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Hatching eggs classification based on deep learning

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Abstract In order to realize the fertility detection and classification of hatching eggs, a method based on deep learning is proposed in this paper. The 5-days hatching eggs are divided into fertile eggs, dead eggs and infertile eggs. Firstly, we combine the transfer learning strategy with convolutional neural network (CNN). Then, we use a network of two branches. In the first branch, the dataset is pre-trained with the model trained by AlexNet network on large-scale ImageNet dataset. In the second branch, the dataset is directly trained on a multi-layer network which contains six convolutional layers and four pooling layers. The features of these two branches are combined as input to the following fully connected layer. Finally, a new model is trained on a small-scale dataset by this network and the final accuracy of our method is 99.5%. The experimental results show that the proposed method successfully solves the multi-classification problem in small-scale dataset of hatching eggs and obtains high accuracy. Also, our model has better generalization ability and can be adapted to eggs of diversity.

Keywords Deep learning · CNN · Transfer learning · Classification · Hatching eggs

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1 Introduction

The prevention of avian influenza is mainly achieved by vaccination. The vaccine is made by the avian influenza virus which was inoculated and cultured in living egg embryos before being inactivated. Dead embryos are not allowed in the process, which will infect the other living embryos. Therefore, the fertility detection and classification of the hatching eggs are important before the proliferation of the virus. At present, the fertility detection and classification of the hatching eggs are artificial. But it is inefficient and vulnerable to subjective factors and large-scale personnel costs are required. The fertility detection of hatching eggs usually can be divided into four periods: 5-days, 9-days, 14-days and 16-days. Hatching eggs in different periods have different blood-vessel features. Especially, the blood-vessel features of 5-days eggs are insufficient and indistinguishable. The fertility detection of hatching eggs of 5-days is the detection in the earliest period. Eggs in this period can be divided into fertile eggs, dead eggs and infertile eggs which do not exist in the other three periods. After the classification, the fertile eggs are vaccinated and the dead eggs are destroyed while the infertile eggs can be recycled for food processing. Therefore, it's very significant to distinguish three kinds of eggs accurately. According to the particularity of the hatching eggs of 5-days, a correct classification of the hatching eggs of 5-days is the basis of the fertility detection in the subsequent period.

In the present research of early embryo, the machine vision methods are widely used. It mainly includes image enhancement, segmentation and classification. Limited by the image acquisition conditions, the classification result is usually affected by image quality and complexity of individual characteristics, which requires robust feature extraction methods. The image feature extraction is a popular and difficult problem. Reference [4] proposes a multi-feature mapping and dictionary learning model (MMDLM) to deeply discover the relationship between different features. Reference [5] evaluates four spatial–temporal features (STIP, Cuboids, MoSIFT and HoG3D). Reference [25] proposes a new multi-task feature selection algorithm which can be applied to the analysis of multimedia. Reference [26] proposes a deep feature learning paradigm using social collective intelligence. Reference [27] proposes a collaborative learning formulation which helps developing an efficient online algorithm. In reference [14], a HC-MTL method is proposed for joint human action grouping and its recognition. Reference [15] proposes the clique-graph and a clique-graph matching method by preserving global and local structures. These methods can improve the accuracy of classification result in most classical machine vision problems.

Several hatching eggs classification methods based on machine vision has been proposed. Among these methods, the state-of-the-art methods determine the embryo's fertility by extracting the blood-vessels information of the embryo image. In reference [13], a near infrared hyperspectral imaging system was developed to detect early embryo. Two types of spectral transmission characteristics extracted from the original and Gabor-filtered images were used for K-means clustering. Reference [24] proposes a new image clustering algorithm using local discriminant models and global integration (LDMGI). This algorithm is more appealing for the real image clustering applications. In reference [22], a non-destructive inspection system was designed. It detected and eliminated speckle noise by minimum univalve segment assimilating nucleus principle, and the nearest neighbor method was applied to classify eggs. In reference [19], weight Fuzzy C-means clustering algorithm is used to find the threshold to segment the blood-vessels of the eggs. The fertility is detected by counting the quality of the blood-vessels. Eggs were classified by BP neural network, which was trained with information fusion of images features, temperature and transmittance in reference [23]. The image features contain area of egg embryo blood-vessels and blackspots extracted from RGB space, mean and standard of each component in the Lab color space. In view of the above methods, the classification accuracy of hatching eggs has been greatly improved compared with the artificial method. However, the accuracy is not high enough. Furthermore, the eggs can only be classified into two kinds: fertile and non-fertile (including infertile and dead), and the infertile and dead eggs are not separated.

