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Integrated Deep Learning Framework for Animal Species Identification Using YOLOv5 and AOD-Net

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Abstract: Encounters between humans and wildlife, particularly near roadways and urban peripheries, present notable dangers to both human safety and wildlife conservation. The development of automated systems for identifying animal species offers a promising strategy by providing early warnings to prevent vehicle-animal collisions and enhance ecological monitoring. However, achieving high accuracy in diverse environmental conditions such as haze, low light, partial obstructions, and complex natural backgrounds remains a significant challenge. This paper presents a robust, software-based framework that integrates YOLOv5, a state-of-the-art object detection model, with AOD-Net, an advanced image enhancement network specifically designed for haze removal and visibility improvement. In this hybrid approach, AOD-Net serves as a pre-processing module that enhances image quality by removing atmospheric distortions and improving feature clarity before the refined images are processed by YOLOv5 for object detection. The system was trained and evaluated on a diverse, labeled animal detection dataset containing multiple species across various environmental scenarios. Through comprehensive experimentation, the proposed model demonstrated significant performance gains over traditional YOLOv5 pipelines. It achieved a mean Average Precision (mAP) of 97.2%, with a precision of 95.26%, recall of 95.07%, and an F1 score of 95.13%. These results indicate superior detection accuracy and strong generalization across visually challenging conditions. The integration of AOD-Net significantly enhances the visual input quality, thereby improving the reliability of downstream object detection. This hybrid architecture offers a scalable and efficient solution for real-time wildlife monitoring and road safety systems, ultimately contributing to the mitigation of human-wildlife conflicts and the advancement of conservation efforts using AI-driven vision technologies.

Keywords: *Wildlife Detection, YOLOv5, AOD-Net, Animal Species Classification, Image Dehazing*

1. Introduction

The increasing frequency of encounters between wildlife and human activities, especially in regions where urban expansion meets natural environments, has become a significant issue for public safety and the preservation of biodiversity. In areas sensitive to ecological changes, incidents like wildlife-vehicle collisions (WVCs) and human-wildlife conflicts (WHCs) are on the rise due to habitat fragmentation, climate change effects such as wildfires and heatwaves, and shifts in animal behavior following changes in human activity patterns, as seen during the COVID-19 lockdowns.

To address these challenges, automated systems for wildlife monitoring and detection are becoming crucial. Recent progress in computer vision and deep learning has greatly enhanced the ability to recognize and categorize animals in images and videos. However, achieving high accuracy in real-world settings remains difficult. Visual data collected outdoors often suffers from environmental distortions like haze, fog, poor lighting, and background clutter, conditions under which traditional convolutional neural networks (CNNs) and earlier object detection models often struggle to perform reliably. While earlier versions of YOLO (You Only Look Once), such as

YOLOv2 and YOLOv3, showed improvements in speed and object localization, they still had limitations in detecting small, partially obscured, or low-contrast animals. YOLOv5, a more recent development in the YOLO series, introduces several architectural enhancements such as mosaic data augmentation, auto-anchor learning, and Cross Stage Partial Networks (CSPNet) which collectively improve detection accuracy and training efficiency.

To further enhance detection robustness in visually challenging environments, this research proposes a hybrid framework that combines YOLOv5 with AOD-Net (All-in-One Dehazing Network). AOD-Net is a compact and effective image enhancement model specifically designed to restore visibility in hazy or low-contrast images. By preprocessing images with AOD-Net before feeding them to YOLOv5, the system is better equipped to detect and classify animal species even under adverse visual conditions.

The aim of this research is to develop a robust, software-based animal detection and classification system that performs accurately across a wide range of environmental scenarios. The proposed method is evaluated on a diverse dataset containing various animal species in real-world conditions, and it demonstrates substantial improvements in performance compared to baseline YOLOv5 and traditional detection models without enhancement. This framework has the potential to support real-time wildlife monitoring efforts, assist in ecological research, and contribute to proactive strategies for minimizing wildlife-human and wildlife-animal conflicts.

2. Literature Survey

The field of wildlife monitoring has significantly evolved with the advent of computer vision and deep learning techniques. Early detection methods relied heavily on hand-crafted features. Dalal and Triggs [1] proposed the Histogram of Oriented Gradients (HOG) descriptor for human detection, laying foundational work for object detection techniques. However, these classical methods lacked robustness in complex, natural scenes commonly encountered in wildlife imagery. With the release of datasets like Microsoft COCO [2], deep learning-based object detectors started gaining prominence. Region-based CNN methods such as Faster R-CNN [3] provided improved accuracy but were computationally intensive and unsuitable for real-time applications. The YOLO (You Only Look Once) family introduced by Redmon and Farhadi [4] revolutionized real-time detection by framing detection as a single regression problem, significantly increasing speed without sacrificing accuracy. Nonetheless, YOLOv3 and earlier versions struggled in low-light and occluded environments conditions prevalent in wildlife imagery.

