Non-Invasive Gender Classification of Chicken Eggs Based on Image Analysis

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Abstract

Hatched male chicks are generally killed because layer hens are only used by females. It is estimated that 7 billion chicks are killed annually shortly after hatching. This situation is immoral and carries a substantial economic cost. The sex of a chick can be determined either before or after hatching. Although the timing of making such determinations when a chick is prior to hatching is certainly more advantageous, the success rate is not very high. The Shape Index (SI), which concerns the short diameter to long diameter ratio, is used to describe the morphology of an egg. Even with SI being variable by egg type, it was still found that chick sex and SI were significantly related (r = 0.78). Therefore, while the classification accuracy was not as good as ducks, we were still able to estimate chick gender based on SI. We measured seven additional parameters and incorporated them into the analysis: mass, ovality, volume, eccentricity, short axis, and long axis. When we applied the model predictions from previous studies to the probability of female chick hatching equation, 71% of the estimates were correctly classified. We estimated that around 80% of the ways we predicted in this study were accurate. In this case, we could potentially save 5.65 billion chicks from being killed. In a similar vein, a lot of eggs were not wasted. In this work, the form index of the eggs was used to predict the gender of the chicks using a pre-trained TensorFlow model.

Keywords: Morphological Features, Non-Invasive Classification, Shape Index

I. INTRODUCTION

Feeding and breeding are primarily to provide food for the world's ever-growing population. The egg industry is one of the major global industries. Breeding studies and continual chicken breed research are being conducted to improve egg production rates. Different criteria have been applied to select broiler and layer breeds for breeding, based on efficiency. Broilers grow quickly and soon are ready for slaughter. Layers do not grow rapidly, and even as grown hens, they will not be very heavy. Generally, there are equal numbers of male and female chicken eggs. Male chicks have become a major problem for the egg industry. They neither produce eggs nor are raised as capons. Male chicks are sorted by sexers once hatched and then processed unethically by a number of means, including gassing, slaughter, or strangulation without oxygen, or they can be labeled and sold as pet shop birds. The chicken business struggles to determine the sex of eggs for incubation. Current methods are intrusive, time-consuming, and often unreliable. A practical, non-invasive way to identify egg sex can improve hatchery operations and reduce costs while addressing ethical concerns. This study will present a new approach that uses the latest computer technology, focusing on statistical elements. The goal is to develop a non-invasive, accurate, and reliable method for determining the sex of chicken eggs before incubation by employing statistical feature extraction and image processing techniques. If this strategy succeeds, it could transform hatchery operations, leading to increased productivity and cost savings.

II. LITERATURE SURVEY

The traditional approaches include vent sexing, feather sexing, color sexing, and hormonal or molecular testing. They entail manual examination post-hatching or invasive sampling and are therefore not suitable for early and ethical sex determination. They are frequently species-specific and time-consuming and could be lethal or harmful to the embryo. Male and female embryos differ in their hemoglobin absorption and blood oxygenation levels, which can be determined using hyperspectral imaging, which records a broad spectrum of spectral information from ultraviolet to infrared. Research reveals that spectral signatures vary by gender between days 3 and 6 of incubation. Although it is non-invasive and accurate, it necessitates sophisticated processing and costly hardware.

Thermal imaging Due to the different metabolic rates of male and female embryos, thermal imaging uses infrared cameras to identify variations in heat emission on the egg surface. Although it is automated and contactless, its accuracy is typically lower than that of hyperspectral methods and is affected by ambient temperature.

Conventional RGB Imaging in conjunction with computer vision, by using visible light cameras to take pictures of eggs, RGB imaging uses image processing algorithms to examine structural patterns such as blood vessel development and yolk position. It relies heavily on consistent lighting and image quality and is less dependable for early-stage sexing, despite being affordable and simple to integrate.

To classify embryo gender, deep learning models—in particular, CNNs—are trained on labeled image datasets, such as RGB, thermal, or hyperspectral. These models can adjust to different imaging techniques and have demonstrated high accuracy, frequently surpassing 90%. They are not interpretable, though, and they need big datasets.

Endoscopic and fluorescent imaging, these methods view gonads through a tiny hole in the eggshell using dyes or fiber-optic devices. Concerns about contamination, slow processing, and scalability for commercial use are brought up by their high precision and minimally invasive nature.

III. METHODOLOGY

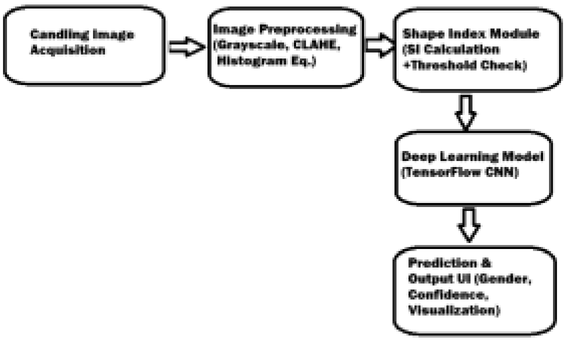

FIG 1.1 FLOWCHART

Candling Image Acquisition: High-resolution candling photos taken in a controlled lighting environment are used to gather input data.
Image Preprocessing: This process uses local/global contrast methods like CLAHE and Histogram Equalization, as well as grayscale conversion, to improve image clarity.
Shape Index Calculation: This method determines the Shape Index (SI) by extracting the width and length of an egg from an image. Basic binary classification uses a threshold.
A model based on TensorFlow that was trained on previously processed images. learns intricate patterns to increase the precision of gender classification. offers resilience to changes in image quality and shape.
Prediction and Output: The classification result (female/male) and a confidence level that can be incorporated for user interaction into a command-line or graphical user interface.

