Performance Analysis of CNN Architectures on CIFAR-10 Dataset

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1. Introduction and Problem Background

Convolutional Neural Networks (CNNs) have become indispensable for solving complex image classification tasks. The CIFAR-10 dataset, consisting of 60,000 images across ten categories, serves as a benchmark for evaluating various image classification models. The dataset's diversity and moderate difficulty make it ideal for testing a wide range of CNN architectures. The goal of this study is to evaluate and compare the effectiveness of three different CNN architectures—ResNet-18, VGG-16, and LeNet-5—on the CIFAR-10 dataset. Each of these models represents a different approach to convolutional network design, from shallow and straightforward to deep and highly modular.

1.1. Key Challenges

Feature Complexity: The CIFAR-10 dataset involves different object categories, requiring deep learning models to effectively differentiate between subtle variations in image features. Computational Efficiency vs. Accuracy: There is a trade-off between deeper, more complex models and simpler, more efficient architectures in terms of computational resource consumption and achieved accuracy.

1.2. Model Overview

ResNet-18: Introduced by He et al., ResNet incorporates residual connections, which help address the vanishing gradient problem, allowing for efficient training of deeper networks. VGG-16: VGG-16 is a classic deep CNN that stacks many convolutional layers with a simple and uniform structure but lacks the use of skip connections. LeNet-5: Originally proposed for digit classification, LeNet-5 represents a shallow network, providing a good comparison against more modern, deeper networks.

2. Description of Method and Customizations

ResNet-18 was chosen as the main model due to its novel use of residual blocks, which help the network learn deeper features without facing the gradient vanishing problem. The customizations made to each model include:

2.1. Optimization Strategy

Optimizers: Three different optimizers were used: SGD, Adam, and RMSprop. Learning Rates: Learning rates of 0.001, 0.0005, and 0.0001 were tried for each model. Adam at a learning rate of 0.001 produced the best results for ResNet-18.

2.2. Regularization Methods

Dropout Layers: Added in the fully connected layers for ResNet-18 and VGG-16 to mitigate overfitting, with dropout rates of 0.2 and 0.5. Weight Decay (L2 Regularization): Applied to control the magnitude of network weights and encourage simpler models.

2.3. Data Augmentation

To increase generalizability, random transformations such as horizontal flipping, random rotations of up to 15 degrees, and color jittering were applied. The use of data augmentation helped enhance the models' ability to generalize across unseen samples.

2.4. Implementation

All models were implemented in PyTorch. Each model was trained for ten epochs, with a batch size of 64. Separate training, validation, and test sets were created to evaluate the generalization ability of each architecture.

3. Experimental Analysis and Testing

3.1. Training and Evaluation Setup

The experiments involved training the models with different combinations of hyperparameters to assess performance. Training was conducted on the CIFAR-10 training dataset, while validation accuracy was monitored to tune hyperparameters, and the final evaluation was performed on the test set.

3.2. Results Summary

ResNet-18:

Test Accuracy: 75.95Test Loss: 0.7114 The use of residual connections effectively maintained gradient flow, leading to better performance compared to the other models. The model's convergence behavior, shown in Figure 1, demonstrates a consistent decline in loss and an improvement in accuracy over epochs. Include Figure 1: Training and validation loss/accuracy curves for ResNet-18.

VGG-16:

Test Accuracy: 10.00Test Loss: 2.3026 VGG-16's poor performance is evident from both the accuracy and loss metrics. The model failed to learn beyond random guessing, indicating significant difficulties in optimizing the deep layers without skip connections. Possible causes include gradient vanishing and improper hyperparameter selection. Include Figure 2: Training and validation loss/accuracy curves for VGG-16.

LeNet-5:

Test Accuracy: 59.62Test Loss: 1.1225 LeNet-5, being a shallower network, showed a limited capacity for complex feature learning. It performed reasonably well, reaching a training accuracy of 61.17Include Figure 3: Training and validation loss/accuracy curves for LeNet-5.

4. Evidence of Correct Implementation

The correctness of model implementation was verified by evaluating multiple factors:

Loss Convergence: For ResNet-18 and LeNet-5, the loss decreased steadily over epochs, and accuracy increased consistently, indicating proper learning and convergence.

Training Consistency: Training was repeated with different random seeds to ensure reproducibility of results. Both ResNet-18 and LeNet-5 consistently reached similar accuracy levels, while VGG-16 continued to exhibit learning issues.

