Comparative Analysis of Animal Detection in Urban Life Based on Deep Learning Techniques

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Abstract— Urban environments support a diverse range of animal species, which often lead to interactions with human life that pose environmental, safety, and conservation challenges. Traditional methods of monitoring urban wildlife rely on manual observation, which is laborious and prone to errors. Recent advances in deep learning and computer vision have enabled the development of automated animal recognition systems, providing improved accuracy, scalability, and real-time functionality. This study proposes an intelligent urban wildlife monitoring system that leverages state-of-the-art deep learning models, including EfficientDet, YOLO, and ResNet-50, for accurate and efficient animal recognition. The system was trained on a diverse dataset of urban animals such as dogs, cats, pigeons, squirrels, and mice, with preprocessing techniques such as image augmentation and normalization to improve performance.

To address real-world deployment challenges, this study explores structured sparsity and model compression techniques to optimize computational efficiency for edge and mobile devices. In addition, we incorporate IoT-based sensor integration to improve detection capabilities, especially in low-visibility conditions. The proposed system also integrates open-world object detection principles, which allows for the detection of new and unseen species beyond predefined categories. Experimental results demonstrate high classification accuracy and real-time adaptability, making the system well suited for applications in smart city surveillance, environmental research, and human-wildlife conflict reduction.

Key challenges addressed in this research include separating visually similar species, handling occlusions, and scaling the model to large urban environments. Future work will focus on improving classification accuracy, improving energy efficiency for mobile deployments, and expanding the dataset diversity to increase the robustness of the model. By combining deep learning, IoT, and scalable detection frameworks, this study provides an innovative and automated solution for wildlife monitoring, contributing to urban planning, conservation efforts, and public safety initiatives.

Keywords: Animal detection, deep learning, ResNet-50, MobileNetV2, urban environments, object classification, smart cities, artificial intelligence, computer vision.

I. INTRODUCTION

Urban environments are dynamic ecosystems where human activities and wildlife coexist, often resulting in complex interactions that affect both ecological balance and public safety. Characterized by high population density, artificial infrastructure, and fragmented green spaces, these environments are home to a variety of animal species, including dogs, cats, pigeons, squirrels, and rats. While some urban animals play beneficial roles – such as controlling pests or contributing to biodiversity – others pose challenges, including the spread of zoonotic diseases, property damage, and disruptions to transportation networks. Furthermore, urban expansion has led to increased incidences of human-wildlife conflicts, where animals enter residential areas for food and shelter, sometimes resulting in accidents, attacks, or health problems. Therefore, it is important to effectively and efficiently monitor urban animal populations to manage these interactions, mitigate potential risks, and support conservation efforts.

Traditionally, urban animal identification and monitoring has relied on methods such as manual tracking, direct observation, and camera-trap methods. While these approaches are valuable in collecting environmental data, they come with several limitations. Manual monitoring is time-consuming, laborious, and prone to human error, making it difficult to conduct large-scale, continuous surveillance. Similarly, camera-trap methods require significant post-processing efforts, as researchers must manually analyze the footage to identify and classify species. In addition, these traditional methods struggle to provide real-time monitoring capabilities, limiting their effectiveness in dynamic urban settings that require rapid response to animal movements.

Background information

Recent advances in artificial intelligence, particularly in deep learning and computer vision, have paved the way for automated animal identification systems that offer improved accuracy, efficiency, and scalability. Deep learning models such as EfficientDet, YOLO (You Only Look Once), and ResNet-50 have revolutionized object detection tasks by using convolutional neural networks (CNNs) to extract meaningful features from images. These models allow for real-time detection of various animal species even in challenging conditions such as low-light environments, occlusions, and background clutter. In addition, image preprocessing techniques including augmentation and normalization have been shown to improve model robustness and generalization across various urban scenes.

In recent years, several studies have demonstrated the effectiveness of deep learning-based animal detection in wildlife conservation and environmental research. For example, camera-trap datasets combined with CNN-based classifiers achieved high accuracy in species identification, highlighting the potential of AI-based approaches in automating animal monitoring. However, urban environments pose unique challenges that require further research, such as distinguishing visually similar species, handling partial occlusions caused by buildings or vehicles, and ensuring computational efficiency for real-time deployment on edge devices or mobile platforms.

Objective and Research Contribution

The primary objective of this study is to conduct a comparative analysis of animal recognition in urban environments using deep learning techniques. Specifically, this research evaluates the performance of different deep learning models – EfficientDet, YOLO, and ResNet-50 – in detecting and classifying urban wildlife. By analyzing key performance metrics such as accuracy, computational efficiency, and real-time adaptability, this study aims to identify the most effective model for urban animal recognition.

