chicken2weight: Estimating the Weight of Chickens from an Image

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ABSTRACT

Given the explosive growth of the poultry industry, it is necessary to develop data driven techniques to improve the efficiency and cost-effectiveness of raising chickens. One metric, weight, is particularly important because it can serve as a good indicator of potential issues like disease and malnutrition. We propose a simple regression model for visualizing and predicting the correlation between perceived size and weight, based on a small dataset of segmented images of chickens. Using Python Scikit Learn (Sklearn) and a decent iPhone camera, we were able to develop a 2D scatter plot of real observations and a curve predicting the mass of a chicken given any image. We learned that regression models, although suitable for many tasks and capable of modeling nearly any function, are less than ideal when used on traditional classification problems that require far much more data. Unfortunately, we were unable to consistently determine the mass of a chicken given an image and appropriate spatial reference.

KEYWORDS

image processing, chicken, weight, perception

1 INTRODUCTION

Suppose you are raising a flock of meat chickens. Regularly weighing and tracking the status of each bird is difficult and time consuming, particularly on the industrial scale when a rough estimate of size and weight is more than sufficient. Although farm operations may attempt to automate the process to learn the weight of individual chickens, such equipment can be costly to set up and maintain. Continuously obtaining the weight of any chicken from an image (supplied from a video stream, for example) is a much cheaper and hands-off alternative that can lend similar insights on the growth and overall health trends of the flock.

Recognizing the potential of data-driven improvements in agriculture, we address the issue of rapidly determining the weight of a live chicken from a 2D image. However, normal images alone are insufficient because they contain a false sense of scale. We must consider the chicken's dimensions, which can be estimated by knowing the dimensions of a reference object within the image and mapping pixels to a more familiar metric. Although the densities of chickens may vary depending on the actual condition of the bird (breed, sex, live or dead product), we make the general assumption that size is a good estimator of weight.

We must first compile a dataset by weighing and photographing my chickens with a small reference item. The area of the chicken shown in the image and the reference item are used for later calculations. With only a few chickens in my backyard, we used data augmentation to expand the dataset with randomized translations and skews. Unfortunately, this limited amount of data naturally results in a limited model. As expected, our regression models are capable of estimating the weight of a chicken extremely quickly, but at equally poor accuracy due to the excess of assumptions made.

2 RELATED WORK

Rapid mass estimation through image analysis is not a unique task. Mass and associated metrics like density, weight and volume have been determined for similarly restrained agricultural tasks (like the weight of pigs [1]) and more generally (like the mass of an apple [3]). Our method is remarkably unique, in part due to its simplicity. It does not require an advanced camera setup [7] nor a custom convolutional neural network [2]; instead we build on a standard iPhone camera, existing segmentation models, and basic tools like polynomial regression. Regardless of our process, we see our work supportive of these like-minded approaches and applications.

3 METHODOLOGY

Here we describe the process used to create the dataset and the type of regressor in this study. Both were used to predict and visualize the weight of chickens given a specific ratio.

3.1 chicken2weight Dataset

There is no comprehensive dataset composed of images with labels including a given chicken's surface area and a point of reference. Regrettably, I failed to create a dataset with either of these characteristics. Of course, the primary challenge was attempting to photograph a chicken with any standardized object in frame as chickens are exceptionally skittish and wary of movement. I opted to use a small blue origami square that could be quickly secured to and removed from the back of a chicken, along with a rolling iPhone video that could be processed to extract unique frames. In total, I collected roughly 100 images in different settings. All images were also randomly transformed with translations up to 30%, rotations up to 360°, dilations between 50% to 100% of their original size, and minor horizontal or vertical shifts half of the time to create a final 300 images (Figure 1). I weighed each bird on an electronic scale and then leveraged PixelLib's pretrained implementation of Mask R-CNN to obtain the area of the chicken and OpenCV to obtain the maximum blue area of the square. Even with varied backgrounds the chicken images were surprisingly easy to process, and for simplicity, I assume PixelLib and OpenCV are 100% accurate. The area of the chicken and the area of the blue square were combined to form a ratio associated with the chicken's weight (Figure 2).

