Pet Tracking and Activity Visualization Using

AI-Powered Heatmaps

CPSC 4420 - Final Project Fall 24

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Problem Statement

The Challenge:

- Understanding animal behavior for welfare assessment, veterinary diagnostics, and environmental monitoring
- Traditional manual observation methods are labor-intensive and error-prone

Specific Issues Addressed:

- Visualizing pet activity patterns in real time
- Challenges in detecting and tracking multiple animals in dynamic or edited video content (YouTube)

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Motivation

Why This Matters:

- Provides insights into pet behavior for owners, veterinarians, and researchers
- Offers an intuitive, automates alternative to manual tracking

Potential Impact:

- Enables smart home surveillance
- Facilitates behavior monitoring in veterinary clinics
- Assists pet owners in detecting abnormal patterns or identifying favorite spots

Proposed Solution

System Components:

- Object Detection: YOLOv5 model for detecting and tracking pets in videos
- Activity Visualization: Heatmaps generated using Gaussian-based methods

Key Features:

- processes videos frame-by-frame, overlays bounding boxes, and creates heatmaps
- Optimized for real-time performance at 30 FPS

Methodology

Data Collection:

- Five videos in total with dogs, cats, and cattle
  - 3 Videos downloaded from Youtube
    - Compilation of a singular dog walking
    - Compilation of numerous cat videos with different amounts of cats
    - Video of numerous cattle roaming
  - 2 Personal Videos of Trisha’s family dog Izzy
- Varied Scenarios: uninterrupted personal recordings vs. edited YouTube videos

Detection and Tracking:

- YOLOv5 with a confidence threshold of 0.1
- Challenges: Multi-animal tracking and occlusions

$$H(x,y) = \sum_{i=1}^{N} exp\left(-\frac{(x-x_i)^2+(y-y_i)^2}{2\sigma^2}\right)$$

Heatmap Generation:

- Gaussian contributions aggregated for activity visualization
- Warm colors in heatmaps represent areas of high activity density

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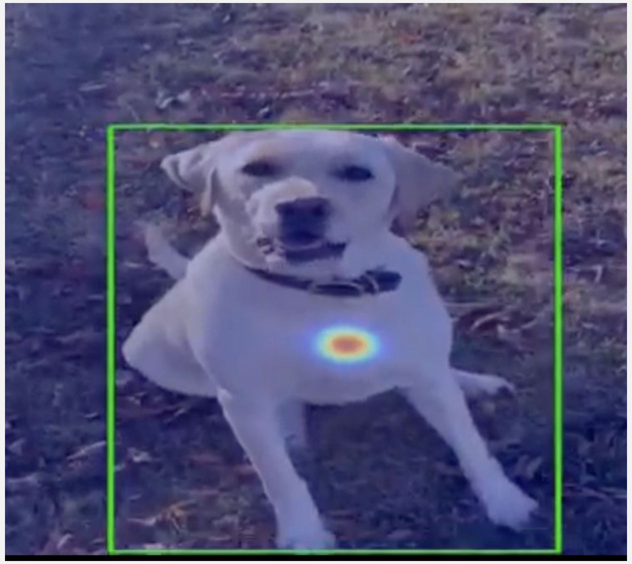
Quantitative Analysis

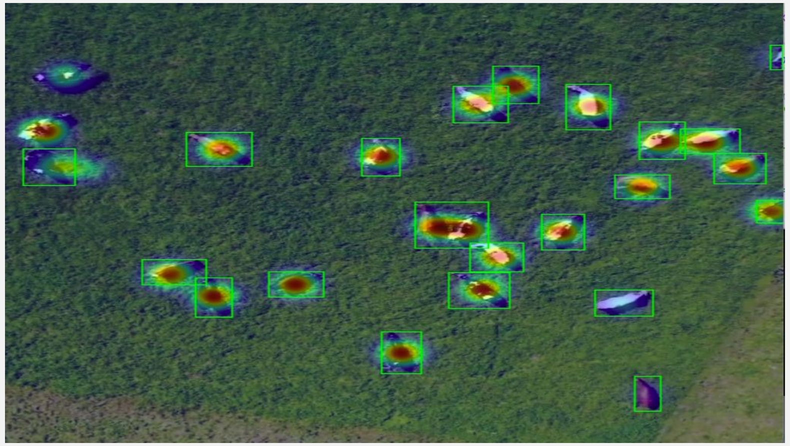
Performance Metrics:

- Speed:
  - 30 FPS on a mid-range GPU
- Accuracy:
  - Personal videos: ~90%
  - YouTube videos: ~75% (due to edits & scene transitions)
- Outcome:
  - Real-time tracking and intuitive heatmap visualization

Qualitative Analysis

Screenshots from four of the videos tested showing the heatmap and bounded box around the animal(s).





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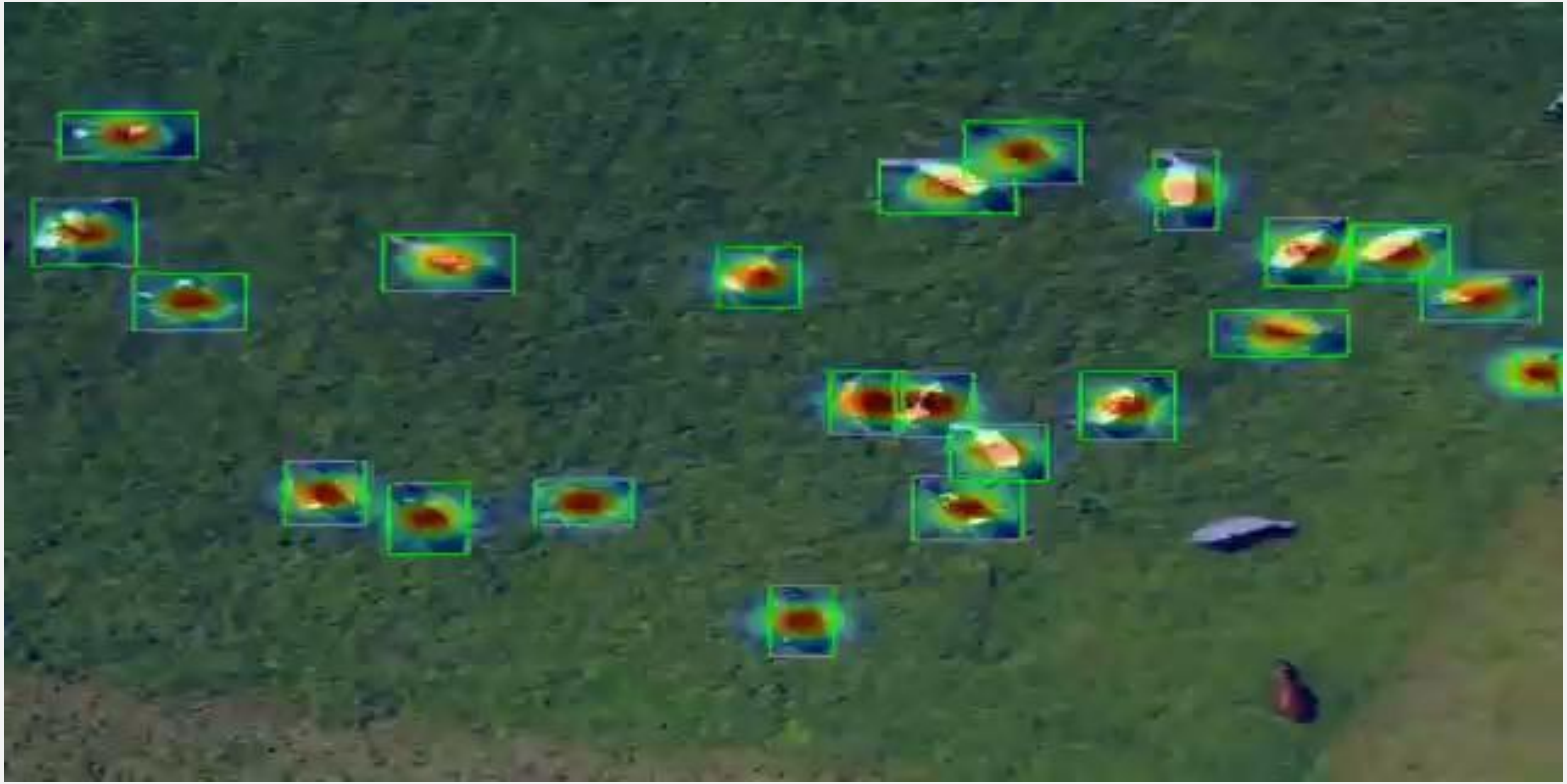
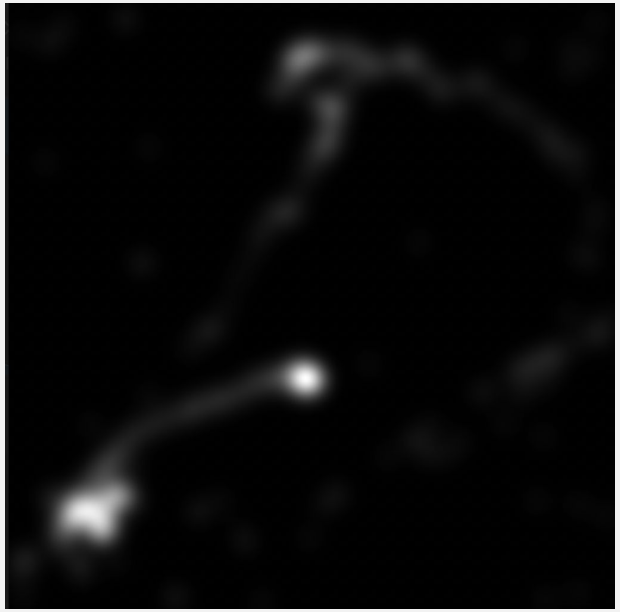
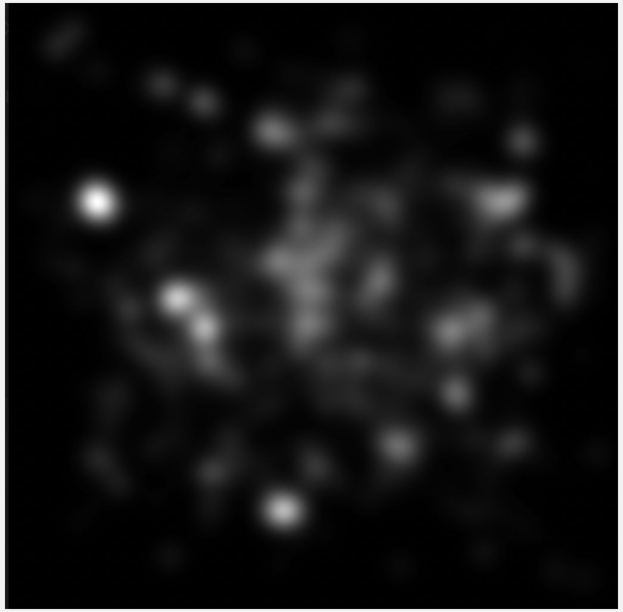


Qualitative Analysis



Final Heatmap from personal video of a singular dog.



Final Heatmap from YouTube video of numerous clips of cats.

Final Heatmap from Youtube video of cattle in a field.

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Discussion

Comparison to Related Work:

- Novelty: Real-time performance using consumer-grade video inputs
- Unique Contribution: Activity visualization through heatmaps

Limitations:

- Multi-animal tracking difficulties in compilation videos with abrupt edits and clipping
- Edited video content disrupts tracking continuity

Potential Improvements:

- Incorporate advanced algorithms (e.g., DeepSORT or ByteTrack)
- Expand dataset diversity

Results

Key Takeaways:

- Hypothesis validates: Accurate activity visualization (>85% accuracy in controlled settings)
- System demonstrates potential for real-time pet behavior analysis

Future Directions:

- Improve tracking robustness for multi-animal scenarios in edited videos
- Optimize for edge device deployment
- Enhance dataset variety for better generalization

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