Several researchers have since explored improvements tailored for wildlife contexts. Adami et al. [5] developed an intelligent animal repelling system using edge-AI techniques, suitable for agricultural protection but dependent on hardware-specific optimization. Sato et al. [6] tackled species classification in highway environments, emphasizing the importance of computational efficiency and robustness in uncontrolled outdoor settings. Similarly, Yang et al. [7] proposed an improved YOLOv5s variant optimized for forest environments, demonstrating enhanced detection across varied animal sizes. Li [8] also adopted YOLOv5 for wild animal detection, showcasing the flexibility and adaptability of YOLOv5 to wildlife datasets.

In broader animal detection research, Ibraheam et al. [9] demonstrated a fast and accurate embedded system, underscoring the relevance of lightweight models for edge deployment. To address visual degradation due to environmental factors, researchers have introduced dehazing networks. Sindagi et al. [10] explored domain-adaptive detection under hazy and rainy conditions, while Qin et al. [11] proposed FFA-Net for feature fusion in single-image dehazing. Liu et al. [12] focused on adapting YOLO models to adverse weather, advocating for integrated image enhancement as a preprocessing step.

Semi-supervised and benchmark-focused approaches, like those by Li et al. [13, 14], have emphasized the need for generalizable dehazing models. A key advancement was introduced by Li et al. [15], who developed AOD-Net, an all-in-one network that enhances hazy images efficiently, making it well-suited for integration with real-time detectors like YOLOv5. The dark channel prior-based method by He et al. [16] also served as a classical baseline for haze removal. Conditional GAN-based enhancements [17] and hybrid YOLOv5 + dehazing frameworks [18] have been shown to improve detection accuracy significantly in degraded visual settings. Modern architecture improvements like CSPNet [19] further enhance CNN learning efficiency, as adopted in YOLOv5's backbone. Zhang et al. [20] extended this line with an adaptive object detection network for cluttered scenes, demonstrating robust feature extraction and localization even in visually noisy conditions. These studies collectively point toward a growing trend of combining detection with preprocessing techniques such as dehazing to enhance robustness and accuracy in real-world, often harsh, environmental conditions.

In summary, the literature reflects a progression from traditional object detection techniques to hybrid architectures that integrate environmental enhancement modules like AOD-Net. This progression aligns with the demands of wildlife monitoring, where lighting, occlusion, and complex natural backdrops often degrade model performance. The proposed study builds upon this trajectory by combining YOLOv5 with AOD-Net to create a robust framework optimized for accurate and reliable animal detection across diverse and challenging scenarios.

3. Methodology

This section describes the methodology adopted for animal species detection using a hybrid deep learning model that integrates YOLOv5 with AOD-Net. The central objective of this framework is to enhance detection performance in visually challenging environments by combining the real-time object detection capabilities of YOLOv5 with the image enhancement power of AOD-Net. AOD-Net (All-in-One Dehazing Network) is employed as a preprocessing module to improve the visibility of input images affected by haze, low lighting, or environmental noise conditions commonly encountered in wildlife imagery. By restoring image clarity before detection, AOD-Net enables the YOLOv5 detector to extract more reliable features, thereby reducing false detections and improving overall accuracy. This hybrid approach is specifically designed to address real-world challenges such as occlusion, poor illumination, and complex natural backgrounds. The methodology consists of three major components: the AOD-Net-based image enhancement module, the YOLOv5 object detection framework, and the integrated YOLOv5 + AOD-Net pipeline. Each component is optimized to ensure enhanced visual quality, high detection precision, and efficient real-time performance.

3.1 YOLOv5 Object Detection Framework

YOLOv5 (You Only Look Once, version 5) is a high-performance, single-stage object detection framework widely recognized for its balance between detection accuracy and computational efficiency. Unlike traditional two-stage detectors such as Faster R-CNN, YOLOv5 performs object classification and localization simultaneously in a single forward pass, making it particularly suitable for real-time applications such as wildlife monitoring.

