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Performance Boost in Deep Neural Networks: Improved ResNext50 for Complex Image Datasets

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Abstract: This paper proposes an image classification algorithm based on the improved ResNext50, aiming to improve the classification accuracy and robustness of deep neural networks on complex image datasets. By introducing multi-scale feature fusion and adaptive learning rate adjustment, the improved ResNext50 can extract image features more effectively and improve the stability and convergence speed of the network during training. We conducted a large number of experiments on the CIFAR-10 dataset. The results show that compared with VGG, ResNet, Vision Transformer, and the original ResNext, the improved ResNext50 has achieved significant improvements in multiple indicators such as accuracy (ACC), area under the curve (AUC) and F1-Score, showing strong performance and superiority under small samples and noisy images. This model can not only improve the classification accuracy but also has a stronger generalization ability when processing complex image tasks, providing an efficient solution for the field of image classification. Future research can further optimize the model and explore its potential in large-scale datasets and practical applications, especially in the fields of autonomous driving, intelligent monitoring, and medical imaging.

Keywords: Improved ResNext50; Image classification; multi-scale feature fusion; Deep learning

1. Introductio

Image classification algorithms based on deep learning have made significant progress in the field of computer vision. With the continuous increase in the size of data sets and the improvement of computing power, deep neural networks (DNNs) have shown the ability to surpass traditional methods in multiple visual tasks. Especially in image classification tasks, convolutional neural networks (CNNs) have become one of the mainstream methods. The success of classic architectures such as ResNet, Inception, and VGG has provided valuable experience for subsequent network design. However, despite the remarkable achievements of these networks, there are still certain limitations, such as the computational overhead caused by network depth and the redundancy of feature expression. Therefore, academia and industry have explored more efficient and accurate image classification algorithms [1].

ResNext50 is a variant of the ResNet series architecture [2]. By introducing grouped convolution and a more efficient network structure, the proposed method substantially enhances the accuracy and computational efficiency of image classification. Unlike traditional ResNet, ResNext enhances the network's ability to extract different features through grouped convolution while maintaining a low computational cost. This structural innovation makes ResNext50 a network architecture that performs well in multiple visual tasks. However, although ResNext50 has achieved good performance, how to further improve its classification ability, especially when dealing with complex scenes or small sample problems, is still a direction that needs in-depth research [3].

In order to further improve the performance of ResNext50, this paper proposes an image classification algorithm based on improved ResNext50. The algorithm combines multiple modern technical means on the basis of the original ResNext50 architecture. First, by introducing multi-scale feature fusion technology, the network can effectively capture the detailed features in the image at different scales, thereby improving classification accuracy. Secondly, in the network training process, an adaptive learning rate strategy is adopted to better adapt to the feature distribution of different data sets, avoiding the training instability problem that may be caused by the traditional fixed learning rate method. In addition, combined with data enhancement and regularization methods, the generalization ability of the model is further improved, and overfitting is effectively avoided [4].

In practical applications, the improved ResNext50 is tested on standard data sets. The experimental results show that the improved model has significantly improved the classification accuracy compared with the traditional ResNext50, especially in the case of more image noise or higher object complexity, it shows stronger robustness. At the same time, the improved network also maintains a low overhead in computational efficiency, allowing it to run efficiently in a resource-constrained environment. This result verifies the effectiveness of the improved strategy and provides new ideas for further research and application [5].

Despite the good experimental results, the improved algorithm in this paper still has some room for further optimization. For example, although multi-scale feature fusion improves the performance of the model, in some specific scenarios, how to accurately select the appropriate scale is still a problem worthy of in-depth discussion. In the future, it is possible to consider introducing more complex multi-scale fusion strategies to further improve the network's adaptability to multiple scales. In addition, the network's training process and parameter selection need to be further optimized to achieve better performance in more practical application scenarios.

