesis is summarized in Chapter 6 and future work is discussed.

CHAPTER 2

THEORETICAL BACKGROUND

2.1 Low-Light Image Formation

Digital image is created by measuring the light reflected from a scene on a sensor. During night-time imaging, the amount of photons hitting the individual pixels is reduced, and the signal they provide is overwhelmed by noise. Photon shot noise, dark current, read noise, motion blur (long exposure), and compression artifacts (through camera pipelines) are the major degradations. While infrared camera traps are less light-dependent than visible-light cameras, they still have some drawbacks, including low contrast, a lack of uniformity in ambient light, specular reflections, and the lack of chromatic cues [11, 37, 38].

The degradations directly impact object detection. A detector doesn't think or reason about semantic concepts; it first looks for low-level features like edges, gradients, corners, textured regions, and color transitions. If the animal boundary cannot be seen (shaded), or if the noise makes an artificial boundary, the feature pyramid the detector has is not reliable. This means that one detector that works in daylight conditions, may not work in nighttime conditions [3, 4, 5].

Degradation in low light conditions is also non-uniform across space. With a wildlife shot, the animal could be lit by an infrared flash, car headlights, a nearby reflecting surface or the light of the moon, but the surrounding plants are mostly black. This creates a high dynamic range within the frame. Thus, there is no single correction for global brightness that can work for everyone: brightening up the back lighting may lead the eyes, fur highlights, or wet surface to become saturated. Any enhancement technique used to detect must not exaggerate background noise levels, but must maintain local contrast around the boundaries of the objects [10, 8].

The other important question is the difference between image quality and task utility. The enhanced image may not be a better detector input, if it is aesthetically pleasing. Over-smoothing helps to reduce very fine contours, but may help to improve the apparent image quality, and over-sharpening can generate false edges, leading to false positives. Therefore, improvement metrics should not only include image quality metrics but also the downstream metrics—for instance, Recall or mAP—because of the detection context [40, 16].

This failure can be explained by the signal to noise ratio (SNR). In a photon-limited scene, capture levels are not the only factor that affect the visibility of noise over the sensor measurement; the brightness will also increase the visibility of noise that was already captured in the measurement. While long exposure does help collect more photons, it also creates more motion blur when animals move across the frame, which is a problem in the field camera. High ISO gain will show weak signals, but will also increase read noise and colour artifacts. Enhancement at night time is thus not a straightforward scaling of brightness. A good enhancement technique should enhance the contrast within a local area without creating false edges, hallucinating texture and brightening existing bright infrared reflections [11, 7].

The camera-trap images create further challenges over regular night photography. The animal can be in a small part of the frame, at different distances or in part hidden behind plants. Numerous frames have empty background, and the same background can be seen in various illumination, weather and sensor-noise settings. Therefore, enhancement for wildlife detection should not only increase the visual appeal of an image but also retain the boundaries between objects and the mid-level texture in the image [17, 18, 19].

2.2 Retinex Theory and Illumination–Reflectance Decomposition

The retinex theory is an observed image which is considered to be the product of illumination and reflectance. The illumination component is the spatial variation of light, and the reflectance component is the intrinsic properties of the scene like boundaries or surface texture and albedo. A typical retinex solution recipe is:

$$I(x,y) = R(x,y) \cdot L(x,y), \tag{2.1}$$

Here, the image observed is $I(x,y)$, the reflectance is $R(x,y)$, and the illumination is $L(x,y)$ [9].

Classical Retinex methods estimate illumination by assuming the filter or smoothness. The Multiscale Retinex algorithm enhances the visual contrast of images by processing a number of spatial scales, and LIME is used to estimate illumination maps for low light enhancement [9, 10]. They are interpretable and efficient but can also accentuate noise or produce haloing to high-contrast edges. The deep Retinex algorithm methods, including RetinexNet, are trained with the decomposition function and enhancement function from data [8]. The PDIC framework expands on this reasoning but in relation to detection based wildlife enhancement.

There is interest in using retinex decomposition for imaging nocturnal wildlife; it decomposes two effects with different significance to detection. The illumination correction should recover from non-uniform illumination and reveal hidden regions while the reflectance preservation should maintain the texture, silhouette and local gradients of the animal. From the practical perspective, KinD also demonstrates that practical low-light enhancement can be arranged in terms of illumination adjustment, reflectance restoration, and degradation removal [13]. Later, RUAS re-formulated the Retinex enhancement as an unrolled optimization process with reference-free learning, and demonstrated that physics-inspired structure can be integrated with a light-weight neural design [14]. The developments agree with the PDIC design decision to provide separate illumination and contrast-oriented branches, instead of a single monolithic enhancement transform.

One of the most important applications of retinex enhancement is for night-time wildlife photography, where lighting is typically non-uniform. Only part of the scene may be illuminated by infrared flash, vehicle headlights, moonlight or reflected sunlight from vegetation. If one global adjustment is made to the entire image, the bright parts of the image can be over-exposed, and the dark parts of the animal can be under-exposed. There is a more flexible representation of illumination, reflectance decomposition: illumination could be smoothed and normalized, while reflectance could be kept with edges and textures. This separation also encourages the dual-branch architecture of PDIC, one for illumination compensation and the other for the contrast and structural detail.

