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EGG SIZE CLASSIFICATION AND WEIGHT PREDICTION

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Abstract: Egg weight classification plays a crucial role in the poultry industry as it helps in determining the quality and market value of eggs. Traditional methods for egg weight classification are often time consuming and labour - intensive. In this research paper, we propose a novel approach for egg weight classification using image processing in deep learning. Our methodology leverages the advancements in computer vision and deep learning techniques to accurately estimate the weight of eggs based on their images. We present the experimental setup and discuss the results obtained from our experiments. The findings demonstrate the effectiveness and potential of our proposed approach in automating the egg weight classification process, leading to improved efficiency and productivity in the poultry industry.

Keywords: egg size classification, weight prediction, image processing, deep learning, computer vision, poultry industry.

INTRODUCTION- Egg size classification and accurate weight prediction are crucial factors in various industries, including agriculture, food processing, and quality control. The ability to automatically classify eggs based on their sizes and accurately predict their weights can significantly streamline production processes and aid in meeting market demands. Traditionally, egg size classification has been carried out manually, relying on subjective visual assessment or physical measurements. However, such approaches are time-consuming, prone to human errors, and lack scalability. In recent years, advancements in deep learning techniques, particularly Convolutional Neural Networks (CNN), have demonstrated great potential in image-based classification tasks. The objective of this study is to propose a novel method for egg size classification and accuracy of weight prediction using CNN. By leveraging the power of deep learning and the capability of CNNs to extract intricate visual features from raw image data, we aim to develop an automated system that can reliably classify eggs into different size categories and accurately estimate their weights. To achieve this, we have collected a comprehensive dataset of egg images, encompassing variations in size, shape, and color.

In our methodology, we utilize a deep learning approach, training a CNN model on the collected dataset. The CNN model is capable of learning and recognizing complex patterns and features within the images, enabling it to distinguish between different egg sizes accurately. By employing a CNN architecture, we aim to overcome the limitations of

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traditional methods and provide a robust and efficient solution for egg size classification and weight prediction.

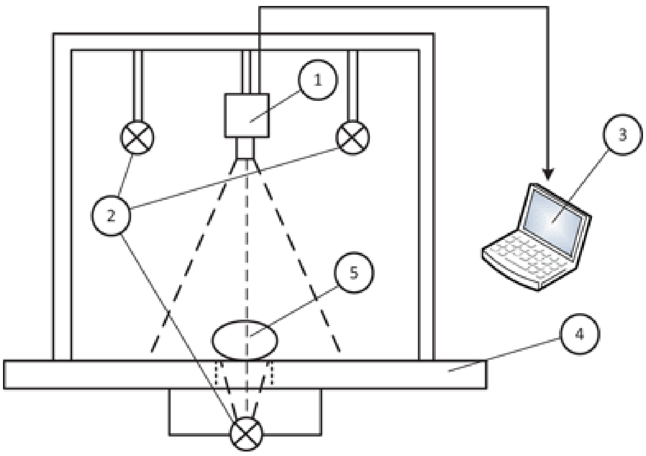
The significance of this research lies in its potential to revolutionize the egg processing industry. By automating the classification and weight estimation processes, the proposed method can reduce manual labour, improve efficiency, and enhance quality control measures. Moreover, accurate egg size classification can facilitate better inventory management, packaging optimization, and meet specific market demands. The ability to predict egg weights with high accuracy further strengthens the application of our proposed method in various industries that rely on weight-based egg processing In this paper, we will present the detailed methodology of our CNN-based approach for egg size classification and weight prediction.

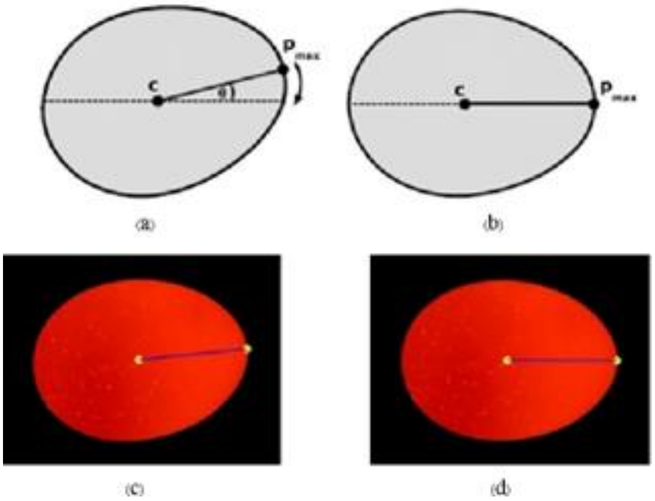
We will provide insights into the training process, model architecture, and the evaluation metrics used to assess the accuracy of our predictions. Additionally, we will present experimental results demonstrating the performance and effectiveness of our proposed method, comparing it with existing approaches and highlighting its advantages.