In recent years, as one of the most popular deep learning methods, CNN shows an outstanding performance in image classification. The ILSVRC (ImageNet large-scale visual recognition challenge) [18] computer vision evaluation is one of the largest standard push evaluation dataset which plays an important role in promoting development of the deep network. A lot of excellent CNN models are built on it and have achieved good results such as Alexnet [11], VGG-Net [20], GoogLeNet [21], ResNet [9], and some new technologies are proposed to optimize neural networks, such as PRelu activation function [8] and Batch Normalization layer [10]. Because the pre-trained CNN is powerful in many classification tasks, we use pre-trained model based on CNN to classify the hatching eggs in this paper. We will combine pre-training and self-learning to design two branches network to train our small-scale dataset to solve multi-classification problems and achieve higher accuracy.

2 Method

The state-of-the-art image recognition method consists of image preprocessing, extracting appropriate image features (such as color feature, texture feature etc.), and designing classifier. In this paper, we propose a CNN method. In this method, only a simple pretreatment is required to process the dataset which is used to train the model for classification.

CNN is a multi-layer self-supervised learning perceptron. It is composed of data layer, multiple alternating convolution layer, pooling layer, fully connected layer and output layer [12]. Compared with other neural networks, CNN has two characteristics of weight sharing and local connection. CNN not only reduces the complexity of the network, but maintains a strong ability to detect the edge of the image information and spatial information.

2.1 Transferring CNN weights

CNN learns features from a large number of samples, so it is difficult to achieve good results in small-scale dataset. In model training, when the parameters scale of the model is bigger than that of dataset, which is equal to solve an under-determined equation, it is prone to get multiple solutions and leads to overfitting. On the contrary, when the parameters scale of the model is smaller, which is equal to solve an over-determined equation, it is prone to get no solutions and leads to under-fitting. Therefore, a better training result can be obtained when the parameters scale of the model is matched with that of dataset. Also, it is difficult for the unbalanced data distribution to accurately describe the true distribution of data, which leads to a wrong classification result [3]. Transfer learning can transfer knowledge from related source to target domains [17]. Reference [16] proposed a method which can transfer the model parameters obtained from large-scale image training to the model with a limited training dataset in vision recognition tasks. In this paper, the target dataset is comparatively small and overfitting occurs more easily. Therefore, the transfer learning is used in the training in our paper.

2.2 Network design

In this paper, the CNN network is divided into two branches (TB-CNN). The architecture is shown in Fig. 1. In the first branch, the transfer learning method is used. The model parameters are initialized with the pre-trained model containing rich low-level features. The pre-trained model is obtained from the training of the ImageNet large-scale dataset with the classical network AlexNet. The model is used to initializes the weights of the first convolutional layer (Conv1) to the last pooling layer (Pool5). The transfer learning method gives the model better initial parameters. In the second branch, an ordinary multi-layer convolutional network is used to train the object dataset directly. 'Xavier' [6] method is used to initialize the network parameters. This network contains six convolutional layers (Conv1_1 ~ Conv6_1) and four pooling layers (Pool2_1 ~ Pool5_1). In order to make the two branches of the network extract features independently and increases the robustness of the whole network, the second branch does not share parameters with the first branch. Thus the original dataset was trained in two branches separately when the dataset is imported. The features of the last pooling layer (Pool5) in the first branch are combined with features of the last convolutional layer (Conv6_1) in the second branch, which enriches the feature information. We splice the vector of features of the two branches according to the ratio of 1:1 and output it to the next full connection layer, so that the full connection layer fully integrates the respective features of the two branch networks and have the generalization ability of the network enhanced.

In the first branch, the architecture of network should keep consistent with that of AlexNet. In the second branch, the design of network architecture is relatively free. We will set steps of convolution kernels at 1 without edge filling. All the pooling layers use 'Max' pooling method which is made of kernels with 2*2 in size and 2 in step.

2.3 Training

In the network architecture mentioned before, the first branch of the network requires a pre-trained model. We use the pre-trained model which is trained on ImageNet dataset to fine-tune the dataset. The training process is shown in Fig. 2.