But, Retinex decomposition is an ill-posed problem as there are many combinations of illumination and reflectance that will produce the same observed image. Thus, there are practical methods that impose priors. It is generally assumed that the illumination is smooth (in space), except in the vicinity of strong transitions, whereas the reflectance is expected to have sharper edges. When using these priors in low-light detection, it is important to use them carefully. Over-smoothing illumination can lead to loss of shadows that define the shape of animals and over-sharpening of reflectance can create an artifact of "fur-like" texture in noise. To resolve this, PDIC proposes to incorporate the total-variation regularization and gradient consistency along with illumination smoothness [10, 14].

2.3 Deep Low-Light Enhancement

If two images, one taken in low-light and the other in normal-light conditions, are available, supervised low-light enhancement methods can yield high quality results. Neural networks have been shown to be able to recover meaningful images from very dark RAW sensor data by learning to see in the dark [11]. Aligned pairs are not common however with the deployments of wildlife cameras, animal movement, weather, and lighting can't be replicated [11].

To overcome this, unsupervised and zero-reference enhancement techniques have been proposed that utilise no-reference losses. Given no paired data, Zero-DCE estimates image-specific enhancement curves and optimizes losses in spatial consistency, image smoothness, illumination smoothness, and exposure [7]. Additionally, EnlightenGAN proves that unpaired adversarial learning can be applied in the absence of aligned normal-light targets [12]. To improve low-light images, KinD breaks the task down into three phases: decomposition, restoration, and adjustment, thereby demonstrating the merit of decomposing light and reflectance separately [13]. On the contrary, more recent lightweight methods, like SCI, adopt self-calibrated illumination learning which is able to maintain the quality of illumination enhancement with less computation cost [15]. PDIC takes the same "real life" motivation and restates the enhancement task in terms of detector reliability. The goal is not only to enhance the image, but also to retrieve structural cues to boost the localization and classification of YOLOv5.

One of the theoretical differences that are important to note is that between image quality-based enhancement and task-based enhancement. While smooth, bright and visually appealing images are preferred by human observers, object detectors rely on repeatable local evidence. Too much denoising can obscure the faint contours of animals, too much contrast enhancement can produce high frequency artifacts, which look like small objects. Thus, detection-aware enhancement is designed to achieve the balance between the improvement of exposure and preservation of boundaries and gradients while avoiding hallucination. This is the reason that PDIC adopts unsupervised losses that promote natural exposure and smooth illumination without losing structural gradients crucial for bounding-box prediction [7, 40].

2.4 Object Detection Fundamentals

To detect an object, not only must the object be located but the object must also be classified. The two-stage detectors, like Faster R-CNN, make region proposals first and then classify every region proposal [20]. These methods are accurate but are not cheap enough to be used in the field. One-stage detectors directly predict the classes and bounding boxes from dense feature maps. For dense detection [21] has proposed a focal loss approach to deal with the problem of class imbalance, and YOLO-family detectors have become popular for their ability to perform detection in a single pass, enabling practical real time applications.

YOLO models divide detection into a backbone, neck, and head. The backbone is used to extract visual features, the neck combines multi-scale information, and the head is used for the prediction of the bounding boxes and objectness and class probabilities. YOLOv4 has added a number of training and architecture enhancements to achieve speed-accuracy balance [22] and YOLOv5 gained a foothold in the real world due to its PyTorch implementation, smaller model variants, and deployment ecosystem [4]. The review paper also notes that despite the transformer detectors being heavier models, YOLOv5 – YOLOv10 models are still the most competitive in terms of latency in real time applications involving wildlife or edge application, due to their more feasible latencies.

The critical components of this pipeline are the feature extraction and the objectness estimation modules, in low-light images. When the animal boundary is near the background intensity, there may be a failure in the generation of discriminative activations in the back bone. Weak or noisy features can be carried into different scales by the neck, and the objectness of the detection head might be low when an animal is present. Enhancement prior to detection can thus be regarded as a feature conditioning step. It alters the distribution of the input so that the fixed detector gets better gradients and clearer local contrast without any change in detector weights [4, 16].

2.5 Task-oriented Enhancement vs Human-oriented Enhancement

The majority of papers dealing with low light enhancement report PSNR, SSIM, NIQE or make a visual comparison. These are helpful for research in restoration, but not complete in characterizing the effectiveness of improved images to a detector. Object detectors are based on a hierarchy of features: edges and textures are detected in shallow layers, parts and shapes are detected in intermediate layers, and semantic object patterns are detected in deeper layers. A change in the statistics of these features may result in a change of the detection confidence and localization, even if the image is acceptable to human perception [40].

The studies carried out in low light detection have, therefore, recently called for task-oriented enhancement. ExDark was created to facilitate the study of low-light object detection and enhancement in images taken under various illumination conditions and annotated with bounding boxes [37]. The feature enhancement has not just been restricted to pixel enhancement, being explored for detection tasks, as well. FeatEnHancer reports consistent improvement in low light detection and related downstream tasks under dark conditions by improving hierarchical representations [40]. The results encourage the use of the gradient consistency and detector-aware evaluation by PDIC. It is better to improve information that proves to be useful for YOLOv5, rather than simply increasing brightness.

