Bird Species Presence Prediction from Remote Sensing Images

Master's Project Report

Submitted by

Hamed Tangestani

Department of Computer Science and Engineering
University of California, Santa Cruz

Project Advisors:

Prof. Luca De Alfaro	Prof. Katherine Isbister

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***Abstract*—Accurately predicting the presence of bird species is essential for ecological monitoring and biodiversity conservation. Traditional methods of species distribution modeling (SDM) often suffer from limited data availability and insufficient scalability. In this project, we propose a refined MobileNet-based approach, leveraging remote sensing imagery and citizen science data from eBird to classify the presence of three North American bird species: Acorn Woodpecker, Oak Titmouse, and Steller's Jay. Our method utilizes transfer learning and fine-tuning techniques to adapt the MobileNet architecture effectively, addressing data scarcity and enhancing prediction accuracy. Experimental results demonstrate that the refined MobileNet model significantly outperforms baseline approaches, highlighting its potential for scalable, efficient, and precise ecological modeling.**

I. Introduction

Biodiversity is undergoing rapid global decline, directly affecting ecosystem services essential for human health, food security, and overall well-being [1], [2]. Accurate modeling and monitoring of species distribution are thus crucial for informed conservation planning, ecological studies, and policy decision-making [3]. However, traditional ecological monitoring methods, which rely heavily on intensive field surveys and expert observations, face significant limitations due to high costs, labor intensity, and limited spatial-temporal coverage [4], [5].

The emergence of citizen science platforms such as eBird and iNaturalist has provided an alternative approach, facilitating the collection of extensive species observations by crowdsourcing data from non-experts and volunteers [6], [7]. Citizen-science data have become valuable due to their broad geographic and temporal coverage, enabling researchers to build robust Species Distribution Models (SDMs) at significantly reduced costs [1], [8]. In particular, platforms like eBird provide comprehensive presence-absence data, allowing accurate modeling of species distribution and overcoming certain biases inherent in presence-only datasets [1], [6].

Recent advances in remote sensing and machine learning have further expanded the potential of SDMs. Remotely sensed satellite imagery, such as data from Sentinel-2, offers high-resolution environmental information—vegetation indices, land use, soil characteristics, and bioclimatic variables—essential for ecological modeling [1], [3], [9]. Deep learning techniques, especially convolutional neural networks (CNNs) and transformer-based models, have demonstrated strong capabilities in extracting meaningful patterns from complex and high-dimensional remote sensing data, significantly enhancing prediction accuracy compared to traditional statistical models like generalized linear models (GLMs) and MaxEnt [5], [8], [10].

Teng et al. recently introduced SatBird, a benchmark dataset integrating remote sensing imagery with citizen science data to jointly predict the distribution of multiple bird species [1]. They demonstrated the advantages of combining deep learning approaches with remote sensing data, showing substantial performance improvements over simpler environmental baselines and traditional methods.

Motivated by these advancements, this project aims to predict the presence and distribution of three North American bird species—Acorn Woodpecker, Oak Titmouse, and Steller's Jay—using refined deep learning approaches. Specifically, we propose refining the MobileNet CNN architecture through transfer learning and fine-tuning techniques, designed explicitly to perform efficiently even on relatively limited datasets.

The remainder of this report is structured as follows. Section II briefly reviews additional related literature. Section III presents a detailed explanation of the methods, including data preparation, model refinement, and training procedures. Section IV discusses the experimental results, followed by conclusions and discussion of future work in Section V.

II. Related Work

Species Distribution Models (SDMs) have traditionally relied on statistical methods such as generalized linear models (GLMs) and maximum entropy models (MaxEnt) to predict the spatial distribution of species based on environmental predictors [2], [5]. While effective, these approaches often struggle with high-dimensional data and complex nonlinear relationships between environmental variables and species occurrence, limiting their accuracy and scalability [4].

The emergence of citizen science databases, notably eBird [6] and iNaturalist [7], has greatly expanded the availability of high-quality species observation data. Such platforms provide extensive geographic and temporal coverage, facilitating more robust ecological modeling compared to traditional field-based methods [8]. eBird, in particular, provides complete checklist data indicating both the presence and absence of species, enabling researchers to create detailed and reliable distribution maps [1], [6].

Recent advances in remote sensing and machine learning have significantly improved the effectiveness of SDMs. For instance, datasets such as SatBird integrate citizen science observations with Sentinel-2 satellite imagery, leveraging deep learning models to jointly predict encounter rates of multiple species [1]. Deep learning techniques, including convolutional neural networks (CNNs) and transformer-based architectures, are increasingly used due to their ability to learn complex spatial features directly from high-dimensional satellite images, outperforming traditional ecological modeling methods [1], [3], [10].