METHODOLOGY:

Image Acquisition: The first step is to acquire images of eggs. This can be done using a variety of cameras, such as a digital single-lens reflex (DSLR) camera or a webcam. The images should be taken from a consistent angle and lighting conditions.

Image Preprocessing: The next step is to preprocess the images. This may involve steps such as cropping, resizing, and converting the images to grayscale. The goal of preprocessing is to remove noise and artifacts from the images, and to make them easier to process.





Feature Extraction: The next step is to extract features from the images. This may involve steps such as edge detection, color segmentation, and shape analysis. The goal of feature extraction is to identify features that are correlated with egg weight.

Feature Selection: The next step is to select a subset of features that are most relevant to egg weight. This can be done using a variety of methods, such as principal component analysis (PCA) and recursive feature elimination (RFE).

Model Training: The next step is to train a model to predict egg weight from the selected features. This can be done using a variety of machine learning algorithms, such as support vector machines (SVMs), decision trees, and neural networks.

Model Evaluation: The next step is to evaluate the performance of the trained model. This can be done by using a holdout dataset of images that were not used to train the model.

Model Deployment: The final step is to deploy the model to a production environment. This may involve steps such as integrating the model with a web application or a manufacturing process.

MATHEMATICAL MODEL:

Convolution:

The convolution operation in CNNs is used to extract features from input images. Given an input image and a set of learnable filters (kernels), the convolution operation is defined as follows:

Output feature map (activation map) at position (i, j) = sum of element-wise multiplication between the filter and the input image patch centered at position (i, j).

This can be expressed mathematically as:

$$H(i, j) = \sum_m \sum_n I(i+m, j+n) . k(m, n)$$

where H(i, j) is the value in the output feature map at position (i, j), I(i+m, j+n) represents the pixel value in the input image at position (i+m, j+n), and K(m, n) represents the corresponding filter coefficient at position (m, n).

Pooling:

Pooling operations, such as max pooling or average pooling, are used to down sample the feature maps and reduce the spatial dimensionality. The pooling operation computes a single output value for a region of the input feature map. The mathematical formulas for max pooling and average pooling are as follows:

$$H(i, j) = \max m \max n\ F(i+m, j+n)$$

Max pooling:

$$H(i, j) = \max m \max n\ F(i+m, j+n)$$

Average pooling:

$$H(i, j) = 1/m\text{-}n \sum m \sum n\ F(i+m, j+n)$$

Activation functions:

Activation functions introduce non-linearity into the CNN model and help in capturing complex patterns. Some commonly used activation functions in CNNs include ReLU (Rectified Linear Unit), sigmoid, and tanh. The mathematical formulas for these activation functions are:

Rectified Linear Unit (ReLU): ReLU is the most popular activation function in CNNs. It sets all negative values to zero and keeps positive values unchanged. The ReLU activation function is defined as f(x) = max(0, x). It helps in addressing the vanishing gradient problem and speeds up convergence.

Sigmoid: The sigmoid activation function squashes the input values between 0 and 1. It is defined as f(x) = 1 / (1 + exp(-x)). Sigmoid is useful in models where we want to interpret the output as probabilities.

Hyperbolic Tangent (Tanh): Tanh is similar to the sigmoid function but squashes the input values between -1 and 1. It is defined as f(x) = (exp(x) - exp(-x)) / (exp(x) + exp(-x)). Tanh is centered at 0 and is sometimes preferred over sigmoid as it provides stronger gradients.

Softmax: Softmax is commonly used as the activation function in the output layer of a CNN for multi-class classification problems. It transforms the logits (raw output) into probabilities. Softmax is defined as f(x) = exp(x) / sum(exp(x)) for each element in the output vector.

