SPRINGBOARD DSC CAPSTONE PROJECT 2

CLASSIFYING IMAGES OF BIRDS

USING THE 2019 iNATURALIST DATASET

by: Lauren Broussard

OUTLINE

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- EXPLORATORY DATA ANALYSIS
- IN-DEPTH ANALYSIS
- RESULTS
- RECOMMENDATIONS
- FURTHER CONSIDERATIONS

Image: Canva.com

PROBLEM & POTENTIAL CLIENT(S)

CAN WE USE DEEP LEARNING TO DISTINGUISH IMAGES OF BIRDS FROM OTHER WILDLIFE TYPES?

> Image classification of the natural world has many benefits
> Can help track migratory patterns without disturbing habitats
> Can be used for website tags and accessibility

POTENTIAL CLIENTS

Zoos, Conservatories
Wildlife Researchers
Social Media Managers

APPROACH & DATASET

> DATA SOURCED FROM INATURALIST/KAGGLE

- This project uses jpeg images and json files comprising 1010 different species and 6 wildlife categories from the iNaturalist 2019 Kaggle competition. The images are taken from a variety of angles and in a variety of environments.

> DOWNLOADED, CLEANED, & PREPROCESSED

- The original, pre-cleaned dataset consisted of 265,213 images, with 18% (47,867) consisting of birds. A subset of the images were randomly chosen, and the dataset was balanced to get a 50/50 split of birds and non-birds for training.

> DEEP LEARNING/CNN FOR IMAGE CLASSIFICATION

- Two models were created using deep learning - one simple neural network, and another using convolutional neural networks - to classify whether or not there was a bird in the presented image.