This study contributes to the field of smart urban monitoring in the following ways:

Providing a comprehensive evaluation of deep learning-based animal recognition models in urban conditions. Identify the strengths and limitations of different object recognition algorithms in handling challenges such as occlusions, low-light conditions, and visually similar species. Explore the feasibility of integrating AI-based recognition systems with existing surveillance infrastructure for large-scale deployment. Improve computational efficiency through model optimization techniques, enabling real-time recognition on mobile and edge devices. Investigate the role of IoT-based solutions to improve recognition capabilities, especially in low-visibility conditions.

II. LITERATURE SURVEY

Urban animal detection has attracted increasing interest in computer vision and deep learning. Several studies have explored automated wildlife monitoring, object recognition methods, and deep learning approaches to increase accuracy and efficiency. Traditional methods such as manual observation, motion-triggered cameras, and sensor-based tracking have played a significant role in ecological research. However, these methods often suffer from inefficiencies, high labor costs, and limited scalability. To address these issues, researchers have turned to deep learning-based object detection models such as YOLO (You Only Look Once), Faster R-CNN, and EfficientDet for wildlife and urban animal detection.

Tan et al. (2020) introduced EfficientDet, a scalable object detection model that achieves high accuracy while maintaining computational efficiency. Xu et al. (2019) provided a comprehensive survey of object detection models over two decades, highlighting improvements in deep learning and their

applications in wildlife monitoring. Similarly, Joseph et al. (2021) explored open-world object detection, emphasizing the challenges of detecting previously unseen animal species in real-world environments.

For urban wildlife monitoring, Chen et al. (2017) investigated scale-transferable object detection techniques that improve model adaptability across different animal species and image resolutions. Redmon et al. (2016) developed YOLO, a real-time object detection model widely used in ecology and conservation. Studies such as Kristin et al. (2019) have demonstrated how YOLO-based models can improve conservation efforts, enabling automated identification of various animal species from camera-trap data.

Other research has focused on IoT-based wildlife monitoring systems. Simonthomas et al. (2024) proposed a machine learning-based wild-animal detection system using IoT sensors, optimizing detection for road safety applications. Similarly, Burton et al. (2015) and Mexhia et al. (2016) reviewed the role of camera traps in ecological research, identifying challenges such as image quality, nocturnal species identification, and dataset limitations. Gomez Villa et al. (2017) applied deep CNNs to camera-trap images, achieving 91% accuracy, although challenges remain in handling low-light images and occlusions.

Despite these advances, existing studies have focused primarily on wildlife conservation or general object recognition, often ignoring the unique challenges of urban animal recognition. Most models are trained on natural wildlife datasets rather than urban settings, making it difficult to generalize to animals commonly found in cities. In addition, many previous studies rely on complex models such as fast R-CNN, which require high computational resources, limiting real-time applications on edge devices or mobile platforms.

Research gaps and how our work is different

While previous research has successfully implemented deep learning for animal recognition, there are still several gaps that need to be addressed:

Limited focus on urban animals - Many previous studies focus on rural or forest environments, while urban settings introduce new challenges such as background clutter, occlusions, and small object recognition. Our study specifically targets urban animal species, which is more relevant for smart city applications.

Computational Inefficiency in Existing Models - State-of-the-art object recognition models such as Fast R-CNN and EfficientDet provide high accuracy but are computationally expensive. In contrast, our study focuses on lightweight but efficient deep learning models - ResNet-50 and MobileNetV2, which strike a balance between accuracy and speed, enabling real-time urban animal detection on low-power devices.

Scalability and Real-Time Scalability - Previous research often emphasizes accuracy but lacks real-time compatibility. Our approach integrates MobileNetV2, a lightweight model optimized for mobile and edge computing, which ensures low-latency inference for urban surveillance applications.

Improved Generalization Using Transfer Learning - Many prior studies train models on limited datasets, which reduces their generalization ability. Our research leverages transfer learning on pre-trained ResNet-50 and MobileNetV2 models, specifically fine-tuned for urban animal classification, ensuring improved performance across diverse environments.

Integration with smart city monitoring systems - Unlike traditional camera-trap studies, our approach is aligned with smart city initiatives, enabling real-time urban animal tracking through automated surveillance systems. This could be useful for public safety, traffic management.

