TanhExp: A Smooth Activation Function with High Convergence Speed for Lightweight Neural Networks

Xinyu Liu\(^1\), Xiaoguang Di\(^1\)\(^*\)

\(^1\) Control and Simulation Center, Harbin Institute of Technology, Harbin 150080, P.R. China
\(^*\) E-mail: dixiaoguang@hit.edu.cn

Abstract: Lightweight or mobile neural networks used for real-time computer vision tasks contain fewer parameters than normal networks, which lead to a constrained performance. In this work, we proposed a novel activation function named Tanh Exponential Activation Function (TanhExp) which can improve the performance for these networks on image classification task significantly. The definition of TanhExp is \( f(x) = x \tanh(e^x) \). We demonstrate the simplicity, efficiency, and robustness of TanhExp on various datasets and network models and TanhExp outperforms its counterparts in both convergence speed and accuracy. Its behaviour also remains stable even with noise added and dataset altered. We show that without increasing the size of the network, the capacity of lightweight neural networks can be enhanced by TanhExp with only a few training epochs and no extra parameters added.

1 Introduction

A lightweight neural network only contains a few layers with trainable parameters, which constrain its ability to simulate a non-linear function precisely. However, these networks are necessary for computer vision tasks in industrial machines and mobile devices which require real-time computation [1-4]. These scenarios further limit the size of the model and the training time and bring a bigger challenge. Noticing the powerful ability to fit a nonlinear function of a neural network lays upon the activation function inside, we consider that an effective activation function can help boost the performance of these networks without sacrificing size and rapidity.

Previous researchers mainly aim at exploring the best design of activation function for normal neural networks. From the initially used Sigmoid to the recent Mish [5], researchers have proposed a great number of activation functions. Among of them, the most widely-used is the Rectified Linear Unit (ReLU) [6] because it is computed straightforward meanwhile shows an acceptable performance. Lightweight neural networks also adopt ReLU as its activation function, because there is no special design for them.

However, with a non-zero mean, ReLU [6] suffers from a bias shift problem. Each unit with ReLU [6] activated will cause a slight bias shift, thus a series of units will make the situation severe. Besides, a mean far from zero decelerates the learning speed as well. But none of the other activation functions proposed by researchers could replace the practical and simple ReLU [6] at present because most of them are complex while the improvement is negligible. Besides, these functions are not robust for the variation of data and the addition of noise.

In this work, we propose a Tanh Exponential Activation Function (TanhExp), which combines the advantages of activation functions similar to ReLU [6] and other non-piecewise activation functions together, meanwhile requires less time for computation, which is suitable for lightweight neural networks. To the best of our knowledge, our work is the first design for enhancing the capacity of lightweight neural networks by proposing a new activation function. TanhExp is a continuous function with negative values and the positive part is approximately linear. These properties of the TanhExp accelerate the training process meanwhile ensure the sparsity of the input data. We demonstrate the efficiency, simplicity, and robustness on various datasets and networks. TanhExp shows much more noteworthy improvement than its counterparts.

The paper is organized as follows. Section 2 introduces the related works. In Section 3 we give a detailed description of our TanhExp, which includes its definition, derivatives, and properties. In section 4, we demonstrate the simplicity and efficiency of TanhExp on several datasets and show the results. Section 5 gives the conclusion of the whole work.

2 Related Work

2.1 The ReLU Family

On the initial stage of DNN, Sigmoid and Tanh were commonly utilized as the activation function due to their non-linearity. However, the saturation of these two functions could severely restrict the fitting ability of the network and may cause a gradient vanishing. Therefore, Rectified linear units, i.e. ReLU [6] was proposed as a new type of activation function, which was defined as \( f(x) = \max(0, x) \). Different from the previous functions, ReLU does not saturate on

![Fig. 1: The Figure of TanhExp, Mish, Swish and ReLU Activation Functions](Image)

The Figure of TanhExp, Mish, Swish and ReLU Activation Functions. We restrict the x coordinate from -5 to 5 for a clear view.
the positive half, thus it has two advantages: avoiding the gradients from vanishing and accelerating the learning speed. Although ReLU [6] has been widely used, people still doubt whether ReLU [6] is the best solution for all circumstances. Later researchers found out that ReLU [6] has several drawbacks. The first is that ReLU [6] is a non-negative activation function, thus it has a mean value above zero, which may cause a bias for the network layers afterward. Therefore, the deeper the network, the larger the bias. Besides, a zero-mean activation function can bring the gradient closer to the natural gradient and accelerate the learning process [7], while ReLU does not have this property. The second is the hard truncation of ReLU [6], which shows zero-mean in the negative part. If a large gradient flows into ReLU [6], it will show no activation to the latter data, which was named as ‘the dying ReLU’ problem.