Image: Canva.com

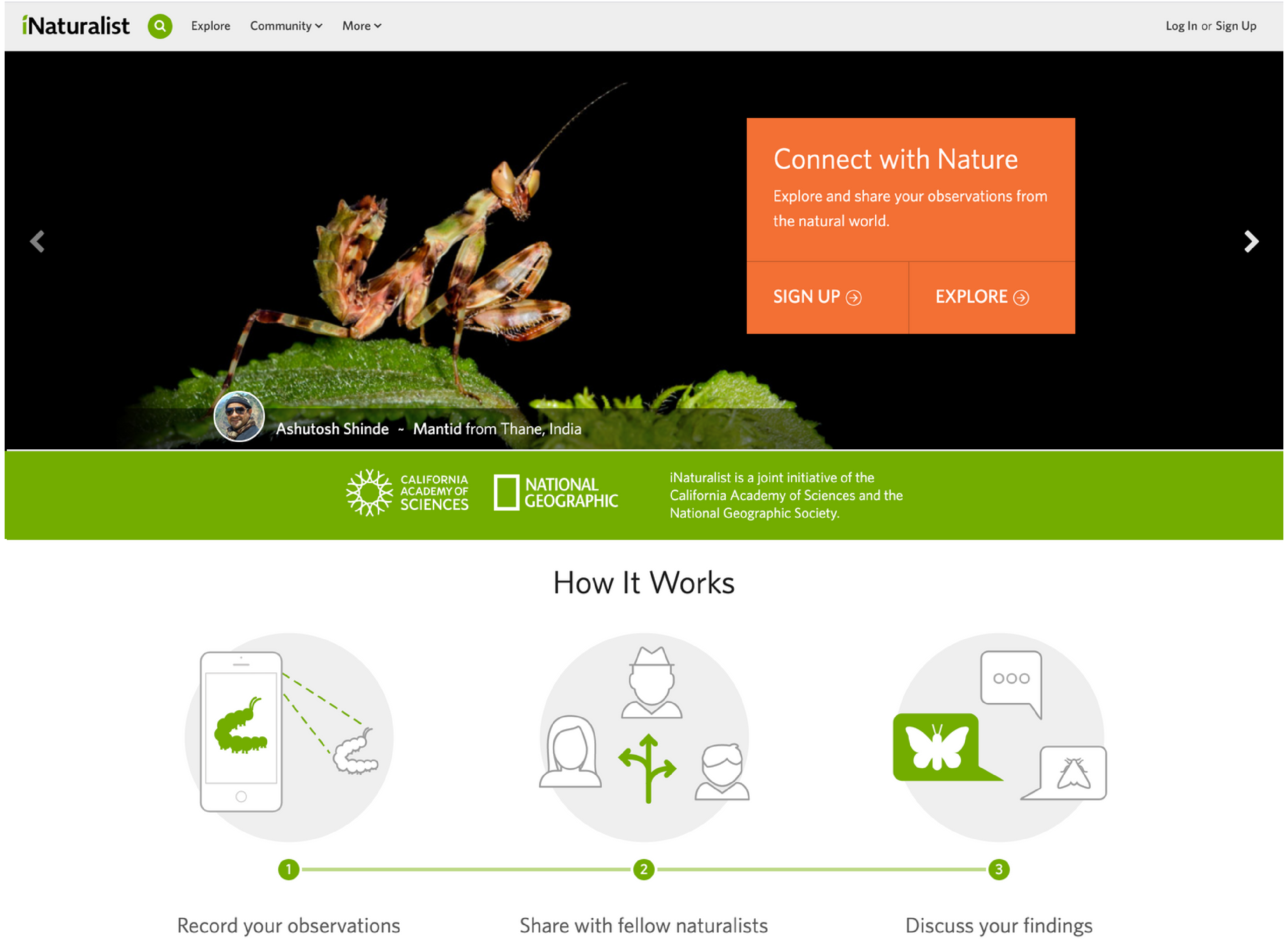


Image: inaturalist.org

ABOUT INATURALIST

iNaturalist allows users to add images of wildlife they observe around the globe. They host an annual Kaggle competition that encourages participants to help improve image classification for their repository of images.

Unless otherwise noted, all images are from iNaturalist's provided dataset.

DATA WRANGLING

The downloaded data was already fairly cleaned and standardized. However, the following steps were taken to prepare the data for modeling:

Loading Data

The download from Kaggle included both annotations and images. Annotations used for this project came in the form of two json files (57MB and 816.46KB respectively). DataFrames were created for each of the files and were eventually merged together. Columns included filename, image width, and image height. The images themselves were stored in folders which included their main category name (i.e. Plants, Birds, Reptiles, etc.) and were further divided into subfolders by species. The image file included a total of 265,213 images (79GB).

