Eggshell biometrics for individual egg identification based on convolutional neural networks

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Abstract

Individual egg identification technology has potential applications in breeding, egg production, and anti-counterfeiting of high-end brand eggs. This study developed a novel method for its individual identification based on eggshell images. A convolutional neural network-based model, named Eggshell Biometric Identification (EBI) model, was proposed and evaluated. The main workflow included eggshell biometric feature extraction, egg information registration, and egg identification. The image dataset of individual eggshell was first collected from the blunt end region of 770 chicken eggs using an image acquisition platform. The ResNeXt network was then trained as a texture feature extraction module to obtain sufficient eggshell texture features. The EBI model was applied to a test set of 1540 images. The results showed that when an appropriate Euclidean distance threshold for classification was set (17.18), the correct recognition rate and the equal error rate reached 99.96% and 0.02%. This new method provides an efficient and accurate solution for individual egg identification for product tracing and anti-counterfeiting.

Keywords: chicken egg identification, eggshell biometrics, computer vision, convolutional neural networks

Introduction

Individual egg identification technology has potential application scenarios. For example, egg identification technology plays an important role in safeguarding the interests of high-end brand egg enterprises and consumers. To solve the problem of egg identification, external physical label methods with specific anti-counterfeiting identity labels attached to eggs are sometimes used, such as brand logos, digital numbers, RFID electronic labels, barcodes, and quick response codes (Arppe and Sorensen, 2017). These methods are likely to be counterfeited and the information in the labels is vulnerable (Lehtonen et al., 2007). Therefore, new authentication methods for egg identification should be based on unclonable identity tokens. Researchers tried to use the chemical composition (Barbosa et al., 2014) naturally contained in eggs as egg identity biomarkers (Tres et al., 2011; Bandoniene et al., 2018) to verify the difference in composition between specialty eggs (Cherian et al., 2002; Dong et al., 2021) and ordinary eggs. However, the above egg identification technologies require a cumbersome and time-consuming series of steps, and are destructive but of low accuracy, which cannot meet the requirements of egg individual identification in commercial settings.

To overcome the problems associated with physical labels and chemical markers for egg identification, computer vision technology based on eggshell texture features can be adapted to collect and process egg image information for identification. Computer vision and image processing techniques have been increasingly used in the egg industry for a range of detection tasks (Nyalala et al., 2021). Existing researches mainly focused on eggshell surface defect detection (Turkoglu, 2021), including cracks (Bao et al., 2019), stains (Yang et al., 2018), pimpled (Liu et al., 2017) and spotted (Zhang et al., 2021) eggs, which can be applied for egg grading and classification. However, the eggshell texture features are complex and it requires more robust image acquisition and processing algorithms to achieve higher recognition accuracy for individual identification. In recent years, Convolutional Neural Networks (CNNs) are particularly effective in image recognition tasks (Russakovsky et al., 2015; Alom et al., 2019). However, there is no research yet for egg individual identification technology based on eggshell texture as biometric features.

In this study, we proposed and designed a residual network ResNeXt-based deep learning method for feature extraction and egg identification. The main workflow included biometric feature extraction, feature information registration, and egg identity authentication steps. The developed method, named Eggshell Biometric Identification (EBI) model, precisely identified individual eggs in the experimental settings. The method provided a reliable solution for egg identification applications, such as traceability in husbandry, traceability in commercial egg distribution, and anti-counterfeiting for high-end brand eggs.

Materials and methods

Image acquisition

A total of 770 pink and brown commercial chicken eggs were procured from various local supermarkets in Hangzhou, China. The proportion of eggshell color was similar to that of the average market share in China with pink and brown eggs dominated (Yang, 2021). All eggs were manually inspected to confirm eggshell surfaces were clean, intact, and free of defects. As shown in Figure 1, each egg was randomly rotated and re-angled before an image was taken, and a total of 10 images were taken for each. A total of 7700 images of the blunt-end of the eggshell were taken with a pixel size of 4096×3000.

