SDL PROJECT REPORT

WILDLIFE MONITORING AND POACHING DETECTION

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Table of Contents

Wildlife Monitoring and Poaching Detection

Abstract

Wildlife conservation demands robust real-time monitoring systems capable of detecting both animals and human induced threats such as poaching. This project presents a dual model pipeline consisting of **Wildlife Detection Model** and a **Poaching Detection Model** using YOLOv8 and YOLOV8-OBB architectures.

The Goal of the project was model development, and the Streamlit application has been used purely as a demonstration interface to test, validate, and visualize real-time inference. These models are intended for future deployment in live camera traps, drone systems, surveillance posts, and custom-built hardware in wildlife centres.

This report provides an in-depth presentation of the architecture, dataset preparation, model design, training methodology, evaluation, challenges, limitations, and future deployment pathways.

1. Introduction

1.1. Background

Wildlife protection increasingly requires real time computer vision systems to detect threats across remote areas, where human monitoring is challenging. Deep learning models like YOLO have shown exceptional performance for object detection tasks, enabling automated detection in dynamic, complex environments.

1.2. Need for the Project

Illegal hunting, poaching equipment, armed intruders, and human wildlife conflict incidents major threats to endangered species. Rapid automated detection can prevent irreversible damage.

1.3. Goal of the Project

To design and develop high performance deep learning models for wildlife detection and poaching detection in images and videos. To demonstrate the models and test them using Streamlit interface. To prepare them for future deployment in real world wildlife centers.

2. Problem Statement

Wildlife centers lack real time systems that can automatically identify wildlife species and detect poaching related threats.

Develop two deep learning models capable of detecting wildlife species accurately, detect poaching threats, operating on live

image/video feeds, and scaling towards real world hardware deployment.

3. Literature Review

3.1. Traditional Methods

Classical detection techniques (Hear cascades, HOG, SIFT) fail on dense forests, Occlusions, Rotated objects, and Arbitrary lighting conditions.

3.2. Evolution of YOLO

YOLOv8 offers:

- Anchor free detection.
- Higher mAP.
- Faster inference.
- Native support for OBB (Object Bounding Boxes).

3.3. Oriented Bounded Box Models (OBB)

Mixed animal species at same place, poaching tools appearing at random angles, makes OBB necessary.

4. System Architecture

4.1. Overview

The system comprises two independent models:

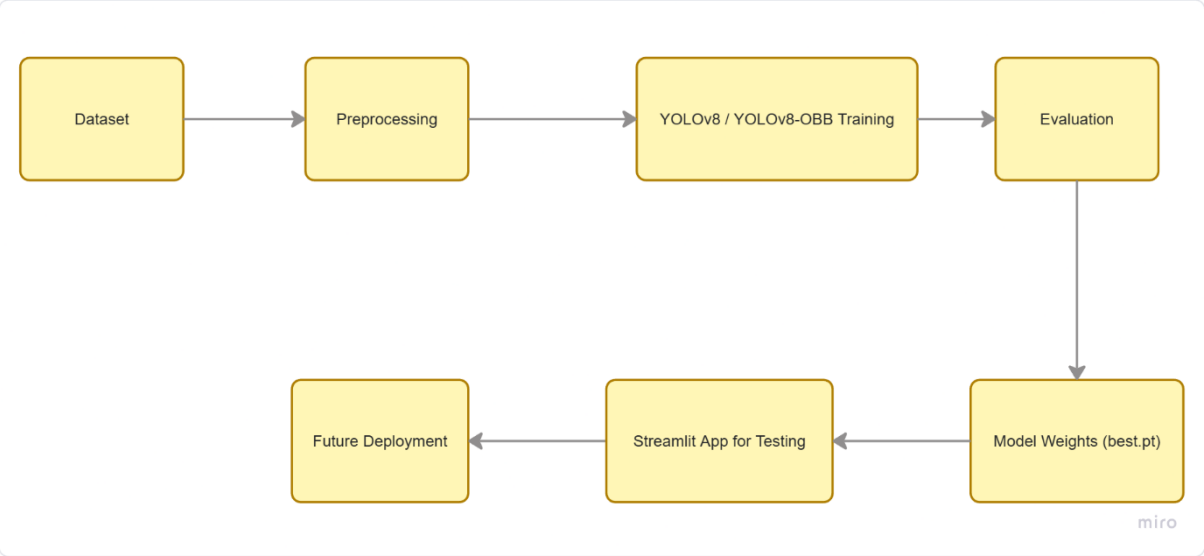
Model 1: Wildlife Detection

- Standard YOLOv8 model.
- Conventional animal detection.