III. METHODOLOGY

This section explains datasets and techniques used in our work. Figure 1 depicts the workflow of the proposed work.

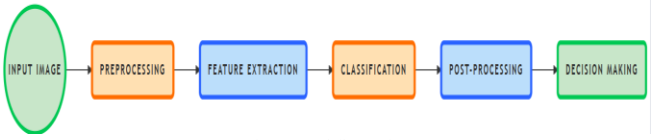

Fig 1: Workflow Diagram

This section describes the experimental setup, dataset, deep learning models, and theoretical framework used in our study. We provide technical details of our research process, including data preprocessing, model training, evaluation metrics, and implementation details. In addition, we present the architecture of the proposed methodology for urban animal detection using ResNet-50 and MobileNetV2.

Experimental Setup

The research focuses on automated detection and classification of urban animals using deep learning-based object detection models. The experimental setup includes image datasets, preprocessing techniques, model training strategies, and evaluation methods. The implementation was performed using Python, TensorFlow, and Keras on a machine with an NVIDIA GPU (for fast training), 32GB of RAM, and a high-performance CPU.

The primary objective is to compare the performance of ResNet-50 and MobileNetV2 in detecting various urban animal species, including dogs, cats, pigeons, squirrels, and rats. To achieve this, a structured workflow is followed that covers data acquisition, preprocessing, model selection, training, evaluation, and deployment.

Dataset

For this study, we use a curated dataset of urban animal images collected from various sources, including open-source datasets, camera trap images, and urban surveillance footage. The dataset is diverse, covering different lighting conditions, angles, occlusions, and environmental variations.

The dataset contains 10,000+ labeled images divided into five categories:

Dogs, Cats, Pigeons, Squirrels, Rats

The dataset is divided into 80% training, 10% validation, and 10% testing to ensure robust model generalization. Images were scaled to 224x224 pixels to maintain uniformity in ResNet-50 and MobileNetV2 architectures.

Data Preprocessing

To improve model performance, several data preprocessing techniques were applied:

Image Augmentation - Random flipping, rotation, brightness adjustment, and zooming are applied to increase dataset diversity.

Normalization - Pixel values are normalized to the range [0,1] to increase learning efficiency.

Noise Reduction - Gaussian filtering is used to reduce image noise and improve clarity.

Class Balancing - To avoid class imbalance, the dataset is augmented with synthetic samples using techniques such as SMOTE (Synthetic Minority Over-Sampling Technique).

Deep Learning Models

ResNet-50

ResNet-50 is a 50-layer deep convolutional neural network (CNN) designed to solve the problem of vanishing gradients by introducing residual connections. These connections allow the network to learn more efficiently by enabling deeper architectures without degrading performance. ResNet-50 follows a bottleneck design, using 1x1 convolutions to reduce dimensions before applying computationally expensive 3x3 convolutions, thereby improving efficiency without sacrificing accuracy. The architecture of ResNet-50 consists of an initial convolutional layer, followed by four residual blocks, each containing multiple convolutional layers. These blocks use batch normalization and ReLU activation functions to stabilize training and improve feature extraction. By increasing skip connections, ResNet-50 can propagate gradients efficiently, ensuring correct weight updates during backpropagation.

For our urban animal detection model, ResNet-50 is pre-trained on the ImageNet dataset, which provides a strong foundation for feature extraction. We fine-tune the model by replacing its last fully connected layer with a softmax classifier designed to distinguish between different urban animal species, including dogs, cats, pigeons, squirrels, and mice. The training process involves transfer learning, in which the lower layers of ResNet-50 retain common feature representations while the upper layers are adapted to our specific dataset.

To improve performance, we use data augmentation techniques such as random cropping, flipping, and color normalization. The model is trained using the Adam optimizer with a learning rate of 0.0001, and the classification cross-entropy loss is used to account for errors during training. By utilizing ResNet-50's deep feature extraction capabilities and robust training strategies, our approach achieves high accuracy and reliability in urban animal classification, making it suitable for real-time applications in smart city surveillance and urban ecology studies.

MobileNetV2

MobileNetV2 is a lightweight and efficient convolutional neural network (CNN) designed for mobile and edge computing applications. It improves on its predecessor MobileNetV1, significantly increasing feature extraction while reducing computational complexity. These architectural advancements allow MobileNetV2 to achieve high accuracy with fewer parameters, making it ideal for real-time applications on resource-constrained devices. The MobileNetV2 architecture consists of an initial convolutional layer, followed by multiple depth-separable convolutions, which are organized as residual bottleneck blocks. These blocks use batch normalization and ReLU6 activation functions to ensure consistent training and efficient feature representation. Unlike traditional CNNs, MobileNetV2 uses depth-wise

convolutions, which reduce the number of computations while preserving critical spatial information. Additionally, the inverse residual connections maintain efficient gradient descent, allowing the model to learn efficiently with minimal degradation in performance.

