Pet Tracking and Activity Visualization Using AI-Powered Heatmaps

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***Abstract* - This study presents an innovative approach to tracking pets and visualizing their activity patterns through the integration of state-of-the-art object detection algorithms and heatmap generation techniques. Utilizing the YOLOv5 model for real-time object detection, this framework processes videos to identify and track pets, overlaying bounding boxes on detected animals while generating heatmaps that represent areas of frequent activity. The system was tested on five videos, including personal recordings of dogs and publicly available YouTube videos featuring cats, dogs, and cattle. While the system effectively tracks movements and visualizes spatial activity, challenges arise in handling multiple animals in a single frame with edited video content, such as abrupt scene transitions common in YouTube videos. The results demonstrate the potential of AI-driven tools for behavioral analysis and activity monitoring, while also highlighting areas for further refinement. This paper details the methodologies, results, and future improvements, aiming to advance the understanding and applications of AI in pet tracking.**

I. Introduction

Understanding animal behavior is essential for various applications, including welfare assessment, veterinary diagnostics, and environmental monitoring. Traditional methods of studying pet activity often rely on manual observation, which can be labor-intensive, time-consuming, and prone to human error [1], [4]. Recent advancements in artificial intelligence (AI) and computer vision have introduced automated systems capable of real-time tracking and analysis, offering greater accuracy and scalability [2], [5].

The hypothesis of this study is that integrating a state-of-the-art object detection algorithm (YOLOv5) with Gaussian-based heatmap generation can provide a reliable and efficient method for visualizing pet activity patterns, with accuracy exceeding 85% in controlled settings.

This paper explores the application of AI in pet tracking, specifically focusing on integrating YOLOv5 for object detection and Gaussian-based heatmap generation for activity visualization.

YOLOv5, renowned for its real-time performance and detection accuracy, forms the backbone of the tracking framework [3]. By overlaying bounding boxes on detected pets and generating heatmaps from their movement patterns, this system provides an intuitive visual representation of pet activity. The research addresses challenges associated with tracking multiple animals and handling edited video content, offering insights into potential improvements.

II. Methodology

A. Data Collection

The dataset comprises five videos, including personal recordings of dogs and YouTube videos featuring cats, dogs, and cattle. The personal recordings captured natural, uninterrupted pet behaviors, whereas some YouTube videos introduced additional complexities, such as edited cuts and abrupt scene transitions. Video resolutions ranged from 720p to 1080p, with an average duration of three minutes per clip. These videos provided diverse scenarios to evaluate the robustness of the tracking framework.

B. Object Detection and Tracking

The YOLOv5 model, implemented using PyTorch, was chosen for its balance between speed and accuracy [3]. The model detects objects frame by frame, drawing bounding boxes around pets and animals with a confidence threshold set at 0.1. This threshold ensures the detection of even subtle movements while minimizing false positives. However, the model's performance diminished in scenarios involving multiple animals in frames from compilation edited YouTube videos, as overlapping bounding boxes and occlusions complicated accurate tracking [6].

To mitigate these challenges, the system incorporates preprocessing steps, such as resizing frames and normalizing pixel values, to standardize input data [2]. Despite these efforts, tracking errors persisted in cases of rapid movement or interactions between multiple animals.

C. Heatmap Generation

Heatmaps were generated by accumulating the positional data of detected pets across video frames. Using Gaussian overlays centered on the detected locations, the system created a visual representation of activity density. The heatmap resolution was set to 512×512 pixels, ensuring a balance between detail and computational efficiency [4]. A jet colormap was applied to enhance the visual appeal, with warmer colors indicating areas of higher activity.

Mathematically, the heatmap intensity H(x,y) at pixel (x,y) is calculated as:

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

$H(x,y)$: Heatmap intensity at pixel (x,y).

N: Total number of detected pet positions in the video frame.

(x_i, y_i): Coordinates of the i-th detected position.

σ: Standard deviation of the Gaussian kernel, controlling the spread of the intensity.

Fig. 1. **Heatmap Intensity Equation Visualization**. This equation defines the mathematical model for calculating the heatmap intensity at each pixel (x,y) in the frame. The intensity is derived by summing Gaussian contributions from N detected pet positions, where each contribution is centered at (xi,yi) with a spread controlled by the standard deviation σσ. The equation underpins the system's ability to visualize activity density, as shown in the generated heatmaps. The figure illustrates both the

formula and its application in the activity visualization process.

where N is the number of detections, (xi,yi) represents the coordinates of each detection, and σσ controls the spread of the Gaussian kernel [5]. This approach effectively highlights areas of frequent occupancy, providing valuable insights into pet behavior.