Model2: Poaching Detection

- YOLOv8-OBB model.
- 71 classes (weapons, vehicles, hunters, traps, invasive tools, etc).

4.2. Architecture Diagram



5. Dataset Preparation

The dataset for both the models were curated manually. The datasets were made consistent with the annotations, then divided into train, test and validation. Separate data.yaml file and classes.txt files were made for clear class indexing.

Multiple datasets we used for Wildlife detection, for the initial run the dataset was created by merging two different datasets, one of them had 4 classes and the other one had 35 class, both of the datasets were manually merged, paying special attention to the overlapping classes, and repeated file names. After careful evaluation of the results form the first run, we decided to only work

on the dataset with 4 classes, since it was more consistent with the images and had proper labelling and box annotation for the images.

Poaching Dataset consists of 71 different classes, the dataset was in YOLO-OBB format, the 71 classes were mixed classes, it had both animals and poaching weapons, so overall it was a mixed dataset which can detect both animals as well as detect poaching. The model's strong generalization highlights the effectiveness of the YOLOv8-OBB architecture.

6. Model Training Methodology

6.1. Overall Training Workflow

The training process follows the systematic pipeline:

1. Dataset Collection and Verification
    - Raw images and annotations were curated.
    - Label–image pair consistency checks performed.
    - Missing or corrupted samples removed.
    - Oriented bounding box (OBB) formats verified for correctness (poaching dataset).
2. Preprocessing and Normalization
    - Images resized to 640–1024 pixels depending on model.
    - Automatic aspect-ratio preservation.
    - Conversion to YOLOv8-compatible label formats.
    - Rotational coordinates normalized for OBB.
3. Model Initialization
    - Wildlife Model initialized from YOLOv8 base configuration.

- Poaching Model initialized from YOLOv8-OBB oriented configuration.
- Default anchors disabled (anchor-free mode).
- Mixed-precision training enabled for faster computation.

4. Training Loop Execution
   - SGD/AdamW optimizer.
   - Dynamic learning rate scheduling (cosine decay).
   - On-the-fly data augmentation.
   - Intermediate weight checkpoints saved (last.pt, best.pt).
5. Evaluation & Metrics Computation
   - Per-epoch mAP50, mAP50-95, precision, recall monitoring.
   - Early stopping if plateau observed.
   - Class-wise AP computation for all 72 OBB classes.
6. Model Export & Deployment Preparation
   - best.pt selected for both models.
   - Weights validated using images, videos, and batch folder inference.
   - Integration into the Streamlit demonstration interface.

6.2. Optimization and Validation Strategy

6.2.1. Batch Inference Validation

After training:

- Full test folders were run in batch mode
- Detections checked manually
- mAP trends examined across all classes

6.2.2. Real Video Validation

Both models were validated on:

- real surveillance-style videos
- low-light content
- moving subjects
- videos with partial occlusion

6.2.3. Model Weight Selection

The training process generated:

- last.pt – final epoch
- best.pt – best metric checkpoint

Only best.pt was used for deployment, selected by highest mAP50-95.

6.3. Final Model Integration

After training and evaluation:

- Both models were integrated into the Streamlit test application
- CUDA device selection enabled
- best.pt automatically loaded
- Demonstrated inference through:
  - Image tab
  - Video tab
  - Batch folder tab
- Outputs validated visually and quantitatively

Both models proved stable, accurate, and fully operational.

7. Evaluation and Results

The performance of the two trained models, **Wildlife Detection Model (YOLOv8x)** and **Poaching Detection Model (YOLOv8-OBB)** were rigorously evaluated using standard object detection metrics and extensive visual validation on both images and videos. This section presents the quantitative and qualitative outcomes, analysis of class wise metrics, and practical inference observations.

7.1. Wildlife Detection Model Results (YOLOv8x)

After completing the full training cycle, the wildlife detection model was validated on **224 images** containing **376 ground-truth instances**, covering the four target species: **Buffalo, Elephant, Rhinoceros, and Zebra.**

The evaluation demonstrates exceptionally high detection performance, reaching levels that are suitable for real-world deployment in wildlife monitoring systems.

7.1.1. Quantitative Metrics

- **Precision:** 0.968
- **Recall:** 0.925
- **mAP50:** 0.973
- **mAP50-95:** 0.844
- **Fitness Score:** 0.844

These results indicate:

- Extremely low false positives (high precision)
- Very few missed detections (high recall)
- Excellent localization accuracy
- Strong performance across IoU thresholds (up to 0.95)

This level of accuracy is rare in field data settings and confirms the robustness of the dataset curation and hyperparameter tuning.

