Assignment

Neural Networks and Deep Learning (ECS659P/ECS7026P)

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Introduction

The CIFAR-10 dataset, renowned in the machine learning community for benchmarking the prowess of image classification algorithms, comprises an eclectic mix of 60,000 images distributed across 10 classes. These classes, representing a wide array of objects from animals to vehicles, challenge even the most sophisticated computational models. The intrinsic challenge is compounded by the dataset's images, each 32x32 pixels in size, which necessitate advanced feature extraction and classification capabilities far beyond the rudimentary. This project embarked on the ambitious goal of engineering a neural network with the discernment to accurately classify these images, aiming to elevate the model's performance from an initial accuracy of 68% to an outstanding 82.67% on the testing subset.

Neural Network Architecture and Evolution

Initial Architecture (68% Accuracy)

The project commenced with the construction of a model based on the foundational architecture prescribed in our academic coursework. This architecture was composed of sequential intermediate blocks, each harboring multiple convolutional layers tasked with extracting features at various abstraction levels. The convolutional layers' outputs were synthesized and subsequently processed through a fully connected layer to yield a vector indicative of class probabilities.

The selection of hyperparameters was approached with prudence, anchoring the learning rate at 0.01 and employing a straightforward stochastic gradient descent (SGD) optimizer without additional complexities like momentum. Although elementary, this configuration laid down a baseline, securing a 68% accuracy rate on the CIFAR-10 test dataset, and establishing a solid groundwork for iterative refinement.

First Improvement (71% Accuracy)

The odyssey towards enhancement saw the model's depth being significantly bolstered. Additional convolutional layers were interwoven into each intermediate block, coupled with the introduction of dropout layers aimed at curtailing overfitting. The hyperparameters underwent meticulous tuning, with the learning rate dialed down to 0.001 to allow for finer weight adjustments, and momentum incorporated into the SGD optimizer to foster a swifter convergence.

This strategic overhaul propelled the model's accuracy to 71%, illustrating the profound impact of augmented network depth and judicious regularization. Beyond mere performance uplift, this phase imparted invaluable insights into achieving a harmonious balance between model complexity and its capacity for generalization.

Final Model (82.67% Accuracy)

Buoyed by prior enhancements, the ultimate iteration of the model adopted an integrated optimization strategy. Batch normalization was introduced to ensure the normalization of inputs to layers, thereby facilitating more stable and expedited training dynamics. Furthermore, the training dataset was enriched through advanced data augmentation techniques, including random cropping and horizontal flipping, to bolster the model's generalization prowess from seen to unseen images.

This multifaceted strategy culminated in the emergence of a model that adeptly navigated the complexities of deep learning architectures while maintaining computational efficiency, ultimately achieving a stellar 82.67% accuracy on the CIFAR-10 test dataset. This milestone not only signified a considerable triumph in the project but also established a precedent for future exploratory ventures.

