Applied Machine Learning: Homework 3

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The dataset used in this assignment is the same handwritten alphabet dataset that was used in homework 2. This dataset contains images of alphabets represented by a total of 785 columns. The first column of the dataset represents the alphabet numbering from 0 to 25, which corresponds to the 26 alphabets from A to Z.

```
In [1]: import pandas as pd
        import matplotlib.pyplot as plt
        import numpy as np
        from sklearn.decomposition import PCA
        from sklearn.manifold import TSNE
        from sklearn.manifold import LocallyLinearEmbedding
        from sklearn.manifold import MDS
        from sklearn.pipeline import Pipeline
        from sklearn.cluster import KMeans
        from sklearn.mixture import GaussianMixture
        from sklearn.metrics import silhouette score
        from sklearn.model_selection import train_test_split
        from sklearn.ensemble import RandomForestClassifier
        from sklearn.preprocessing import StandardScaler
        from sklearn.tree import DecisionTreeClassifier
        from sklearn.metrics import accuracy_score
        from tensorflow import keras
        from tensorflow.keras import layers
        import seaborn as sns
        import time
        import warnings
        warnings.filterwarnings("ignore")
```

```
In [129]: #Load the dataset
           data=pd.read csv("alphabet handwritten.csv")
           data = data.sample(frac=1).reset index(drop=True) #shuffling and resetting the
           data.head(10)
Out[129]:
               0 0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 ... 0.639 0.640 0.641 0.642 0.643 0.644 0.64
            0
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           10 rows × 785 columns
 In [59]: data.shape
 Out[59]: (79988, 785)
In [130]: #splitting data into training and testing sets.
           #The stratify parameter ensures that the label distribution is maintained betwe
           train,test = train test split(data, test size=0.20, stratify=data['0'])
           train.shape, test.shape
Out[130]: ((63990, 785), (15998, 785))
In [131]: #dropping the first column ('0') from the train
           x = train.drop('0', axis=1)
           #extracting the label data from the train
           y = train['0']
           #splitting the training data into a new training set and a validation set.
           x_train, x_val, y_train, y_val = train_test_split(x, y, test_size=0.20, strati-
           x_test = test.drop('0', axis=1)
           y_test = test['0']
In [117]: # standarizing the dataset before applying PCA
           scaler = StandardScaler()
           x train = scaler.fit transform(x train)
           x_val = scaler.transform(x_val)
           x test = scaler.transform(x test)
```

Apply PCA to the training portion of the dataset. How many components do you need to preserve 95% of the variance?

```
In [132]: pca_model = PCA()
    pca_model.fit(x_train)
    cum_sum = np.cumsum(pca_model.explained_variance_ratio_)
    dim = np.argmax(cum_sum >= 0.95) + 1
In [64]: print(dim)
112
```

Answer:- We need 112 components to preserve 95% of the variance.

Train a Random Forest classifier on the reduced dataset. Was training much faster than in Homework 2? Evaluate the classifier on the test set. How does it compare to the classifier from Homework 2?

```
In [113]: pca model = PCA(n components=112)
          x reduced = pca model.fit transform(x train)
In [10]: # calculating the runtime of Random forest classifier without applying PCA
          rf = RandomForestClassifier(n estimators=100, max depth=20, min samples split=
          start time = time.time()
          rf.fit(x train, y train)
          end_time = time.time()
          runtime = end time - start time
          print(f"Runtime of Random Forest without PCA: {runtime:.2f} seconds")
          Runtime of Random Forest without PCA: 32.82 seconds
In [11]: model rf = RandomForestClassifier(n estimators=100, max depth=20, min samples
          start time = time.time()
          model rf.fit(x reduced, y train)
          end time = time.time()
          runtime = end time - start time
          print(f"Runtime of Random Forest: {runtime:.2f} seconds")
```

Runtime of Random Forest: 65.82 seconds

```
In [12]: # calculating accuracy for the reduced dataset
    x_reduced_test = pca_model.fit_transform(x_test)

y_pred_test = model_rf.predict(x_reduced_test)
    accuracy_test = accuracy_score(y_test, y_pred_test)
    print("Test Accuracy:", accuracy_test)
```

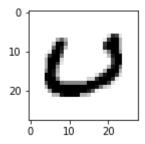
Test Accuracy: 0.663895486935867

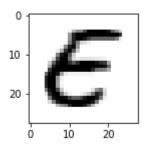
Previous result HW2: It was observed that the Random forest classifier model with n_estimators = 100, max_depth = 20, and min_samples_split = 2 had the best accuracy with value of 0.944 on both the validation and test sets

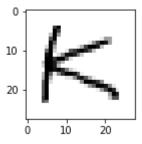
Answer:-The training time for the random forest on the reduced training dataset was 65.82 seconds, which was twice as slow compared to the original dataset. Therefore, the application of dimensionality reduction did not lead to faster training time. Additionally, the accuracy of the classifier trained on the reduced dataset dropped to 66%, whereas the classifier trained on the original training dataset had a prediction accuracy of 94%. Therefore, it can be concluded that applying PCA not only slowed down the training process but also reduced the performance of the classifier.

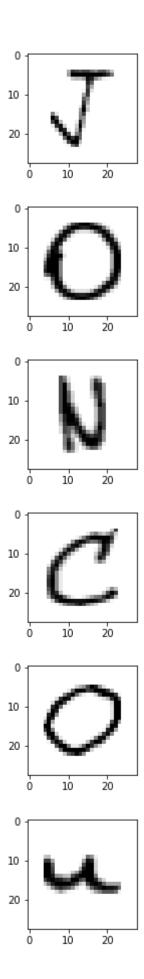
Plot 10 random images in the original form (without PCA) and then plot them after you kept 95% of variance using PCA.

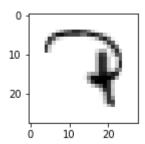
```
In [114]: # 10 random images in the original form (without PCA)
          for m in range(1,11):
              img_data = []
              k = []
              cnt = 1
              for z in x_train.iloc[m]:
                   if(int(cnt)%28 == 0):
                       k.append(z)
                       img_data.append(k)
                       cnt+=1
                       k=[]
                   else:
                       k.append(z)
                       cnt+=1
              plt.figure(figsize=(2, 2))
              plt.imshow(img_data, cmap=plt.cm.binary)
              plt.show()
```





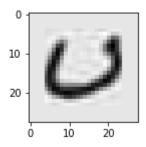


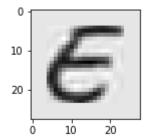


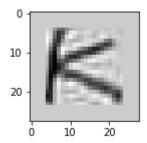


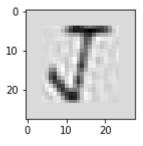
In [115]: x_recovered = pca_model.inverse_transform(x_reduced)

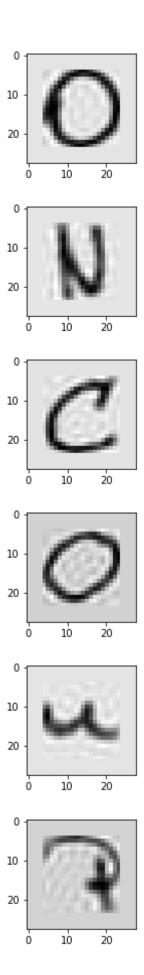
In [116]: # 10 random images in the reduced form (with PCA) for m in range(1,11): img_data = [] k = []cnt = 1for z in x_recovered[m]: **if**(int(cnt)%28 == 0): k.append(z) img_data.append(k) cnt+=1 k=[] else: k.append(z) cnt+=1 plt.figure(figsize=(2, 2)) plt.imshow(img_data, cmap=plt.cm.binary) plt.show()











How much of the variance is explained with the first two principal components?

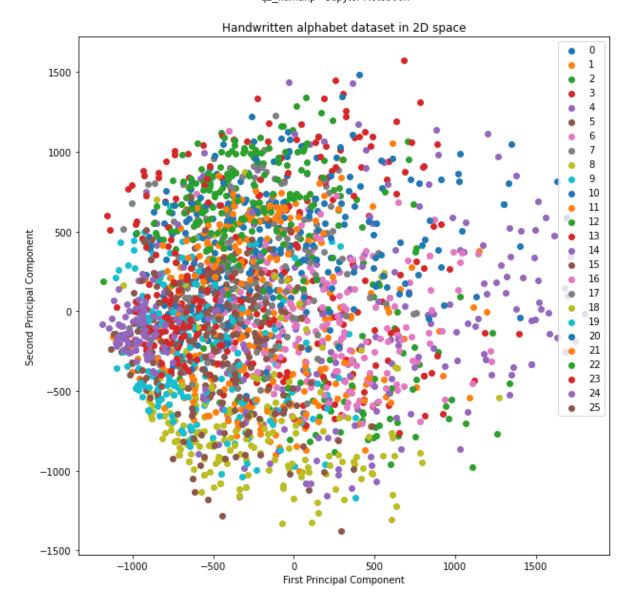
```
In [66]: pca_model = PCA(n_components = 2)
    x_2D = pca_model.fit_transform(x_train)

In [67]: pca_model.explained_variance_ratio_
Out[67]: array([0.12045042, 0.08577677])
```

Answer:- 12% of the dataset's variance lies along the first principal component and 8% lies along the second principal component. Therefore the first two principal components explain about 20% of the dataset's variance.

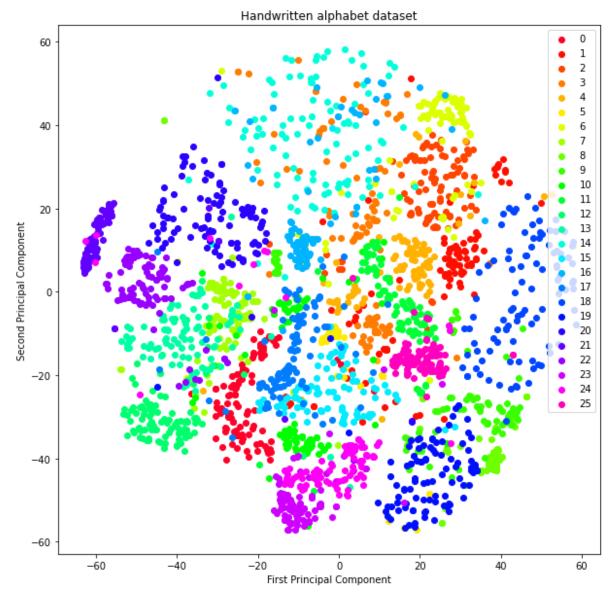
Use PCA to reduce dimensionality to only 2 dimensions. Plot 1000 random images from the training set in the 2D space spanned by the first two principal components. Use a scatterplot with 10 different colors to represent each image's target class. Repeat the process and create the same type of plots for t-SNE, LLE and MDS. Which of the visualizations do you prefer and why?

```
In [99]: # PCA plot
         x train reshape = x train.to numpy().reshape(-1, 28*28)
         pca = PCA(n components=2, random state=42)
                                                                  #selecting 2 components
         x_train_reduced = pca.fit_transform(x_train_reshape)
         fig, ax = plt.subplots(figsize=(10, 10))
         for i in range(26):
                                                                  #for 26 alphabets
             indices = np.where(y_train == i)[0]
             random indices = np.random.choice(indices, 100)
             ax.scatter(x train reduced[random indices, 0], x train reduced[random indices, 0], x
         ax.legend()
         ax.set_xlabel('First Principal Component')
         ax.set ylabel('Second Principal Component')
         ax.set title('Handwritten alphabet dataset in 2D space')
         plt.show()
```



Based on the scatter plot obtained from the PCA analysis, it appears that there are some distinct groupings or clusters of data points. However, it is also evident that there is a significant degree of overlap between these clusters.

```
In [19]: # t-SNE Plot
         x_train_reshape = x_train.to_numpy().reshape(-1, 28*28)
         tsne = TSNE(n components=2, random state=42)
         x_train_reduced = tsne.fit_transform(x_train_reshape)
         color_map = plt.get_cmap('gist_rainbow', 26)
         fig, ax = plt.subplots(figsize=(10, 10))
         for i in range(26):
                                                              # for 26 alphabets
             indices = np.where(y_train == i)[0]
             random_indices = np.random.choice(indices, 100)
             ax.scatter(x_train_reduced[random_indices, 0], x_train_reduced[random_indices]
         ax.legend()
         ax.set_xlabel('First Principal Component')
         ax.set_ylabel('Second Principal Component')
         ax.set title('Handwritten alphabet dataset')
         plt.show()
```



Based on the t-SNE plot, it can be observed that the majority of the alphabet images are clearly separated from each other and grouped into distinct clusters of similar images. This indicates that the t-SNE algorithm has been successful in capturing the underlying structure of the dataset

Handwritten alphabet dataset

and visualizing it in a meaningful wav.

