

Domain Gap Reduction In CNN Based In-Ovo Embryo Classification Via CLAHE Optimization

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ABSTRACT

Previous research utilizing Convolutional Neural Network (CNN)-based deep learning has successfully identified chicken embryo development through candling images. However, challenges arise in spinner-rack incubators equipped with a single candling camera, eggs in non-optimal positions receive insufficient illumination, making it difficult to recognize embryonic patterns. Adding more cameras or incandescent lights risks increasing both costs and incubation temperatures. This study aims to reduce the domain gap by optimizing preprocessing using Contrast Limited Adaptive Histogram Equalization (CLAHE) on RGB candling images. The dataset comprises 12,782 candling images 11,800 for training and 982 for evaluation labeled as fertile, infertile, or dead across days 1 through 10. The CNN model was trained using a batch size of 32 and an image size of 224×224, and was evaluated based on accuracy, precision, recall, and F1-score. Experimental results demonstrate that RGB images processed with CLAHE yielded the best performance, achieving 97.37% accuracy surpassing grayscale (96.36%), RGB without CLAHE (96.16%), and grayscale with CLAHE (93.84%). Testing on 107 external images further confirmed the superiority of the RGB + CLAHE method, which produced 103 correct predictions and only 4 errors, compared to standard RGB, which yielded 101 correct predictions and 6 errors. Remaining classification errors primarily occurred in the class of embryos that failed to develop due to the blood ring phenomenon, which visually resembles a fertile embryo at day 5.



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I. PENDAHULUAN

The use of deep learning based on Convolutional Neural Networks (CNN) has made a significant contribution to the field of detection and analysis of biological egg images [1]. One application is in the process of identifying chicken embryo development using the candling technique. In previous studies, this method was employed with conventional incubators to enable the observation of embryo conditions without removing the eggs from the incubation

rack, thereby avoiding disruption to the incubation process [2]. However, the limitations of the spinner-rack incubation system and the use of a single candling camera created challenges during model detection testing—particularly for eggs in non-optimal positions, such as those at the edges. These eggs did not receive maximal illumination, making the embryonic blood vessels difficult to discern. This suboptimal lighting obscured the embryo pattern, resulting in reduced detection accuracy, with the errors predominantly occurring in eggs subjected to poor lighting conditions.

In previous research, detection errors also stemmed from test images taken from other incubators with different lighting configurations. While adding a camera or an incandescent bulb to an incubator could indeed improve image quality, such a solution risks increasing production costs making mass production for independent farmers economically unviable and the addition of an incandescent bulb could destabilize the incubator's temperature, thereby affecting the temperature of the eggs during incubation and potentially leading to fatal consequences for the embryos [3].

To address this issue, a more cost-effective approach is required one that avoids adding extra camera hardware (thereby keeping production costs down) and avoids using incandescent lights (thereby preventing temperature fluctuations within the incubator during the incubation period). A viable solution involves performing color normalization on candling images prior to training the CNN model. One such image normalization preprocessing method is Contrast Limited Adaptive Histogram Equalization (CLAHE), which enhances image contrast and reduces the domain gap during the preprocessing stage [4]. CLAHE works by dividing the image into small, tile-like sections, after which the contrast in each section is adjusted locally. Subsequently, the histogram is constrained according to specific rules to prevent artifacts such as glare spots or excessive noise [5]. Using this method, embryo images where blood vessel patterns are not clearly visible due to suboptimal lighting or variations arising from incubators with differing volumes and lighting positions can be normalized to match images captured under optimal conditions and proper lighting, thereby enabling the CNN model to learn from uniform image data [6].

This study aims to reduce the domain gap in a CNN-based in-ovo embryo classification model originally developed in prior research by optimizing the preprocessing stage. Evaluation is conducted using accuracy, precision, recall, and F1-score metrics to assess the method's effectiveness in improving the model's generalization capabilities regarding test images of eggs that were previously misclassified, as well as misclassified images from other incubators resulting from color variations caused by differing lighting conditions [7], [8], [9].

The novelty of this research lies in the RGB image preprocessing stage, where images are processed using CLAHE before being fed into the CNN model [10]. Unlike previous studies that relied solely on cropping and background removal without lighting normalization, this approach incorporates a contrast optimization step to enhance image quality. In addition to RGB images processed with CLAHE, the model is also trained using several other variations: grayscale images, a combination of grayscale and CLAHE, and three-channel RGB images further processed with CLAHE [11], [12]. All these variations serve as a basis for comparison to determine the optimal approach for detecting and resolving detection failures in chicken egg

embryo development issues caused by domain gaps and uneven coloration in eggs positioned at suboptimal points.

