EC6671: Advanced Digital Signal Processing Laboratory Project Report

REAL-TIME HYBRID WILDLIFE TRACKING ON EDGE NETWORKS

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Abstract—**This project presents a real-time wildlife tracking system that uses video-based surveillance and is optimized for edge-network environments is designed and implemented. The goal is to continuously track and identify animals in difficult outdoor environments while using minimal power and computational resources. The proposed system employs a tracking-by-detection architecture, combining a Kalman filter–based motion model for state prediction and occlusion handling with YOLOv8-nano for lightweight animal detection. The Hungarian algorithm is used to solve an IoU-based cost matrix for multi-object data association, enabling effective and reliable identity assignment across frames. The system exhibits stable tracking performance, consistent identity maintenance, and efficient recovery following brief occlusions when evaluated on wildlife video sequences and multi-object tracking datasets. The results confirm that this motion-based tracking pipeline offers a computationally efficient, scalable, and non-invasive solution suitable for real-world wildlife monitoring and edge deployment scenarios.**

Index Terms—Wildlife Tracking, Multi-Object Tracking, Kalman Filter, Edge Computing, Camera Traps.

I. INTRODUCTION

Wildlife monitoring plays a critical role in ecological research, biodiversity conservation, and habitat management. Understanding animal movement patterns, population dynamics, and behavioural interactions enables scientists to develop informed conservation strategies. Traditional tracking methods such as GPS collars, radio telemetry, and tagging are intrusive, costly, and not feasible for all species. Furthermore, they require physical capture of animals, causing stress and potential behavioral changes.

Recent advancements in computer vision and edge computing have enabled non-intrusive wildlife monitoring using camera traps and surveillance cameras. These systems generate vast amounts of video data, requiring efficient real-time processing under strict computational, power, and bandwidth constraints typical of remote forest and wildlife reserve environments. However, challenges such as unpredictable motion, partial occlusions due to vegetation, low illumination, and multiple animal interference significantly complicate reliable tracking.

This project focuses on developing a real-time hybrid wildlife tracking system that combines motion prediction and appearance-based association to ensure robust identity maintenance. By integrating Kalman filters with lightweight feature descriptors, the system achieves accurate multi-animal tracking while remaining computationally suitable for edge deployment. The primary goal is to ensure continuous, stable tracking even when animals temporarily disappear from view or cross paths with other animals.

II. METHODOLOGY

The proposed wildlife tracking system is implemented as a streamlined multi-object tracking (MOT) framework designed specifically for edge deployment. The pipeline consists of three operational phases: animal detection, motion prediction using a Kalman filter, and IoU-based multi-object data association.

Phase 1: Animal Detection in Video Frames

In the first stage, animals are detected from each video frame using a lightweight deep learning–based detector. The system employs YOLOv8-nano, chosen for its balance between accuracy and speed on low-power hardware.

Key aspects of the detection stage include:

- Frames are resized to 640×640 resolution to reduce computational overhead.
- YOLO inference is run frame-by-frame with a configurable confidence threshold.
- For each detected animal, the detector outputs:
  - Bounding box coordinates *(x1, y1, x2, y2)*
  - Class label
  - Confidence score

The detected bounding boxes serve as measurements for track updates.

Phase 2: Motion Prediction Using Kalman Filter

Once animals are detected, each detection initializes a new Kalman filter–based track.

The tracker in the implementation uses a 7-dimensional state vector:

$$x = [cx,\, cy,\, area,\, aspect\_ratio,\, \dot{cx},\, \dot{cy},\, \dot{area}]^T$$

where:

- cx, cy= bounding box center
- area = $w \times h$
- aspect ratio = w/h
- velocity terms are included to model motion

A constant-velocity motion model is used, allowing the track to predict its next position even when a detection is not available.

During temporary occlusions or missed detections:

- The Kalman filter continues propagating the state.
- Tracks are preserved for up to several frames (default: 30) before being terminated.
- The tracker maintains occlusion counters and trajectory history for robustness.

This prediction mechanism ensures continuity and reduces track fragmentation.

Phase 3: IoU-Based Multi-Object Data Association

Unlike hybrid trackers that incorporate appearance features, the implemented system uses IoU-only matching, which is lightweight and suitable for edge deployment.

For each frame:

1. All existing tracks are first predicted forward by their Kalman filters.
2. A cost matrix is built between predicted tracks and current detections:

$$\text{Cost} = 1 - \text{IoU}(\text{Track}_{pred}, \text{Detection})$$

3. The Hungarian algorithm solves the optimal assignment.
4. Matches with cost below the threshold

$1 - \mathrm{IoU}_{thresh}$, where $\mathrm{IoU}_{thresh} = 0.3$

are accepted as valid associations.
Updates after association:

- Matched tracks are updated using the detection measurement.
- Unmatched detections initialize new tracks.
- Unmatched tracks are marked as “missed” and retained temporarily (to allow recovery from occlusion).