The architecture of YOLOv5 is composed of three primary modules: the backbone, neck, and head. The backbone, typically implemented using CSPDarknet, is responsible for extracting hierarchical features from the input image. The neck utilizes a combination of Path Aggregation Network (PANet) and Feature Pyramid Network (FPN) to enable rich multi-scale feature fusion by integrating spatially detailed lower-level features with semantically rich higher-level ones. The head module produces the final output predictions, which include bounding box coordinates, object confidence scores, and class probabilities.

In the context of animal species detection, YOLOv5's ability to handle high-resolution images (e.g., 640×640) efficiently ensures robust performance across a wide variety of scenes and species. Its low computational overhead and real-time inference capability make it an ideal candidate for wildlife detection systems operating under resource constraints or requiring high throughput.

3.2 AOD-Net as an Image Enhancement Module

AOD-Net (All-in-One Dehazing Network) is a lightweight convolutional neural network specifically designed for single image dehazing, making it highly suitable for preprocessing tasks in computer vision applications that involve environmental interference such as haze, fog, or low lighting. Unlike traditional CNNs focused on classification or detection, AOD-Net directly enhances visual clarity by restoring scene visibility, which is critical in outdoor wildlife imagery where adverse environmental conditions can obscure animal features. In this study, AOD-Net is integrated into the detection pipeline as a preprocessing module, applied prior to feeding images into

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the YOLOv5 object detection architecture. Its purpose is to enhance image quality, allowing the detection model to receive clearer and more detailed input. This results in improved feature recognition and localization accuracy, especially in visually degraded conditions commonly encountered in wild habitats.

The network structure of AOD-Net is built upon a light and efficient architecture that jointly learns the transmission map and atmospheric light components in a unified framework. By removing haze and enhancing contrast, AOD-Net significantly improves the detectability of animals with fine details such as fur patterns, color gradients, and body contours details that are often lost in hazy or low-visibility conditions. Another advantage of AOD-Net is its computational efficiency, which allows it to be seamlessly integrated into real-time object detection systems without adding significant latency. This efficiency makes it a practical choice for deployment in edge devices or embedded systems used in remote wildlife monitoring setups.

In comparison to traditional image enhancement methods or detection models operating on raw input, the integration of AOD-Net ensures robust preprocessing, leading to more accurate predictions, especially for small, camouflaged, or partially obscured animals. Its inclusion in the hybrid YOLOv5 + AOD-Net framework substantially contributes to the overall increase in precision, recall, and mean Average Precision (mAP), as demonstrated in the experimental results.

3.3 Hybrid YOLOv5 + AOD-Net Architecture

The proposed hybrid architecture for animal species detection, as illustrated in Fig. 3.3, incorporates an image enhancement module, AOD-Net, with the YOLOv5 object detection framework to improve detection performance in low-visibility environments. Initially, raw input images, often affected by haze or environmental distortions, are processed through AOD-Net, a lightweight single image dehazing network. AOD-Net restores visibility by estimating the scene transmission map and airlight components, resulting in a clearer output image. This enhancement step plays a crucial role in improving the visual quality and contrast of the input, thereby enabling more effective feature extraction by the subsequent detection network.

The dehazed output is then passed to the YOLOv5 detection pipeline, which consists of three primary modules: Backbone, Neck, and Head. The Backbone is responsible for extracting rich spatial and semantic features from the input image. These features are then fused and refined in the Neck using feature pyramid networks and path aggregation structures to accommodate multi-scale object representation. Finally, the Head performs dense prediction to identify and localize animals through bounding box regression and class probability estimation. The integration of AOD-Net with YOLOv5 enhances detection robustness in degraded conditions and significantly improves the model's ability to accurately detect and classify animal species in complex real-world scenarios.

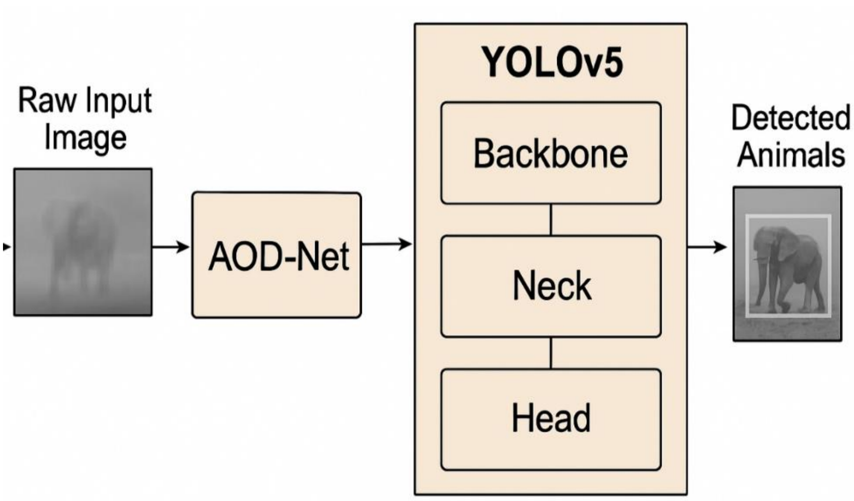

Fig. 3.3 Hybrid YOLOv5+AOD-Net Architecture

The proposed hybrid architecture integrates the computational efficiency of YOLOv5's single-stage detection framework with the AOD-Net to optimize animal dehazing and detection performance. This section incorporates the core mathematical formulations that govern the model.