II. RESEARCH METHOD

This research began with the collection of a dataset from a previous study, followed by a preprocessing stage involving background removal, resizing, and the application of CLAHE to RGB images for model training; additionally, the model was trained using grayscale images, grayscale combined with histogram equalization, grayscale combined with CLAHE, and RGB images combined with histogram equalization. The dataset was then split into training and testing sets and used to train the CNN model. Finally, the model was evaluated using a confusion matrix; the research workflow is illustrated in Figure 1.

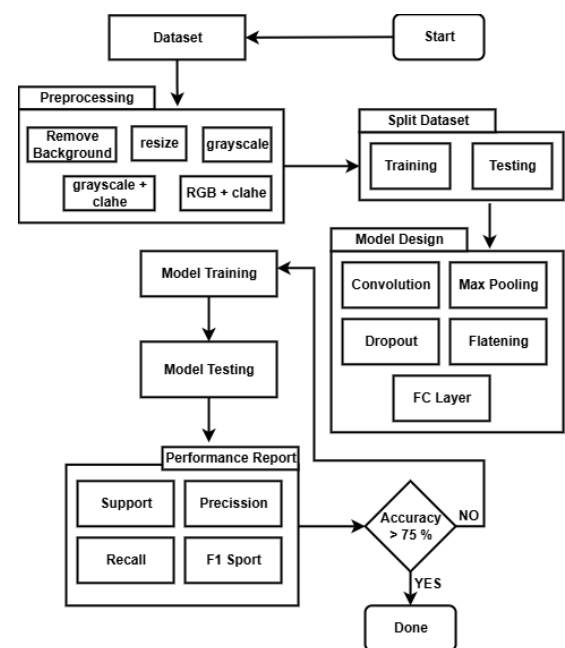


Figure 1. Research Flow

A. Datasets

The dataset obtained was the same as that used in the previous study, generated through a candling process using an incubator equipped with a Logitech B525 camera with a resolution of 1280 x 720 pixels. The camera was placed 35 cm above the rotating rack as illustrated in Figure 2, which shows the rack model used, while the candling images are presented in Figure 3. The collected data were categorized into 4,261 images of fertile eggs, 4,261 images of infertile eggs, and 4,260 images of eggs with embryo development failure, resulting in a total dataset of 12,782 images taken during the 10-day candling period and separated into fertile, infertile, and dead classes for days 1 to 10.

To address data gaps due to embryo mortality and infertility, we performed repeated incubation cycles to obtain additional data, allowing the model to be trained using actual egg candling images without relying on data augmentation.



Figure 2. Front view of the incubator

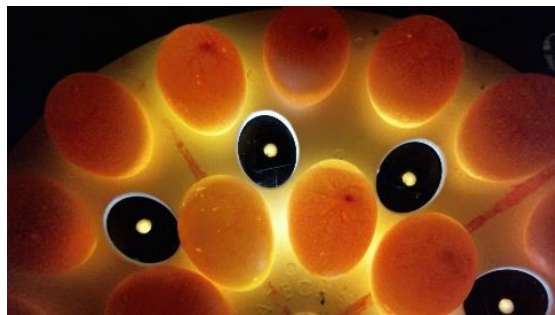


Figure 3. Sample results of egg image candling

B. Preprocessing

The collected images are then preprocessed by cropping using the object detection method which is then cropped, then the image is removed from the background using the rembg library, where in the process of removing the background from the egg background only removes the outer area of the egg without damaging the visualization of the egg and also the visual pattern of blood vessels in the egg embryo [13], [14], [15]. Then the image that has been removed from the background is further preprocessed by changing the candling image from RGB to grayscale by changing the value of the three color channels in each image pixel into a single value of the gray degree but this process is configured to remain 3 channels so that it can be used by CNN [16].

