

Report on

Deep Learning Approaches for Feature Generation, Visualization, and Classification on CIFAR-10



Submitted by

Jannatun Ferdous
Student ID: 1912076147
Dept. of Computer Science and Engineering
University of Rajshahi

Contents

Problem 1	2
Problem 1: Autoencoder as a 2D Feature Generator	2
Problem2	2
Problem3	3
Problem4	4

Problem 1

Training an autoencoder as a 2D feature generator and displaying CIFAR10 dataset's features.

A convolutional autoencoder was trained on the CIFAR-10 dataset to compress 32×32 images into a 2-dimensional latent space. The encoder progressively reduced the spatial dimensions while increasing feature depth, and the decoder reconstructed the original image using transpose convolutions.

The model was trained for 10 epochs using the Adam optimizer and mean squared error (MSE) loss function.

After training, the encoder was used to transform the CIFAR-10 images into their corresponding 2D latent feature vectors.

The following figure shows a scatter plot of the 2D features. Each point represents an image and is colored according to its class label. The visible clustering indicates that the model has successfully learned separable and meaningful low-dimensional features.

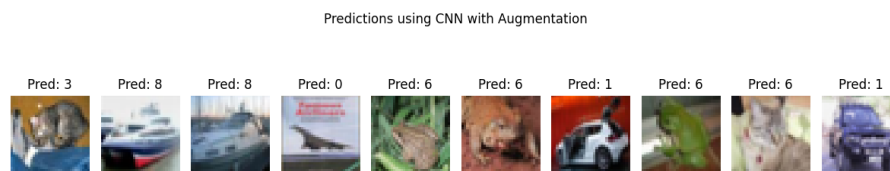


Figure 1: 2D feature vector generated by a segmentation model.

Problem2

Comparing autoencoder generated features with features extracted by a pre-trained CNN and reduced by dimension reduction techniques like PCA, t-SNE.