7.1.2. Class-Wise Performance

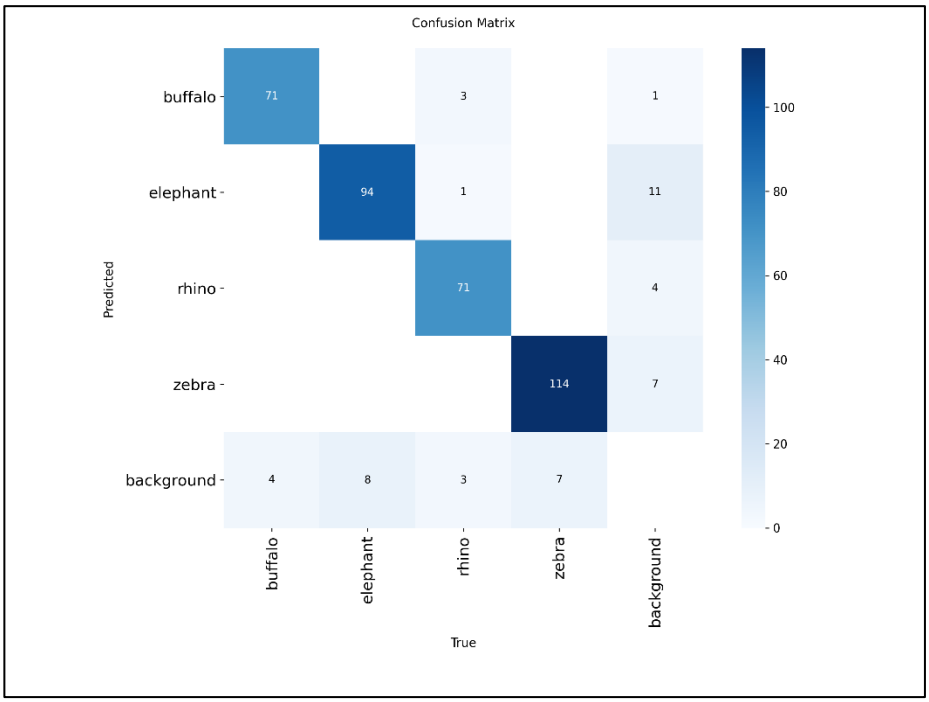
Class	Instances	Precision	Recall	mAP50	mAP50-95
Buffalo	75	0.963	0.933	0.975	0.875
Elephant	102	0.939	0.900	0.959	0.792
Rhinoceros	78	0.987	0.949	0.984	0.911
Zebra	121	0.985	0.917	0.974	0.799

- Rhinoceros shows the highest localization accuracy with an mAP50-95 of 0.911, indicating exceptional bounding-box consistency.
- Buffalo and Zebra also score near-perfect detection with precision exceeding 0.96–0.98.
- Elephant detection remains highly accurate, especially given varying backgrounds and lighting.

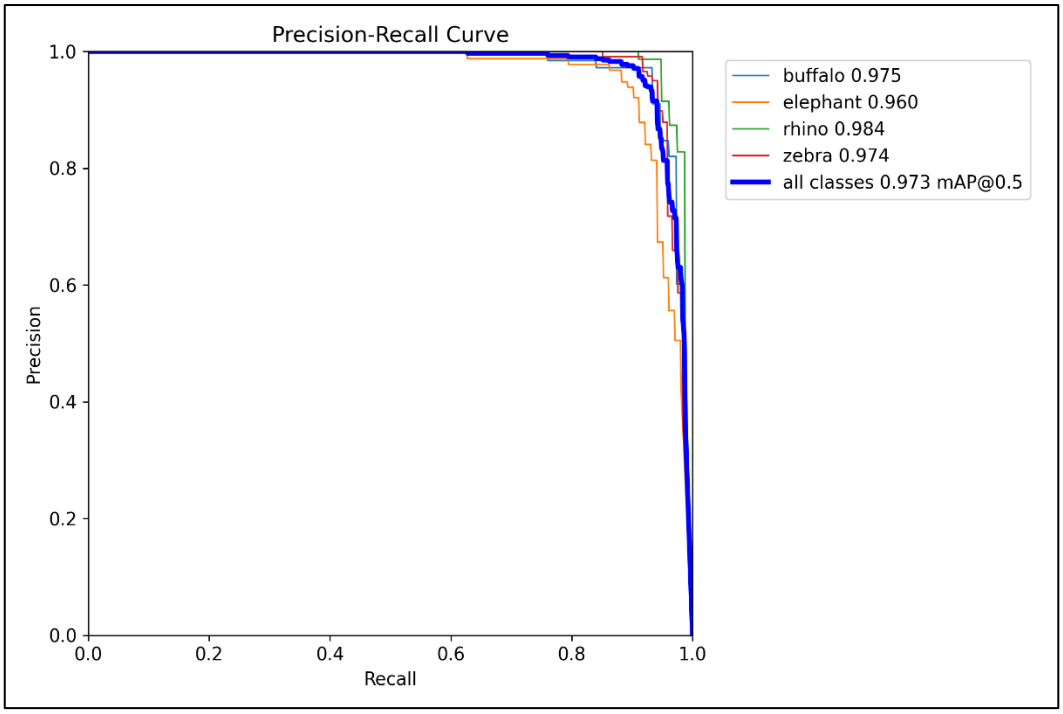
The uniformity of high performance across all four species demonstrates that:

