Automated Pest Control: Computer Vision for Wildlife Surveillance

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Abstract

The integration of artificial intelligence in agriculture has revolutionized farming practices, enhancing crop yields and resource efficiency. However, existing machine learning systems primarily focus on livestock, overlooking the impact of wildlife on agricultural productivity. This study addresses the gap by introducing two classification pipelines utilizing VGG16 and ResNet50 models for identifying five major classes of wildlife (foxes, rats, pigeons, raccoons, and squirrels) affecting agricultural sectors. A comprehensive dataset, comprising existing datasets and trail-camera footage, is compiled for training and validation. The results show that models trained on clear images struggle to generalize to real-world environments (the best accuracy being 48.19%). Grey-scaled models perform worse with a 2-6% decrease. Training on the training dataset and evaluating the validation set yields better average results for the weaker-performing model. This study contributes to invasive animal control in agriculture, providing a foundation for effective wildlife management with computer vision.

CCS Concepts

• **Applied computing** → **Agriculture**; • **Computing methodologies** → **Computer vision**; • **Information systems** → *Decision support systems*.

Keywords

computer vision, wildlife management, agriculture, invasive species detection, classification pipelines

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1 Introduction

Throughout history, the field of agriculture has benefited from advances in technology [29]. In recent times, artificial intelligence (AI) has been applied to farming applications, which has brought about an agricultural revolution. This revolution has contributed to larger crop yields and more efficient water and pesticide usage while complementing existing infrastructure [29].

AI is now being utilised in livestock farming, specifically computer vision. Systems have been developed for tracking animal measurements and herd monitoring for health management [10, 23]. While these systems have been very useful to the livestock industry, even contributing to economic growth in the sector, very few of the existing machine learning systems focus on the wildlife that affects the sector. Certain animals, such as rodents and badgers, contribute to the spread of infectious diseases through contact with farm animals and feed [8, 26, 36]. Additionally, predatory animals have also impacted farming, particularly the poultry industry. Animals such as foxes are considered pests by some farmers and historically have had their populations culled, as a result, [24, 30]. Traditionally, surveying these invasive animals relied on physical indicators such as stool or prints. However, modern farms have introduced visual surveillance systems for more accurate analysis, including closed circuits, WiFi, or trail cameras.

As a result of the emergence of these surveillance systems in agriculture, computer vision applications have become feasible for wildlife management. This paper includes several contributions to invasive animal control within a farming context. A compiled dataset that was utilised for the training of these pipelines consists of two distinct parts. Firstly, a training part, compiled from several existing datasets [5, 11, 18, 21, 22, 28, 31, 32, 35] to create a comprehensive collection for the classification of foxes, rats, pigeons, raccoons, and squirrels. Secondly, a validation set consists of the same classes but specifically captured from trail-camera or trail-camera-like footage.

The novelty of this research lies in the development of a specialized computer vision system for the detection and classification of invasive wildlife species that impact agriculture. Unlike previous studies that focus on livestock or general wildlife detection without an agricultural context, this paper specifically targets five major classes of wildlife, which include, foxes, rats, pigeons, raccoons, and squirrels. These animals have been identified to be detrimental to farming productivity. Two classification pipelines that utilize the pre-trained models VGG16 [25] and ResNet50 [14] are trained on the compiled dataset with various subsets and methodologies to ensure a thorough exploration of the problem space.

The paper is organised as follows: The Problem Background section provides a brief overview of the context behind the research. The Existing Systems section reviews relevant research conducted in this field. The Methods section describes the pipelines and experiments used to gather results. The Experiment Setup section explains the experimental protocol, dependencies and dataset. The

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outcomes of the experiments are shown in the Results section, and finally, the findings are discussed in detail in the Discussion section.

2 Problem Background

The management of invasive species on farms has been a necessary oversight for centuries [36]. Many methods, such as poisoning and trapping, have been used to cull their population. However, these methods are often destructive to other animals in an environment, such as in the case of poisoning, or too specific and ineffective, such as trapping [20]. It is noted that both of these methods rely on a general understanding of the wildlife in an area. Farmers must know what animal the problems originate from before its population can be managed. Historically, this was done through animal tracking and environment indicators and has extended to drone tracking, infrared, radar, and other modern sensor technology [9]. However, while some of these systems are effective in insect management, they are often economically infeasible for the agriculture sector.