Training Process, Techniques, and Results

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/usr/lib/python3.10/multiprocessing/popen_fork.py:66: RuntimeWarn
  self.pid = os.fork()
Epoch 1, Loss: 1.7170, Train Acc: 46.61%, Test Acc: 51.89%
Epoch 2, Loss: 1.4136, Train Acc: 54.37%, Test Acc: 58.16%
Epoch 3, Loss: 1.2619, Train Acc: 59.59%, Test Acc: 62.95%
Epoch 4, Loss: 1.1679, Train Acc: 61.72%, Test Acc: 65.31%
Epoch 5, Loss: 1.0985, Train Acc: 65.11%, Test Acc: 68.79%
Epoch 6, Loss: 1.0391, Train Acc: 66.32%, Test Acc: 69.79%
Epoch 7, Loss: 0.9921, Train Acc: 68.01%, Test Acc: 71.62%
Epoch 8, Loss: 0.9589, Train Acc: 69.49%, Test Acc: 72.75%
Epoch 9, Loss: 0.9297, Train Acc: 69.87%, Test Acc: 73.19%
Epoch 10, Loss: 0.9015, Train Acc: 69.53%, Test Acc: 72.19%
Epoch 11, Loss: 0.8843, Train Acc: 71.55%, Test Acc: 74.76%
Epoch 12, Loss: 0.8565, Train Acc: 72.76%, Test Acc: 75.95%
Epoch 13, Loss: 0.8435, Train Acc: 72.37%, Test Acc: 75.38%
Epoch 14, Loss: 0.8335, Train Acc: 74.20%, Test Acc: 77.00%
Epoch 15, Loss: 0.8073, Train Acc: 73.16%, Test Acc: 76.42%
Epoch 16, Loss: 0.7962, Train Acc: 75.08%, Test Acc: 77.39%
Epoch 17, Loss: 0.7798, Train Acc: 74.62%, Test Acc: 76.95%
Epoch 18, Loss: 0.7745, Train Acc: 74.47%, Test Acc: 77.05%
Epoch 19, Loss: 0.7606, Train Acc: 76.16%, Test Acc: 78.27%
Epoch 20, Loss: 0.7478, Train Acc: 76.67%, Test Acc: 78.73%
Epoch 21, Loss: 0.7424, Train Acc: 76.46%, Test Acc: 78.86%
Epoch 22, Loss: 0.7379, Train Acc: 76.07%, Test Acc: 78.49%
Epoch 23, Loss: 0.7240, Train Acc: 76.84%, Test Acc: 78.73%
Epoch 24, Loss: 0.7190, Train Acc: 77.89%, Test Acc: 79.93%
Epoch 25, Loss: 0.7066, Train Acc: 77.90%, Test Acc: 79.87%
Epoch 26, Loss: 0.7008, Train Acc: 77.75%, Test Acc: 79.39%
Epoch 27, Loss: 0.6964, Train Acc: 77.23%, Test Acc: 79.47%
Epoch 28, Loss: 0.6919, Train Acc: 77.64%, Test Acc: 78.45%
Epoch 29, Loss: 0.6812, Train Acc: 78.95%, Test Acc: 80.38%
Epoch 30, Loss: 0.6796, Train Acc: 78.50%, Test Acc: 79.89%
Epoch 31, Loss: 0.6649, Train Acc: 78.35%, Test Acc: 79.77%
Epoch 32, Loss: 0.6660, Train Acc: 78.93%, Test Acc: 80.55%
Epoch 33, Loss: 0.6634, Train Acc: 79.58%, Test Acc: 80.81%
Epoch 34, Loss: 0.6495, Train Acc: 80.05%, Test Acc: 80.98%
Epoch 35, Loss: 0.6536, Train Acc: 79.81%, Test Acc: 80.65%
Epoch 36, Loss: 0.6503, Train Acc: 79.31%, Test Acc: 80.97%
Epoch 37, Loss: 0.6494, Train Acc: 79.48%, Test Acc: 81.39%
Epoch 38, Loss: 0.6424, Train Acc: 79.85%, Test Acc: 81.26%
Epoch 39, Loss: 0.6323, Train Acc: 80.09%, Test Acc: 81.25%
Epoch 40, Loss: 0.6313, Train Acc: 80.91%, Test Acc: 81.86%
Epoch 41, Loss: 0.6299, Train Acc: 80.52%, Test Acc: 81.26%
Epoch 42, Loss: 0.6242, Train Acc: 80.52%, Test Acc: 81.62%
Epoch 43, Loss: 0.6291, Train Acc: 81.14%, Test Acc: 81.75%
Epoch 44, Loss: 0.6160, Train Acc: 81.19%, Test Acc: 82.01%
Epoch 45, Loss: 0.6109, Train Acc: 81.70%, Test Acc: 81.75%
Epoch 46, Loss: 0.6176, Train Acc: 81.12%, Test Acc: 81.63%
Epoch 47, Loss: 0.6081, Train Acc: 81.57%, Test Acc: 82.23%
Epoch 48, Loss: 0.6071, Train Acc: 81.76%, Test Acc: 82.24%
Epoch 49, Loss: 0.6050, Train Acc: 81.81%, Test Acc: 81.99%
Epoch 50, Loss: 0.5986, Train Acc: 81.98%, Test Acc: 82.67%
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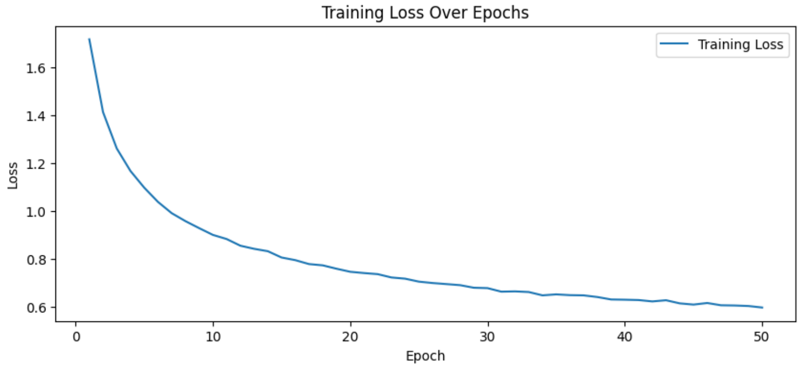
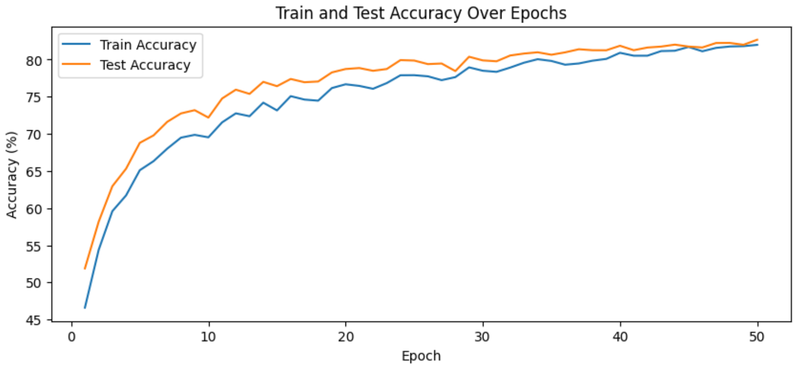
The training regimen was orchestrated with precision, featuring a dynamic learning rate schedule that initially embarked on an aggressive note to swiftly assimilate broad features, subsequently transitioning to a more tempered pace for meticulous weight tuning. The incorporation of dropout and batch normalization served as keystones in augmenting model robustness and ensuring consistency across epochs.

