Identification of Chicken Diseases Using VGGNet and ResNet Models

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Abstract. Nowadays, food security is essential in human life, especially for poultry meat. Therefore, the poultry raising is growing over years. This leads to the development of diseases on poultry, resulting in potentially great harm to human and the surrounding environment. It is estimated that when the diseases spread, the economic and environmental damages are relatively large. In addition, small-scale animal husbandry and an automated process to identify diseased chickens are essential. Therefore, this work presents an application of machine learning algorithms for automatic poultry disease identification. Here, the deep convolutional neural networks (CNNs) namely VGGNet and ResNet are used. The algorithms can identify four common diseases in chickens namely Avian Pox, Infectious Laryngotracheitis, Newscalte, and Marek against healthy ones. The obtained experimental results indicate that the highest achievable accuracies are 74.1% and 66.91% for VGGNet-16 and ResNet-50 respectively… The initial results showed positive results, serving the needs of the building and improving the model to achieve higher results.

Keywords: Chicken · Disease · Pox · VGGNet · ResNet

1 Introduction

The population is growing in significant numbers, which boosts the demand for food and requires a large amount of protein to support the whole of humanity [1, 2]. Estimates of demand for poultry - representing a relatively healthy and efficient source of protein to feed the world's population will grow to more than 9 billion by 2050. This leads to expected consumption demand that the world will consume 40% more eggs [3]. Vietnam is no exception, according to Vietnam Livestock magazine [4], the total meat output reaches over 1 million tons of poultry, 11 billion eggs, thus poultry farming is increasing to on average over 6% annually.

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In only 3 years 2016–2018, the total poultry population increased very high by 6.33%. In 2018, 317 million chickens accounted for 77.6%, while laying hens accounted for 22.44%. In Table 1, the number of broilers increased to 7.24% and the number of laying hens also increased by 5.88% per year. This led to an increase in meat output to 6.46% and egg count to 13.30%. This shows that the demand for chicken products of the world and Vietnam is huge. Therefore, the development of the poultry industry is necessary. However, for the livestock industry to develop, it is necessary to pay attention to the factors of nutrition, environment, seed quality, water quality, and, importantly, the disease issue.

Table 1. Total number of samples of sick and normal chickens collected.

Label	# Species
Normal chicken	130
Chicken with Avian Pox	145
Chicken with Infectious Laryngotracheitis	111
Chicken with Newscalte	65
Chicken with Marek	96
Total	547

The development of poultry industry has led to the development of a disease affecting humans and poultry. In the world, the H5N2 pandemic on Turkey farms in the US in 2015 destroyed more than 47 million chickens in 21 states of the United States [5], followed by the appearance of the influenza virus H7N9 in China [6]. In particular, in Vietnam, according to the Department of Animal Health (Ministry of Agriculture and Rural Development) [7] avian influenza A/H5N1 epidemic took place in Vietnam from 2014 to March 2019, each year nearly 90,000 poultry were culled, with 127 people infected with bird flu and 65 people died from 2003 to April 2019, the amount spent on prevention is about VND 180 billion per year. Besides, there are losses of other diseases such as Newscalte, Marek, ILT, IC, etc. This shows that the need for predicting infectious diseases in poultry is becoming feasible when the new technologies and algorithms can build predictive models.

The detection of disease in chickens is a very urgent issue, but recent studies have focused on solving detailed problems of the disease and its origin. In particular, the study of Jake Astill et al. [8] to detect and predict new disease in poultry is based on new technology of big data, but only focus on avian influenza virus. In this study, the author Jake Astill focused on analysis and showed the need for a disease detection and prediction system based on gathering information from big data and analysis. In addition, big data is accompanied by data that changes during the prediction process based on time-varying activities.

Unlike Jake Astill's research, Hemalatha's team [9] focused on the identification of poultry diseases with machine learning methods such as Support Vector Machine (SVM) with Gaussian Radial Basis Function (GRBF)) and Extreme Learning Machine

(ELM). This study uses gray-level matrices to calculate mean values, standard deviations, noise, etc. They used Matrix Mean Square Error method to evaluate the performance of the Support Vector Machine model with Gaussian Radial Basis Function. However, Hemalatha's research stopped at detecting chicken pox in chickens. A new method to mention is the identification of chicken disease based on its sound, Muhammad Rizwan and et al. [10] used the extreme machine learning method extreme learning machine and support vector machine to detect rales, it helps to detect healthy or sick chickens. To conduct healthy and sick chicken stratification based on 20 min of recorded and labeled data for 25 consecutive days, the results of the study show the potential for automatic sound monitoring health of herd of chicken.