In order to overcome these drawbacks, researchers came up with several ideas. Leaky ReLU [8] \( f(x) = \max(0, x) + \text{leak} \cdot \min(0, x) \) adds a small slope in the negative part, where \( \text{leak} \) is a constant defined before training. PReLU [9] gives a similar solution as Leaky ReLU [8], with the slope rate in the negative part learned through data. However, it leads to a cost of learning extra parameters. SReLU [10], which consists of three piecewise linear functions with the inflect point and the slope rate learned, suffers from additional parameters as well. RReLU [11] also uses \( \max(0, x) \) as the positive part, but the negative part was replaced by a randomized Leaky ReLU. ELU [7], defined as \( f(x) = \max(0, x) + \min(e^{x} - 1, 0) \), uses the exponential function to generate a more smooth activation function. SELU [12] is a modified version of ELU [7], defined as \( f(x) = \lambda \max(0, x) + \min(\alpha (e^{x} - 1), 0) \) where \( \lambda \approx 1.0507, \alpha \approx 1.6732 \), which was derived from a mathematical deduction. GELU [13] was utilized in BERT [14], it combines properties from dropout, zoneout, and ReLUs. These methods tend to design a piecewise function with a smooth figure and force its mean close to zero. Nevertheless, the negative part of these activation functions loses the sparsity of ReLU [6]. Besides, the improvement is trivial. As a result, none of them could be widely used like the ReLU [6]. People are more tend to use the traditional ReLU [6] rather than these more complicated functions with additional parameters.

### 2.2 Non-piecewise Activation Functions

As mentioned above, Sigmoid and Tanh were initially used as activation functions in neural networks, but their saturation on infinity restricts their performance, i.e. a gradient vanishing problem. However, the ReLU family overcame the saturation problem, while led to other drawbacks. Therefore, is there an activation function that can meet all the above requirements? Swish [15] proposed a novel solution to design the activation function. It took advantage of an automated search technique to obtain activation functions, with a search space containing unary and binary functions. The experimental results indicate that \( f(x) = x\sigma(\beta x) \) outperforms all other counterparts on several tasks, which was named as Swish, where \( \sigma \) refers to the Sigmoid function in Eq. (1).

\[
\sigma(x) = \frac{1}{1 + e^{-x}}
\]

Inspired by Swish, Mish [5] proposed a similar solution, its definition is \( f(x) = x \tanh(\ln(1 + e^{x})) \). Mish [5] also provided many detailed experiments to demonstrate its superiority. Consequently, these activation functions not only inherit the advantages of ReLU [6] but also bring about some other virtues. In detail, these functions are non-linear, which constructs the basic non-linearity of a deep neural network. They are unsaturated above, which could avoid the gradient vanishing problem. Close to a linear transformation on the positive part, this enables the network does not alter the input significantly with the increase of the depth. Approximately being zero-mean, as elaborated above, a zero-mean function will lead the gradient closer to the natural gradient and accelerate the learning process.

However, the research does not actually halt since the current activation functions are still not perfect, with the following problems existing. The first is a high computational complexity. For instance, the first derivative of Mish [5] can be calculated in Eq. (2). It is complicated and slows down the backpropagation process critically. We will prove it in the experiment section.

\[
f'_{\text{Mish}}(x) = \frac{e^x(4(x + 1) + 4e^{2x} + 3e^{3x} + e^{5}(4x + 6))}{(2e^{x} + e^{2x} + 2)^2}
\]

The second is the introduction of parameters. Once a hyper-parameter is introduced in a network, the performance varies as the hyper-parameter varies, which cannot obtain a general solution to all tasks. Besides, if the parameter is trainable, it will definitely enlarge the size of the network, especially in a lightweight neural network. Therefore it leads to our proposed Tanh Exponential Activation Function, which can be abbreviated as TanhExp. Different from Swish [15] and Mish [5], TanhExp generates a steeper gradient and alleviates the bias shift better.

### 3 Tanh Exponential Activation Function

In this section, we introduce the Tanh Exponential Activation Function(TanhExp), which can be defined in Eq. (3).

\[
f(x) = x \tanh(e^{x})
\]

where tanh refers to the hyperbolic tangent function:

\[
tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}
\]

In the subsections below, we give a detailed description of the TanhExp and illustrate the properties.