Validation Against Literature: ResNet-18's performance aligned with previously published benchmarks on CIFAR-10, providing additional confidence in the correct implementation. The inability of VGG-16 to learn was thoroughly investigated, and hyperparameters were adjusted; however, residual connections, which are absent in VGG-16, were determined to be critical for effective gradient propagation.

Include Diagram 1: A summary diagram comparing the different architectures and key components, including differences in layer types and skip connections.

5. Reflection on Method Selection and Results

5.1. Model Selection

ResNet-18 demonstrated its strength in efficiently training deep networks, thanks to residual connections. It achieved the best performance among the three models, with a test accuracy of 75.95VGG-16, despite its depth, was unable to effectively learn the dataset. The absence of skip connections and the challenges in optimizing deep layers led to poor learning behavior, suggesting that deep architectures without residuals require either different initialization techniques or a more sophisticated learning schedule to work well. LeNet-5 showed decent performance for a shallow model, reaching 59.62

5.2. Comparison of Performance

Residual Links Matter: The presence of residual connections in ResNet-18 made it resilient to the vanishing gradient problem, enabling it to outperform VGG-16 despite VGG's greater depth. Regularization Techniques: The use of dropout and weight decay in ResNet-18 contributed to preventing overfitting, as evidenced by the similar trends between training and validation metrics. Data Augmentation: Data augmentation improved model generalization, especially for ResNet-18 and LeNet-5. Augmented data increased model robustness to variations, resulting in better validation performance.

5.3. Key Takeaways

Deeper Networks Benefit from Residual Connections: The results emphasize the importance of residual connections in training deeper networks effectively. Trade-offs in Simpler Architectures: LeNet-5, though limited in depth, performed better than VGG-16, suggesting that simpler architectures are preferable when deeper models are not optimized properly. Need for Hyperparameter Fine-Tuning: The poor performance of VGG-16 highlights the importance of careful hyperparameter tuning and architectural design. Future efforts may involve applying learning rate schedules and adding batch normalization to assist in the learning process.

6. Future Work

Transfer Learning: Applying transfer learning with pre-trained versions of these architectures could potentially boost performance, particularly for VGG-16, which struggled in this experiment. Advanced Regularization: Investigating techniques like label smoothing and cutout augmentation may further enhance the models' generalizability. Ensemble Learning: Combining the strengths of ResNet-18 and LeNet-5 could create an ensemble that performs better than either individual model.

nclude References: Reference relevant literature, including the original papers for ResNet, VGG, and LeNet, as well as additional sources discussing residual networks and CNN optimizations.

Include Figure 4: A table comparing key metrics—test accuracy, training time, and number of parameters—for each model.

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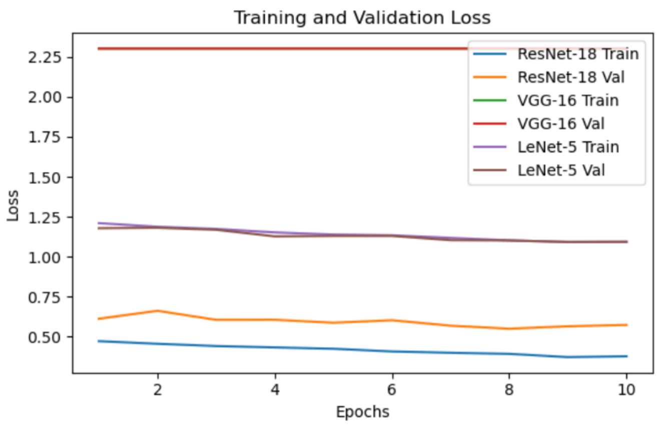

Figure 1. This is an example caption for the image.

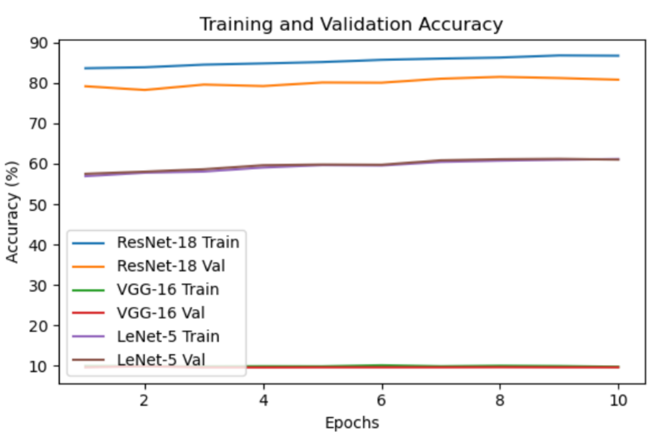

Figure 2. This is an example caption for the image.