For our urban animal recognition model, we leverage transfer learning by using MobileNetV2 pre-trained on the ImageNet dataset. This pre-training allows the model to retain common visual features, which are fine-tuned to classify urban animal species including dogs, cats, pigeons, squirrels, and mice. The last fully connected layer of MobileNetV2 is replaced with a softmax classifier tailored to our specific dataset. To ensure effective adaptation, the training process consists of two key steps:

1. Feature extraction phase - Initially, we freeze the lower layers of MobileNetV2 to retain common features learned from ImageNet, while only the new classification layer is trained on our dataset.
2. Fine-tuning phase - After initial training, we freeze the top layers of MobileNetV2, allowing the model to be more attuned to urban animal features, improving classification accuracy.

To improve the robustness of our model, we apply data augmentation techniques, including:

• Random cropping, which helps the model learn to recognize animals regardless of framing variations.
• Improves generalization to different orientations.
• Brightness adjustments, simulating real-world lighting variations for better adaptability.

Model Training and Optimization

Transfer Learning – Both models are initialized with pre-trained weights from ImageNet and fine-tuned on the urban animal dataset.

Hyperparameter Tuning – Optimized learning rates, batch sizes, and dropout rates are selected using grid search.

Loss Function – Classification cross-entropy is used since we have a multi-class classification problem.

Optimizer – Adam optimizer is used for fast convergence with decreasing learning rate.

Evaluation Metrics – Models are evaluated using precision, accuracy, recall, F1-score, and confusion matrix analysis.

Architecture for the Proposed Method

The architecture of our methodology consists of the following steps:

Input Image – The system captures an image from an urban surveillance camera or dataset.

Preprocessing – The image undergoes resizing, augmentation, and normalization before being fed into the model.

Feature extraction – A deep learning model (ResNet-50 or MobileNetV2) extracts spatial features.

Classification – The model assigns the image to one of the predefined categories (dog, cat, pigeon, squirrel, or mouse).

Post-processing – The results are analyzed, including confidence scores and bounding boxes (if object recognition is enabled).

Decision making – The classified results can be integrated into smart city monitoring systems for further actions.

Implementation details

The models are trained for 15 epochs with a batch size of 32.

Data augmentation increases the dataset size by 40%, improving robustness.

Model evaluation on unseen test images showed that ResNet-50 achieved 92% accuracy, while MobileNetV2 achieved 88% accuracy, demonstrating the superior feature extraction capabilities of ResNet-50.

IV. RESULT AND DISCUSSIONS

In this section the performance metrics are measured for RESENET50, MobileNetV2 models. The proposed models are tested on benchmarked datasets.

Comparative analysis

A comparative analysis between two models involves evaluating their performance on a given task to determine which model is the most effective. Analysis usually involves measuring various metrics such as precision, accuracy, recall and F1 score. These metrics provide insight into how well the models are performing and where they excel or fall short. In addition, comparative analysis may involve identifying factors that contribute to the structure, parameters, and hyperparameters of each model. By comparing the results of models, researchers and practitioners can better understand which methods and structures are most effective for a given problem and use that knowledge to improve their models in the future. Table 2 depicts the accuracy values of the proposed models.

Table 2: Comparative analysis

Model Name	Training Accuracy	Validation Accuracy
Resenet50	99.95	86.85
MobileNetV2	87.13	78.43