Adding/Removing Columns

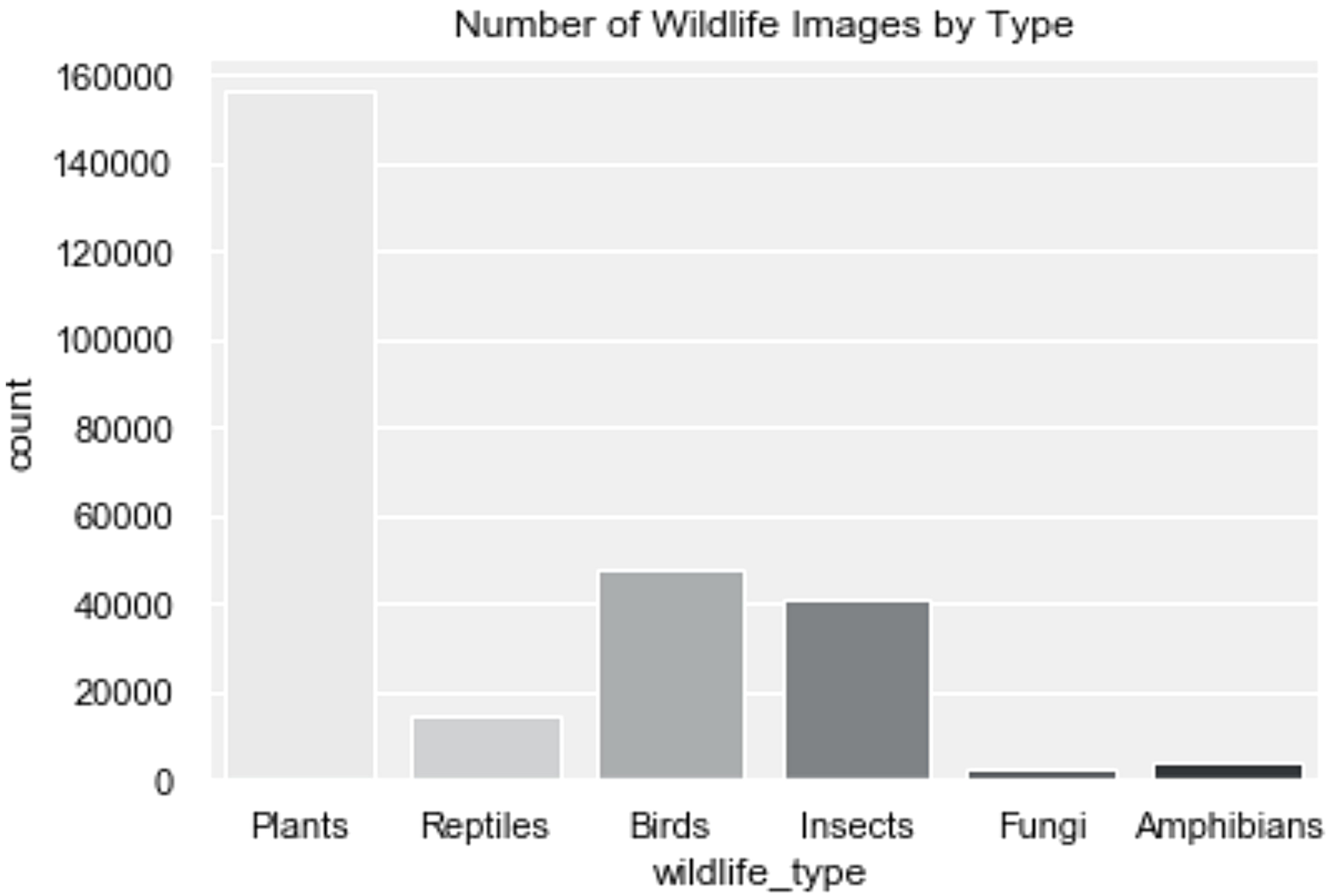
Information was pulled from the 'annotations' and 'images' keys and put into a dataframe. To be more descriptive, the column ‘category_id’ was changed to ‘species_id’.
 Additionally, ince we were interested in labeling Birds, we pulled the ‘iconic category’ name from the subfolders in the ‘file_name’ field. This created field was named “wildlife_type.”

Numerical Encoding

The "wildlife_type" column was used to create another binary column called "is_bird," that gives a 1 if the ‘wildlife_type’ is Birds, and 0 if it is not, This field was used as the target value for the classification problem.

EXPLORATORY DATA ANALYSIS (EDA)

The vast majority of images in the dataset (nearly 160,000) are of Plants, followed by Birds and Insects. **The dataset included 47,867 images of birds, or 18% of all images.** There is a class imbalance, which could affect our model -- this was remedied later in the project by randomly selecting equal samples of birds vs all other categories.



