Fedorov E., Utkina T., Neskorodieva T.V. Intellectual Identification Method of the Egg Development State Based on Deep Neural Nets. Lecture Notes in Networks and Systems, 2022, 552, pp. 159–174. (doi:10.1007/978-981-19-6634-7_12). URL: https://link.springer.com/chapter/10.1007/978-981-19-6634-7_12

Abstract

In the article for the solution of the classification process automation problem and interpretation of ovoscoping eggs visualization results at an incubation, the intellectual identification method of chicken embryos development state based on deep neural networks is offered. The created generalized LeNet 2D model has the following advantages—the input image is not square that expands a scope; the input image contracts previously, and the new size is defined empirically and depends on the initial size of the image that increases the training speed of model and identification accuracy of the model; the number of couples “a convolution layer–the down sampling layer” is defined empirically and depends on the image size that increases identification accuracy on the model; full-connected layers are absent that increases the speed of model training; the quantity of layers planes is defined automatically that accelerates determination of model structure. The created one-block ViT model has the following advantages—the input image is not square that expands a scope; the image contracts previously, and the new size is defined empirically and depends on the initial size of the image that increases the model training speed and identification accuracy of the model; the size of a patch is defined empirically and depends on the image size that increases identification accuracy on the model; there is only one block that increases the speed of training of model and accelerates determination of model structure. The offered method of intellectual identification of chicken embryos development state based on deep neural networks can be used in various intellectual systems of visualization results identification of egg ovoscoping at an incubation on industrial production of poultry.

Keywords

- Ovoscoping
- Intellectual identification of eggs development state
- Deep neural networks
- Convolution neural network
- Transformer

References

1. Yeo C, Park H, Lee K, Song C (2016) Avian Embryo monitoring during incubation using multi-channel diffuse speckle contrast analysis. Biomed Opt Express 7(1):93–98
2. Hashemzadeh M, Farajzadeh N (2016) A Machine vision system for detecting fertile eggs in the incubation industry. Intl J Comput Intell Syst 9(5):850–862. https://doi.org/10.1080/18756891.2016.1237185
3. Tsai S-Y, Li C-H, Jeng C-C, Cheng C-W (2020) Quality assessment during incubation using image processing. Sensors 20:5951. https://doi.org/10.3390/s20205951
4. Yu H, Wang G, Zhao Z, Wang H, Wang Z (2019) Chicken embryo fertility detection based on ppg and convolutional neural network. Infrared Phys Technol 103:103075. https://doi.org/10.1016/j.infrared.2019.103075
5. Wan L, Chen Y, Li H, Li C (2020) Rolling-element bearing fault diagnosis using improved LeNet-5 network. Sensors (Basel, Switzerland) 20(6):1693. https://doi.org/10.3390/s20061693
6. Krizhevsky A, Sutskever I, Hinton GE (2012) ImageNet classification with deep convolutional neural networks. Adv Neural Inf Process Syst 25:1097–1105

7. He K, Zhang X, Ren S, Sun J (2016) Deep residual learning for image recognition. In: 2016 IEEE conference on computer vision and pattern recognition (CVPR), pp 770–778. https://doi.org/10.1109/CVPR.2016.90
8. Huang G, Liu Z, van der Maaten L, Weinberger KQ (2018) Densely connected convolutional networks, pp 1–9. arXiv preprint arXiv:1608.06993
9. Szegedy C, Liu W, Jia Y, Sermanet P, Reed S, Anguelov D, Erhan D, Vanhoucke V, Rabinovich A (2014) Going deeper with convolutions, pp 1–12. arXiv preprint arXiv:1409.4842
10. Szegedy C, Vanhoucke V, Ioffe S, Shlens J, Wojna Z (2015) Rethinking the inception architecture for computer vision, pp 1–10. arXiv preprint arXiv:1512.00567
11. Szegedy C, Ioffe S, Vanhoucke V, Alemi A (2016) Inception-v4, inception-ResNet and the impact of residual connections on learning, pp 1–12. arXiv preprint arXiv:1602.07261
12. Chollet F (2017) Xception: Deep learning with depthwise separable convolutions, pp 1–8. arXiv preprint arXiv:1610.02357
13. Howard AG, Zhu M, Chen B, Kalenichenko D, Wang W, Weyand T, Andreetto M, Adam H (2017) MobileNets: efficient convolutional neural networks for mobile vision applications, pp 1–9. arXiv preprint arXiv:1704.04861
14. Sandler M, Howard A, Zhu M, Zhmoginov A, Chen L-C (2018) MobileNetV2: inverted residuals and linear bottlenecks. In: 2018 IEEE conference on computer vision and pattern recognition (CVPR), pp 4510–4520. https://doi.org/10.1109/CVPR.2018.00474
15. Geng L, Hu Y, Xiao Z, Xi J (2019) Fertility detection of hatching eggs based on a convolutional neural network. Appl Sci 9(7):1408. https://doi.org/10.3390/app9071408
16. Dosovitskiy A, Beyer L, Kolesnikov A et al. (2021) An image is worth 16 × 16 words: transformers for image recognition at scale. In: 9th International conference on learning representations, pp 1–22
17. Touvron H, Cord M, Douze M, Massa F, Sablayrolles A, Jégou H (2020) Training data-efficient image transformers and distillation through attention, pp 1–22. arXiv preprint arXiv:2012.12877v2
18. Zhou D, Kang B, Jin X, Yang L, Lian X, Jiang Z, Hou Q, Feng J (2021) DeepViT: towards deeper vision transformer, pp 1–12. arXiv preprint arXiv:2103.11886
19. Touvron H, Cord M, Sablayrolles A, Synnaeve G, Jégou H (2021) Going deeper with image transformers, pp 1–30. arXiv preprint arXiv:2103.17239
20. Chen C-F, Fan Q, Panda R (2021) CrossViT: cross-attention multi-scale vision transformer for image classification, pp 1–12. arXiv preprint arXiv:2103.14899
21. Shekhawat SS, Shringi S, Sharma H (2021) Twitter sentiment analysis using hybrid spider monkey optimization method. Evol Intel 3:1–10
22. Fedorov E Chicken eggs image models. https://github.com/fedorovee75/ArticleChicken/raw/main/chicken.zip