Various machine learning benchmarks, such as GeoLifeCLEF, have demonstrated the efficacy of remote sensing data combined with citizen science records for biodiversity monitoring tasks, confirming the potential of deep learning in predicting species distributions across extensive geographic scales [1], [10]. These studies highlight both the importance and the complexity of accurately modeling ecological distributions with scalable computational approaches.

Motivated by this body of work, our study applies transfer learning and fine-tuning methods to refine the lightweight MobileNet CNN architecture, specifically targeting the classification of three bird species. This approach aims to maintain high performance while addressing limitations posed by smaller datasets, thus extending the practical applicability of SDMs in ecological studies.

III. Approach

Our approach leverages deep learning to predict the presence of three bird species—Acorn Woodpecker, Oak Titmouse, and Steller's Jay—from remote sensing imagery. We employed a refined MobileNet model [11] due to its lightweight architecture and efficiency, making it ideal for classification tasks with limited labeled data. Figure 1 provides an overview of our methodology.

A. Dataset Preparation

We utilized a dataset derived from citizen-science observations from eBird [6] combined with remotely sensed images. The dataset was initially provided as a CSV file ('stejay_data.csv') containing abundance ratios and associated images. We performed the following preprocessing steps:

- **Data Cleaning:** Images smaller than 100KB were discarded, as these were likely corrupted or empty.
- **Resizing:** Images were resized to 224×224 pixels to match MobileNet's input dimensions.
- **Balancing:** Data was balanced between two classes—presence ('1') or absence ('0') of target bird species—to prevent model bias. We limited each class to a maximum of 1000 images.
- **Splitting:** The dataset was split into training and validation subsets with an 80/20 ratio using a random state seed for reproducibility.

B. Model Architecture: Refined MobileNet

We chose MobileNet as the baseline architecture due to its computational efficiency and effectiveness in image classification tasks [11]. MobileNet leverages depthwise separable convolutions, significantly reducing the computational load and number of parameters while maintaining high accuracy.

We applied the following refinement steps to the MobileNet model:

- **Transfer Learning:** The pre-trained MobileNet (trained on ImageNet [12]) was utilized, leveraging its capability to recognize general image features.
- **Fine-Tuning:** We fine-tuned the last few layers of MobileNet by replacing the original classification layer with custom layers tailored specifically to the binary classification task.
- **Data Augmentation:** To further alleviate the limited data problem and enhance the robustness of the model, we performed extensive data augmentation, including random rotations, flips, shifts, and zoom operations.

C. Training Procedure

As shown in Figure 1, we trained the refined MobileNet model using the Adam optimizer [13] with a learning rate of 0.001. A binary cross-entropy loss function was employed due to the binary nature of our classification task. The dataset was split into batches of size 32, and training was conducted over multiple epochs, monitoring validation loss and accuracy to prevent overfitting. Early stopping criteria were also implemented based on validation loss.

D. Evaluation Metrics

We evaluated model performance using accuracy and ROC-AUC scores, which provide a comprehensive understanding of the model's predictive capabilities. These metrics, highlighted in the final stage of our workflow (Figure 1), were crucial for assessing the effectiveness of our approach across the three target bird species.

IV. Results

The refined MobileNet model was evaluated using training and validation accuracy curves along with receiver operating characteristic (ROC) curves for three bird species: **Acorn Woodpecker, Oak Titmouse, and Steller's Jay**. These results illustrate the model's convergence during training and its overall classification performance.

A. Training and Validation Accuracy

The training and validation accuracy curves for each species are presented in Figures 2, 3, and 4. The results indicate that the model achieved **stable convergence** for all three species.

The accuracy curves suggest that while **some degree of overfitting is observed**, the validation performance remains stable, particularly for Acorn Woodpecker and Steller's Jay. The Oak Titmouse model demonstrates a more gradual increase in validation accuracy, suggesting it benefited from additional training epochs.

