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Function and Accuracy of Neural Network Based on Different Hyper-parameters

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Abstract. This study explores the application of deep learning in image classification, with a particular focus on the overfitting problem and its solutions. The performance of Convolutional Neural Network (CNN) and Fully Connected Neural Network (FCN) in animal image classification tasks was compared experimentally. Experimental results show that the CNN model has higher accuracy and robustness than the FCN model when dealing with practical challenges such as diversification, illumination variation and image blurring. In addition, this study also explored the effects of early stop and dropout techniques in reducing overfitting, and found that an appropriate dropout ratio can significantly improve the generalization ability of the model. Finally, the generalization ability of the model is verified by testing on the Stanford pets image dataset, and suggestions for future research directions are put forward.

Keywords: Deep learning, Image classification, Overfitting, Convolutional Neural Network, Fully connected network.

1. Introduction

1.1. Background

With the development of artificial intelligence technology, image classification has become an important research field, which is widely used in safety monitoring, medical diagnosis, and autonomous driving.

1.2. Problem Statement

Animal image classification faces a variety of challenges, including scale variation, deformation, occlusion, lighting conditions, and background clutter, all of which can affect the accuracy of classification results.

1.3. Motivation

Promote the application of deep learning models in image classification, solve challenges in real-world scenarios, such as diversity and lighting changes, and improve the robustness and generalization ability of models. We think combining classical method with deep learning method can reduce the overfitting

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issue. We propose a method that utilize the output layer of deep learning and classical methods to do classification.

1.4. Main focus

The main focus of this study is to avoid model overfitting, verify the performance of different deep learning models through experiments, and explore effective ways to reduce overfitting. We visualized the overfitting issues exist in different model size. And draw some conclusions about which model is better at handling the overfitting issues. We did a comprehensive experiment to show the results.

2. Related work

Existing studies have proposed a variety of ways to solve neural network overfitting, including imposing penalties on network parameters, changing the randomness of the network, or transforming input data. Some previous work shown that by increasing stochastic effect in the training process, the overfitting issue can be significantly reduced [1,2].

On the one hand, the paper proposes a new regularization method to improve the generalization ability of neural networks by ensuring a minimum amount of supporting evidence for parameter fitting for each neuron in the training data. This method was benchmarked on the Fashion-MNIST dataset and compared with various regularization techniques.[1] The study found that by prompting each neuron to at least partially partition its input data, networks using this regularization method were able to activate neurons more frequently and earlier, thus avoiding neuronal saturation and making deep networks easier to train. The paper also explores the potential advantages of this approach in terms of improving learning rates, preventing gradient vanishing and explosion, and training deeper networks.

On the other hand, this paper shows that during training, Dropout randomly "drops" a subset of neurons, so that the model is not dependent on a specific neuron, so that it learns more robust features. [2,3] This method is seen as an ensemble learning strategy to improve the generalization ability of the model by reducing the co-adaptation between neurons. Experimental results show that the model using Dropout outs outperforms the models without this technique on multiple datasets (such as MNIST and CIFAR-10), and the training time is also reduced. Dropout is widely used in the field of deep learning because of its ease of use, and has become one of the standard technologies to improve model performance.[4]

3. Methodology

3.1. Architecture Introduction:

CNN: Extracts local features of data through convolution operations, and uses hierarchies to abstract features step by step. The filter of convolutional layer is used to carry out convolution operation on input data, which can effectively identify local patterns in image and other data and realize feature extraction. In image recognition, image edge, texture and other features can be extracted. And the ability to learn the hierarchical features of data, from low-level simple features (such as edges and textures) to high-level complex features (such as parts of objects and overall objects), which is conducive to more accurate classification and understanding of data. In our experiment, the basic four-layer convolution layer is used to obtain results and find problems by increasing the number of epochs.

