Title: "Enhancing Backyard Chicken Safety: Advanced Wild Animal Detection Model for ChickenGuard"

Abstract: This paper outlines the development of a specialized model for **ChickenGuard**, a backyard surveillance system designed to protect chickens from wild animal threats. The model leverages transfer learning with EfficientNetV2B0, employing Bayesian optimization to refine its architecture. A unique dataset, crafted through logical analysis of animal labels, underpins the ChickenGuard classification pipeline, enabling accurate identification of potential dangers to chickens.

Introduction

Backyard chicken farming has become increasingly popular [4] due to various reasons such as self-sustainability, organic food sourcing, and as a hobby. With this rise, the threat from wild animals like foxes, raccoons, and predatory birds also increases, necessitating effective protection measures. Traditional surveillance systems may not be sufficient for protecting chickens because they often rely on simple motion detection, which can be triggered by non-threatening movements, leading to false alarms. An advanced system like ChickenGuard aims to specifically identify threats, reducing false positives and improving reaction times to real dangers. EfficientNetV2B0 is a state-of-the-art neural network architecture known for its efficiency and effectiveness in image classification tasks. Using transfer learning, ChickenGuard leverages a pre-trained EfficientNetV2B0 model. Transfer learning involves taking a model trained on a large dataset and fine-tuning it for a specific task. This approach is beneficial as it reduces the need for a large custom dataset and computational resources, while still achieving high accuracy. To fine-tune the model for the specific task of identifying potential threats to chickens, ChickenGuard uses a custom dataset. This dataset is composed of images of various wild animals that pose a threat, as well as common non-threatening animals. The logical analysis using a predetermined tabular dataset of animal characteristics means that the model focuses on distinguishing animals while the dataset can be leveraged to enable a human-understandable characterization of predatory animals. By accurately identifying threats, the system can trigger alarms or take other protective measures to safeguard the chickens. This proactive approach not only protects the chickens but also provides peace of mind to the owners.

In summary, ChickenGuard's approach of using an advanced AI model with a specialized dataset represents a significant advancement in backyard chicken protection. It showcases how modern machine learning techniques, particularly transfer learning and custom datasets, can be applied to very specific and practical problems in everyday life.

Methods

- **Dataset Creation Strategy:** The dataset was uniquely constructed using a logic-based approach. Animals were categorized as dangerous or not based on size (compared to a

chicken), diet type (Carnivore, Herbivore, Omnivore), and non-aquatic nature (aquatic/not-aquatic).
- **Model Selection and Transfer Learning:** The choice of EfficientNetV2B0 [1], pre-trained on ImageNet weights, provided a robust foundation for transfer learning. The base model was kept frozen while the architecture of additional model layers was optimized [3]. A training/validation/test (8/1/1 split) dataset was created for the training and evaluation of the transfer-learning approach.
- **Hyperparameter and Architecture Optimization:** Bayesian optimization [2] was employed to determine the optimal configuration of the model's architecture. Hyperparameters included architecture search and learning rate optimization.

Results

Our model demonstrated high efficacy in identifying potential wild animal threats to chickens. The performance metrics, including accuracy, precision, recall, AUC, and loss (MSE) were significantly enhanced post-optimization. Visual representations of these metrics are provided for a comprehensive understanding of the model's capabilities.

Index	Animal	Diet	biggerChicken	aquatic	dangerous
0	Antelope	Herbivore	1	0	0
1	Badger	Omnivore	1	0	1
2	Bat	Omnivore	0	0	0
3	Bear	Omnivore	1	0	1
4	Bee	Herbivore	0	0	0

Table 1: Example of dataset which contains ‘dangerous’ logic

A simple dataset of animal diet, whether or not the animal was bigger than a chicken, and whether or not the animal was an aquatic animal was created. The simple logic of animals that are not herbivores, larger than a chicken and not aquatic was used to create the binary classification of dangerous/not_dangerous.

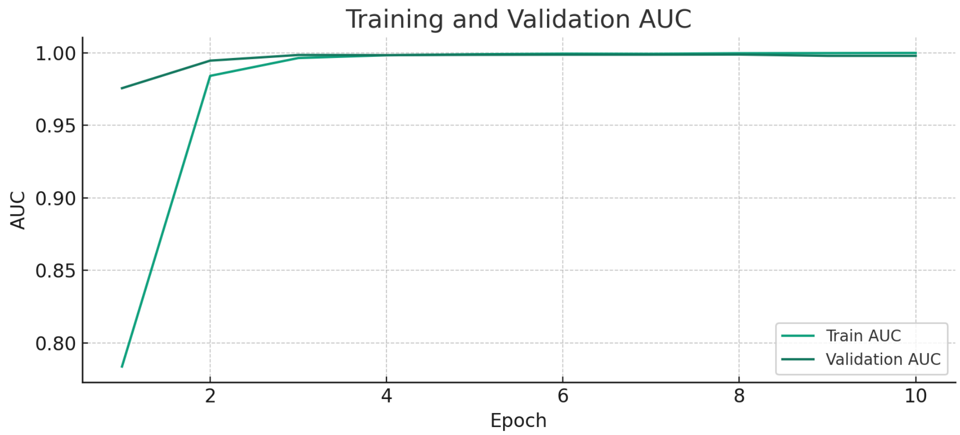

Figure 2: Training and Validation AUC for EfficientNetV2B0 Transfer Learning Model

Figure 2 does not indicate the model was overfit after 10 epochs of training.