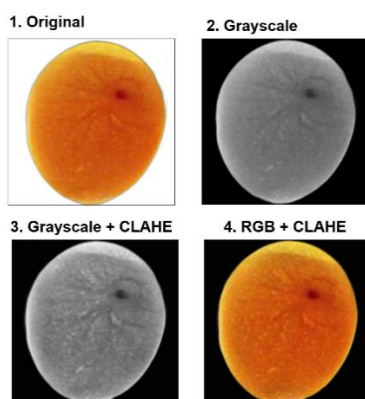


Figure 4. Process of converting an RGB image to Grayscale and CLAHE

Furthermore, the images were processed from RGB to grayscale using CLAHE with a clip limit of 2.0 and a tile grid size of 8.8. The RGB candling images were also preprocessed using CLAHE to enhance the blood vessel pattern. Each preprocessing method was then combined into a separate dataset and used as training data in the CNN model [17], [18], [19]. As shown in Figure 4.

C. Model Design

The CNN model was trained using a total of 12,782 preprocessed candling images, 11,800 of which were used as training data and 982 were used as evaluation or testing data. The model was built with a Convolutional Neural Network (CNN) architecture that accepts 224×224 pixel image input with a batch size of 32 [20]. The architecture consists of several Conv2D layers with a 3×3 kernel followed by Batch Normalization and MaxPooling to extract spatial features, and Dropout to reduce overfitting [21], [22], [23]. After the feature extraction process, a Flatten layer is used to flatten the output before entering a 128-neuron Dense layer with ReLU activation, and ending with an output Dense layer according to the number of classes with Softmax activation [24]. The model was trained using the Adam optimizer with a learning rate of 0.001 and a categorical crossentropy loss function [25], [26]. The visualization of the CNN model is shown in Figure 5.

Layer (type)	Output Shape	Param #
rescaling (Rescaling)	(None, 224, 224, 3)	0
conv2d (Conv2D)	(None, 224, 224, 32)	896
batch_normalization (BatchNormalization)	(None, 224, 224, 32)	128
conv2d_1 (Conv2D)	(None, 224, 224, 32)	9,248
max_pooling2d (MaxPooling2D)	(None, 112, 112, 32)	0
dropout (Dropout)	(None, 112, 112, 32)	0
conv2d_2 (Conv2D)	(None, 112, 112, 64)	18,496
batch_normalization_1 (BatchNormalization)	(None, 112, 112, 64)	256
conv2d_3 (Conv2D)	(None, 112, 112, 64)	36,928
max_pooling2d_1 (MaxPooling2D)	(None, 56, 56, 64)	0
dropout_1 (Dropout)	(None, 56, 56, 64)	0
conv2d_4 (Conv2D)	(None, 56, 56, 128)	73,656
batch_normalization_2 (BatchNormalization)	(None, 56, 56, 128)	512
conv2d_5 (Conv2D)	(None, 56, 56, 128)	147,584
max_pooling2d_2 (MaxPooling2D)	(None, 28, 28, 128)	0
dropout_2 (Dropout)	(None, 28, 28, 128)	0
flatten (Flatten)	(None, 100352)	0
dense (Dense)	(None, 128)	12,845,184
dropout_3 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 2)	258

Figure 5. Visualization of the CNN model and the parameters used.

D. Model Training

In the training process of each dataset, namely the grayscale dataset, the grayscale dataset with CLAHE, and the RGB datasets with CLAHE, each was trained with a total of 52 epochs and each found its best performance at epoch 24, during the training period we used the earllystopping method for 5 consecutive times to find the best performance for each method [27]. And using the checkpoint method at each epoch completion to avoid re-training from epoch 1 to epoch 52

[28], [29]. The validation and loss graphs for training and validation are shown in Figure 6.

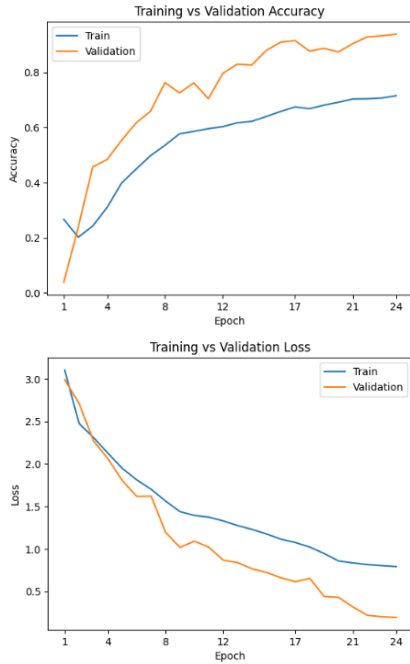


Figure 6. Visualization of model training results for one of the preprocessing methods.