From the above analysis, it is feasible to identify disease in chickens with the development of machine learning algorithms, including deep convolution neural networks (CNN). Deep CNN [11] is a prediction algorithm using neural networks which is widely used in data stratification, it consists of a CNN. When building the network, CNN was developed from basic neural networks from 1 to 100 players, from there, it evolved into many different architectures.

Therefore, the construction of a prediction system can be based on changes in depth and width such as ResNet [12] or VGGNet [13] to classify images. Both algorithms are easier to use in training deeper networks than previously used networks. Thus, it is used in image classification studies [14–20]. In terms of the structure of VGGNet and ResNet, there are relatively similar architectures with many stack layers, making the model learn more deeply, but ResNet easily training with hundreds of layers.

Based on these important insights, we propose design recommendations to identify disease in chickens. The contributions of this research are:

- Firstly, we have collected samples from chickens for use in the study, which can be considered as a standard data set for comparison.
- Secondly, we propose a combination of deep CNN, namely ResNet and VGGNet, to formulate ideas and foundations for building a toolkit that has never been done before.
- Thirdly, we obtained the results after making the comparison, assessing the advantages and disadvantages of the two models, thereby strengthening the theory about them.

2 The Proposed Methodology

2.1 ResNet Model

Deep residual network (ResNet) [12] is a network of many "Residual Units" stacked on top of each other. Each unit can be expressed in general form as [21]:

$$y_l = h(x_l) + F(x_l, W_l), \tag{1}$$

$$x_l + 1 = f(y_l) \tag{2}$$

where, x_l và $x_l + 1$are input and output of the i$^{\text{th}}$ units, and F is residual function. In [2], $h(x_l) = x_l$ is identity map and f is ReLU function [22].

The main idea of ResNet is to find the residual function F related to $h(x_l)$, with the main option to use mapping $h(x_l) = x_l$. The basic idea of ResNet is to use a uniform off connection to cross one or more layers. Such block is called a residual block as shown in Fig. 1.

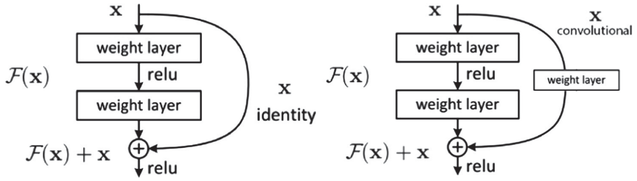

Fig. 1. Residual learning: a building Identity block and convolutional block. Left: identity block; Right: convolutional blocks.

Identity Block is the standard block used in ResNet and corresponds to the input trigger case ($a^{|i|}$) having the same size with trigger output ($a^{|i+2|}$). One Identity Block is defined as:

$$y_l = W_s x_l + F(x_l, W_l) \tag{3}$$

Here, x_l and y_l are the input and output vectors of the considered layers. $F(x_l, W_l)$ function represents the rest of the learned model. I.e., in Fig. 1, there are two layers, $F = W_2\sigma(W_1 x_l)$ when σ represents rectified linear unit (ReLU) and errors are ignored to simplify symbols. The expression F + x_l are shown briefly connected and supplemented for the elements. We adopt the second non-linear properties after addition. In Fig. 1, Convolutional block is another block of ResNet. In general, Convolutional Block and Identity Block are relatively similar. However, Convolutional Block has 1 CONV2D block in shortcut path by applying linear projection W_s so that the dimensions match. CONV2D in the shortcut path is used to change the input size to another size so that the dimensions match the last addition before the shortcut path returns to the main path.

Based on that idea, the ResNet-50 model [16] is built with Convolution Block as shown. In particular, the Convolutional Block is used to handle when the input and output sizes do not match (Fig. 2). The ResNet block is divided into 5 stages corresponding to the increasing order of the size of the set filters from the 2nd stage: [64, 64, 256], [128, 128, 512], [256, 256, 1024] and [512, 512, 2048].