The surveillance and analysis of a pest population also demand many man hours to determine thorough data accurately [19]. Often, this means that the typical manual operations of detection and professional consultation are not a feasible expense with regard to crop or livestock loss as a result of infestation.

Table 1: Comparison of Pest Detection Systems

System	Cost	Description
Drone	8118-16236 ZAR [3]	Drones are used to explore regions from an aerial perspective, identifying macro indicators like nests and burrows. They can also optimize plant growth and distribute pesticides/fertilizers but require an operator, adding to labour costs.
Radar/Infrared System	Approx. 60 USD (for sensors)	Systems like LoRaWAN [17] estimate sensor and processor costs around 60 USD. These systems detect pests but don't classify them, offering only rough estimates based on sensor data.
Surveillance Network	700-10000 ZAR [4]	Surveillance networks depend on camera quality and coverage. Computer vision may be applied, but a central server may be needed to handle recorded footage.
Trail Camera	3000-6000 ZAR [1]	Trail cameras are triggered by motion sensors, capturing video feed with limited battery life. Some models can transmit live video and may need multiple cameras for broader coverage.

Implementing systems like the examples mentioned in Table 1 can be vital for preventing the spread of disease from quarantine pests[1]. For example, in central Britain, badgers spread bovine-borne tuberculosis [8]. This can lead to the quarantine of entire herds of cows, as well as rendering any meat or dairy unfit for human consumption. Other animals identified as pests, invasive animals, or quarantine pests on farms include the following:

Table 2: Common Invasive Wildlife and Their Impact on Agriculture

Animal	Impact on Agriculture
Rats and Mice	Spread several diseases to livestock through contact with animal feed and stool particles. Common diseases include salmonellosis, pasteurellosis, leptospirosis, swine dysentery, trichinosis, toxoplasmosis, and rabies [26, 27].
Foxes	Kill poultry and other adolescent livestock. Foxes are estimated to cause up to 1–30% of lamb deaths in agricultural contexts [24].
Squirrels	Damage infrastructure and controlled ecosystems. Responsible for spreading Lyme disease via ticks and rabies to livestock [16].
Raccoons	Cause crop yield losses, particularly in the Mid-West of the United States, where a growing population of raccoons has damaged corn crops [6].
Pigeons	Consume sowed seeds, reducing crop yield, and spread diseases like avian uvula virus, which affects poultry livestock, including chickens [13, 33].

The animals discussed in Table 2 are selected from a range of animals that affect the agriculture sector to emphasise diversity in classification.

2.1 Existing Systems

There are many applications of computer vision outside the agriculture sector, however the quantity of detection systems within the agriculture sector is limited. Therefore, the discussed existing systems focus broadly on animal detection and identification. This is done to gather a broader understanding of the research context.

2.1.1 Pest Detection and Extraction Using Image Processing Techniques. This paper [19] was focused on the detection of insect pests on rice paddies. Their model does this using WiFi camera footage to capture a template background. When the insect pests appear in the footage, the template is compared to the current footage. Using subtraction and several filters, they can segment the insects from the background.

Their approach serves as an early solution to pest detection using camera footage. Unlike the pipelines proposed in this paper, their system cannot perform automated classification on pests and does not use a modern machine learning architecture to perform

[1] A pest of potential economic importance to the area endangered thereby and not yet present there, or present but not widely distributed and being officially controlled [2].

detection. Instead, it utilises a non-learned approach and does not require a dataset.

2.1.2 Wild Animal Detection Using Deep Convolutional Neural Network. The system proposed in this paper [34] is within the same field as this project. It employs a deep convolutional neural network (DCNN) architecture in order to perform object detection regression on trail camera images. The dataset used is trail camera footage of several types of animals, [12] with many examples of video sequences that have been converted to images, which is ideal for object detection.

While this project does explore machine learning, specifically computer vision as a solution, it is not focused in an agricultural context. While good for object detection, the dataset used is not ideal for classification (the task of the pipelines proposed in this paper), which performs better on data with high variance [7].

3 Methods

Two pipelines are proposed as a way to explore the problem domain effectively. Each pipeline relies on a pre-trained model as a backbone. The selected pre-trained models are ResNet50 [14] and VGG16 [25] because they are specifically trained for classification-like problems.

