Deep Learning Experiments on CIFAR-10

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1 Introduction

The CIFAR-10 dataset is a widely used benchmark for image classification. In this report, we explore several deep learning techniques:

- Training an autoencoder for feature extraction and visualization.
- Comparing autoencoder features with those from a supervised CNN.
- Training a denoising autoencoder.
- Training CNN classifiers with and without data augmentation.

2 Task 1: Autoencoder as a 2D Feature Generator

2.1 Methodology

A convolutional autoencoder was trained on CIFAR-10. The encoder's output was used as a compressed feature representation. t-SNE was applied to project these features into 2D for visualization.

2.2 Findings

The t-SNE plot of autoencoder features showed some clustering by class, but clusters were not well-separated. This indicates that the autoencoder's latent space is not highly discriminative for class labels.

2.3 Analysis

Autoencoders optimize for reconstruction, not class separation. Thus, their features capture general image structure but are suboptimal for classification.

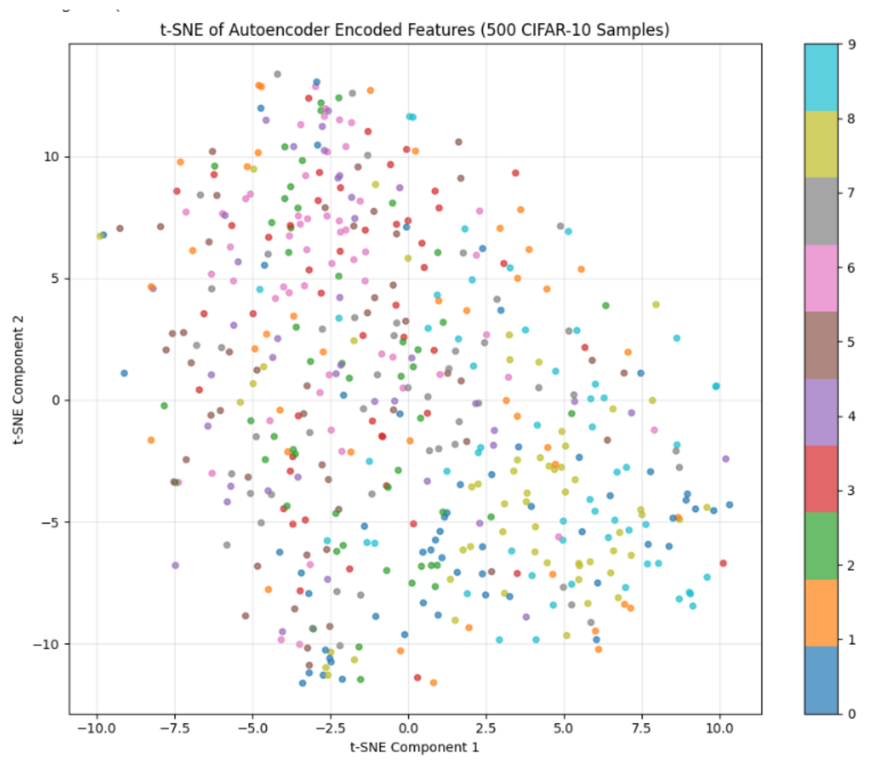

Figure 1: t-SNE visualization of autoencoder features.

3 Task 2: Comparing Autoencoder and CNN Features

3.1 Methodology

A custom CNN classifier was trained, and features were extracted from an intermediate dense layer. Both PCA and t-SNE were used for dimensionality reduction and visualization.

3.2 Findings

CNN features showed much clearer and more distinct clusters for each class in t-SNE plots compared to autoencoder features.

3.3 Analysis

Supervised CNNs learn features that are more discriminative for classification, as they are trained with class labels.

