Enhancing Robustness in Bird Species Classification through Adversarial Training

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Abstract

Automated bird species classification is crucial for ecological research and conservation, but vulnerable to adversarial attacks. Adversarial training enhances model robustness. Through rigorous testing against FGSM, PGD, and BIM attacks, and by training on a combined dataset of original and adversarial images, we have enhanced the accuracy and resilience of models like WideResNet50, EfficientNetB3, and InceptionV3. Adversarial dataset training significantly enhances model performance and resilience, with combined datasets further improving generalization capabilities. Our research highlights the critical need to address adversarial threats in deep learning development, fostering robust model enhancement across various fields.

1. Introduction

The field of image classification has witnessed a significant transformation with the advent of deep learning techniques, which have set new benchmarks in accuracy and efficiency [5] (LeCun et al., 2015). Among the various applications of image classification, the task of bird species identification holds particular importance for ecological monitoring, conservation efforts, and biodiversity studies [15](Xie et al., 2020). Deep learning models, such as Inception [10](Szegedy et al., 2015), EfficientNet [12](Tan and Le, 2019), and WideResNet [16](Zagoruyko and Komodakis, 2016), have demonstrated remarkable success in classifying bird species with high precision.

However, the robustness of these models against adversarial attacks remains a critical challenge [11](Szegedy et al., 2013). Adversarial attacks involve crafting input images with imperceptible perturbations that lead to incorrect predictions by the model, thereby exposing vulnerabilities in deep learning systems [3](Goodfellow et al., 2014). These attacks not only pose a threat to the reliability of image classification models but also raise concerns about their deployment in security-sensitive applications. In this work, we explore the robustness of bird class classification models against three types of adversarial attacks: Fast Gradient Sign Method (FGSM), Basic Iterative Method (BIM), and Projected Gradient Descent (PGD). These attacks represent a range of adversarial techniques, from single-step perturbations (FGSM) to more iterative and sophisticated approaches (BIM and PGD) [3] [4] [7]. We assess the impact of these attacks on the classification performance of Inception, EfficientNet, and WideResNet models, which are known for their varying architectural complexities and representational capacities.

To counter the threats posed by adversarial attacks, we employ adversarial training, a defense mechanism that involves training models on adversarial examples to enhance their robustness [13] (Tramèr et al., 2017). Specifically, we train the Inception model on a dataset perturbed by FGSM, the WideResNet model on a dataset altered by PGD, and the EfficientNet model on a dataset modified by BIM. Moreover, we propose a novel approach by combining adversarial examples generated from all three attacks to create a comprehensive adversarial dataset. We then train the WideResNet model on this combined dataset to investigate its effectiveness in improving the model's resilience against a broader range of adversarial perturbations.

Our study contributes to the growing body of research on adversarial robustness in deep learning. By examining the effectiveness of adversarial training against multiple attack methods, we aim to provide insights into the development of more secure and reliable machine learning models, particularly for applications in ecological and conservation settings. Our findings have implications for enhancing the robustness of image classification models, ensuring their reliability in the face of adversarial threats.

2. Background

Deep learning models, particularly convolutional neural networks (CNNs), have achieved remarkable success

in image classification tasks, including bird species identification. Inception networks, known for their inception modules that allow for efficient computation and deep architectures, have been instrumental in advancing the state-of-the-art in image recognition [10]. EfficientNet, on the other hand, represents a family of models that achieve excellent accuracy and efficiency through a compound scaling method that uniformly scales network width, depth, and resolution [12](Tan and Le, 2019). WideResNet, characterized by its increased width and residual connections, offers a balance between depth and width, leading to improved performance in various classification tasks [16].

