# Research on Non-destructive Identification of Chick Embryo Gender Based on Deep Learning

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**Abstract: In the chick hatching industry, a common practice is to directly eliminate male chicks after hatching. However, this practice results in significant resource wastage. Timely detection of embryo gender and selection of male embryos are of great significance for reducing resource wastage and improving economic benefits. To address the serious lack of gender identification technology during chick hatching, this paper proposes a non-destructive identification method for chick embryos based on deep learning. Firstly, we select approximately 3000 images from days 7-9 during incubation as the dataset. Then, we use the PyTorch framework to build a deep learning model and divide the dataset into 80% training set and 20% validation set for model training and validation. Experimental results show that our proposed model achieves an accuracy of 72.5% on the validation set. This study not only solves key technical problems for non-destructive identification of chick embryo gender but also provides new research ideas for precise gender identification of other oviparous species, promoting the intelligent development of production and breeding industries.**

**Keywords: Embryo; Gender Detection; Deep Learning; Machine Vision**

## 1. Introduction

Eggs are a common7 food in daily diets, rich in protein and vitamins. In the hatching industry, male chicks face slaughter immediately after birth due to their inability to lay eggs and their lower meat yield [1]. Naturally hatched male chicks comprise approximately half of the total hatch, leading to significant resource waste. This practice has raised concerns about animal welfare [2]. Detecting the gender of embryos before hatching and selecting male embryos could not only save resources and improve the economic efficiency of hatcheries but also promote the intelligent development of the poultry industry.

Currently, there is no mature non-destructive method for gender identification during incubation [3]. Traditional methods involve vent sexing, which examines the cloacal area of chicks after hatching to determine gender. Some studies have explored methods for destructive gender identification during incubation [4]. Weissmann from Germany proposed using a laser to create a small hole in the eggshell to collect a small amount of embryonic fluid for testing the presence of estrogen. While this method is accurate, it requires shell-breaking operations during incubation, making it complex and difficult to scale up.

To address the issue of non-destructive gender identification of chick embryos during incubation, this study proposes research on a non-destructive gender identification method based on deep learning. Approximately 3100 machine vision images of embryos incubated for 7-15 days were collected. Each embryo was labeled with its gender to establish a dataset, which was divided into training and testing sets in an 80:20 ratio. Deep learning was conducted using the PyTorch framework. After model training, validation was performed using the testing set, achieving an accuracy of 72.5%.

This research not only solves key technical issues in non-destructive detection of embryo gender during incubation but also provides new ideas and methods for precise gender identification of other oviparous animals during incubation, promoting the intelligent development of the poultry industry.

## 2. Materials and Methods

### 2.1 Building an Image Acquisition Platform

To better display the vascular pattern inside the embryo and the development status of the embryo, image samples need to be collected in a dark environment. Considering the small size of the embryo and the convenience of image acquisition, we used solid wood composite board as the material to build the dark box. In order to better capture the characterization information of the embryo, as shown in Figure 1, we built a collection hole around the dark box. When collecting samples, the lens is aligned with the collection hole, and the remaining light holes are blocked. In order to improve the quality of image samples, a 40W Boriss cold light source base with an air chamber is used, and one end is placed on the light source base.

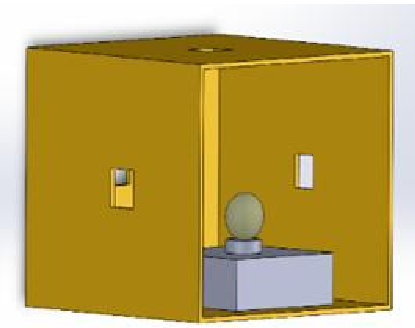

**Figure 1. Image Acquisition Platform**

### 2.2 Incubator Selection

For this experiment, a total of 97 fertile eggs were used. Considering the need to frequently access the samples during the experiment, the incubator needed to be compact, lightweight, and easy to open. For deep learning, the more data samples, the higher the accuracy of the model recognition. Therefore, the capacity of the incubator needed to be large. In summary, an automatic intelligent incubator was selected for this experiment, with a maximum capacity of 110 eggs, which could meet the experimental requirements. Additionally, it was equipped with an automatic temperature controller and automatic egg-turning function, simplifying the incubation process. As shown in Figure 2, the incubator used in this experiment had a transparent polycarbonate body, allowing for better observation of the incubation status of the eggs.