Three experiments are performed on each pipeline to determine which approach produces the best-performing model. The first approach uses the dataset's three channels (RGB). The second is to grayscale the channels and repeat them to be compatible with the structure of the pre-trained models. Finally, in the third approach, only the dataset's training distribution is used and separated into training and validation. This is done to first train the model on clear image classification and then determine model effectiveness by evaluating the actual validation set.

The same pre-processing steps are done for all experiments (except for grey scaling in the second experiment). This acts as a control to prevent introducing bias through unnecessary fine-tuning that could impact metrics. Pre-processing is as follows: each image is resized to 128 x 128 through scaling, and their labels are one-hot encoded for simple backpropagation. Each model also uses the same learning rate (0.001), batch size (64), loss (categorical cross-entropy), and optimiser (stochastic gradient descent). Each experiment is conducted over 100 epochs in order to evaluate the training of each model exhaustively.

Stochastic gradient descent (SGD) is chosen over adaptive movement estimation (Adam) because it often generalises better, especially in large, balanced datasets [15]. Preliminary experimentation also showed higher quality results with SGD than Adam.

Model architectures are defined using Keras with Python. The structure of each of the pipelines differs between experiments in the following manner:

- **Colour evaluation**. Images are passed directly to the pre-trained model (VGG or ResNet, depending on the pipeline). The pre-trained model outputs are flattened and then passed through a 64-length, fully connected layer with a sigmoid activation and 5 5-length, fully connected layer with a softmax activation.
- **Grayscale evaluation**. Images are passed to a function that copies the grayscaled channel three times and then passes it to the pre-trained model. The output of the model is the same as the colour evaluation.
- **Training distribution evaluation**. The training distribution is split into train and validation sets along a 20% split with seed 11 (randomly sourced). The structure of the model is the same as the colour evaluation. However, the model is evaluated after training using the actual validation set.

Model metrics are visualised using the matplotlib library.

3.1 Interface and Recommendation

The system introduces an interface for simple inference. It allows users to input single or groups of images for automated classification. Based on the provided images, the model performs a simple calculation to determine (based on the provided images) which class is the most common. Using that information, the user is provided with a simple recommendation for controlling the invasive animal in that class. This recommendation is not holistic and serves as a proof of concept for developing a more refined system.

Data that may contain no animals or animals not within the classes can affect the quality of the recommendation. To fix this, the probability distribution from the model can be used as a confidence score. If the probability of the most probable class is below 70%, the class is marked as none.

4 Experiment Setup

This section describes the dependencies, dataset and evaluation protocol needed to create an environment where the system pipelines can be effectively evaluated.

The models are trained in Windows subsystem Linux to utilise the Cuda Toolkit. This is done to improve training capabilities by allowing graphics processing computation. The hardware used to train the model is an RTX 3060 with 12GB of virtual random access memory.

Models will be evaluated on accuracy, precision, recall and F1 score. The best model will be selected based on the metrics gathered from the validation distribution of the dataset. Accuracy is the main consideration for this system because the classes are balanced, providing a comprehensive understanding of the quality of the trained models.

4.1 Dataset

A dataset has been specifically compiled to evaluate invasive wildlife. It is divided into two separate parts, training and validation, each with its composition and selected content.

Table 3: Dataset Composition for Wildlife Classification

Animal Class	# Examples	Description
Fox	1125	High variance in environment and pose. Contains some augmented data and is biased towards red foxes (Vulpes vulpes) [21, 32].
Pigeon	1314	Contains a lot of augmented data due to the scarcity of pigeon-specific datasets. Decent variance with no bias toward any specific species [28, 35].
Raccoon	1044	High variance with no augmented data [11, 22, 31].
Rat	1201	The original dataset contained some sequences of images, which were reduced for better distribution. Includes some augmented data [5].
Squirrel	1251	High variance and no augmented data [18].

The training part of the dataset consists of 5935 individual images with five unique classes. This part of the dataset was compiled from preexisting datasets. Each class is listed, along with considerations and their distribution, in Table 3.

Figure 1: Examples of images within the validation distribution. These images would be labelled as a fox and a rat, respectively.

