Visvesvaraya National Institute of Technology

MTech in Applied AI

Mini Project Report

Wildlife Detection using Drone Footage Images

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Contents

1 Abstract

This project uses drones and YOLOv9 for real-time wildlife monitoring, ensuring accurate species detection with minimal human intervention. Data augmentation improves model performance, leading to higher precision and recall. The results confirm effective learning, making this a scalable and efficient conservation tool.

2 Introduction

Wildlife conservation is a pressing global issue, but traditional monitoring methods are often inefficient, labor intensive, and prone to errors. This project introduces an innovative solution by combining drone technology and YOLOv9, a cutting-edge object detection model, to automate wildlife monitoring. The system aims to provide real-time, accurate, and noninvasive monitoring of wildlife, significantly improving conservation efforts while minimizing human interference.

3 Problem Statement

Manual monitoring is time-consuming and error-prone. Relying on human observers leads to inconsistencies and inaccuracies in data collection. Environmental factors and human limitations further reduce the reliability of traditional methods.

4 Importance of this project

Boosting Conservation Efforts: Real-time, accurate data enables conservationists to make informed decisions and respond quickly to threats. Reducing Human Impact: Minimizing human presence in sensitive areas helps preserve the natural behavior of wildlife.

5 Literature Review

Wildlife detection has advanced significantly with the integration of drones and deep learning models. Traditional manual monitoring is slow and prone to errors, whereas automated detection using UAVs and machine learning offers greater efficiency and accuracy.

Recent studies highlight various approaches: one study combined drones with machine learning for faster and more precise wildlife detection. ORACLE, an advanced computer vision model, demonstrated effective bird tracking from drone footage using a layered detection and tracking system. Another approach improved YOLOv5s to enhance wildlife detection in forest environments, reducing errors caused by complex backgrounds.

Thermal imaging has also been explored for wildlife monitoring. UAV-based thermal cameras and predictive navigation models help detect animals by identifying heat signatures, generating real-time maps for conservation efforts. Additionally, real-time detection using UAV-derived RGB and thermal images was tested, showing promising results but facing challenges like sensor resolution limitations.

These studies collectively emphasize the potential of drones and AI in wildlife monitoring, making conservation more efficient and less intrusive.

6 Methodology

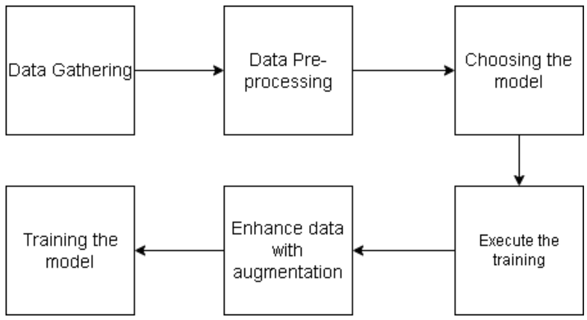

Figure 1: Flowchart

6.1 Preparing the Data Resizing Images:

Images were initially resized to 320×320 for consistency and then to 640×640 for enhanced clarity. Normalizing Pixel Values: Pixel values were scaled to the range [0, 1] to improve training efficiency. Augmenting the Dataset: Techniques like flipping, rotating, scaling, HSV adjustments, mosaic, mixup, and copy-paste were used to diversify the dataset and prevent overfitting. Caching for Speed: Images were stored in memory to accelerate the training process.

6.2 Choosing YOLOv9

Speed and Precision: YOLOv9 strikes a balance between fast processing and high accuracy, making it ideal for real-time applications. Advanced Capabilities: Its superior feature extraction is particularly effective for detecting small and diverse wildlife.

6.3 Training the Model

Model: YOLOv9
Training Parameters:
Epochs: Increased from 20 to 30 for better learning.
Batch Size: 16 for efficient processing.
Image Size: Scaled from 320×320 to 640×640.
Regularization: Weight decay set to 0.0005 to prevent overfitting.
Augmentation: Enabled to enhance generalization.
Optimizer: AdamW for efficient weight updates.
Learning Rate: Adaptive, starting at 0.01 and adjusting as needed.

6.4 Enhancing Data with Augmentation

Techniques such as flips, rotations, scaling, shearing, mixup, mosaic, and copy-paste were applied to create a more robust and varied dataset.

6.5 Execute the Training

The model was trained using the YOLOv9 architecture. Validation and Early Stopping: The model's performance was continuously evaluated, and training was halted if no improvement was detected.

