North American Bird Species Identifier

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Goal/Problem

Design a complex image classification model capable of identifying various birds by species

Criteria:

- Adaptable model for a large labeled data set (525 Species)
- Versatility to work with images of varying angles and quality
- Ideal specificity (Bias/Variance Tradeoff)
    - Species may only have slight differences in features
    - The model can't be too specific to one set of features (overfitting)

Methods/Approach used

- To speed training we employed a transfer learning process…
    - Meaning we employed a pre-trained model (InceptionV3) that was experienced in recognizing general patterns, but not bird species
- We preserved/isolated the model’s pattern recognition while giving it the opportunity to learn species features
- To limit overfitting the Dropout method allowed us to temporarily remove random neurons/nodes in the network and generalize

Data

- In our model we utilized a dataset from Kaggle containing images of 525 different North American bird species, with 84,635 training images, as well as 2625 test images and 2625 validation images(5 images per bird species)
- This was a high quality dataset, with images containing only one bird in each image as well as the bird in most cases occupying over 50% of the pixels in each image
- However, one shortcoming of the data used was that roughly 80% of images were of male birds and 20% female, and since male birds are typically more diversely colored than females, the dataset may not perform as well for images of female birds

Challenges

- The main two challenges we encountered while working on the model were runtime and the dataset used
- Since we were using a local laptop to run model, even with GPU acceleration it took ~1 hour to run a decent model
- We initially used a much larger dataset that was far too big for the requirements of our project and not well organized, so we decided to opt for a smaller, more compact dataset

Performance Metrics Evaluated/Results

- The main two metrics that we aimed to optimize were accuracy of identification and loss
- Over the course of 10 epochs, the model demonstrated notable improvements in both training and validation accuracy
- The best validation loss achieved was 0.8157, with a corresponding accuracy of 79.12%
- Early stopping was necessary in preventing overfitting and ensuring the model's generalization for validation data.