Detecting Chickens From Social Media Data

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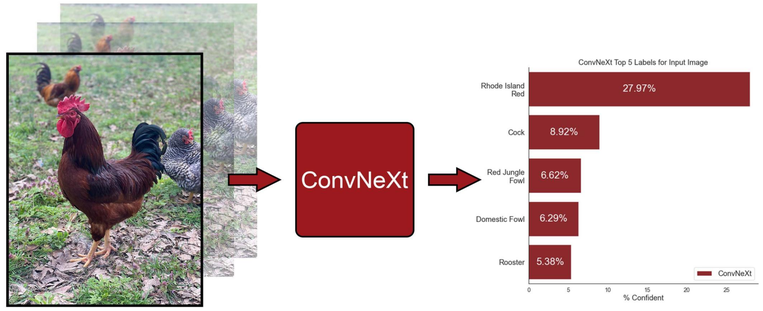
1. Motivation

- **Out-of-the-box** computer vision models (ResNet10, ResNet50, etc.) tend to have a **hard time classifying different breeds** of the **same species**
- This **problem** becomes increasingly **more pronounced** with **data scraped** from various **social media sources** (Twitter, Craigslist, etc.)
- We propose a way to use **state-of-the-art** (SOTA) computer vision models to accurately label **different breeds** of the **same species** (in our case, Chickens)
- We utilize **ConvNeXt** and **transfer learning** to achieve breed specific classification where possible



Using ConvNeXt and transfer learning, our implementation achieves breed-specific labeling and, when not available, differentiation between game fowl and domestic fowl.

2. Challenges

There are times that our model didn't classify images even remotely correct. For example, the middle image was classified as a lapdog.

3. Initial Modeling of Chicken Body Shape

- **Given** two broad categories of chicken game and farm
- **Estimate** social media websites for chicken data
- Also, **jointly estimate** type of chicken, game or farm based for diseased protection and isolation

Visual depiction of game versus farm fowl

- Need to **identify contours** and feather data properly
- **Deeper layers perform better** with more expressive details documented
- **Model needs to be as discriminative** as possible, so we train against similar looking animals (e.g. squirrels)
- Handle different **species, color, and orientation** of chickens including texture of feathers.
- Solve **limited data issues** with stitching, translation, and warping
- Model needs to be of the **"chickens versus the world"** type, where chickens are classified against other animals / observable items in the world.

4. Experiments

- We experimented with four different models:
  - **Baseline CNN,** horrible classification when other animals were introduced (10-15%).
  - **ResNet50,** decent classification, but not good enough to be breed specific
  - **ConvNeXt,** good breed specific classification and excellent species classification(90% top5)
  - **ViT,** mediocre species classification(~35%)

5. Results

ConvNeXt SOTA performance on farm vs game fowl. Green border indicates correct classification whereas red border indicates incorrect classification. Train/Test images obtained from Kaggle, Reddit, and Google.

Method	Layers/epochs	Parameters (Million)	Optimizer / Loss Function
CNN (baseline)	3/25	0.001	adam/Binary Cross entropy
VGG-19	19/20	138	adam/Cross entropy
ResNET-50	50/9	23	adam/Cross entropy
ConvNext	**-/2(90 actual)**	350	adamw/Cross entropy
ViT	12/20	87	adam/Cross entropy

Based on results, ConvNeXt is best suited for our purpose. It has the lowest false positives and negatives. Test detection time needs to reduced.

Above: *Model complexity. All images use adam and cross entropy loss*
Right: *Comparison to various models in terms of top 1 test , training accuracy and time to detect .*

Method	Top 1 Accuracy	Train Accuracy	Time to train/detect(s)
Neural Networks			
CNN(Baseline)	75	95.8	240/60
VGG-19	87	89	28800/720
ResNET-50	98	99	3600/300
ConvNext	**94**	**99**	**60/30**
Transformers			
ViT	35	45	600/5

6. Future Work

- Refinement of ConvNeXt labeling techniques
- Applying ConvNeXt to video as compared to images
- More broad data collection strategies and sources
- Try DeiT and other modern transformers.

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