

# Assignment\_7\_NN

March 10, 2021

Assignment 7: Neural Networks using Keras and Tensorflow Please see the associated document for questions

If you have problems with Keras and Tensorflow on your local installation please make sure they are updated. On Google Colab this notebook runs.

## Group 6:

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```
[ ]: # imports
from __future__ import print_function
import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras import backend as K
import tensorflow as tf
from matplotlib import pyplot as plt
import numpy as np
```

```
[ ]: # Hyper-parameters data-loading and formatting

batch_size = 128
num_classes = 10
epochs = 10

img_rows, img_cols = 28, 28

(x_train, lbl_train), (x_test, lbl_test) = mnist.load_data()

if K.image_data_format() == 'channels_first':
    x_train = x_train.reshape(x_train.shape[0], 1, img_rows, img_cols)
    x_test = x_test.reshape(x_test.shape[0], 1, img_rows, img_cols)
```

```

        input_shape = (1, img_rows, img_cols)
    else:
        x_train = x_train.reshape(x_train.shape[0], img_rows, img_cols, 1)
        x_test = x_test.reshape(x_test.shape[0], img_rows, img_cols, 1)
        input_shape = (img_rows, img_cols, 1)

    print('Train: X=%s, y=%s' % (x_train.shape, lbl_train.shape))
    print('Test: X=%s, y=%s' % (x_test.shape, lbl_test.shape))

```

Downloading data from <https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz>

11493376/11490434 [=====] - 0s 0us/step

Train: X=(60000, 28, 28, 1), y=(60000,)

Test: X=(10000, 28, 28, 1), y=(10000,)

## Preprocessing

```

[ ]: x_train = x_train.astype('float32')
      x_test = x_test.astype('float32')

      x_train /= 255
      x_test /= 255

      y_train = keras.utils.to_categorical(lbl_train, num_classes)
      y_test = keras.utils.to_categorical(lbl_test, num_classes)

```

**1) Preprocessing.** In the notebook, the data is downloaded from an external server imported into the notebook environment using the `mnist.load_data()` function call. Explain the data pre-processing high-lighted in the notebook.

[Answer] After loading dataset into variables using `mnist.load_data()` from the previous cell, which gives about 60000 examples in the training dataset and 10000 in the test dataset and the images are square with 28×28 pixel.

Since the pixel values for each image in the dataset are unsigned integers in the range between black and white, or 0 and 255 and there is no known best way to scale the pixel values for modeling, but some scaling is required.

Therefore, we normalize the pixel values of grayscale images, e.g. rescale them to the range [0,1], which is done by converting the data\_type from unsigned integers to floats, then dividing the pixel values by the maximum value (255).

There are 10 classes (`num_classes`) and the classes are represented as unique integers. we use an one hot encoding for the class element of each sample, transforming the integer into a 10 element binary vector with a 1 for the index of the class value. We do this using `to_categorical()` utility function.

```

[ ]: ## Define model ##
      model = Sequential()

```

```

model.add(Flatten())
model.add(Dense(64, activation = 'relu'))
model.add(Dense(64, activation = 'relu'))
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.SGD(lr = 0.1),
              metrics=['accuracy'],)

fit_info = model.fit(x_train, y_train,
                    batch_size=batch_size,
                    epochs=epochs,
                    verbose=1,
                    validation_data=(x_test, y_test))

score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss: {}, Test accuracy {}'.format(score[0], score[1]))

```

```

Epoch 1/10
469/469 [=====] - 2s 4ms/step - loss: 0.8092 -
accuracy: 0.7631 - val_loss: 0.2581 - val_accuracy: 0.9245
Epoch 2/10
469/469 [=====] - 1s 3ms/step - loss: 0.2450 -
accuracy: 0.9289 - val_loss: 0.1932 - val_accuracy: 0.9427
Epoch 3/10
469/469 [=====] - 1s 3ms/step - loss: 0.1923 -
accuracy: 0.9443 - val_loss: 0.1658 - val_accuracy: 0.9504
Epoch 4/10
469/469 [=====] - 1s 3ms/step - loss: 0.1569 -
accuracy: 0.9548 - val_loss: 0.1373 - val_accuracy: 0.9589
Epoch 5/10
469/469 [=====] - 1s 3ms/step - loss: 0.1312 -
accuracy: 0.9630 - val_loss: 0.1291 - val_accuracy: 0.9618
Epoch 6/10
469/469 [=====] - 1s 3ms/step - loss: 0.1152 -
accuracy: 0.9662 - val_loss: 0.1176 - val_accuracy: 0.9642
Epoch 7/10
469/469 [=====] - 1s 3ms/step - loss: 0.0966 -
accuracy: 0.9717 - val_loss: 0.1129 - val_accuracy: 0.9672
Epoch 8/10
469/469 [=====] - 1s 3ms/step - loss: 0.0892 -
accuracy: 0.9728 - val_loss: 0.1068 - val_accuracy: 0.9663
Epoch 9/10
469/469 [=====] - 1s 3ms/step - loss: 0.0777 -
accuracy: 0.9779 - val_loss: 0.0980 - val_accuracy: 0.9687
Epoch 10/10

```

469/469 [=====] - 1s 3ms/step - loss: 0.0749 -  
accuracy: 0.9782 - val\_loss: 0.0945 - val\_accuracy: 0.9698  
Test loss: 0.09454242885112762, Test accuracy 0.9697999954223633