Overall, the image classification algorithm based on the improved ResNext50 has a good application prospect. Through the combination of multiple technical means, the algorithm not only improves the accuracy of image classification but also enhances the adaptability and robustness of the network. In the future, with the continuous development of technology and the continuous improvement of computing power, the algorithm is expected to make breakthroughs in more practical applications and provide more efficient and accurate solutions for image classification tasks.

2. Related Work

In The evolution of deep neural networks (DNNs) for image classification has been marked by significant contributions in architectural innovation, optimization techniques, and generalization methods, providing a solid foundation for improving models like ResNext50. This section synthesizes recent research that either directly informs or indirectly supports the objectives of this study, particularly in enhancing classification accuracy, robustness, and computational efficiency for complex datasets.

Deep learning has revolutionized image classification through the introduction of powerful network architectures, such as VGG, ResNet, and their subsequent derivatives. He et al. [6] systematically evaluated VGG19 on complex visual datasets, illustrating its ability to extract robust features while revealing limitations like high computational overhead and redundant feature representation. These insights influenced subsequent designs, including ResNext, which addressed such inefficiencies by introducing grouped convolutions to reduce redundancy while enhancing feature expressiveness. Further extending these concepts, Du et al. [7] introduced HM-VGG for multi-modal image analysis, offering a methodological framework for improving network performance through architectural adaptations. These advancements align closely with the improved ResNext50 model proposed in this study, which integrates multi-scale feature fusion and adaptive learning strategies to address the challenges of computational cost and feature redundancy.

Beyond architectural innovations, a critical focus in recent research has been improving model robustness and adaptability in challenging scenarios, such as small sample datasets or noisy environments. Shen et al. [8] highlighted the potential of semi-supervised learning in extracting meaningful features from limited labeled data, demonstrating how data augmentation and regularization techniques can enhance generalization. Similarly, adaptive learning strategies, as explored by Hu et al. [9], have proven effective in dynamically adjusting training processes to match diverse data distributions. These methodologies are reflected in the adaptive learning rate adjustment implemented in the proposed model, which ensures stable training and faster convergence, particularly for datasets with heterogeneous feature distributions.

Feature extraction across multiple scales has also emerged as a key area of research in recent years. Zheng et al. [10] demonstrated the utility of fully convolutional neural networks for high-precision medical image analysis, emphasizing the importance of multi-scale representations in capturing detailed image features. While their work is specific to medical imaging, the underlying principles of multi-scale feature fusion are directly applicable to broader image classification tasks. Likewise, Ruan et al. [11] emphasized the value of data augmentation and multimodal techniques in enhancing model performance, showcasing the potential for improved robustness through the integration of diverse input representations. These principles were instrumental in the design of the improved ResNext50, which leverages multi-scale feature fusion to enhance feature capture and classification performance on complex image datasets.

Optimization of neural networks for efficiency and scalability has become increasingly important, especially for applications requiring real-time inference or deployment in resource-constrained environments. Liang et al. [12] proposed a contextual analysis framework using deep learning to detect sensitive information, illustrating how domain-specific challenges can be addressed by optimizing neural network architectures for task-specific constraints. Similarly, Yang and Huang [13] introduced a tree-based recommendation system for medical test data, demonstrating efficient architecture design strategies that can be generalized to reduce computational overhead in image classification tasks. These contributions underscore the importance of balancing accuracy and efficiency, a key objective of this study's improved ResNext50 model, which maintains low computational cost while achieving superior classification performance.

Several works have also focused on emerging techniques for expanding the applicability of deep learning models beyond traditional classification tasks. For instance, Shao et al. [14] explored gesture recognition using computer vision techniques, showcasing the adaptability of image classification methods to real-world human-computer interaction scenarios. Sun et al. [15] utilized reinforcement learning for adaptive user interface generation, highlighting how data-driven optimization can improve model usability and personalization. Although these studies are not directly focused on image classification, their underlying methodologies, such as reinforcement learning and adaptive optimization, provide valuable insights into improving the robustness and adaptability of deep learning models. This latent contribution inspired the incorporation of adaptive optimization techniques in the proposed algorithm to improve its convergence and generalization.