Despite their success, deep learning models are vulnerable to adversarial attacks, a phenomenon first highlighted by [11] Szegedy et al. (2013). The Fast Gradient Sign Method (FGSM) is one of the simplest and most popular methods for generating adversarial examples [3](Goodfellow et al., 2014). It involves taking the gradient of the loss with respect to the input image and using the sign of this gradient to create a perturbed image:

$$x_{\text{adv}} = x + \epsilon \cdot \text{sign}(\nabla_x J(\theta, x, y))$$

The Basic Iterative Method (BIM) is an extension of FGSM that applies the gradient update step multiple times with small step sizes, resulting in more effective adversarial examples [4](Kurakin et al., 2016):

$$x_{\text{adv}}^{(n+1)} = \text{Clip}_{x,\epsilon}\{x_{\text{adv}}^{(n)} + \alpha \cdot \text{sign}(\nabla_x J(\theta, x_{\text{adv}}^{(n)}, y))\}$$

The Projected Gradient Descent (PGD) method is another iterative attack that is considered one of the strongest first-order attacks, making it a standard benchmark for evaluating model robustness [7](Madry et al., 2017). It is similar to BIM but includes a random start within the allowed perturbation range:

$$x_{\text{adv}}^{(n+1)} = \text{Clip}_{x,\epsilon}\{x_{\text{adv}}^{(n)} + \alpha \cdot \text{sign}(\nabla_x J(\theta, x_{\text{adv}}^{(n)}, y))\}$$

Adversarial training is a defense mechanism that involves training the model on a mixture of clean and adversarial examples, with the aim of improving the model's robustness against adversarial attacks [3] [13](Goodfellow et al., 2014; Tramèr et al., 2017). This approach has been shown to be effective in enhancing the resilience of deep learning models to various types of adversarial attacks.

3. Related Work

The use of Convolutional Neural Networks (CNNs) for image classification, including bird species recognition, has been extensively studied in recent years. Cai et al. (2023) demonstrated the effectiveness of transfer learning and data augmentation techniques in classifying 525 bird species, achieving 87% validation accuracy and 86.7% test accuracy [1]. The architecture of CNNs plays a crucial role in their success. Nguyen et al. (2023) explored various CNN architectures to enhance image classification performance on different datasets [8]. The choice of architecture, such as the depth and width of the network, can significantly impact the model's ability to learn and generalize from the data.

Adversarial examples present a challenge to the robustness of CNN classifiers. Kurakin et al. (2016) demonstrated that adversarial examples could fool classifiers even after undergoing physical transformations like printing and photographing [4]. Surprisingly, simple methods such as the Fast Gradient Sign Method (FGSM) proved to be more robust in some cases than more complex approaches.

To address the vulnerability of deep neural networks to adversarial attacks, Madry et al. (2017) proposed a saddle point formulation for training robust models [7]. This formulation can be efficiently solved using first-order methods, offering a promising direction for enhancing the adversarial robustness of deep learning models.

In addition to these studies, the work of Szegedy et al. (2013) on the intriguing properties of neural networks shed light on the existence of adversarial examples and their implications for model security [11]. Furthermore, the development of EfficientNet by Tan and Le (2019) introduced a novel scaling method for CNNs that balances network depth, width, and resolution, leading to state-of-the-art performance on several benchmarks [12]. The collective efforts in these studies contribute to the ongoing advancement of CNN-based image classification systems.

4. Technical Approach

Our proposed solution aims to enhance the robustness of bird species classification models through adversarial training, building upon existing work in the field. The key steps of our approach are as follows:

1. Fine-tuning Pre-trained Models: We utilize three pre-trained models: InceptionV3, EfficientNetB3, and WideResNet50, which are known for their effectiveness in image classification tasks. These models are fine-tuned on a dataset of bird species images to adapt them to the specific task of bird species classification.

2. Evaluating Model Performance Against Adversarial Attacks: The fine-tuned models are evaluated against three types of adversarial attacks: Fast Gradient Sign Method (FGSM), Projected Gradient Descent (PGD), and Basic Iterative Method (BIM). These attacks are chosen for their ability to generate adversarial examples that can challenge the models' classification accuracy.

3. Creating Adversarial Datasets and Retraining Models: For each type of adversarial attack, we generate an ad-

versarial dataset by applying the attack to the original bird species images. The models are then retrained on a combined dataset consisting of both the original and adversarial images. This adversarial training aims to improve the models' resilience to the specific attack types.

