# **Pretrained Neural Networks for Poultry Image Classification: A Pilot Study**

## **Abstract**

Visual inspection of chicken breast quality remains the standard method for identifying meat affected by pathologies such as Woody Breast Syndrome (WBS) and Spaghetti Meat (SM). These conditions alter the morphology of chicken breast muscle, but manual inspection is subjective and inefficient. In this pilot study, we explored the feasibility of applying a pretrained ResNet50 model to classify chicken breast images into Normal, WBS, and SM categories. A small dataset of 33 images of chicken breast was collected and preprocessed to enhance texture patterns. Features extracted from the network were evaluated using 3 classifiers: logistic regression, k-nearest neighbors (k-NN) and a decision tree. Performance was assessed with accuracy, sensitivity, specificity, and confusion matrices. While the model achieved limited success in distinguishing WBS from Normal samples, the study demonstrates the potential of transfer learning for poultry quality classification and highlights the need for standardized imaging and larger datasets.

## **Introduction**

Visual inspection of meat quality is essential for food safety and bioprocessing. The increasing scale of broiler production has led to the emergence of muscle abnormalities such as Woody Breast Syndrome (WBS) and Spaghetti Meat (SM). WBS is characterized by enlarged, marbled breast tissue, while SM produces disconnected fibers that give the meat a stringy appearance. These pathologies can be distinguished morphologically using imaging, and prior studies suggest that physical features alone may enable classification of affected versus healthy samples.[1] Building on this, pretrained convolutional neural networks (CNNs) offer an opportunity to automate the classification of poultry meat at scale. The aim of this study was to classify images of chicken breasts into Normal, WBS, or SM categories. We decided to use a pretrained neural network (ResNet-50) in conjunction with a simple classifier model.

## **Methods**

* 1. *Data Collection*

Chicken breast samples were obtained from a farm on the Eastern Shore of Maryland (courtesy of Dr. Sunoh Che). Samples were sorted into Normal, WBS, and SM categories and photographed on a laboratory benchtop using a smartphone. Samples were first imaged starting with images of each category before moving to individual chicken breast images.

* 1. *Dataset*

A total of 33 images were collected: Normal, WBS, and SM. Twenty-seven images were used for training and six for validation. Due to the small dataset, no independent test set was constructed.

* 1. *Preprocessing*

Preprocessing emphasized texture enhancement to highlight morphological differences. Local binary patterns were applied in the HSV color space, followed by cropping and conversion to tensors. Images were prepared for training in PyTorch.[2]

* 1. *Model and Training*

ResNet50 pretrained on ImageNet was used as the feature extractor. An Adam optimizer (learning rate = 0.001) trained the network for 100 epochs. Extracted features were evaluated on 3 classifier models as a preliminary analysis of the data. Logistic regression was used through the scikit-learn package. Next, k-nearest neighbors were used with 5 neighbors. Finally, a decision tree was used to classify the images. All models were evaluated using the validation set.

* 1. *Evaluation Metrics*

Performance was assessed with accuracy, sensitivity, specificity, and confusion matrices computed on the validation set.

## **Results**

*A group of graphs showing different types of data

AI-generated content may be incorrect.*

*Figure 1: Training vs Validation Loss, Training Accuracy vs Validation Accuracy*

*A chart with a yellow square

AI-generated content may be incorrect.*

*Figure 2: Confusion Matrix of Pretrained ResNet50 Model*

|  |  |  |  |
| --- | --- | --- | --- |
| *Classifier* | *Sensitivity* | *Specificity* | *Accuracy* |
| **Logistic Regression** | 1 | 1 | 1 |
| **K – Nearest Neighbors** | 1 | 1 | 1 |
| **Decision Tree** | 0.333 | 0.333 | 0.333 |

*Table 1: Comparison of Evaluation Metrics for 3 simple classification models.*

## **Discussion**

* 1. *Interpretation of Results*

This pilot highlights both the promise and the challenges of applying pretrained CNNs to poultry image classification.

* 1. *Strengths and Weaknesses*

The approach successfully extracted features from small datasets and provided a framework for evaluating sensitivity and specificity. However, the images were collected using smartphone cameras by multiple researchers, introducing variability in angle, illumination, and scale. These inconsistencies limited the ability to capture size and texture differences reliably. The samples used for this pilot study mainly arose from several overhead images of the chicken breasts organized by disease category. Additionally, the original intent—to image samples using a hyperspectral microscope—was unsuccessful, as sample preparation diminished visible striations.

* 1. *Next Steps*

Future work should focus on standardized imaging: fixed apparatus height, consistent illumination, and controlled moisture levels on meat surfaces. This would allow for reliable comparisons and the inclusion of additional features such as absolute size. A larger dataset would also be essential for training more robust models.

## **Conclusion**

This pilot study explored the classification of chicken breast images into Normal, WBS, and SM categories using a ResNet50 pretrained network. Despite limited differentiation between WBS and Normal samples, the experiment demonstrates the feasibility of transfer learning for poultry image classification. Improved data collection protocols and larger datasets will be required to realize the full potential of this approach.

## **References**

[1] S. Che *et al.*, “Characteristics of broiler chicken breast myopathies (spaghetti meat, woody breast, white striping) in Ontario, Canada,” *Poultry Science*, vol. 101, no. 4, p. 101747, Apr. 2022, doi: 10.1016/j.psj.2022.101747.

[2] A. Paszke *et al.*, “PyTorch: An Imperative Style, High-Performance Deep Learning Library,” Dec. 03, 2019, *arXiv*: arXiv:1912.01703. doi: 10.48550/arXiv.1912.01703.