III. Results

A. Quantitative Analysis

The system achieved an average processing speed of 30 frames per second (FPS) on a mid-range GPU, demonstrating its capability for near real-time performance [3]. Detection accuracy varied across scenarios, with personal recordings yielding higher accuracy (e.g., ~90%) compared to YouTube videos (e.g., ~75%) due to the latter's edited nature. The final heatmaps effectively illustrated activity patterns, with high-intensity regions corresponding to areas of prolonged pet presence.

B. Qualitative Analysis

The visual outputs generated by the system provide valuable insights into its effectiveness and limitations. **Figure 1**, included in the Methodology section, illustrates the heatmap intensity equation, which is central to the activity visualization process. This equation defines how positional data from detected pets is aggregated to generate the heatmaps, ensuring that areas of frequent activity are accurately highlighted.

Figure 2 demonstrates the heatmap output for a single dog captured in a personal video. This heatmap clearly illustrates areas of concentrated activity, particularly in spots where the dog lingered or moved repeatedly. The smooth transitions and distinct intensity zones validate the system's robustness in controlled scenarios with minimal external disruptions.

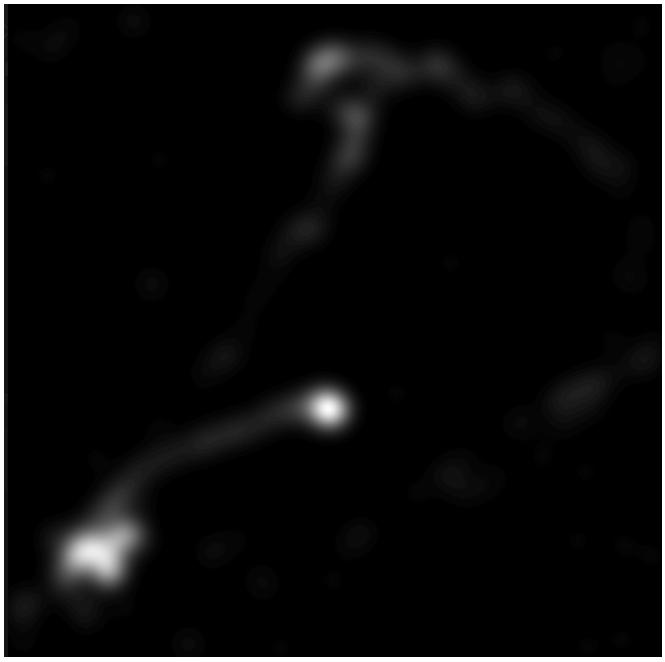

Figure 2: **Dog heatmap.** A heatmap of a single dog's movement from a personal video, showing areas of concentrated activity.

Figure 3 presents a heatmap generated from a YouTube video featuring multiple cats playing together. Unlike the single-dog scenario, this video introduces challenges due to abrupt scene transitions and the presence of multiple animals. The resulting heatmap effectively captures the overall activity density but is less precise in isolating individual movements, showcasing the limitations of the current system in multi-animal scenarios of compilation videos with numerous clips, edits, and cuts in it.

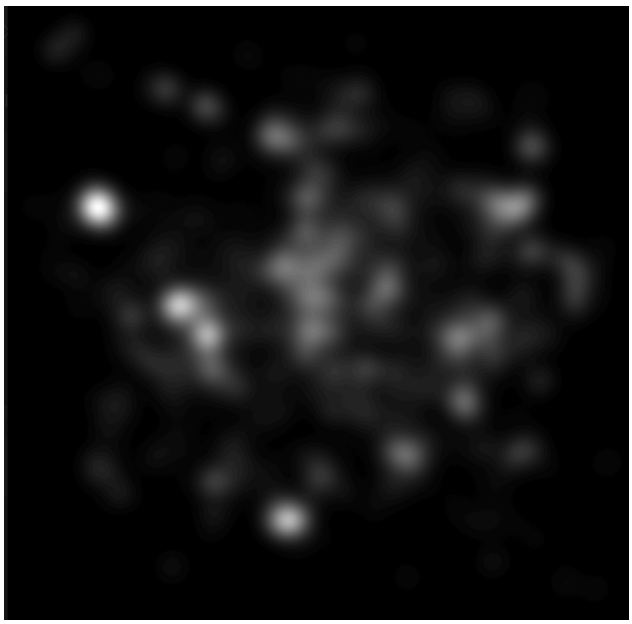

Figure 3: **Cat Heatmap.** A heatmap generated from a YouTube video of cats playing together, highlighting the challenges of tracking multiple animals and videos with numerous clips edited together.