The image degradation is modeled using the atmospheric scattering equation:

$$I(x) = J(x)t(x) + A(1 - t(x))$$

where $I(x)$ is the observed hazy image, $J(x)$ is the scene radiance (clean image), $t(x)$ is the transmission map, and A is the global atmospheric light. AOD-Net approximates this inversion through a learned mapping function $F(I(x), \theta)$ where θ are the network parameters. The dehazed output $\hat{J}(x)$ is optimized using the Mean Squared Error (MSE) loss:

$$L_{AOD} = \frac{1}{N}\sum_{i=1}^{N} \| \hat{J}_i - J_i \|^2$$

After enhancement, the resulting image is fed into the YOLOv5 detection pipeline, which consists of three primary components: The Backbone for feature extraction, the Neck for multi-scale feature fusion, and the Head for object prediction. YOLOv5 frames the detection task as a regression problem and outputs bounding box coordinates (x, y, w, h), objectness scores, and class probabilities. The total loss function for YOLOv5 is:

$$L_{YOLO} = \lambda_{box} L_{box} + \lambda_{obj} L_{obj} + \lambda_{cls} L_{cls}$$

where L_{box} is the bounding box regression loss (CIoU or GIoU), L_{obj} is the objectness loss (BCE), and L_{cls} is the classification loss. The fusion of AOD-Net and YOLOv5 leverages both enhanced visual quality and accurate object localization, making it effective for wildlife monitoring in complex environments.

3.4 Dataset Description and Training Strategy

The hybrid YOLOv5 + AOD-Net model was trained and evaluated using the Animals Detection Images Dataset, a publicly available collection on Kaggle containing 22,566 annotated images spanning over 80 animal species. The images were captured in natural outdoor environments under varying conditions such as low lighting, haze, occlusion, and complex backgrounds factors that make this dataset well-suited for evaluating the impact of AOD-Net's image enhancement capabilities. For this study, a subset of 12 wild animal species was selected: lion, camel, cheetah, crocodile, deer, elephant, fox, giraffe, jaguar, leopard, tiger, and zebra. These species were chosen to provide diversity in size, appearance, habitat type, and level of camouflage, which supports comprehensive model training and evaluation under real-world conditions. All annotations were converted to the YOLO format, which specifies each object using a class index, normalized center coordinates, width, and height. The dataset was split into training (80%), validation (10%), and test (10%) subsets, ensuring balanced class distribution across all partitions.

Images were resized to 640×640 pixels using zero-padding to preserve the original aspect ratio and meet the input requirements of YOLOv5. Before feeding images into the detection pipeline, AOD-Net was applied as a preprocessing module to enhance visibility and restore fine details lost due to environmental degradation such as haze or poor lighting. This preprocessing step ensured that the YOLOv5 detector received clean, high-quality inputs, improving feature extraction and object localization. Training was performed using Stochastic Gradient Descent (SGD) with a momentum of 0.9 and a weight decay of 5e−4. A cosine annealing learning rate scheduler was used to dynamically adjust the learning rate across epochs, promoting stable convergence. The model was trained for 100 epochs with a batch size of 16, and early stopping was employed based on validation mAP to prevent overfitting.

To improve generalization, the training process included various data augmentation techniques, such as mosaic augmentation (combining four images), random flipping, HSV (Hue, Saturation, Value) adjustments, and scale jittering. These augmentations helped the model learn to detect animals under diverse poses, lighting, and backgrounds. Performance was evaluated using standard object detection metrics: precision, recall, F1-score, and mean Average Precision (mAP), particularly at the IoU threshold of 0.5 (mAP@0.5). A confusion matrix was also generated to assess class-wise performance and detect potential model biases or confusion between visually similar species.