The validation distribution of the dataset will be used to evaluate a model's ability to identify wildlife from trail cameras or surveillance footage. All the images are compiled from trail-camera images, and surveillance camera captures such as the examples in Figure 1. There are 552 individual examples: 103 examples of foxes, 116 of pigeons, 88 of raccoons, 127 of rats and 118 of squirrels. The classes are well-varied with some sequences of images. However, this is less of an issue in the validation test set as it is a fixed distribution, and results will be comprehensible as any bias will be carried to all models.

The images within both the training and validation distributions have varied resolutions and aspect ratios. Some of the images have transparency, which is removed during pre-processing. The classes are separated into different files for easy import into a usable format.

5 Results

Results are shown for each of the experiments. Graphs give visual representations of the model loss and accuracy, while other metrics will be discussed.

5.1 Colour Evaluation

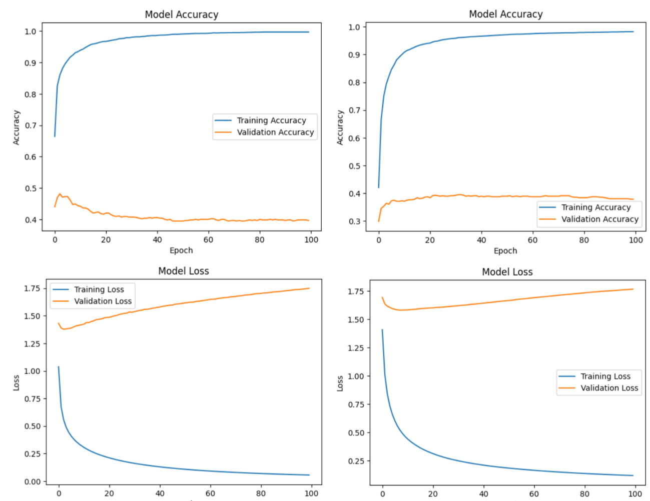

Figure 2: The accuracy and loss of each pipeline with RGB (3 channel) images during training. (ResNet, left. VGG, right)

As shown in Figure 2, the ResNet pipeline generalised faster than the VGG pipeline. It reached its best accuracy in the third epoch with 48.19% accuracy on the validation distribution. The best accuracy achieved with the VGG model was 39.49%. VGG also achieved a lower overall training accuracy of 98.44%, in comparison to the ResNet pipeline, which achieved 99.62%.

Both models' loss began increasing shortly after the best accuracy, suggesting that their metrics would not have improved with further training.

5.2 Grayscale Evaluation

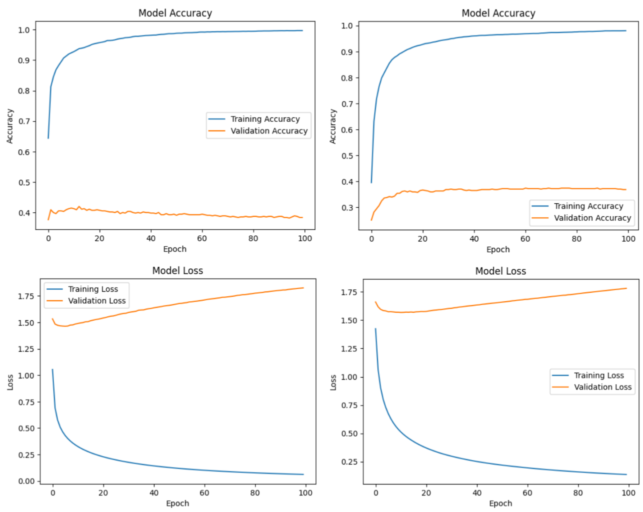

Figure 3: The accuracy and loss of each pipeline with only a single channel (grayscale) during training. (ResNet, left. VGG, right)

The results are similar to the colour evaluation but are, on average, lower. The best ResNet model had an accuracy of 42.03% and, as can be seen in Figure 3, generalised slower compared to the colour dataset evaluation. VGG also obtained a lower accuracy of 37.32% and generalised slower.

The training loss remained similar to the colour pipeline, with very little to no disparity in final accuracy after the final epoch.

