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Application of Deep Learning in Garbage Classification

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Abstract

In terms of deep learning, after the entire process of research, Resnext101 32x8d WSL was finally used as the deep learning network model, sgd was the optimization function loss function using Cross Entropy Loss, the initial learning rate was set to 0.001, and the learning rate strategy of ReduceLROnPlateau was adopted, and adopted The Auto Augment algorithm is used as a data enhancement strategy. Finally, the accuracy of the deep learning model reached 0.9470, the precision reached 0.9212, the recall rate was 0.8420, and the F1 measurement value was 0.8799. Through intuitive observation and the test results of samples outside the data set, the model has good generalization ability and no overfitting. Since the Resnext101 32x8d WSL network has performed weakly supervised learning based on 940 million images, and its pre-training model is already relatively powerful, it has achieved good performance in actual application scenarios. After the data set is enhanced by AutoAugment, it is equal to Partial disturbances are added to enhance the robustness of the model.

Keywords

Deep learning; Resnet 50; AutoAugment; Learning Strategy.

1. Introduction

Everyone throws out a lot of garbage every day. In some areas with better garbage management, most of the garbage will be sanitary landfill, incineration, composting and other harmless treatment, while the garbage in more places is often simply piled or landfilled. , Causing odor to spread and pollute soil and groundwater.

The cost of harmless treatment of garbage is very high. Depending on the treatment method, the cost of treating one ton of garbage ranges from one hundred to several hundred yuan. People consume a lot of resources, mass-produce, consume a lot, and produce a lot of garbage, and the consequences will be disastrous.

Deep learning is a machine learning technology that is developed to a deeper level based on the shallow machine learning model. It has the ability to learn from big data on its own, and as the amount of data increases, the generalization ability of deep learning algorithms It will also be stronger. Deep learning is widely used in many pattern recognition and classification scenarios, which can provide important technical support for garbage classification. Therefore, this paper studies the garbage type recognition technology based on deep learning, which can effectively meet the needs of large-scale garbage identification and classification, and promote the smooth development of garbage classification in an orderly manner.

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2. Optimization attempts based on different learning strategies

Throughout the research process, using network open source data sets, based on different neural networks and optimization methods, the following optimizations were carried out.

2.1 Replace the learning network

Initially, the classic Resnet50 network [1] was used for 20 rounds of training with a learning rate of 0.001. The model achieved a classification accuracy of 0.9078, a precision of 0.8632, a recall rate of 0.8476, and an F1 metric of 0.8481. Keeping the control learning rate is always 0.001. Using Resnext101 32x8d network, EfficientNet-b3 network [2], EfficientNet-b5 network to train the same data set in the case of the strategy .

2.2 Adjust the learning rate strategy

Adjust the learning rate strategy for the above 4 kinds of networks. The specific strategies adopted include two methods of adaptively adjusting the learning rate ReduceLROnPlateau[3] and fixed value optimization, and they cannot achieve complete control variables. Different models have different learning rate requirements; among them, ReduceLROnPlateau Use the following strategies. When an indicator does not change (decrease or increase), adjust the learning rate, which is a very practical learning rate adjustment strategy. For example, when the loss of the verification set no longer drops, adjust the learning rate; or monitor the accuracy of the verification set, and adjust the learning rate when the accuracy no longer rises.

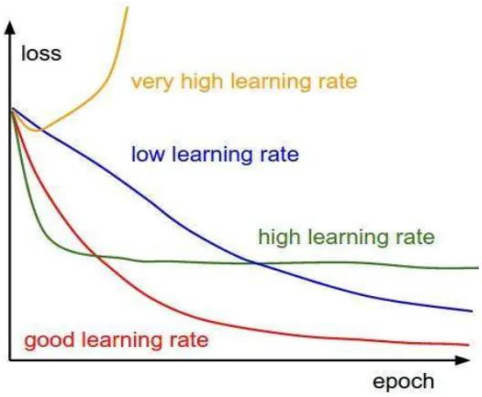

Fig. 1 The impact of different learning rates on learning outcomes

2.3 Choice of loss function

In terms of loss function, by consulting the data, it is found that in multi-classification tasks, softmax activation function + cross entropy loss function is often used. Therefore, I tried to use the cross entropy loss function CrossEntropyLoss as the loss function of the above network. In the case of balance, according to this feature, I also tried the Focal loss loss function.

2.4 Data enhancement methods

I chose Imagenet AutoAugment for data enhancement. The reason for using it is that Imagenet AutoAugment uses Google's pre-finished strategy on Imagenet to search for the best strategy, and it has achieved good results in image classification.

