

Detection of Embryo Eggs Based on Tensor Depth Calculation Model

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ABSTRACT

With the improvement of people's living standards, poultry has become accustomed to appearing on the table. However, the emergence of the bird flu virus not only harms the lives of poultry but also harms human health. The vaccine and epidemic prevention method is the main prevention and control method for the bird flu epidemic. The quality of bird flu vaccine is directly related to the safety of poultry and human life. The culture of bird flu vaccine is mainly through the inoculation of chicken embryos with avian influenza strains and inactivated by the proliferation and cultivation of strains in the embryonated eggs of the strains. Therefore, the detection of embryogenesis activity of strains is an important part of the proliferation and culture of avian influenza strains. For some traditional detection methods such as artificial egg-thinning, there are shortcomings such as visual fatigue, low detection efficiency, and subjective factors that are easily detected by human eyes. This paper proposes a tensor depth calculation model, which extends the data from the vector space to the tensor space, which can better reflect the underlying relevance of the data. The activity detection of embryonated eggs was performed on real data sets. Comparison with convolutional neural network on vector space can get better recognition rate of this algorithm.

Keywords: Strain Embryonic Egg, Tensor Depth Calculation Model, Tensor Space, Recognition Rate

1. INTRODUCTION

Since 2001, different types of bird flu viruses have killed hundreds of millions of poultry and human deaths have occurred. The main transmission source of bird flu virus is various virus migratory birds and poultry. At present, the main bird flu prevention and control method is the bird flu inactivated vaccine epidemic prevention method, which is to inject poultry flu vaccine into poultry to induce its own complete immune protection to block the infection and spread of bird flu virus and cut off the source of poultry virus infection.

Most of the current influenza vaccines for poultry use the 9-12-day-old Specific Pathogen Free (SPF) chicken embryo to inoculate avian influenza strains for proliferation and isolation. Finally, the virus is inactivated with formaldehyde to inactivate the bird flu virus. The cyst fluid, supplemented by an adjuvant to prepare an oil emulsion vaccine, therefore, the preparation of the bird flu vaccine is not only related to the vital interests of the large poultry breeding industry, but also closely related to the human life safety itself [1].

At the early stage of the embryonic egg formation assay of virus strains, most major vaccine manufacturers use artificial egg-based methods and human eye-detection methods for the detection of the viability of embryos of eggs [2]. However, this method of using manpower to determine the activity of the embryos and eggs of the virus strain requires a large amount of labor, and the labor intensity of the workers is large, which may cause the human eyes to suffer from fatigue and emotions for a long time, resulting in a decrease in the detection accuracy. Therefore, the traditional manual inspection method has been difficult to meet the pursuit of maximum efficiency. In recent years, the research on the detection technology of embryogenesis activity has attracted the interest of relevant researchers. Literature [3] and [4] attempted to judge the activity of embryonated eggs by measuring the size of the embryonic egg biopotentials to reflect the activity of the embryogenic eggs; Literature [5] carries on the appropriate pressure detection to the egg shell, then collects the egg shell image, analyzes the egg shell to realize the egg classification, reaches 80% of the recognition rate; Literature [6] uses the vibration signal that the ultrasonic sensors produces to carry on the activity detection to the egg embryos and eggs, and the vibration measurement analysis is performed by the signals fed back from the egg embryos; In literature [7], an adaptive threshold image processing method based on the minimum intraclass index variance is proposed to perform image edge detection and mathematical morphology processing on the denoised embryonic egg image to accurately construct the binary morphology of the embryonic egg main blood and determine the embryogenic activity by calculating the area percentage of the main blood in embryonic egg; The literature [8] proposes the fusion of machine vision and percussive vibration, and the use of an artificial neural network to construct a fusion method for predicting the fertility of duck eggs at the early hatching stage. Although this method can achieve a rec-

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ognition rate of 98%, the embryonic eggs of the strains cannot undergo knocking vibrations during the culture period, so this method is not suitable for the detection of the embryonic egg activity of the virus strains; With more and more research on deep learning, the literature [9] uses convolutional neural network to detect the activity of embryos and eggs, although it can achieve a good recognition rate, but it does not take into account the data. The correlation between. At present, most of the studies are aimed at the detection of the activity of common hatching eggs, but the eggs of the strains are different from the common eggs, and their detection requirements for the activity are also more stringent than those of the general hatching eggs. Firstly, the activity of embryonic egg formation of strains is generally detected at the mid-to-late stage (9-12 days) of embryonic egg incubation. However, the activity of normal hatching eggs is generally detected at the early stage of incubation. Secondly, the detection of the activity of the embryonic egg growth of the virus strain is carried out during the propagation of the avian influenza virus. Therefore, it is required to maintain the sterility of the detection environment so as not to cause contamination of the seedlings. However, the ordinary hatching egg has no special requirements for the detection environment. Finally, the strain Embryonic eggs cannot withstand large oscillations during the activity assay to prevent destruction of embryonic eggs.