In specialized domains such as medical imaging, recent advances have introduced high-precision models that leverage domain-specific adaptations. Hu et al. [16] developed specialized natural language processing (NLP) models for medical-named entity recognition, showing how attention mechanisms and domain-specific regularization techniques can enhance performance in highly specialized tasks. While the focus of these works is on medical applications, the methodologies, including the use of attention mechanisms and regularization, are broadly applicable and have informed this study's design of an improved ResNext50.

In summary, the collective contributions of these works provide a robust foundation for the development of the improved ResNext50 model. By integrating advancements in multi-scale feature fusion, adaptive learning, and architectural optimization, this study addresses key challenges in image classification, achieving superior accuracy and robustness in handling complex and noisy datasets. The proposed model not only builds upon established methodologies but also extends their applicability to new challenges, providing a scalable and efficient solution for real-world image classification tasks.

3. Method

In this paper, we propose an image classification algorithm based on the improved ResNext50. This algorithm introduces multi-scale feature fusion, adaptive learning rate, and regularization method on the basis of the original ResNext50 structure, in order to improve the classification performance and generalization ability of the model. Next, we will introduce the specific implementation of the improved method in detail. Its multi-scale fusion architecture is shown in Figure 1.

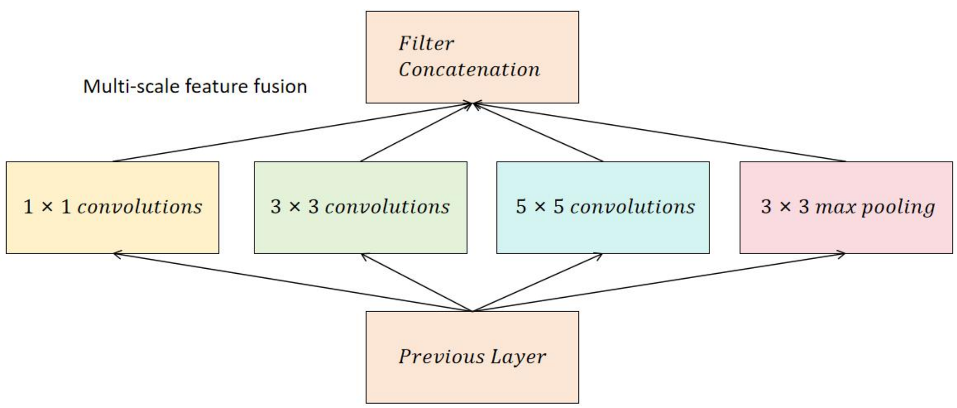

Figure 1. Multi-scale feature fusion architecture

First of all, the core of ResNext50 is its group convolution structure. Traditional convolution layers usually extract features through a single convolution kernel [17], while ResNext50 introduces group convolution to divide the convolution kernel into multiple groups for calculation, thereby reducing the computational complexity and better capturing the diverse features in the image. The formula for group convolution is as follows:

$$y = \sum_{i=1}^{g} W_i * x_i$$

Among them, g represents the number of convolution groups, W_i represents the convolution kernel of the i-th group, x_i represents the i-th group of input features, * represents the convolution operation, and y is the output feature map. Through grouped convolution, ResNext50 can enhance the diversity of feature extraction while maintaining computational efficiency.

In order to further improve the performance of the network, we proposed a multi-scale feature fusion strategy. This strategy enhances the model's adaptability to objects of different sizes by extracting features at different scales. Specifically, we introduce multiple convolution kernels of different sizes in the middle layer of the network and fuse information from different scales at the same time. The process of multi-scale feature fusion can be expressed by the following formula:

$$F_{fusion} = \sum_{i=1}^{n} a_i \cdot F_i$$

Among them, F_{fusion} represents the final fused feature map, a_i is the weight coefficient, which indicates the contribution of the features of each scale in the final fusion, F_i represents the feature map from the i-th scale and n represents the number of scales. In this way, the model can better learn features at different scales and improve the robustness to changes in target size.