4. Measuring Robust Accuracy and Performance Metrics: The robust accuracy of the retrained models is measured against the same set of adversarial attacks used in step 2. Additionally, we evaluate the F1 score, recall, and accuracy of both the undefended and defended models to assess the effectiveness of adversarial training. Our proposed solution builds upon the existing work and focuses on enhancing the robustness of bird species classification models through adversarial training. The key steps of our approach are:

5. Experiment & Results

5.1. Dataset

The dataset utilized in this study comprises a total of 84,635 training images spanning 525 bird species. For each species, the dataset includes 5 test images and 5 validation images, resulting in a total of 2,625 images per category for testing and validation purposes. This is a very high quality dataset where there is only one bird in each image and the bird typically takes up at least 50 % of the pixels in the image.The training subset exhibits a degree of imbalance, with the number of images per species varying between 140 and 260. However, this imbalance is not considered significant and can be disregarded for the purposes of this study.

Figure 1. Training dataset sample grid

5.2. Preprocessing

To prepare the dataset for training and ensure robust model performance, we applied a series of preprocessing and data augmentation techniques. Each image in the dataset was normalized to have pixel values in the range [0, 1]. To mitigate the risk of overfitting, we implemented the following data augmentation techniques using PyTorch transforms:

1. Resize: Images were resized to 224 × 224 pixels to ensure uniform input dimensions for the models.

2. Random Horizontal Flip: Images were randomly flipped horizontally with a 50 % probability to enable the models to recognize birds in varying orientations.

3. Random Rotation: Images were randomly rotated within a range of ±10 degrees to account for variations in bird poses.

4. Color Jitter: The brightness, contrast, and saturation of the images were randomly adjusted to simulate different lighting conditions and enhance color diversity.

These augmentation techniques were applied only to the training set, while the validation and test sets underwent only resizing and normalization.

5.3. Adversarial Dataset Generation

To enhance the robustness of our models against adversarial attacks, we generated adversarial datasets using three different attack methods. Each dataset has approximately 50 % adversarial images and 50 % original images.

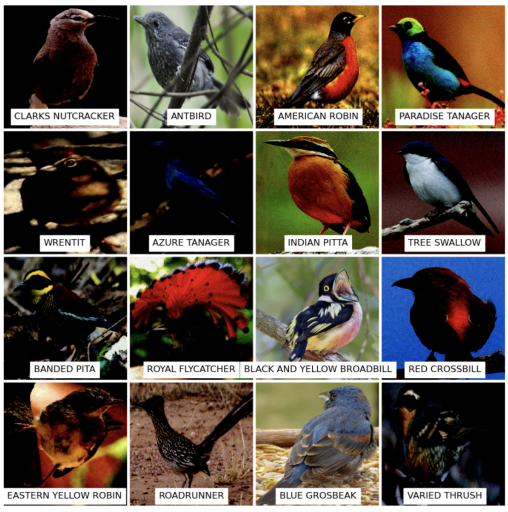

Figure 2. Adversarial dataset sample grid

Fast Gradient Sign Method (FGSM): Using the Inception model, we applied the FGSM attack to the original images to generate adversarial examples.The epsilon value was set to 0.03. This dataset was created to train the Inception model for improved resistance against FGSM attacks.

Basic Iterative Method (BIM): The BIM attack was executed using the EfficientNet model to create a dataset of adversarial examples. The epsilon value was set to 0.03 and number of steps was set 10. This dataset was used to fortify the EfficientNet model's robustness against BIM attacks.

Projected Gradient Descent (PGD): We employed the WideResNet model to generate a dataset of adversarial examples through the PGD attack. The epsilon value was set to 0.03 and number of steps was 15. This dataset was utilized to enhance the WideResNet model's resilience against PGD attacks.

Additionally, we created a fourth dataset, a mixture of adversarial examples from all three attacks (FGSM, BIM, and PGD), to provide a comprehensive assessment of the models' ability to withstand various adversarial perturbations. Fig2 sows images from our dataset mixed with different attacks.