Based on the existing problems in the detection of embryo activity of egg strains by traditional methods, this paper proposes a tensor depth calculation model to test the activity of the collected real data sets and extends the image data from the vector space to the tensor space to form a three-order tensor. The depth calculation model is formed by stacking multiple convolutional neural networks, which increases the depth of feature learning so that the detection effect is better.

The rest of the paper is organized as flows. In Section 2, the theory of tensor depth calculation model in high-dimensional space are introduced. The third section gives the results and analysis of the experiment. Finally, Section 5 concludes the discussion and specifies future research related to this study.

2. THEORY

2.1 Tensor Convolutional Neural Network

The tensor convolutional neural network is divided into a tensor convolutional layer, a tensor pooling layer, and a tensor fully connected layer, as shown in Fig. 1 [10].

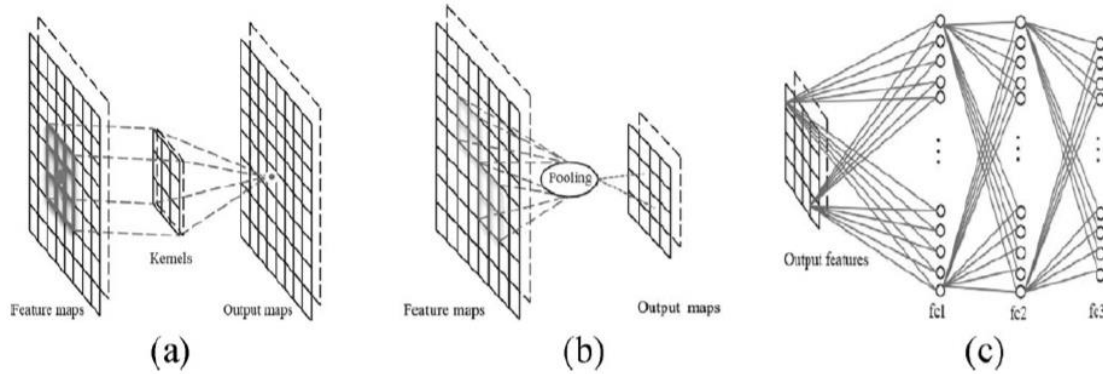


Fig.1 (a) Tensor convolution (b)Tensor pooling (c)Fully connected

2.2 Tensor Convolutional Layer

In the convolutional layer, the feature map is convolved by a learnable convolution kernel, and then an output function can be obtained through an activation function, as shown below [11]:

$$Y_c = f(U) \quad (1)$$

$$U = K * X + b \quad (2)$$

Where, the N-order tensor $X \in R^{I_1 \times I_2 \times \dots \times I_N}$ carries the dimension h_n of the convolutional input, the N-order tensor $K \in R^{I_1 \times I_2 \times \dots \times I_N}$ represents the convolution kernel with dimensions I_n , the N-order tensor $Y_c \in R^{I_1 \times I_2 \times \dots \times I_N}$ represents the tensor characteristic of the output layer, and f is a nonlinear activation function, usually using functions such as sigmoid and tanh, b is a bias tensor and $*$ indicates the convolution symbol.

2.3 Tensor Pooling Layer

The pooled layers of the convolutional neural network are divided into maximum pooling and average pooling, and each input feature is pooled by the following formula to output the feature map [12]:

$$Y_p = f(U) \quad (3)$$

$$U = \beta \cdot \text{pooling}(X) + b \quad (4)$$

Where, N-order tensors $X \in R^{I_1 \times I_2 \times \dots \times I_N}$ with dimensions h_n represent the input of the normalized pooling layer then the N-order tensors Y_p represent the mapping output of the pooling layer. Through the sampling function, the input layer is mapped to the output layer. However, f means that an activation function such as sigmoid or tanh, b is a bias tensor and β is a weight coefficient.