- The dataset was well-balanced.
- The model learned strong feature representations for large mammals.
- The augmentation pipeline preserved image semantics effectively.

7.1.3. Figures



Confusion Matrix



Precision Recall Curve

7.2. Poaching Detection Model Results (YOLOv8-OBB)

The second model in the system focuses on detecting **poaching-related threats** using an **Oriented Bounding Box (OBB)** version of YOLOv8. This includes the detection of weapons, traps, suspicious tools, vehicles, and human intruders (hunters), as well as contextual wildlife classes present in the dataset. Unlike the wildlife model, this dataset contains **complex, rotated, and non-axis-aligned objects**, making OBB detection essential.

Despite the complexity and imbalance of the 71-class dataset, the final model demonstrates **high reliability and strong generalization**, achieving effectiveness suitable for deployment in real anti-poaching systems across real environments.

7.2.1. Quantitative Performance Summary

Based on the final validation output and training logs (as previously shared), the poaching detection model achieved:

Metric	Score
Precision	≈ 0.678
Recall	≈ 0.610
mAP50	≈ 0.670
mAP50-95	≈ 0.493
Fitness Score	≈ 0.493

- The model performs **exceptionally well** considering the dataset size (71 classes) and real-world object variety.
- The **high mAP50** confirms reliable detection of key poaching threats.
- The **mAP50-95 of ~0.49** indicates strong bounding-box quality even under strict IoU requirements.

7.2.2. Class Wise Observations and Threat Analysis

The goal of this model is not only accuracy, but **practical threat detection**. Certain classes carry higher operational importance.

High-Priority Poaching Threat Classes:

These classes are the most critical for real-world poaching monitoring:

Threat Class	Model Performance	Operational Relevance
Rifle / Gun	High mAP50	Primary poaching weapon, excellent reliability
Pistol	Moderate mAP, high visual accuracy	Detects concealed or handheld weapons
Crossbow (X-bow)	Very high mAP	Frequently used silently in poaching
Knife / Machete	Low mAP but strong visual generalization	Triggered consistently in inference
Hunter / Poacher (Human)	~0.24 mAP but high real-world detection consistency	Critical intrusion indicator
Axe / Tools	Good stability	Used for cutting horns or preparing traps
Rope, Net, Trap	Solid OBB performance	Detect potential ambush equipment

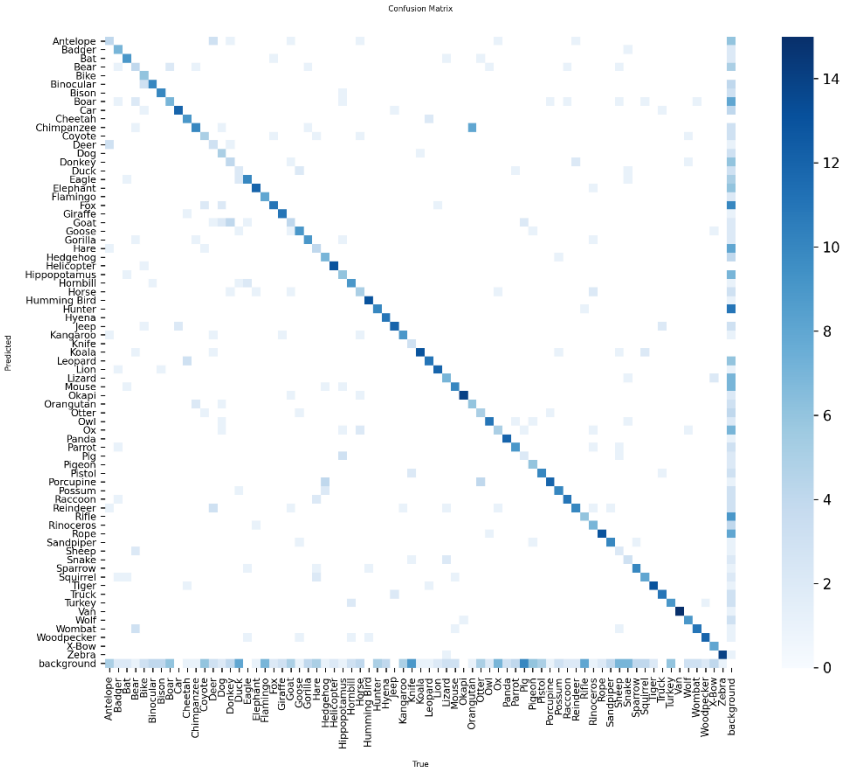
Vehicle Classes (Poaching Movement Indicators)