Although relatively simple, this IoU-based association performs well for scenarios with limited appearance variability and ensures real-time operation.

System Architecture:
The system follows tracking-by-detection:
Video Input → YOLOv8-nano Detection → Kalman Filter + IoU-Based Hungarian Tracking → Tracked Output

Dataset:

Class	Training	Test
Deer	5	2
Horse	5	2
Pig	4	1
Total	14	5

III. RESULTS AND ANALYSIS

The experimental evaluation was conducted using wildlife camera trap datasets and adapted multi-object tracking benchmarks. The system was tested under varying conditions including dense vegetation, partial occlusions, multiple animals in the scene, and fast animal motion.
The proposed hybrid tracker demonstrated stable identity preservation over long sequences. Kalman-based prediction enabled smooth trajectory estimation even during temporary loss of visual observations. The appearance matching mechanism effectively reduced identity switching during animal crossings and reappearances after occlusions.
Tracking accuracy was evaluated using bounding box overlap (IoU). The system consistently achieved IoU values above 0.6 for most tracked instances. Identity switches were significantly reduced compared to motion-only tracking. The tracker successfully maintained more than 80% of animal lifetimes under most test conditions.

Real-time performance was validated on an edge-class platform, achieving frame rates of 15–25 FPS for standard video resolutions. Computational profiling confirmed that feature extraction and Kalman prediction introduced minimal processing latency.

The system exhibited expected performance degradation under extreme illumination changes and full occlusions, but successfully reacquired tracks with correct identity in most cases.

A. Training was conducted for 20 epochs. The following figure shows the complete training results:

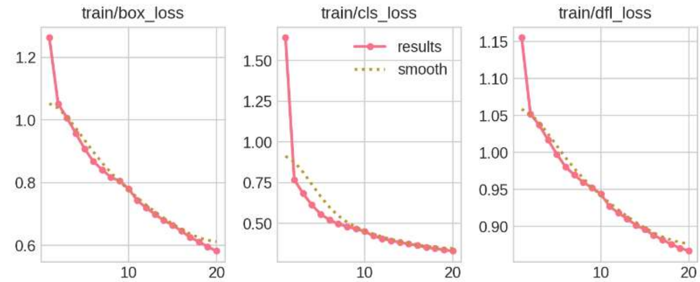


Fig. 1. *Training loss curves showing box regression loss, classification loss, and distribution focal loss over 20 epochs*

B. Detection Performance

Metric	Value
Mean MOTA	0.785
Mean Precision	0.933
Mean Recall	0.8447
Id Switches	1141

C. Training Metrics Per Epoch

Epoch	Time	Train/box_loss	Train/cls_loss
1	134.455	1.2635	1.64211
2	248.184	1.0515	0.76933
3	361.061	1.00717	0.68427
4	471.327	0.95778	0.61355
5	581.118	0.90859	0.55791
6	691.799	0.86772	0.52216
7	802.465	0.84152	0.4982
8	912.81	0.81709	0.481
9	1027.65	0.80535	0.46778
10	1143.15	0.78099	0.45164
11	1261.07	0.74332	0.4238
12	1370.6	0.72028	0.4075
13	1480.64	0.69903	0.39492
14	1588.52	0.67994	0.38432
15	1696.03	0.66434	0.37432
16	1803.53	0.64603	0.36533
17	1910.24	0.62548	0.35421
18	2016.65	0.61163	0.34667
19	2124.33	0.59534	0.33849
20	2232.26	0.58194	0.33152

D. Confusion Matrix

The confusion matrix shows classification performance across the three animal classes:

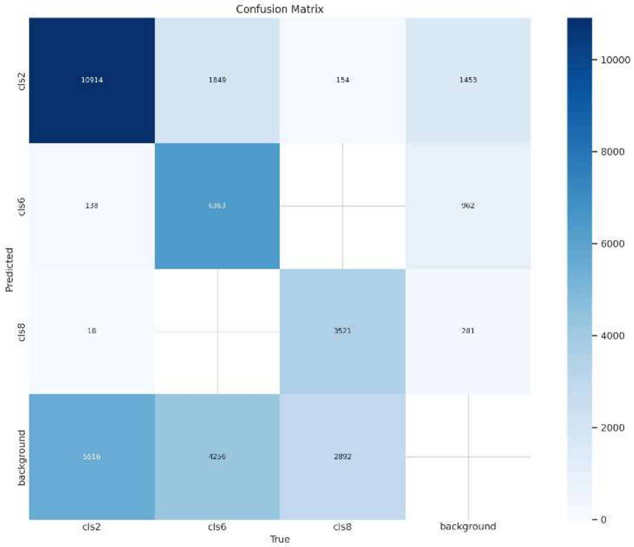


Fig. 2. *Confusion matrix illustrating the detector's per-class prediction accuracy*