7 Results and Performance

7.1 Loss Analysis

Training Loss: Decreased steadily, indicating effective learning. Both training loss (blue) and validation loss (red) decrease steadily over epochs. This indicates that the model is learning well and improving its ability to predict bounding boxes.

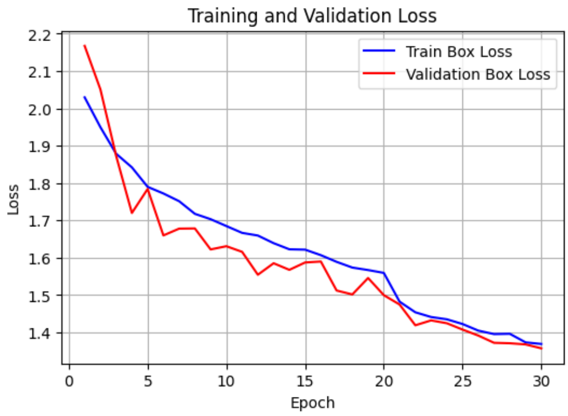

Figure 2: Training and Validation Loss Curves

Final Training Loss: 1.3692 Final Validation Loss: 1.3575

7.2 Precision Analysis

The precision steadily increases as training progresses, indicating that the model is learning to make more accurate predictions.

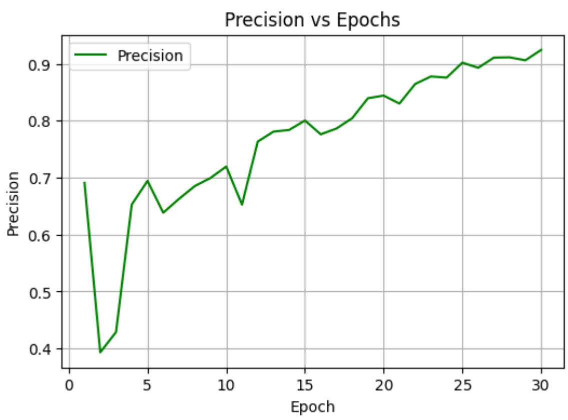

Figure 3: Precision vs Epoch

7.3 Recall Analysis

The recall steadily increases as training progresses, indicating that the model is learning to classify wildlife species more accurately with fewer misclassifications.

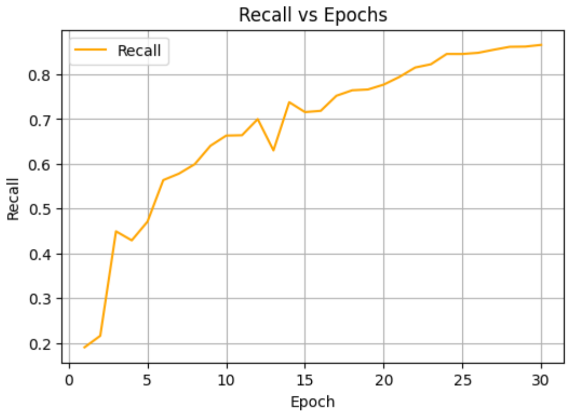

Figure 4: Recall vs Epoch

7.4 mAp50 Analysis

The mAP@50 steadily increases as training progresses, indicating that the model is improving its ability to accurately detect and classify wildlife species.

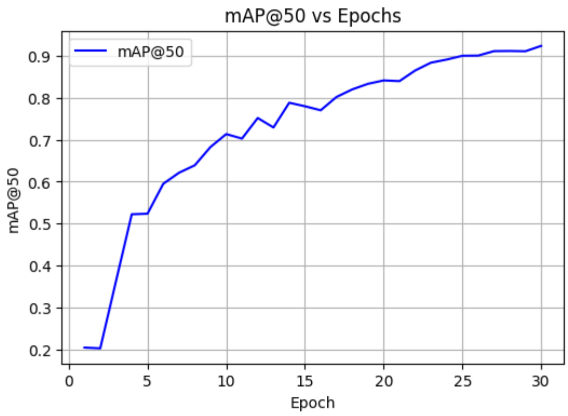

Figure 5: Recall vs Epoch

8 Conclusion

The training and validation loss are gradually decreasing, indicating that the model is learning well without overfitting. The precision and recall are both increasing, with precision reaching 90

9 Future Scope

Better Data Augmentation: Increase variations in lighting, angles, and backgrounds for better class generalization.

Experiment with different architectures for better detection performance and comparative analysis.