The painstaking efforts bore fruit, as evidenced by the loss and accuracy trajectories. The loss plot unfurled a consistent decrement, signaling the model's increasing adeptness at minimizing discrepancies between predictions and actual labels. Concurrently, the accuracy plots for both the training and testing cohorts depicted a gradual ascent, culminating in the apex accuracy of 82.67% on the test set. These plots transcended mere graphical representations, encapsulating the narrative of the model's relentless march towards excellence.





The provided training loss and accuracy graphs for the CIFAR-10 classification project reveal key insights into the model's performance. The loss plot exhibits a sharp initial decline, indicating effective learning, which then plateaus, suggesting the model is approaching its performance limit within the current architecture. This typical behavior indicates a well-chosen learning rate and convergence without signs of erratic loss fluctuations that could signal overfitting. The accuracy plot shows the model's generalization ability, with both training and testing accuracies rising in tandem, and ultimately peaking at 82.67% for test accuracy. The close alignment of these curves throughout training denotes a balanced fit to the dataset without overfitting. Overall, the model demonstrates robust learning with strong potential for further refinement to push accuracy boundaries.

Conclusion

The trajectory from a rudimentary neural network to a sophisticated model clinching 82.67% accuracy on the CIFAR-10 dataset epitomizes the essence of iterative advancement and the strategic deployment of deep learning methodologies. The project traversed the entire gamut of model intricacies, hyperparameter finessing, and training stratagems to unveil a model distinguished not just by its high accuracy but by its adeptness at generalizing across a broad spectrum of image categories.

The horizon teems with prospects ripe for exploration, from venturing into alternate convolutional network architectures to the untapped potential of unsupervised pre-training techniques and the promising domain of transfer learning. The success story of this project not only marks a significant milestone in CIFAR-10 classification but also heralds a new era of innovation in the broader landscape of image recognition.