EDA: BIRD IMAGES

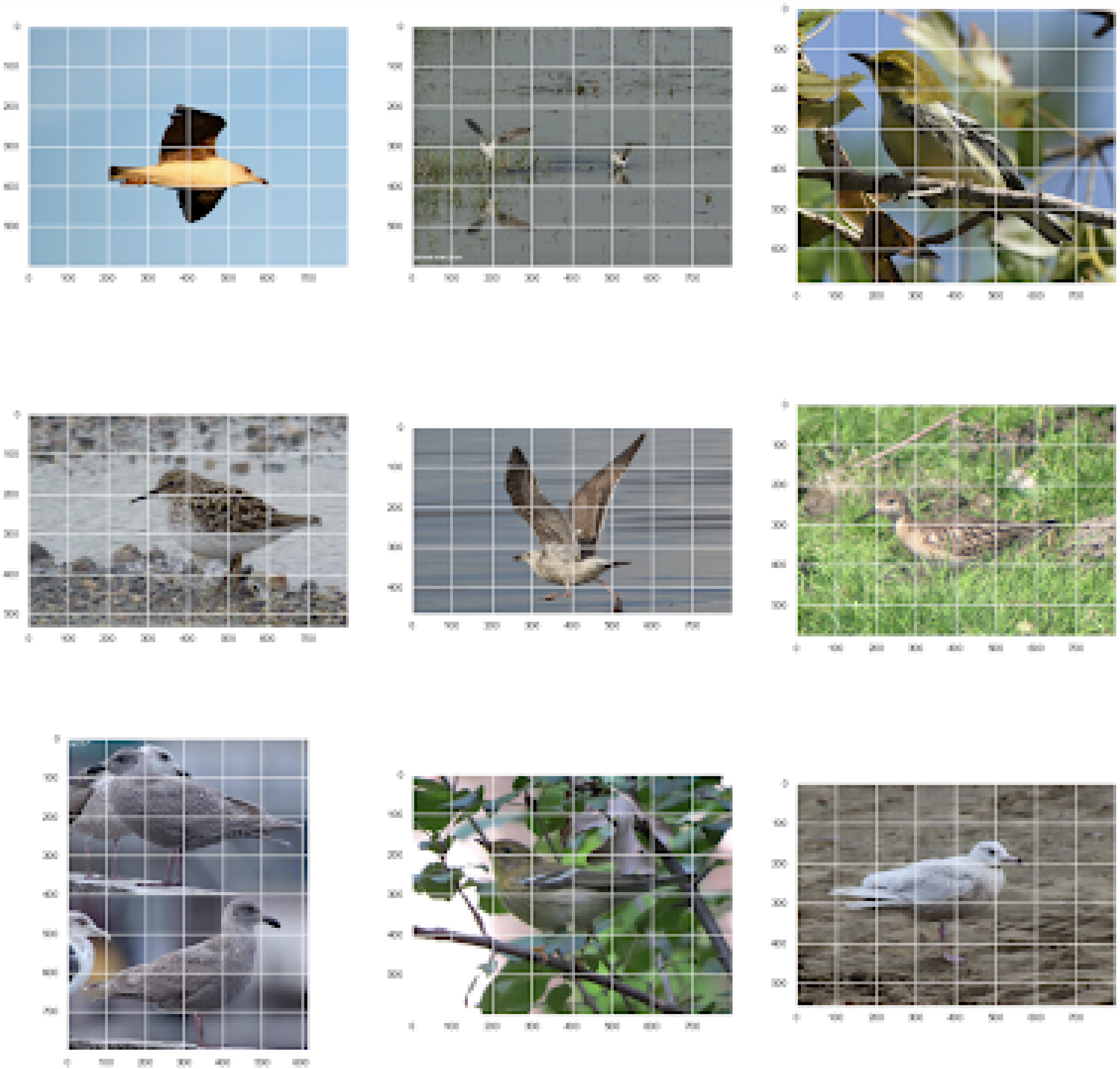
FULL DATASET

47,867	**126**
Number of Images	Number of Species
130/188	**800/800**
Min. Pixel Height/Width	Max Pixel Height/Width

Image: Canva.com

EDA:
BIRD IMAGES

The images consist of wildlife often in their natural environments - in grass, in the air, in trees, etc. The images are also taken in different orientations and at different angles. This requires a model that is able to cut through the background noise of a particular image.