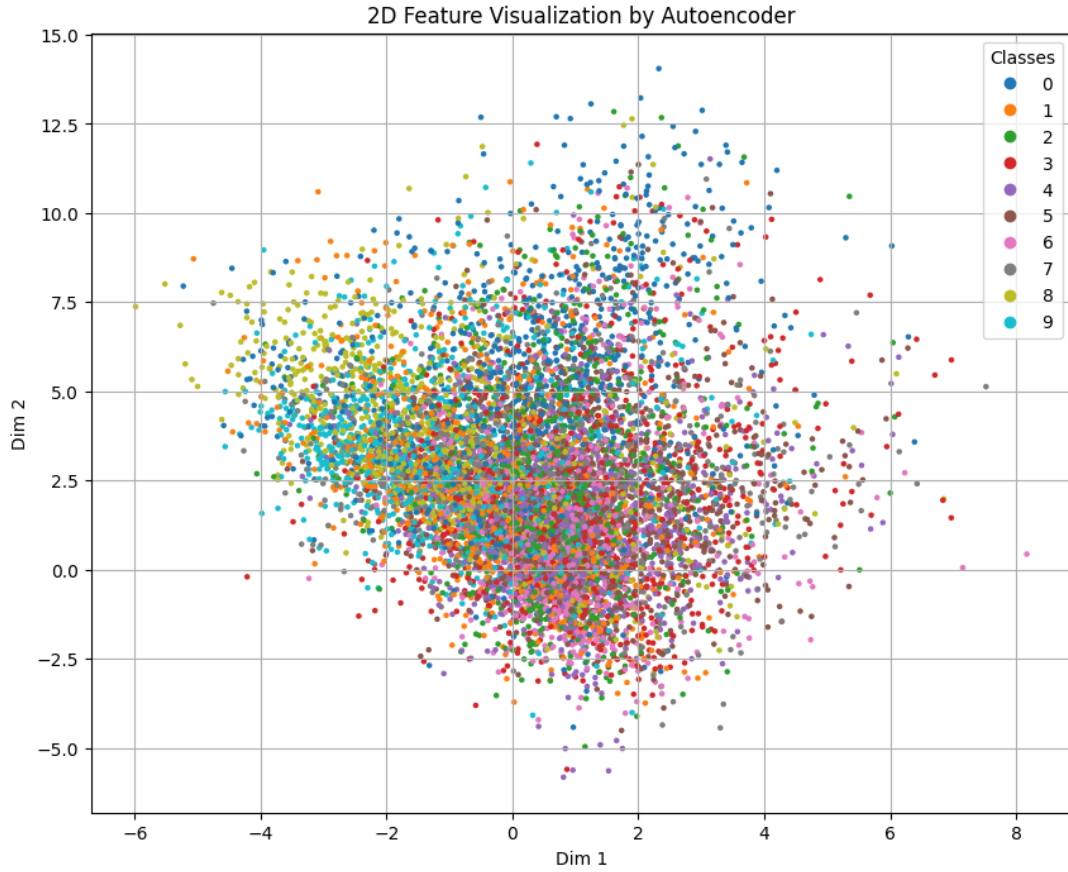


Figure 2: 2D latent space visualization of CIFAR-10 images colored by class.

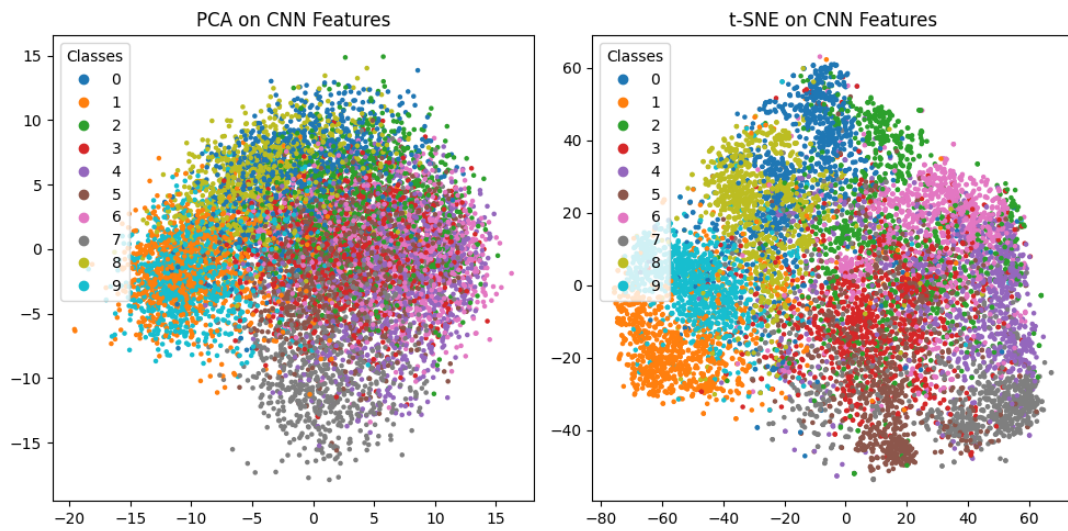


Figure 3: Visualization of CIFAR-10 images By PSA And T-SNE.

Problem3

Training a denoising autoencoder for CIFAR10 dataset.

The problem involves training a denoising autoencoder on the CIFAR10 dataset, which consists of 32x32 RGB images. The goal is to reconstruct clean images from noisy versions. Gaussian noise with a factor of 0.2 is added to the training and test sets, and the pixel values are clipped to ensure they remain within the valid range $[0, 1]$. The autoencoder architecture includes an encoder with two convolutional layers followed by max-pooling to reduce dimensionality, and a decoder with two upsampling layers to reconstruct the original image dimensions. The model uses ReLU activation for hidden layers and sigmoid for the final output, optimizing mean squared error (MSE) loss with the Adam optimizer. Training runs for 10 epochs with a batch size of 128, shuffling the data, and validating on the noisy test set. The training history, including loss metrics, is saved for further analysis. The approach aims to demonstrate the autoencoder's ability to learn robust features and effectively remove noise while preserving image structure.