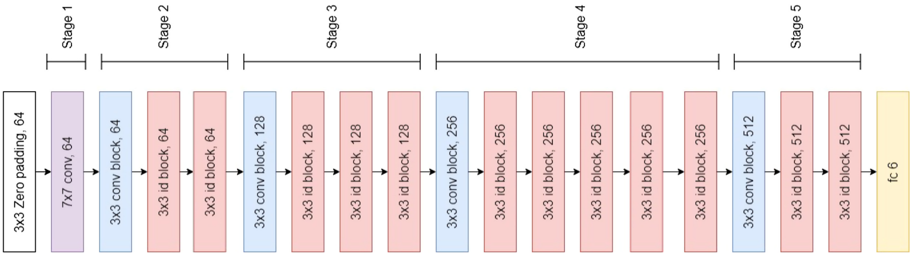

Fig. 2. Building ResNet with 50 Players.

2.2 VGGNet

The VGG network architecture (VGGNet) was introduced by Simonyan and Zisserman [18]. VGGNet architecture (see Fig. 3) uses 3 × 3 convolutional layers stacked on top of each other in increasing depth, which helps to minimize processing size. The two classes are fully connected, each with 4,096 nodes which are then followed by a softmax classifier, consisting of 138 million parameters. The design principles of VGGNets are generally very simple: 2 or 3 layers Convolution (Conv) and followed by a Max Pooling 2D layer. Immediately after the last Conv is a Flatten layer to convert the 4-dimensional matrix of the Conv layer to a 2-dimensional matrix. Following are the Fully-connected layers and 1 Softmax layer. Because VGGNet is trained on the ImageNet data [28] set of 1000 classes, the final Fully-connected layer will have 1000 units (Fig. 3).

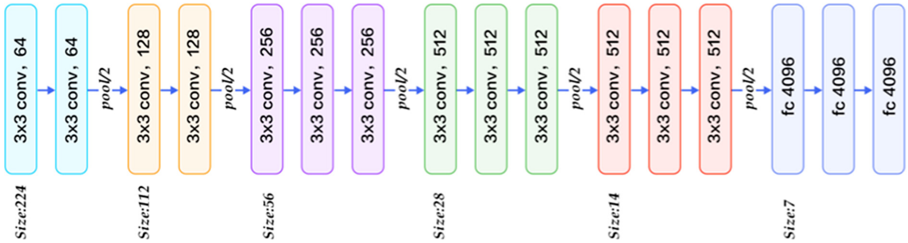

Fig. 3. Illustration of the VGGNet architecture.

3 Experimental Setup

3.1 Data Collection

This research, with the support of animal experts at FVET Vietnam Co., Ltd., has collected 600 picture samples of chicken diseases from 30 to 90 days old. The images were randomly collected in the natural environment like in a barn, natural stocking, etc. The photos have the same caption from the experts. At the end of the collection process, we obtained a total of 547 samples with 5 layers, of which there were 4 disease classes and 1 distinguished normal class which is shown in Table 1.

In these 4 diseases, signs to identify diseases are shown in chickens as follows:

Chicken with Avian pox disease:

- Chicken with Infectious Laryngotracheitis disease
- Chicken with Newscalte disease
- Chicken with Marek disease
- Normal chicken: Chickens do not show any disease and are different from the above.

3.2 Implementation

In our tests, we put the necessary hyper-parameters as follows. The learning rate is {0.05}. The number of epochs is {1500}. We have used different learning rates from 0.01 to 0.1 on 2 training models VGGNet-16 and ResNet-50. The training process on the 2 models has a big difference in time. To test the run time difference of the two models, we have installed a running timer on both models for epochs {10}, the result is VGGNet takes about 200.5 s, to train and ResNet. It took about 821.3 s for our dataset, thus the ResNet model ran about 4.2 times slower. In addition, we also tried training on 3 different epochs: {1000, 1500, 2000}.

Here we retrained the final layers of the model using our dataset. We randomly divided the dataset into a training set, a test set in a 75/25 ratio. Because both the VGGNet and ResNet models have a fixed set size filter at the stages, we set the input size of the model to 64 × 64 × 3 for height, width and channel respectively. These resolutions are common settings of running convolutional networks. The classification decision is made at the softmax layer where its input is the probability distribution of 5 labels of adult chickens. In each combination, we carefully run the model again and again, however the exact score does not change.