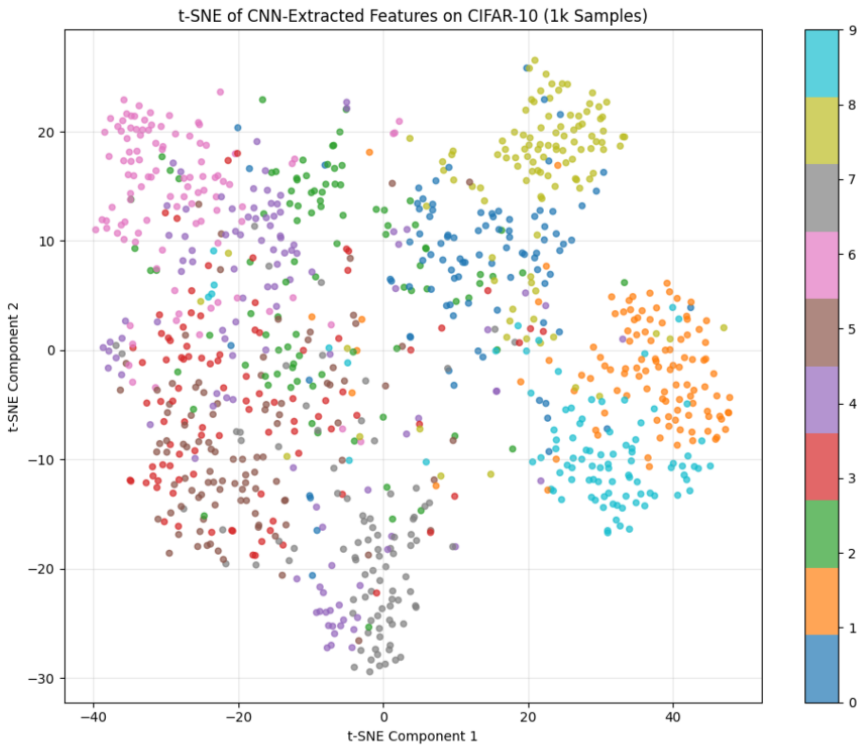

Figure 2: t-SNE visualization of CNN features.

4 Task 3: Denoising Autoencoder

4.1 Methodology

A denoising autoencoder was trained by adding Gaussian noise to images and training the model to reconstruct the original images.

4.2 Findings

The denoising autoencoder effectively removed noise and reconstructed images similar to the originals.

4.3 Analysis

Denoising autoencoders are useful for learning robust representations and can generalize to unseen noisy images.