Problem4

Training a CNN based CIFAR-10 classifier without and with any single-image data augmentation techniques. This experiment test the performance of a Convolutional Neural Network (CNN) trained on the CIFAR-10 dataset without any single-image data augmentation techniques. The model was trained for 10 epochs.

The CNN architecture consisted of three convolutional layers followed by max-pooling layers, leading to dense layers for classification. The Adam optimizer was used with sparse categorical cross-entropy loss.

The CNN architecture consisted of three convolutional layers followed by max-pooling layers, leading to dense layers for classification. The Adam optimizer was used with sparse categorical cross-entropy loss.

The model achieved a validation accuracy of approximately 70.03% after 10 epochs, indicating reasonable performance without data augmentation. There is a noticeable gap between training and validation accuracy, suggesting some degree of overfitting, which data augmentation typically helps to mitigate. Further improvements could involve regularization or deeper architectures.

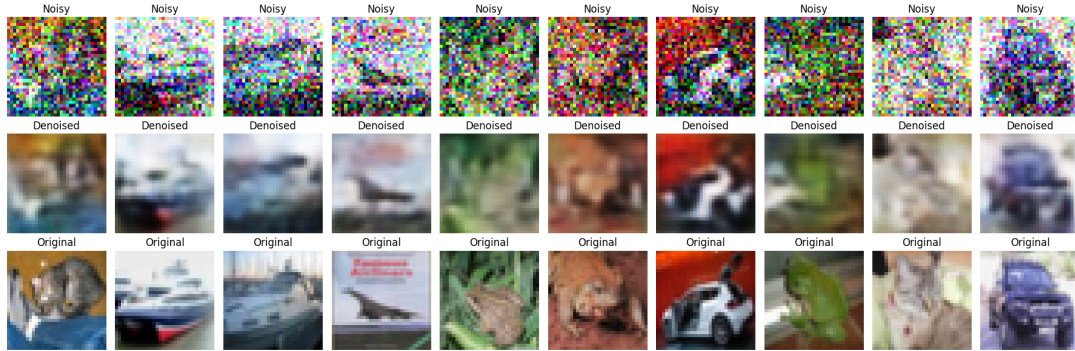


Figure 4: Sample Denoising results.

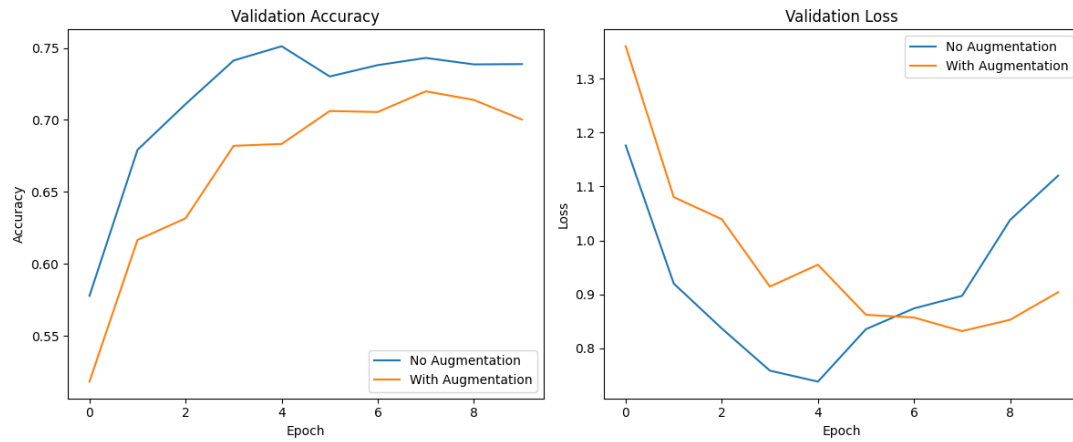


Figure 5: Training and validation metrics (Accuracy, Loss) without using augmentation.