As shown in Figure 1(b), the tensor pooling layer further reduces the number of connections and the weights. At the same time, the tensor pooling layer satisfies the invariance in the high-dimensional heterogeneous space.

2.4 Tensor Fully Connected Layer

In a fully connected network, feature maps of all images are stitched into one-dimensional features as input to a fully connected network. The output of the fully connected layer can be obtained by weighting the inputs and passing the response of the activation function [13]:

$$H = f(W \square X + b) \quad (5)$$

Where, the N-order tensors $X \in R^{I_1 \times I_2 \times \dots \times I_N}$ and $H \in R^{I_1 \times I_2 \times \dots \times I_N}$ denote the input tensor and output tensor of the hidden layer, respectively, where f is the sigmoid activation function, b is the bias tensor, and $W \in R^{\beta \times I_1 \times I_2 \times \dots \times I_N}$ is the $(N+1)$ order weight matrix.

As shown in Fig. 1(c), the tensor fully connected layer maps multiple features of the constrained network as a total tensor, and the inputs are divided into different categories to further reveal the hidden distribution between the data.

2.5 Tensor Depth Calculation Model

In this paper, several high-order convolutional neural network models are stacked to form a depth calculation model. Neural networks have two basic modes of operation: forward propagation and back propagation [14]. Forward propagation means that the input signal passes the signal between one or more network layers in the previous section, and then the output at the output layer is also equivalent to the pre-training process. Backpropagation is a method of supervised learning in neural networks and is a fine-tuning phase. The convolutional neural network mainly optimizes the convolution kernel parameters k , the pooling layer network weight β , the full-connection layer network weight W , and the bias parameters b of each layer.

In this paper, we use the tensor distance as the loss function. For a given two N-order tensors $X \in R^{I_1 \times I_2 \times \dots \times I_N}$ and $Y \in R^{I_1 \times I_2 \times \dots \times I_N}$, x and y represent the unfolded representations of the tensors X and Y vectors respectively, then the tensor distance between the tensor X and Y is defined as [15]:

$$d_{TD} = \sqrt{\sum_{l,m=1}^{I_1 \times I_2 \times \dots \times I_N} g_{lm} (x_l - y_l)(x_m - y_m)} = \sqrt{(x - y)^T G (x - y)} \quad (6)$$

Where g_{lm} is a coefficient and G is the coefficient matrix, which reflects the internal relations of different coordinates of high-order data and are defined as follows:

$$g_{lm} = \frac{1}{2\pi\sigma^2} \exp \left\{ -\frac{\|p_l - p_m\|_2^2}{2\sigma^2} \right\} \quad (7)$$

Where, $\|p_l - p_m\|_2$ is the positional distance between $X_{i_1 i_2 \dots i_N}$ (corresponding to x_l) and $X_{i'_1 i'_2 \dots i'_N}$ (corresponding to x_m), defined as:

$$\|p_l - p_m\|_2 = \sqrt{(i_1 - i'_1)^2 + (i_2 - i'_2)^2 + \dots + (i_N - i'_N)^2} \quad (8)$$

3. EXPERIMENT

In order to verify the validity of the proposed algorithm, a nine-day embryo was used for evaluation. The nine-day embryos were divided into two categories: dead embryos and live embryos, as shown in Figure 2. We chose 1000 dead embryos and live embryos as training sets, and 200 dead embryos and live embryos as test sets. The hardware configuration of the simulation computer is server 8 core 40 threads, CPU is Intel Xeon E5-2620, frequency is 2.2GHZ, memory capacity is 64GB, and experiments [17] are carried out in matlabR2014 [16] and PyCharm based deep learning framework.