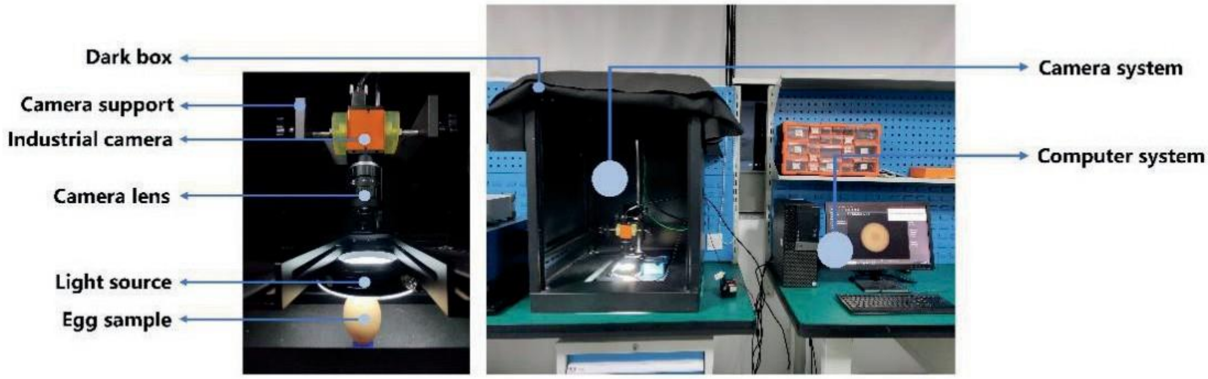

Figure 1: Proposed eggshell images capture system

Image preprocessing

The egg images were preprocessed to remove background to obtain the region of interest (ROI) (Figure 2). The K-means algorithm was used to cluster the color information of the image (Sodjinou et al., 2021). The Gaussian filtering operation was used to reduce image noise to generate a binary mask image of the egg ROI (Figure 2 (c)). The Hough circle detection algorithm was then performed on the egg mask image to identify the center position coordinates and radius size information of the egg ROI (Figure 2 (f)).

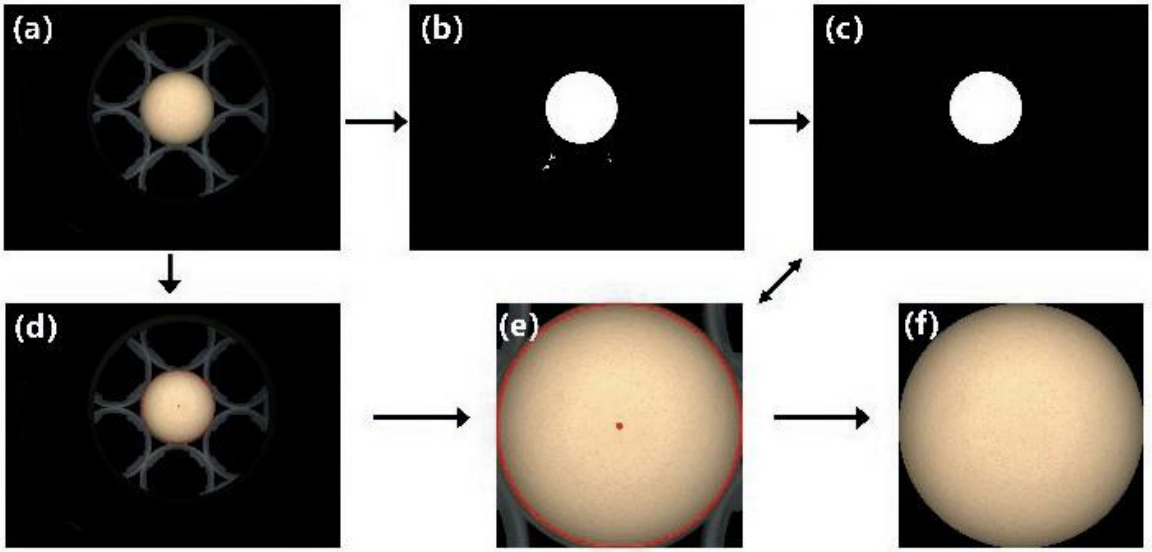

Figure 2: Image preprocessing

Dataset preparation

The 770 egg samples were first randomly divided into two groups by a ratio of 8:2. For the 10 images of the same egg, it was randomly split into two parts by a ratio of 7:3, eventually forming a training set and a validation set with 4312 images *vs.* 1848 images, respectively (Table 1).