```
[ ]: # get the summary
model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 784)	0
dense (Dense)	(None, 64)	50240
dense_1 (Dense)	(None, 64)	4160
dense_2 (Dense)	(None, 10)	650

Total params: 55,050  
Trainable params: 55,050  
Non-trainable params: 0

#2) 4 points. Network model, training, and changing hyper-parameters.

- A) How many layers does the network in the notebook have? How many neurons does each layer have? What activation functions and why are these appropriate for this application? What is the total number of parameters for the network? Why do the input and output layers have the dimensions they have?

[Answer] - Network Layers and neurons in each layer (in bold)

Layer (type) :: Output Shape :: Param

**Input** : flatten (Flatten) :: (None, **784**) :: 0

---

**1st**: dense (Dense) :: (None, **64**) :: 50240

---

**2nd**: dense\_1 (Dense) :: (None, **64**) :: 4160

---

**3rd**: dense\_2 (Dense) :: (None, **10**) :: 650

- Activation functions - There are 2 uses here :

1.) *ReLU* - The rectified linear activation function or ReLU for short is a piecewise linear function that will output the input directly if it is positive, otherwise, it will output zero. It has become the default activation function for many types of neural networks because a model that uses it is easier to train and often achieves better performance. ReLU returns the element-wise maximum of (0, x), x is the input tensor. The advantage of using this function is that the neurons that get a negative value don't get activated and their output is not considered in the next layer.

2.) *Softmax*- It is alogistic regression function that normalizes values to be between (0,1) and is needed to convert the values to probabilities.

- Total Number of params :: **Total params: 55,050** For each neuron layer : we can calculate the total number of params using  $((\text{neurons}_{\text{previous layer}}) + 1 \text{ neurons})$  The input\_layer:: 0

First dense\_layer::  $64 * 784 + 1 * 64 = 50176$

2nd dense\_layer\_1::  $64 * 64 + 64 = 4160$

3rd dense\_layer\_2::  $10 * 64 + 64 = 704$

Total ::  $50176 + 4160 + 704 = 55,050$  (Total params: 55,050 and Trainable params: 55,050)

- *Why does the input and output layers have the dimensions they have?*

The mnist images are square with big  $28 \times 28$  pixel. The first flatten (Flatten) layer with (784, 1) neurons probably flattens the big  $28 \times 28$  squares to a 1D array.

As there are a total of 10 classes, thereby we have 10 neurons in the output layer (as is explained before).

**B) What loss-function is used to train the network? What is the functional form(mathematical expression) of the loss function? and how should we interpret it?Why is it appropriate for the problem at hand?**

[Answer]

The loss-function used to train the network is the **categorical crossentropy loss** from the keras API. The functional form (mathematical expression) is: 
$$\text{Loss} = - \sum_{i=1}^{\text{outputsize}} y_i \cdot \log \hat{y}_i$$

Where  $\hat{y}_i$  is the i-th scalar value in the model output,  $y_i$  the target value and output size the number of scalar values in the model output.

This loss function measures the distinguishability between two discrete probability distributions.  $y_i$  is the probability that event i occurs and the sum of all  $y_i$  is 1 which means that only one event may occur. A minus sign is present to ensure that the loss gets reduced when the distributions get closer to each other.