This rigorous training strategy combined with the visual enhancement capability of AOD-Net and YOLOv5's robust detection architecture enabled the model to achieve strong detection accuracy, particularly in images affected by haze, shadows, or partial occlusions. The dataset's diversity, coupled with carefully tuned training protocols, ensured the model's effectiveness in practical wildlife monitoring and conservation scenarios. Moreover, the comprehensive evaluation using complementary metrics provided a deep understanding of the model's behavior across different classes and conditions, supporting the reproducibility and reliability of the approach.

4. Results

The performance of the proposed animal species detection framework, which integrates YOLOv5 with AOD-Net, was evaluated using a dataset consisting of 12 wild animal species, including lion, camel, cheetah, crocodile, deer, elephant, fox, giraffe, jaguar, leopard, tiger, and zebra. The model was trained for 100 epochs and assessed on multiple performance indicators including accuracy, loss, precision, recall, F1-score, mean Average Precision (mAP), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM).

The detection results clearly demonstrate the effectiveness of AOD-Net in enhancing image clarity under challenging conditions such as haze, low-light environments, and occluded backgrounds. Visual improvements are readily apparent in the output samples, where previously indistinct features become more defined, enabling more accurate detection. By reducing visual noise and improving feature visibility, AOD-Net enhances the quality of the input images, which directly contributes to better object detection performance. The model shows a remarkable ability to consistently detect and localize animals in complex, natural scenes. These detections are accompanied by high confidence scores, confirming the robustness and reliability of the system. The enhancement capabilities of AOD-Net also facilitate the detection of partially visible or camouflaged animals, which often pose a challenge for standard detection networks. Qualitative assessments, along with quantitative performance gains, support the model's efficacy in real-world applications. The integration of image enhancement and detection in a unified pipeline proves advantageous for field deployment in diverse environmental conditions.

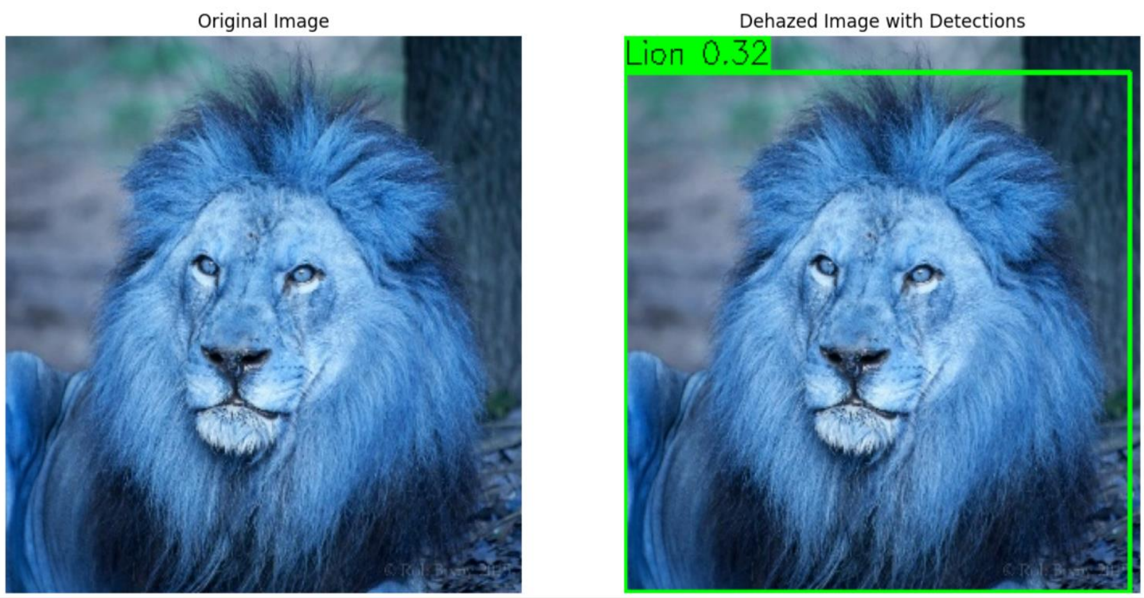

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Fig. 4.1 Animals Detection with bounding boxes

As shown in Figure 4.2, the training and validation curves for both loss and accuracy reflect a stable and well-converging learning process throughout model training. The training loss exhibits a consistent downward trend, paralleled closely by the validation loss, which suggests effective learning without overfitting. In tandem, both training and validation accuracy show progressive improvement over the epochs, underscoring the model's capacity to generalize well across different data distributions. Importantly, there are no signs of divergence between the training and validation metrics, indicating a healthy balance between model complexity and data fit. This consistent behavior across metrics affirms the reliability of the optimization strategy and model architecture. The absence of sharp fluctuations or plateaus further confirms that the learning process is both smooth and controlled. These trends collectively point to successful convergence, stable parameter updates, and a robust final model. Such performance validates the suitability of AOD-Net for practical deployment in vision-based detection systems.