1 2

> 10 11 12

> 13 14 15

> 17 18

> 21

0.25

0.20

0.15

0.10

0.05

0.00

-0.35

-0.30

-0.25

-0.20

-0.15

First Principal Component

-0.10

-0.05

Second Principal Component

```
In [93]: # LLE plot
         x_train_reshape = x_train.reshape(-1, 28*28)
         1le = LocallyLinearEmbedding(n components=2, random state=42)
         x_train_reduced = lle.fit_transform(x_train_reshape)
         color map = plt.get cmap('gist rainbow', 26)
         fig, ax = plt.subplots(figsize=(10, 10))
         for i in range(26):
             indices = np.where(y_train == i)[0]
             random_indices = np.random.choice(indices, 100)
             ax.scatter(x_train_reduced[random_indices, 0], x_train_reduced[random_indices]
         ax.legend()
         ax.set_xlabel('First Principal Component')
         ax.set_ylabel('Second Principal Component')
         ax.set title('Handwritten alphabet dataset ')
         plt.show()
```



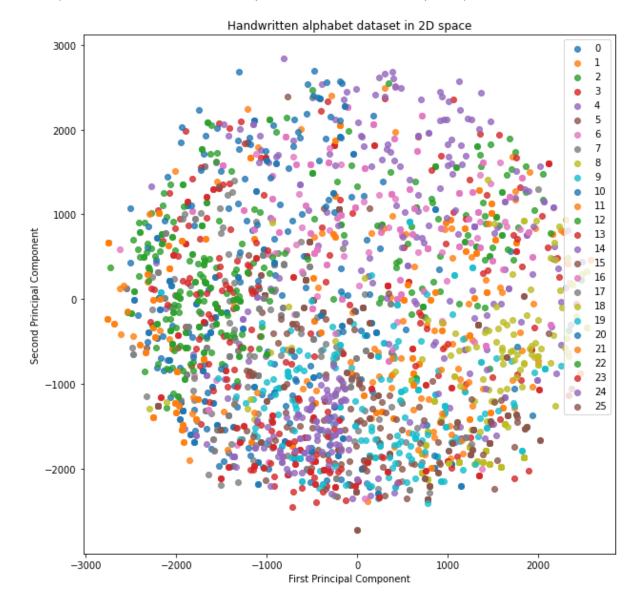
0.00

0.05

The Locally Linear Embedding (LLE) require more time to run compared to other dimensionality reduction techniques such as Principal Component Analysis (PCA) and t-Distributed Stochastic Neighbor Embedding (t-SNE). Additionally, the resulting plot is not visually appealing as those produced by PCA and t-SNE.

```
In [127]: # MDS plot
          x_train_reshape = x_train.to_numpy().reshape(-1, 28*28)
          indices = np.random.choice(x_train_reshape.shape[0], size=5000, replace=False)
          x train sampled = x train reshape[indices]
          y_train_sampled = y_train.iloc[indices]
          mds = MDS(n_components=2, random_state=42)
          x train reduced = mds.fit transform(x train sampled)
          fig, ax = plt.subplots(figsize=(10, 10))
          for i in range(26):
              indices = np.where(y_train_sampled == i)[0]
              if indices.size == 0:
                   continue # skip this iteration if there are no training examples with
              random_indices = np.random.choice(indices, 100)
              ax.scatter(x_train_reduced[random_indices, 0], x_train_reduced[random_indices]
          ax.legend()
          ax.set_xlabel('First Principal Component')
          ax.set ylabel('Second Principal Component')
          ax.set_title('Handwritten alphabet dataset in 2D space')
```

Out[127]: Text(0.5, 1.0, 'Handwritten alphabet dataset in 2D space')



MDS takes a long time to run, and the resulting plot is not visually appealing or useful due to significant overlap between clusters.

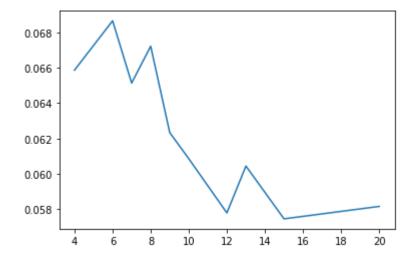
In conclusion, among all the visualization plots generated above for the dataset, t-Distributed Stochastic Neighbor Embedding (t-SNE) produced a better result by separating the data points into various clusters.

Take 10000 samples of the training portion of fashion MNIST dataset and cluster the images using KMeans. To speed up the algorithm, use PCA to reduce the dimensionality of the dataset. Ensure that you have a good number of clusters using one of the techniques we discussed in class. Visualize the clusters (you can show only a subset of images): do you see similar clothing items in each cluster?

```
In [69]:
         x_train_reshape = x_train.to_numpy().reshape(-1, 28*28)
         np.random.seed(42)
         indices = np.random.choice(x train reshape.shape[0], size=10000, replace=False
         x train sampled = x train reshape[indices]
         pca = PCA(n components=112, random state=42)
                                                            #taking n component as 112
         x_train_reduced = pca.fit_transform(x_train_sampled)
         num clusters = [4,6,7,8,9,10,12,13,15,20]
         s score = []
         inertia = []
         for k in num_clusters:
             kmeans = KMeans(n clusters=k, random state=42)
             labels = kmeans.fit_predict(x_train_reduced)
             s_score.append(silhouette_score(x_train_reduced, kmeans.labels_))
             inertia.append(kmeans.inertia )
```

```
In [70]: # Silhouette score versus number of clusters
plt.plot(num_clusters, s_score)
```

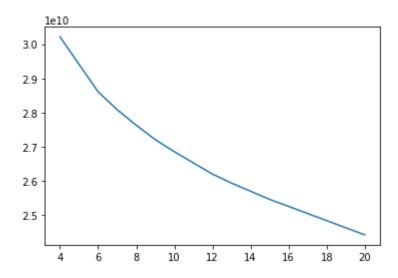
Out[70]: [<matplotlib.lines.Line2D at 0x7f233d157d68>]



There is a peak in the Silhouette score at around cluster 6, and the score then decreases as the number of clusters increases. This graph suggests that using 6 clusters may be the best choice for this particular data set, as it produces the highest Silhouette score and thus the best separation between clusters.

```
In [125]: # Inertia versus number of clusters
plt.plot(num_clusters, inertia)
```

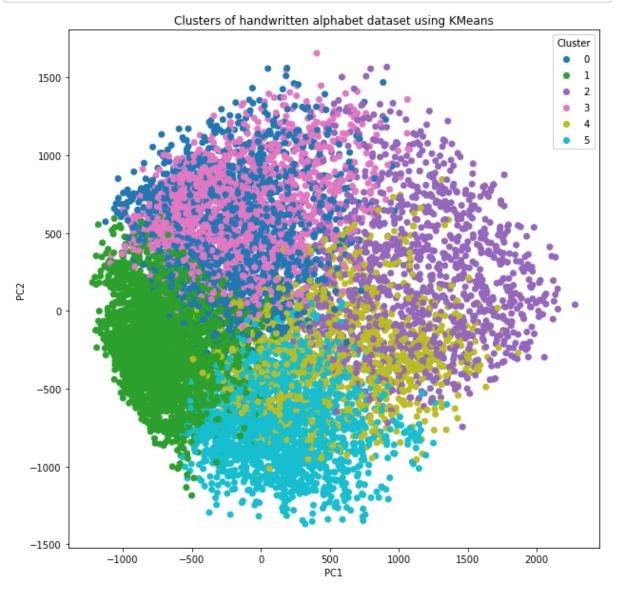
Out[125]: [<matplotlib.lines.Line2D at 0x7f233c39fd30>]



In the graph, there is a clear elbow point at around cluster 6, where the Inertia score starts to level off. This suggests that using 6 cluster may be the optimal choice for this particular data set.

```
In [72]: #using cluster 6
kmeans = KMeans(n_clusters=6, random_state=42)
labels = kmeans.fit_predict(x_train_reduced)
```

```
In [73]: fig, ax = plt.subplots(figsize=(10, 10))
    scatter = ax.scatter(x_train_reduced[:, 0], x_train_reduced[:, 1], c=labels, collegend = ax.legend(*scatter.legend_elements(), loc="upper right", title="Cluston ax.add_artist(legend)
    ax.set_xlabel('PC1')
    ax.set_ylabel('PC2')
    ax.set_title('Clusters of handwritten alphabet dataset using KMeans')
    plt.show()
```



```
In [74]:
    fig, ax = plt.subplots(nrows=6, ncols=10, figsize=(10, 10))
    for i in range(6):
        cluster_indices = np.where(labels == i)[0]
        sample_indices = np.random.choice(cluster_indices, size=10, replace=True)
        for j, idx in enumerate(sample_indices):
            ax[i, j].imshow(x_train_sampled[idx].reshape(28, 28), cmap='gray')
            ax[i, j].axis('off')
    plt.suptitle('Images from each cluster of handwritten alphabet dataset using KN plt.show()
```

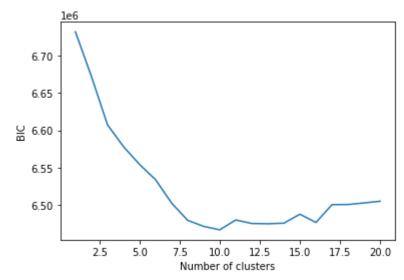
Images from each cluster of handwritten alphabet dataset using KMeans



Answer:- Yes similar looking alphabets in each cluster is visible.

Take 10000 samples of the training portion of fashion MNIST dataset and cluster the images using a Gaussian mixture model. To speed up the algorithm, use PCA to reduce the dimensionality of the dataset. Ensure that you have a good number of clusters using one of the techniques we discussed in the class. Visualize the clusters (you can show only a subset of images): do you see similar clothing items in each cluster? Use the model to generate 20 new clothing items (using the sample() method), and visualize them (since you used PCA, you will need to use its inverse_transform() method).

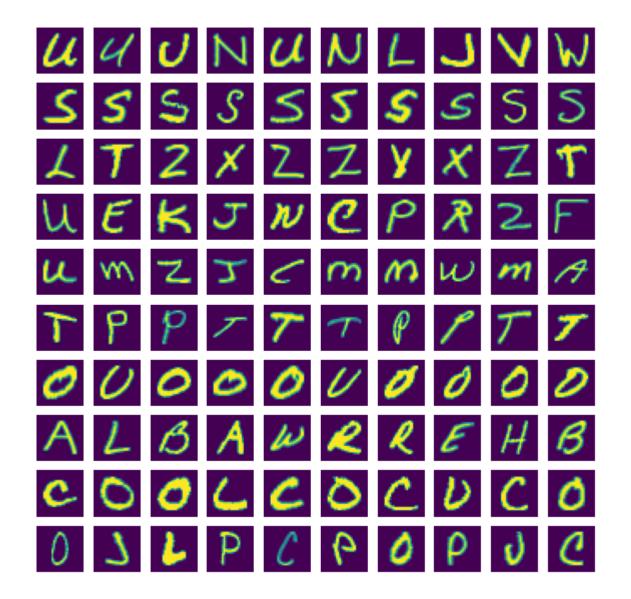
```
In [133]:
          x_train_reshape = x_train.to_numpy().reshape(-1, 28*28)
          np.random.seed(42)
          sample idx = np.random.choice(x train reshape.shape[0], size=10000, replace=Fal
          x sample = x train reshape[sample idx]
          x sample flat = x sample.reshape(-1, 784)
          pca = PCA(n components=112)
          x_sample_pca = pca.fit_transform(x_sample_flat)
          # Use Bayesian information criterion to determine the optimal number of cluster
          n components = np.arange(1, 21)
          models = [GaussianMixture(n, covariance type='full', random state=0).fit(x sam
          bic = [m.bic(x sample pca) for m in models]
          plt.plot(n_components, bic)
          plt.xlabel('Number of clusters')
          plt.ylabel('BIC')
          plt.show()
```



Based on the BIC plot, it appears that the curve initially shows a decreasing trend, but then it starts to level off or possibly even increase after a certain point, which may indicate the optimal number of clusters for this particular dataset. This point is observed to be at or after 10 clusters.

```
In [136]:
# Visualize a subset of images from each cluster
fig, axs = plt.subplots(n_clusters, 10, figsize=(10, 10))
for i in range(n_clusters):
    idxs = np.where(labels == i)[0]
    for j in range(10):
        axs[i, j].imshow(np.reshape(x_train, (x_train.shape[0], 28, 28))[idxs[:
        axs[i, j].axis('off')
plt.suptitle('Clustered Images')
plt.show()
```

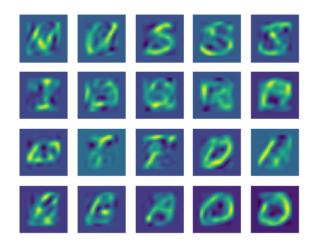
Clustered Images



Similar looking alphabets are clustered together

```
In [137]: # Generate 20 new alphabets using the GMM and PCA
    new_samples_pca = gmm.sample(n_samples=20)[0]
    new_samples_flat = pca.inverse_transform(new_samples_pca)
    new_samples = new_samples_flat.reshape(-1, 28, 28)
    fig, axs = plt.subplots(4, 5, figsize=(5, 4))
    for i in range(4):
        for j in range(5):
            axs[i, j].imshow(new_samples[i * 5 + j])
            axs[i, j].axis('off')
    plt.suptitle('Generated alphabets')
    plt.show()
```

Generated alphabets



Answer:- We can see that similar looking alphabets are mostly grouped together indicating that the GMM and PCA have captured the main features of the dataset.