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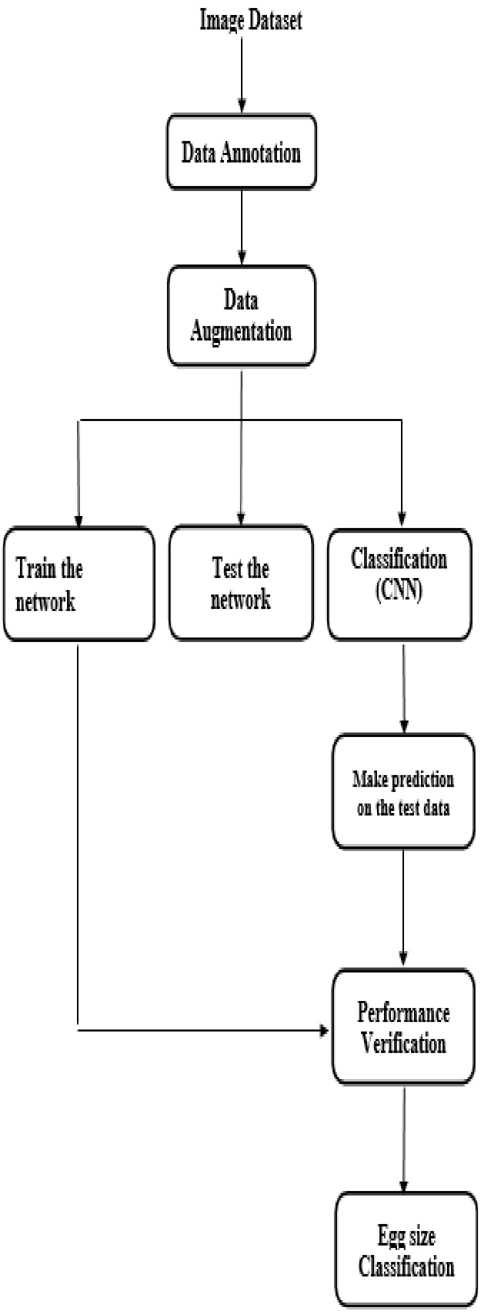
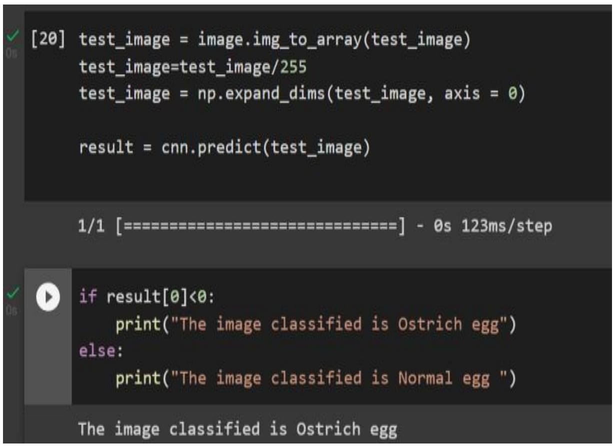
Relu:
F(x) = max(0,x)
Sigmoid:
F(x)=1/1+e^-x
Where f(x) represents the output value given the input x.

FLOW CHART:



Results:



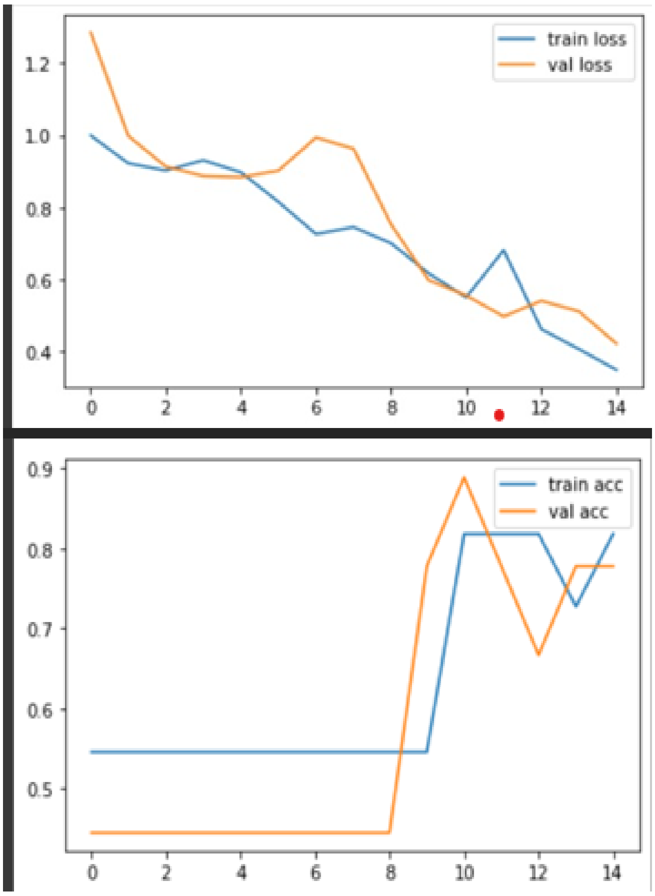
```
[20] test_image = image.img_to_array(test_image)
     test_image=test_image/255
     test_image = np.expand_dims(test_image, axis = 0)

     result = cnn.predict(test_image)

1/1 [==============================] - 0s 123ms/step

if result[0]<0:
    print("The image classified is Ostrich egg")
else:
    print("The image classified is Normal egg ")

The image classified is Ostrich egg
```



CONCLUSION:

The size classification system provides useful information not only for consumers and egg producers but also for profiling breed characteristics in conservation and genetic improvement studies. It also improves the methods of selection of eggs. The current study focusses on determining whether the egg is normal egg (medium) or Ostrich egg (large) based on the size of the images of various eggs. Tensorflow and Keras frameworks have been used as keras is better for small datasets. Nineteen types of eggs are taken as reference with each 5 records of various observations. Species, Length and width of the egg are the main parameters considered for the study. Further selected ML Techniques viz. Decision Tree, Random Forest, Linear Regression, Lasso Regression, and Ridge Regression are appliedto determine the accuracy scores. The results have been interpreted and visualized. The accuracy scoreof CNN algorithm gave highest accuracy score compared to the rest of selected algorithms forthe given datasets.

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