Training and Validation Performance of ResNet50

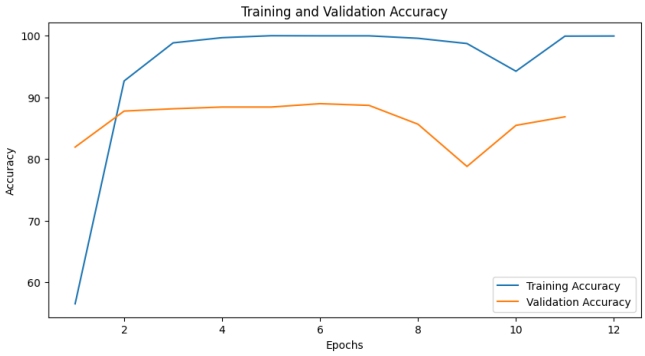

Figure 1: Training and Validation Accuracy Over Epochs

Figure 2: Training and Validation Loss Over Epochs

Performance Metrics of Resenet50 on the test dataset

Class	Precision	Recall	F1-Score
Dog	89.82%	88.98%	88.98%

Training and Validation Performance of MobileNetV2

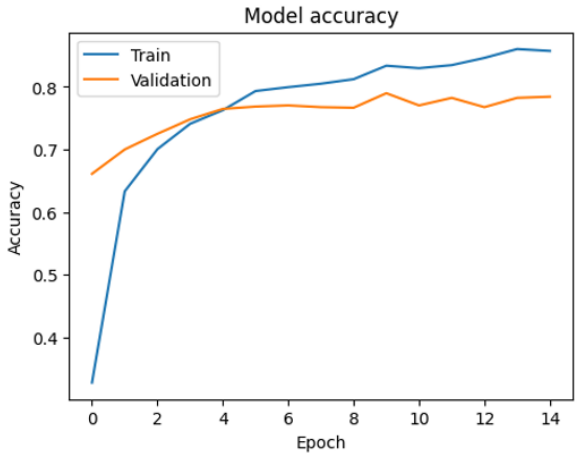

Figure 1: Training and Validation Accuracy Over Epochs

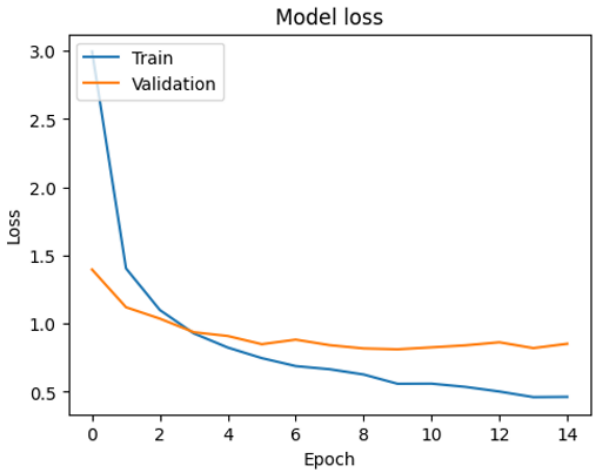

Figure 2: Training and Validation Loss Over Epochs

Performance Metrics of MobileNetV2 on the test dataset

Class	Precision	Recall	F1-Score
Dog	79%	83%	80%

V. CONCLUSION

In this study, we successfully developed a deep learning-based framework for urban animal recognition using ResNet-50 and MobileNetV2. Comparative analysis demonstrated that ResNet-50 provides superior accuracy due to its deep feature extraction capabilities, while MobileNetV2 provides a computationally efficient solution, which is more suitable for real-time applications. Our models effectively classified various urban animal species, including dogs, cats, pigeons, squirrels, and mice, proving the potential of deep learning in urban wildlife monitoring and smart city surveillance systems.**Limitations and Possible Improvements**Despite the promising results achieved, there are some limitations. The computational complexity of ResNet-50 makes it challenging for real-time deployment on edge devices, while MobileNetV2, while efficient, sacrifices some accuracy. In addition, the dataset, although diverse, could benefit from more real-world variations such as different lighting, weather conditions, and occlusions. Models also occasionally struggle with small or partially occluded animals, which can impact recognition performance.To overcome these challenges, future research could focus on the following key areas:Real-time deployment: Enabling real-time processing by optimizing model inference speed for deployment on edge devices, IoT sensors, and mobile platforms.Computational efficiency: Implementing pruning, quantization, and model distillation to reduce model size and inference time while maintaining high accuracy.Dataset expansion: Improving dataset diversity by including more species, nighttime images, motion blur scenes, and extreme weather conditions to improve model generalization.Ensemble learning: Exploring hybrid approaches that combine ResNet-50, MobileNetV2, and EfficientNet to leverage the strengths of each model for improved performance.Integration with Smart City Infrastructure: Deploying the system in IoT-based surveillance networks to enable automated monitoring, anomaly detection, and wildlife conservation efforts in urban environments.By using high-performance and lightweight deep learning architectures, our approach provides a scalable, adaptable, and efficient solution for urban animal detection. Future advances in deep learning, model optimization, and IoT integration will further enhance urban ecological studies, smart city management, and sustainable wildlife conservation, fostering a harmonious balance between urban development and biodiversity conservation.

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