Build a fully connected (dense) feedforward neural network with two hidden layers using Keras (within Tensorflow) and train it on 50k Fashion MNIST training images. First hidden layer should contain 200 neurons and second hidden layer should contain 50 neurons. The hidden layers should have ReLU activation function. Train the network for 100 epochs. Plot training and validation loss and accuracy as a function of training epochs. Try three different learning rates of your choice (make the plots for each learning rate). Run the network on the test portion of the dataset using best-performing learning rate and report loss and accuracy. How many parameters does the network have? How many of those parameters are bias parameters?

```
In [90]:
         # Normalize the pixel values to be between 0 and 1
         x_train = x_train.astype("float32") / 255.0
         x_{test} = x_{test.astype}("float32") / 255.0
         learning rates = [0.1, 0.01, 0.001]
         for lr in learning rates:
             # Define the model architecture
             model = keras.Sequential(
                 Γ
                      keras.Input(shape=(784)),
                      layers.Dense(200, activation="relu"),
                      layers.Dense(50, activation="relu"),
                      layers.Dense(26),
                 ]
             # Compile the model
             model.compile(
                 loss=keras.losses.SparseCategoricalCrossentropy(from logits=True),
                 optimizer=keras.optimizers.SGD(lr=lr),
                 metrics=["accuracy"],
             )
             # Train the model
             history = model.fit(
                 x train,
                 y train,
                 epochs=100,
                 batch_size=32,
                 validation_split=0.1,
             )
             # Plot the training and validation loss and accuracy as a function of train
             plt.plot(history.history["loss"], label="training loss")
             plt.plot(history.history["val_loss"], label="validation loss")
             plt.plot(history.history["accuracy"], label="training accuracy")
             plt.plot(history.history["val accuracy"], label="validation accuracy")
             plt.xlabel("epoch")
             plt.ylabel("loss/accuracy")
             plt.title(f"Learning Rate: {lr}")
             plt.legend()
             plt.show()
             # Evaluate the model on the test set
             test loss, test accuracy = model.evaluate(x test, y test)
             print(f"Learning Rate: {lr}")
             print("Test loss:", test_loss)
             print("Test accuracy:", test_accuracy)
             # Count the total number of parameters and the number of bias parameters in
             total params = model.count params()
             bias_params = sum([len(layer.get_weights()[1]) for layer in model.layers])
             print("Total number of parameters:", total params)
```

print("Number of bias parameters:", bias_params)

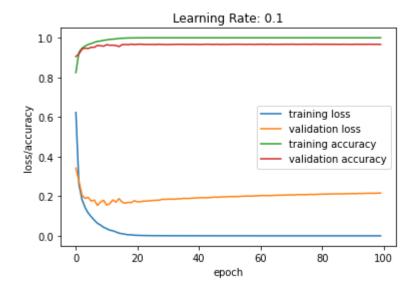
```
Epoch 1/100
uracy: 0.8243 - val loss: 0.3420 - val accuracy: 0.9053
uracy: 0.9271 - val_loss: 0.2759 - val_accuracy: 0.9186
Epoch 3/100
uracy: 0.9480 - val_loss: 0.2049 - val_accuracy: 0.9430
Epoch 4/100
uracy: 0.9583 - val_loss: 0.1893 - val_accuracy: 0.9479
Epoch 5/100
uracy: 0.9664 - val loss: 0.1941 - val accuracy: 0.9457
Epoch 6/100
uracy: 0.9710 - val_loss: 0.1756 - val_accuracy: 0.9521
Epoch 7/100
uracy: 0.9772 - val_loss: 0.1805 - val_accuracy: 0.9521
Epoch 8/100
uracy: 0.9818 - val_loss: 0.1540 - val_accuracy: 0.9617
Epoch 9/100
uracy: 0.9837 - val loss: 0.1704 - val accuracy: 0.9600
Epoch 10/100
uracy: 0.9872 - val_loss: 0.1797 - val_accuracy: 0.9576
Epoch 11/100
uracy: 0.9892 - val_loss: 0.1554 - val_accuracy: 0.9654
Epoch 12/100
uracy: 0.9920 - val loss: 0.1625 - val accuracy: 0.9623
Epoch 13/100
uracy: 0.9931 - val loss: 0.1815 - val accuracy: 0.9627
Epoch 14/100
uracy: 0.9944 - val loss: 0.1701 - val accuracy: 0.9615
Epoch 15/100
uracy: 0.9968 - val_loss: 0.1878 - val_accuracy: 0.9555
Epoch 16/100
uracy: 0.9975 - val_loss: 0.1706 - val_accuracy: 0.9654
Epoch 17/100
1440/1440 [============= ] - 2s 1ms/step - loss: 0.0081 - acc
uracy: 0.9983 - val loss: 0.1649 - val accuracy: 0.9662
Epoch 18/100
uracy: 0.9993 - val loss: 0.1691 - val accuracy: 0.9652
Epoch 19/100
uracy: 0.9992 - val loss: 0.1679 - val accuracy: 0.9678
```

```
Epoch 20/100
uracy: 0.9997 - val_loss: 0.1774 - val_accuracy: 0.9662
Epoch 21/100
uracy: 0.9999 - val_loss: 0.1719 - val_accuracy: 0.9672
Epoch 22/100
uracy: 0.9999 - val_loss: 0.1725 - val_accuracy: 0.9678
Epoch 23/100
uracy: 1.0000 - val_loss: 0.1756 - val_accuracy: 0.9664
Epoch 24/100
uracy: 1.0000 - val loss: 0.1756 - val accuracy: 0.9666
uracy: 1.0000 - val_loss: 0.1773 - val_accuracy: 0.9664
Epoch 26/100
uracy: 1.0000 - val_loss: 0.1789 - val_accuracy: 0.9666
Epoch 27/100
uracy: 1.0000 - val_loss: 0.1796 - val_accuracy: 0.9662
Epoch 28/100
uracy: 1.0000 - val_loss: 0.1802 - val_accuracy: 0.9674
Epoch 29/100
accuracy: 1.0000 - val loss: 0.1843 - val accuracy: 0.9662
Epoch 30/100
accuracy: 1.0000 - val_loss: 0.1844 - val_accuracy: 0.9664
Epoch 31/100
accuracy: 1.0000 - val_loss: 0.1854 - val_accuracy: 0.9658
Epoch 32/100
accuracy: 1.0000 - val loss: 0.1854 - val accuracy: 0.9666
Epoch 33/100
1440/1440 [============== ] - 2s 1ms/step - loss: 7.6555e-04 -
accuracy: 1.0000 - val_loss: 0.1853 - val_accuracy: 0.9668
Epoch 34/100
accuracy: 1.0000 - val_loss: 0.1871 - val_accuracy: 0.9668
Epoch 35/100
accuracy: 1.0000 - val loss: 0.1869 - val accuracy: 0.9672
Epoch 36/100
accuracy: 1.0000 - val loss: 0.1895 - val accuracy: 0.9670
Epoch 37/100
accuracy: 1.0000 - val loss: 0.1886 - val accuracy: 0.9666
Epoch 38/100
1440/1440 [=============== ] - 2s 1ms/step - loss: 6.1175e-04 -
accuracy: 1.0000 - val loss: 0.1894 - val accuracy: 0.9666
```

```
Epoch 39/100
1440/1440 [=============== ] - 2s 1ms/step - loss: 5.8793e-04 -
accuracy: 1.0000 - val_loss: 0.1904 - val_accuracy: 0.9670
Epoch 40/100
1440/1440 [=============== ] - 2s 1ms/step - loss: 5.6698e-04 -
accuracy: 1.0000 - val_loss: 0.1913 - val_accuracy: 0.9670
Epoch 41/100
accuracy: 1.0000 - val_loss: 0.1921 - val_accuracy: 0.9664
Epoch 42/100
accuracy: 1.0000 - val_loss: 0.1933 - val_accuracy: 0.9666
Epoch 43/100
accuracy: 1.0000 - val loss: 0.1926 - val accuracy: 0.9674
Epoch 44/100
1440/1440 [=============== ] - 2s 1ms/step - loss: 4.9183e-04 -
accuracy: 1.0000 - val_loss: 0.1930 - val_accuracy: 0.9674
Epoch 45/100
1440/1440 [=============== ] - 2s 1ms/step - loss: 4.7565e-04 -
accuracy: 1.0000 - val_loss: 0.1940 - val_accuracy: 0.9668
Epoch 46/100
accuracy: 1.0000 - val_loss: 0.1958 - val_accuracy: 0.9666
Epoch 47/100
1440/1440 [=============== ] - 2s 1ms/step - loss: 4.4704e-04 -
accuracy: 1.0000 - val loss: 0.1951 - val accuracy: 0.9674
Epoch 48/100
1440/1440 [=============== ] - 2s 1ms/step - loss: 4.3424e-04 -
accuracy: 1.0000 - val loss: 0.1962 - val accuracy: 0.9662
Epoch 49/100
accuracy: 1.0000 - val_loss: 0.1972 - val_accuracy: 0.9670
Epoch 50/100
accuracy: 1.0000 - val_loss: 0.1970 - val_accuracy: 0.9664
Epoch 51/100
1440/1440 [============== ] - 2s 1ms/step - loss: 3.9848e-04 -
accuracy: 1.0000 - val loss: 0.1988 - val accuracy: 0.9670
Epoch 52/100
accuracy: 1.0000 - val loss: 0.1982 - val accuracy: 0.9674
Epoch 53/100
accuracy: 1.0000 - val_loss: 0.1989 - val_accuracy: 0.9674
Epoch 54/100
accuracy: 1.0000 - val loss: 0.1986 - val accuracy: 0.9672
Epoch 55/100
accuracy: 1.0000 - val loss: 0.2003 - val accuracy: 0.9672
Epoch 56/100
accuracy: 1.0000 - val loss: 0.2006 - val accuracy: 0.9666
Epoch 57/100
accuracy: 1.0000 - val loss: 0.2011 - val accuracy: 0.9672
```

```
Epoch 58/100
accuracy: 1.0000 - val_loss: 0.2007 - val_accuracy: 0.9672
Epoch 59/100
accuracy: 1.0000 - val_loss: 0.2018 - val_accuracy: 0.9664
Epoch 60/100
accuracy: 1.0000 - val_loss: 0.2020 - val_accuracy: 0.9674
Epoch 61/100
1440/1440 [=============== ] - 2s 1ms/step - loss: 3.1201e-04 -
accuracy: 1.0000 - val_loss: 0.2036 - val_accuracy: 0.9672
Epoch 62/100
accuracy: 1.0000 - val loss: 0.2035 - val accuracy: 0.9676
Epoch 63/100
accuracy: 1.0000 - val_loss: 0.2035 - val_accuracy: 0.9666
Epoch 64/100
accuracy: 1.0000 - val_loss: 0.2037 - val_accuracy: 0.9676
Epoch 65/100
accuracy: 1.0000 - val_loss: 0.2042 - val_accuracy: 0.9670
Epoch 66/100
accuracy: 1.0000 - val loss: 0.2050 - val accuracy: 0.9668
Epoch 67/100
accuracy: 1.0000 - val loss: 0.2053 - val accuracy: 0.9670
Epoch 68/100
accuracy: 1.0000 - val_loss: 0.2052 - val_accuracy: 0.9672
Epoch 69/100
accuracy: 1.0000 - val_loss: 0.2060 - val_accuracy: 0.9674
Epoch 70/100
1440/1440 [============ ] - 2s 1ms/step - loss: 2.6014e-04 -
accuracy: 1.0000 - val loss: 0.2065 - val accuracy: 0.9672
Epoch 71/100
accuracy: 1.0000 - val loss: 0.2067 - val accuracy: 0.9676
Epoch 72/100
accuracy: 1.0000 - val_loss: 0.2067 - val_accuracy: 0.9674
Epoch 73/100
1440/1440 [============== ] - 2s 1ms/step - loss: 2.4605e-04 -
accuracy: 1.0000 - val loss: 0.2083 - val accuracy: 0.9668
Epoch 74/100
accuracy: 1.0000 - val loss: 0.2080 - val accuracy: 0.9674
Epoch 75/100
accuracy: 1.0000 - val loss: 0.2084 - val accuracy: 0.9674
Epoch 76/100
accuracy: 1.0000 - val loss: 0.2077 - val accuracy: 0.9674
```

```
Epoch 77/100
accuracy: 1.0000 - val_loss: 0.2095 - val_accuracy: 0.9666
Epoch 78/100
accuracy: 1.0000 - val_loss: 0.2090 - val_accuracy: 0.9676
Epoch 79/100
accuracy: 1.0000 - val_loss: 0.2094 - val_accuracy: 0.9676
Epoch 80/100
accuracy: 1.0000 - val_loss: 0.2101 - val_accuracy: 0.9672
Epoch 81/100
accuracy: 1.0000 - val loss: 0.2105 - val accuracy: 0.9672
1440/1440 [=============== ] - 2s 1ms/step - loss: 2.1127e-04 -
accuracy: 1.0000 - val_loss: 0.2109 - val_accuracy: 0.9674
Epoch 83/100
accuracy: 1.0000 - val_loss: 0.2110 - val_accuracy: 0.9672
Epoch 84/100
accuracy: 1.0000 - val_loss: 0.2115 - val_accuracy: 0.9670
Epoch 85/100
accuracy: 1.0000 - val loss: 0.2120 - val accuracy: 0.9674
Epoch 86/100
accuracy: 1.0000 - val loss: 0.2120 - val accuracy: 0.9670
Epoch 87/100
accuracy: 1.0000 - val_loss: 0.2120 - val_accuracy: 0.9670
Epoch 88/100
accuracy: 1.0000 - val_loss: 0.2124 - val_accuracy: 0.9674
Epoch 89/100
1440/1440 [============= ] - 2s 1ms/step - loss: 1.9036e-04 -
accuracy: 1.0000 - val loss: 0.2129 - val accuracy: 0.9672
Epoch 90/100
accuracy: 1.0000 - val loss: 0.2133 - val accuracy: 0.9666
Epoch 91/100
accuracy: 1.0000 - val_loss: 0.2138 - val_accuracy: 0.9670
Epoch 92/100
accuracy: 1.0000 - val loss: 0.2133 - val accuracy: 0.9674
Epoch 93/100
accuracy: 1.0000 - val loss: 0.2143 - val accuracy: 0.9672
Epoch 94/100
accuracy: 1.0000 - val loss: 0.2138 - val accuracy: 0.9672
Epoch 95/100
accuracy: 1.0000 - val loss: 0.2148 - val accuracy: 0.9670
```



```
500/500 [============ ] - 1s 1ms/step - loss: 0.2035 - accur
acy: 0.9693
Learning Rate: 0.1
Test loss: 0.20347315073013306
Test accuracy: 0.9693086743354797
Total number of parameters: 168376
Number of bias parameters: 276
Epoch 1/100
uracy: 0.6008 - val loss: 0.8362 - val accuracy: 0.7955
Epoch 2/100
uracy: 0.8187 - val loss: 0.6109 - val accuracy: 0.8342
Epoch 3/100
uracy: 0.8557 - val loss: 0.5373 - val accuracy: 0.8605
Epoch 4/100
uracy: 0.8749 - val loss: 0.4699 - val accuracy: 0.8748
Epoch 5/100
uracy: 0.8891 - val_loss: 0.4343 - val_accuracy: 0.8865
Epoch 6/100
uracy: 0.8997 - val_loss: 0.4010 - val_accuracy: 0.8928
Epoch 7/100
uracy: 0.9079 - val_loss: 0.3737 - val_accuracy: 0.9014
Epoch 8/100
uracy: 0.9157 - val_loss: 0.3531 - val_accuracy: 0.9057
Epoch 9/100
uracy: 0.9207 - val_loss: 0.3333 - val_accuracy: 0.9104
Epoch 10/100
uracy: 0.9269 - val_loss: 0.3105 - val_accuracy: 0.9176
Epoch 11/100
uracy: 0.9310 - val_loss: 0.3003 - val_accuracy: 0.9187
Epoch 12/100
uracy: 0.9356 - val_loss: 0.2852 - val_accuracy: 0.9246
Epoch 13/100
uracy: 0.9395 - val loss: 0.2708 - val accuracy: 0.9279
Epoch 14/100
uracy: 0.9435 - val_loss: 0.2631 - val_accuracy: 0.9275
Epoch 15/100
uracy: 0.9461 - val_loss: 0.2543 - val_accuracy: 0.9322
Epoch 16/100
uracy: 0.9496 - val_loss: 0.2473 - val_accuracy: 0.9330
Epoch 17/100
```