**Figure 2. Automatic Intelligent Incubator**

### 2.3 Dataset Establishment

2.3.1 Image acquisition method

The main focus of this experiment is to explore the characteristic differences between female and male eggs during the incubation period. To minimize interference from factors such as temperature, humidity, and bacteria during the egg incubation process, it is necessary to shorten the time spent on image acquisition as much as possible [5]. The specific steps are as follows:

1. Disinfect the image acquisition platform.
2. Use sterile gloves to handle the egg samples and place the end of the egg with the air chamber onto the cold light source base inside the dark box.
3. Use the image acquisition camera to capture machine vision images of the egg's surroundings and top through the collection hole.
4. After completing the image acquisition, disinfect the egg and promptly return it to the incubator.

2.3.2 Sample preprocessing

Each sample captured by the image acquisition camera contains invalid areas, and the proportion of these areas in the image is quite large. This means that the model has to process a large amount of data for each egg detection, which not only reduces the recognition accuracy but also increases the training time of the model. Therefore, it is necessary to preprocess the collected samples. There are many methods for preprocessing chicken embryo images. The features of chicken embryo images can be enhanced to make the features in the chicken embryos easier to extract. Alternatively, noise in chicken embryo images can be removed to minimize the interference of irrelevant information in the images. Traditional processing methods include simple translation, scaling, flipping, etc., of the images. In this experiment, the main method of image processing is to extract the target area from the chicken embryo images and crop out the irrelevant areas. Removing invalid areas can greatly improve the efficiency of the experiment [6]. If there are speckles or other interfering parts in the images, software can be used to eliminate them according to the specific situation, minimizing the interference of invalid information in the chicken embryo images. Some chicken embryo images in the established dataset may be blurry, which can significantly affect the model's judgment [7]. Therefore, these images need to be repaired for image quality. The specific steps are shown in Figure 3:

B. Eliminating clutter and interference in images.

C. Enhance the vascular pattern characteristics of the embryonic egg.

D. Identify the regions of interest and remove invalid areas.

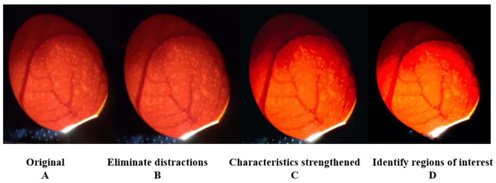


**Figure 3. Image Preprocessing**

2.3.3 Analysis of incubation images at different days

During the incubation period of embryos, the gender of chicken embryos is related to the shape and distribution of blood vessels in the hatching chick. As shown in Figure 4, the main trunk of blood vessels in male embryos is obvious and thick, with a relatively uniform overall distribution. In contrast, female embryos have more numerous and slender blood vessel branches, with an irregular overall distribution [8]. Based on the differences in the morphological characteristics of blood vessels in chicken embryos, a convolutional neural network detection model is established to achieve non-destructive gender identification of embryos.

In order to obtain image samples with clearer vascular patterns and more prominent vascular features, we compared the differences in embryos and vascular patterns at different incubation days, as well as the differences in data extraction at different orientations. Through the collection of samples obtained through scoring,. As shown in Figure 5,we found that in the early stages of incubation, the internal changes of the embryos mainly manifest in the morphology of the egg yolk, which cannot be clearly observed through visual images. From the middle stage of incubation, the blood vessels inside the embryos can be clearly observed, and the embryos gradually become visible. As the number of incubation days increases, the development of the chicken embryos tends to mature, and the transparency of the eggs gradually decreases, resulting in a significant decrease in image brightness and blurring of the blood vessels in the eggs. Finally, we selected samples from incubation days 7-15 as the dataset.