Overall, the structure of the VGGNet-16 model is shown in Table 2. The structure of the ResNet-50 model is presented with 50 layers. Our experiments were conducted on a workstation Intel Xeon X5675 with 3.07 GHz clock speed, 16 GB of RAM. The GPU Quad Quad K2200 with 4 GB of GDDR5 is activated by default.

Table 2. VGGNet-16 architecture.

Layers (type)	Output shape	Param #
conv2d_19 (Conv2D)	(None, 64, 64, 32)	896
activation_25 (Activation)	(None, 64, 64, 32)	0
batch_normalization_22 (Batch)	(None, 64, 64, 32)	128
max_pooling2d_10 (MaxPooling)	(None, 32, 32, 32)	0
dropout_13 (Dropout)	(None, 32, 32, 32)	0
conv2d_20 (Conv2D)	(None, 32, 32, 64)	18496
activation_26 (Activation)	(None, 32, 32, 64)	0
batch_normalization_23 (Batch)	(None, 32, 32, 64)	256
conv2d_21 (Conv2D)	(None, 32, 32, 64)	36928
activation_27 (Activation)	(None, 32, 32, 64)	0
batch_normalization_24 (Batch)	(None, 32, 32, 64)	256
max_pooling2d_11 (MaxPooling)	(None, 16, 16, 64)	0
dropout_14 (Dropout)	(None, 16, 16, 64)	0
conv2d_22 (Conv2D)	(None, 16, 16, 128)	73856
activation_28 (Activation)	(None, 16, 16, 128)	0

(*continued*)

Table 2. (*continued*)

Layers (type)	Output shape	Param #
batch_normalization_25 (Batch)	(None, 16, 16, 128)	512
conv2d_23 (Conv2D)	(None, 16, 16, 128)	147584
activation_29 (Activation)	(None, 16, 16, 128)	0
batch_normalization_26 (Batch)	(None, 16, 16, 128)	512
conv2d_24 (Conv2D)	(None, 16, 16, 128)	147584
activation_30 (Activation)	(None, 16, 16, 128)	0
batch_normalization_27 (Batch)	(None, 16, 16, 128)	512
max_pooling2d_12 (MaxPooling)	(None, 8, 8, 128)	0
dropout_15 (Dropout)	(None, 8, 8, 128)	0
flatten_4 (Flatten)	(None, 8192)	0
dense_7 (Dense)	(None, 512)	4194816
activation_31 (Activation)	(None, 512)	0
batch_normalization_28 (Batch)	(None, 512)	2048
dropout_16 (Dropout)	(None, 512)	0
dense_8 (Dense)	(None, 5)	2565
activation_32 (Activation)	(None, 5)	0

4 Results

Figure 4 presents the samples of sick and normal chickens. From left to right, the labels of the chickens are: normal chicken, chicken with head disease, and chicken with ITL, Newcastle, and Marek diseases.

Fig. 4. Samples of sick and normal chickens. From left to right, the labels are normal chickens, chickens with chicken head disease, and chickens with ILT, Newscalte, and Marek diseases.

In this work, the training and test accuracies of VGGNet and ResNet are shown in Fig. 5 and Fig. 6 respectively. By looking at the figures, one observes that the results of accuracies are not much different between the two models. Both achieves approximately 70% of accuracy after only 200 training epochs. Overall, the model converges between epoch {60} and epoch {80}.

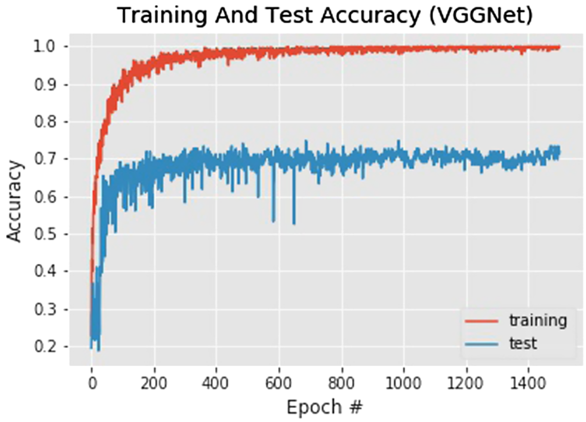

Fig. 5. The classification accuracy on the training and test sets in case of model VGGNet, learning rate = 0.05, epochs = 1500 and input size = 64 × 64.