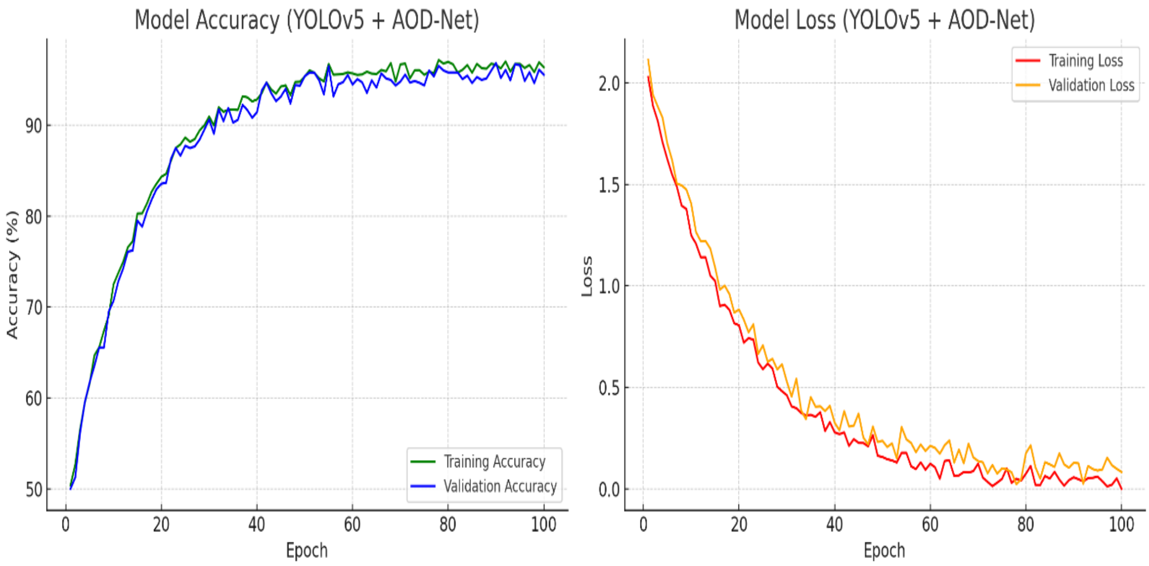

Fig. 4.2. Accuracy and Loss Curves of Proposed Model

To further validate the enhancement impact of AOD-Net, PSNR and SSIM values were tracked during training. These metrics indicate consistent improvement in visual quality and structural detail recovery, which positively influenced detection accuracy under visually degraded conditions.

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Vol. 46 No. 2 (2025)