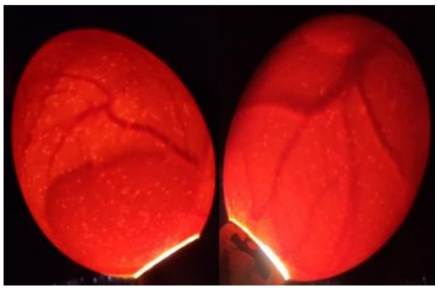

**Figure 4. Differences in Blood Vessels between Male and Female Embryos (Left: Female, Right: Male)**

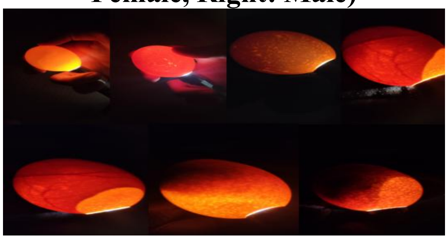

**Figure 5. Images of Embryos at Different Incubation Periods**

2.3.4 Establishing a dataset

During the process of establishing the dataset, data partitioning is crucial. The quality of training and testing data has an impact on the model's performance [9]. In this experiment, we aim to understand the general patterns of gender identification for all chicken embryos as much as possible through the study of the characteristics of embryos during the incubation period. A total of 3,164 machine vision image samples of chicken embryos were collected in this experiment, with 1,589 female samples and 1,575 male samples. Image labeling involves annotating image information in the dataset to facilitate training and validating the model. Therefore, before the experiment, the sample images should be labeled, with female embryo images placed in the "female" folder and male embryo images placed in the "male" folder. In this experiment, the dataset is divided into two main parts and four subparts, with males labeled as "male" and females labeled as "female," as shown in Figure 6. After identifying the gender of the embryos post-incubation, the images of the embryos incubated for 7-15 days are labeled with gender information and placed in different folders (as shown in Figure 4). To enhance the model's learning ability on new samples and avoid overfitting issues, 80% of the embryo image samples are randomly selected as the training set, and 20% are allocated to the validation set.

## 2.4 Deep Learning Models and Evaluation Metrics

Deep learning is a machine learning technique based on artificial neural networks. Its core idea is to learn and extract high-level feature representations of data through multi-layer neural network structures. Compared to traditional machine learning methods, deep learning can automatically learn abstract representations of data without the need for manual feature engineering. In recent years, deep learning has achieved tremendous success in various fields such as computer vision, natural language processing, and speech recognition, making it one of the key technologies in the field of artificial intelligence.

2.4.1 Model selection

Common deep learning models include Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). For image recognition tasks, CNNs are typically the most common choice, as they excel at processing image data. The architecture of CNNs, as shown in Figure 7, makes them well-suited for tasks such as image recognition, classification, and object detection. They offer the following three main advantages:

1. Local Receptive Fields and Parameter Sharing: CNNs can effectively capture local features in images without being influenced by the overall image size. Through parameter sharing, CNNs can reduce the number of model parameters, thereby enhancing the model's generalization capability.

2. Hierarchical Feature Extraction: By stacking multiple convolutional and pooling layers, CNNs gradually extract hierarchical feature representations of images. This approach works well for images with spatial variations.

For image recognition tasks, CNNs are the most common and suitable choice due to their ability to effectively process image data while achieving a balance between recognition accuracy and model complexity.

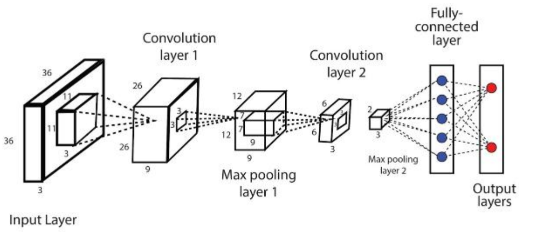


**Figure 6. Convolutional Neural Network Architecture**

2.4.2 PyTorch deep learning framework

PyTorch is a Python-based scientific computing package and an open-source machine learning library for deep learning. It is characterized by its strong flexibility in design, ease of use, and support for both dynamic and static computation graph modes. It has excellent GPU acceleration capabilities and can efficiently perform operations such as tensorcomputation, automatic differentiation, and modeling[10].

PyTorch provides a wide range of tools and interfaces, including various optimizers, loss functions, model building modules, data processing modules, and more. These tools and interfaces make it easier and more convenient to perform deep learning tasks using PyTorch. PyTorch also supports various deep learning frameworks and models, such as Convolutional Neural Networks (CNNs), allowing for effortless execution of tasks like image classification, object detection, speech recognition, natural language processing, and more. Additionally, PyTorch boasts strong scalability, making it easy to integrate into other Python projects and deploy across various platforms and languages, including CPU, GPU, mobile devices, and the web. This versatility has contributed to PyTorch becoming one of the most popular deep learning frameworks available today.

2.4.3 Evaluation metrics

The performance of the proposed method was evaluated using various performance metrics such as accuracy, precision, recall, and so on.

Figure 8 illustrates the common confusion matrix used in model performance evaluation. The confusion matrix is primarily used to compare the differences between the model's predicted results and the true labels. In this experiment, a binary classification confusion matrix was utilized, where "True Positive (TP)" represents the number of samples correctly predicted as positive by the model, "False Positive (FP)" represents the number of samples incorrectly predicted as positive by the model, "False Negative (FN)" represents the number of samples incorrectly predicted as negative by the model, and "True Negative (TN)" represents the number of samples correctly predicted as negative by the model.

