**ICP-6**

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**GitHub Link**: <https://github.com/SreejaReddyKonda/Neural-Network-Sreeja/blob/main/Neural%20Networks/ICP-6/700756597_Autoencoders.ipynb>

**VIDEO LINK**: <https://drive.google.com/file/d/1kgUhmlVnxJMu91nGvsTkmIchMZGKFty0/view?usp=sharing>

**1.**

**Code:**

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**Explanation:**

1. Autoencoder Architecture: An input layer, an encoded layer for input compression, a further hidden layer for perhaps capturing more complicated patterns, and a decoded layer for reconstructing the input from its encoded representation make up the layout of the network.

2. Encoding Dimension: Assuming the input images are 28x28 pixels, flattened to 784 floats for a fully connected network, the encoded layer compresses the input to 32 floating point integers, greatly lowering the dimensionality from the original 784 floats.

3. Hidden Layer: After the encoding layer, a second hidden layer with 64 units is added. This can facilitate the decoding process and aid in the learning of increasingly complicated representations. ReLU (Rectified Linear Unit), the activation function for both the encoded layer and the hidden layer, adds non-linearity to the model.

4. Loss Function and Optimizer: The model uses binary cross-entropy as the loss function, which is common for reconstruction tasks, and the 'adadelta' optimizer, which is an adaptive learning rate method.

5. Data Preparation: The Fashion MNIST dataset is loaded, transformed to match the input requirements of the model, and normalized to have pixel values between 0 and 1 (by dividing by 255). The dataset is made up of grayscale, 28 × 28-pixel photos of apparel that have been flattened to fit the model's input layer's 784 dimensions.

6. Model Training: Using both the training and validation datasets, the autoencoder is trained for 5 epochs with a batch size of 256 on the Fashion MNIST dataset. In this case, the model learns to both compress (encode) and rebuild (decode) the input data in a way that is as near to the original as feasible.

7. Purpose and Application: Autoencoders like this one are used for dimensionality reduction, feature learning, and denoising images. By learning to reconstruct the input data from a compressed representation, the model can discover important features and patterns in the data.

**Output:**

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**2.**

**Code:**

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**Explanation:**

1. Architecture: An additional hidden layer with 64 units for more complex feature extraction, an encoding layer to compress the input to a 32-dimensional representation, a decoding layer to reconstruct the original image from the compressed form, and an input layer that accepts flattened 28x28 grayscale images (784 pixels) make up the model.

2. Compilation: The autoencoder is compiled with the Adadelta optimizer and binary crossentropy loss, a common setup for autoencoders since the task is to reproduce the input image as closely as possible.

3. Data Preparation: The Fashion MNIST dataset, comprising 28x28 grayscale images of clothing items, is loaded, normalized (pixel values scaled between 0 and 1), and reshaped to fit the model.

4. Training: The model is trained on the Fashion MNIST training data for 5 epochs, using a batch size of 256. Validation is performed using the test set.

5. Visualization: Following training, the model predicts on the test set, and for ten example examples, a comparison between the original and reconstructed images is displayed. In terms of how well the model can rebuild the input images after compression and decompression, this phase aids in the visual evaluation of the model's performance.

**Output:**

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**3.**

**Code:**

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**Explanation:**

1. Autoencoder Architecture: A simple neural network with an input layer, one hidden layer (encoded representation), and an output layer (decoded representation). The network compresses the input to a lower-dimensional encoded representation and then reconstructs the output from this encoding.