E. Evaluation

In the evaluation stage of the model that has been trained previously using different preprocessing images, then from the total test data, namely 990 test images from each preprocessing method, namely grayscale, grayscale with CLAHE and RGB with CLAHE, an evaluation was carried out using a confusion matrix to find out how much each method provides correct and incorrect prediction results, and also used the evaluation metrics Precision, Recall, Accuracy, and F1-Score on each preprocessing method trained using CNN [30], [31].

III. RESULTS AND DISCUSSION

A. Results For Grayscale

When the model was trained using grayscale images without additional contrast enhancement techniques, its performance was actually good. Of the total 990 test data, 950 images were successfully classified correctly while only 40 images were still mispredicted. The overall accuracy obtained reached 96.36%, as shown in the confusion matrix in Figure 7. These results indicate that although the grayscale images omit color information, the texture and shape patterns captured by the CNN are sufficient to distinguish the details of the blood vessel patterns of egg embryos between classes so that performance remains good.

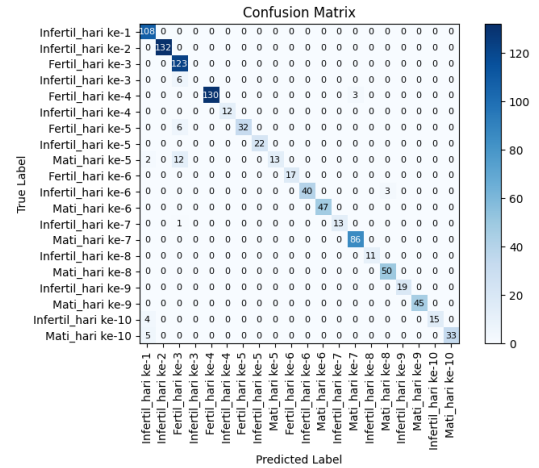


Figure 7. Confusion Matrix CNN trained with grayscale

B. Results For Combination Grayscale and CLAHE

The model trained using grayscale images with preprocessing through CLAHE showed a decrease in results, where out of a total of 990 test data, 929 images were successfully predicted correctly while 61 other images still had errors. The distribution of these prediction results can be observed in the confusion matrix in Figure 8. The overall accuracy achieved was 93.84%, although this accuracy is slightly lower than using grayscale images, the results still show the effectiveness of this preprocessing method in reducing the domain gap due to suboptimal lighting.

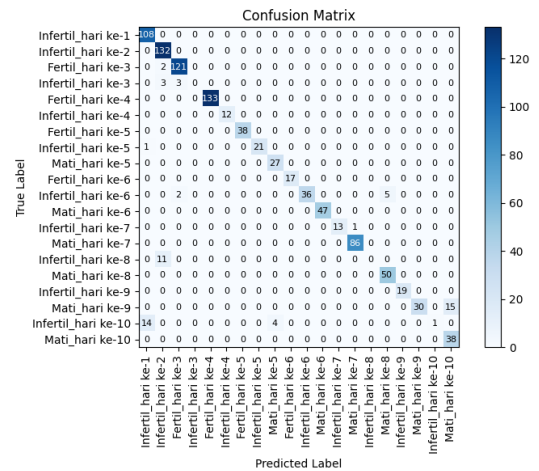


Figure 8. Confusion Matrix CNN trained with gray scale and CLAHE

C. Results For Combination RGB and CLAHE

The use of RGB images processed with CLAHE provided quite good results compared to other preprocessing methods. Of the total 990 test data, the model was able to produce 964 correct predictions, while 26 images were still misclassified. The overall accuracy value of 97.37% indicates that the use of CLAHE on RGB-based egg embryo images can help improve the visual pattern of blood vessels in egg embryos that receive minimal lighting or are not at the optimal camera point, this result is seen in the confusion matrix in Figure 9,

however, in some classes there are still relatively smaller prediction errors compared to other preprocessing methods. These errors, when observed from the results of the trial samples, show that the error lies in the class of embryos that experience developmental failure at the beginning of the incubation period, namely on days 3 and 4 to day 5 of the incubation period.