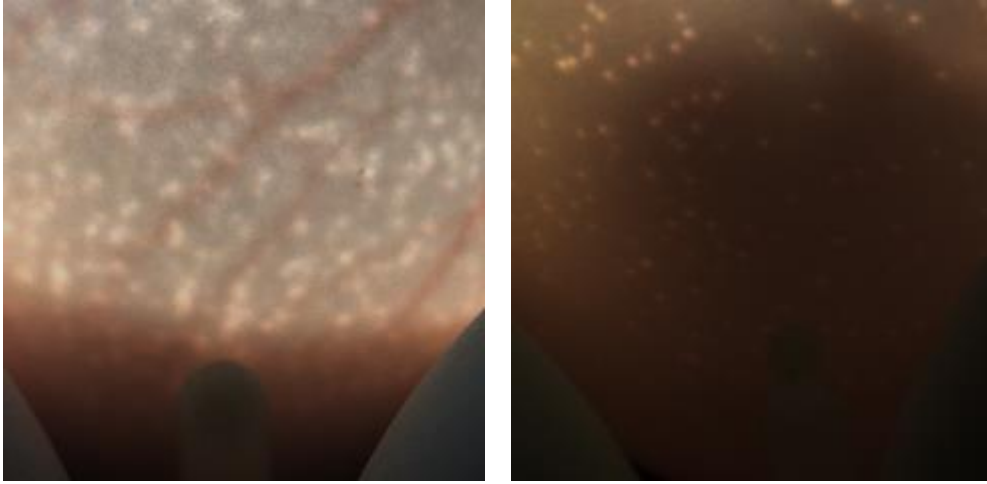


Fig.2 (a) Living embryo

(b) Dead embryo

Each image can be expressed as a three-order tensor $R^{480 \times 480 \times 3}$, where 480×480 is the resolution of the image, and 3 represents the three channels of the red, green and blue color images. The experimental results are shown in Table 1. It can be seen that as the number of iterations and iterations increase, the recognition rate also increases, but when it increases to a certain degree, the recognition rate increases very little, but the time required is very large, resulting in Computer crashes.

Table 1. The iterative result of the tensor depth calculation model.

Epoch	Iteration	Time Elapsed (seconds)	Mini-batch Loss	Test Loss	Mini-batch Accuracy	Test accuracy
1	1	3.25	1.3693	2.0582	62%	51.98%
5	20	67.71	0.3935		95%	
10	40	87.14	0.0954		99%	
13	50	96.89	0.0759	0.4683	98%	93.85%
15	60	122.73	0.4924		96%	
20	80	141.55	0.0358		98%	
25	100	160.73	0.0423	0.3802	97%	94.53%
30	120	195.72	0.0800		98%	
35	140	214.62	0.1553		96%	
38	150	224.03	0.0990	0.4742	98%	93.33%
40	160	249.62	0.1488		97%	
45	180	268.53	0.1073		98%	
50	200	287.44	0.0879	0.3934	96%	93.85%

Table 2 and Figure 3 show the comparison of experimental results between the convolutional neural network and the algorithm of this paper. The recognition rate is obtained based on the average of five epochs. In order to make the results clearer, this paper gives the receiver operating characteristic curve (ROC). The closer to the top left, the higher the accuracy. It can be clearly seen that the recognition effect of this algorithm is higher than that of convolutional neural networks.

Table 2 Detection algorithm comparison results

Detection algorithm	Average recognition rate
Convolutional neural network(CNN)	90%
Tensor depth calculation model(TDCM)	95%