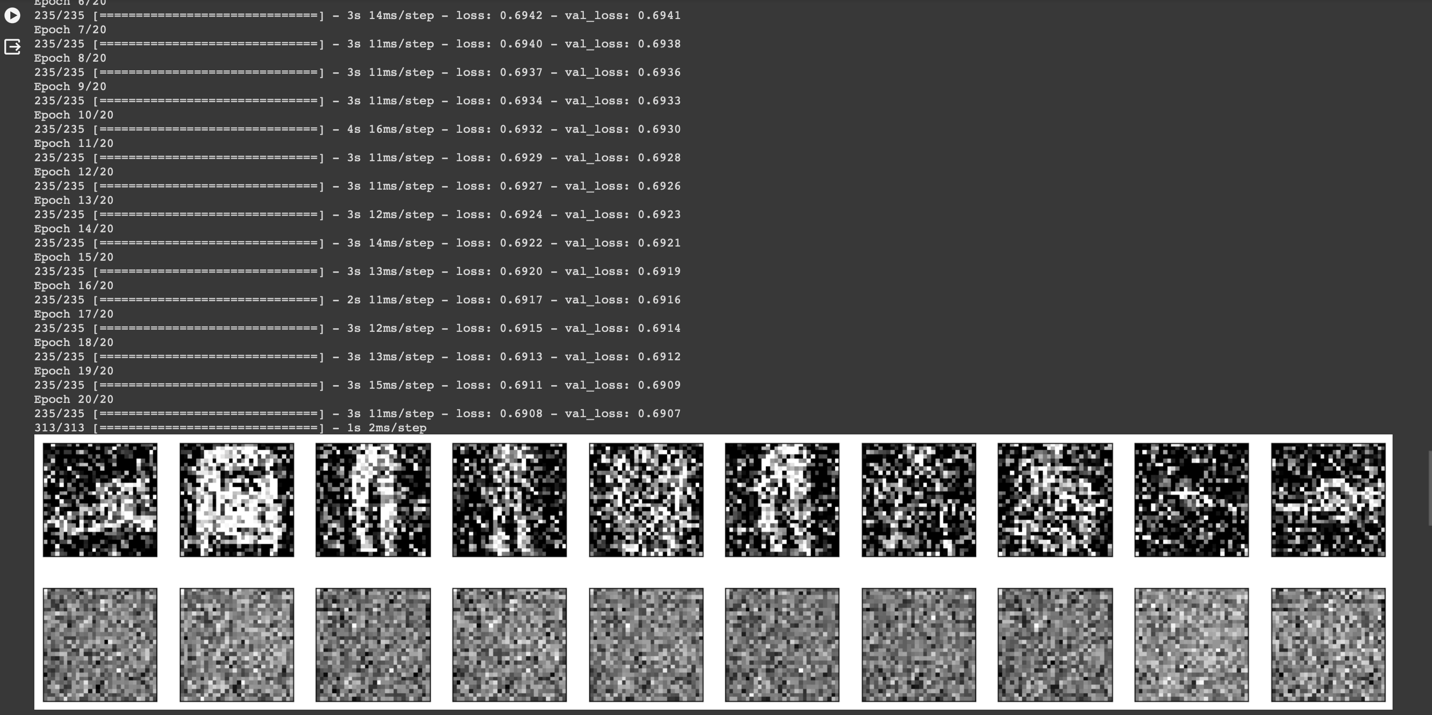
2. Data Preparation: The Fashion MNIST dataset, consisting of 28x28 grayscale images of clothing items, is loaded and normalized. The images are flattened and converted to floating-point arrays with values between 0 and 1.

3. Noise Addition: Artificial noise is added to the images to simulate corrupted input data. This is done by adding Gaussian noise to the training and test sets, followed by clipping to ensure the pixel values remain between 0 and 1.

4. Training: The autoencoder is trained using the noisy images as input and the original, clean images as the target for reconstruction. The model learns to filter out the noise and recover the original images from the noisy inputs.

5. Evaluation and Visualization: After training, the autoencoder is used to predict (denoise) the test set images. The original noisy images and their denoised reconstructions are then visualized side by side for comparison.

**Output:**

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**Question- 4:**

**Code:**

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**Explanation:**

1. Data Preparation: The Fashion MNIST dataset, consisting of 28x28 grayscale images of fashion items, is loaded, normalized, and flattened to prepare for training. Labels are one-hot encoded to fit the classification model.

2. Model Architecture: A basic neural network with an input layer, a hidden layer of 128 neurons with ReLU activation, and an output classification layer of 10 neurons (one for each class) with softmax activation is defined. This architecture is suitable for multi-class classification tasks.

3. Compilation and Training: The model is compiled with the Adam optimizer and categorical crossentropy loss, which are standard choices for classification tasks. It also tracks accuracy as a performance metric. The model is trained for 10 epochs with a batch size of 256, using both training and validation datasets to monitor performance.

4. Performance Visualization: After training, the code plots the training and validation accuracy and loss over epochs. This visualization helps in understanding how well the model is learning and generalizing to unseen data, indicated by its performance on the validation set.

**Output:**

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