Table 1: The training and testing datasets of egg images

	Training data		Testing data
	Train set	Validation set	
Egg classes	616	616	154
Egg images	4312	1848	1540

Eggshell biometric identification model development

To capture more comprehensive and finer-grained image features, the ResNeXt was used, based on the principle of residual networks, and its structure is shown in Figure 3 (a). In this study, the specifically ResNeXt-50 (32×4d) network was adopted. The model backbone is primarily composed of five stages; stage0 includes 1 convolutional layer, 1 BatchNorm layer, and 1 max pooling layer; stage1 to stage4 mainly extract features by multiple stacking grouped convolutional layers (CONV2_X, CONV3_X, CONV4_X, CONV5_X), using the residual structure; finally, connect the global average pooling layer. The ResNeXt-50 (32×4d) architecture is shown in Figure 4.

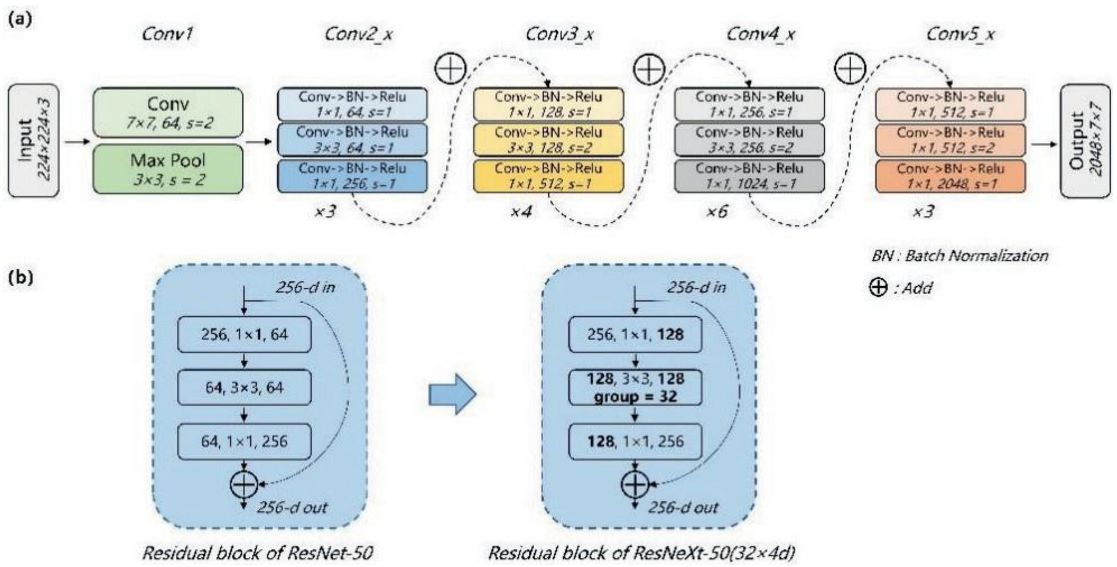

Figure 3: (a) ResNeXt flow diagram, (b) Residual block structure of ResNet-50 and ResNeXt-50