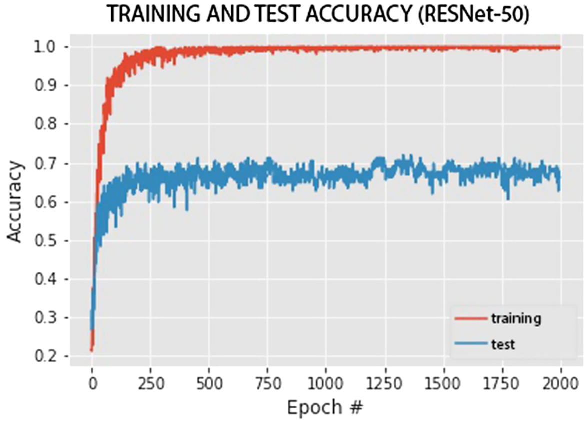

Fig. 6. The classification accuracy on the training and test sets in case of model VGGNet, learning rate = 0.02, epochs = 2000 and input size = 64 × 64.

The complete performance on 20 different combinations of our models is presented in Table 3. Here, it is seen that the best achievement of our tuned model architectures happens at learning rate equals to 0.05. For VGGNet-16 the best classification accuracy is 74.1% while the minimum one is 65.47% happened at learning rates of 0.05 and 0.04 respectively. Meanwhile, for ResNet-50, the highest achieved accuracy is 66.91% and the least achieved one is 61.15% happened for at learning rates of 0.05 and 0.06 correspondingly. In general, VGGNet-16 model performs better than ResNet-50. At close to 75% of accuracy, with further fine-tuning steps, VGGNet-16 will be suitable for used at poultry plant.

Table 3. Classification accuracies of VGGNet-16 and ResNet (%).

Learning rate\models	0.01	0.02	0.03	0.04	0.05	0.06	0.07	0.08	0.09	0.1
VGGNet-16	68.35	70.05	72.66	**65.47**	**74.10**	71.22	69.06	66.91	69.78	69.06
ResNet-50	65.47	62.59	64.03	62.59	**66.91**	**61.15**	63.31	63.31	61.87	62.59

5 Conclusions

With limited resources, the use of state-of-the-art deep CNN greatly reduces the time it takes to perform. As seen from the presented work, VGGNet-16 is more time-efficient and more accurate compared to 50-layer ResNet model. However, VGGNet requires more parameters used for learning deeper the data. The achievable accuracy of approximately 75% by using VGGNet-16 shows the positive results. In future, we will further improve the model's accuracy and deploy the developed application for field trial at poultry plant.

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References

1. Godfray, H.C.J., et al.: Food security: the challenge of feeding 9 billion people. Science **327**, 812–818 (2010). https://doi.org/10.1126/science.1185383
2. Fraser, E., et al.: Biotechnology or organic? Extensive or intensive? Global or local? A critical review of potential pathways to resolve the global food crisis. Trends Food Sci. Technol. **48**, 78–87. https://doi.org/10.1016/J.TIFS.2015.11.006
3. Smith, D., Lyle, S., Berry, A., Manning, N., Zaki, M., Neely, A.: Internet of animal health things opportunities and challenges data and analytics. Internet of Animal Health Things (2015)
4. Tổng quan về chăn nuôi gà. http://nhachannuoi.vn/tong-quan-ve-nganh-chan-nuoi-gia-cam-cua-viet-nam-p1-tong-dan-va-san-pham-giai-doan-2016-2018/
5. Reuters TIMELINE-Tracing the Bird Flu Outbreak in N. American Poultry Flocks (2015). https://www.reuters.com/article/health-birdflu-usa-timeline/timeline-tracing-the-bird-flu-outbreak-in-n-american-poultry-flocks-idUSL1N0Y334G20150612
6. Gilbert, M., Xiao, X., Robinson, T.P.: Intensifying poultry production systems and the emergence of avian influenza in China: a "One Health/Ecohealth" epitome. Arch. Public Health **75**, 1–7 (2017). https://doi.org/10.1186/s13690-017-0218-4
7. Cục Thú y (Bộ Nông nghiệp và phát triển nông thôn), Kế hoạch quốc gia phòng chống bệnh cúm gia cầm giai đoạn 2019–2025, Số: 172/QĐ-TTg, Thư tư´ơng Chính phư