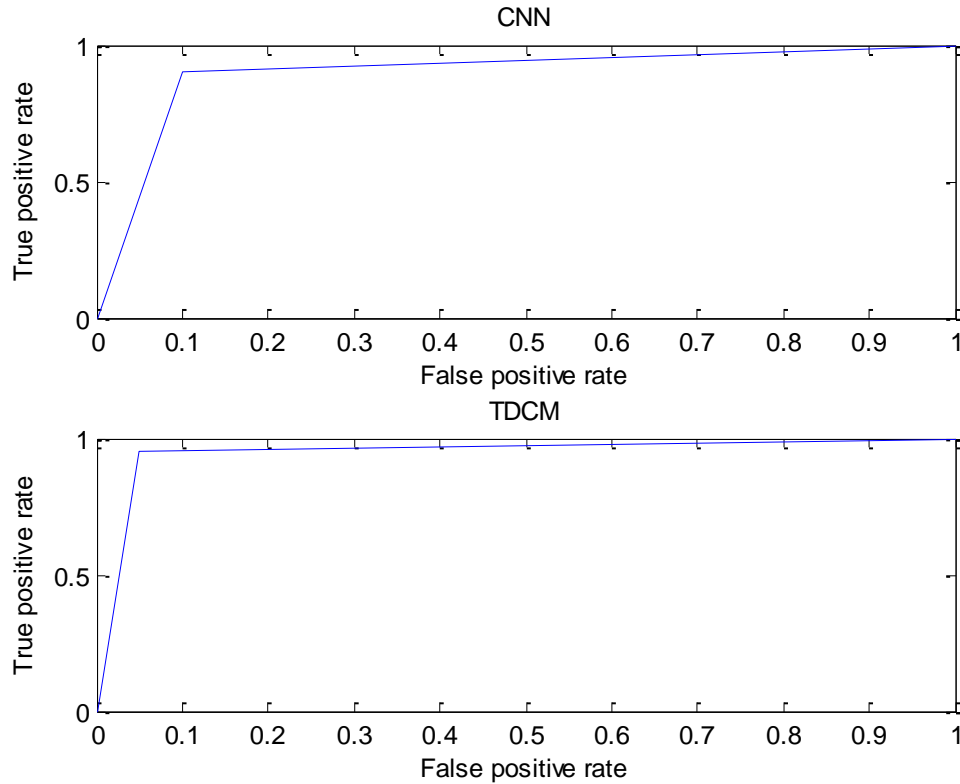


Fig.3 ROC curve

4. DISCUSSIONS AND CONCLUSION

In order to improve the accuracy and efficiency of the activity detection of embryos in the vaccine preparation process, a tensor depth calculation model solving method is proposed in this paper. The high dimensional tensor space is used to represent the data and the deep extraction features can effectively remove noise. Interference, get better recognition characteristics. The experimental data show that compared with the traditional convolutional neural network model, this algorithm can achieve a good recognition rate, and the network performance is better. It can be applied to the actual industrial automation non-destructive testing system.

REFERENCES

- [1] Baoming Dan. Detection of Embryogenesis in Vaccine Preparation Based on Machine Vision. *Journal of Agricultural Machinery*, 2010, 41(5): 178-181.
- [2] Jinguo Hu. Research on automatic non-destructive detection system based on machine vision in embryos and egg-forming plants. Qingdao University of Science and Technology, 2014.
- [3] Romanoff A L. Detection of Fertility in Fresh Eggs. *World's Poultry Science Journal*, 1947, 3(01): 12-14.
- [4] Romanoff A L. Evaluation of future perishability of intact fresh eggs by radio-frequency conductivity. *Journal of Food Science*, 1949, 14(4): 310-313.
- [5] L.Jenshin, Y Lin, M.Hsich. An automatic system for eggshell quality monitoring. *Transactions of the ASAE*.2001, vol.44(3):1323-1328.
- [6] Biao Lin. Nondestructive testing of egg quality based on percussion vibration, machine vision and near-infrared spectroscopy Jiangsu University, 2010.
- [7] Chao Huang, Yancong Liu. Study on the Detection of Embryogenic Activity of Vaccine Strains. *Journal of Agricultural Machinery*, 2017, 48(10): 300-306.
- [8] Wei Zhang, Kang Tu, Peng Liu, et al. Detection of Duck Egg Hatching Characteristics Based on Machine Vision and Percussive Vibration Fusion. *Journal of Agricultural Machinery*, 2012, 43(2):140-145.
- [9] Mingshuai Bi, Jiasong Mu. Application of convolutional neural network in the classification of embryos of virus strains. *Journal of Tianjin Normal University (Natural Science)*, 2018(1):56-58.
- [10] Liang Chang, Xiaoming Deng, Mingquan Zhou, et al. Convolutional Neural Networks in Image Understanding. *Acta Automatica Sinica*, 2016, 42(9):1300-1312.
- [11] Zhou Feiyan, Jin Linpeng, Dong Jun. A Survey of Convolutional Neural Networks. *Chinese Journal of Computers*, 2017, 40(6): 1229-1251.
- [12] Li P, Chen Z, Yang L T, et al. Deep Convolutional Computation Model for Feature Learning on Big Data in Internet of Things. *IEEE Transactions on Industrial Informatics*, 2017, PP(99):1-1.
- [13] Simonyan K, Zisserman A. Very Deep Convolutional Networks for Large-Scale Image Recognition. *Computer Science*, 2014.
- [14] Qingqing Zhang, Yong Liu, Jieli Pan, et al. Consecutive speech recognition based on convolutional neural networks. *Journal of University of Science and Technology Beijing*, 2015, 37(9):1212-1217.
- [15] Zhang Q, Yang L T, Chen Z. Deep Computation Model for Unsupervised Feature Learning on Big Data[J]. *IEEE Transactions on Services Computing*, 2016, 9(1):161-171.
- [16] <https://ww2.mathworks.cn/products/matlab/whatsnew.html>
- [17] <https://www.jetbrains.com/pycharm/>