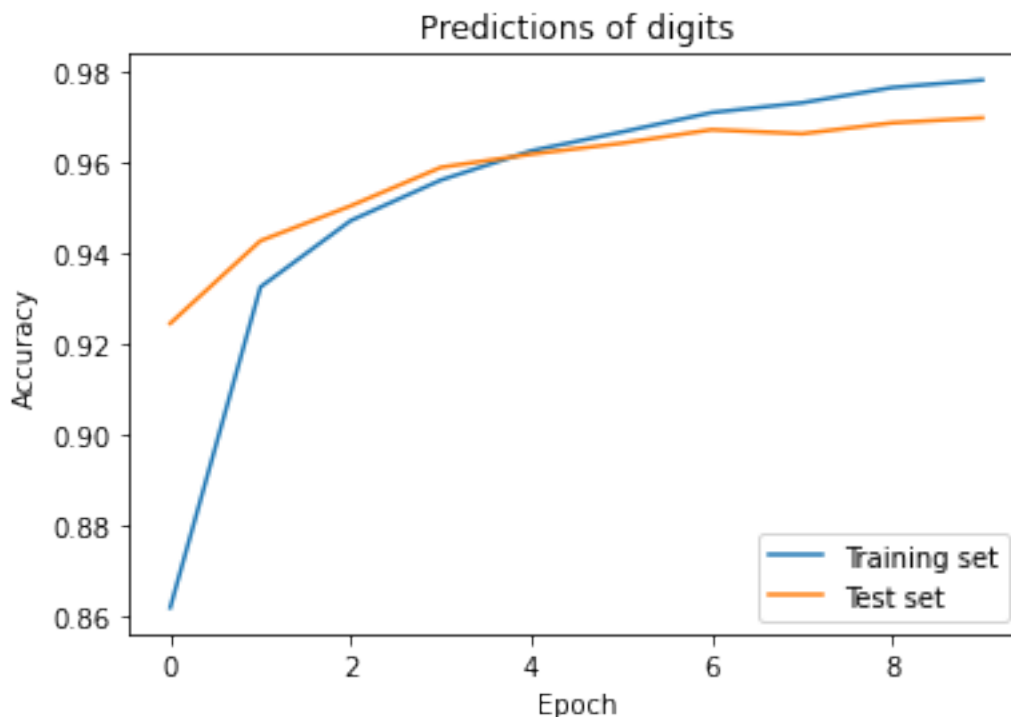
The loss function considers only one example belonging to a specific category with probability 1 and the others 0.

Which is well suited for our problem at hand because we want to learn the model to give a high probability to the correct digit and a low to the other digits.

**C) Train the network for 10 epochs and plot the training and validation accuracy for each epoch.**

```
[ ]: plt.plot(fit_info.history['accuracy'])
plt.plot(fit_info.history['val_accuracy'])
plt.title('Predictions of digits')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
```

```
plt.legend(['Training set', 'Test set'], loc='lower right')
plt.show()
```



Here we can see that the model is a little bit off but does quite a good job on predicting the values. In this example we only run for 40 epochs, training the model for more epochs can make the training set more accurate to the test set or also make the model overfit/underfit which is when a validation set comes in handy because then we will know when to stop training, which is when performance on the validation data stops improving.

**D) Update model to implement a three-layer neural network where the hidden-layers has 500 and 300 hidden units respectively. Train for 40 epochs. What is the best validation accuracy you can achieve? –Geoff Hinton (a co-pioneer of Deep learning) claimed this network could reach a validation accuracy of 0.9847 (<http://yann.lecun.com/exdb/mnist/>) using weight decay (L2 regularization of weights (kernels): <https://keras.io/api/layers/regularizers/>). Implement weight decay on hidden units and train and select 5 regularization factors from 0.000001 to 0.001. Train 3 replicates networks for each regularization factor. Plot the final validation accuracy with standard deviation (computed from the replicates) as a function of the regularization factor. How close do you get to Hinton's result? –If you do not get the same results, what factors may influence this? (hint: What information is not given by Hinton on the MNIST database that may influence Model training)**