Among the processing, the data set pictures are flipped and parts are randomly cropped. Since there are so many ways to apply and combine transformations on images, they add some restrictions to the methods that can be selected.

A main strategy consists of 5 sub-strategies. Each sub-strategy applies 2 image operations in turn. Each image operation has two parameters: the probability of applying it and the amplitude of the operation (70% probability of performing the operation of rotating 30 degrees).

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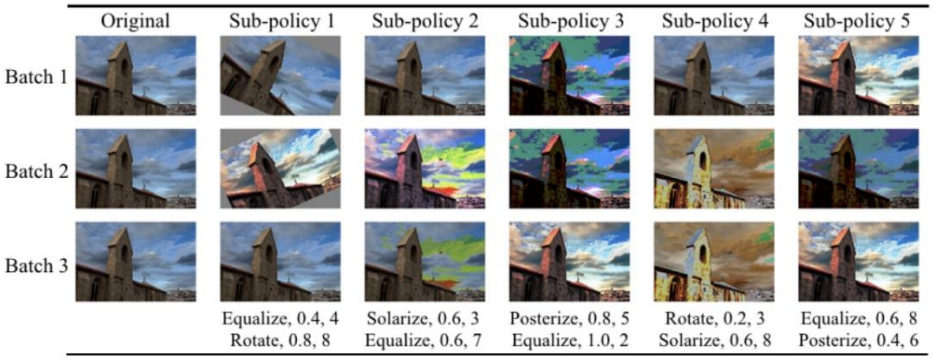

Fig. 2 Data enhanced performance in ImageNet [4]

3. Various strategy optimization results

3.1 The result of changing network model

Table 1. The score of different network

Net	**Score** (baseline accuracy)
Resnet50	90.78
Resnext101 32x8d WSL	91.71
EfficientNet-b3	91.33
EfficientNet-b5	91.44

In the follow-up work, based on the same hardware parameters as above, I set the goal on how to obtain a higher score, that is, the accuracy rate, and reduce the comparison between the accuracy rate and the recall rate. The purpose is to simplify the model comparison process. This determines the basic network to select Resnext101 32x8d WSL.

3.2 Adjust the results of training strategies

Table 2. The score of different training strategies

Loss function	Initial learning rate	Learning rate strategy	Validation set score
CrossEntropyLoss	0.0001	ReduceLROnPlateau	92.23
CrossEntropyLoss	0.001	ReduceLROnPlateau	93.81
CrossEntropyLoss	0.001	Fixed value optimization	92.30
Focal loss	0.001	ReduceLROnPlateau	92.35
CrossEntropyLoss	0.01	ReduceLROnPlateau	92.51

Compared with the performance of other classification tasks, the network accuracy of the sgd function is higher. The sgd function is selected as the optimization function, and the final parameters used are:

Optimization function: sgd

Loss function: CrossEntropyLoss [5]

Initial learning rate: 0.001

Learning rate strategy: ReduceLROnPlateau

3.3 Use data augmentation strategy

Under the existing network and hyperparameters, try to add data enhancement methods, using Google's data enhancement algorithm Imagenet AutoAugment to rotate, invert, pixel flip, histogram equalization, Cutout, Mixup, and Sample Pairing.

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Among them, the operation of Cutout is to randomly select an area in the image and block the content. The Mixup operation mixes the same batch of pictures with each other and keeps the original picture label. The Sample Pairing operation selects one of the same batch of images to graft its content onto the original picture during training, while also keeping the original picture label. [6]

Fig. 3 Examples of original images in the data set

Fig. 4 The effect of AutoAugment processing on the data set image

Fig. 5 Cutout, Mixup and Sample Pairing operation renderings

Table 3. The results obtained after data enhancement by AutoAugment are as follows:

Resnext101 32x8d WSL	**93.81**
+AutoAugment	**94.70**

After the entire optimization, the final model parameters obtained are as follows:

Network model: Resnext101 32x8d WSL

Optimization function: sgd

Loss function: CrossEntropyLoss

Initial learning rate: 0.001

Learning rate strategy: ReduceLROnPlateau

Data enhancement strategy: AutoAugment

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4. Conclusion

The final model Accuracy is 0.9470, Precision is 0.9212, recall rate is 0.8420, and F1 measurement value is 0.8799. Through intuitive observation and the test results of samples outside the data set, the model has good generalization ability and no over-fitting or under-fitting is shown. feature. Since the Resnext101 32x8d WSL network has performed weakly supervised learning based on 940 million images, and its pre-training model is already relatively powerful, it has achieved good performance in actual application scenarios. After the data set is enhanced by AutoAugment, it is equal to Partial disturbances are added to enhance the robustness of the model.

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