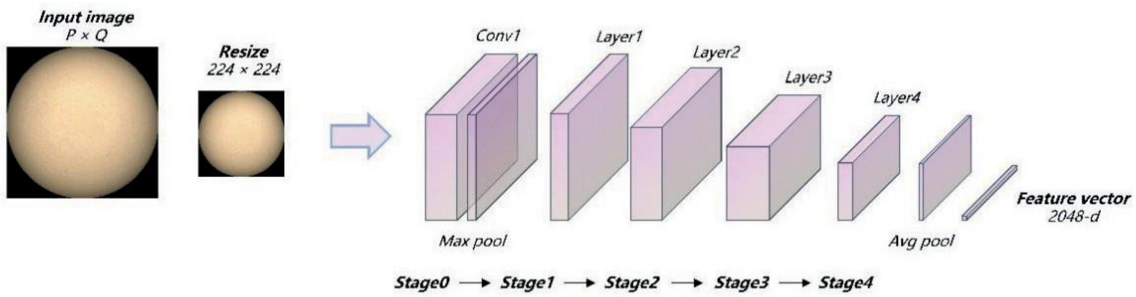

Figure 4: The ResNeXt-50 (30×4d) architecture

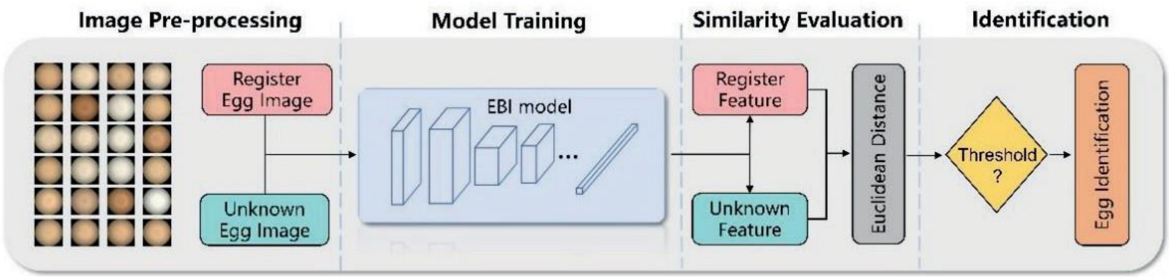

Figure 5: The architecture of egg biometric identification (EBI) model

Eggshell biometric identification can be divided into two stages, namely eggshell feature extraction by ResNeXt module and eggshell feature matching by egg identification module. The feature extraction module was obtained by deleting the last Softmax layer of the ResNeXt-50 network structure and output feature vectors. The eggs matching module mainly included feature vector registration and similarity calculation. The identification result was determined by calculating the similarity between the feature vectors based on Euclidean distance (Kumar et al., 2022). The feature extraction module and matching module were combined and entitled EBI model in this study. The architecture of the EBI model is shown in Figure 5.

Results and discussion

Model training for eggshell feature extraction

The accuracy and loss curves of the training and validation datasets at the batch size of 64 are shown in Figure 6. The model obtained a validation accuracy of 96.30% with the lowest loss value of 0.2300 at 39th epoch. The training accuracy and loss were 95.30% and 0.5240 respectively, indicating that the model performed well on the training dataset.

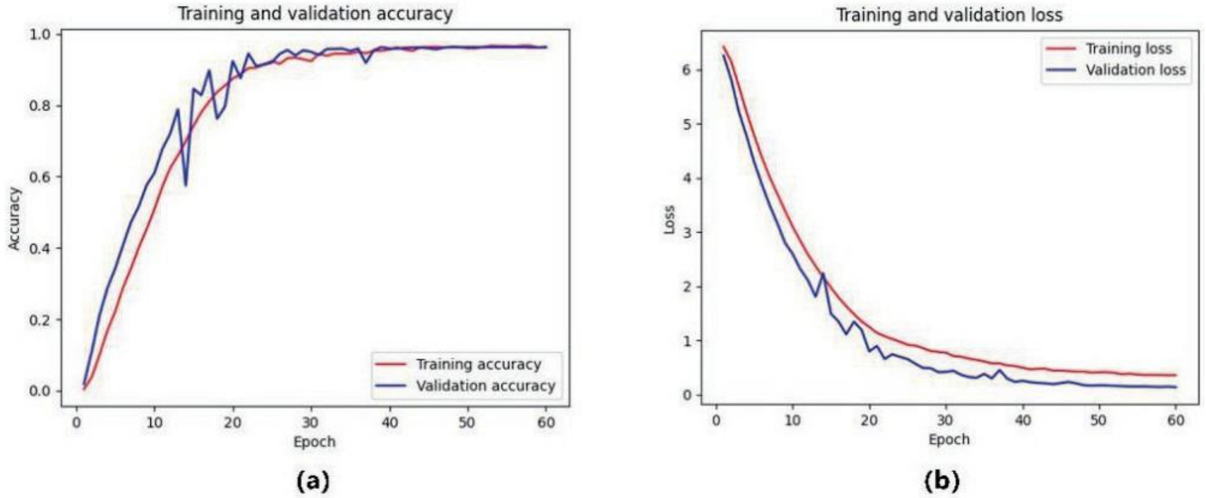

Figure 6: (a) Accuracy curves, (b) Loss curves of the training and validation datasets

A total of 13,860 intra-class matching and 2,356,200 inter-class matching were performed. According to the pre-experimental results, and the changes of FAR and FRR under threshold values between 15.00 and 20.00 are shown in Figure 7(a). The receiver operating characteristic (ROC) curve is further given in Figure 7(b).

