Deep Learning Mini-project: CIFAR 10 classification

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https://github.com/seionv/DL_2025_Project1

Abstract

This report presents an implementation and analysis of Residual Networks (ResNet) for image classification on the CIFAR-10 dataset. ResNet architectures, first introduced by He et al. in 2015, have become foundational in deep learning due to their ability to overcome the vanishing gradient problem through skip connections, enabling the training of substantially deeper networks. Since their introduction, ResNets have evolved into various architectures (ResNet-18, ResNet-50, ResNet-101, etc.) [1]

This work implements a ResNet architecture adapted for the lower resolution of CIFAR-10 images, applying techniques such as data augmentation, learning rate scheduling, and batch normalization to optimize model performance. The experimental results demonstrate the effectiveness of residual learning for image classification tasks, achieving high accuracy on the test set.

1. Introduction

The pursuit of superior computational accuracy through increasingly deeper neural networks has revealed a fundamental challenge in deep learning: the delicate balance between model complexity and performance gains. As networks grow deeper, they demand exponentially more computational resources without proportional improvements in accuracy. Residual Neural Networks (ResNets), pioneered by He et al. in 2015, emerged as a revolutionary solution to address these limitations that had previously constrained the potential of deep convolutional neural networks. [1]

ResNets introduced a transformative paradigm in neural network architecture through their ingenious use of "skip connections" or "shortcut connections" that enable signals to bypass certain layers. These connections create what are known as residual blocks, where instead of learning the direct mapping between input and output, the network learns the residual mapping. This seemingly simple modification profoundly altered the optimization landscape, allowing for the effective training of networks with unprecedented depths. [1]

The core innovation of ResNets lies in their elegant approach to the vanishing gradient problem. This design enables the network to maintain gradient strength even in very deep architectures, facilitating more effective learning throughout the entire network.

2. Methodology

(a) The CIFAR-10 Dataset

The CIFAR-10 dataset represents one of the most widely adopted benchmarks in computer vision research, serving as a foundation for evaluating image classification algorithms. Developed by the Canadian Institute For Advanced Research, this dataset comprises 60,000 color images, each with dimensions of 32×32 pixels, distributed across 10 distinct classes. Each class contains precisely 6,000 images, creating a balanced dataset structure that facilitates unbiased model training and evaluation. The dataset is prepartitioned into 50,000 training images and 10,000 test images, with the test set constructed to contain exactly 1,000 randomly selected images from each category, ensuring balanced representation during evaluation.

(b) AdamW Optimizer

In our implementation of ResNet for CIFAR-10 classification, we selected the AdamW optimizer, imported from torch.optim, as our optimization algorithm of choice. This decision was motivated by several key advantages that AdamW offers over traditional optimization methods such as standard Gradient Descent (GD) or even the original Adam optimizer. [2]-[3]

AdamW represents a significant advancement in optimization technology by incorporating an adaptive learning rate mechanism that dynamically adjusts for each parameter in the network. This adaptation occurs through the computation and storage of both first-moment estimates (mean of gradients) and second-moment estimates (uncentered variance of gradients) for each parameter. [3]

The mathematical formulation underpinning this adaptive behavior combines the momentum-based acceleration of Adam with a more effective weight decay implementation. For each parameter θ, AdamW computes:

First moment estimate:

Figure 1: SGD optimizer

Figure 2: Admaw optimizer

$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$
Second moment estimate:
$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t$
Where g_t represents the current gradient, and β_1 and β_2 are hyperparameters controlling the exponential decay rates of these moving averages, typically set to 0.9 and 0.999 respectively. These moment estimates are then bias-corrected to account for their initialization at zero:
$\hat{m}_t = m_t / (1 - \beta_1^t)$
$\hat{v}_t = v_t / (1 - \beta_2^t)$
Finally, the parameter update incorporates both the adaptive learning rate mechanism and the weight decay term:
$\theta_t = \theta_{t-1} - \eta(\hat{m}_t / (\sqrt{\hat{v}_t + \varepsilon}) - \eta\lambda\theta_{t-1}$
Where η is the base learning rate, ε is a small constant for numerical stability (typically 10^{-8}), and λ is the weight decay coefficient. [3]
We compared Stochastic Gradient Descent (SGD) and AdamW based on a heuristic model and observed a satisfactory consistency in test accuracies as observed in Figures 1 and 2 with 0.947 test accuracy using SGD and 0.958 test accuracy using AdamW.