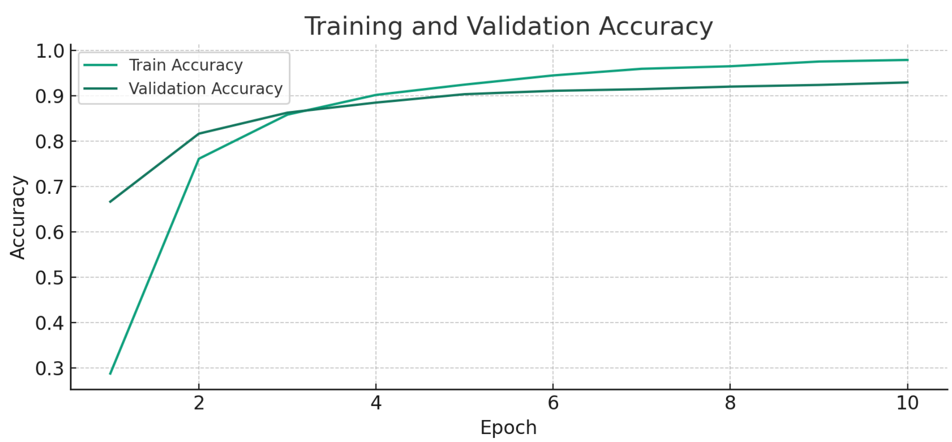

Figure 3: Training and Validation Accuracy for EfficientNetV2B0 Transfer Learning Model

Figures 1 and 2 are the training/validation plots of the transfer-learning model which classifies animals into 90 different categories. There is an indication of slight overfitting in figure 2.

Metric	Score
Test Loss	0.27673
Test Accuracy	0.92592
Test Precision	0.95381
Test Recall	0.87962

Test AUC	0.99771

Figure 4: Test metrics for EfficientNetV2B0 Transfer Learning Model

The test set created to evaluate the transfer learning model for the 90 animal classification showed a strong AUC [0.99771], indicating the ability of the model to distinguish between different classifications of animals.

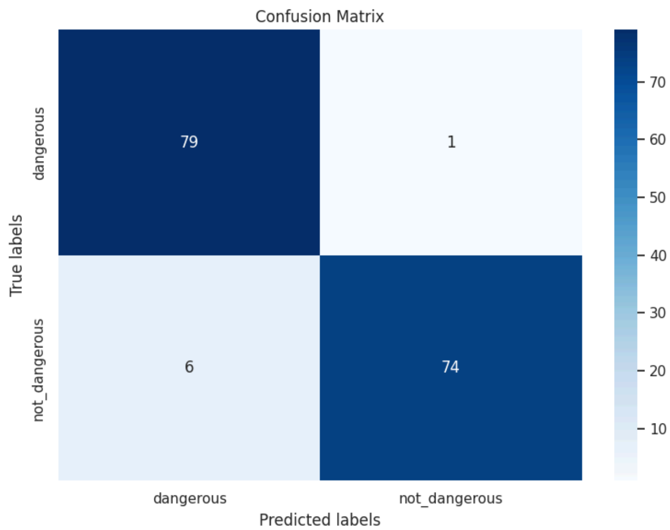

Figure 5: Confusion Matrix for ChickenGuard classification pipeline.

Figure 4 depicts the confusion matrix for the pipeline that incorporates the classification model and the dataset which classifies the animals into dangerous and not dangerous. This pipeline achieved an overall accuracy of **96%**.

Discussion

The development of Chicken Guard's detection model marks a significant step in backyard chicken protection. The model's reliance on logical animal categorization and optimized transfer learning sets it apart in the field of wildlife surveillance. This enables quick changes to be made to the classification of dangerous/not_dangerous without having to retrain the classification model, saving computing resources and engineering time. Use of logic based classification enables a human-driven understanding of danger to chickens, rather than employing a deep-learning model which is hard to audit and explain.

Future enhancements could include expanding the dataset with more varied animal behavior observations and further refining the model to adapt to different backyard environments. Datasets could be devised for different animals which have different safety interactions with animals that may be picked up by the backyard camera.

References

- [1] "EfficientNetV2: Smaller Models and Faster Training," Tan and Le, 2021.
- [2] "Bayesian Optimization in Deep Learning," Snoek et al., 2012.
- [3] Transfer Learning for Beginners
- [4] Backyard Chicken Growth