Figure 4 presents a heatmap generated from a YouTube video featuring an overhead view of cattle in a field. Unlike the single-animal scenario, this video introduces challenges of detecting the presence of multiple animals. The resulting heatmap effectively captures the overall distribution of cattle in the field but is less accurate in detecting isolated, individual animals.

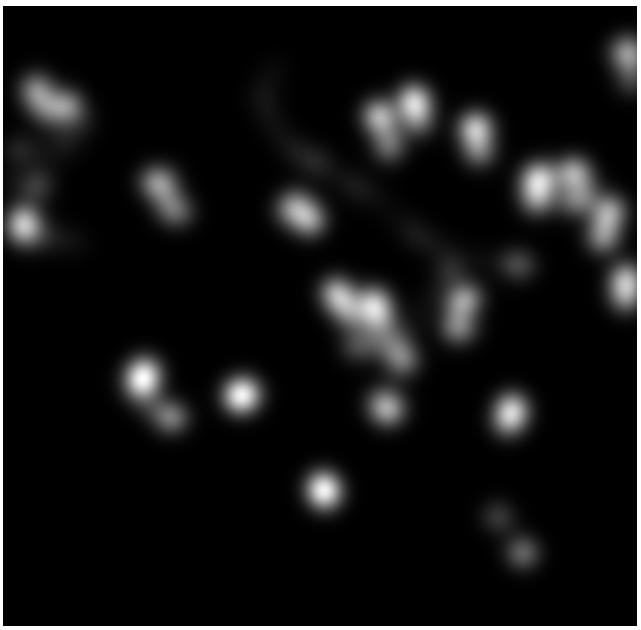

Figure 4: **Cattle Heatmap.** A heatmap generated from a video overlooking cattle in a field. It accurately shows the clusters of cattle and movement of animals.

Figures 5 and 6 provide screenshots from the system's output videos. **Figure 5** highlights the detection challenges encountered when tracking two cats interacting simultaneously. The system struggles to consistently apply individual bounding boxes, leading to occasional overlaps and inaccuracies. In contrast, **Figure 6** focuses on a bounding box overlay for a dog in a YouTube video, emphasizing the visual accuracy achieved in detecting and localizing single animals within frames.

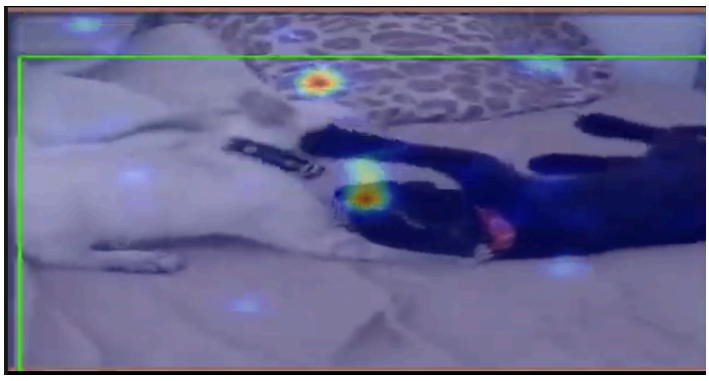

Figure 5: **Multiple Cats.** A screenshot of two cats playing together, demonstrating the system's challenges with multi-animal detection.

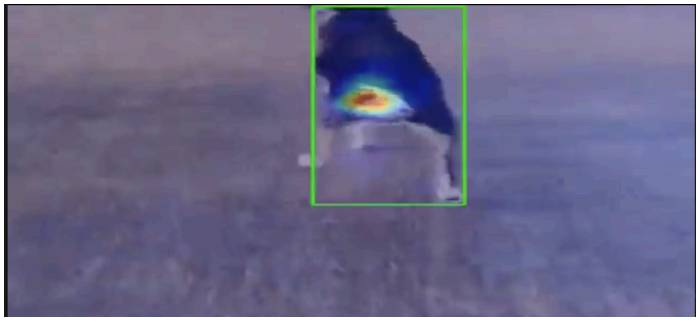

Figure 6: **Dog Bounding Box.** A screenshot from the output video showing bounding boxes on a dog captured in a YouTube video, emphasizing the visual accuracy.