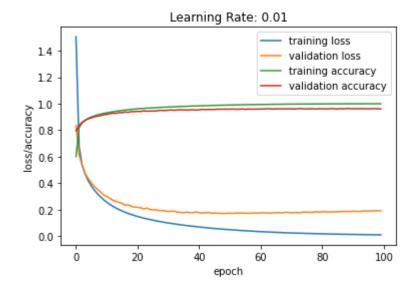
```
uracy: 0.9515 - val loss: 0.2340 - val accuracy: 0.9371
Epoch 18/100
uracy: 0.9547 - val loss: 0.2375 - val accuracy: 0.9350
Epoch 19/100
uracy: 0.9572 - val loss: 0.2250 - val accuracy: 0.9402
Epoch 20/100
uracy: 0.9592 - val loss: 0.2190 - val accuracy: 0.9402
Epoch 21/100
uracy: 0.9615 - val loss: 0.2179 - val accuracy: 0.9418
Epoch 22/100
uracy: 0.9634 - val loss: 0.2152 - val accuracy: 0.9414
Epoch 23/100
uracy: 0.9642 - val loss: 0.2059 - val accuracy: 0.9451
Epoch 24/100
uracy: 0.9667 - val loss: 0.2119 - val accuracy: 0.9438
Epoch 25/100
uracy: 0.9672 - val_loss: 0.2013 - val_accuracy: 0.9443
Epoch 26/100
uracy: 0.9687 - val_loss: 0.1986 - val_accuracy: 0.9447
Epoch 27/100
uracy: 0.9701 - val_loss: 0.2007 - val_accuracy: 0.9451
Epoch 28/100
1440/1440 [============= ] - 2s 1ms/step - loss: 0.1114 - acc
uracy: 0.9712 - val loss: 0.1930 - val accuracy: 0.9494
Epoch 29/100
uracy: 0.9727 - val_loss: 0.1938 - val_accuracy: 0.9488
Epoch 30/100
uracy: 0.9737 - val_loss: 0.1908 - val_accuracy: 0.9482
Epoch 31/100
uracy: 0.9749 - val_loss: 0.1871 - val_accuracy: 0.9510
Epoch 32/100
uracy: 0.9760 - val loss: 0.1877 - val accuracy: 0.9529
Epoch 33/100
uracy: 0.9764 - val_loss: 0.1883 - val_accuracy: 0.9500
Epoch 34/100
uracy: 0.9780 - val_loss: 0.1819 - val_accuracy: 0.9531
Epoch 35/100
uracy: 0.9788 - val_loss: 0.1800 - val_accuracy: 0.9541
Epoch 36/100
```

```
uracy: 0.9800 - val loss: 0.1776 - val accuracy: 0.9527
Epoch 37/100
uracy: 0.9807 - val loss: 0.1809 - val accuracy: 0.9520
Epoch 38/100
uracy: 0.9817 - val loss: 0.1783 - val accuracy: 0.9529
Epoch 39/100
uracy: 0.9827 - val loss: 0.1777 - val_accuracy: 0.9539
Epoch 40/100
uracy: 0.9825 - val loss: 0.1830 - val accuracy: 0.9520
Epoch 41/100
uracy: 0.9833 - val loss: 0.1778 - val accuracy: 0.9533
Epoch 42/100
uracy: 0.9844 - val loss: 0.1747 - val accuracy: 0.9574
Epoch 43/100
uracy: 0.9856 - val loss: 0.1781 - val accuracy: 0.9557
Epoch 44/100
uracy: 0.9854 - val_loss: 0.1782 - val_accuracy: 0.9566
Epoch 45/100
uracy: 0.9867 - val_loss: 0.1739 - val_accuracy: 0.9564
Epoch 46/100
uracy: 0.9869 - val_loss: 0.1742 - val_accuracy: 0.9566
Epoch 47/100
uracy: 0.9880 - val loss: 0.1724 - val accuracy: 0.9586
Epoch 48/100
uracy: 0.9885 - val_loss: 0.1720 - val_accuracy: 0.9580
Epoch 49/100
uracy: 0.9888 - val_loss: 0.1714 - val_accuracy: 0.9588
Epoch 50/100
uracy: 0.9894 - val_loss: 0.1728 - val_accuracy: 0.9582
Epoch 51/100
uracy: 0.9900 - val loss: 0.1727 - val accuracy: 0.9586
Epoch 52/100
uracy: 0.9903 - val_loss: 0.1724 - val_accuracy: 0.9594
Epoch 53/100
uracy: 0.9908 - val_loss: 0.1744 - val_accuracy: 0.9582
Epoch 54/100
uracy: 0.9909 - val_loss: 0.1744 - val_accuracy: 0.9586
Epoch 55/100
```

```
uracy: 0.9919 - val loss: 0.1737 - val accuracy: 0.9602
Epoch 56/100
uracy: 0.9926 - val loss: 0.1738 - val accuracy: 0.9576
Epoch 57/100
uracy: 0.9926 - val loss: 0.1726 - val accuracy: 0.9598
Epoch 58/100
uracy: 0.9933 - val loss: 0.1739 - val accuracy: 0.9586
Epoch 59/100
uracy: 0.9930 - val loss: 0.1747 - val accuracy: 0.9590
Epoch 60/100
uracy: 0.9939 - val loss: 0.1743 - val accuracy: 0.9594
Epoch 61/100
uracy: 0.9939 - val loss: 0.1773 - val accuracy: 0.9596
Epoch 62/100
uracy: 0.9945 - val loss: 0.1765 - val accuracy: 0.9602
Epoch 63/100
uracy: 0.9946 - val_loss: 0.1746 - val_accuracy: 0.9613
Epoch 64/100
uracy: 0.9949 - val_loss: 0.1742 - val_accuracy: 0.9615
Epoch 65/100
uracy: 0.9956 - val_loss: 0.1765 - val_accuracy: 0.9596
Epoch 66/100
uracy: 0.9958 - val loss: 0.1774 - val accuracy: 0.9609
Epoch 67/100
uracy: 0.9958 - val_loss: 0.1773 - val_accuracy: 0.9607
Epoch 68/100
uracy: 0.9963 - val_loss: 0.1766 - val_accuracy: 0.9611
Epoch 69/100
uracy: 0.9965 - val_loss: 0.1802 - val_accuracy: 0.9607
Epoch 70/100
uracy: 0.9969 - val loss: 0.1792 - val accuracy: 0.9613
Epoch 71/100
uracy: 0.9970 - val_loss: 0.1774 - val_accuracy: 0.9611
Epoch 72/100
uracy: 0.9969 - val_loss: 0.1783 - val_accuracy: 0.9604
Epoch 73/100
uracy: 0.9973 - val_loss: 0.1784 - val_accuracy: 0.9617
Epoch 74/100
```

```
uracy: 0.9975 - val loss: 0.1781 - val accuracy: 0.9631
Epoch 75/100
uracy: 0.9975 - val loss: 0.1818 - val accuracy: 0.9611
Epoch 76/100
uracy: 0.9977 - val loss: 0.1806 - val accuracy: 0.9607
Epoch 77/100
uracy: 0.9976 - val loss: 0.1805 - val accuracy: 0.9613
Epoch 78/100
uracy: 0.9979 - val loss: 0.1803 - val accuracy: 0.9619
Epoch 79/100
uracy: 0.9981 - val loss: 0.1852 - val accuracy: 0.9600
Epoch 80/100
uracy: 0.9982 - val loss: 0.1808 - val accuracy: 0.9623
Epoch 81/100
uracy: 0.9984 - val loss: 0.1851 - val accuracy: 0.9613
Epoch 82/100
uracy: 0.9985 - val_loss: 0.1838 - val_accuracy: 0.9609
Epoch 83/100
uracy: 0.9985 - val_loss: 0.1829 - val_accuracy: 0.9613
Epoch 84/100
uracy: 0.9987 - val_loss: 0.1835 - val_accuracy: 0.9625
Epoch 85/100
1440/1440 [============= ] - 2s 1ms/step - loss: 0.0157 - acc
uracy: 0.9988 - val loss: 0.1837 - val accuracy: 0.9615
Epoch 86/100
uracy: 0.9989 - val_loss: 0.1844 - val_accuracy: 0.9604
Epoch 87/100
uracy: 0.9988 - val_loss: 0.1853 - val_accuracy: 0.9625
Epoch 88/100
uracy: 0.9990 - val_loss: 0.1865 - val_accuracy: 0.9611
Epoch 89/100
uracy: 0.9990 - val loss: 0.1866 - val accuracy: 0.9635
Epoch 90/100
uracy: 0.9991 - val_loss: 0.1863 - val_accuracy: 0.9627
Epoch 91/100
uracy: 0.9992 - val_loss: 0.1887 - val_accuracy: 0.9617
Epoch 92/100
uracy: 0.9993 - val_loss: 0.1867 - val_accuracy: 0.9617
Epoch 93/100
```

```
uracy: 0.9993 - val loss: 0.1867 - val accuracy: 0.9619
Epoch 94/100
uracy: 0.9994 - val_loss: 0.1891 - val_accuracy: 0.9625
Epoch 95/100
uracy: 0.9994 - val loss: 0.1902 - val accuracy: 0.9623
Epoch 96/100
1440/1440 [=============] - 2s 1ms/step - loss: 0.0113 - acc
uracy: 0.9995 - val loss: 0.1894 - val accuracy: 0.9611
Epoch 97/100
uracy: 0.9994 - val loss: 0.1911 - val accuracy: 0.9623
Epoch 98/100
uracy: 0.9995 - val loss: 0.1906 - val accuracy: 0.9623
Epoch 99/100
uracy: 0.9995 - val loss: 0.1925 - val accuracy: 0.9619
Epoch 100/100
1440/1440 [============= ] - 2s 1ms/step - loss: 0.0102 - acc
uracy: 0.9996 - val loss: 0.1918 - val accuracy: 0.9609
```



```
acy: 0.9592
Learning Rate: 0.01
Test loss: 0.17338040471076965
Test accuracy: 0.9592449069023132
Total number of parameters: 168376
Number of bias parameters: 276
Epoch 1/100
uracy: 0.2651 - val loss: 2.3760 - val accuracy: 0.3633
Epoch 2/100
uracy: 0.4429 - val loss: 1.9841 - val accuracy: 0.4855
Epoch 3/100
uracy: 0.5274 - val loss: 1.6838 - val accuracy: 0.5555
Epoch 4/100
uracy: 0.5935 - val loss: 1.4346 - val accuracy: 0.6199
Epoch 5/100
1440/1440 [============= ] - 2s 1ms/step - loss: 1.3203 - acc
uracy: 0.6498 - val_loss: 1.2391 - val_accuracy: 0.6732
Epoch 6/100
uracy: 0.6954 - val_loss: 1.0976 - val_accuracy: 0.7129
Epoch 7/100
uracy: 0.7311 - val_loss: 0.9932 - val_accuracy: 0.7436
Epoch 8/100
uracy: 0.7551 - val_loss: 0.9130 - val_accuracy: 0.7703
Epoch 9/100
uracy: 0.7720 - val loss: 0.8544 - val accuracy: 0.7836
Epoch 10/100
uracy: 0.7853 - val_loss: 0.8074 - val_accuracy: 0.7937
Epoch 11/100
uracy: 0.7966 - val_loss: 0.7702 - val_accuracy: 0.8021
Epoch 12/100
uracy: 0.8055 - val_loss: 0.7388 - val_accuracy: 0.8113
Epoch 13/100
1440/1440 [============ ] - 2s 1ms/step - loss: 0.7059 - acc
uracy: 0.8132 - val loss: 0.7130 - val accuracy: 0.8160
Epoch 14/100
uracy: 0.8185 - val_loss: 0.6908 - val_accuracy: 0.8201
Epoch 15/100
uracy: 0.8244 - val_loss: 0.6712 - val_accuracy: 0.8258
Epoch 16/100
uracy: 0.8295 - val_loss: 0.6539 - val_accuracy: 0.8299
Epoch 17/100
```