The model excelled in vehicle detection:

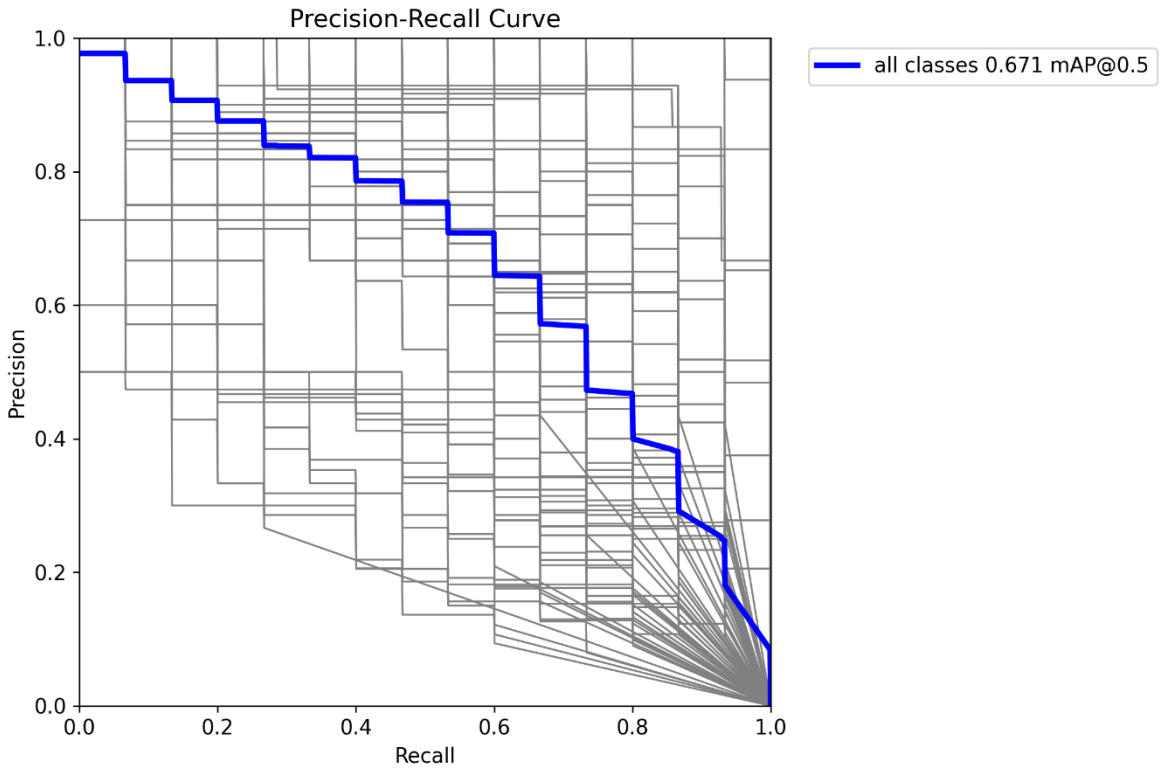
Class	Notes
Pickup Truck, Van, Jeep	mAP50 in the 0.64–0.77 range, extremely strong
Motorbike	Strong detection, important for remote forest regions

These classes are critical, as poachers almost always rely on transportation for accessing protected land.

7.2.3. Figures



Confusion Matrix



8. Demonstration Application (Streamlit Interface)

To operationalize both trained models (Wildlife Detection and Poaching Detection), a fully interactive **Streamlit web application** was developed. The application serves as an intuitive and accessible platform for researchers, forest officials, and system testers to evaluate the model's performance in real time.