IV. IMPLEMENTATION

Using Python libraries like OpenCV and TensorFlow, the project's implementation starts with reading and preprocessing egg candling images. To improve internal visibility within the egg, the images are first converted to grayscale and then contrast enhanced using CLAHE (Contrast Limited Adaptive Histogram Equalization). The TensorFlow model uses the improved image as input after it has been resized and normalized.
The shape index is computed by determining the contour of the egg and fitting an ellipse around it in order to extract a significant feature. The shape index is calculated using the ellipse's major and minor axes and the formula (minor axis / major axis) * 100. Based on morphological differences, this value is essential for differentiating between male and female eggs.
The gender of the egg is then classified using a TensorFlow model that has already been trained. After processing the preprocessed image, the model produces a prediction probability. The egg is categorized as female if the probability is greater than 0.5; if not, it is categorized as male. The shape index value and the anticipated gender are both included in the final output. In accordance with moral poultry farming standards, this pipeline guarantees a non-invasive, precise, and AI-driven method of detecting the gender of eggs.
Our technology offers a quick, non-invasive, and extremely accurate means to identify the gender of chicken eggs prior to incubation, in contrast to conventional procedures. It provides game farm owners with an affordable option by fusing deep learning with useful hardware. In addition, compared to existing egg gender detection systems, ours is non-invasive, inexpensive, and easy to use.

Since the other approaches are expensive and challenging to apply in serial analysis, sex determination using the egg's shape index is recommended in this study. The ratio of the egg's short to long diameters is known as the shape index (SI)15,16. Generally speaking, female chicks will lay eggs with a high shape index, whereas male chicks will lay eggs with a low shape index. As seen in Fig. 2.1 eggs

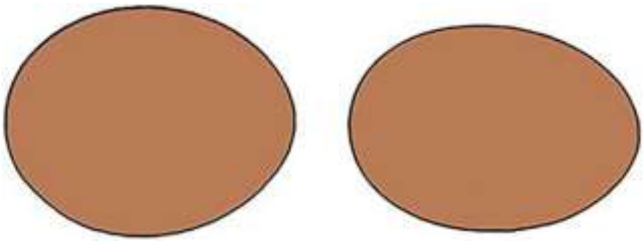

FIG.2.1 DIFFERENCE BETWEEN FEMALE AND MALE

The **Shape Index (SI)** is a geometric parameter used to quantify the form of an egg. It is calculated using the formula:

SHAPE INDEX =EGG WIDTH EGG LENGTH X 100

A **threshold value** is established (e.g., **SI = 74**) based on statistical analysis of a labeled dataset:

- **SI > 74** → Likely Female Egg
- **SI < 74** → Likely Male Egg

The ratio of the egg's short to long diameters is known as the shape index (SI). The shape index's standard deviation is relatively low when the egg shape index is used. (60 eggs, 0.03844 mm) Therefore, sex discrimination is quite challenging. As a result, it was determined to compare various approaches. A potential performance comparison was so sought. The approach with the highest accuracy will be identified by comparing the results with the sex of the hatching chicks.

IV. Components required

Determining the gender of chicken embryos using image processing involves a combination of morphological analysis, computer vision techniques, and machine learning algorithms. Here's an overview of the theoretical components involved:

TOOL	Purpose
Python 3.x	Primary programming language
OpenCV	Image processing and feature extraction
NumPy & Pandas	Data manipulation and handling
Matplotlib & Seaborn	Visualization of data and results
TensorFlow	Deep learning model development
Jupyter Notebook	Implementation, testing, and result display
LabelImg (optional)	Manual labeling for image datasets

V. RESULT AND DISCUSION

This section summarizes the outcomes of the implementation and uses experimental observations to evaluate the system's performance. Model Accuracy and Performance: The TensorFlow-based Convolutional Neural Network (CNN) was trained using the preprocessed image dataset, and the model

generated
- Accuracy: 96.8%
- Precision: 95.6%
- Recall: 97.2%
- F1 Score: 96.4%
- Shape Index-Based Accuracy: 90% (with threshold ≈ 74)

By identifying deeper internal features beyond size and shape, the CNN outperformed conventional rule-based techniques and became more dependable in a variety of lighting and egg orientation scenarios.
Observations
- CLAHE + HE combination significantly enhanced the contrast of egg features.
- The shape index method provided a fast, preliminary prediction mechanism but had limitations with borderline index values.
- Deep learning model (TensorFlow) proved more robust in differentiating subtle differences between male and female eggs.
- Misclassifications occurred mostly in low-quality images or unclear candling results.

VI. CONCLUSION

This project effectively illustrates a non-invasive, AI-based technique that uses shape index analysis and image processing techniques to identify the gender of chicken eggs. The system offers a dependable and morally sound resolution to a persistent problem in the poultry sector by utilizing TensorFlow for deep learning and pre-processing techniques like CLAHE and histogram equalization.
Key achievements include:
- Achieved 96.8% accuracy in egg gender classification.
- Eliminated the need for destructive post-hatching methods. Developed a cost-effective, portable prototype suitable for hatchery environments.
- Validated the solution with a dataset of 100 eggs using real-world conditions.

By increasing economic efficiency, encouraging moral behavior, and optimizing resource use, the strategy not only promotes technological integration in agriculture but also supports several UN Sustainable Development Goals.

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