IN-DEPTH ANALYSIS

SUPERVISED LEARNING

APPROACH:
DEEP LEARNING &
CONVOLUTIONAL NEURAL NETWORKS (CNN)

> STEP: PRE-PROCESSING

- Balance Dataset: 50/50 Random Split of Birds and Non-Bird Images
- Split Dataset: Train/Validation/Testing
- Augment Images & Set Up Training/Validation Generators

> STEP: RUN INITIAL MODEL: MODEL 1

- **Simple Neural Network,** 5 hidden layers
- 5,000 Images | 25 Epochs
- Prediction Accuracy = 0.50

> STEP: UPDATE ARCHITECTURE/ PARAMETERS

- Increase: Epochs, # of Images, Batch Size
- Add: Cov2D and MaxPooling Layers

> STEP: RUN NEW MODEL: MODEL 2

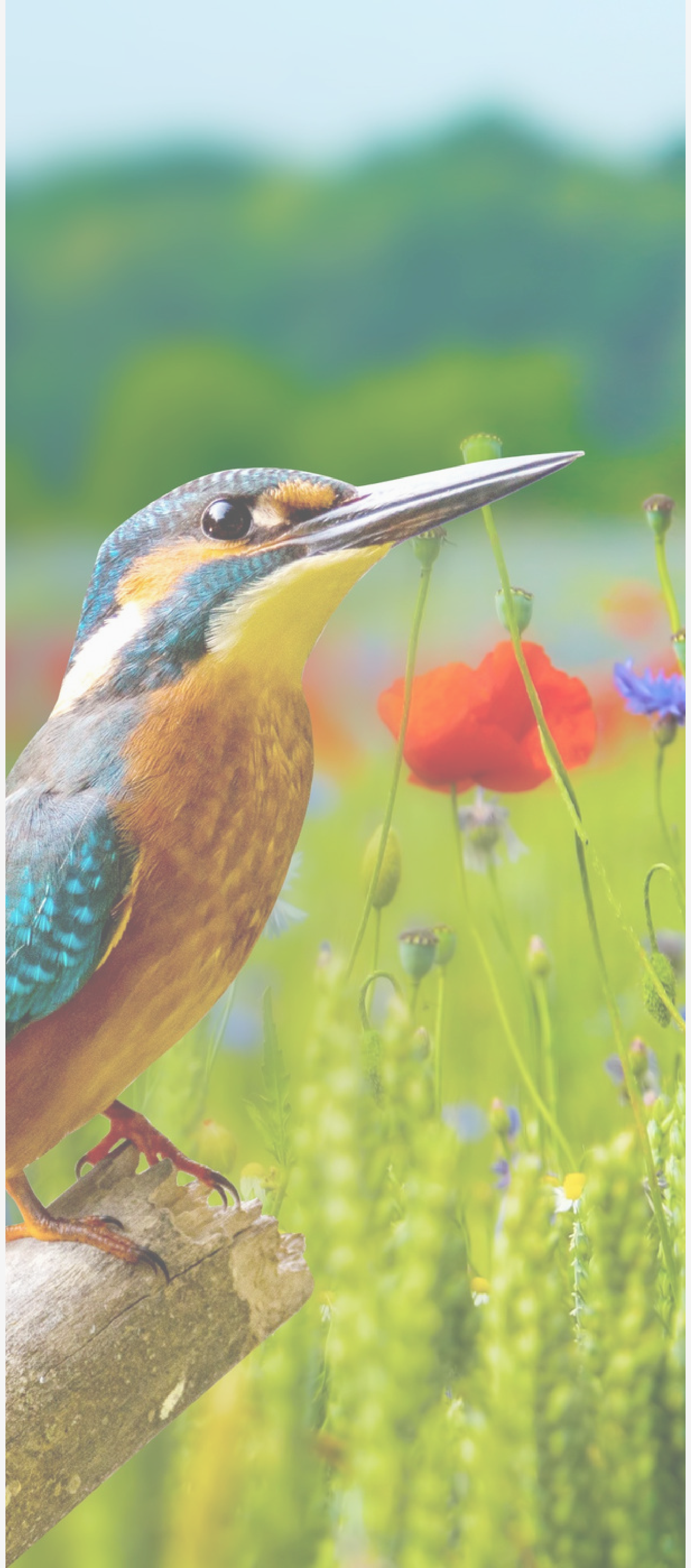
ARCHITECTURE: MODEL 2

COV2D (4): Since pixels are typically correlated with their neighbors. Looks for correlation between edges and contours.