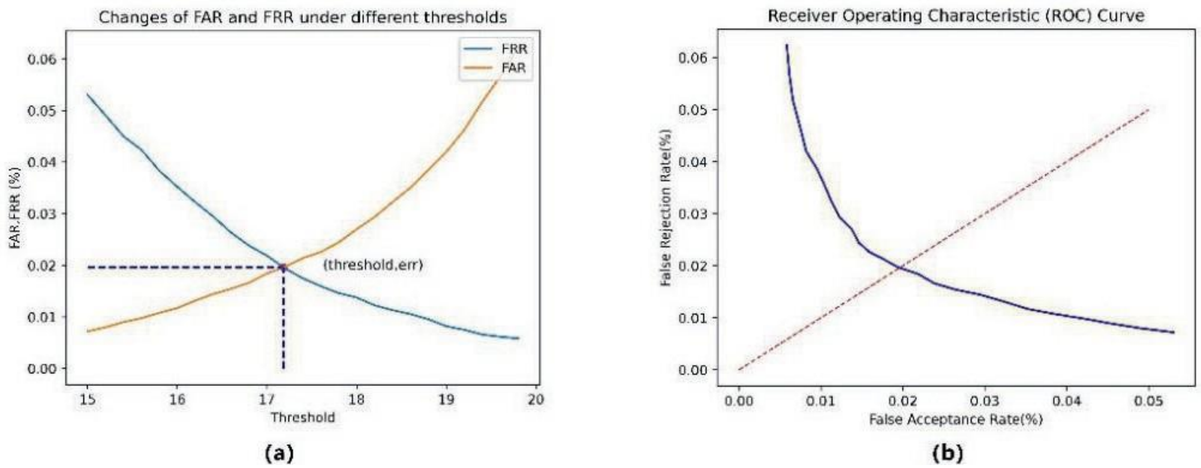

Figure 7: (a) Changes of FAR and FRR, (b) ROC curve of the egg identification model

Eggshell biometric identification performance

Eggshell images from six different eggs (inter-class) and six images from one individual egg (intra-class) were randomly selected and fed into the developed feature extraction model. The feature maps of the five stages of the network during the forward pass were visualized as shown in Figure 8. It can be seen from the feature maps extracted from each convolution layer that the low-level convolution layer extracted the texture features of the image, while the more abstract features were obtained from the high-level convolution layer. The inter-class showed significant differences in their feature maps, especially from Layer4_3. However, the intra-class showed small differences according to the obtained feature maps, especially from Layer4_2 and Layer4_3.