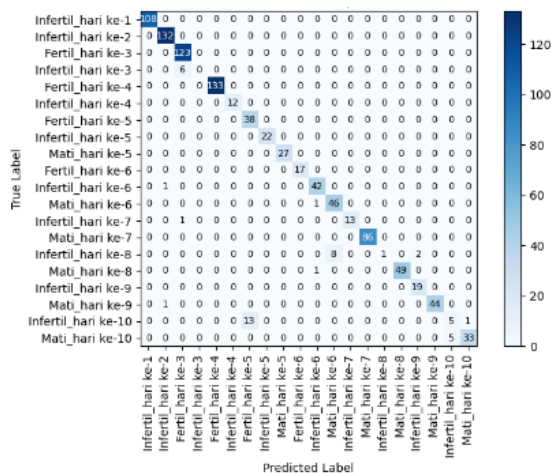


Figure 9. Confusion Matrix CNN trained with RGB and CLAHE

D. Results For RGB

The model trained using RGB images without any lighting maximization or color normalization in the preprocessing stage in previous research showed that from a total of 990 test image data, 952 images were successfully predicted correctly, while 38 other images still experienced misclassification. The distribution of these prediction results can be observed more clearly in the confusion matrix evaluation results in Figure 10, which shows how the model is able to distinguish fertile, infertile, and dead classes [2]. The overall accuracy achieved was 96.16%, this result shows that CLAHE on RGB images trained on the CNN model is also able to provide good results even though there are still a small number of errors.

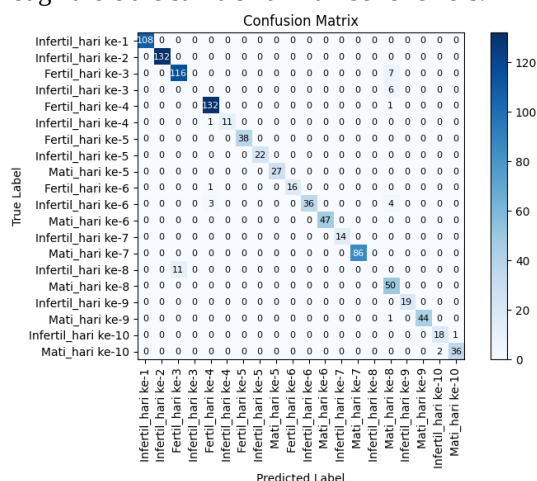


Figure 10. Confusion Matrix CNN trained with RGB

Overall, the results of this study indicate that the quality of preprocessing greatly determines the performance of CNN in the classification of egg embryo images. The use of pure grayscale provides an accuracy of 96.36%, the application of grayscale combined with CLAHE actually decreases the performance by 93.84%, while the combination of RGB with CLAHE is able to increase the accuracy to 97.33%, which in this result is slightly higher than the results of the previous model development which was only trained using RGB images which reached 96.16%. The comparative results can be seen in Table 1.

TABLE I
SUMMARY OF CNN MODEL TEST RESULTS WITH VARIOUS PRE-PROCESSING METHODS

Preprocessing Method	Data Test	Correct	Incorrect	Accuracy (%)
Grayscale	990	954	36	96.36
Grayscale + CLAHE	990	929	61	93.84
RGB + CLAHE	990	964	26	97.37
RGB	990	952	38	96.16

E. Classification Evaluation by Preprocessing Method

The use of RGB images with CLAHE provided the best performance with an accuracy of 97.37% and relatively high precision, recall, and macro f1-score values of 0.94, 0.92, and 0.93. Meanwhile, pure grayscale images also showed quite good results with an accuracy of 96.36%, even though color information was removed. In contrast, the combination of grayscale and CLAHE produced a lower accuracy of 93.84%, indicating that increasing contrast in grayscale images does not always improve classification performance. RGB images still provided a high accuracy of 96.16% with balanced evaluation metrics. Overall, these results indicate that preprocessing also affects CNN performance, where CLAHE on RGB images proved most effective in improving the model's ability to distinguish embryo classes.