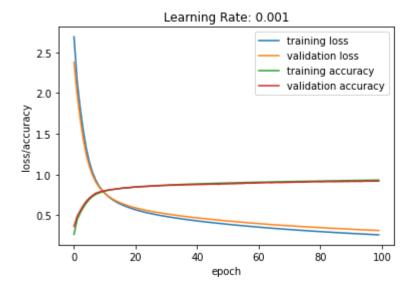
```
uracy: 0.8348 - val loss: 0.6386 - val accuracy: 0.8357
Epoch 18/100
uracy: 0.8395 - val loss: 0.6264 - val accuracy: 0.8361
Epoch 19/100
uracy: 0.8421 - val loss: 0.6125 - val accuracy: 0.8381
Epoch 20/100
uracy: 0.8461 - val loss: 0.6010 - val accuracy: 0.8441
Epoch 21/100
uracy: 0.8491 - val loss: 0.5918 - val accuracy: 0.8471
Epoch 22/100
1440/1440 [=============== ] - 2s 1ms/step - loss: 0.5577 - acc
uracy: 0.8511 - val loss: 0.5817 - val accuracy: 0.8484
Epoch 23/100
uracy: 0.8545 - val loss: 0.5731 - val accuracy: 0.8514
Epoch 24/100
uracy: 0.8553 - val loss: 0.5646 - val accuracy: 0.8543
Epoch 25/100
uracy: 0.8592 - val_loss: 0.5573 - val_accuracy: 0.8549
Epoch 26/100
uracy: 0.8610 - val_loss: 0.5488 - val_accuracy: 0.8594
Epoch 27/100
uracy: 0.8630 - val_loss: 0.5419 - val_accuracy: 0.8605
Epoch 28/100
uracy: 0.8656 - val loss: 0.5362 - val accuracy: 0.8619
Epoch 29/100
uracy: 0.8673 - val_loss: 0.5315 - val_accuracy: 0.8635
Epoch 30/100
uracy: 0.8690 - val_loss: 0.5235 - val_accuracy: 0.8656
Epoch 31/100
uracy: 0.8708 - val_loss: 0.5167 - val_accuracy: 0.8670
Epoch 32/100
uracy: 0.8732 - val loss: 0.5125 - val accuracy: 0.8693
Epoch 33/100
uracy: 0.8744 - val_loss: 0.5068 - val_accuracy: 0.8691
Epoch 34/100
uracy: 0.8760 - val_loss: 0.5018 - val_accuracy: 0.8701
Epoch 35/100
uracy: 0.8773 - val_loss: 0.4959 - val_accuracy: 0.8715
Epoch 36/100
```

```
uracy: 0.8790 - val loss: 0.4908 - val accuracy: 0.8721
Epoch 37/100
uracy: 0.8806 - val loss: 0.4870 - val accuracy: 0.8748
Epoch 38/100
uracy: 0.8820 - val loss: 0.4811 - val accuracy: 0.8746
Epoch 39/100
uracy: 0.8836 - val loss: 0.4772 - val accuracy: 0.8758
Epoch 40/100
uracy: 0.8852 - val loss: 0.4728 - val accuracy: 0.8770
Epoch 41/100
uracy: 0.8859 - val loss: 0.4681 - val accuracy: 0.8781
Epoch 42/100
uracy: 0.8873 - val loss: 0.4645 - val accuracy: 0.8781
Epoch 43/100
uracy: 0.8883 - val loss: 0.4601 - val accuracy: 0.8793
Epoch 44/100
uracy: 0.8895 - val_loss: 0.4564 - val_accuracy: 0.8799
Epoch 45/100
uracy: 0.8908 - val_loss: 0.4519 - val_accuracy: 0.8822
Epoch 46/100
uracy: 0.8919 - val_loss: 0.4485 - val_accuracy: 0.8826
Epoch 47/100
1440/1440 [============= ] - 2s 1ms/step - loss: 0.4052 - acc
uracy: 0.8931 - val loss: 0.4456 - val accuracy: 0.8836
Epoch 48/100
uracy: 0.8944 - val_loss: 0.4414 - val_accuracy: 0.8816
Epoch 49/100
uracy: 0.8952 - val_loss: 0.4372 - val_accuracy: 0.8855
Epoch 50/100
uracy: 0.8961 - val_loss: 0.4336 - val_accuracy: 0.8859
Epoch 51/100
1440/1440 [============= ] - 2s 1ms/step - loss: 0.3896 - acc
uracy: 0.8972 - val loss: 0.4296 - val accuracy: 0.8865
Epoch 52/100
uracy: 0.8984 - val_loss: 0.4270 - val_accuracy: 0.8879
Epoch 53/100
uracy: 0.8994 - val loss: 0.4241 - val accuracy: 0.8877
Epoch 54/100
uracy: 0.9004 - val_loss: 0.4199 - val_accuracy: 0.8902
Epoch 55/100
```

```
uracy: 0.9010 - val loss: 0.4176 - val accuracy: 0.8910
Epoch 56/100
uracy: 0.9020 - val loss: 0.4147 - val accuracy: 0.8914
Epoch 57/100
uracy: 0.9033 - val loss: 0.4100 - val accuracy: 0.8951
Epoch 58/100
uracy: 0.9038 - val loss: 0.4068 - val accuracy: 0.8947
Epoch 59/100
uracy: 0.9049 - val loss: 0.4032 - val accuracy: 0.8961
Epoch 60/100
uracy: 0.9060 - val loss: 0.4013 - val accuracy: 0.8957
Epoch 61/100
uracy: 0.9069 - val loss: 0.3981 - val accuracy: 0.8980
Epoch 62/100
uracy: 0.9069 - val loss: 0.3944 - val accuracy: 0.8992
Epoch 63/100
uracy: 0.9076 - val_loss: 0.3928 - val_accuracy: 0.9000
Epoch 64/100
uracy: 0.9090 - val_loss: 0.3890 - val_accuracy: 0.9020
Epoch 65/100
uracy: 0.9097 - val_loss: 0.3864 - val_accuracy: 0.8994
Epoch 66/100
1440/1440 [============= ] - 2s 1ms/step - loss: 0.3395 - acc
uracy: 0.9108 - val loss: 0.3834 - val accuracy: 0.9020
Epoch 67/100
uracy: 0.9114 - val_loss: 0.3808 - val_accuracy: 0.9039
Epoch 68/100
uracy: 0.9120 - val_loss: 0.3794 - val_accuracy: 0.9020
Epoch 69/100
uracy: 0.9128 - val_loss: 0.3754 - val_accuracy: 0.9037
Epoch 70/100
uracy: 0.9139 - val loss: 0.3742 - val accuracy: 0.9045
Epoch 71/100
uracy: 0.9144 - val_loss: 0.3701 - val_accuracy: 0.9051
Epoch 72/100
uracy: 0.9149 - val_loss: 0.3701 - val_accuracy: 0.9059
Epoch 73/100
uracy: 0.9154 - val_loss: 0.3665 - val_accuracy: 0.9074
Epoch 74/100
```

```
uracy: 0.9168 - val loss: 0.3638 - val accuracy: 0.9074
Epoch 75/100
uracy: 0.9171 - val loss: 0.3618 - val accuracy: 0.9076
Epoch 76/100
uracy: 0.9178 - val loss: 0.3602 - val accuracy: 0.9076
Epoch 77/100
uracy: 0.9187 - val loss: 0.3575 - val accuracy: 0.9098
Epoch 78/100
uracy: 0.9186 - val loss: 0.3549 - val accuracy: 0.9109
Epoch 79/100
uracy: 0.9192 - val_loss: 0.3524 - val_accuracy: 0.9111
Epoch 80/100
uracy: 0.9205 - val loss: 0.3507 - val accuracy: 0.9121
Epoch 81/100
uracy: 0.9213 - val loss: 0.3495 - val accuracy: 0.9105
Epoch 82/100
uracy: 0.9214 - val_loss: 0.3464 - val_accuracy: 0.9121
Epoch 83/100
uracy: 0.9230 - val_loss: 0.3438 - val_accuracy: 0.9133
Epoch 84/100
uracy: 0.9229 - val_loss: 0.3416 - val_accuracy: 0.9141
Epoch 85/100
1440/1440 [============= ] - 2s 1ms/step - loss: 0.2907 - acc
uracy: 0.9244 - val loss: 0.3409 - val accuracy: 0.9131
Epoch 86/100
uracy: 0.9246 - val_loss: 0.3392 - val_accuracy: 0.9131
Epoch 87/100
uracy: 0.9247 - val_loss: 0.3372 - val_accuracy: 0.9143
Epoch 88/100
uracy: 0.9259 - val_loss: 0.3350 - val_accuracy: 0.9139
Epoch 89/100
uracy: 0.9263 - val loss: 0.3328 - val accuracy: 0.9158
Epoch 90/100
uracy: 0.9268 - val_loss: 0.3317 - val_accuracy: 0.9148
Epoch 91/100
uracy: 0.9272 - val_loss: 0.3295 - val_accuracy: 0.9168
Epoch 92/100
uracy: 0.9282 - val_loss: 0.3276 - val_accuracy: 0.9160
Epoch 93/100
```

```
uracy: 0.9282 - val loss: 0.3246 - val accuracy: 0.9170
Epoch 94/100
uracy: 0.9295 - val_loss: 0.3231 - val_accuracy: 0.9158
Epoch 95/100
uracy: 0.9296 - val loss: 0.3215 - val accuracy: 0.9186
Epoch 96/100
uracy: 0.9306 - val loss: 0.3197 - val_accuracy: 0.9193
Epoch 97/100
uracy: 0.9308 - val loss: 0.3180 - val accuracy: 0.9191
Epoch 98/100
uracy: 0.9310 - val loss: 0.3169 - val accuracy: 0.9193
Epoch 99/100
uracy: 0.9320 - val loss: 0.3148 - val accuracy: 0.9195
Epoch 100/100
uracy: 0.9321 - val_loss: 0.3138 - val_accuracy: 0.9199
```



500/500 [============] - 1s 1ms/step - loss: 0.2915 - accur

acy: 0.9238

Learning Rate: 0.001

Test loss: 0.2915424406528473
Test accuracy: 0.9238029718399048
Total number of parameters: 168376
Number of bias parameters: 276

All three models have high test accuracies. However, the second model has the lowest test loss of 0.1734, indicating that it may have better generalization performance.