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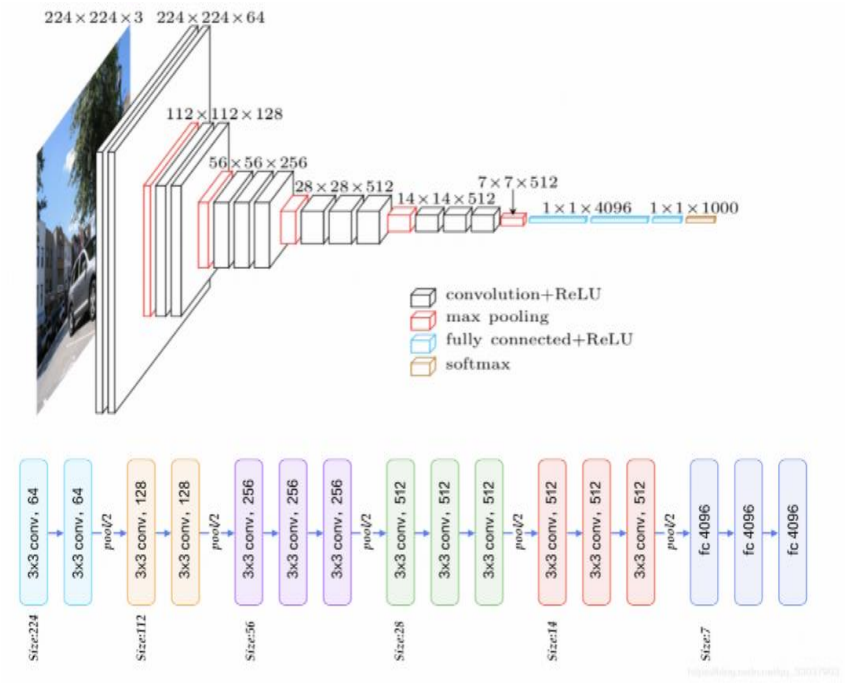

Figure 1. Structure diagram of CNN

FCN: Neurons in each layer are connected to each neuron in the previous layer, forming a dense network structure. It can accept input images of any size, avoiding the need for pre-processing operations such as cropping or scaling due to fixed-size input in traditional convolutional neural networks. And Each pixel in the image can be classified, so as to achieve accurate semantic segmentation, and the detailed information such as the boundary of the target in the image can be better processed.

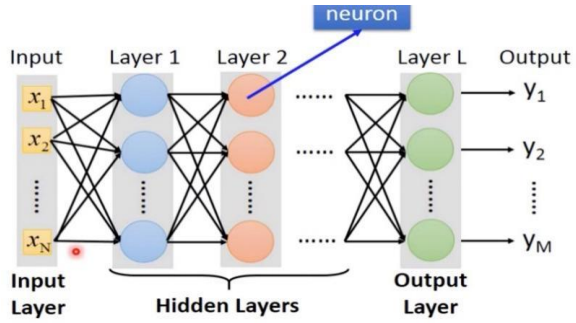

Figure 2. Structure diagram of MLP

Preparation work: The effectiveness of different architecture models in classification accuracy was compared. The Adam optimization method was used in the experiment, NVIDIA GeForce RTX 3050 Laptop GPU, the learning rate was 0.001, the training cycle was 10 times, and the dataset was The Oxford-IIIT Pet Dataset.

3.2. Impact of model complexity on overfitting

If the complexity of a model is too low, it will result in underfitting, and if the complexity of the model is too high, it will be overfitting. Therefore, by comparing models of different complexity , we choose the model with better effect through comparison.

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3.3. Current methods for addressing overfitting

There are many ways to solve the problem of overfitting. We'll choose dropout and early stopping to find the best one by changing the parameters.

3.4. Individual case analysis

In the process of the experiment, examples of classification errors will be generated. Through the analysis of these Figures, the reasons for the wrong classification of these Figures (For example light, background and other factors) will be analyzed, so as to better select data sets and modify them.

4. Experiment content

4.1. Experimental basic framework

The experimental framework for this study is designed to systematically evaluate the performance of different neural network architectures in image classification tasks, with a particular emphasis on animal images. The framework is structured to address the primary research questions and to test the hypotheses derived from the literature review and problem statement. Here is a detailed outline of the experimental setup:

4.1.1. Experimental Objectives

The primary objectives of our experiments are to, firstly, compare the performance of CNN and FCN in classifying animal images. Secondly, analyze the impact of model complexity on overfitting. Thirdly, evaluate the effectiveness of overfitting mitigation techniques such as dropout and early stopping. And lastly, assess the generalization ability of the models on new datasets.

4.1.2. Data Preparation

The Oxford-IIIT Pet Dataset is used as the primary dataset for training and testing our models. This dataset provides a rich collection of animal images, which is suitable for our classification tasks. The dataset is preprocessed to ensure that all images are resized to a uniform size, normalized, and augmented to increase the diversity of the training data.

4.1.3. Model Architectures

Two types of neural network architectures are considered in our experiments:

Firstly, CNN model is designed to automatically and adaptively learn spatial hierarchies of features from input images. Our CNN architecture consists of multiple convolutional layers followed by pooling layers to reduce spatial dimensions, and fully connected layers for classification.

Secondly, FCN model serves as a baseline for comparison. It is a simple neural network with multiple fully connected layers, lacking the ability to capture spatial hierarchies inherent in image data.[5,6]

4.1.4. Training Procedure

Both CNN and FCN models are trained using the Adam optimizer with a learning rate of 0.001. The training cycle is set to 10 epochs to ensure that the models have sufficient time to learn from the data without overfitting. The NVIDIA GeForce RTX 3050 Laptop GPU is utilized to accelerate the training process.