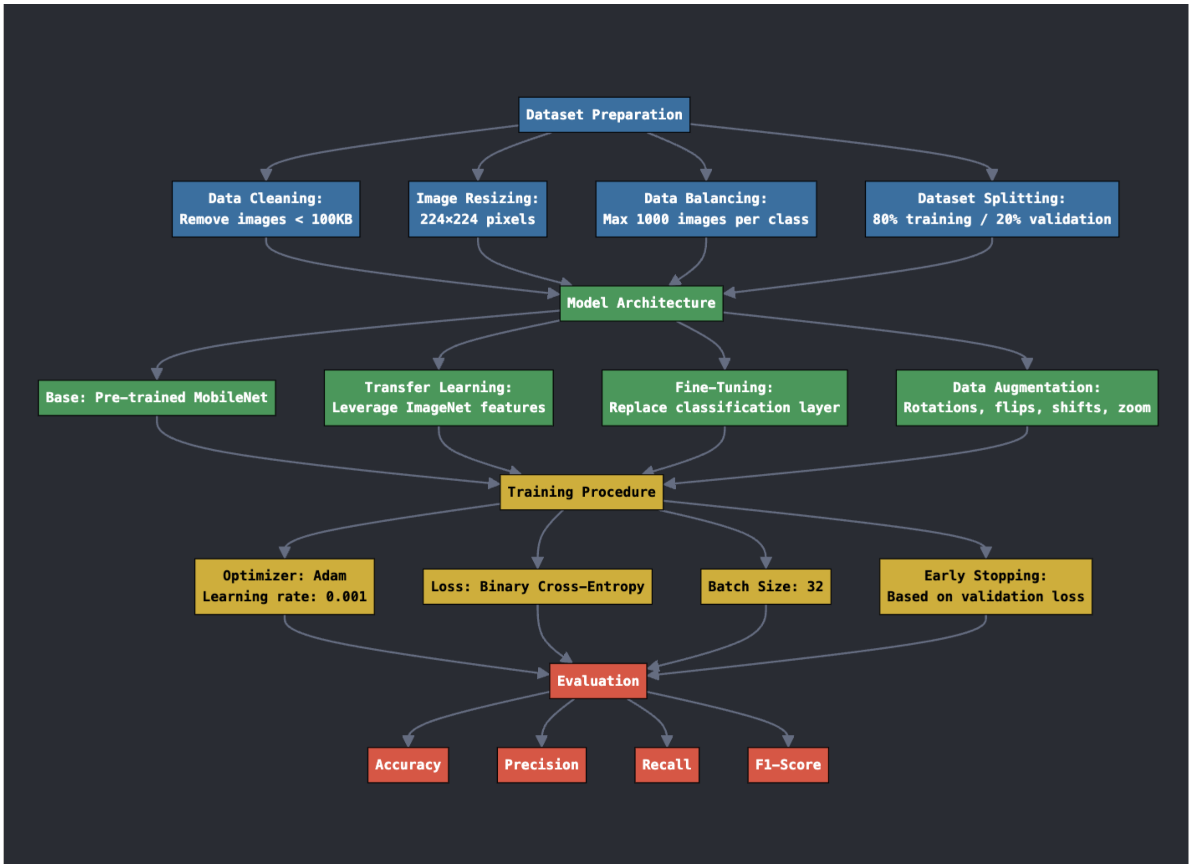

Fig. 1. Workflow of the bird species detection approach using refined MobileNet.

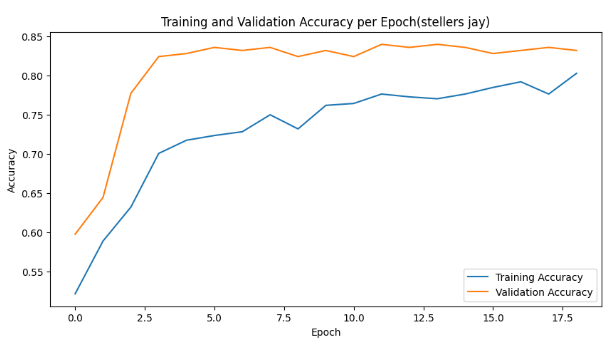

Fig. 2. Training and validation accuracy per epoch for Steller's Jay.

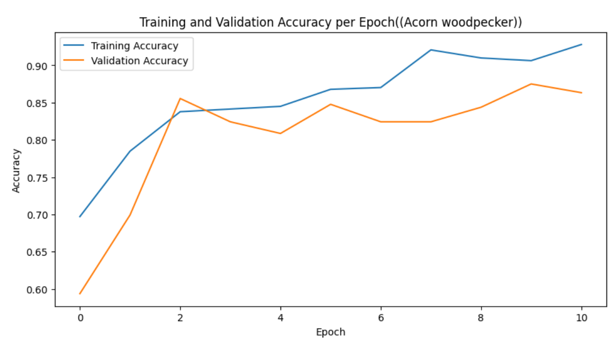

Fig. 3. Training and validation accuracy per epoch for Acorn Woodpecker.

B. Model Performance and ROC Curves

The ROC curves for each species, shown in Figures 5, 6, and 7, illustrate the model's ability to distinguish between presence and absence classifications. The area under the ROC curve (AUC) values indicate strong classification performance.

