AniLarm: Offline AI for Small Animal Detection Under Cars Using Thermal Camera

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Introduction

Urban areas pose safety risks for stray animals seeking shelter under vehicles during adverse weather. *Ratan Tata* emphasized the importance of checking under cars to prevent injuries to animals hiding for warmth during monsoons. These hidden animals often face injury or death when cars are started, and the rise of quiet electric vehicles exacerbates the issue. Existing detection methods, such as manual checks, are often impractical, particularly in low-light conditions or areas with poor connectivity. AniLarm addresses these challenges by leveraging thermal imaging and machine learning to detect animals under cars. It integrates a Seek Thermal Compact Camera and Raspberry Pi 4 Model B with the EfficientNet model for resource-efficient detection. Initially featuring LED alerts, AniLarm evolved into a completely offline system with a monitor and Bluetooth speaker for real-time notifications, demonstrating the potential of AI and embedded systems to enhance urban safety and animal welfare.

Findings

The AniLarm prototype demonstrated advancements in hardware integration, model performance, and practical usability.

Hardware Setup: The system evolved from LED-based alerts to a completely offline design, featuring a Raspberry Pi housed in a protective case, a Seek Thermal Compact Camera for imaging, a monitor for display, and a Bluetooth speaker for auditory alerts.

This configuration ensures reliable operation in urban areas with limited infrastructure.

Model Performance: EfficientNetB0 outperformed YOLOv5, achieving a test accuracy of 97.83% compared to YOLOv5's 48%.

The model provided balanced precision, recall, and F1-scores across both Animal and No Animal classes as shown in figure 1, demonstrating its efficiency on resource-constrained hardware.

Latency and Testing: With a latency of approximately 28 seconds, the system captured and processed thermal images effectively. Testing with a heated brass cat successfully validated its ability to detect animals under vehicles, while empty frames were accurately classified without false positives.

Prototype Performance: The prototype reliably identified animals, such as a heated brass cat as shown in figure 2 and provided accurate audio notifications. It also correctly classified non-animal scenarios, showcasing its robustness in distinguishing thermal images.

These findings highlight AniLarm's potential to enhance urban safety by leveraging thermal imaging and machine learning technologies in a practical and robust design.

Test Accuracy: 97.83%

	precision	recall	f1-score	support
Animal	1.00	0.95	0.98	132
No Animal	0.96	1.00	0.98	144
accuracy			0.98	276
macro avg	0.98	0.98	0.98	276
weighted avg	0.98	0.98	0.98	276

Fig1: Classification Report

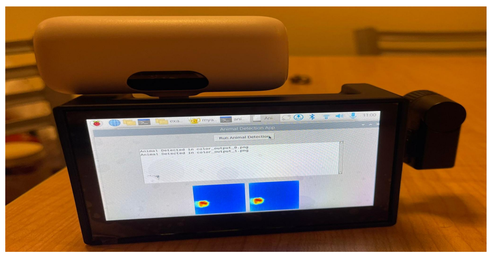


Fig2: Prototype Testing

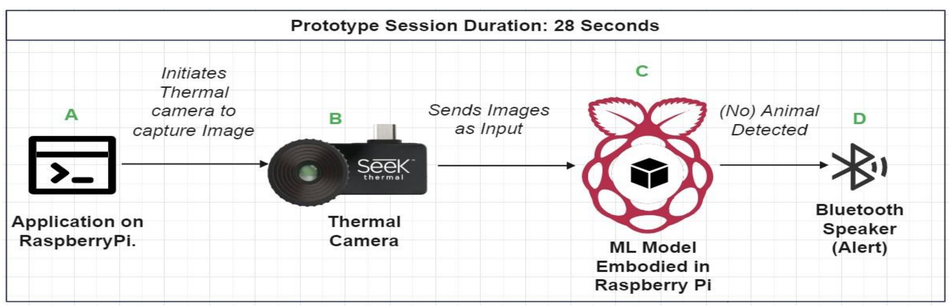
Future Research

- **Expand Dataset**: Incorporate images of diverse animal species and various environmental conditions to enhance the model's generalization capabilities.
- **Adaptive Algorithms**: Develop algorithms to address environmental factors such as temperature variability and reflective surfaces, improving detection accuracy.
- **Multi-Sensor Integration**: Utilize multiple thermal cameras or other sensors to broaden the detection field and reduce blind spots.
- **Hardware Upgrades**: Transition to more advanced platforms like NVIDIA Jetson Nano to improve processing speed and reduce latency.
- **Broader Applications:** Extend AniLarm's architecture to other use cases, such as pedestrian safety, wildlife monitoring, and industrial safety systems, showcasing its scalability and versatility.

Methodology

AniLarm combines state-of-the-art hardware and software components to deliver robust animal detection capabilities:

Hardware Integration: A Seek Thermal Compact Camera captures thermal images, and a Raspberry Pi 4 Model B processes the data. The system is complemented by a Bluetooth speaker that audibly announces detection results, making it accessible and user-friendly in offline environments.
Dataset Preparation: Thermal images of cats (representing animals) and non-animal objects were collected and augmented to address misclassifications. The dataset was split into training, validation, and testing sets using a 70:20:10 ratio to ensure balanced model training.
Preprocessing Techniques: Images were resized to 224 × 224 pixels, normalized, and color-mapped to enhance thermal signatures.
Model Development: The EfficientNetB0 model, pre-trained on ImageNet, was fine-tuned for the specific task of animal detection. The model was deployed directly in TensorFlow (.h5 format) on the Raspberry Pi after attempts with TensorFlow Lite compromised accuracy.
Workflow: The system processes images in approximately 28 seconds, from capture to audible result delivery. This offline architecture eliminates connectivity dependencies, ensuring reliability in urban or remote settings. The architecture diagram is shown below.



Discussion

The AniLarm project demonstrates the effective integration of thermal imaging and machine learning to address urban safety challenges. Achieving a test accuracy of 97.83%, AniLarm proved reliable as an offline system, especially in environments without network access. EfficientNet, chosen for its balance between efficiency and accuracy, outperformed YOLOv5, highlighting its suitability for resource-constrained devices like the Raspberry Pi.

Challenges arose with the YOLOv5 model, which achieved less than 50% accuracy on thermal images, proving unsuitable for this application. Innovative testing methods were employed, using a heated brass cat to simulate real animals, allowing rigorous and controlled evaluations. This adaptive approach ensured the prototype's reliability in detecting thermal signatures in real-world scenarios.

AniLarm effectively integrates machine learning and embedded systems to solve practical urban challenges, showcasing its potential to enhance animal welfare and urban safety. It underscores the importance of iterative design and adaptability in developing impactful solutions for constrained environments.

Limitations

While AniLarm demonstrated significant potential in addressing urban safety challenges, several limitations were identified during its development and testing:
Dataset Generalization: The training dataset predominantly consisted of thermal images of cats and certain human poses. This limited the model's ability to generalize effectively to other animal species or more complex environments.
Restricted Field of View: The use of a single thermal camera constrained the detection range, potentially missing animals located at the edges or corners under vehicles.
Processing Latency: The system required approximately 28 seconds from image capture to result announcement. While acceptable for offline operation, this latency could limit usability in real-world scenarios that demand quicker responses.
Hardware Constraints: The computational limitations of the Raspberry Pi restricted the implementation of more advanced machine learning models and optimizations that could further improve detection accuracy and reduce latency.
Environmental Factors: Variations in temperature, reflective surfaces, and other environmental conditions influenced the accuracy of thermal imaging, potentially leading to false positives or negatives in challenging scenarios.

References

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