4.1.5. Evaluation Metrics

The performance of the models is evaluated using accuracy, which is the proportion of correct classifications out of the total number of test samples. Additionally, we will use confusion matrices to visualize the performance of the CNN model across different classes.

4.1.6. Overfitting Mitigation Techniques

To address overfitting, we experiment with two techniques:

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Firstly, the Early Stopping technique stops the training process when the model's performance on a validation set begins to degrade, thus preventing overfitting to the training data.

Secondly, the Dropout technique randomly sets a fraction of input units to 0 at each update during training, which helps to prevent neurons from co-adapting too much.

4.1.7. Experimental Design

The experiments are divided into several stages:

1. Baseline Performance: We start by establishing a baseline performance using the simplest version of both CNN and FCN.
2. Complexity Analysis: We then incrementally increase the complexity of the CNN model to observe the effect on overfitting and classification accuracy.
3. Overfitting Techniques: We apply dropout and early stopping techniques to the CNN model and compare their effects on overfitting and model performance.
4. Generalization Testing: Finally, we test the generalization ability of the best-performing model on the Stanford pets image dataset.

4.2. Contrast test

After that, we found that only increasing the number of convolutional layers is not enough, and then we found a method to increase the number of loops and dropout to conduct a comparison test and draw a line graph of accuracy.

4.3. Find the problem

4.3.1. Problems in the performance comparison between MLP and CNN

When comparing the performance of MLP and CNN, we find that the MLP model has obvious limitations when dealing with image classification tasks.[7] Due to the lack of spatial perception ability, the MLP model does not capture the local features and spatial relationships in the image, resulting in low accuracy of animal image classification under complex backgrounds and diverse postures. In addition, MLP models are more prone to overfitting during the training process, especially when the feature dimension is high, and the generalization ability of the model decreases significantly.

4.3.2. CNN performance problems with different structural complexity

When studying CNN models with different structural complexity, we find that the complexity of the model has a significant impact on performance. The low-complexity CNN model exhibits underfitting in the face of high-variability animal images, and cannot effectively capture the key features of the images. Models with high complexity, on the other hand, are more susceptible to overfitting than they can capture, although they are able to capture more detailed information, especially if the training samples are insufficient. In addition, the computational cost and time cost of high-complexity models have also increased significantly, which poses a challenge for practical applications.

4.3.3. Solve the challenges in overfitting problems

When trying to solve the overfitting problem, we found that although dropout and early stop techniques can effectively improve the generalization ability of the model, the application of these techniques requires careful adjustment of parameters. For example, a dropout ratio that is too low may not be effective in reducing overfitting, while a dropout ratio that is too high may result in degraded model performance. Although the early stop technique can prevent the model from over-optimizing on the training set, if the early stop threshold is not set properly, the model may not learn the training data sufficiently. In addition, these techniques work differently on different types of datasets and models of varying complexity, and need to be adapted on a case-by-case basis.

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4.3.4. The effect of the model applied to the new dataset

When applying the model to a new dataset, we found that the model could experience performance degradation in the face of the new dataset. This may be due to inconsistencies in the distribution of the new dataset and the training dataset. For example, images in a new dataset may contain more background noise, different lighting conditions, or more complex scenes, all of which can affect the model's classification accuracy. In addition, the distribution of categories in the new dataset may be different from the training dataset, resulting in insufficient recognition of certain categories by the model.

In summary, we found a series of problems that affect the performance of the model during the experiment, and the solution of these problems is crucial to improve the accuracy and generalization ability of the model. Future research can further explore these issues and find more effective solutions..