Conclusion: The best performing model is the model with learning rate 0.01, which gives an accuracy of 95.9% on test dataset. There are 168376 total parameters and 276 bias parameters.

Repeat everything from the previous step but make the hidden layers have linear activation functions. Discuss how this impacts accuracy and why.

```
In [91]: learning rates = [0.1, 0.01, 0.001]
         for lr in learning rates:
             # Define the model architecture
             model = keras.Sequential(
                      keras.Input(shape=(784)),
                      layers.Dense(200, activation="linear"),
                      layers.Dense(50, activation="linear"),
                      layers.Dense(26),
                 ]
             )
             # Compile the model
             model.compile(
                 loss=keras.losses.SparseCategoricalCrossentropy(from logits=True),
                 optimizer=keras.optimizers.SGD(lr=lr),
                 metrics=["accuracy"],
             )
             # Train the model
             history = model.fit(
                 x train,
                 y_train,
                 epochs=100,
                 batch size=32,
                 validation split=0.1,
             )
             # Plot the training and validation loss and accuracy as a function of train
             plt.plot(history.history["loss"], label="training loss")
             plt.plot(history.history["val_loss"], label="validation loss")
             plt.plot(history.history["accuracy"], label="training accuracy")
             plt.plot(history.history["val accuracy"], label="validation accuracy")
             plt.xlabel("epoch")
             plt.ylabel("loss/accuracy")
             plt.title(f"Learning Rate: {lr}")
             plt.legend()
             plt.show()
             # Evaluate the model on the test set
             test loss, test accuracy = model.evaluate(x test, y test)
             print(f"Learning Rate: {lr}")
             print("Test loss:", test loss)
             print("Test accuracy:", test accuracy)
             # Count the total number of parameters and the number of bias parameters in
             total params = model.count params()
             bias params = sum([len(layer.get weights()[1]) for layer in model.layers])
             print("Total number of parameters:", total_params)
             print("Number of bias parameters:", bias params)
```

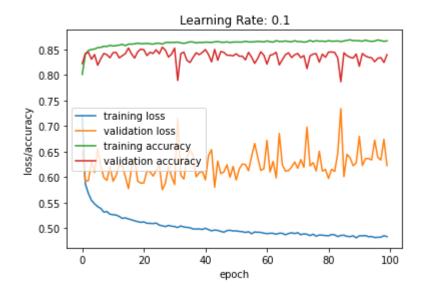
```
Epoch 1/100
uracy: 0.8014 - val loss: 0.6500 - val accuracy: 0.8225
1440/1440 [============= ] - 2s 1ms/step - loss: 0.5866 - acc
uracy: 0.8406 - val_loss: 0.5922 - val_accuracy: 0.8424
Epoch 3/100
uracy: 0.8482 - val_loss: 0.5933 - val_accuracy: 0.8447
Epoch 4/100
uracy: 0.8502 - val_loss: 0.6326 - val_accuracy: 0.8311
Epoch 5/100
uracy: 0.8510 - val loss: 0.6092 - val accuracy: 0.8402
Epoch 6/100
uracy: 0.8538 - val_loss: 0.6553 - val_accuracy: 0.8193
Epoch 7/100
uracy: 0.8543 - val_loss: 0.6228 - val_accuracy: 0.8318
Epoch 8/100
uracy: 0.8565 - val_loss: 0.5991 - val_accuracy: 0.8424
Epoch 9/100
uracy: 0.8561 - val loss: 0.5937 - val accuracy: 0.8400
Epoch 10/100
uracy: 0.8584 - val_loss: 0.6208 - val_accuracy: 0.8340
Epoch 11/100
uracy: 0.8571 - val_loss: 0.5921 - val_accuracy: 0.8439
Epoch 12/100
uracy: 0.8577 - val loss: 0.6033 - val accuracy: 0.8445
Epoch 13/100
uracy: 0.8588 - val loss: 0.6232 - val accuracy: 0.8338
Epoch 14/100
uracy: 0.8603 - val loss: 0.6230 - val accuracy: 0.8379
Epoch 15/100
uracy: 0.8578 - val loss: 0.6009 - val accuracy: 0.8422
Epoch 16/100
uracy: 0.8607 - val_loss: 0.5775 - val_accuracy: 0.8531
Epoch 17/100
1440/1440 [============== ] - 2s 1ms/step - loss: 0.5163 - acc
uracy: 0.8607 - val loss: 0.6176 - val accuracy: 0.8416
Epoch 18/100
uracy: 0.8613 - val loss: 0.6363 - val accuracy: 0.8334
Epoch 19/100
uracy: 0.8626 - val loss: 0.5922 - val accuracy: 0.8457
```

```
Epoch 20/100
uracy: 0.8615 - val_loss: 0.5883 - val_accuracy: 0.8510
Epoch 21/100
uracy: 0.8617 - val_loss: 0.5887 - val_accuracy: 0.8498
Epoch 22/100
uracy: 0.8622 - val_loss: 0.6119 - val_accuracy: 0.8383
Epoch 23/100
uracy: 0.8613 - val_loss: 0.6108 - val_accuracy: 0.8447
Epoch 24/100
uracy: 0.8607 - val loss: 0.6021 - val accuracy: 0.8424
uracy: 0.8624 - val_loss: 0.6131 - val_accuracy: 0.8496
Epoch 26/100
uracy: 0.8624 - val_loss: 0.6242 - val_accuracy: 0.8418
Epoch 27/100
uracy: 0.8609 - val_loss: 0.5753 - val_accuracy: 0.8547
Epoch 28/100
uracy: 0.8637 - val_loss: 0.5881 - val_accuracy: 0.8490
Epoch 29/100
uracy: 0.8642 - val loss: 0.6217 - val accuracy: 0.8354
Epoch 30/100
uracy: 0.8639 - val_loss: 0.6015 - val_accuracy: 0.8412
Epoch 31/100
uracy: 0.8641 - val_loss: 0.5856 - val_accuracy: 0.8529
Epoch 32/100
uracy: 0.8646 - val loss: 0.7147 - val accuracy: 0.7895
Epoch 33/100
uracy: 0.8631 - val_loss: 0.6038 - val_accuracy: 0.8420
Epoch 34/100
uracy: 0.8622 - val_loss: 0.5964 - val_accuracy: 0.8451
Epoch 35/100
uracy: 0.8635 - val loss: 0.6384 - val accuracy: 0.8289
Epoch 36/100
uracy: 0.8652 - val loss: 0.6528 - val accuracy: 0.8248
Epoch 37/100
uracy: 0.8649 - val loss: 0.6424 - val accuracy: 0.8348
Epoch 38/100
uracy: 0.8631 - val_loss: 0.6006 - val_accuracy: 0.8438
```

```
Epoch 39/100
uracy: 0.8642 - val_loss: 0.6087 - val_accuracy: 0.8400
Epoch 40/100
uracy: 0.8637 - val_loss: 0.6114 - val_accuracy: 0.8443
Epoch 41/100
uracy: 0.8646 - val_loss: 0.5947 - val_accuracy: 0.8500
Epoch 42/100
uracy: 0.8644 - val_loss: 0.6423 - val_accuracy: 0.8404
Epoch 43/100
uracy: 0.8641 - val loss: 0.6539 - val accuracy: 0.8260
1440/1440 [============= ] - 2s 1ms/step - loss: 0.4963 - acc
uracy: 0.8651 - val_loss: 0.5803 - val_accuracy: 0.8504
Epoch 45/100
uracy: 0.8658 - val_loss: 0.6314 - val_accuracy: 0.8291
Epoch 46/100
uracy: 0.8645 - val_loss: 0.6070 - val_accuracy: 0.8463
Epoch 47/100
uracy: 0.8643 - val_loss: 0.6102 - val_accuracy: 0.8445
Epoch 48/100
uracy: 0.8652 - val loss: 0.6242 - val accuracy: 0.8391
Epoch 49/100
uracy: 0.8638 - val_loss: 0.6000 - val_accuracy: 0.8389
Epoch 50/100
uracy: 0.8648 - val_loss: 0.6211 - val_accuracy: 0.8377
Epoch 51/100
uracy: 0.8649 - val loss: 0.5944 - val accuracy: 0.8418
Epoch 52/100
uracy: 0.8648 - val_loss: 0.6162 - val_accuracy: 0.8371
Epoch 53/100
uracy: 0.8648 - val_loss: 0.6258 - val_accuracy: 0.8371
Epoch 54/100
uracy: 0.8663 - val loss: 0.6249 - val accuracy: 0.8299
Epoch 55/100
uracy: 0.8650 - val loss: 0.6126 - val accuracy: 0.8445
Epoch 56/100
uracy: 0.8651 - val loss: 0.6405 - val accuracy: 0.8354
Epoch 57/100
uracy: 0.8654 - val_loss: 0.6660 - val_accuracy: 0.8230
```

```
Epoch 58/100
uracy: 0.8662 - val_loss: 0.6390 - val_accuracy: 0.8328
Epoch 59/100
uracy: 0.8657 - val_loss: 0.6132 - val_accuracy: 0.8457
Epoch 60/100
uracy: 0.8650 - val_loss: 0.6165 - val_accuracy: 0.8391
Epoch 61/100
uracy: 0.8670 - val_loss: 0.6721 - val_accuracy: 0.8215
Epoch 62/100
uracy: 0.8653 - val loss: 0.6103 - val accuracy: 0.8389
uracy: 0.8647 - val_loss: 0.6309 - val_accuracy: 0.8406
Epoch 64/100
uracy: 0.8675 - val_loss: 0.5984 - val_accuracy: 0.8447
Epoch 65/100
uracy: 0.8659 - val_loss: 0.6857 - val_accuracy: 0.8199
Epoch 66/100
uracy: 0.8659 - val_loss: 0.6240 - val_accuracy: 0.8301
Epoch 67/100
uracy: 0.8669 - val loss: 0.6118 - val accuracy: 0.8400
Epoch 68/100
uracy: 0.8658 - val_loss: 0.6129 - val_accuracy: 0.8438
Epoch 69/100
uracy: 0.8653 - val_loss: 0.6197 - val_accuracy: 0.8344
Epoch 70/100
uracy: 0.8674 - val loss: 0.6298 - val accuracy: 0.8398
Epoch 71/100
uracy: 0.8656 - val_loss: 0.6172 - val_accuracy: 0.8424
Epoch 72/100
uracy: 0.8658 - val_loss: 0.6344 - val_accuracy: 0.8342
Epoch 73/100
uracy: 0.8646 - val loss: 0.6193 - val accuracy: 0.8383
Epoch 74/100
uracy: 0.8654 - val loss: 0.6981 - val accuracy: 0.8127
Epoch 75/100
uracy: 0.8680 - val loss: 0.6220 - val accuracy: 0.8377
Epoch 76/100
uracy: 0.8657 - val_loss: 0.6284 - val_accuracy: 0.8412
```

```
Epoch 77/100
uracy: 0.8675 - val_loss: 0.6122 - val_accuracy: 0.8420
Epoch 78/100
uracy: 0.8665 - val_loss: 0.6507 - val_accuracy: 0.8254
Epoch 79/100
uracy: 0.8667 - val_loss: 0.6119 - val_accuracy: 0.8410
Epoch 80/100
uracy: 0.8658 - val_loss: 0.6152 - val_accuracy: 0.8350
Epoch 81/100
uracy: 0.8674 - val loss: 0.5973 - val accuracy: 0.8451
uracy: 0.8664 - val_loss: 0.6155 - val_accuracy: 0.8453
Epoch 83/100
uracy: 0.8665 - val_loss: 0.6112 - val_accuracy: 0.8445
Epoch 84/100
uracy: 0.8670 - val_loss: 0.6469 - val_accuracy: 0.8336
Epoch 85/100
uracy: 0.8657 - val_loss: 0.7342 - val_accuracy: 0.7869
Epoch 86/100
uracy: 0.8669 - val loss: 0.6010 - val accuracy: 0.8438
Epoch 87/100
uracy: 0.8682 - val_loss: 0.6449 - val_accuracy: 0.8381
Epoch 88/100
uracy: 0.8692 - val_loss: 0.6378 - val_accuracy: 0.8350
Epoch 89/100
uracy: 0.8674 - val loss: 0.6223 - val accuracy: 0.8334
Epoch 90/100
uracy: 0.8678 - val_loss: 0.6280 - val_accuracy: 0.8412
Epoch 91/100
uracy: 0.8672 - val_loss: 0.6798 - val_accuracy: 0.8174
Epoch 92/100
uracy: 0.8665 - val loss: 0.6228 - val accuracy: 0.8424
Epoch 93/100
uracy: 0.8686 - val loss: 0.6362 - val accuracy: 0.8375
Epoch 94/100
uracy: 0.8667 - val loss: 0.6365 - val accuracy: 0.8350
Epoch 95/100
uracy: 0.8662 - val_loss: 0.6337 - val_accuracy: 0.8340
```



```
500/500 [============ ] - 1s 1ms/step - loss: 0.6095 - accur
acy: 0.8414
Learning Rate: 0.1
Test loss: 0.6094640493392944
Test accuracy: 0.8413551449775696
Total number of parameters: 168376
Number of bias parameters: 276
Epoch 1/100
uracy: 0.7085 - val loss: 0.7240 - val accuracy: 0.8133
Epoch 2/100
uracy: 0.8273 - val loss: 0.6192 - val accuracy: 0.8396
Epoch 3/100
uracy: 0.8468 - val loss: 0.5871 - val accuracy: 0.8432
Epoch 4/100
uracy: 0.8563 - val loss: 0.5674 - val accuracy: 0.8502
Epoch 5/100
uracy: 0.8618 - val_loss: 0.5554 - val_accuracy: 0.8590
Epoch 6/100
uracy: 0.8654 - val_loss: 0.5431 - val_accuracy: 0.8613
Epoch 7/100
uracy: 0.8678 - val_loss: 0.5397 - val_accuracy: 0.8611
Epoch 8/100
uracy: 0.8703 - val_loss: 0.5407 - val_accuracy: 0.8629
Epoch 9/100
uracy: 0.8701 - val loss: 0.5286 - val accuracy: 0.8664
Epoch 10/100
uracy: 0.8724 - val_loss: 0.5293 - val_accuracy: 0.8684
Epoch 11/100
uracy: 0.8742 - val_loss: 0.5251 - val_accuracy: 0.8684
Epoch 12/100
uracy: 0.8736 - val_loss: 0.5246 - val_accuracy: 0.8656
Epoch 13/100
1440/1440 [============= ] - 2s 1ms/step - loss: 0.4733 - acc
uracy: 0.8751 - val loss: 0.5227 - val accuracy: 0.8676
Epoch 14/100
uracy: 0.8759 - val_loss: 0.5183 - val_accuracy: 0.8678
Epoch 15/100
uracy: 0.8769 - val_loss: 0.5225 - val_accuracy: 0.8678
Epoch 16/100
uracy: 0.8788 - val_loss: 0.5186 - val_accuracy: 0.8701
Epoch 17/100
```