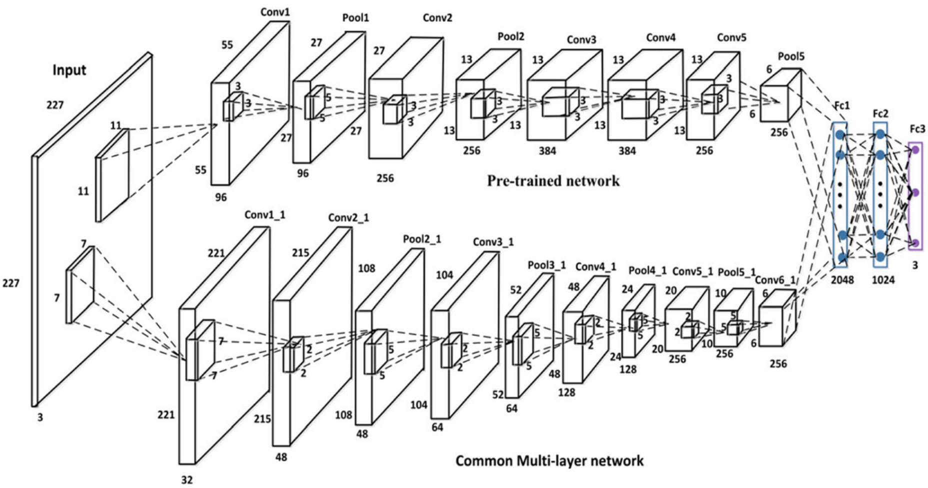


Fig. 1 TB-CNN Architecture

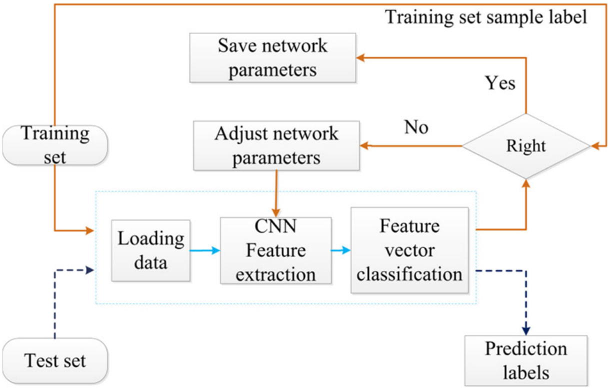


Fig. 2 Flowing-chart of Training

In [7], the Relu (Rectified Linear Units) function has advantages of unilateral inhibition and broad excitation boundary which is better fitted to the characteristics of sparse activation in Biology. Compared with the Relu function, the PRelu function modifies the data distribution and stores the negative value so that the negative value will not lose completely. The PRelu function updates an additional parameter a_i by using the back propagation algorithm similar to update the weights [8]. In terms of the number of weights, parameters that the PRelu function updates can be ignored, so it will not increase the influence of overfitting. Therefore, in this paper, the PRelu function is used as activation function. x_i represents the i-th input value. The expression of the PRelu is as follows.

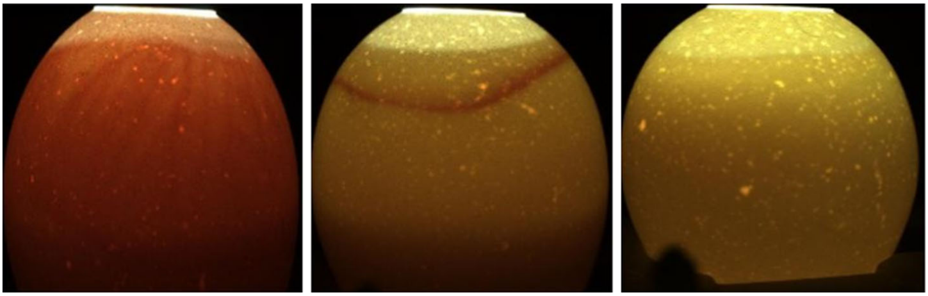
$$PRelu(x_i) = \begin{cases} x_i & if\, x_i > 0 \\ a_i x_i & if\ \ x_i \leq 0 \end{cases} \tag{1}$$

Besides, to avoid the overfitting, the dropout layer is introduced into the network. In [2], the overfitting of neural network and the function of dropout are introduced in details. The local response normalization layer LRN is also included to improve the generalization ability of the network.