5. Result

5.1. About the impact of model complexity on overfitting

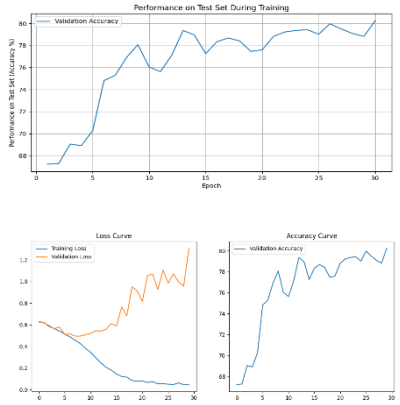

Figure 3. The accuracy of the CNN model

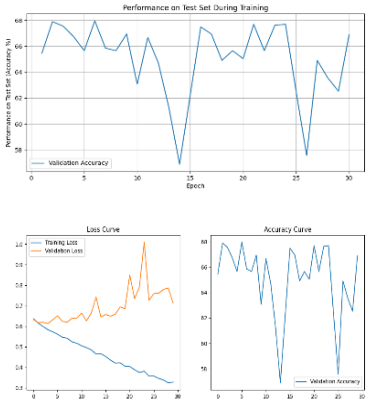

Figure 4. The accuracy of the MLP model

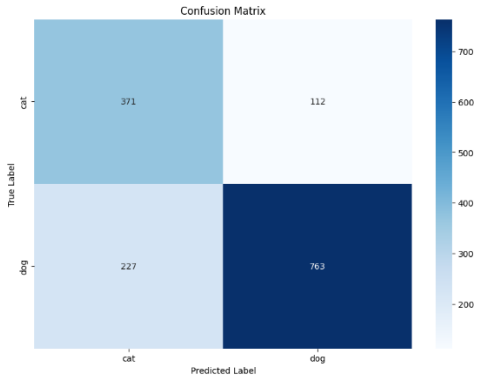

Figure 5. CNN confusion matrix

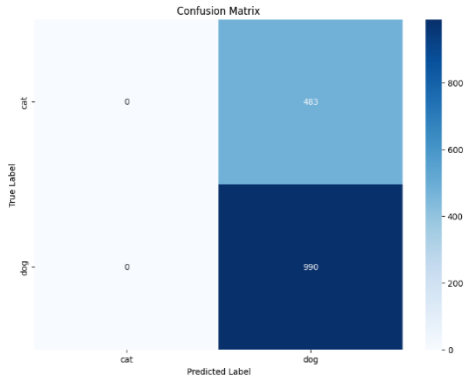

Figure 6. CNN confusion matrix

As can be seen from these two graphs, the accuracy of CNN model is generally higher than that of MLP model, so it is more appropriate to choose CNN for image classification above model selection.

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5.2. On the results of current methods for addressing overfitting



Figure 7. dropout=0.1 epoch=30



Figure 8. dropout=0.2 epoch=30

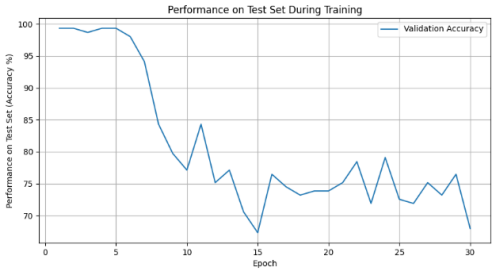

Figure 9. dropout=0.3 epoch=30



Figure 10. dropout=0.5 epoch=30

The effectiveness of dropout in mitigating overfitting is visualized in Figures 7 to 10.[8-13]These graphs plot the accuracy of the CNN model under different dropout rates and epochs.[8-13] From these four graphs, we can see that the image accuracy rate at dropout=0.2 is relatively high, about 80 percent, suggesting an optimal balance between regularization and model complexity.

5.3. About the results of individual case analysis(Bad example)



Figure 11. Because someone in the picture causes occlusion and the background color is similar, the picture prediction is wrong.

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Figure 12. Because the picture color is dark, the picture appearance is not clear enough, resulting in the picture prediction error.

These two figures provide examples of misclassifications and the factors contributing to these errors. Figure 11 shows an instance where occlusion due to a person in the image and similar background colors led to incorrect classification. Figure 12 illustrates a case where poor lighting and unclear image appearance resulted in misclassification.

6. Conclusion

6.1. Conclusion highlights

6.1.1. Overfitting Mitigation

Our experiments validated the efficacy of dropout in mitigating overfitting, with a dropout rate of 0.2 optimizing model performance. This finding underscores the importance of regularization in enhancing model generalization.

6.1.2. Model Complexity and Generalization

A balance between model complexity and dataset size is crucial for generalization. We observed that complex models are prone to overfitting, while simpler models may underfit, highlighting the need for tailored model selection based on data characteristics.

6.1.3. Generalization to New Datasets

The CNN models exhibited robust generalization capabilities when applied to the Stanford pets dataset, indicating their potential for real-world applications beyond the training dataset.[14]

6.2. Limitations and future work

Despite the promising results, our study has some limitations. The performance of our models was primarily evaluated on datasets with controlled variations. Future work should explore the models' performance on more diverse and uncontrolled datasets. Additionally, while dropout and early stopping were effective, there is a need to explore other regularization techniques and their combinations to further enhance model generalization.

In conclusion, our research has made significant strides in understanding the role of deep learning models in image classification, particularly in the context of animal images.[15] By addressing overfitting and improving model generalization, we have taken steps towards developing models that can be reliably applied in real-world scenarios. We look forward to building on these findings and exploring new avenues in the pursuit of more accurate and robust image classification systems.

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