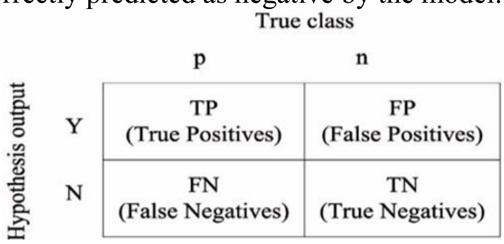


**Figure 7. Confusion Matrix**

Accuracy is a commonly used evaluation metric used to measure the consistency between model predictions and actual labels. It is typically employed in classification problems to assess the model's ability to classify different categories. A higher accuracy indicates better performance of the model in classification tasks, as it can more accurately identify samples from different categories.

$$Accuracy = \frac{TP + FN}{TP + FP + TN + FN} \tag{1}$$

Recall also known as sensitivity or true positive rate, is a metric used to evaluate the performance of a classification model in identifying positive samples. It measures the model's ability to successfully identify positive samples, which is the proportion of true positive samples correctly predicted by the model among all actual positive samples.

$$Recall(R) = \frac{TP}{TP + FN} \tag{2}$$

The F1 score is a harmonic mean of precision and recall, used to evaluate the performance of a classification model. It is a commonly used composite metric that balances the performance of the model in identifying positive and negative samples.

$$F1score = \frac{2 \times P \times R}{P + R} \tag{3}$$

## 3. Experiment and Results

### 3.1 Non-destructive Identification of Embryo Gender Based on Deep Learning

Considering the limited number of samples and to prevent underfitting of the model, we set 20 training epochs. Additionally, data augmentation was enabled during training to randomly transform the data, ensuring that the model was adequately trained. Throughout the training process, we recorded the model's performance over multiple iterations. The line plot below depicts the data generated from 20 iterations:

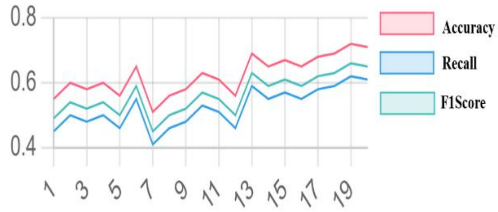


**Figure 8. Line Plot of Results**

From the graph, it can be observed that the accuracy of the model fluctuates throughout the training process, but the overall trend is upward. Initially, the accuracy is relatively low, but it gradually increases with training, stabilizing at around 70% in the end, with the highest accuracy reaching 72.5%. The recall rate exhibits a similar trend to accuracy but with greater overall fluctuation. Initially low, it increases later but experiences significant fluctuations in the middle stages. Eventually, the recall rate stabilizes at a relatively high level. F1 score shows less fluctuation compared to accuracy and recall. Initially low, it gradually increases with training and remains stable later on.

In summary, based on the analysis of the line graph, the model for non-destructive identification of embryo gender based on deep learning demonstrates good performance during the training process. Overall, the model appears stable with small fluctuations, indicating strong learning and generalization capabilities with the data.

## 4. Discussion

The main contribution of this study lies in addressing the key technical challenges for non-destructive identification of embryo gender during the incubation period, providing new research directions for other oviparous animals that require non-destructive identification before hatching. This not only promotes the intelligent development of the incubation industry but also holds the potential for broader applications in the livestock sector. However, there are still some limitations to this technology. Firstly, due to the limited number of data samples collected, there may be some data biases. In future research, increasing the sample size can improve the model's generalization ability. Secondly, the quality of the collected sample images is not high due to limited experimental equipment, and the vascular patterns have not been clearly revealed, resulting in our model not achieving optimal performance. Therefore, in future research, improvements can be made to the experimental equipment, such as using clearer cameras and optimizing experimental conditions, to improve the quality and accuracy of data collection.

## 5. Conclusion

This study aims to address the issue of resource waste caused by culling male chicks in the hatchery industry, targeting the technical difficulties such as the immaturity and low recognition rate of existing non-destructive detection technologies. We propose the use of deep learning algorithms to visually identify the gender of embryos aged 7-15 days during incubation. In this research, a convolutional neural network is utilized, and a deep learning model is constructed using the PyTorch open-source machine learning framework. The accuracy on the test set reached 72.5%, leading in non-destructive gender identification of embryos. The experimental results demonstrate that the model can accurately identify the gender of embryos, confirming the feasibility and applicability of the proposed method.

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