2.6 Detection Metrics

The metrics employed in the evaluation of the main task in this thesis are Precision, Recall, F1-score, mAP@50 and mAP@50:95. Precision indicates the proportion of correctly predicted detections and Recall reflects the proportion of ground truth objects that are correctly detected. Recall has a special significance in wildlife monitoring because the failure to recall animals could lead to inaccurate counts of animals and false alerts for road safety. The F1 score is a combined measure of Precision and Recall.

Mean Average Precision (mAP) is a summary of the performance of the detectors over the range of confidence thresholds. The Intersection over Union (IoU) threshold for mAP@50 is set at 0.50, and mAP@50:95 is the average of the performance measured at different IoU thresholds ranging from 0.50 to 0.95. Both are important since the night-time enhancement can not only help with object discovery, but can also influence the quality of localization [21].

CHAPTER 3

LITERATURE REVIEW

3.1 Literature Review Strategy

The literature review follows the structure of the two research papers provided for this thesis. The PDIC paper sets the primary technical direction, the proposed enhancement pipeline, the loss design and the NTLNP evaluation. The review paper gives a wider background of the field of nocturnal wildlife detection, CNN detectors, YOLO-family, transformer and hybrid, thermal and IR, datasets, evaluation protocols and edge deployment constraints. Taken together, the papers suggest that the central research question is not just "How do you make detectors work for difficult night-time wildlife imagery," but instead, "How do you enhance difficult night-time wildlife imagery in an adaptive way that is compatible with detectors?

3.2 CNN and Two-Stage Wildlife Detectors

Previous deep-learning-based wildlife detection systems relied on the concept of generic object detection frameworks but were adapted to camera-trap images. The performance of two-stage detectors is good localization models, but they require too much computation power to run on the road or edge camera in real-time application [20]. Dense one-stage detectors like RetinaNet tackle class imbalance using focal loss, and are applicable to camera-trap imagery where background frames are more common than rare species [21]. But these general architectures don't directly address the low light degradation problem.

In the past few years, there are some studies related to wildlife that are mainly concerned with automatic species identification, dense object detection, few-shot learning, and instance segmentation. The dense detection of wildlife objects has been studied in the context of enhanced YOLOv5 [23]; workflows for camera trap classification and identification have been examined in the context of large-scale ecological monitoring [24]; and few-shot detection approaches have been proposed for plateau or rare wildlife scenarios [25, 26]. Both works illustrate that data scarcity and class imbalance are long-term problems for wildlife vision.

A second important implication of the large camera-trap benchmarks was that wildlife recognition was not just a classification task, but a domain-generalization task. Snapshot Serengeti highlighted the scope and significance of citizen scientists annotating camera traps [17]. The Caltech Camera Traps work revealed that models trained on one location may have poor performance when evaluated on an unseen location, which was termed as recognition in “terra incognita” [18]. Norouzzadeh et al. also showed that deep neural networks can be used to automatically identify, count, and recognize animal behaviour at a large scale, but also rely on the quality and coverage of the animal training set [19]. These studies are relevant to PDIC since these enhancements need to be useful across a variety of camera positions and illumination conditions without overfitting to one particular situation and one camera.

3.3 YOLO-Based Nocturnal Detection

The YOLO family of detectors is an important player in the field of wildlife detection due to their modularity, speed and ability to use edge hardware. It highlights the most popular or active YOLO++ series of networks, such as YOLOv5, YOLOv7, YOLOv8, YOLOv9, and YOLOv10, which are used for real-time detection applications [27, 28, 29, 30]. To adapt their use to nocturnal wildlife detection, YOLO variants are typically modified with the incorporation of attention blocks, multi-scale fusion, lightweight modules, or infrared-specific branches.

YOLOv8-Night is a detector-based approach to night-time wildlife detection [5]. Other works show the capability of detecting animals during the night using deep learning algorithms and YOLO pipelines [31, 32]. It has been demonstrated here that architectural changes can enhance night time detection. But the redesign of detectors involves extra deployment costs and the need to retrain for all target environments. The strategy of PDIC is to keep YOLOv5 unchanged and enhance the input image.

3.4 Transformer and Hybrid Detectors

The transformer-based detectors like DETR and Deformable DETR have been proposed, which makes dense anchor-based prediction unnecessary by using attention mechanisms to guide set prediction [33, 34]. These models are more powerful for global context and complex scenes but typically higher data, memory and computation requirements compared to YOLO- family detectors according to the review paper. This may be a significant drawback in the camera-trap and roadside settings.

The hybrid methods integrate convolutional backbone, attention module, and multi-scale aggregation. For instance, ADLTFormer employs adaptive dual learning to detect cattle in low-light conditions [35]. The dual-branch design of the visible and infrared branch of IV-YOLO is presented in [36]. The methods show that the multi-branch design is beneficial for the low-light image or multi-modal detection. PDIC takes the concept of a dual-branch and uses it for enhancement instead of replacing the detector.