5.3 Training Distribution Evaluation

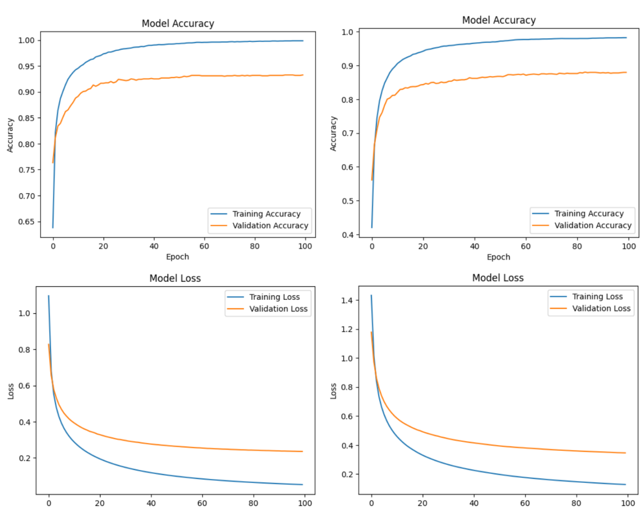

Figure 4: The accuracy and loss of each pipeline on only the training distribution during training. (ResNet, left. VGG, right)

Figure 4 indicates that the training distribution generalised well for both models. ResNet showed a validation accuracy from the training distribution fold of 93.34% and VGG achieved 87.95%. These indicators show that further training may have slightly improved both models, but the evaluation is still comprehensive since they are trained to only 100 epochs.

Evaluation of both models on the actual validation distribution resulted in the ResNet and VGG achieving 40.58% and 42.39% , respectively.

5.4 Confusion Matrix

Table 4 gives a comprehensive breakdown of the metrics gathered from each model based on their performance in each experiment. Accuracy, area under curve (AUC), F1 score, precision, and recall were specifically chosen to comprehensively analyse the models' performance and highlight the impact of the different experimental conditions.

Table 4: Evaluation Metrics for ResNet50 and VGG16 Pipelines

Model	Evaluation	Acc. (%)	AUC (%)	F1 (%)	Precision (%)	Recall (%)
	Colour	48.19	73.26	43.38	61.36	19.57
ResNet50	Grayscale	42.03	71.36	39.55	51.74	29.71
	Training Dist.	40.58	72.34	38.24	45.63	34.06
	Colour	39.49	67.73	36.18	47.83	27.90
	Grayscale	37.32	67.89	35.31	44.51	27.90
VGG16	Training Dist.	42.39	70.55	39.99	49.60	33.33

6 Discussion

After experimentation and result collection, certain observations are of particular note. It was hypothesised that because most trail cameras and surveillance cameras have a built-in night mode feature, grey scaling images might be a better approach than using full-colour images. However, as can be seen in Figure 2 and Figure 3, greying the images caused the model to generalise slower and to be less accurate. This suggests either that colour is important for the classification of some of the coloured images in the dataset or that grey scaling reduces the amount of information that can be passed to the model, which may make distinguishing between classes more challenging.

ResNet50 outperforms VGG16 in the colour and grayscale experiments but does worse in the training distribution evaluation. It is suspected that this is because of the simplicity of the VGG16 architecture, which could generalise clear training images faster within a limited number of epochs. As a result, the accuracy of the VGG16 model also improved, which could suggest that transfer learning may improve the performance of VGG on the evaluation dataset. On the other hand, ResNet50 performs better on the other experiments, likely due to the residual connections built into its architecture. These connections help with managing vanishing gradients, which, as a result, could enable deeper feature extraction, leading to better results on the more complex validation dataset.

The validation distribution, while comprehensive, should be expanded with a focus on including more trail camera footage. However, the training distribution can also be improved by removing the augmented data from the affected classes and replacing it with more varied data. Furthermore, because the dataset tries to encapsulate invasive species in various environments, it may be worth exploring specific environments for classification. Annotating the dataset and converting the problem to an object detection problem also may be worthwhile. Finally, adding a non-class (a class that contains examples of wildlife that aren't invasive) could be useful. This approach could make the metric more appropriate and precise, which is desirable. This is because precision emphasises capturing the specific features of the invasive animal over classifying based on general features.

7 Conclusion

This paper explored the use of computer vision to classify invasive animals from trail cameras and surveillance footage. Three experiments have been performed on two pipelines in order to determine the best approach for this task. The results show that the ResNet50 pipeline had an accuracy of 48.19% on colour and 42.03% on grayscale images. This is better than the VGG16 pipeline which had an accuracy of 39.49% on colour and 37.32% on grayscale images. Utilising only the clear images from the training distribution of the dataset for training, VGG16 performed better than ResNet50, with an accuracy of 42.39% and 40.58%, respectively. It can be concluded that the classification of invasive wildlife with computer vision is promising but requires a more comprehensive dataset.