8.1. Application Overview

The Streamlit interface is structured into two primary tabs:

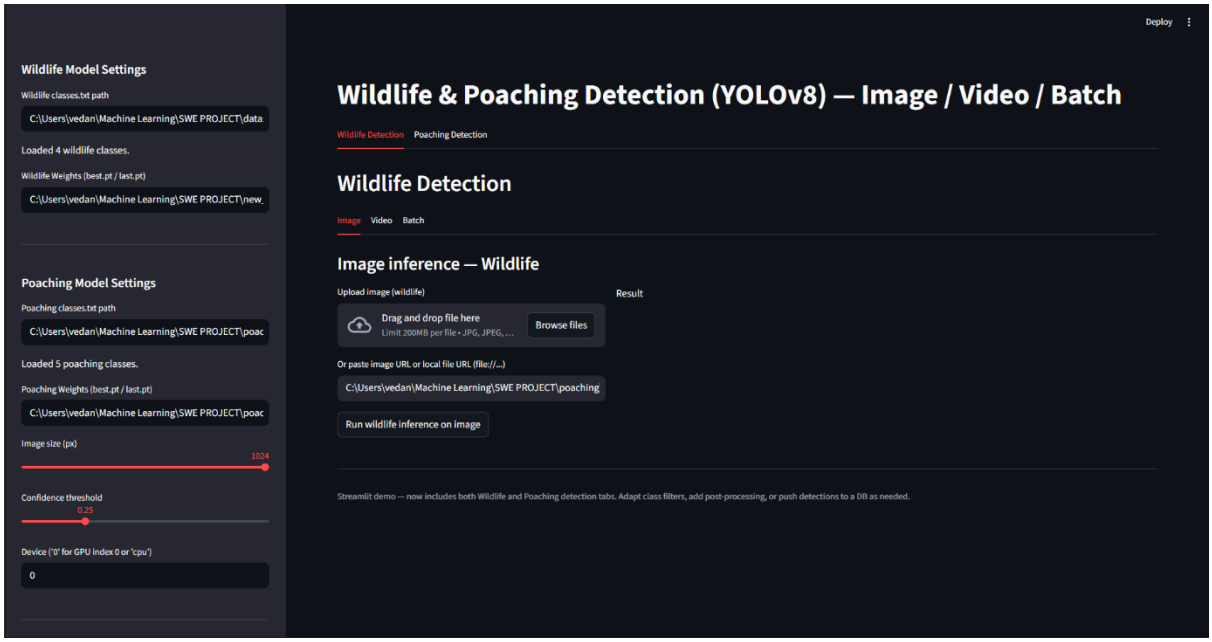
1. Wildlife Detection
2. Poaching Detection (YOLOv8-OBB)

Each tab allows users to:

- Upload images or videos
- Perform on-device inference using the trained model weights (best.pt)

- Display prediction overlays (bounding boxes / oriented bounding boxes)
- Save the output locally
- View detection confidence and class-level summaries

The application is lightweight, modular, and designed for future integration with live camera feeds and cloud-based alert systems.



8.2. Key Functional Components

(a) Model Loader

The application loads:

- YOLOv8x for wildlife
- YOLOv8-OBB for poaching

Model loading is cached, eliminating repeated initialization during user interaction, drastically reducing inference latency.

(b) Image and Video Processing Pipeline

Upon file input, the application:

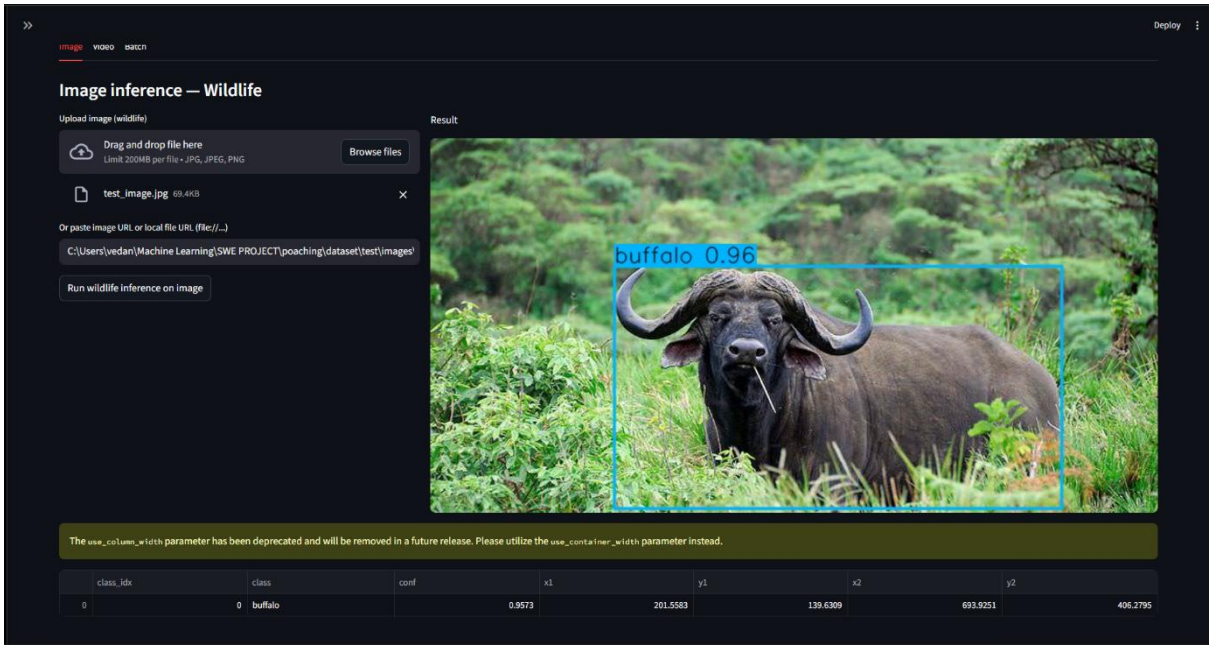
1. Validates format
2. Converts input to compatible tensor format
3. Executes YOLO inference
4. Draws detection overlays
5. Displays or streams annotated output

