

A male Orchard Oriole is perched on a dark, textured branch. The bird has a black head and back, a bright yellow-orange breast and belly, and black and white striped wings. It has a sharp, pointed beak and is looking to the right. The background is a soft, out-of-focus green.

Capstone Project: Classifying North American Birds

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Background: Image Classification

4 Areas of Computer Vision

Classification



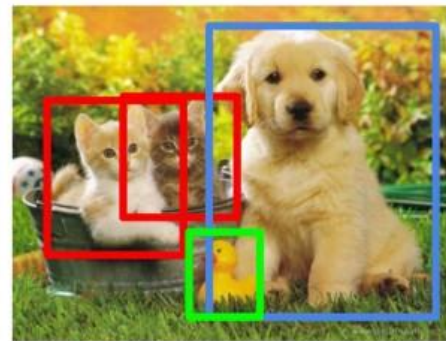
CAT

**Classification
+ Localization**



CAT

Object Detection



CAT, DOG, DUCK

**Instance
Segmentation**



CAT, DOG, DUCK



- Image classification is the foundation of computer vision problems and has many applications in everyday life and technology advancements

Background: Why birds?

- Gaining a foundational knowledge about birds allows us to appreciate biodiversity and promote their conservation



Problem Statement

This project aims to develop a model and tool to accurately identify North American birds in order to promote a fundamental knowledge of bird taxonomy, with the goal of empowering users to further conservation efforts to protect birds.

- ❖ Can we use deep learning techniques to accurately predict bird images with their respective species?
- ❖ Can we create a useful tool to identify birds?

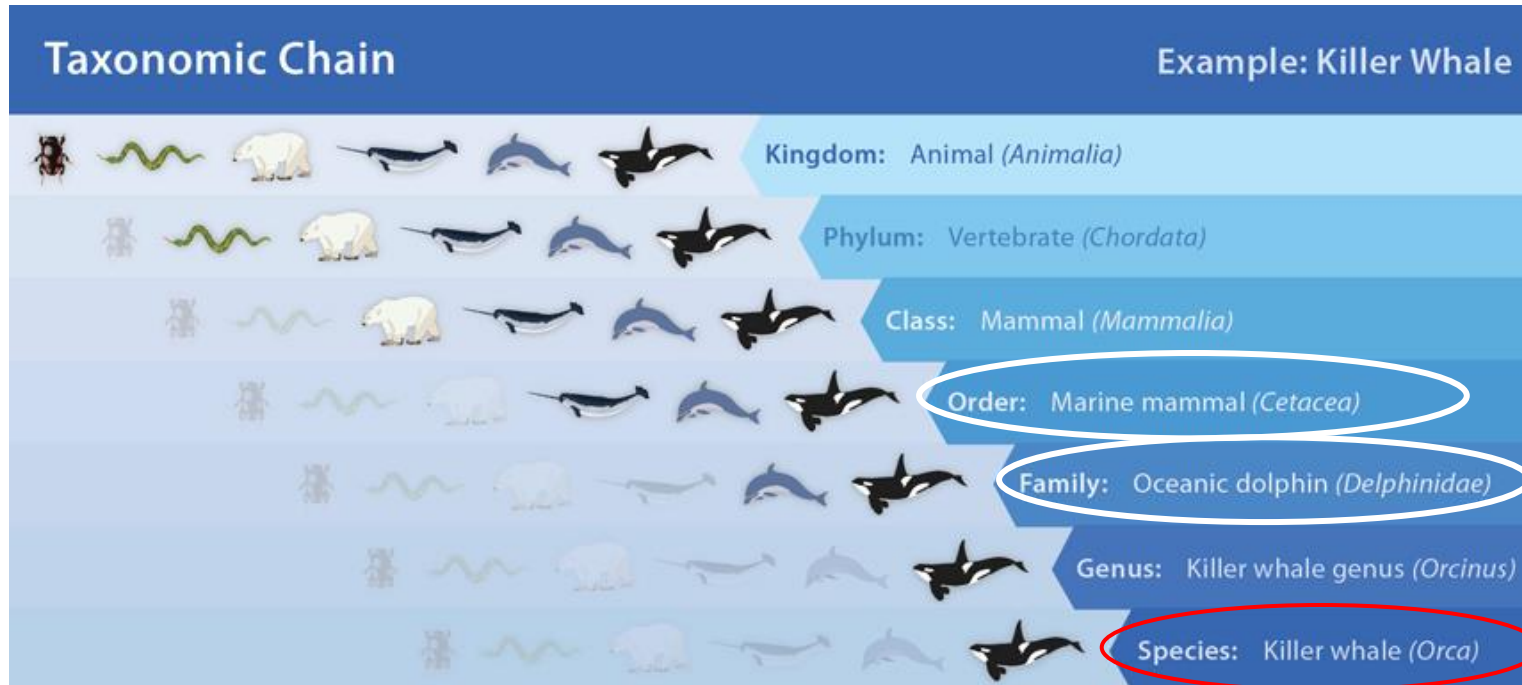
Data Introduction

- 11,788 images from the Caltech Vision Dataset archive
- 200 species, 60 images per species
- Data Cleaning:
 - Extract, clean, transform images into arrays, condense and scale
 - Map images to labels