3 Experiments

3.1 Data preparation

The experimental dataset contains 2000 images of hatching eggs, of which 1200 images are randomly selected to train the model, the rest are used to verify the model. The dataset is divided into three types: fertile eggs, dead eggs and infertile eggs. The original dataset, which is in big size and of large background area, requires pretreatment and extraction of the region of interest (ROI). These two pretreatments normalizes the scales and make the features more obvious in order to facilitate the input for CNN. The contour of eggs in the binarization of images with threshold 20 is extracted to get the ROI. Then, the ROI images are normalized and taken as the input to the CNN. As shown in Fig. 3.

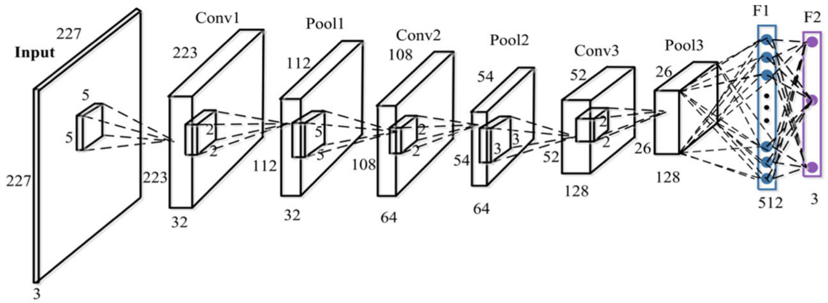


(a) Fertile eggs (b) Dead eggs (c) Infertile eggs

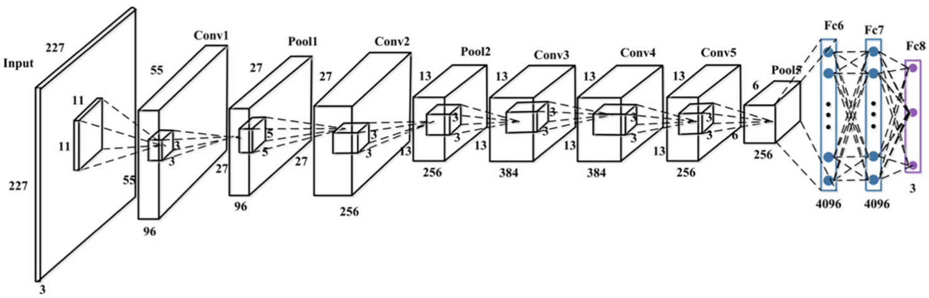
Fig. 3 Pretreatment results

3.2 Comparison to other network

Since CNN has not been used in hatching egg classification, we need to design different network architecture to find an optimized model. In this paper, we compare the training results of the network architectures with TB-CNN and two other networks (Egg-CNN). These two methods are called E1-CNN and E2-CNN. In the E1-CNN method, our small-scale dataset is directly trained by a common multi-layer convolutional network without transfer learning. Even in the large-scale dataset, deep network is also prone to overfitting [1]. To avoid overfitting in our network with limited training dataset scale which makes it difficult to train deeper models, the target dataset is trained with a shallow network. The network architecture is