The **Acorn Woodpecker model achieved the highest AUC score (0.87)**, followed by **Steller's Jay (0.85)** and **Oak Titmouse (0.79)**. These results suggest that the **model generalized well to unseen data**, with **better classification performance for Acorn Woodpecker and Steller's Jay compared to Oak Titmouse**.

C. Discussion

- The results indicate that **transfer learning and fine-tuning** effectively improved classification accuracy for all three bird species.

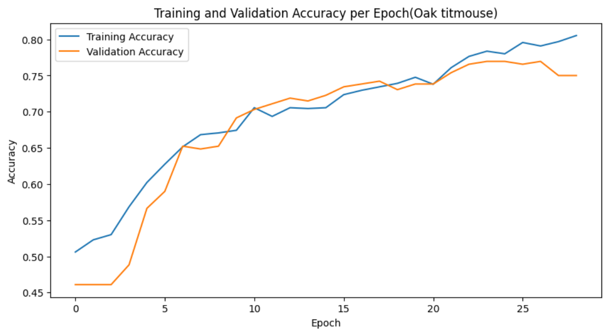

Fig. 4. Training and validation accuracy per epoch for Oak Titmouse.

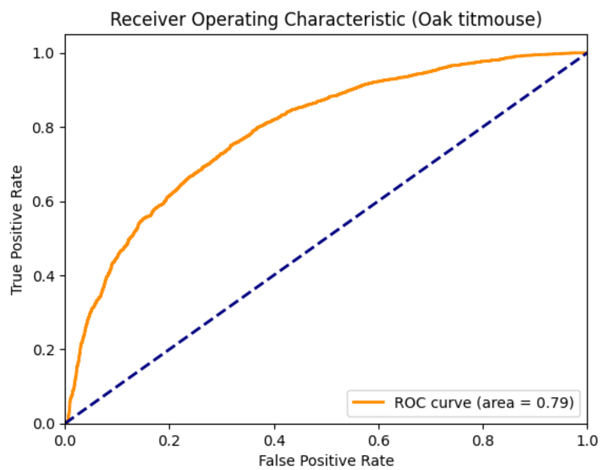

Fig. 5. ROC curve for Oak Titmouse (AUC = 0.79).

- The **training and validation accuracy trends** show **stable learning**, though Oak Titmouse required additional training epochs.
- **AUC scores suggest reliable species classification**, with **Acorn Woodpecker achieving the best performance**.
- **Future work** could explore additional **data augmentation techniques** and fine-tuning strategies to further optimize classification performance.

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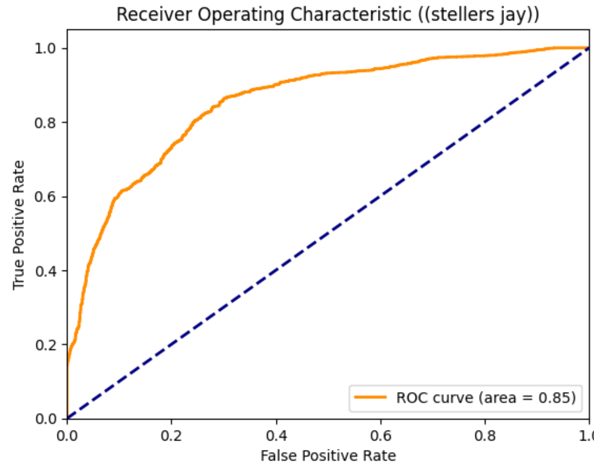

Fig. 6. ROC curve for Steller's Jay (AUC = 0.85).

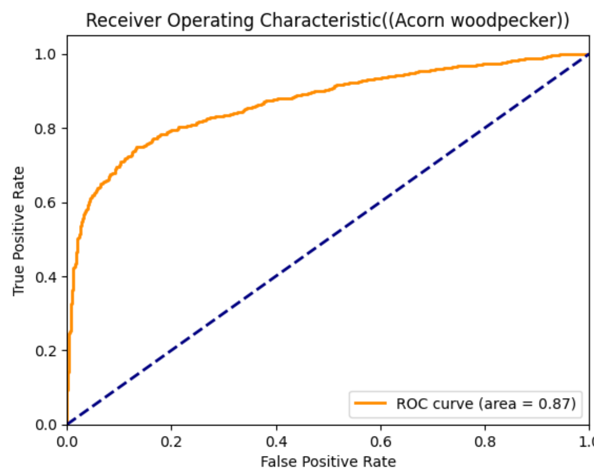

Fig. 7. ROC curve for Acorn Woodpecker (AUC = 0.87).

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