EDA: Class Reduction Through Taxonomic Hierarchy

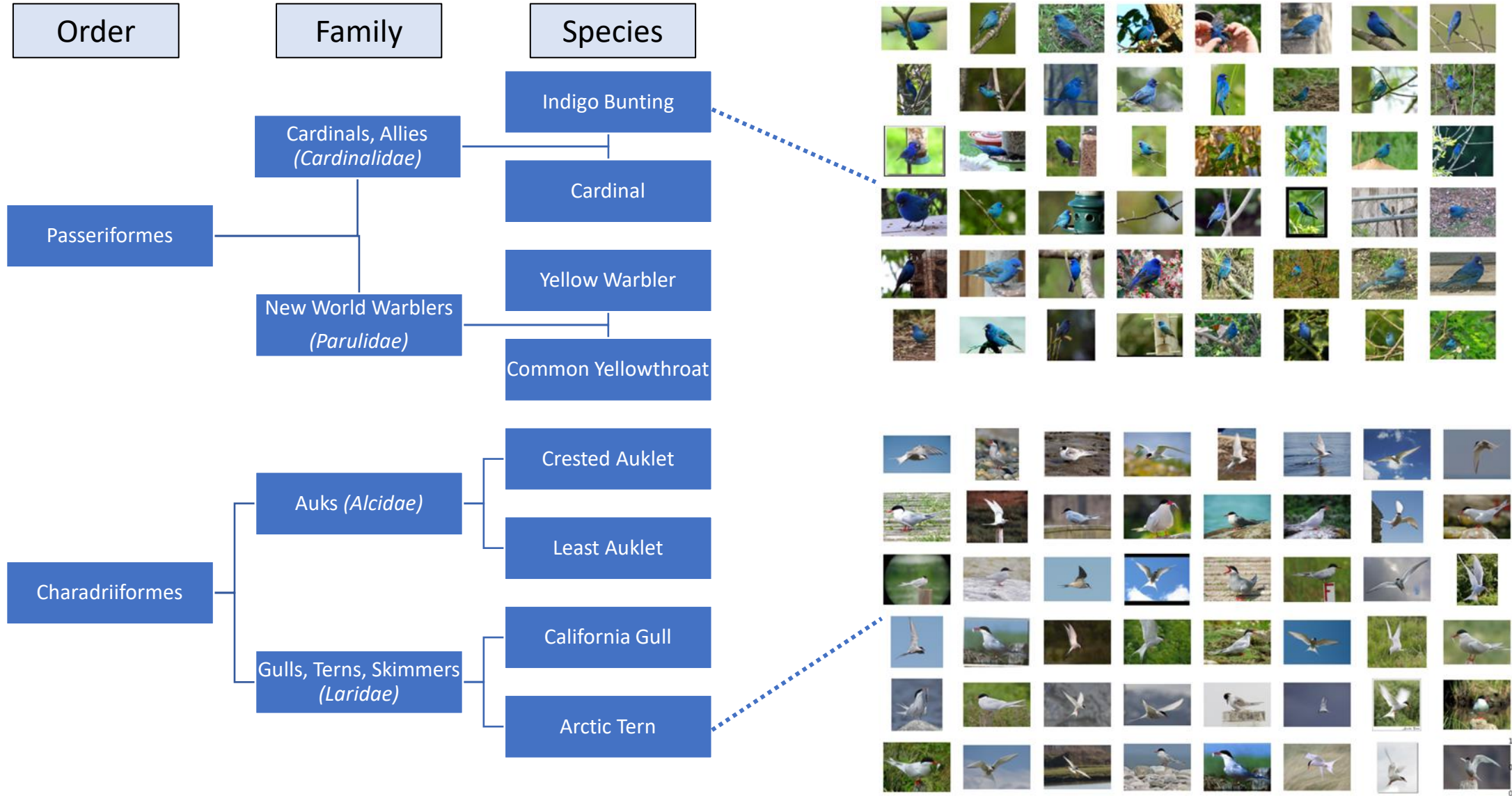
🚩 First issue to address: too many classes at 200 (species level)



Reduce classes by going up the taxonomic chain to group images by:

1. Order
2. Family

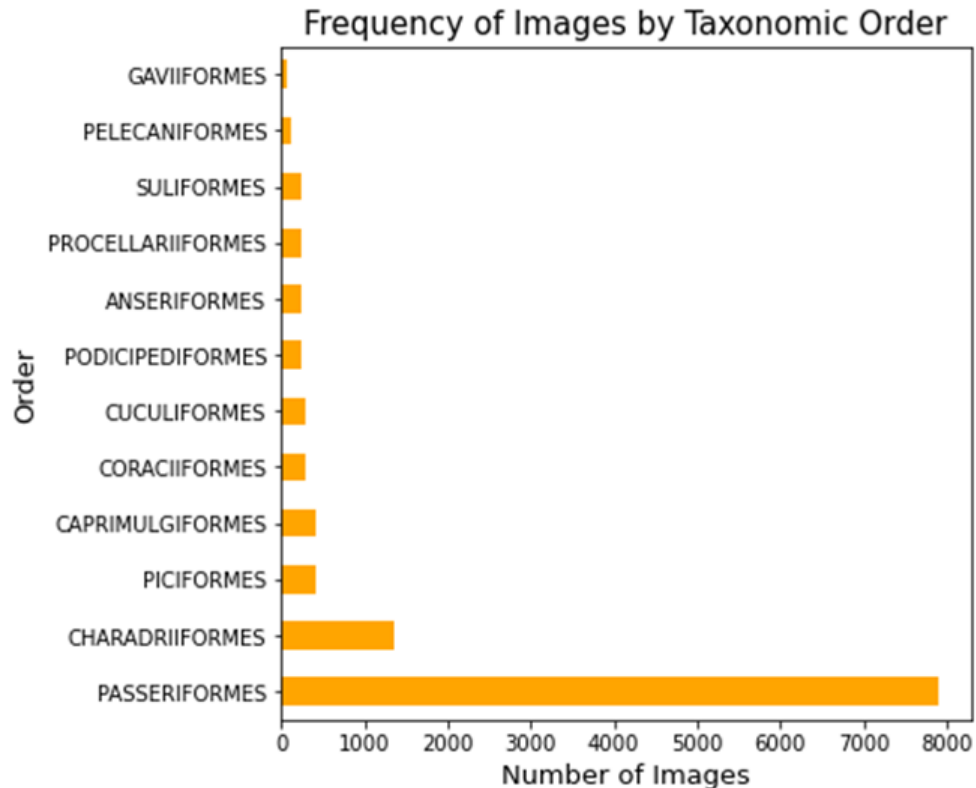
EDA: Taxonomic Hierarchy



EDA: Order, Family, Species

When aggregating by taxonomic order and family, there are imbalanced classes:

- Passeriformes make up 67% of orders
- New World Warblers and Sparrows make up 27% of families



Top 5 Most Common Families

Order	Family	Images	% of Total
PASSERIFORMES	New World Warblers ~ Parulidae	1790	15.18
PASSERIFORMES	New World Sparrows ~ Passerellidae	1424	12.08
CHARADRIIFORMES	Gulls, Terns, Skimmers ~ Laridae	940	7.97
PASSERIFORMES	Troupials and Allies ~ Icteridae	774	6.57
PASSERIFORMES	Tyrant Flycatchers ~ Tyrannidae	656	5.56

Modeling Goals

1. Build 3 neural networks to optimize for **accuracy** and classify bird images at the following levels:
 1. Order (12 classes)
 2. Family (35 classes)
 3. Species (200 classes)
2. Iterate & experiment with the following techniques to optimize performance:
 - Image data augmentation
 - Transfer learning- leverage a pretrained model
 - Explore regularization techniques, early stopping, batch normalization
3. Create an interactive tool in Streamlit to accurately classify images

Modeling Results: Summary

Final Model Selection Summary				
Class Level	Number of Classes	Baseline Accuracy	Training Accuracy	Testing Accuracy
Order	12	67.0%	99.4%	87.6%
Family	35	15.2%	99.0%	64.0%
Species	200	0.5%	86.3%	30.5%