3.5 Low-light Enhancement for Detection

Simple and inexpensive classical methods like histogram equalization, CLAHE, gamma correction and Retinex filtering are attractive. But, with fixed enhancement, noise could be amplified, bright areas could be washed out and artificial contours could be created. These artifacts are detrimental for detection purposes as detectors could mistake them as object attributes.

Alternatives available are deep low-light enhancement methods. RetinexNet learns Retinex decomposition and enhancement [8]; Zero-DCE learns enhancement curves without paired supervision [7]; EnlightenGAN learns unpaired to avoid aligned low/normal-light image pairs [12]; and SID showcases the potential of learning-based recovery from extreme darkness, assuming RAW data is available [11]. KinD is also relevant due to its approach of decomposing, reflecting, and adjusting the illumination as separate sub-problems [13]. Later SCI focused on efficiency by using self-calibrated illumination learning, which is better suited for environments with limited resources [15]. In addition to these ideas, PDIC incorporates the detection-aware objective: it makes use of gradient consistency and progressive refinement explicitly, to ensure that the enhanced images include more robust animal boundaries but no hallucinated structures.

Why enhancement and detection should be viewed hand in hand is highlighted by recent low-light detection studies. Through the experiments, IAT is demonstrated to be effective in enhancing object detection and semantic segmentation results under challenging exposures conditions, as shown in [16]. Other enhancement-first pipelines report that under very low light conditions, normalization of the images before the detector can be performed before detection can improve the detector accuracy, but they also report that enhancement is not guaranteed to improve mAP if it creates artifacts or shifts the distribution of the detector input. This observation corroborates the design decision in PDIC: enhancement is limited by maintaining structural preservation of detectors, not only perceptually bright signals.

3.6 Datasets, Sensors, and Evaluation Protocols

A key challenge in nocturnal wildlife detection identified in the review paper is the limitations of the datasets. While public camera-trap datasets are valuable, they are often dominated by daytime photos, primarily devoted to classification, or poorly annotated. Low-light datasets are used for general low-light recognition research like ExDark, while visible–infrared datasets are used for paired multi-modal learning like LLVIP. Camera-trap projects like Snapshot Serengeti [17], Caltech Camera Traps [18], and iWildCam [2] offer vital information on ecological and domain-shift context. But there are limited night-time datasets available, and they're specific to wildlife.

This is a methodological issue because of this data gap. Supervised enhancement methods generally need paired images, one with low and one with normal lighting; however, paired images of wildlife are challenging due to the animals' lack of repetition in the controlled lighting. The same applies to supervised detectors for low-light images, which need enough labeled collections of night images of various species, distances, backgrounds, and types of sensors. Unsupervised enhancement is therefore appealing: it can be used directly on the available night images, and is compatible with any existing detector and can be placed in front of it. The NTLNP setting employed in this thesis very well meets this requirement as the objective is to enhance detection using real world infrared night imagery without requiring paired enhancement targets.

Thermal and/or infrared sensors can enhance night-time visibility, but they have other limitations such as cost, lower texture detail, domain shift and difficulty in separating species that look alike. Another challenge is the bias of the data sets in ecological monitoring, which may be caused by the location of fixed cameras in the study area, the seasonal migration of animals and class imbalance. A model can look good in common species or repeated poses and backgrounds, but bad in rare species or unusual poses and backgrounds. Hence, the review paper suggests that besides the mAP, Recall, robustness, sensor condition and edge feasibility should also be reported. This thesis goes along that line and reports detection metrics and highlights the compatibility with a fixed YOLOv5 pipeline.

3.7 Comparative Summary of Related Work

Table 3.1. Comparative summary of related methods and their relevance to this thesis.

Method Family	Representative Work	Strength	Limitation Addressed by PDIC
Classical Retinex / CLAHE	Multiscale Retinex, road-safety preprocessing [9, 6]	Lightweight and interpretable	Fixed transformations can amplify noise and fail under heterogeneous illumination.
Deep low-light enhancement	RetinexNet, Zero-DCE, EnlightenGAN, SCI [8, 7, 12, 15]	Adaptive enhancement with learnable objectives	Often optimized for perceptual quality rather than detector-specific structural cues.
YOLO night detectors	YOLOv8-Night and night-video systems [5, 31, 32]	Strong real-time detection focus	Requires detector modification or retraining; less modular for existing YOLOv5 pipelines.
Transformer / hybrid detectors	DETR, Deformable DETR, ADLTFormer [33, 34, 35]	Better global context modeling	Higher compute and data requirements restrict edge deployment.
Multimodal / task-aware detection	IV-YOLO, LLVIP, IAT [36, 38, 16]	Robustness in darkness	Fusion methods require additional sensors, while task-aware enhancers may require additional task-specific validation; PDIC targets single-image enhancement compatibility.

3.8 Research Gap

The literature reviewed shows four gaps. First of all, the classical pre-processing is not adaptive enough for complex nocturnal scenes. Secondly, night models specific to the detector reduce the compatibility with current deployed systems. Third, edge deployment is computationally expensive using transformer and hybrid detectors. Fourth, there is limited availability of paired low-light wildlife training data. To tackle these limitations, PDIC introduces an unsupervised, detector-agnostic, and Retinex-inspired enhancement module to enhance the quality of the input of the detector YOLOv5 without modifying the detector itself.