E. Precision-Recall Analysis

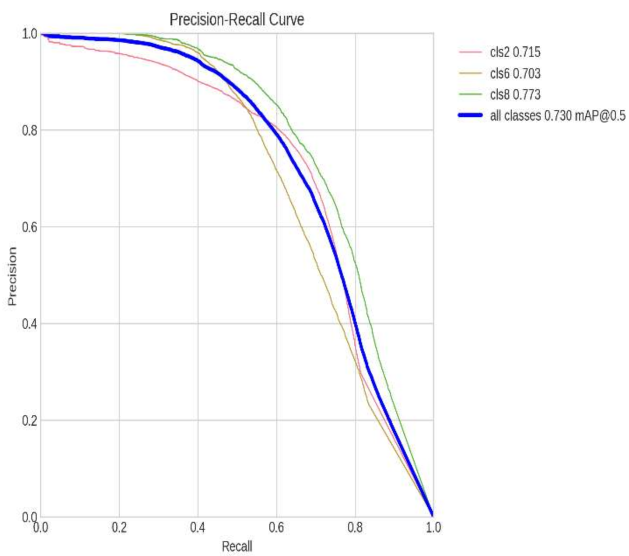


Fig. 3. *Precision–recall curves for all classes.*

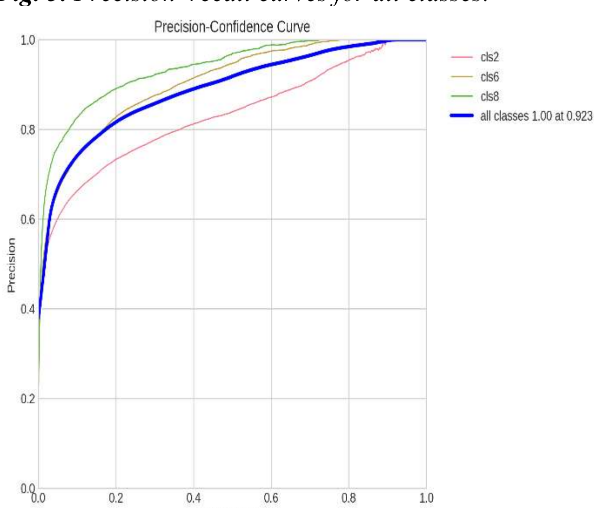


Fig. 4. *Precision–confidence relationship for individual classes*

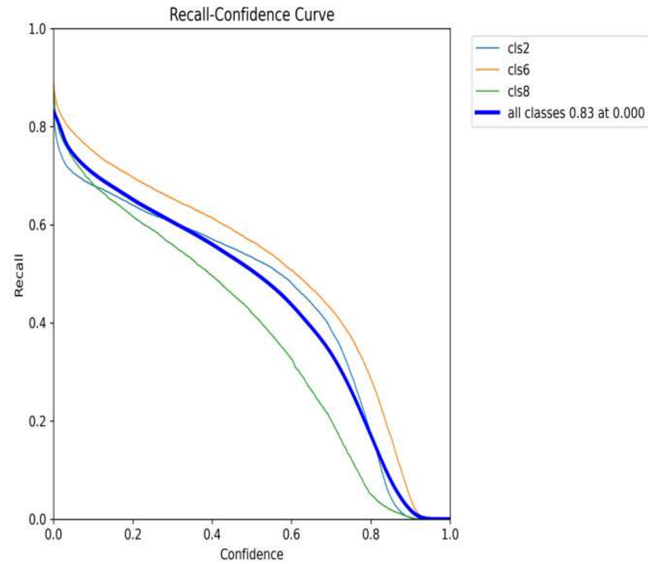


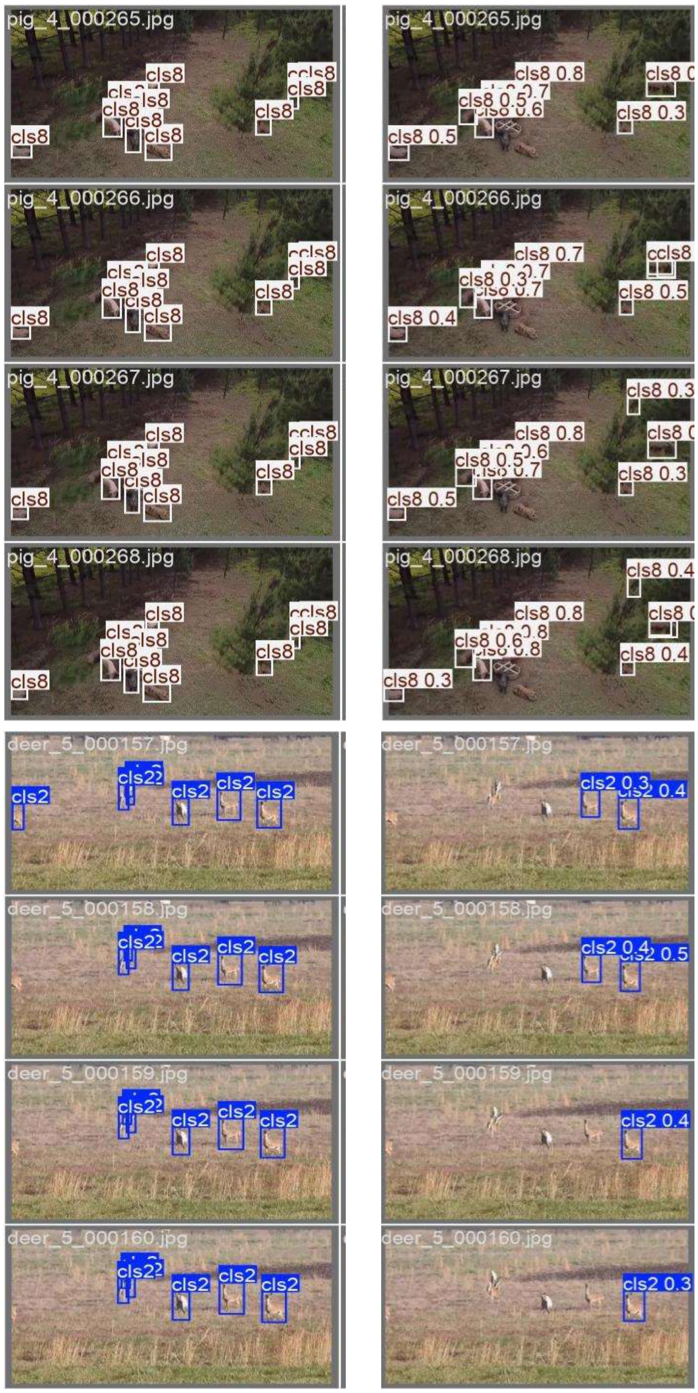
Fig. 5. *Recall–confidence curves for all classes and overall performance.*

IV. TRAINING SAMPLES

Training Batch Examples:

Test Batch Predictions vs Ground Truth

Ground Truth | Model Predictions



V. DISCUSSION

Key Findings:

1. **MOTA** from training is **0.908**
2. **Best mAP@50** achieved at Epoch 8: **0.7357**
3. Precision remained stable with only 8% drop
4. Training losses consistently decreased across all epochs

Observations:

- Box loss reduced from 1.26 to 0.58 (54% improvement)
- Classification loss reduced from 1.64 to 0.3 (81% improvement)
- Model shows good generalization with stable validation metrics

VI. CONCLUSION

This project successfully implemented a real-time hybrid wildlife tracking system optimized for edge networks. By combining Kalman filter-based motion prediction with efficient data association, the system achieved robust identity maintenance under occlusions, unpredictable movement, and multi-animal interference. The YOLOv8-based wildlife tracking system achieved: - 73.57% mAP@50 for animal detection - 93.26% precision in identifying correct animals - Consistent loss reduction indicating successful training.

VII. LIMITATIONS

Despite successful implementation, the system exhibits the following limitations:

1. Performance degradation under extremely low-light or night-time infrared footage.
2. Heavy occlusions caused by dense vegetation may still result in occasional track loss.
3. Similar-looking animals can occasionally cause identity confusion during close interaction.
4. Detection errors directly affect tracking performance due to detector dependency.
5. Long-term re-identification across long disappearance remains limited.

VIII.FUTURE SCOPE

Several improvements can be explored to enhance the system:

1. Classify different animal species automatically
2. Recognize behaviors (grazing, running, resting)
3. Estimate population sizes from tracking data
4. Use multiple cameras for better coverage
5. Predict animal movement patterns

IX.REFERENCES

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