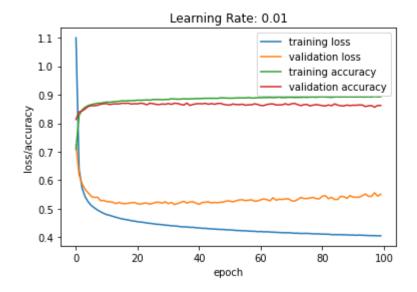
```
uracy: 0.8778 - val loss: 0.5182 - val accuracy: 0.8695
Epoch 18/100
uracy: 0.8793 - val loss: 0.5193 - val accuracy: 0.8703
Epoch 19/100
uracy: 0.8791 - val loss: 0.5213 - val accuracy: 0.8672
Epoch 20/100
uracy: 0.8795 - val loss: 0.5220 - val accuracy: 0.8684
Epoch 21/100
uracy: 0.8809 - val loss: 0.5178 - val accuracy: 0.8680
Epoch 22/100
uracy: 0.8806 - val loss: 0.5165 - val accuracy: 0.8703
Epoch 23/100
uracy: 0.8809 - val loss: 0.5198 - val accuracy: 0.8687
Epoch 24/100
uracy: 0.8818 - val loss: 0.5200 - val accuracy: 0.8645
Epoch 25/100
uracy: 0.8808 - val_loss: 0.5162 - val_accuracy: 0.8701
Epoch 26/100
uracy: 0.8830 - val_loss: 0.5195 - val_accuracy: 0.8686
Epoch 27/100
uracy: 0.8830 - val_loss: 0.5227 - val_accuracy: 0.8662
Epoch 28/100
uracy: 0.8832 - val loss: 0.5228 - val accuracy: 0.8652
Epoch 29/100
uracy: 0.8824 - val_loss: 0.5199 - val_accuracy: 0.8676
Epoch 30/100
uracy: 0.8833 - val_loss: 0.5244 - val_accuracy: 0.8664
Epoch 31/100
uracy: 0.8833 - val_loss: 0.5182 - val_accuracy: 0.8689
Epoch 32/100
1440/1440 [============= ] - 2s 1ms/step - loss: 0.4405 - acc
uracy: 0.8856 - val loss: 0.5223 - val accuracy: 0.8662
Epoch 33/100
uracy: 0.8850 - val_loss: 0.5148 - val_accuracy: 0.8699
Epoch 34/100
uracy: 0.8843 - val_loss: 0.5183 - val_accuracy: 0.8693
Epoch 35/100
uracy: 0.8845 - val_loss: 0.5221 - val_accuracy: 0.8662
Epoch 36/100
```

```
uracy: 0.8859 - val loss: 0.5264 - val accuracy: 0.8637
Epoch 37/100
uracy: 0.8850 - val loss: 0.5201 - val accuracy: 0.8705
Epoch 38/100
uracy: 0.8853 - val loss: 0.5235 - val accuracy: 0.8625
Epoch 39/100
uracy: 0.8856 - val loss: 0.5245 - val accuracy: 0.8658
Epoch 40/100
uracy: 0.8865 - val loss: 0.5198 - val accuracy: 0.8680
Epoch 41/100
uracy: 0.8861 - val loss: 0.5158 - val accuracy: 0.8687
Epoch 42/100
uracy: 0.8869 - val loss: 0.5220 - val accuracy: 0.8680
Epoch 43/100
uracy: 0.8874 - val loss: 0.5230 - val accuracy: 0.8697
Epoch 44/100
uracy: 0.8875 - val_loss: 0.5245 - val_accuracy: 0.8666
Epoch 45/100
uracy: 0.8874 - val_loss: 0.5205 - val_accuracy: 0.8689
Epoch 46/100
uracy: 0.8875 - val_loss: 0.5225 - val_accuracy: 0.8664
Epoch 47/100
uracy: 0.8870 - val loss: 0.5210 - val accuracy: 0.8693
Epoch 48/100
uracy: 0.8891 - val_loss: 0.5231 - val_accuracy: 0.8695
Epoch 49/100
uracy: 0.8887 - val_loss: 0.5240 - val_accuracy: 0.8658
Epoch 50/100
uracy: 0.8882 - val_loss: 0.5277 - val_accuracy: 0.8643
Epoch 51/100
1440/1440 [============= ] - 2s 1ms/step - loss: 0.4260 - acc
uracy: 0.8877 - val loss: 0.5269 - val accuracy: 0.8637
Epoch 52/100
uracy: 0.8881 - val_loss: 0.5245 - val_accuracy: 0.8674
Epoch 53/100
uracy: 0.8885 - val_loss: 0.5278 - val_accuracy: 0.8654
Epoch 54/100
uracy: 0.8891 - val_loss: 0.5310 - val_accuracy: 0.8650
Epoch 55/100
```

```
uracy: 0.8887 - val loss: 0.5316 - val accuracy: 0.8668
Epoch 56/100
uracy: 0.8887 - val loss: 0.5288 - val accuracy: 0.8631
Epoch 57/100
uracy: 0.8900 - val loss: 0.5300 - val accuracy: 0.8646
Epoch 58/100
uracy: 0.8883 - val loss: 0.5315 - val accuracy: 0.8645
Epoch 59/100
uracy: 0.8884 - val loss: 0.5268 - val accuracy: 0.8680
Epoch 60/100
uracy: 0.8897 - val_loss: 0.5273 - val_accuracy: 0.8660
Epoch 61/100
uracy: 0.8893 - val loss: 0.5317 - val accuracy: 0.8621
Epoch 62/100
uracy: 0.8902 - val loss: 0.5344 - val accuracy: 0.8621
Epoch 63/100
uracy: 0.8899 - val_loss: 0.5320 - val_accuracy: 0.8656
Epoch 64/100
uracy: 0.8907 - val_loss: 0.5280 - val_accuracy: 0.8674
Epoch 65/100
uracy: 0.8896 - val_loss: 0.5387 - val_accuracy: 0.8678
Epoch 66/100
uracy: 0.8904 - val loss: 0.5302 - val accuracy: 0.8641
Epoch 67/100
uracy: 0.8914 - val_loss: 0.5335 - val_accuracy: 0.8643
Epoch 68/100
uracy: 0.8899 - val_loss: 0.5326 - val_accuracy: 0.8645
Epoch 69/100
uracy: 0.8902 - val_loss: 0.5346 - val_accuracy: 0.8684
Epoch 70/100
uracy: 0.8910 - val loss: 0.5351 - val accuracy: 0.8646
Epoch 71/100
uracy: 0.8909 - val_loss: 0.5282 - val_accuracy: 0.8682
Epoch 72/100
uracy: 0.8903 - val_loss: 0.5270 - val_accuracy: 0.8695
Epoch 73/100
uracy: 0.8907 - val_loss: 0.5324 - val_accuracy: 0.8652
Epoch 74/100
```

```
uracy: 0.8908 - val loss: 0.5396 - val accuracy: 0.8617
Epoch 75/100
uracy: 0.8914 - val loss: 0.5362 - val accuracy: 0.8650
Epoch 76/100
uracy: 0.8906 - val loss: 0.5359 - val accuracy: 0.8658
Epoch 77/100
uracy: 0.8917 - val loss: 0.5379 - val accuracy: 0.8609
Epoch 78/100
uracy: 0.8919 - val loss: 0.5399 - val accuracy: 0.8633
Epoch 79/100
uracy: 0.8909 - val loss: 0.5358 - val accuracy: 0.8656
Epoch 80/100
uracy: 0.8921 - val loss: 0.5348 - val accuracy: 0.8637
Epoch 81/100
uracy: 0.8928 - val loss: 0.5436 - val accuracy: 0.8617
Epoch 82/100
uracy: 0.8921 - val_loss: 0.5462 - val_accuracy: 0.8605
Epoch 83/100
uracy: 0.8916 - val_loss: 0.5355 - val_accuracy: 0.8641
Epoch 84/100
uracy: 0.8906 - val_loss: 0.5401 - val_accuracy: 0.8613
Epoch 85/100
uracy: 0.8923 - val loss: 0.5327 - val accuracy: 0.8678
Epoch 86/100
uracy: 0.8924 - val_loss: 0.5327 - val_accuracy: 0.8637
Epoch 87/100
uracy: 0.8920 - val_loss: 0.5439 - val_accuracy: 0.8613
Epoch 88/100
uracy: 0.8923 - val_loss: 0.5425 - val_accuracy: 0.8605
Epoch 89/100
1440/1440 [============= ] - 2s 1ms/step - loss: 0.4087 - acc
uracy: 0.8921 - val loss: 0.5368 - val accuracy: 0.8639
Epoch 90/100
uracy: 0.8924 - val_loss: 0.5460 - val_accuracy: 0.8617
Epoch 91/100
uracy: 0.8923 - val_loss: 0.5412 - val_accuracy: 0.8633
Epoch 92/100
uracy: 0.8921 - val_loss: 0.5403 - val_accuracy: 0.8629
Epoch 93/100
```

```
uracy: 0.8925 - val loss: 0.5408 - val accuracy: 0.8641
Epoch 94/100
uracy: 0.8921 - val loss: 0.5459 - val accuracy: 0.8639
Epoch 95/100
uracy: 0.8918 - val loss: 0.5520 - val accuracy: 0.8584
Epoch 96/100
uracy: 0.8927 - val loss: 0.5437 - val accuracy: 0.8609
Epoch 97/100
uracy: 0.8918 - val loss: 0.5436 - val accuracy: 0.8619
Epoch 98/100
uracy: 0.8938 - val loss: 0.5559 - val accuracy: 0.8561
Epoch 99/100
uracy: 0.8925 - val loss: 0.5447 - val accuracy: 0.8623
Epoch 100/100
1440/1440 [============= ] - 2s 1ms/step - loss: 0.4053 - acc
uracy: 0.8928 - val loss: 0.5509 - val accuracy: 0.8623
```



```
500/500 [============ ] - 1s 1ms/step - loss: 0.5193 - accur
acy: 0.8663
Learning Rate: 0.01
Test loss: 0.5193240642547607
Test accuracy: 0.8662958145141602
Total number of parameters: 168376
Number of bias parameters: 276
Epoch 1/100
uracy: 0.4085 - val loss: 1.7844 - val accuracy: 0.5510
Epoch 2/100
uracy: 0.6015 - val loss: 1.3696 - val accuracy: 0.6475
Epoch 3/100
uracy: 0.6706 - val loss: 1.1410 - val accuracy: 0.7066
Epoch 4/100
uracy: 0.7175 - val loss: 1.0005 - val accuracy: 0.7451
Epoch 5/100
uracy: 0.7491 - val_loss: 0.9079 - val_accuracy: 0.7660
Epoch 6/100
uracy: 0.7705 - val_loss: 0.8415 - val_accuracy: 0.7834
Epoch 7/100
uracy: 0.7850 - val_loss: 0.7942 - val_accuracy: 0.7934
Epoch 8/100
uracy: 0.7965 - val_loss: 0.7567 - val_accuracy: 0.8039
Epoch 9/100
uracy: 0.8068 - val loss: 0.7280 - val accuracy: 0.8090
Epoch 10/100
uracy: 0.8132 - val_loss: 0.7041 - val_accuracy: 0.8158
Epoch 11/100
uracy: 0.8196 - val_loss: 0.6850 - val_accuracy: 0.8215
Epoch 12/100
uracy: 0.8248 - val_loss: 0.6704 - val_accuracy: 0.8242
Epoch 13/100
uracy: 0.8289 - val loss: 0.6572 - val accuracy: 0.8289
Epoch 14/100
uracy: 0.8330 - val_loss: 0.6450 - val_accuracy: 0.8311
Epoch 15/100
uracy: 0.8363 - val_loss: 0.6361 - val_accuracy: 0.8328
Epoch 16/100
uracy: 0.8383 - val_loss: 0.6275 - val_accuracy: 0.8338
Epoch 17/100
```