(a) E1-CNN



(b) E2-CNN

Fig. 4 The network architecture

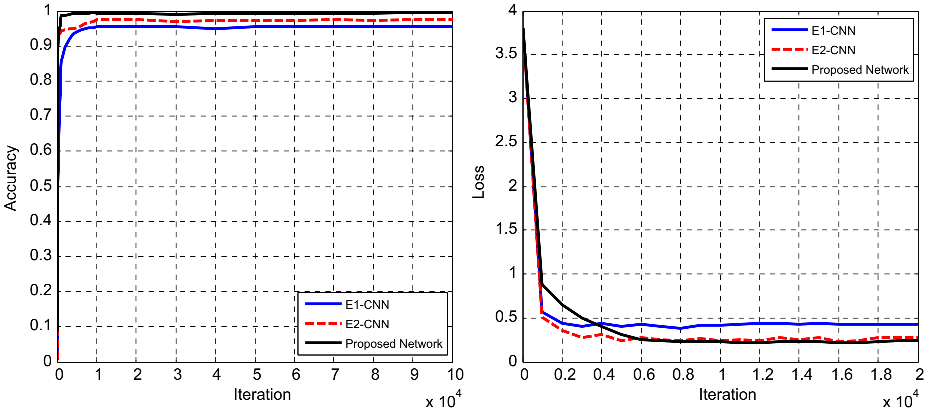


Fig. 5 Accuracy and Loss of each network

shown in Fig. 4a. The final accuracy reaches 95.5%. The E2-CNN method combines transfer learning to train the dataset. We use the classical network AlexNet. In this network architecture, only the last whole connection layer is modified as the adaptive feature layer. The network architecture is shown in Fig. 4b. The target set is fine-tuned by pre-trained models trained on ImageNet dataset. The accuracy is 97.3%, which is improved compared with the E1-CNN method. In the TB-CNN, the accuracy reaches 99.5%, which is improved a lot compared with the first two methods. Fig. 5 shows the accuracy and the loss of the test set in the model training process.

3.3 Experiments evaluation

The performance of the proposed methods is evaluated on our dataset. In order to illustrate the feasibility of the method, the experiment results of the classification accuracy of 5-days hatching eggs obtained by state-of-the-art methods and our CNN method are compared. The methods we compare with are listed in the first column. The feature extraction is the first steps in each method. Then the egg images are classified according to the features extracted. In this paper, we compare the different feature extraction method and selections of classification method which are listed in the second and third column. The contract of final result of classification accuracy are shown in column four with the classification categories finally

Table 1 Comparison of experimental results

The Method	Feature extraction method	Classification method	Accuracy	Classification
Proposed method	TB-CNN	TB-CNN	99.5%	Fertile, Dead and Infertile
Liu, L et al. (2013) [13]	Gabor-filter	K-means clustering	84.1%	Fertile and Non-fertile
Xu, Q. L et al. (2014) [22]	SUSAN principle	The nearest neighbor	97.78%	Fertile and Non-fertile
Shan, B et al. (2010) [19]	Thresholding by Histogram-based WFCM	Criterions of blood-vessels	99.33%	Fertile and Non-fertile
Xu, Y et al.(2015) [23]	Information fusion	BP neural network	96.25%	Fertile and Non-fertile

listed. Due to the lack of public dataset, the results compared in our evaluation are got from difference methods which are based on their own datasets. The results are shown in Table 1.

Compared with the state-of-the-art methods, our approach has several advantages. In these methods, the near infrared hyperspectral imaging system is based on an InGaAs camera connected to a line-scan spectrograph with high cost. On the contrary, the images used in our approach are acquired by ordinary CCD camera and general point light source. In these methods, the image features are difficult to extract and the extraction of some thin blood-vessel is ineffective. By contrast, the features extracted in CNN method are not specified but extracted by training with different convolution kernels. These features are found by distributed representation of data, which has a higher classification accuracy. To solve the problem of the low accuracy of the complete pre-trained method and the shallow network training method, we use TB-CNN. The first branch of TB-CNN initializes network parameters with a pre-trained model which diversify the features (especially the low-level features). The second branch of TB-CNN trains dataset directly from a multi-layer network. The combination of the outputs of the two branches enhances network robustness and achieves better classification results. The classification accuracy of our method is higher than those of previous methods, which is benefit from the advantages of CNN. Most important of all, in the previous methods the multi-classification which divides fertile eggs, dead eggs and infertile eggs cannot be achieved in 5-days hatching eggs, but TB-CNN methods can and achieve a high accuracy with multi-classification.

4 Conclusion

This paper proposed a classification method for the hatching eggs based on deep learning. The training method which combines the features of the pre-trained network and multi-layer network achieves a higher accuracy than canonical network. The experiment is made on 5-days hatching eggs in special period with obsolete feature which is very difficult to extract. The result shows that this model is effective in hatching eggs classification and its accuracy reached 99.5%. Compared with the state-of-the-art methods, the proposed method achieves higher accuracy and solves the multi-classification problem in small-scale dataset while avoiding complex computing of image processing. However, Deep learning algorithms depend on large-scale dataset. Through enlarging the dataset and combing the method proposed in this paper, a more optimized model will be obtained in the future work.

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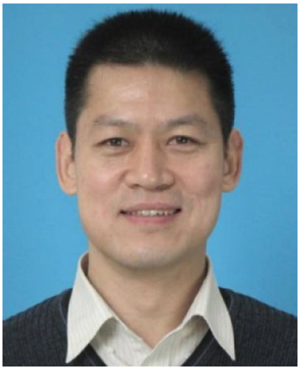

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