MAX POOLING LAYERS (4): Helps with a large number of parameters, as is the case with the original model. It summarizes groups of pixels based on their max value.

DROPOUT (1): The dropout layer randomly sets inputs to 0 at a rate of 0.6 at each step during training, which according to the documentation can help prevent overfitting.

DENSE (1): Every node/pixel is connected to all the units of the previous layer.



```
model2 = Sequential()

model2.add(Conv2D(32, (3, 3), input_shape=(img_width,img_height,3)))
model2.add(Activation('relu'))
model2.add(MaxPooling2D(pool_size=(2, 2)))

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model2.add(Conv2D(32, (3, 3)))
model2.add(Activation('relu'))
model2.add(MaxPooling2D(pool_size=(2, 2)))

model2.add(Conv2D(64, (3, 3)))
model2.add(Activation('relu'))
model2.add(MaxPooling2D(pool_size=(2, 2)))

model2.add(Flatten())
model2.add(Dense(100))
model2.add(Activation('relu'))
model2.add(Dropout(0.6))
model2.add(Dense(1))
model2.add(Activation('sigmoid'))
```
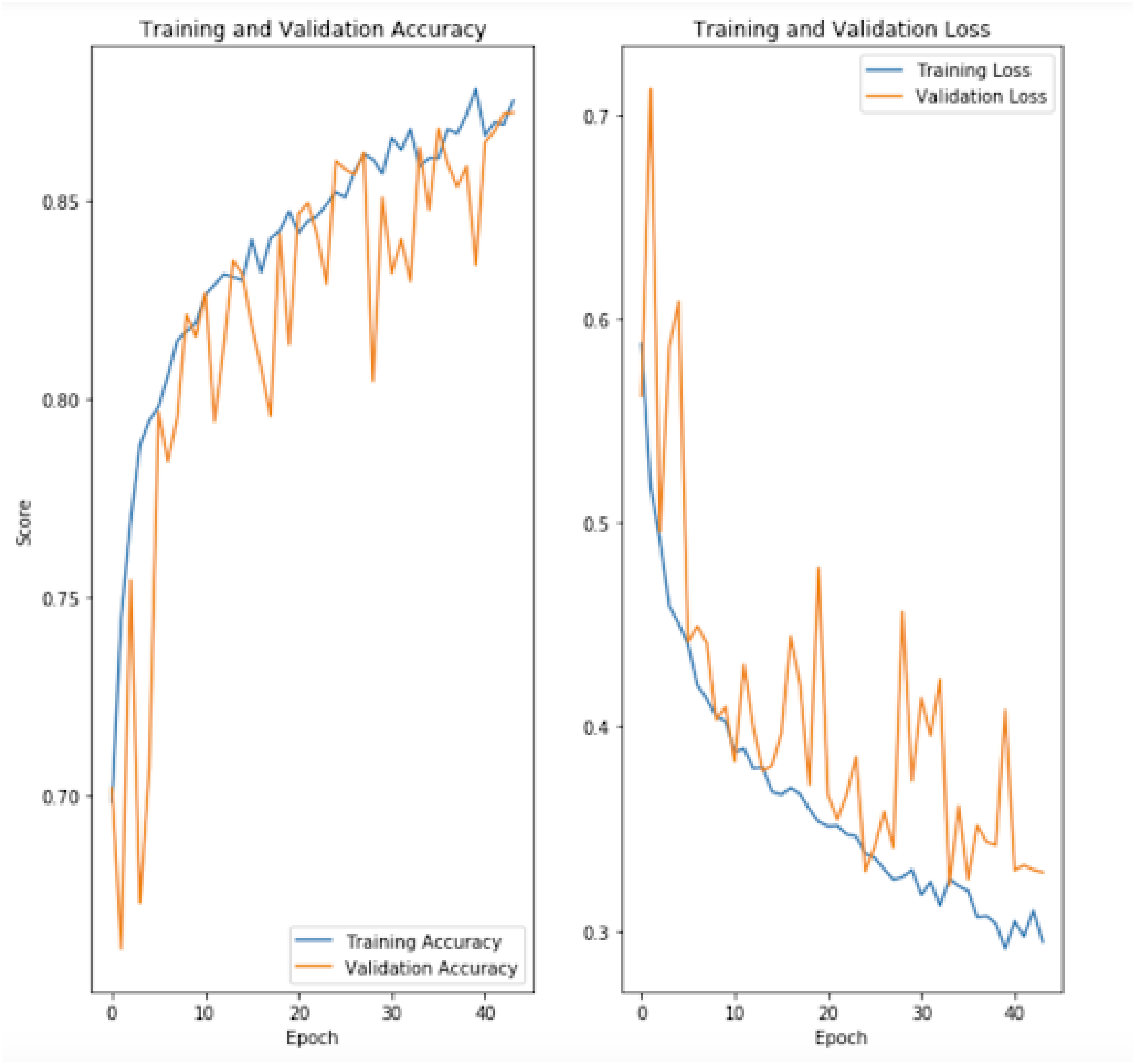