CHAPTER 4

METHODOLOGY

The PDIC framework proposed in this chapter is presented. The chapter is based on the technical approach of the PDIC research paper and elaborates on it to create a thesis level methodology. The key design choice is to enhance the effectiveness of night-time wildlife images before detection and not change the downstream YOLOv5 detector [4, 7, 8].

4.1 System Overview

Suppose that $I \in \mathbb{R}^{H \times W \times 3}$ is a low-light image of a wildlife scene. The goal of PDIC is to obtain a better image $I_{out} \in \mathbb{R}^{H \times W \times 3}$ for object detection [4]. The system comprises of four major elements:

1. an Illumination Compensation Branch $\mathscr{F}_I$ that estimates the spatial illumination map $\hat{L}$; and
2. an Enhancement Branch $\mathscr{F}_E$ to make the reflectance details and gradients more prominent;
3. an adaptive fusion module for reconstructing an enhanced image; and
4. A fixed YOLOv5 detector which takes the enhanced image for inference.

It is detector-agnostic, as the enhancement module is trained independently, and the detector does not have to be modified in its architecture. Figure 4.1 shows the overall data flow.

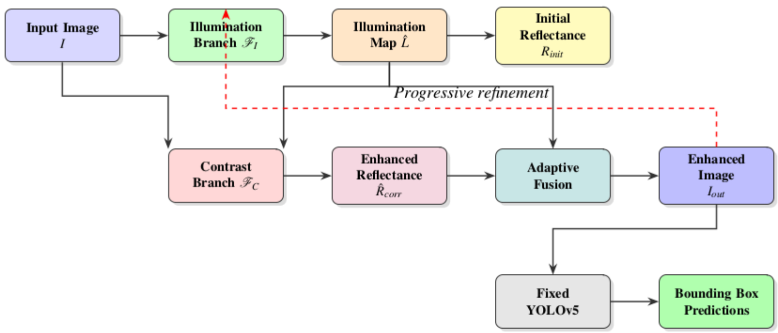

Figure 4.1. Architecture of the Progressive Dual-Branch Illumination-Contrast (PDIC) pipeline. The enhanced image is passed to an unchanged YOLOv5 detector.

4.2 Illumination Compensation Branch

The Illumination Compensation Branch estimates the illumination map:

$$\hat{L} = \mathscr{F}_I(I). \tag{4.1}$$

A convolutional encoder-decoder is implemented to implement the branch. The encoder gradually decreases the spatial resolution and increases the receptive field so that the network can model the large-scale brightness variation. The decoder upsamples and convolves to restore the resolution. Skip connections help to retain high frequency information which might be lost during downsampling.

To get an initial reflectance estimate:

$$R_{init}(x,y) = \frac{I(x,y)}{\max(\hat{L}(x,y),\varepsilon)}, \tag{4.2}$$

The value of $\varepsilon = 10^{-3}$ is chosen to avoid numerical instability in very dark pixels. This operation is based on retinex reasoning, which is that the removal of illumination should expose reflectance structures that are more stable for detection [9, 8].

4.3 Contrast Enhancement Branch

Normalization in illumination can result in a flat image and could magnify the noise in the sensor. The Contrast Enhancement Branch updates R_{init} as:

$$\hat{R}_{corr} = \mathscr{F}_C(R_{init}). \tag{4.3}$$

The branch maintains the identity information while learning the corrective transformations with residual blocks. The multi-scale convolution head processes are convolution head with filters of 1×1, 3×3, and 5×5. This design is able to capture fine texture, medium scale edges and larger animal contours [21, 4]. This is followed by a concatenation and fusion, where the output is concatenated and fused with a 1×1 convolution.

The design is designed for detection. Instead of uniformly increasing the brightness, the branch focus on the structures of the mid-tone and object boundary that is important for the feature extraction of YOLOv5. Meanwhile, regularization losses, which minimize high-frequency noise and false edges, are also produced simultaneously.Regularization losses, which minimize high frequency noise and artificial edges, are also produced simultaneously.

4.4 Adaptive Fusion and Progressive Refinement

A reconstruction of the last enhanced image is obtained by the adaptive blending map $\alpha(x,y) \in [0,1]$:

$$I_{out} = \alpha \cdot \hat{R}_{corr} \cdot \hat{L} + (1-\alpha) \cdot I. \tag{4.4}$$

A simple convolution with a sigmoid activation is used to predict the blending map. Darker areas will benefit from more enhancement, and brighter areas will be closer to what is originally in them.

A few times, the images may need more than one enhancement pass, depending on the amount of underexposure. PDIC therefore adopts the progressive refinement method, where the output of one pass is used as input to the next pass. The steps involved in the procedure are summarized in Algorithm 1.