![Fig. 2: The first and second derivatives of TanhExp, Swish, and Mish.](image)

![Fig. 3: The figure of landscapes on a 5-layer network with different activation functions.](image)
3.1 Graph and Derivatives of TanhExp

The graph of TanhExp is shown in Fig. 1. Similar to other smooth functions, TanhExp also extends below zero at the negative part but has a larger gradient. The figure of TanhExp is intuitively similar to the figures of Mish [5] and Swish [15], while they are not actually the same. Although they are close to each other, TanhExp requires less calculations. The first derivative of TanhExp can be calculated in Eq. (5).

$$f'_{\text{TanhExp}}(x) = \tanh(e^x) + xe^x\text{sech}^2(e^x)$$

$$= \tanh(e^x) - xe^x(\tanh^2(e^x) - 1)$$

The first and second derivatives of TanhExp, Swish, and Mish are shown in Fig. 2.

3.2 Properties of TanhExp

TanhExp has a minimum value near $x = -1.100$, which is approximately $-0.3532$. TanhExp also inherits the so-called ‘self-gated’ property in Swish [15]. The form of $f(x) = xg(x)$ is a multiply of the input itself and a function with input as its argument, so the network will not change the initial distribution of the input on the positive part, meanwhile generates a buffer at the negative part near zero. And with a negative infinity approaching zero, TanhExp also ensures a sparsity of its output.

Although TanhExp seems similar to other smooth activation functions, it has several advantages over other smooth functions.

Firstly, in the positive part, TanhExp is almost equal to a linear transformation once the input is larger than 1, with the output value and input value no more than 0.01 variation. As mentioned above, the ReLU family are all aiming at modifying the negative part while leaving the positive part its initial form. It is because the linear transformation is reasonable in training, yet the previous non-piecewise smooth activation functions ignored this problem.

Secondly, TanhExp shows a steeper gradient near zero that can accelerates the update of the parameters in the network. During backpropagation, the network updates its parameters.

$$w_{\text{new}} = w_{\text{old}} - \eta \nabla w$$

Where $\eta$ refers to the current learning rate, and $\nabla w$ refers to the backpropagation gradient. Based on the calculated loss $L$, $\nabla w$ could be calculated as

$$\nabla w = \frac{\partial L}{\partial w_{\text{old}}}$$

Therefore, if $\nabla w$ is slightly larger, the update speed of the weight would be accelerated, thus leads to fast convergence. However, as our goal is to reach the global minimum value, an activation function with too large gradient might cause the network not to converge, while an approximately linear function is a rational option. Besides, from the theorem proved in ELU [7], we know that the bias shift of ReLU [6] activated unit leads to oscillations and impede learning and the unit natural gradient can mitigate the problem. Moreover, a bias shift correction of the unit natural gradient is equivalent to shifting the incoming units towards zero and scaling up the bias unit. So the steeper gradient of TanhExp can also help to push the mean value of the function to zero, which further speeds up the learning process.

We also visualized a simple 5-layer fully connected network built with different activation functions in Fig. 3. Compared with ReLU [6], the other three activation functions shows a smoother landscape which indicates that Swish [15], Mish [5], and TanhExp avoid sharp transitions as ReLU [6] does. Among these three smooth functions, TanhExp shows an especially continuous and fluent transition shape. This property guarantees TanhExp is able to synthesize the advantages of both piecewise and non-piecewise activation functions and leads to outstanding performance.

4 Experiments

In this section, we demonstrate the properties of TanhExp in three aspects: efficiency, robustness, and simplicity. We use ReLU [6], Swish [15], Mish [5] as comparisons. For all experiments in this section, we only altered the activation functions and left all other settings unchanged at the same time.
Fig. 7: The figure of testing accuracy (in percentage) while tuning the layers on MNIST with different activation functions. While tuning the layers, the accuracy of TanhExp remains stable.

Fig. 8: The figure of testing accuracy (in percentage) with 15 layers on MNIST with different activation functions, with a multiplicative 1-centered Gaussian noise implemented in each layer.

4.1 MNIST

MNIST [16] is a dataset aiming at classifying the handwritten digits into 10 classes, with 60,000 training samples and 10,000 test samples. We show that TanhExp is efficient and robust to noise.