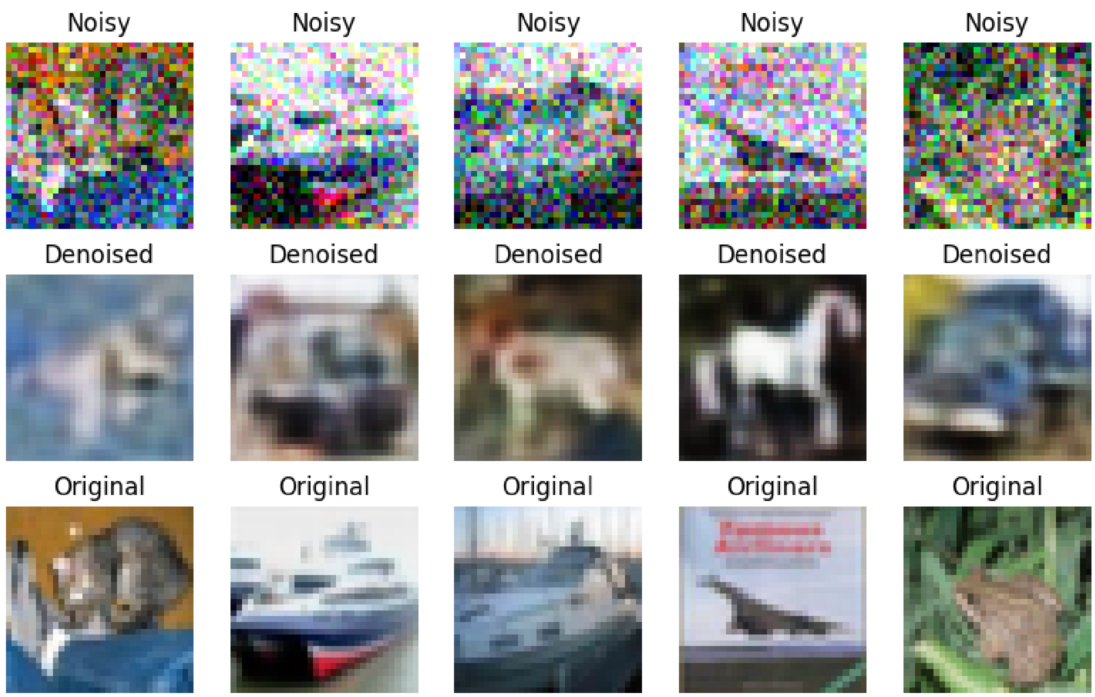

Figure 3: Noisy, denoised, and original images.

5 Task 4: CNN Classifier without Data Augmentation

5.1 Methodology

A CNN was trained on CIFAR-10 without data augmentation. Training and validation accuracy and loss were monitored.

5.2 Findings

The model achieved reasonable training accuracy but showed a gap between training and validation accuracy, indicating overfitting.

5.3 Analysis

Without data augmentation, the model is more likely to overfit and may not generalize well to new images.

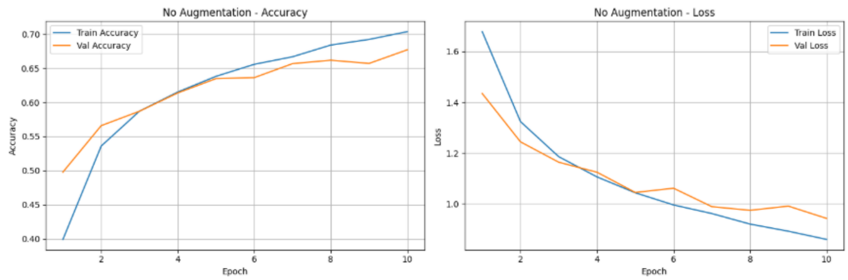

Figure 4: Training/validation accuracy and loss with augmentation.

6 Task 5: CNN Classifier with Data Augmentation

6.1 Methodology

The same CNN was trained with data augmentation (random rotations, shifts, flips).

6.2 Findings

The model with data augmentation achieved higher validation accuracy and lower validation loss. The gap between training and validation accuracy was reduced.

6.3 Analysis

Data augmentation increases the diversity of the training set, helping the model learn more robust features and generalize better.

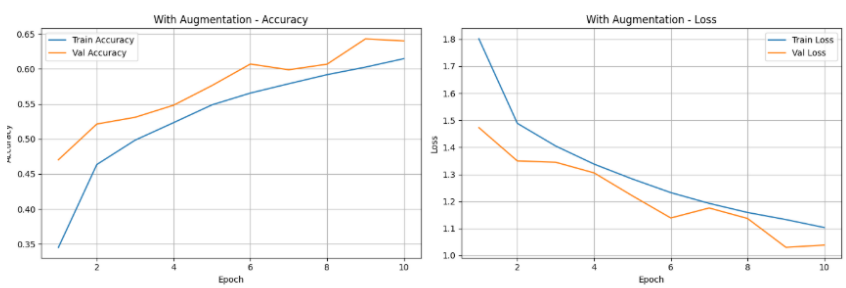

Figure 5: Training/validation accuracy and loss with augmentation.

7 Conclusion

- Autoencoders are effective for unsupervised feature learning and denoising, but not for classification.
- Supervised CNNs learn features that are well-suited for classification.
- Denoising autoencoders can reconstruct clean images from noisy inputs.

- Data augmentation significantly improves the generalization of CNN classifiers.

Code is in this link: Link