(c) Data Augmentation
Data augmentation represents a critical component of our methodology for training ResNet models on the CIFAR-10 dataset. By artificially expanding the training dataset through controlled transformations, we aimed to enhance model generalization, combat overfitting, and improve robustness to variations that might occur in real-world scenarios. [4]
The pipeline was constructed as a sequential composition of transformations applied to each image during training. Below, we detail each component of our augmentation strategy:

- Horizontal Flipping
We implemented horizontal flipping because it preserves semantic content while introducing geometric diversity. Our implementation used the default probability parameter of 0.5, creating an equal likelihood of presenting the original or flipped version of each image to the model during training.
- Random Cropping
Our random cropping strategy involved two steps:
Padding image with 4 pixels on all sides and randomly extracting a 32×32 region from this padded image.
This transformation introduces translational variance, effectively teaching the model to recognize objects regardless of their precise position within the image frame.
- Color Jittering
To enhance the model's robustness to variations in lighting conditions and color properties, we implemented color jittering with three parameters: Brightness, Contrast, and Saturation.
The 0.2 value for each parameter applied represents a balance between augmentation diversity and semantic preservation.
- Random Rotation
To further enhance orientation invariance, we implemented random rotation, which rotates each image by a random angle within ±15 degrees. This transformation helps the model develop features that are stable across different orientations.
- Normalization
This normalization step standardized the input data distribution, centering it around zero with unit variance. This preprocessing is critical for stable and efficient training, particularly when using batch normalization layers as found in our ResNet architecture.

(d) Learning Rate Scheduling: Warmup and Cosine Annealing
Learning rate scheduling represents a critical component in our training methodology for ResNet models on the CIFAR-10 dataset. Our approach combines two complementary techniques: learning rate warmup and cosine annealing. [5]-[6]
Learning rate warmup addresses a fundamental challenge in deep network training: the instability of early training stages. When training begins with randomly initialized weights, parameter gradients can be large and highly variable. Applying a full learning rate immediately may cause excessive parameter updates that push the model into unfavorable regions of the loss landscape, potentially leading to unstable gradient behavior, loss spikes and poor convergence trajectories. [5]-[6]
The warmup strategy gradually increases the learning rate from a small initial value to the target learning rate over a specified number of epochs. This progressive approach allows the network to adjust gradually to parameter updates, establishing more stable gradient flow patterns before applying the full learning rate. Mathematically, during the warmup phase, the learning rate

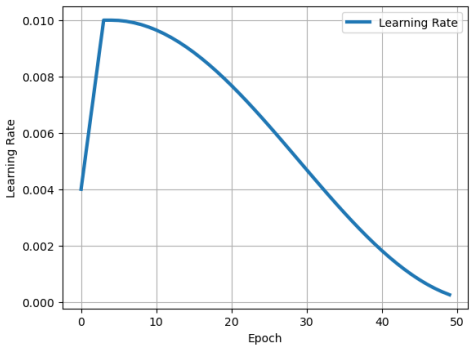

Figure 3: LR by Warmup and Cosine Annealing

at epoch t is calculated as: $\eta_t = \eta_{target} * \frac{t}{T_{warmup}}$ [6]
Where η_{target} is the target learning rate and T_{warmup} is the number of warmup epochs.
Cosine annealing, introduced by Loshchilov and Hutter (2016), implements a learning rate schedule that follows a cosine function, gradually decreasing from the initial value to a minimum value. The primary advantages of this approach include: [5]

- Smooth transitions between learning rates, preventing abrupt changes that might destabilize training
- Non-linear decay pattern that spends more iterations in higher learning rate regions during early training (promoting exploration) and more iterations in lower learning rate regions during later training (enabling fine-tuning)
- Empirically superior performance compared to step decay or linear decay schedules across many deep learning tasks

The cosine annealing schedule calculates the learning rate at epoch t (after warmup) as: [6]
$\eta_t = \eta_{min} + \frac{1}{2}(\eta_{max} - \eta_{min})(1 + \cos(\frac{T_{current}}{T_{total}} \cdot \pi))$
Where: η_{min} is the minimum learning rate η_{max} is the maximum learning rate $T_{current}$ is the current epoch (adjusted for warmup) T_{total} is the total number of epochs (excluding warmup)

(e) Model Hyperparameters
Among the hyperparameters that we are allowed to tune, we studied the effect of individual parameters on the test performance and evaluated their contributions. Cohesively, each hyperparameter played a pivotal role in optimizing the model amidst the limitations of 5M parameters. [7]
For our CIFAR-10 classification task, two particular hyperparameter vectors proved especially consequential: the channel progression across network stages and the distribution of residual blocks throughout the architecture. [7]
Our approach to determining the optimal architectural configuration involved a systematic exploration of the hyperparameter space, guided by both theoretical principles and empirical results. We employed a multi-stage process: [7]