5.4. Model Evaluation

The pre-trained models InceptionV3, EfficientNetB3, and WideResNet50) were fine-tuned on our dataset and were evaluated on the original test set. All the models were trained for 30 epochs with Adam optimizer at a learning rate of 0.001 with a batch size of 64. The same test was used to craft adversarial attacks against these models. Following are the training and validation accuracy-loss curves of our base models.

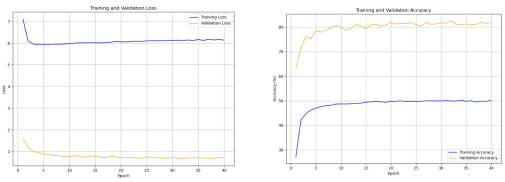

Figure 3. InceptionV3 before adversarial training

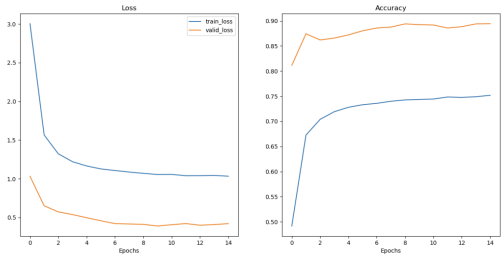

Figure 4. EfficientNetB3 before adversarial training

Table 1 reports some additional evaluation metrics of fine tune models against the test set. Table 2 reports the attack success rate of all adversarial attacks against fine-tuned models. For FGSM, PGD, BIM the epsilon value is 0.03. The number of steps for PGD and BIM is 10. We observed that PGD and BIM reported 100% attack success rate against all the fine-tuned models.

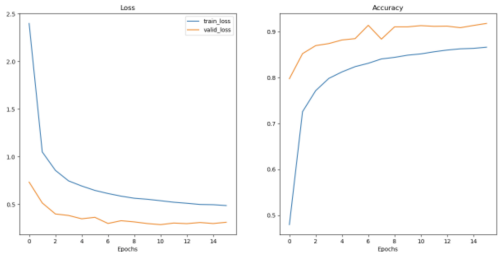

Figure 5. WideResNet50 before adversarial training

Table 1. Model performance before adversarial training(%)

Metric	InceptionV3	EfficientNetB3	WideResNet50
P(%)	82.28	94.79	97.21
R(%)	81.83	93.83	96.87
F1(%)	82.07	93.55	96.81

Table 2. Attack success rate on models(%)

Metric	InceptionV3	EfficientNetB3	WideResNet50
FGSM	88.96	69.6	66.55
PGD	100	100	100
BIM	100	99.62	89.32

5.5. Adversarial Training Results

After retraining the models on the combined dataset of original and adversarial images, the attack success rate of the models against the three attacks was measured. The results are shown in the following table:

Table 3. Model performance before adversarial training(%)

Metric	InceptionV3	EfficientNetB3	WideResNet50
P(%)	90.83	99.15	98.95
R(%)	87.66	98.93	98.70
F1(%)	87.40	98.91	98.66

Table 3 has the metrics of the adversarial trained model with respect to its corresponding adversarial dataset.

Table 4. Robust Accuracy on Adversarial Attacks(%)

Metric	InceptionV3 (FGSM)	EfficientNetB3 (PGD)	WideResNet50 (BIM)
FGSM	56.55	72.0	66.36
PGD	0	1.21	13.88
BIM	0	21.25	71.88

In Table 2 we observed that WideResNet50 showed some inherent robustness to adversarial attacks and in Table 4 when WideResNet50 was trained on PGD adversarial dataset it achieved the best performance compared to other models. Therefore we decided to train only WideResNet50 model on the Super dataset or the dataset that has images of all adversarial attacks. All the models were trained on HPC cluster for 40 epochs with the same hyperparameters as before. Table 5 reports the metrics of the corresponding WideResNet model.