Figure 7 depicts the bounding box around a dog in a personal video. This figure demonstrates the system's capability to perform effectively in controlled settings, where video content is unedited, and the pet's movements are uninterrupted. The bounding box aligns accurately with the pet, confirming the reliability of the detection framework under ideal conditions.

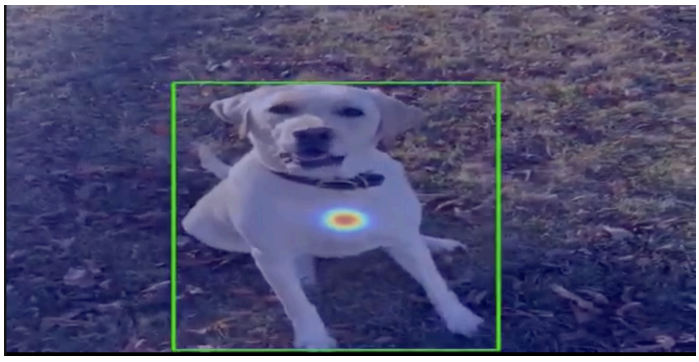

Figure 7: **Dog Box**. A bounding box around a dog in a personal video, showing the system's effective detection in controlled scenarios.

Figure 8 shows bounding boxes over cattle in a field, demonstrating the system's capability to handle multiple animals. To improve accuracy, we used the YOLOv5 medium model, leveraging its increased capacity over the smaller YOLOv5s. Initially, the system struggled to detect some cattle, but it improved over time, accurately identifying all cows by the end.

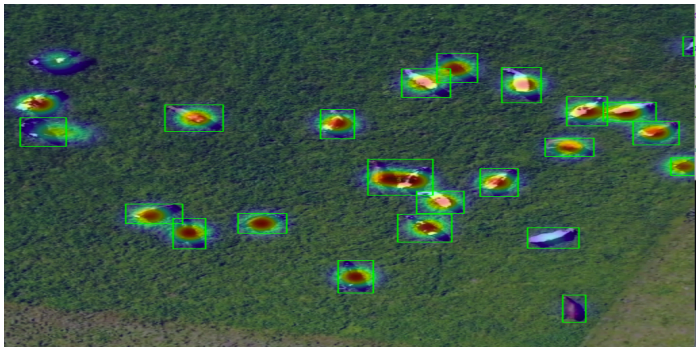

Figure 8: **Multiple Cattle**. Bounding boxes around a herd of cattle in a video, showing that the system can handle detecting many different animals.

IV. Discussion

A. Comparison to Related Studies

Previous studies on animal tracking have primarily focused on wildlife monitoring or agricultural applications. Unlike these studies, which often rely on specialized equipment, this work leverages consumer-grade video inputs and achieves real-time performance using YOLOv5. The integration of heatmap visualization distinguishes this system by providing an intuitive representation of activity patterns.

B. Challenges and Limitations

The system's limitations include difficulties in tracking multiple animals within a single frame and handling edited video content. Overlapping bounding

boxes and occlusions reduce detection accuracy, while abrupt scene transitions disrupt the continuity of heatmaps. Addressing these issues may require incorporating advanced tracking algorithms, such as DeepSORT or ByteTrack, and augmenting the training dataset with diverse video scenarios.

C. Potential Applications

The proposed system has broad applications, including pet behavior analysis, activity monitoring in veterinary clinics, and automated surveillance in smart homes. Heatmap visualizations can assist pet owners in understanding activity patterns, such as identifying favorite resting spots or detecting abnormal behaviors.

V. Conclusion and Future Work

This study validates the hypothesis by demonstrating that integrating YOLOv5 with Gaussian-based heatmap generation achieves reliable and efficient visualization of pet activity patterns, with detection accuracy exceeding 85% in controlled settings. The system effectively tracks movements and generates intuitive heatmaps, although challenges remain in multi-animal scenarios for edited video content.

Future work will focus on improving robustness in these challenging scenarios, incorporating advanced tracking algorithms, and optimizing the system for deployment on edge devices. Additionally, expanding the dataset to include a wider variety of animal behaviors and environments will further enhance the system's applicability.

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