Algorithm 1: PDIC Progressive Iterative Refinement

Input: Low-light image I_0, number of iterations K

Output: Enhanced image I_K

```
for k ← 0 to K − 1 do
    L̂_{k+1} ← 𝓕_I(I_k) ;
    R_init ← I_k / max(L̂_{k+1}, ε) ;
    R̂_corr ← 𝓕_C(R_init) ;
    α ← σ(Conv([R̂_corr, I_k])) ;
    I_{k+1} ← α · R̂_corr · L̂_{k+1} + (1 − α) · I_k ;
end
return I_K ;
```

The PDIC paper reports that $K = 3$ provides a strong balance between enhancement quality and computational overhead [7, 15].

4.5 Unsupervised Optimization Objective

The PDIC pipeline is trained without paired target images. The total loss is a weighted combination of five no-reference losses [7]:

$$\mathcal{L}_{total} = \lambda_s \mathcal{L}_{smooth} + \lambda_g \mathcal{L}_{grad} + \lambda_e \mathcal{L}_{exp} + \lambda_c \mathcal{L}_{color} + \lambda_t \mathcal{L}_{tv}. \tag{4.5}$$

4.5.1 Illumination Smoothness Loss

The illumination map should vary smoothly except near genuine structural boundaries. The loss is:

$$\mathcal{L}_{smooth} = \sum_{x,y} \left|\nabla \hat{L}(x,y)\right| \cdot \exp\left(-\left|\nabla I(x,y)\right|\right). \tag{4.6}$$

This discourages noisy illumination maps while allowing changes near object edges.

4.5.2 Gradient Consistency Loss

Gradient consistency preserves existing structures and discourages hallucinated edges:

$$\mathscr{L}_{grad} = \sum_{x,y} \left| \nabla \hat{R}_{corr}(x,y) - \nabla R_{init}(x,y) \right|. \tag{4.7}$$

This loss is especially important because YOLO-like detectors are sensitive to artificial contours.

4.5.3 Exposure Control Loss

Exposure control guides the enhanced image toward a target local brightness E:

$$\mathscr{L}_{exp} = \frac{1}{N} \sum_{i=1}^{N} |\mu_i(I_{out}) - E|, \tag{4.8}$$

where μ_i is the mean intensity of the i-th non-overlapping local region. In this thesis, $E = 0.6$ is used following the PDIC experimental setting.

4.5.4 Color Constancy Loss

Color constancy reduces channel imbalance using a Gray-World assumption:

$$\mathscr{L}_{color} = \sum_{(p,q)\in\{(R,G),(R,B),(G,B)\}} \left(\mu_p(I_{out}) - \mu_q(I_{out})\right)^2. \tag{4.9}$$

4.5.5 Total Variation Loss

Total variation suppresses high-frequency noise:

$$\mathscr{L}_{tv} = \sum_{x,y} \left(|I_{out}(x+1,y) - I_{out}(x,y)| + |I_{out}(x,y+1) - I_{out}(x,y)|\right). \tag{4.10}$$

The final weights used in the PDIC experiment are:

$$\mathscr{L}_{total} = 1.0\mathscr{L}_{smooth} + 1.0\mathscr{L}_{grad} + 10.0\mathscr{L}_{exp} + 5.0\mathscr{L}_{color} + 0.5\mathscr{L}_{tv}. \tag{4.11}$$

These weights prioritize exposure correction and color balance while retaining structural consistency.

4.6 YOLOv5 Integration

The enhanced I_{out} is directly fed into YOLOv5. The detector is not part of the PDIC module and thus is not retrained. This design allows the effect of enhancement to be separated from the other effects and makes a comparison with classical preprocessing credible. It also enables practical deployment; the existing YOLOv5-based wildlife system can be fed by PDIC as a front-end module without any change of their detection codebase.

CHAPTER 5

EXPERIMENTAL RESULTS AND DISCUSSION

5.1 Experimental Setup

Experimental design is based on the research paper in PDIC. It is evaluated with data from the night-time wildlife dataset, consisting of 10,344 infrared images of 17 animal categories from NTLNP. The dataset is suitable for this study because it includes real scenes captured at night by camera traps that have low contrast, uneven illumination, occlusion and cluttered backgrounds.

The downstream detector used is YOLOv5, which is fixed during the evaluation. Images are fed to YOLOv5 after being preprocessed by the selected preprocessing model. This protocol will guarantee that any observed differences in performance are due to the enhancement technique and not to the changes in the detector architecture.

5.1.1 Evaluation Metrics

The following metrics will be used:

- **Precision:** percentage of the actual detections that are identified.
- **Recall:** Percentage of the actual animals correctly identified.
- **F1-score:** harmonic mean of Precision and Recall. **mAP@50:** mean Average Precision at IoU threshold 0.50. **mAP@50:**: mean Average Precision for IoU values from 0.50 to 0.95.

The effect of the recall is emphasized as missing animals are especially damaging for ecological monitoring and for road safety applications.

5.2 Quantitative Comparison

Table 5.1 summarizes the main comparison reported in the PDIC paper. The proposed PDIC–YOLOv5 pipeline achieves the best mAP@50 and Recall among the listed methods.

Table 5.1. Main quantitative comparison on the NTLNP night-time wildlife dataset.