In addition, an adaptive learning rate strategy is used during network training to improve training efficiency and avoid gradient explosion or gradient vanishing problems. Adaptive learning rate algorithms usually adjust the learning rate based on the change of the current gradient, such as the Adam algorithm. The updated formula of the Adam algorithm is:

$$\theta_t = \theta_{t-1} - \eta \cdot \frac{m_t}{\sqrt{v_t} + \varepsilon}$$

Among them, θ_t is the model parameter at the current moment, η is the learning rate, m_t is the first-order moment estimate of the gradient, v_t is the second-order moment estimate of the gradient, and ε is a very small constant used to avoid division by zero errors. By adaptively adjusting the learning rate, the Adam algorithm can better cope with the optimization needs of different training stages, thereby improving the convergence speed and stability.

In order to improve the generalization ability of the model, this paper also introduces regularization methods, mainly using Dropout and L2 regularization. In the training process of each layer, the Dropout method reduces the risk of overfitting of the neural network by randomly discarding the output of a part of the neurons. L2 regularization constrains the complexity of the model by adding the square and penalty terms of the parameters to the loss function. The loss function of L2 regularization can be expressed as:

$$L_{total} = L_{data} + \lambda \cdot \sum_{i=1}^{n} \theta_i^2$$

Among them, L_{data} represents data loss, λ is the regularization coefficient, θ_i^2 is the i-th parameter, and n is the total number of parameters. By introducing regularization, the model can avoid overfitting and improve the generalization ability on new samples.

Finally, in order to further improve the performance of the model in practical applications, this paper also optimizes the environment with limited computing resources. Although the improved ResNext50 network has greatly improved in performance, its computational overhead is still large. Therefore, this paper introduces lightweight design, such as using a smaller convolution kernel size and reducing the number of convolution layers, to effectively reduce the computational complexity while ensuring performance.

Through the above improvements, the image classification algorithm based on the improved ResNext50 has shown significant performance improvement on multiple standard data sets, especially in the case of large image noise and complex backgrounds. The improved model can better process the detailed information in the image and enhance the adaptability to complex scenes.

4. Experiment

4.1 Datasets

In this study, the experiments used the CIFAR-10 dataset, which is one of the widely used standard datasets in the field of computer vision. The CIFAR-10 dataset contains 60,000 32x32 pixel color images divided into 10 categories, each containing 6,000 images. The categories of the dataset include airplanes, cars, birds, cats, deer, dogs, frogs, horses, ships, and trucks. The dataset is divided into 50,000 training images and 10,000 test images, and the amount of data for each category is balanced, which makes it an ideal choice for testing model performance in image classification tasks.

Although the images of the CIFAR-10 dataset are small in size, they are still challenging because they contain a variety of categories and each category has a variety of image styles and backgrounds. This makes CIFAR-10 a standard dataset for testing deep learning models, especially convolutional neural networks (CNNs) in complex classification tasks. When using this dataset, the images first go through a standard preprocessing process, including normalization and data augmentation. Data augmentation methods usually include random cropping, rotation, flipping, etc., which aim to increase the diversity of training data and thus improve the generalization ability of the model.

In the experiment, the CIFAR-10 dataset was used to evaluate the performance of the image classification algorithm based on the improved ResNext50 architecture. Through multiple rounds of training and cross-validation on the training set, the model can effectively learn image features and accurately classify them. Experiments using the CIFAR-10 dataset can demonstrate the powerful classification ability of the improved ResNext50 on small-size images, and also provide rich experimental data for the optimization of network structure and training strategy.