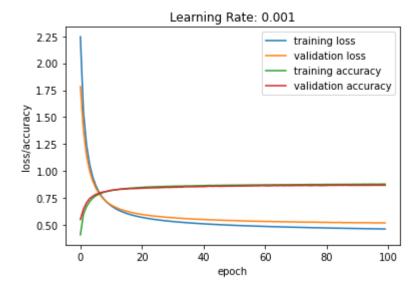
```
uracy: 0.8411 - val loss: 0.6206 - val accuracy: 0.8371
Epoch 18/100
uracy: 0.8430 - val loss: 0.6135 - val accuracy: 0.8375
Epoch 19/100
uracy: 0.8449 - val loss: 0.6078 - val accuracy: 0.8381
Epoch 20/100
uracy: 0.8470 - val loss: 0.6023 - val accuracy: 0.8395
Epoch 21/100
uracy: 0.8486 - val loss: 0.5978 - val accuracy: 0.8412
Epoch 22/100
uracy: 0.8508 - val loss: 0.5933 - val accuracy: 0.8422
Epoch 23/100
uracy: 0.8523 - val loss: 0.5898 - val accuracy: 0.8434
Epoch 24/100
uracy: 0.8531 - val loss: 0.5854 - val accuracy: 0.8439
Epoch 25/100
uracy: 0.8545 - val_loss: 0.5825 - val_accuracy: 0.8449
Epoch 26/100
uracy: 0.8555 - val_loss: 0.5802 - val_accuracy: 0.8451
Epoch 27/100
uracy: 0.8557 - val_loss: 0.5766 - val_accuracy: 0.8461
Epoch 28/100
1440/1440 [============ ] - 2s 1ms/step - loss: 0.5408 - acc
uracy: 0.8569 - val loss: 0.5747 - val accuracy: 0.8473
Epoch 29/100
uracy: 0.8582 - val_loss: 0.5711 - val_accuracy: 0.8490
Epoch 30/100
uracy: 0.8584 - val_loss: 0.5698 - val_accuracy: 0.8480
Epoch 31/100
uracy: 0.8598 - val_loss: 0.5671 - val_accuracy: 0.8498
Epoch 32/100
uracy: 0.8602 - val loss: 0.5652 - val accuracy: 0.8500
Epoch 33/100
uracy: 0.8604 - val_loss: 0.5630 - val_accuracy: 0.8512
Epoch 34/100
uracy: 0.8611 - val_loss: 0.5610 - val_accuracy: 0.8512
Epoch 35/100
uracy: 0.8622 - val_loss: 0.5594 - val_accuracy: 0.8539
Epoch 36/100
```

```
uracy: 0.8625 - val loss: 0.5576 - val accuracy: 0.8545
Epoch 37/100
uracy: 0.8628 - val loss: 0.5566 - val accuracy: 0.8545
Epoch 38/100
1440/1440 [============== ] - 2s 1ms/step - loss: 0.5161 - acc
uracy: 0.8638 - val loss: 0.5542 - val accuracy: 0.8547
Epoch 39/100
uracy: 0.8648 - val loss: 0.5536 - val accuracy: 0.8551
Epoch 40/100
uracy: 0.8646 - val loss: 0.5520 - val accuracy: 0.8562
Epoch 41/100
uracy: 0.8654 - val loss: 0.5511 - val accuracy: 0.8555
Epoch 42/100
uracy: 0.8663 - val loss: 0.5490 - val accuracy: 0.8574
Epoch 43/100
1440/1440 [=============== ] - 2s 1ms/step - loss: 0.5075 - acc
uracy: 0.8671 - val loss: 0.5482 - val accuracy: 0.8602
Epoch 44/100
uracy: 0.8663 - val_loss: 0.5479 - val_accuracy: 0.8584
Epoch 45/100
uracy: 0.8677 - val_loss: 0.5457 - val_accuracy: 0.8602
Epoch 46/100
uracy: 0.8670 - val_loss: 0.5451 - val_accuracy: 0.8588
Epoch 47/100
1440/1440 [============= ] - 2s 1ms/step - loss: 0.5017 - acc
uracy: 0.8682 - val loss: 0.5441 - val accuracy: 0.8588
Epoch 48/100
uracy: 0.8686 - val_loss: 0.5423 - val_accuracy: 0.8600
Epoch 49/100
uracy: 0.8685 - val_loss: 0.5423 - val_accuracy: 0.8605
Epoch 50/100
uracy: 0.8695 - val_loss: 0.5408 - val_accuracy: 0.8600
Epoch 51/100
1440/1440 [============= ] - 2s 1ms/step - loss: 0.4966 - acc
uracy: 0.8690 - val loss: 0.5410 - val accuracy: 0.8611
Epoch 52/100
uracy: 0.8701 - val_loss: 0.5391 - val_accuracy: 0.8613
Epoch 53/100
uracy: 0.8697 - val_loss: 0.5383 - val_accuracy: 0.8611
Epoch 54/100
uracy: 0.8703 - val_loss: 0.5378 - val_accuracy: 0.8613
Epoch 55/100
```

```
uracy: 0.8705 - val loss: 0.5364 - val accuracy: 0.8619
Epoch 56/100
uracy: 0.8713 - val loss: 0.5360 - val accuracy: 0.8625
Epoch 57/100
uracy: 0.8714 - val loss: 0.5353 - val accuracy: 0.8623
Epoch 58/100
uracy: 0.8714 - val loss: 0.5345 - val accuracy: 0.8637
Epoch 59/100
uracy: 0.8719 - val loss: 0.5339 - val accuracy: 0.8627
Epoch 60/100
uracy: 0.8717 - val loss: 0.5338 - val accuracy: 0.8654
Epoch 61/100
uracy: 0.8723 - val loss: 0.5325 - val accuracy: 0.8641
Epoch 62/100
uracy: 0.8725 - val loss: 0.5326 - val accuracy: 0.8631
Epoch 63/100
uracy: 0.8726 - val_loss: 0.5323 - val_accuracy: 0.8639
Epoch 64/100
uracy: 0.8737 - val_loss: 0.5307 - val_accuracy: 0.8654
Epoch 65/100
uracy: 0.8731 - val_loss: 0.5315 - val_accuracy: 0.8643
Epoch 66/100
uracy: 0.8735 - val loss: 0.5298 - val accuracy: 0.8658
Epoch 67/100
uracy: 0.8738 - val_loss: 0.5299 - val_accuracy: 0.8645
Epoch 68/100
uracy: 0.8737 - val_loss: 0.5292 - val_accuracy: 0.8654
Epoch 69/100
uracy: 0.8741 - val_loss: 0.5289 - val_accuracy: 0.8648
Epoch 70/100
uracy: 0.8743 - val loss: 0.5289 - val accuracy: 0.8648
Epoch 71/100
uracy: 0.8744 - val_loss: 0.5281 - val_accuracy: 0.8664
Epoch 72/100
uracy: 0.8745 - val_loss: 0.5268 - val_accuracy: 0.8656
Epoch 73/100
uracy: 0.8747 - val_loss: 0.5271 - val_accuracy: 0.8662
Epoch 74/100
```

```
uracy: 0.8748 - val loss: 0.5256 - val accuracy: 0.8670
Epoch 75/100
uracy: 0.8757 - val loss: 0.5269 - val accuracy: 0.8660
Epoch 76/100
uracy: 0.8756 - val loss: 0.5260 - val accuracy: 0.8652
Epoch 77/100
uracy: 0.8756 - val loss: 0.5261 - val accuracy: 0.8670
Epoch 78/100
uracy: 0.8759 - val loss: 0.5251 - val accuracy: 0.8668
Epoch 79/100
uracy: 0.8757 - val loss: 0.5250 - val accuracy: 0.8654
Epoch 80/100
uracy: 0.8761 - val loss: 0.5239 - val accuracy: 0.8664
Epoch 81/100
uracy: 0.8763 - val loss: 0.5245 - val accuracy: 0.8666
Epoch 82/100
uracy: 0.8763 - val_loss: 0.5233 - val_accuracy: 0.8680
Epoch 83/100
uracy: 0.8766 - val_loss: 0.5227 - val_accuracy: 0.8678
Epoch 84/100
uracy: 0.8771 - val_loss: 0.5226 - val_accuracy: 0.8674
Epoch 85/100
uracy: 0.8769 - val loss: 0.5239 - val accuracy: 0.8686
Epoch 86/100
uracy: 0.8768 - val_loss: 0.5218 - val_accuracy: 0.8680
Epoch 87/100
uracy: 0.8772 - val_loss: 0.5215 - val_accuracy: 0.8687
Epoch 88/100
uracy: 0.8771 - val_loss: 0.5216 - val_accuracy: 0.8684
Epoch 89/100
1440/1440 [============= ] - 2s 1ms/step - loss: 0.4680 - acc
uracy: 0.8771 - val loss: 0.5214 - val accuracy: 0.8676
Epoch 90/100
uracy: 0.8779 - val_loss: 0.5209 - val_accuracy: 0.8684
Epoch 91/100
uracy: 0.8779 - val_loss: 0.5206 - val_accuracy: 0.8676
Epoch 92/100
uracy: 0.8778 - val_loss: 0.5204 - val_accuracy: 0.8680
Epoch 93/100
```

```
uracy: 0.8787 - val loss: 0.5206 - val accuracy: 0.8678
Epoch 94/100
uracy: 0.8784 - val_loss: 0.5211 - val_accuracy: 0.8682
Epoch 95/100
uracy: 0.8786 - val loss: 0.5203 - val accuracy: 0.8682
Epoch 96/100
uracy: 0.8792 - val loss: 0.5195 - val accuracy: 0.8689
Epoch 97/100
uracy: 0.8783 - val loss: 0.5190 - val accuracy: 0.8686
Epoch 98/100
uracy: 0.8786 - val loss: 0.5191 - val accuracy: 0.8689
Epoch 99/100
uracy: 0.8795 - val loss: 0.5198 - val accuracy: 0.8684
Epoch 100/100
uracy: 0.8791 - val_loss: 0.5188 - val_accuracy: 0.8686
```



500/500 [============] - 1s 1ms/step - loss: 0.5001 - accur

acy: 0.8714

Learning Rate: 0.001

Test loss: 0.500124454498291 Test accuracy: 0.8714214563369751 Total number of parameters: 168376 Number of bias parameters: 276

Answer:- We achieve a maximum test accuracy of 87.1% using linear activation function, which is worse than ReLU activation function. The reason for this decrease in accuracy is that linear activation functions can lead to vanishing or exploding gradients during training. This makes it more difficult for the network to learn meaningful representations of the data, which in turn leads to lower accuracy. ReLU activation functions, on the other hand, are known to be more effective at avoiding the vanishing gradient problem, which makes them a better choice for most deep learning tasks.