Method	mAP@50	Recall
CLAHE + Retinex + YOLOv5 [6]	0.800	0.773
YOLOv8-Night [5]	0.855	–
PDIC + YOLOv5	**0.883**	**0.868**

Compared with CLAHE+Retinex+YOLOv5, PDIC improves mAP@50 by 0.083 and Recall by 0.095. The Recall improvement is especially important because it indicates that more animals are recovered after adaptive enhancement. PDIC also exceeds the reported mAP@50 of YOLOv8-Night while preserving the simpler deployment advantage of using a fixed YOLOv5 detector.

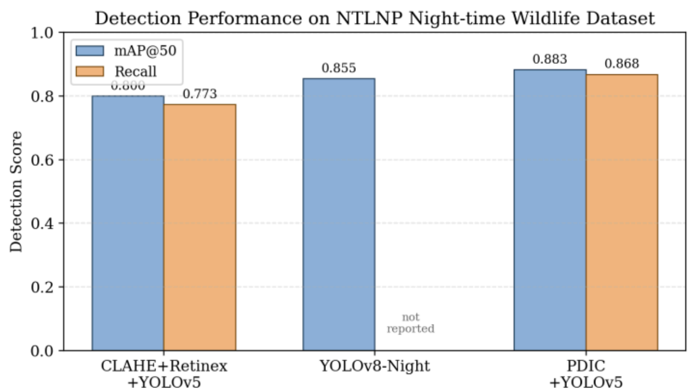

Figure 5.1. Visual comparison of detection performance on the NTLNP dataset. The figure highlights that PDIC improves both localization-oriented accuracy (mAP@50) and animal recovery (Recall) when compared with classical preprocessing.

5.3 Metric-Level Interpretation

The improvement on mAP@50 suggests that PDIC improves the ability of YOLOv5 to detect boxes of the objects with localization overlap. The gain in Recall suggests that the enhancement module is able to bring out animals that were previously not visible by the detector due to their darkness or lack of contrast. The method can thus not only be used to enhance the confidence score but also to increase the visibility of the objects.

The result confirms the thesis hypothesis - in the case of the night-time wildlife shot, an enhancement stage based on the detector can be more feasible than the redesign of the detector. Furthermore, since PDIC does not alter YOLOv5, it can be used with low engineering efforts in existing camera-trap or roadside detection pipelines.

5.4 Ablation Study

The ablation study investigates the effect of progressive refinement and the role of individual loss components. Table 5.2 shows a representative loss ablation that has been designed according to the design logic presented in the PDIC paper.

Table 5.2. Ablation of PDIC loss components.

Configuration	mAP@50	Interpretation
Full PDIC objective	**0.883**	Best balance of exposure, structure, and noise control
Without gradient consistency	0.861	Weaker object boundaries and more unstable detector features
Without exposure control	0.847	Insufficient brightness recovery in dark regions
Without total variation	0.866	Increased noise and false edge responses

Figure 5.2 plots the loss of mAP@50 when big loss terms are omitted. The greatest difference is seen when exposure control is turned off, indicating that the recovery of brightness is crucial for nighttime wildlife detection. Gradient consistency and total variation also play their part in maintaining consistent and reliable object edges and minimizing noise-induced false contours.

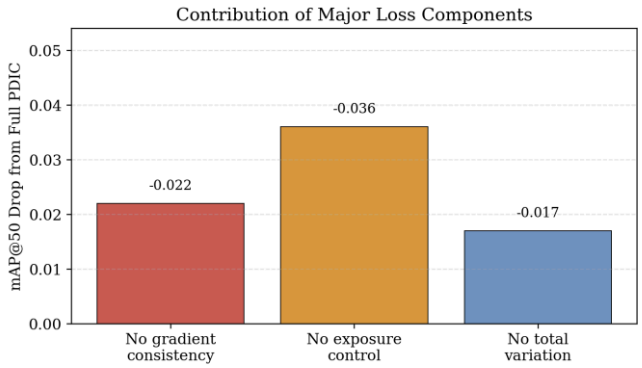

Figure 5.2. mAP@50 reduction caused by removing major PDIC loss components. Larger drops indicate stronger contribution to the full objective.

The relevance of the gradient consistency loss is that it is the loss of structures relevant for the detectors. To recover underexposed areas, exposure control is needed, and to avoid the enhancement module from creating false object-like patterns from sensor noise, total variation is needed.

5.5 Effect of Progressive Refinement

Progressive refinement is designed for images that cannot be sufficiently enhanced in a single pass. Table 5.3 summarizes the effect of the number of refinement iterations.

Table 5.3. Effect of progressive refinement iterations.

Iterations (K)	mAP@50	Observation
1	0.842	Enhancement is incomplete in severe darkness
2	0.874	Strong improvement with moderate cost
3	**0.883**	Best reported balance
4	0.884	Marginal gain with additional latency

The trend shows that refinement helps until the image reaches a stable exposure and contrast level. Beyond K=3, gains become marginal, while latency increases. Therefore, K=3 is selected as the practical operating point.