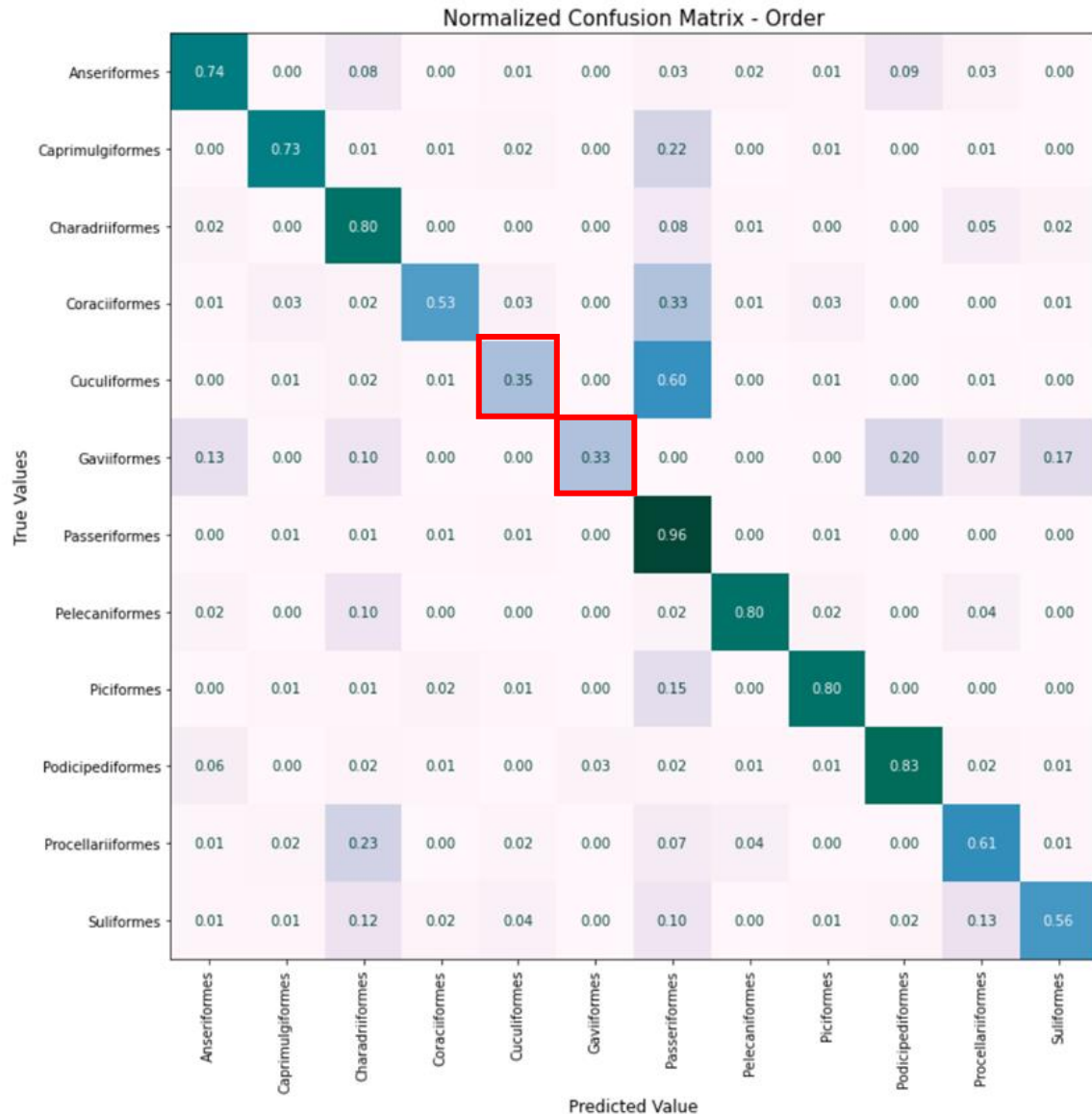
Highlights

- All models significantly outperformed their baseline accuracy!
- Data augmentation improved accuracy
- Transfer learning and working from a pretrained model drastically increased performance

Drawbacks

- All models were largely overfit, even with regularization techniques implemented
- Predicting at the species and family level proved to be difficult

Modeling Results: Order



Where did the model do well? ✓

- Passeriformes (the majority class) had the highest accuracy

Where did the model fall short? ✗

- 60% of Cuculiformes were classified as Passeriformes
- Only 33% of Gaviiformes were classified correctly
- *Let's look at an example of misclassification...*

Modeling Results: Order

Can you tell the difference?



Laysan Albatross
Order: Procellariiformes

?



Slaty Backed Gull
Order: Charadriiformes

- Although the color and images are relatively similar, **scale** is not reflected in the images
- The model may not pick up small differences, like beak shape and subtle colors

Predictive Tool

To the Streamlit demo!



Conclusion

Findings:

- Reducing the classes and using taxonomic hierarchy greatly improved the model's predictive power
- Different modeling techniques worked better than others at each level of class

Next Steps:

- Improve modeling performance by gathering more data and images per species to address the issue of imbalanced classes
- Expand the dataset to include other species
- Further research reliable hosted servers for more modeling power

Thank you!

Appendix

Sources

Page 1:

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Page 2:

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