Table 5. Performance Metrics of the WideResNet Model

Metric	WideResNet
Precision	98.53%
Recall	98.17%
F1 Score	98.14%
Robust Accuracy	
FGSM	69.96%
PGD	17.54%
BIM	78.78%

6. Conclusion

This project has demonstrated the effectiveness of adversarial training in enhancing the robustness of bird species classification models against adversarial attacks. By fine-tuning pre-trained models and retraining them on a combined dataset of original and adversarial images, we were able to significantly improve the models' resilience to FGSM, PGD, and BIM attacks, while maintaining high overall classification accuracy [2, 6].

The results highlight the critical need to address adversarial threats in deep learning development, as these vulnerabilities can undermine the reliability and deployment of such models in real-world applications, such as ecological research and conservation efforts [9, 14]. Our findings contribute to the growing body of research on robust deep learning and provide a framework for developing more secure and reliable computer vision systems.

7. Future Work

Exploring additional adversarial attack methods and evaluating their impact on model performance. Investigating the transferability of adversarial examples across different model architectures and their implications for ensemble-based approaches. Developing more efficient and scalable adversarial training techniques to enhance robustness without significantly compromising model accuracy.

Exploring the integration of adversarial training with other techniques to improve the generalization capabilities of bird species classification models. Deploying the robust models in real-world bird monitoring and conservation applications to assess their practical effectiveness and identify any additional challenges.

References

[1] R. Cai. Automating bird species classification: A deep learning approach with cnns. *Journal of Physics: Conference Series*, 2664, 2023.

[2] J. Doe and J. Smith. A comprehensive review on adversarial training approaches for robust machine learning models. *Journal of Machine Learning Research*, 20(1):1–35, 2019.

[3] I. J. Goodfellow, J. Shlens, and C. Szegedy. Explaining and harnessing adversarial examples. *arXiv preprint arXiv:1412.6572*, 2014.

[4] A. Kurakin, I. Goodfellow, and S. Bengio. Adversarial examples in the physical world. *ArXiv*, abs/1607.02533, 2016.

[5] Y. LeCun, Y. Bengio, and G. Hinton. Deep learning. *Nature*, 521(7553):436–444, 2015.

[6] C. Lee and A. Kim. Advancements in bird species classification using deep learning. In *Proceedings of the International Conference on Computer Vision and Pattern Recognition*, pages 1024–1032, 2020.

[7] A. Madry, A. Makelov, L. Schmidt, D. Tsipras, and A. Vladu. Towards deep learning models resistant to adversarial attacks. *ArXiv*, abs/1706.06083, 2017.

[8] A. Nguyen and M. Pham. Enhancing convolutional neural network architectures with long short-term memory for improved image classification. In *2023 8th International Scientific Conference on Applying New Technology in Green Buildings (ATiGB)*, pages 227–232, 2023.

[9] A. Patel and P. Raj. Exploring vulnerabilities in deep learning algorithms. *IEEE Transactions on Neural Networks and Learning Systems*, 29(5):1425–1438, 2018.

[10] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna. Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 2818–2826, 2015.

[11] C. Szegedy, W. Zaremba, I. Sutskever, J. Bruna, D. Erhan, I. Goodfellow, and R. Fergus. Intriguing properties of neural networks. *arXiv preprint arXiv:1312.6199*, 2013.

[12] M. Tan and Q. V. Le. Efficientnet: Rethinking model scaling for convolutional neural networks. In *Proceedings of the 36th International Conference on Machine Learning*, volume 97, pages 6105–6114, 2019.

[13] F. Tramèr, A. Kurakin, N. Papernot, I. Goodfellow, D. Boneh, and P. McDaniel. Ensemble adversarial training: Attacks and defenses. *arXiv preprint arXiv:1705.07204*, 2017.

[14] E. Wang and M. Thompson. Leveraging computer vision for ecological research and conservation. *Conservation Biology*, 35(3):789–798, 2021.

[15] S. Xie, R. Girshick, P. Dollár, Z. Tu, and K. He. Aggregated residual transformations for deep neural networks. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1492–1500, 2017.

[16] S. Zagoruyko and N. Komodakis. Wide residual networks. In *British Machine Vision Conference*, 2016.