References

[1] [n. d.]. *Buy The Latest Tech in South Africa.* https://newtech-sa.co.za/product-category/trail-cameras-and-outdoor/trail-cameras/

[2] [n. d.]. *EPPO activities on plant quarantine.* https://www.eppo.int/ACTIVITIES/quarantine_activities#:~:text=Quarantine%20pest%3A%20A%20pest%20of,(ISPM%205%2C%20FAO).

[3] [n. d.]. *How Much Does A Drone Cost in 2024? Here's a Price Breakdown.* https://www.jouav.com/blog/how-much-does-a-drone-cost.html

[4] [n. d.]. *State-of-the-art security and surveillance camera solutions in South Africa.* https://miro.co.za/11-10-surveillance

[5] annproject zu8n9. [n. d.]. Rat Detection Dataset. https://universe.roboflow.com/annproject-zu8n9/rat-detection-6ezx2/dataset/3

[6] James Beasley and Olin Rhodes. 2023. Contemporary Analysis of Raccoon Population Dynamics and Their Impact on Crop Yield. *Human-Wildlife Interactions* 15, 1 (2023), 50–70. https://doi.org/10.1016/hwi.2023.01.005

[7] C. M. Bishop and H. T. Nguyen. 2022. *Pattern Recognition and Machine Learning: Recent Advances* (2nd ed.). Springer.

[8] Laura M. Brown, Peter T. Green, and Susan K. White. 2023. Long-Term Effects of Badger Culling on Bovine Tuberculosis in Cattle: A Comprehensive Study. *Veterinary Epidemiology* 58, 4 (2023), 345–360. https://doi.org/10.1016/j.ve.2023.04.007

[9] Matheus Cardim Ferreira Lima, Maria Elisa Damascena de Almeida Leandro, Constantino Valero, Luis Carlos Pereira Coronel, and Clara Oliva Gonçalves Bazzo. 2020. Automatic Detection and Monitoring of Insect Pests—A Review. *Agriculture* 10, 5 (2020). https://doi.org/10.3390/agriculture10050161

[10] Youngjoon Cho and Jongwon Kim. 2023. AI-Based Intelligent Monitoring System for Estrus Prediction in the Livestock Industry. *Applied Sciences* 13 (02 2023), 2442. https://doi.org/10.3390/app13042442

[11] Debasisdotcom. [n. d.]. Racoon Detection Dataset. https://www.kaggle.com/datasets/debasisdotcom/racoon-detection

[12] Missouri University Electrical and Computer Engineering. [n. d.]. Camera Trap Dataset. https://videonet.ece.missouri.edu/cameratrap/videonet.ece.missouri.edu/cameratrap/

[13] Hany F. Ellakany, Ahmed R. Elbestawy, Hatem S. Abd El-Hamid, Rasha E. Zedan, Ahmed R. Gado, Ayman E. Taha, Mohamed A. Soliman, Mohamed E. Abd El-Hack, Ayman A. Swelum, Islam M. Saadeldin, Hani Ba-Awadh, and Elsayed O.S. Hussein. 2019. Role of Pigeons in the Transmission of Avian Avulavirus (Newcastle Disease-Genotype VIId) to Chickens. *Animals* 9, 6 (2019). https://doi.org/10.3390/ani9060338

[14] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2015. Deep Residual Learning for Image Recognition. arXiv:1512.03385 [cs.CV] https://arxiv.org/abs/1512.03385

[15] Emily A. Johnson and Daniel R. Lee. 2023. Enhancing Stochastic Gradient Descent for Deep Learning Applications. *Journal of Machine Learning Research* 24, 1 (2023), 1–25. https://doi.org/10.1007/s10994-023-06250-5

[16] R. Kenward and Laura K. Smith. 2023. Recent Trends in Squirrel-Related Agricultural Damage and Management Practices. *Mammal Review* 53, 3 (2023), 300–315. https://doi.org/10.1111/mam.12346

[17] Shin-Chi Lai, Szu-Ting Wang, Kuan-Lin Liu, and Chang-Yu Wu. 2023. A Remote Monitoring System for Rodent Infestation Based on LoRaWAN. *Sensors* 23, 9 (2023). https://doi.org/10.3390/s23094185