4.1.1 Comparison of Learning Speed: Firstly, we did the experiments with a basic network. The network architecture is illustrated in Fig. 4. The default settings contain 15 layers, with the last 12 dense layers composed of 500 neurons, a batch normalization [17] part, an activation function, and a dropout [18] rate of 0.25 each, following the original Mish implementation [5]. We also implemented Mish [5], Swish [15] and ReLU [6] in the same settings. With the increasing of the training epoch, the testing accuracy steadily increases while the loss decreases on all activation functions. However, in Fig. 5 and Fig. 6, TanhExp outperforms Mish [5], Swish [15], and ReLU [6] in both the convergence speed and the final accuracy. Notice that the testing accuracy of TanhExp after the first epoch is 0.8986, while Mish [5] is 0.6568 and Swish [15] is 0.4030, it demonstrates that TanhExp is able to update the parameters rapidly and forces the network to fit the dataset in a most effective way, thus leads to high accuracy and low loss.

4.1.2 Comparison of the Ability of Preventing Overfitting: To verify that TanhExp remains stable with the number of layers growing, we varied the number of layers from 15 to 25, which is consistent with the settings in Mish [5]. Experiments were carried out with the same hyper-parameters as the above, and we visualized the final results in Fig. 7. The results of Mish [5] and Swish [15] remained the same as the Mish [5]. Once the number of layers reaches more than 21, ReLU [6] and Swish [15] show a significant decrease in accuracy, Mish [5] also suffers from a slight decrease in accuracy, while TanhExp hardly drops its accuracy, with 0.9763 at 25 layers. We assessed the results and realized that the network suffers from over-fitting while the layers go deeper. Therefore, TanhExp can prevent the network from overfitting markedly meanwhile other smooth activation functions do not maintain the stability as the increasing of the number of layers.

4.1.3 Comparison of Added Noise: To further prove the robustness of TanhExp, we implemented a multiplicative 1-centered Gaussian noise in each layer which is named Gaussian Dropout [18]. Its standard deviation is

\[ \text{Stdev} = \frac{\text{rate}}{1 - \text{rate}} \]

where drop rate remained 0.25 in this experiment. The result in Fig. 8 illustrates that only TanhExp is barely affected by the noise.
Another experiment is to alter the first dropout layer to an alpha dropout layer [12] with a rate of 0.2 since the network can hardly reach the global minimum value when modifying the rate to 0.25. As Fig. 9 illustrates, alpha dropout restrains the ability of neural networks significantly, but TanhExp is still able to converge more quickly than the other activation functions. Therefore, the experiments support the statement that TanhExp is a robust activation function with fast convergence speed.

To validate our result in a more visualizable way, we extracted the figures of the hidden layer representations. From Fig. 10 which is the output of the alpha dropout [12] layer, TanhExp shows smoother and clearer representations than the other three activation functions. It is due to the network with TanhExp as its activation function can recognize and extract key information from the entire input image more quickly, while the others with coarse representations illustrate that the network only extracts information partially.

Next, we explore whether the performance of TanhExp remains stable on different datasets.

4.2 Fashion MNIST

Fashion MNIST [19] is a dataset aiming at classifying 10 different real-world clothing classes, which consists of T-shirt, trouser, pullover, dress, coat, sandal, shirt, sneaker, bag, and ankle boot. It is similar to the original MNIST dataset [16] but with higher complexity. Fashion MNIST [19] contains 70000 samples, with each sample is a 28*28 grayscale image.

The model we utilized remains the same as the basic 15 layer network as in the MNIST dataset [16]. Because the Fashion MNIST dataset [19] is more difficult for such a simple network, we trained different models for 20 epochs each. We only changed the activation functions while tuning the model for a fair comparison. The testing accuracy and loss are illustrated in Fig. 11 and Fig. 12. The results show that TanhExp outruns other activation functions evidently, on both convergence speed and eventual accuracy.

4.3 Kuzushiji-MNIST

Kuzushiji-MNIST [20], also known as KMNIST, is an image classification dataset for classical Japanese literature and its 10 classes are hiragana characters. It has the same number of images as the MNIST dataset [16]. However, the diverse distribution and the complexity of the dataset make it a more complicated task than MNIST [16].