Anyone familiar with machine learning will immediately recognize a fatal flaw: there is simply not enough data. The 300 images were divided into 225 training images and 75 for testing and validation, which can hardly be called a high quality dataset with varied samples. Furthermore, the dataset introduces a series of variables that will almost certainly create inaccuracies. It does not, for example, consider gender or breed (factors that contribute to density and therefore mass).

However, despite its limitations, this approach is not without select benefits. With the target only pertaining to chickens, the model does not have to be shape aware to distinguish between objects – it only needs to receive a ratio of the chicken's surface area to a known quantity (ie: the amount of blue present) to determine weight.

Figure 1: a rotated image including the chicken and the blue square

ratio	weight (lbs)
115.64	3.0
148.85	3.2
59.16	3.4

Figure 2: subset of dataset with ratios of chicken area to blue square area and weight

3.2 Implementation & Results

We used a polynomial regression model from Sklearn (a powerful framework that provides high-level access to popular machine learning algorithms) to predict the weight of the chicken. Polynomial regression provides stability and simplicity that other regression models lack, which is critical in smaller datasets such as this one which cannot be split effectively. For this method, the best degree (n) was 7 (although we did not fine-tune any other hyperparameters).

Although we showcase polynomial regression due to its highest accuracy (Figure 3), we also tested almost all of the regression models available in Sklearn including the random forest regressor and support vector machine. The model was calibrated and fitted on a stock laptop. As mentioned previously, the models rely heavily on data augmentation to account for the lack of data.

We report the performance of the models with R-squared. All of the models achieved at least 50% accuracy, with the highest being polynomial regression at 64.5%. Perhaps the poor accuracy indicates excessive assumptions and inadequate data; the graphed data is seemingly random - a heavier bird, for example, can have both a low and high ratio. Either way, the relationship between the ratio of chicken area to a standard known value and an expected weight is not fully clear and appears to contradict standard intuition that a bigger chicken is indeed a heavier chicken. Evidently, the dataset size and bias as a result of the limited dataset size are real problems that should be addressed in future experiments.

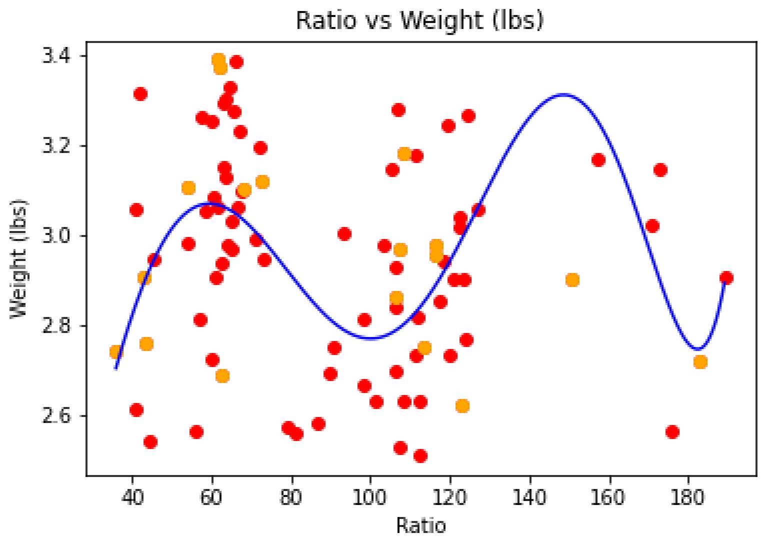

Figure 3: scatter plot of data (red) & test (yellow) points superimposed with the polynomial regression model

4 CONCLUSION

Although not necessarily novel, we tackled the issue of estimating the weight of chickens. As reflected in the figures and results, regression models may not be the ideal choice for predicting weight through image analysis. We used image segmentation to extract the area of a chicken and the area of a blue square, assembling a dataset made of scale-independent ratios to expected weights. Unfortunately, we also introduced bias through the limited sample size and variations in chicken breed and gender, effectively handicapping the model's limiting performance. Despite the poor results, we believe further research with higher-quality datasets must be conducted before concluding the inefficacy of this method. Should future experiments prove to be more successful, the results will have many applications in predictive animal care and disease containment.

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