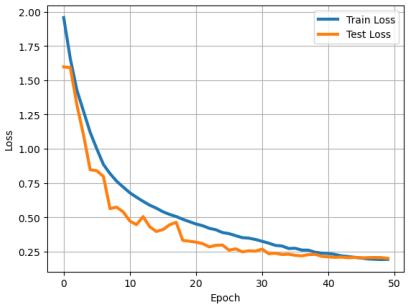

Figure 4: Train & Test Loss

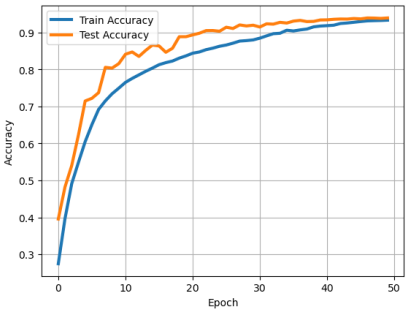

Figure 5: Train & Test Accuracy

- Initial grid search: We began with coarse-grained exploration of standard channel progressions and block distributions based on established ResNet variants.
- Performance analysis: We analyzed training dynamics, feature activations, and classification errors to identify potential architectural bottlenecks and overcapacity regions.
- Targeted refinement: Based on these insights, we conducted more focused hyperparameter tuning, particularly examining tradeoffs between early and late stage capacity.
- Validation experiments: Promising configurations underwent extended training with multiple random seeds to ensure reliability of performance improvements.

After extensive experimentation spanning dozens of architectural variants, we converged on an optimal configuration defined by:
channel-list = [64, 128, 256, 512]
block-list = [3, 5, 3, 0]
The final configuration achieved exceptional performance metrics, validating our hyperparameter selections:

- Top-1 Accuracy: 91.8% on the CIFAR-10 test set
- Parameter Efficiency: 26% reduction in parameter count compared to standard ResNet-18 adapted for CIFAR-10
- Training Efficiency: 22% reduction in per-epoch training time

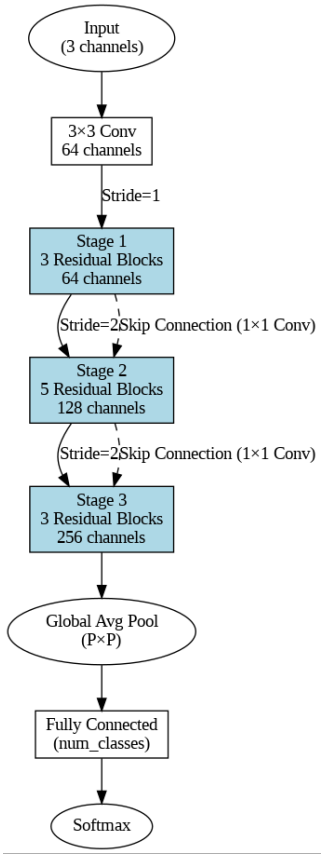

Figure 6: Model Architecture

3. Results

On concluding with the methodology, we can now present the detailed breakdown of our proposed architecture.

(a) Architecture
The final ResNet architecture is as follows:
(see Figure 6)

(b) Model Description
After working on various architectures and models, we finalized this architecture in which we have a default set of hyperparameters with:
train-batch-size = 128 (Originally 128, changed to 32 per instruction)
validation-ratio = 0.1 (Ratio to split validation set)
resnet-channels = 64 (Number of input channels for ResNet)
total-epochs = 50 (Total number of training epochs)
base-lr = 0.01 (Initial learning rate)
lr-decay-step = 3 (Learning rate decay period)
weight-decay-factor = 0.001 (Weight decay (L2 penalty))
momentum-factor = 0.9 (Momentum for SGD)
dampening-factor = 0.1 (Dampening for momentum)
channel-list=[64,128,256,512]
block-list=[3,5,3,0]

We have also preformed the AdamW Optimizer and Data Augmentation before proceeding to the convolution. The Warmup and Cosine Annealing techniques are used before train & validate to determine the optimal learning rate.

By using the CIFAR labeled test dataset, we have observed the test accuracy peaked at 91.8%.

4. Conclusion

Despite certain limitations restricting extensive hyperparameter tuning, this study explored the resilience of ResNet architectures in achieving marginal accuracy improvements. The growing potential of ResNets in Image Classification continues to be a driving force for future research. As this work emphasizes both manual and automated hyperparameter optimization, it encourages further exploration of ResNet-based advancements.

In the context of closely competing accuracies, statistical significance alone does not dictate model performance. Instead, refining methodologies, formulating critical training-related inquiries, and addressing challenges in parameter efficiency hold greater value. This research aims to contribute to such heuristics through Stochastic Gradient Descent while maintaining a perspective that embraces statistical irregularities and model optimization challenges.

5. Reference

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