FINAL MODEL PARAMETERS

- **Total # of Images: 15,000**
  - The addition of more training images helps the model better learn what an image of a bird looks like.
- **Increased Epochs: 50**
  - The number of epochs increased from 25 to 50 for longer training.
- **Callbacks: Early Stopping Monitor**
  - The early stopping monitor was increased from 2 to 7 to allow the model more time for learning.
- **Prediction Batch Size:** From 128 to 1.
  - Allowed the model to look at one image at a time for predictions.
- **Total Training Parameters**: 268,489
  - Decreased between models from original 16,782,889.

IN-DEPTH ANALYSIS



TRAINING & VALIDATION

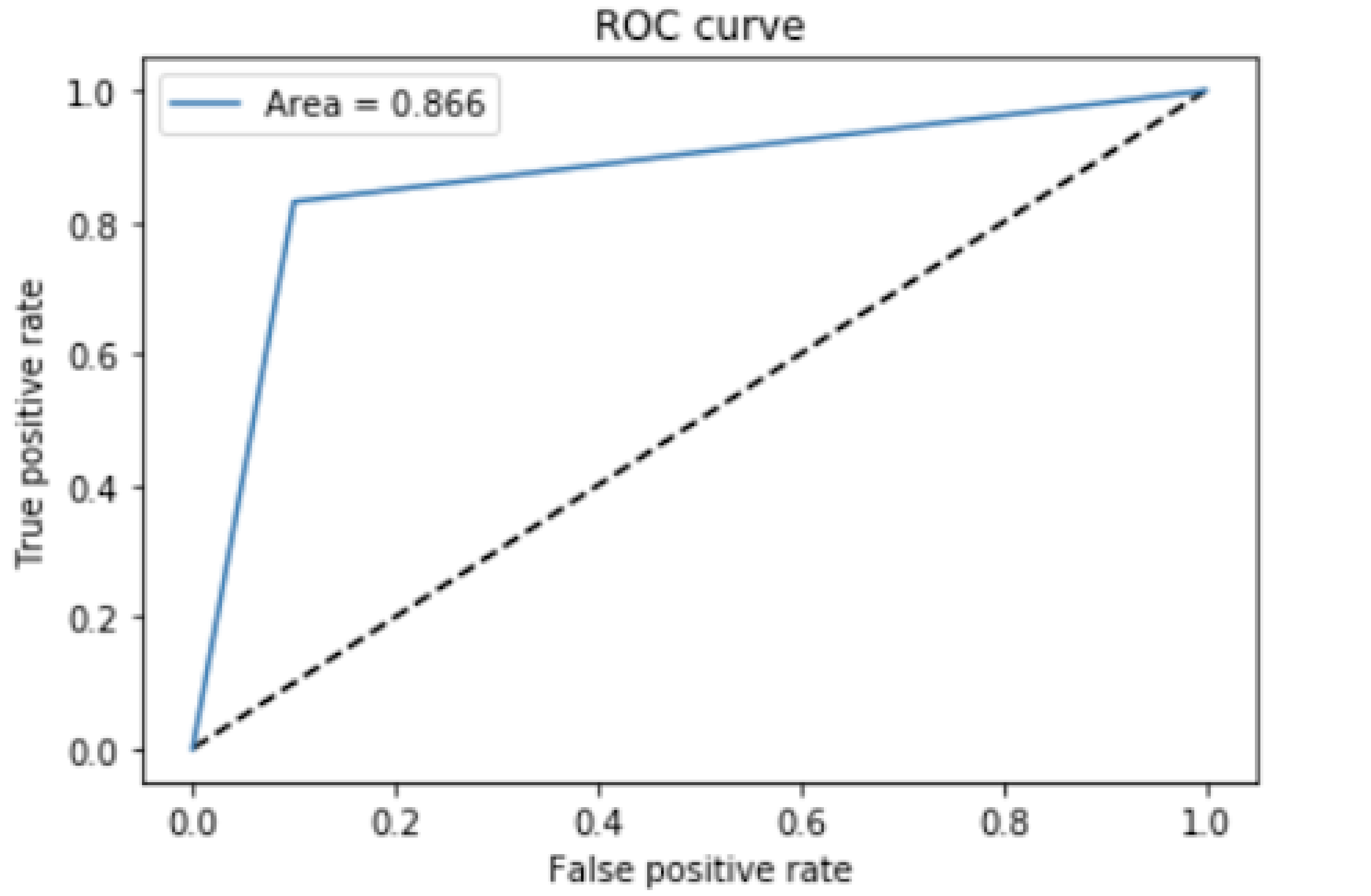
Running the generator through 50 epochs of training and validation, **the model achieved its highest validation accuracy at 87%**. The training seemed to increase the accuracy at a fairly steady pace, though the validation accuracy seemed to bounce around between 80% and 87%.

RESULTS

CLASSIFICATION REPORT & ROC CURVE

Classification Report

	precision	recall	f1-score	support
Not Bird	0.85	0.90	0.87	1830
Bird	0.89	0.83	0.86	1770
accuracy			0.87	3600
macro avg	0.87	0.87	0.87	3600
weighted avg	0.87	0.87	0.87	3600



The model appeared to be able to identify images where there was no bird slightly better than it was able to predict images where there was a bird. However, **the model was still able to classifying birds well, with an F1 score of 86%.**

RESULTS

EXAMPLE PREDICTIONS: CORRECT (86%)

BIRD

NOT BIRD

BIRD

The model did well at classifying birds, especially since many of the birds are in their natural habitats and the photo could be obscured. This is promising for automatic classification where it is necessary to not disturb an animal's habitat.

RESULTS

EXAMPLE PREDICTIONS: INCORRECT (13%)

GUESS: BIRD
ACTUAL: NOT BIRD

GUESS: NOT BIRD
ACTUAL: BIRD

GUESS: NOT BIRD
ACTUAL: BIRD

The model incorrectly classified 13% of the test images presented to it. When the model made an error in classification, it was more often that the model did not find a bird, when there was in fact one there.

RECOMMENDATIONS

& FUTURE CONSIDERATIONS

More Training Images

More training images will allow the model to learn more features of birds. This will require increased computing power, which was not available for this project.

Classify By Species

Identification by individual species can help track migration patterns of particular birds, or identify when endangered species are brought to a habitat they should not be in.

Different Model

Future iterations of the project could also look to other pre-trained models, such as VGG16, which is a CNN model trained on the ImageNet database.

THANK YOU

LAUREN BROUSSARD

linkedin.com/in/laurenbroussard