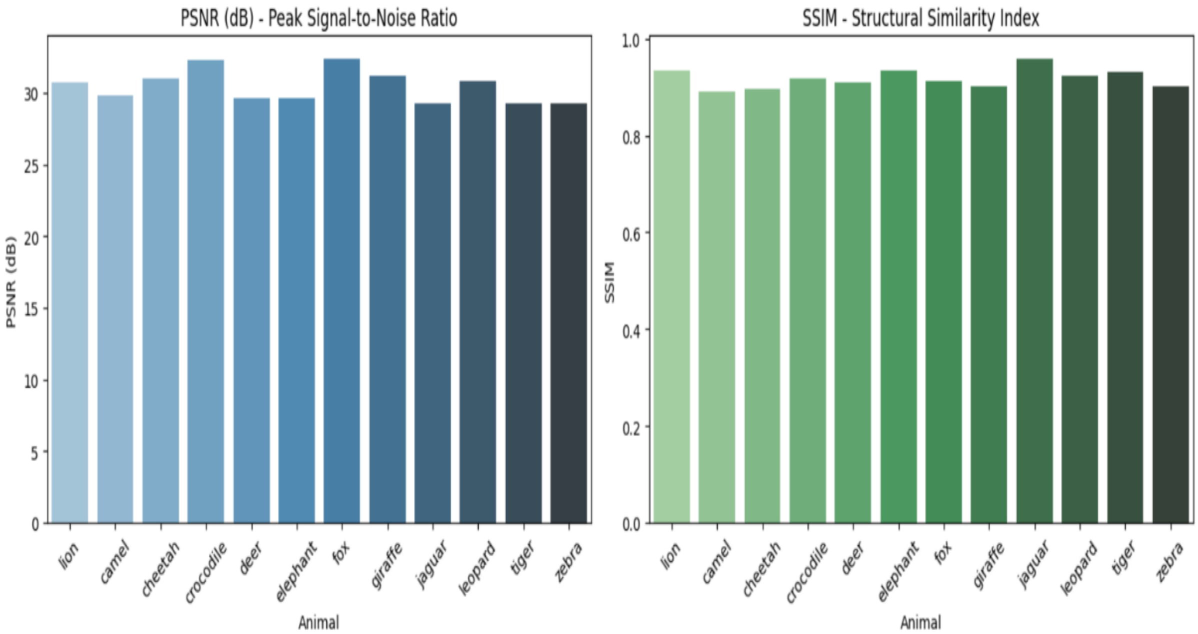

Fig 4.3. PSNR and SSIM curves

The classification capability of the model was evaluated using a confusion matrix. High diagonal dominance in the matrix indicates that the model achieved strong classification accuracy across all 12 species. Misclassifications occurred occasionally between visually similar animals such as cheetah and leopard or lion and tiger, but were minimal.