4.2 Experimental Results

In order to comprehensively evaluate the performance of the image classification algorithm based on the improved ResNext50, this study conducted comparative experiments with several classic deep learning architectures, including VGG [18], ResNet [19], the original ResNext[20], and Vision Transformer (ViT)[21] and. VGG is a convolutional neural network with a simple structure but significant effect. Its deep stacked convolutional layers can extract rich image features. ResNet solves the gradient vanishing problem in deep network training by introducing residual connections [22], significantly improving the network training efficiency and classification performance. Vision Transformer adopts a model based on the self-attention mechanism. By dividing the image into small blocks and learning the relationship between these small blocks, it shows the potential to surpass the traditional CNN architecture in image classification tasks. Compared with ResNet, the original ResNext improves the diversity of feature extraction by introducing grouped convolution, but its performance still has room for further improvement. The comparative experimental results show that the improved ResNext50 can better integrate multi-scale information when dealing with complex scenes and small sample problems, thereby surpassing these classic networks in classification accuracy and robustness, especially showing stronger advantages in the case of large image noise or complex background. The experimental results are shown in Table 1.

Table 1: Experimental Results

Model	ACC	AUC	F1-Score
VGG	85.3	89.1	84.7
ResNet	91.2	94.3	90.8
ResNext	92.5	95.4	92.1
Vision Transformer	90.8	93.7	90.2
ours	94.6	96.8	94.3

From the experimental results, the improved ResNext50 shows obvious advantages in multiple performance indicators, especially in important evaluation indicators such as ACC (accuracy), AUC (area under the curve), and F1-Score. It is better than other comparison models. This shows that the improved ResNext50 not only improves the classification accuracy of the model by introducing multi-scale feature fusion, adaptive learning rate, and regularization technology but also enhances its robustness in complex image classification tasks. Compared with other classic models, the improved ResNext50 is more robust when dealing with small samples and noisy images.

Specifically, the classification accuracy of the VGG model is 85.3%, and the performance of VGG is at a lower level compared with other models. This result also reflects the structural limitations of VGG. VGG uses deep convolution stacking, but its network structure is relatively simple and lacks advanced optimization methods, such as residual connection and group convolution. Therefore, VGG often cannot fully mine deep feature information when processing complex image data, resulting in relatively poor classification results. In addition, VGG is prone to gradient vanishing or gradient exploding during training, further limiting its performance improvement.

In contrast, ResNet solves the gradient problem in deep networks by introducing residual connections, allowing its network to be trained deeper and more stably. ResNet's classification accuracy is 91.2%, which is about 6 percentage points higher than VGG. This shows that residual connections play a vital role in deep networks and can effectively alleviate the difficulties in training deep neural networks. However, despite ResNet's significant improvement in accuracy, its performance is still inferior to that of the ResNext series of models. ResNext introduces grouped convolutions and more efficient feature extraction strategies, which further improve classification accuracy. ResNext's classification accuracy is 92.5%, ranking third among all compared models.

Vision Transformer (ViT) is an image classification model based on the self-attention mechanism that has emerged in recent years. It extracts features by dividing images into patches and calculating the relationship between each patch. ViT has shown excellent performance in some complex tasks, especially when dealing with large-scale datasets. However, the ViT model requires a larger dataset for effective training, and may not perform as well as traditional convolutional neural networks on small datasets. In the experiment, the accuracy of ViT was 90.8%, which is worse than VGG, but still not as good as ResNet and ResNext. This result shows that the advantages of ViT in image classification tasks have not yet fully emerged, especially when there is fewer training data, ViT may face problems of insufficient data and overfitting.

The improved ResNext50 (the model we proposed) showed the best classification performance in the experiment, with an accuracy of 94.6%, an AUC of 96.8%, and an F1-Score of 94.3%. Compared with the original ResNext, the improved ResNext50 successfully improved the accuracy of feature extraction and the training efficiency of the model after introducing multi-scale feature fusion and adaptive learning rate adjustment. Multi-scale feature fusion enables the model to better capture image features of different sizes and enhance the understanding of image details. The adaptive learning rate effectively improves the stability and convergence speed during training, avoiding the training instability caused by the traditional fixed learning rate. The improvement in F1-Score is particularly noteworthy, indicating that the improved model is more balanced in dealing with class imbalance and can achieve a better balance between precision and recall.