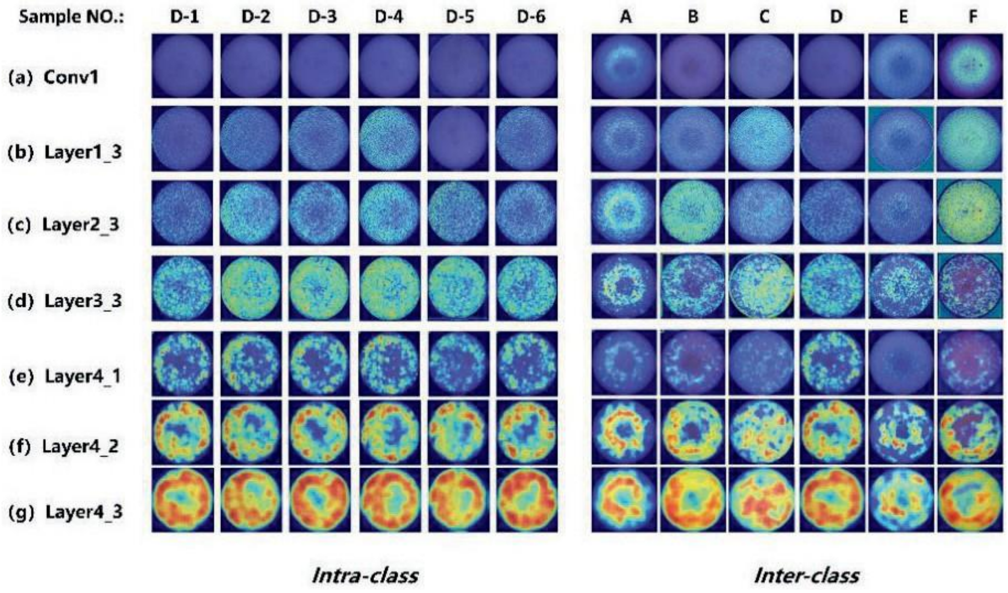

Figure 8: Partial feature maps extracted from the convolution layers

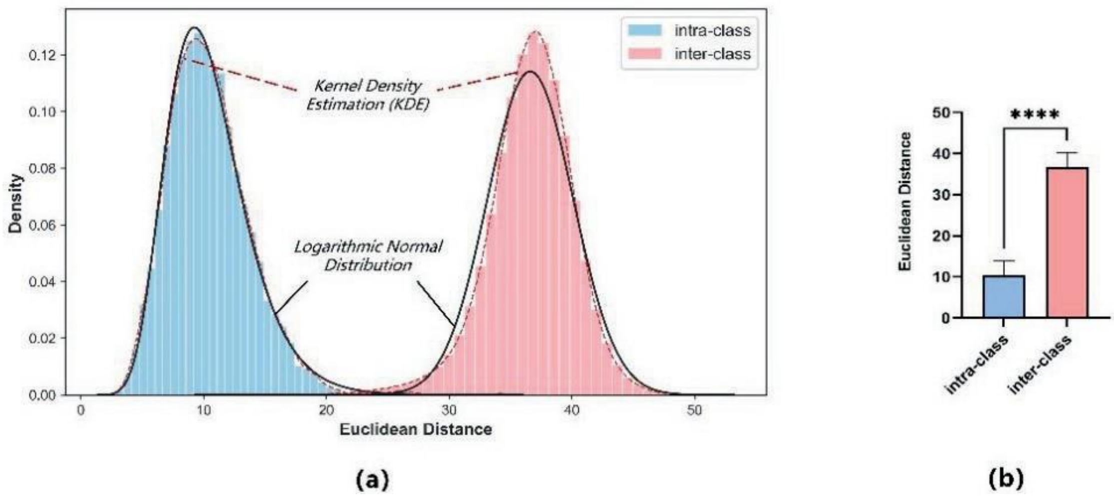

Figure 9: (a) Probability distribution histogram, (b) significance result

The Euclidean distances of inter-class matching and intra-class matching were further analyzed statistically. The probability distribution histogram shows that the inter-class and intra-class differences of each eggshell feature conform to the Logarithmic Normal distribution (Figure 9). The Kernel Density Estimation curve shows an obvious bimodal shape, indicating that the matching results of intra-class and inter-class are distinct. The Euclidean distance at the peak of intra-class nears 9, while the inter-class nears 27. The mean Euclidean distance of intra-class is 10.50 and the mean Euclidean distance of inter-class is 36.61. Furthermore, the distance of the inter-class is significantly larger than the intra-class ($P < 0.0001$), indicating that there exists a reasonable threshold to distinguish individual egg. According to the results above, the proposed model achieving the individual egg identification with a correct recognition rate (CRR) of 99.96% and an EER of 0.02% under the threshold is 17.18.

Conclusions

Recent related researches have explored approaches to egg identification, such as the instrumental analysis of the egg's chemical composition, and the detection of defective eggs through computer vision technology. However, no practical method has been developed for the rapid and accurate identification of individual egg. In this study, an improved convolutional neural network algorithm, named EBI model, was proposed to identify the biological features of egg and obtained more accurate results than chemical analysis methods. Specifically, in the egg identification test, the CRR of the model was 99.96% and the EER was 0.02%, and the model could distinguish different egg identities significantly. The amount of data in the dataset and the complexity of eggshell biometric characteristics may affect the recognition accuracy of EBI model. Our goal is to promote this approach for egg identification in the egg industry, thereby realizing the application of product tracing and anti-counterfeiting. This will help alleviate the problem of egg information forgery, protect the rights and interests of egg companies and consumers, and also assist companies in their production management.

Acknowledgments

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