TABLE II
SUMMARY OF CNN MODEL EVALUATION RESULTS WITH DIFFERENT PREPROCESSING METHODS

Preprocessing Method	Accuracy (%)	Precision (macro)	Recall (macro)	F1-score (macro)
Grayscale	96.36	0.94	0.92	0.93
Grayscale + CLAHE	93.84	0.92	0.91	0.91
RGB + CLAHE	97.37	0.94	0.92	0.93
RGB	96.16	0.93	0.91	0.92

Testing was also carried out on other incubator test images that were not included in the datasets, the purpose of this test was to measure the extent to which the model developed using additional preprocessing methods, namely by adding the CLAHE channel to the RGB channel, showed good results by

producing correct classifications on test images that were previously incorrectly predicted by models trained with RGB images, by using the clahe preprocessing method on RGB images the model can also correctly predict fertile and infertile classes, but errors also still exist in the class of embryos that failed to develop which were predicted as fertile classes. As shown in figure 11 and the accumulated results using test images from external incubators that use sliding shelves with a total of 107 test images for all classes are shown in Table 3.

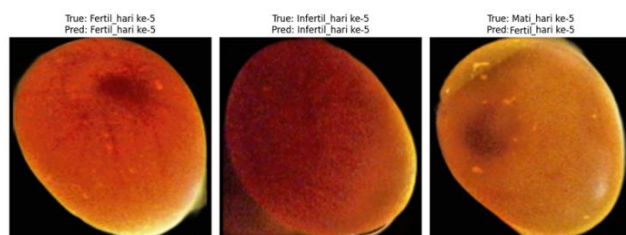


Figure 11. Classification test results using images from various incubators.

TABLE III
COMPARISON OF CNN MODEL EVALUATION RESULTS USING VARIOUS
PREPROCESSING METHODS ON EXTERNAL TEST IMAGES

Preprocessing Methods	Class	Samples	Correct	Incorrect
RGB	Fertile	36	34	2
	Infertile	32	32	0
	Developmental Failure	39	35	4
	Total	107	101	6
RGB + CLAHE	Fertile	36	35	1
	Infertile	32	30	2
	Developmental Failure	39	38	1
	Total	107	103	4

Classification errors are also caused by a circular blood vessel pattern or what is called a blood ring phenomenon, where the embryo's blood vessels move to the edge to resemble a ring which breeders can sometimes mispredict and assume it is an early phase of embryo development when in fact it is the beginning of embryo death so that the blood vessels no longer branch like a spider's web, it will be clearly visible if it is on the 5th to 10th day because the blood vessel rings have begun to accumulate on the edge and there is a thickening of the ring as shown in Figure 12 on the arrow line. This is shown in Figure 12 where on the left side is the beginning of embryo death and on the right side is embryo death on day 5.

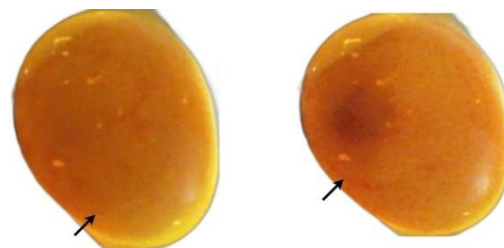


Figure 12. Blood ring on day 4 and day 5, predicted to be fertile.

IV. CONCLUSION

From the overall series of trials and experiments conducted, the CNN model trained with 12,782 candle images, 11,800 images for training and 982 images for evaluation showed that preprocessing affected the performance of the classification results. The use of pure grayscale resulted in an accuracy of 96.36% with 950 correct images and 40 incorrect ones, while the combination of grayscale with CLAHE actually decreased to 93.84% with 929 correct images and 61 incorrect ones. On the other hand, the combination of RGB + CLAHE gave the best results with an accuracy of 97.37% with 964 correct images, 26 incorrect ones, which are higher than the results in previous studies where the CNN model was only trained using RGB images without CLAHE with an accuracy of 96.16% with a total of 952 correctly predicted images, and 38 incorrectly predicted images [2].

Testing on 107 external test images also showed that the RGB method with CLAHE was better, with 103 correct images and only 4 incorrect ones, compared to pure RGB which produced 101 correct and 6 incorrect ones. The remaining misclassifications mostly occurred in the failed embryo class, mainly due to the blood ring phenomenon which visually resembles a fertile embryo on day 5, thus causing ambiguity.

Overall, it can be concluded that RGB preprocessing with CLAHE in this study is the best approach to improve CNN accuracy in egg embryo classification, both on internal test image data and external test images originating from different incubators. However, biological phenomena such as blood rings remain a challenge that needs to be addressed, so integrating biological understanding of egg embryos with technology is crucial for more accurate classification results.

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