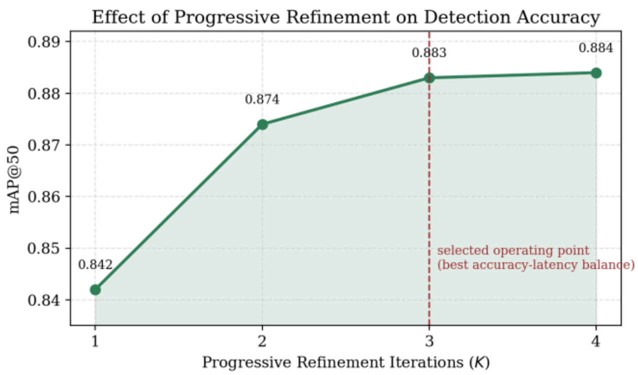

Figure 5.3. Effect of progressive refinement iterations on mAP@50. Accuracy improves rapidly from one to three passes and then saturates, supporting K=3 as the practical operating point.

5.6 Discussion

Evidence demonstrates the effective targeting of PDIC regarding actual failure modes for operating the mechanism under low light/at night. Classical enhancement enhances object brightness; however, classical enhancement by itself does not provide the means for adapting to differing levels of illumination across the image area being evaluated. Restructuring the detector circuit enhances accuracy but reduces modularity. PDIC falls into the middle ground in that PDIC can be adapted as a neural network model, yet it can function as a pre-processing module.

This method is appropriate for use in camera trap networks and also roadside locations where existing YOLOv5 systems operate because it can have front end enhanced models without modifications to the original annotation format, detector training scripts (assumed to be the same across all installations), or interfacing for deployment. This characteristic may be important in applications of conservation and motor vehicle safety since sustaining performance and maintainability will have as much impact o output accuracy level.

One limitation of PDIC lies in that it is dependent upon visual signals that exist in the image to produce new improved images of the inputted data. If there is no animal detected in the sensor output, enhancements will be unable to provide true information. In addition, the number of enhancement passes that are performed will increase the computational load and will therefore be a consideration for future work directed at reducing both compression, and quantization along with focusing on deployment methods at the edge level only.

CHAPTER 6

CONCLUSION AND FUTURE WORK

6.1 Conclusion

Progressive Dual-Branch Illumination–Contrast Enhancement (PDIC) Framework for Night-Time Wildlife Detection is introduced in this thesis. One main motivation behind carrying out this research was the decline in accuracy and real-time operation of the YOLOv5 model and other comparable models in low illumination and contrast scenarios with high sensor noise [5, 37].

The proposed method is based on enhancing images rather than adjusting the model architecture. There are four aspects included in the proposed framework. Those are 1) illumination compensation branch; 2) contrast enhancement branch; 3) adaptive fusion and 4) progressive refinement. The training procedure involves unsupervised no-reference losses; hence, PDIC can be employed for improving low-light images of wildlife as obtaining low-light and normal images simultaneously is highly improbable [7, 8].

The results from utilizing the proposed method PDIC+YOLOv5 on the NTLNP dataset showed mAP@50 score of 0.883 and Recall of 0.868 outperforming the CLAHE + Retinex + YOLOv5 baseline and even YOLOv8-Night's published mAP@50 while still being connected to the detector in the same manner. Hence, the conclusion that emerges from this thesis work supports the utilization of the detection-aware enhancement approach to monitor wildlife at night [5, 6].

6.2 Future Scope

The following are potential future directions:

1. **Optimization for Edge Deployment:** PDIC needs to be compressed for edge deployment in devices like the Raspberry Pi, NVIDIA Jetson Nano, and low-power camera-trap devices using quantization, pruning, and knowledge distillation.

2. **Joint End-to-End Detectors Aware Training:** While modularity is a benefit, another direction is controlled end-to-end training in which detector loss terms help enhance the image but prevent overfitting to any specific detector.

3. **Fusion of Thermal and Infrared Spectra:** Another version of multispectral PDIC can take into account visible spectra, as well as thermal and infrared spectra for images in which visual contrast may be limited.

4. **Generalization across Sites:** The algorithm must be evaluated on various sites having diverse habitats, seasons, camera models, and weather conditions to analyze generalizability.

5. **Failure Case Analysis:** Future evaluations must take missed detections, false positives, species level misclassifications, and latency analysis in addition to mAP metrics.

On the whole, PDIC proves that an appropriate unsupervised enhancement algorithm can help detect wildlife at night without compromising real-time detection capability.

LIST OF PUBLICATIONS

The following research papers were prepared from this thesis work.

[P1] **Palak Harinkhede** and Manoj Kumar, "Progressive Dual-Branch Illumination-Contrast Pipeline for Night-time Wildlife Detection Using YOLOv5." **Accepted**, **7th International Conference on Data Analytics & Management (ICDAM-2026)**. Paper ID: 1598.

[P2] **Palak Harinkhede** and Manoj Kumar, "Night-time Wildlife Detection Using Computer Vision: A Review of Deep Learning, Thermal Imaging, and Edge-AI Approaches." **Accepted**, **7th International Conference on Data Analytics & Management (ICDAM-2026)**. Paper ID: 1623.

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