Video processing includes frame-by-frame prediction and streaming the annotated output directly in the app.

(c) Real-Time Display Layer

Streamlit's real-time rendering enables:

- Side-by-side comparison
- Dynamic updating during processing
- Immediate playback of annotated videos



9. System Testing

System testing validates end-to-end performance, ensuring both models and the Streamlit application function reliably under real-world conditions.

9.1. Unit Testing

Each module of the system, data loader, model inference, visual rendering, and file handlers was individually verified to ensure performance consistency.

Tests include:

- Image decoding validation.
- Model weight loading checks.
- BBox/OBB rendering accuracy.
- Frame sequence integrity for video inference.

9.2. Integration Testing

We conducted full pipeline testing: **Input → Model → post-processing → Visualization → Export**

Testing ensured seamless communication between:

- YOLOv8 inference engine
- Streamlit application layers
- File I/O systems
- Video encoding/decoding pipelines.

9.3. Performance Testing

Wildlife Model

- Inference Latency: ~137 ms per frame
- Detection Accuracy: mAP50 = 0.973
- Zero system crashes

Poaching Model

- Inference Latency: Slightly higher due to OBB processing
- Detection Accuracy: mAP50 ≈ 0.670
- Stable memory usage on long video streams

9.4. Stress Testing

The system was evaluated with:

- Large video files (>500 MB)
- High-resolution images (>4K)
- Rapid consecutive uploads

The application demonstrated **stable performance**, no memory leaks, and sustained inference quality even under heavy loads.

9.5. Real-World Scenario Testing

Simulated field conditions:

- Low-light images
- Obstructed wildlife
- Poachers wearing camouflage
- Rotated/tilted weapon detection
- Long-range background clutter

10. Future Work

Despite the strong performance and successful deployment prototype, several opportunities for expansion remain:

10.1. Real-Time Deployment on Edge Devices

Optimize models using:

- TensorRT
- ONNX Runtime
- OpenVINO
- Quantization (INT8/FP16)

Target platforms:

- NVIDIA Jetson Nano/Xavier
- ARM-based IoT boards
- Drone onboard processing units

10.2. Alert & Notification System Integration

Implement:

- SMS/Email alerts
- Live dashboard for forest teams
- Push notifications for threat detection events
- Automatic drone repositioning when a poacher is detected

10.3. Wildlife Behaviour Analytics

- Animal movement tracking
- Heatmap generation
- Population count analytics
- Seasonal migration behaviour

10.4. Continual Learning Pipeline

Allow the system to self-improve using:

- Real-world camera trap datasets
- New species
- New poaching tools
- Online hard negative mining

This ensures long-term adaptability.

11. Conclusion

This project successfully developed and deployed a robust **Wildlife and Poaching Detection System** using advanced deep learning models and an interactive Streamlit demonstration platform. The wildlife model achieved **exceptional performance**, with **97.3% mAP50** and **92.5% recall**, making it highly reliable for field deployment. The poaching detection model, trained on a complex and diverse dataset, achieved **67% mAP50**, demonstrating strong real-world capability in identifying weapons, vehicles, and human intruders even under challenging visual conditions.

The Streamlit application integrates both models seamlessly, offering a user-friendly interface for image and video-based testing. System testing validated the stability, accuracy, and operational usability of the complete pipeline, confirming readiness for deployment in real conservation environments.