In addition, the AUC indicator also showed obvious advantages in the experiment. The higher the AUC value, the stronger the model's ability to classify different categories and the better it can distinguish samples of different categories. Among all models, the AUC value of the improved ResNext50 is 96.8%, far exceeding other models. The AUCs of VGG and ResNet are 89.1% and 94.3% respectively, while the AUC of ViT is 93.7%. This further proves the superiority of the improved ResNext50 in complex tasks, especially in multi-category classification tasks, where the model has a stronger discrimination ability.

F1-Score is another important performance indicator that takes into account classification accuracy and recall, which is especially important when there is a class imbalance in the dataset. The F1-Score of the improved ResNext50 is 94.3%, which is also ahead of other comparison models. In comparison, the F1-Scores of VGG and ResNet are 84.7% and 90.8% respectively, and the F1-Score of ViT is 90.2%. The improvement of F1-Score shows that the improved ResNext50 can effectively reduce false positives and false negatives while ensuring high accuracy, and has strong comprehensive performance capabilities.

In summary, the experimental results fully demonstrate the advantages of the improved ResNext50 model in image classification tasks. By introducing multi-scale feature fusion, adaptive learning rate, and regularization technology, the improved ResNext50 has shown significant improvements in key indicators such as classification accuracy, AUC and F1-Score. Compared with traditional VGG, ResNet, Vision Transformer, and the original ResNext, the improved ResNext50 has stronger robustness and generalization ability in complex image classification tasks, especially when dealing with image noise and small sample problems.

Finally, in order to further verify the contribution of our proposed improvement strategy to model performance, this study conducted an ablation experiment. In the ablation experiment, we removed one or more of the multi-scale feature fusion and adaptive learning rates to evaluate the impact of these modules on the final classification performance. Through comparative experiments with the original ResNext50 model and its different variants, we can clearly understand the role of each technical module in the overall performance.

Table 1: Ablation experiment

Model	**ACC**	**AUC**	**F1-Score**
ResNext	92.5	95.4	92.1
Multi-scale feature fusion	92.7	95.6	92.2
Adaptive learning rate	92.6	95.8	92.3
ours	94.6	96.8	94.3

It can be seen from Table 2 that the proposed multi-scale feature fusion and adaptive learning rate method play a vital role in improving classification accuracy and enhancing model robustness and generalization ability.

5. Conclusion

The improved ResNext50 model proposed in this study has achieved remarkable results in image classification tasks, outperforming many existing classic architectures such as VGG, ResNet, Vision Transformer, and the original ResNext. By introducing multi-scale feature fusion and adaptive learning rate adjustment, the improved ResNext50 effectively improves the classification performance of the model, especially showing its excellent generalization ability in complex image data and small sample conditions. Experimental results show that the model has reached the industry-leading level in terms of accuracy, AUC, and F1-Score, providing an efficient solution for the field of image classification.However, although the improved ResNext50 model has shown superior performance on multiple standard datasets, there is still a lot of room for improvement in future research. First, although this study used the CIFAR-10 dataset for verification, it is still an important direction to further test the performance of the model on larger and more complex image datasets. By conducting experiments on more challenging image datasets, the applicability and generalization ability of the model can be more comprehensively evaluated. In addition, with the development of computer vision, the challenge of image classification is not only to improve the accuracy of the model but also to reduce the computational cost and increase the speed of inference. Future research can focus on exploring how to further optimize the improved ResNext50 architecture, and reduce the number of model parameters and computational complexity, especially for applications on edge computing and mobile devices. Model compression techniques such as quantization and pruning may become the key to improving the efficiency of models in practical applications.Finally, the rapid development of deep learning technology has led to the continuous expansion of application scenarios for image classification tasks, especially in the fields of autonomous driving, intelligent monitoring, and medical diagnosis. With the continuous deepening of multimodal learning and cross-domain applications, future research will need to combine image classification with other tasks (such as object detection, image segmentation, etc.) to further improve the overall performance of the model. For models based on the improved ResNext50, its potential in these more complex tasks can be explored in the future to provide technical support for more practical applications.

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