Similarly, we utilized the 15 layer network to demonstrate that TanhExp is able to perform well in various datasets and remains a high accuracy with just a few epochs. Results are shown in Fig. 13 and Table 1. We further explore the ability of TanhExp on other datasets that are more difficult. The images in the CIFAR-10 [21] dataset contain 10 classes, with 6000 images per class and was divided into 50000 training images and 10000 test images, each image is a 32*32 color image. These 3-channel images require a stronger learning ability of the neural network. Therefore, we used more complex lightweight neural networks in this dataset. we utilized batch normalization [17]

### Table 1 Testing accuracy of various models on the CIFAR-10 dataset.

| Model          | TanhExp | ReLU | Mish  |
|----------------|---------|------|-------|
| LeNet [16]     | 0.7262  | 0.7033 | 0.7217 |
| AlexNet [23]   | 0.7703  | 0.7565 | 0.7626 |
| MobileNet [26] | 0.8538  | 0.8412 | 0.8527 |
| MobileNet v2 [24] | 0.8641 | 0.8594 | 0.8605 |
| ResNet20 [22]  | 0.9193  | 0.9150 | 0.9181 |
| ResNet32 [22]  | 0.9299  | 0.9178 | 0.9229 |
| ShuffleNet [25] | 0.8757  | 0.8705 | 0.8731 |
| ShuffleNet v2 [28] | 0.8743 | 0.8700 | 0.8737 |
| SqueezeNet [29] | 0.8852  | 0.8785 | 0.8813 |
| SE-Net18 [27]  | 0.9086  | 0.9016 | 0.9053 |
| SE-Net34 [27]  | 0.9119  | 0.9167 | 0.9109 |

![Fig. 11: The figure of testing accuracy (in percentage) with 15 layers on Fashion MNIST with different activation functions.](image1)

![Fig. 12: The figure of testing loss with 15 layers on Fashion MNIST with different activation functions.](image2)

![Fig. 13: The figure of testing accuracy (in percentage) with 15 layers on KMNIST with different activation functions.](image3)
activation function not only convergences rapidly, but also is stable and effective, even on challenging datasets.

4.6 Comparison of the Computation Speed

In this subsection, we demonstrate that TanhExp not only achieves a better result in lightweight neural networks but also simpler and requires less computation. Through computing TanhExp and Mish [5] on a 2.20GHz Intel Xeon Cpu for 10^5 times, the mean computation time of Mish [5] is 2.0351 times longer than TanhExp. Following the same setting, we also tested the first and second derivatives of Mish and TanhExp. The results are shown in Table 2. With a far less computation time, TanhExp performs better than Mish [5] on the most experiments.

5 Conclusion

In this work, we propose a novel non-piecewise activation function, Tanh Exponential Activation Function, abbreviate as TanhExp, for lightweight neural networks. The equation of TanhExp is \( f_{\text{TanhExp}}(x) = x \cdot \text{tanh}(e^x) \). It is bounded below with a minimum value -0.3532 and unbounded above. The negative value could push the mean of the activations close to zero, thus accelerates the learning process. The positive part is approximately linear, with no more than 0.01 variation when the input is larger than 1, and the gradient is slightly larger than other smooth activation functions. These properties enable TanhExp to calculate and converges faster than its counterparts meanwhile provides a better result. We carried out several experiments on various datasets to demonstrate the efficiency, robustness, and simplicity of TanhExp. On MNIST, TanhExp could converge at a higher speed, with a test accuracy of 0.8986 after the first epoch on a 15-layer network, meanwhile Swish and Mish show a test accuracy of 0.4030 and 0.6568, respectively. The accuracy of TanhExp also remains stable despite the network becomes deeper.

On Fashion MNIST and KMNIST, TanhExp shows the most outstanding performance in comparison with other activation functions with settings unchanged. On CIFAR-10 and CIFAR-100, TanhExp also performs well, especially on lightweight neural networks. We expect our work will promote the development of real-time manufactures. Future work will concentrate on the utilization of TanhExp on other computer vision tasks.