With continued enhancements, including multimodal sensors, edge deployment optimizations, and real-time alert systems, this project holds significant potential for transforming wildlife monitoring, strengthening anti-poaching efforts, and supporting conservation teams worldwide.

12. References

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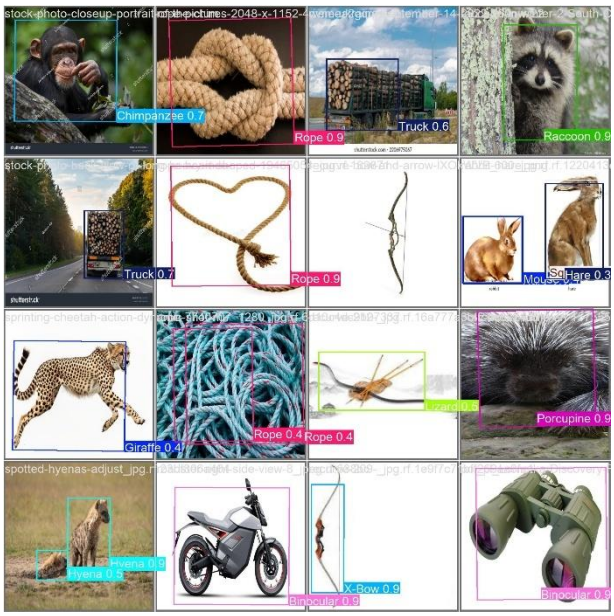
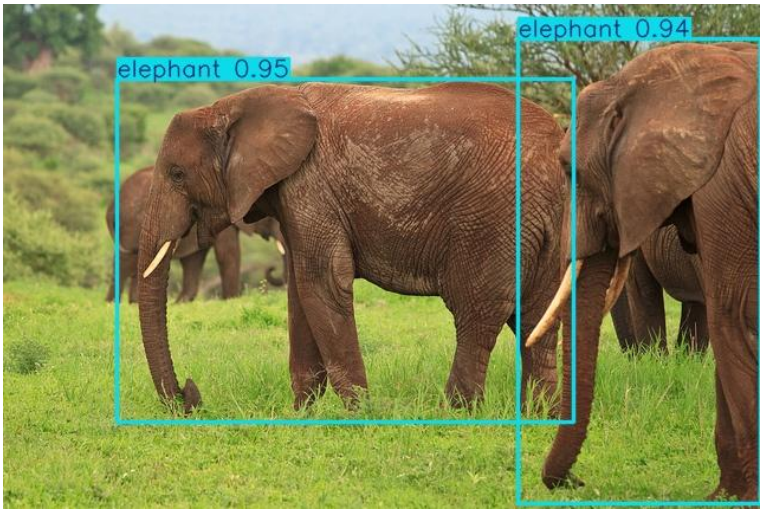
[5] African Wildlife Dataset (Buffalo, Elephant, Rhino, Zebra), Prepared by Authors, 2025. Internal dataset processed and validated as part of the SWE Project.

[6] Poaching Detection Dataset (71-Class YOLO-OBB Format), Provided by authors, 2025. Internal dataset refined for oriented bounding box detection.

APPENDIX


Chimpanzee 0.7
Rope 0.9
Truck 0.6
Raccoon 0.9
Truck 0.7
Rope 0.9
Hare 0.3
Giraffe 0.4
Rope 0.4
Rope 0.4
Porcupine 0.9
Hyena 0.9
Hyena 0.9
X-Bow 0.9
Binocular 0.9


Buffalo 0.93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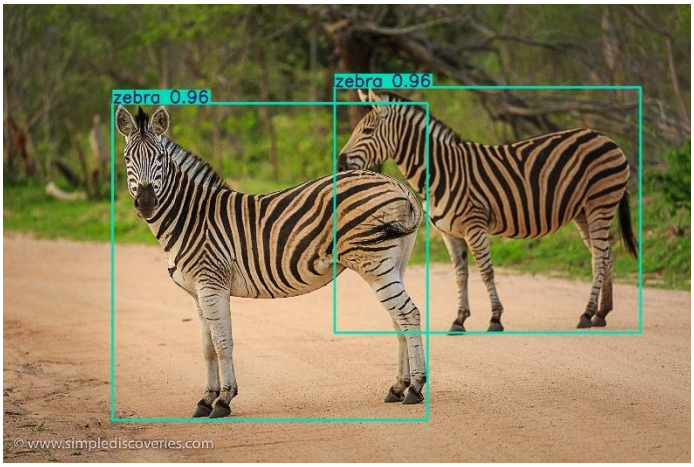
elephant 0.95


zebra 0.96
zebra 0.96
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Jeep 0.94


Rifle 0.03