8. Astill, J., Dara, R.A., Fraser, E., Sharif, S.: Detecting and predicting emerging disease in poultry with the implementation of new technologies and big data: a focus on Avian Influenza Virus. Front. Vet. Sci. **5**, 263 (2018). https://doi.org/10.3389/fvets.2018.00263
9. Hemalatha, Muruganand, S., Maheswaran, R.: Recognition of poultry disease in real time using extreme learning machine. In: Proceedings of the International Conference on Inter Disciplinary Research in Engineering & Technology, ICIDRET 2014, pp. 44–50 (2014)
10. Rizwan, M., et al.: Identifying rale sounds in chickens using audio signals for early disease detection in poultry. In: 2016 IEEE Global Conference on Signal and Information Processing (GlobalSIP), USA, pp. 55–59 (2016). https://doi.org/10.1109/globalsip.2016.7905802
11. Krizhevsky, A., Sutskever, I., Hinton, G.E.: ImageNet classification with deep convolutional neural networks. In: Advances in Neural Information Processing Systems, pp. 1097–1105 (2012)
12. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 770–778 (2016)
13. Simonyan, K., Zisserman, A.: Very deep convolutional networks for large-scale image recognition. In: ICLR (2015)
14. Habibzadeh, M., Jannesari, M., Rezaei, Z., Baharvand, H., Totonchi, M.: Automatic white blood cell classification using pre-trained deep learning models: ResNet and Inception. In: Tenth International Conference on Machine Vision, ICMV 2017, vol. 10696, p. 1069612. International Society for Optics and Photonics, April 2018
15. Akbar, S., Peikari, M., Salama, S., Nofech-Mozes, S., Martel, A.L.: Determining tumor cellularity in digital slides using ResNet. In: Medical Imaging 2018: Digital Pathology, vol. 10581, p. 105810U. International Society for Optics and Photonics, March 2018
16. Lin, B., Xle, J., Li, C., Qu, Y.: DeepTongue: tongue segmentation via ResNet. In: 2018 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 1035–1039, April 2018
17. Reddy, A.S.B., Juliet, D.S.: Transfer learning with ResNet-50 for malaria cell-image classification. In: 2019 International Conference on Communication and Signal Processing (ICCSP), pp. 0945–0949, April 2019
18. Ke, H., Chen, D., Li, X., Tang, Y., Shah, T., Ranjan, R.: Towards brain big data classification: epileptic EEG identification with a lightweight VGGNet on global MIC. IEEE Access **6**, 14722–14733 (2018)
19. Singh, V.K., et al.: Classification of breast cancer molecular subtypes from their micro-texture in mammograms using a VGGNet-based convolutional neural network. In: CCIA, pp. 76–85, October 2017
20. Muhammad, U., Wang, W., Chattha, S.P., Ali, S.: Pre-trained VGGNet architecture for remote-sensing image scene classification. In: 2018 24th International Conference on Pattern Recognition (ICPR), pp. 1622–1627, August 2018
21. Nair, V., Hinton, G.E.: Rectified linear units improve restricted Boltzmann machines. In: Proceedings of the 27th International Conference on Machine Learning, ICML 2010, pp. 807–814 (2010)
22. Nair, V., Hinton, G.E.: Rectified linear units improve restricted Boltzmann machines. In: ICML (2010)
23. Maggiori, E., Tarabalka, Y., Charpiat, G., Alliez, P.: Convolutional neural networks for large-scale remote-sensing image classification. IEEE Trans. Geosci. Remote Sens. **55**(2), 645–657 (2017)
24. Nair, V., Hinton, G.E.: Rectified linear units improve restricted Boltzmann machines. In: Proceedings of the International Conference on Machine Learning (ICML), pp. 807–814 (2010)

25. Schuster, M., et al.: TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems (2015). http://tensorflow.org/
26. Xie, S., Girshick, R., Dollár, P., Tu, Z., He, K.: Aggregated residual transformations for deep neural networks. In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 1492–1500 (2017)
27. Simonyan, K., Zisserman, A.: Very Deep Convolutional Networks for Large-Scale Image Recognition. arXiv preprint arXiv:1409.1556 (2014) (2015)
28. Deng, J., Dong, W., Socher, R., Li, L.J., Li, K., Fei-Fei, L.: ImageNet: a large-scale hierarchical image database. In: 2009 IEEE Conference on Computer Vision and Pattern Recognition, pp. 248–255, June 2009