6 References

[1] Redmon, J, Divvala, S, Girshick, R, et al.: 'You Only Look Once: Unified, Real-Time Object Detection', IEEE Conference on Computer Vision and Pattern Recognition, 2016.
[2] Li, H, Xiong, P, Fan, H, et al.: 'DFANet: Deep Feature Aggregation for Real-Time Semantic Segmentation', IEEE Conference on Computer Vision and Pattern Recognition, 2019.
[3] Bolya, D, Zhou, C, Xiao, F, et al.: 'YOLACT: Real-time Instance Segmentation', IEEE International Conference on Computer Vision, 2019.
[4] Held, D., Thrun, S., Savarese, S.: 'Learning to Track at 100 FPS with Deep Regression Networks', European Conference on Computer Vision, 2016.
[5] Mish: A Self Regularized Non-Monotonic Neural Activation Function, https://arxiv.org/pdf/1908.08681.pdf, accessed 23 August 2019.
[6] Hinton, G.: 'Rectified linear units improve restricted boltzmann machines vinod nair', International Conference on Machine Learning, 2010.
[7] Clevert, D., Unterthiner, T., Hochreiter, S.: 'Fast and accurate deep network learning by exponential linear units (elus)', Computer Science, 2015. 2.
[8] Hannun, A., Maas, A., Ng, A.: 'Rectifier nonlinearities improve neural network acoustic models', International Conference on Machine Learning, 2013. 2.
[9] He, K., Zhang, X., Ren, S., et al.: 'Delving deep into rectifiers: Surpassing human-level performance on imagenet classification', IET Research Journals, pp. 1-7 © The Institution of Engineering and Technology 2015.
[10] Jin, X., Xu, C., Feng, X., et al.: 'Deep learning with s-shaped rectified linear activation unit', The National Conference on Artificial Intelligence, 2016.

[11] Xu, B., Wang, N., Chen, T., et al.: 'Empirical evaluation of rectified activations in convolutional network.' Computer Science, 2015.

[12] 'Self-normalizing neural networks', https://arxiv.org/abs/1706.02515, accessed 8 June 2017

[13] 'Bridging nonlinearities and stochastic regularizers with gaussian error linear units', http://arxiv.org/abs/1606.08415v1] accessed 27 June 2016

[14] 'BERT: pre-training of deep bidirectional transformers for language understanding', https://arxiv.org/abs/1810.04805, accessed 11 October 2018

[15] 'Searching for activation functions', https://arxiv.org/abs/1710.05941, accessed 16 October 2017

[16] Lecun, Y., Bottou, L., Bengio, Y., et al.: 'Gradient-based learning applied to document recognition', Proceedings of the IEEE, 86:2278 â ˘A¸S 2324, 12 1998.

[17] 'Batch normalization: Accelerating deep network training by reducing internal covariate shift', http://www.arxiv.org/abs/1502.03167, accessed 11 February 2015

[18] Srivastava, N., Hinton, G., Krizhevsky, A.: 'Dropout: A simple way to prevent neural networks from overfitting.', Journal of Machine Learning Research, 15:1929â ˘A¸S1958, 2014.

[19] 'Fashion-mnist: a novel image dataset for benchmarking machine learning algorithms', https://github.com/zalandoresearch/fashion-mnist, accessed 2017

[20] 'Deep Learning for Classical Japanese Literature', https://arxiv.org/abs/1812.01718, accessed 3 December 2018

[21] Krizhevsky, A., Hinton, G.: 'Learning multiple layers of features from tiny images', Computer Science Department, University of Toronto, Tech. Rep, 1, Jan 2009.

[22] He, K., Zhang, X., Ren, S., et al.: 'Deep Residual Learning for Image Recognition', IEEE Conference on Computer Vision and Pattern Recognition, 2016.

[23] Krizhevsky, A., Sutskever, I., Hinton, G.: 'Imagenet classification with deep convolutional neural networks', Advances in Neural Information Processing Systems 25, pages 1097â ˘A¸S1105, 2012.

[24] Sandler, M., Howard, A., Zhu, M.: 'Inverted residuals and linear bottlenecks: Mobile networks for classification, detection and segmentation', IEEE Conference on Computer Vision and Pattern Recognition, 2018.

[25] Zhang, X., Zhou, X., Lin, M., et al.: 'Shufflenet: An extremely efficient convolutional neural network for mobile devices.' IEEE Conference on Computer Vision and Pattern Recognition, 2018.

[26] 'Mobilenets: Efficient convolutional neural networks for mobile vision applications', https://arxiv.org/abs/1704.04861, accessed 17 April 2017

[27] Hu, J., Shen, L., Albanie, S., et al.: 'Squeeze-and-excitation networks', IEEE Conference on Computer Vision and Pattern Recognition, 2018.

[28] Ma, N., Zhang, X., Zheng, H., et al.: 'Shufflenet V2: practical guidelines for efficient CNN architecture design'. European Conference on Computer Vision. 2018.

[29] 'SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size', https://arxiv.org/abs/1602.07360, accessed 24 February 2016

[30] 'Cifar-zoo: Pytorch implementation of cnns for cifar dataset', https://github.com/BIGBALLON/CIFAR-ZOO, accessed 2019