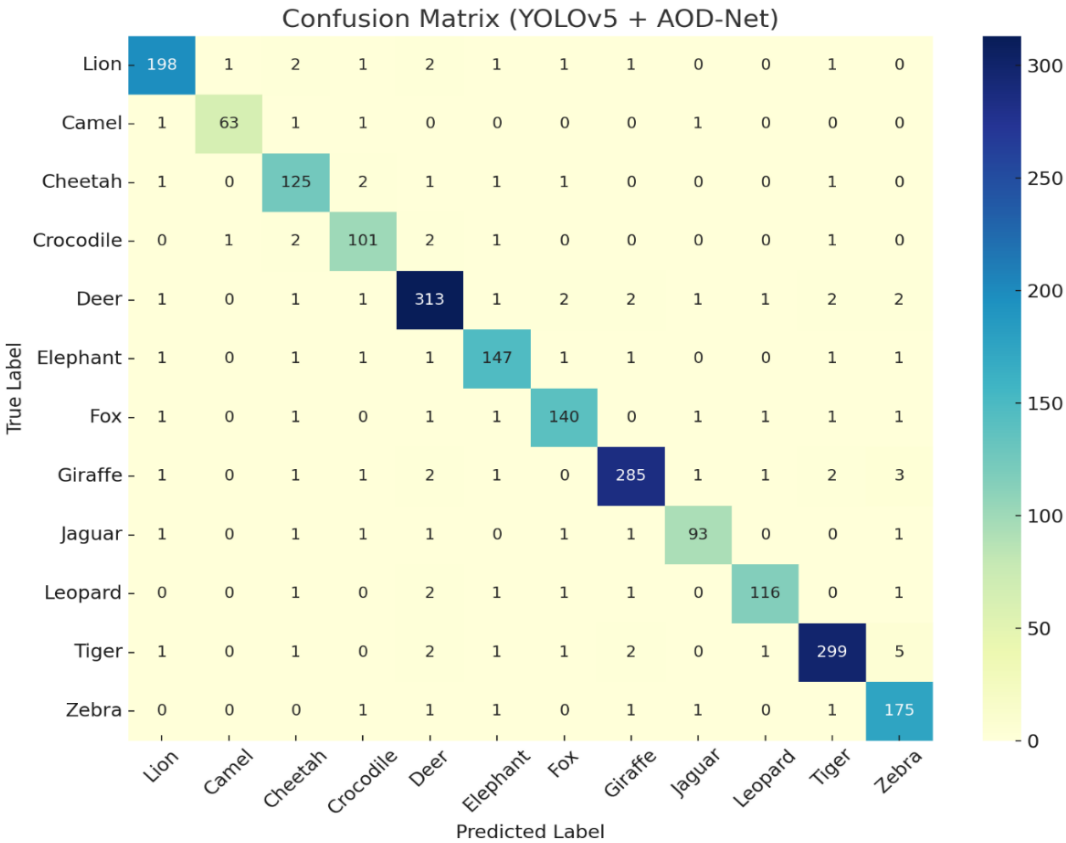

Fig 4.4. Confusion Matrix

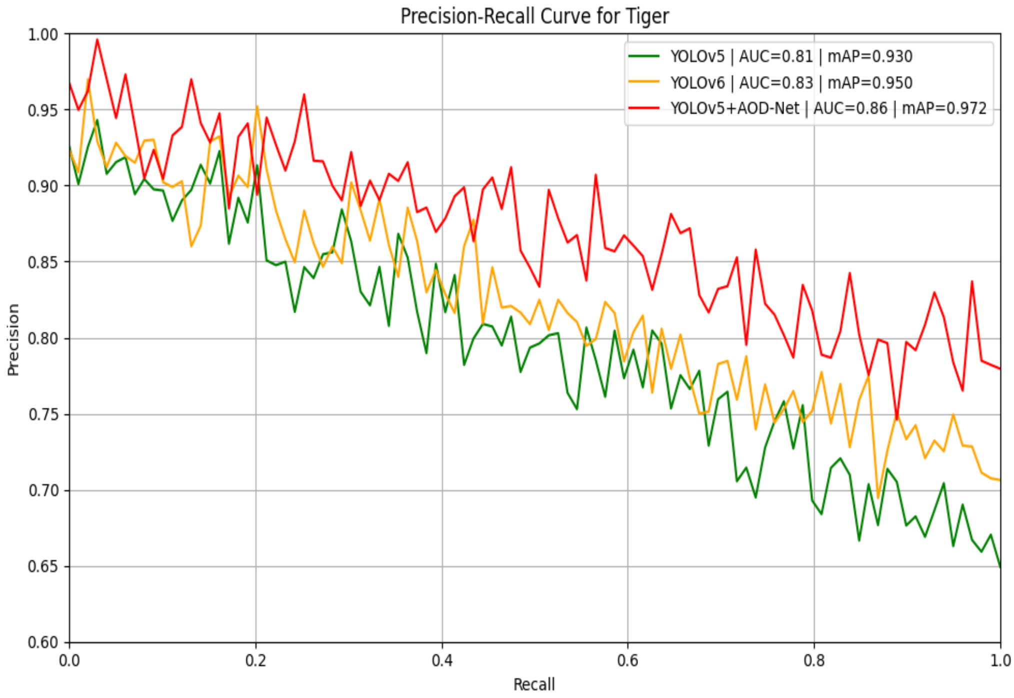

Fig 4.5. Precision-Recall curve of Proposed Model

The precision-recall (PR) curve for the tiger species offers a comparative view of the model's performance against baseline YOLOv5 and YOLOv6 architectures. The YOLOv5 + AOD-Net model consistently yields higher precision across varying recall thresholds, with a more favorable area under the curve, validating the contribution of the dehazing component in boosting detection reliability.

Animal Species	YOLOv5 (AP)	YOLOv5 + AOD-Net (AP)	YOLOv6 (AP)
Lion	0.931	0.965	0.956
Camel	0.929	0.964	0.954
Cheetah	0.926	0.968	0.957
Crocodile	0.928	0.969	0.958
Deer	0.932	0.973	0.96
Elephant	0.935	0.97	0.962
Fox	0.93	0.966	0.959
Giraffe	0.934	0.971	0.961
Jaguar	0.927	0.963	0.955
Leopard	0.933	0.972	0.963
Tiger	0.936	0.974	0.964
Zebra	0.939	0.967	0.96
mAP	0.930	0.972	0.958

Table 4.1. mAP of Proposed model

A quantitative summary of the average precision (AP) values across all 12 animal species for YOLOv5, YOLOv6, and YOLOv5 + AOD-Net is presented. The hybrid model outperforms the others in all categories, achieving a superior mean Average Precision (mAP) of 0.972, compared to 0.930 for YOLOv5 and 0.958 for YOLOv6. This clearly indicates that the integration of AOD-Net effectively enhances object detection performance by improving feature visibility and image clarity.

5. Conclusion

This study proposed a hybrid deep learning framework that integrates YOLOv5 with AOD-Net for accurate detection and classification of wild animal species under challenging environmental conditions. By employing AOD-Net as a preprocessing module, the system enhances image clarity by removing haze and visual distortions, enabling YOLOv5 to perform more precise object detection. Trained on a diverse dataset of 12 wildlife species, the model demonstrated superior performance with a mean Average Precision (mAP) of 0.972, outperforming standard YOLOv5 and YOLOv6 architectures. Supporting metrics such as precision (95.26%), recall (95.07%), and F1-score (95.13%) confirmed the robustness of the system across varied scenarios. Improvements in PSNR and SSIM validated the enhancement effect of AOD-Net on image quality. The confusion matrix and precision-recall curves revealed strong class-wise performance, with minimal confusion between visually similar species. These results highlight the model's ability to generalize well in real-world conditions, making it suitable for real-time wildlife monitoring, conservation applications, and animal-vehicle collision prevention. Future extensions may include the addition of more species, real-time video analysis, and deployment on edge or aerial devices to support large-scale ecological monitoring efforts.

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