[18] lyyup. [n. d.]. Squirrels Dataset. https://universe.roboflow.com/squirrels-lyyup/robin_squirrels/dataset/3

[19] Johnny Miranda, Bobby Gerardo, and Bartolome Iii. 2014. Pest Detection and Extraction Using Image Processing Techniques. *International Journal of Computer and Communication Engineering* 3 (01 2014), 189–192. https://doi.org/10.7763/IJCCE.2014.V3.317

[20] Catherine Mougenot and Laurence Roussel. 2022. Sustainable Pest Control: Balancing Ecological Impact and Agricultural Needs. *Sociologia Ruralis* 62, 4 (2022), 450–467. https://doi.org/10.1111/soru.12456

[21] Peacehegemony. [n. d.]. 494 Fox Labeled Image Dataset. https://www.kaggle.com/datasets/peacehegemony/494-fox-labeled-image-dataset

[22] Roboflow. [n. d.]. Raccoon Object Detection Dataset. https://public.roboflow.com/object-detection/raccoon

[23] Cagatay Catal Roel Dohmen and Qingzhi Liu. 2022. Computer vision-based weight estimation of livestock: a systematic literature review. *New Zealand Journal of Agricultural Research* 65, 2-3 (2022), 227–247. https://doi.org/10.1080/00288233.2021.1876107

[24] Glen Saunders, Matthew Gentle, and Christopher Dickman. 2023. Modern Management Strategies for Foxes (Vulpes vulpes) and Their Impact on Australian Agriculture. *Mammal Review* 53, 2 (2023), 200–220. https://doi.org/10.1111/mam.12345

[25] Karen Simonyan and Andrew Zisserman. 2015. Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv:1409.1556 [cs.CV] https://arxiv.org/abs/1409.1556

[26] John A. Smith and Jane B. Doe. 2023. Recent Advances in Understanding Rodent-Borne Diseases and Their Impact on Public Health. *Journal of Public Health* 45, 2 (2023), 150–170. https://doi.org/10.1016/j.jpubhealth.2023.02.005

[27] John D. Smith. [n. d.]. *Advanced Rodent Control Strategies in Modern Livestock and Poultry Facilities.* https://www.thepoultrysite.com/articles/advanced-rodent-control-in-livestock-and-poultry-facilities

[28] Spirosmakris. [n. d.]. Pigeons Dataset. https://universe.roboflow.com/spirosmakris/pigeons-visup/dataset/1

[29] Tanha Talaviya, Dhara Shah, Nivedita Patel, Hiteshri Yagnik, and Manan Shah. 2020. Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. *Artificial Intelligence in Agriculture* 4 (2020), 58–73. https://doi.org/10.1016/j.aiia.2020.04.002

[30] Emily R. Taylor and Mark S. Johnson. 2023. Modern Approaches to Fox Population Management and Their Impact on Agricultural Practices. *Journal of Wildlife Management* 87, 1 (2023), 50–65. https://doi.org/10.1002/jwmg.12345

[31] (unknown). [n. d.]. Raccoon Image Classification Dataset. https://images.cv/dataset/raccoon-image-classification-dataset

[32] (unknown). [n. d.]. Red Fox Image Classification Dataset. https://images.cv/dataset/red-fox-image-classification-dataset

[33] Johann van Niekerk and C.M. Ginkel. 2023. Modern Feeding Behaviors of Pigeons on Sown Grain Crops in South Africa: Implications for Crop Management. *Ostrich - Journal of African Ornithology* 94, 1 (2023), 50–60. https://doi.org/10.2989/00306520409485411

[34] Gyanendra K. Verma and Pragya Gupta. 2018. Wild Animal Detection Using Deep Convolutional Neural Network. In *Proceedings of 2nd International Conference on Computer Vision & Image Processing*, Bidyut B. Chaudhuri, Mohan S. Kankanhalli, and Balasubramanian Raman (Eds.). Springer Singapore, Singapore, 327–338.

[35] Wiings. [n. d.]. Pigeon Dataset. https://universe.roboflow.com/wiings/pigeon-mg46t/dataset/1

[36] Gary Witmer. 2022. Rodents in Agriculture: A Broad Perspective. *Agronomy* 12, 6 (2022). https://doi.org/10.3390/agronomy12061458