[Answer]

```
[ ]: def update_model(reg_factor, epochs):
    #make network wider
    model2 = Sequential()
    model2.add(Flatten())
    model2.add(Dense(500, activation='relu', activity_regularizer=keras.
    ↳regularizers.l2(reg_factor)))
    # 500 hidden units + l2 weight decay on the regularization factors from 0.
    ↳000001 - 0.001
    model2.add(Dense(300, activation='relu', activity_regularizer=keras.
    ↳regularizers.l2(reg_factor)))
    # 300 hidden units + l2 weight decay on the regularization factors from 0.
    ↳000001 - 0.001
    model2.add(Dense(num_classes, activation='softmax'))
    # convert vector of numbers into vector of probabilities

    #define the model
    model2.compile(loss=keras.losses.categorical_crossentropy,
                    optimizer=keras.optimizers.SGD(lr = 0.1),
                    metrics=['accuracy'])
    #train the model
    fit_info2 = model2.fit(x_train, y_train,
                           batch_size=batch_size,
                           epochs=epochs,
                           verbose=1,
                           validation_data=(x_test, y_test))

    return fit_info2.history['val_accuracy'][-1]
    # return the last element which is the best validation accuracy we get.

val_accuracys = []
reg_factors = [0.001, 0.0001, 0.00005, 0.00001, 0.000001]
# [0.000001, 0.00005, 0.00001, 0.0001, 0.001] #5 regularization factors from 0.
↳000001 to 0.001

#5 regularization factors from 0.000001 to 0.001 and 3 replicas
for reg_f in reg_factors:
    temp=[]
    for rep_network in range(0,3):
        temp.append(update_model(reg_factor=reg_f, epochs=40))
    val_accuracys.append(temp)
```

Epoch 1/40

469/469 [=====] - 6s 12ms/step - loss: 0.7652 - accuracy: 0.8335 - val\_loss: 0.2776 - val\_accuracy: 0.9414

Epoch 2/40

469/469 [=====] - 5s 11ms/step - loss: 0.2550 - accuracy: 0.9485 - val\_loss: 0.1974 - val\_accuracy: 0.9605

Epoch 3/40  
469/469 [=====] - 5s 11ms/step - loss: 0.1831 - accuracy: 0.9650 - val\_loss: 0.1614 - val\_accuracy: 0.9682  
Epoch 4/40  
469/469 [=====] - 5s 12ms/step - loss: 0.1468 - accuracy: 0.9734 - val\_loss: 0.1420 - val\_accuracy: 0.9721  
Epoch 5/40  
469/469 [=====] - 5s 12ms/step - loss: 0.1244 - accuracy: 0.9784 - val\_loss: 0.1313 - val\_accuracy: 0.9741  
Epoch 6/40  
469/469 [=====] - 5s 11ms/step - loss: 0.1058 - accuracy: 0.9831 - val\_loss: 0.1169 - val\_accuracy: 0.9769  
Epoch 7/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0916 - accuracy: 0.9870 - val\_loss: 0.1104 - val\_accuracy: 0.9786  
Epoch 8/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0834 - accuracy: 0.9884 - val\_loss: 0.1032 - val\_accuracy: 0.9797  
Epoch 9/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0743 - accuracy: 0.9915 - val\_loss: 0.0971 - val\_accuracy: 0.9819  
Epoch 10/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0654 - accuracy: 0.9932 - val\_loss: 0.0943 - val\_accuracy: 0.9815  
Epoch 11/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0597 - accuracy: 0.9949 - val\_loss: 0.0927 - val\_accuracy: 0.9807  
Epoch 12/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0540 - accuracy: 0.9965 - val\_loss: 0.0883 - val\_accuracy: 0.9822  
Epoch 13/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0501 - accuracy: 0.9971 - val\_loss: 0.0875 - val\_accuracy: 0.9819  
Epoch 14/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0470 - accuracy: 0.9978 - val\_loss: 0.0844 - val\_accuracy: 0.9834  
Epoch 15/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0436 - accuracy: 0.9983 - val\_loss: 0.0827 - val\_accuracy: 0.9821  
Epoch 16/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0404 - accuracy: 0.9988 - val\_loss: 0.0803 - val\_accuracy: 0.9837  
Epoch 17/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0384 - accuracy: 0.9989 - val\_loss: 0.0804 - val\_accuracy: 0.9827  
Epoch 18/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0362 - accuracy: 0.9995 - val\_loss: 0.0784 - val\_accuracy: 0.9841



Epoch 19/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0339 -  
accuracy: 0.9996 - val\_loss: 0.0782 - val\_accuracy: 0.9836  
Epoch 20/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0324 -  
accuracy: 0.9996 - val\_loss: 0.0781 - val\_accuracy: 0.9841  
Epoch 21/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0311 -  
accuracy: 0.9997 - val\_loss: 0.0744 - val\_accuracy: 0.9839  
Epoch 22/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0300 -  
accuracy: 0.9997 - val\_loss: 0.0746 - val\_accuracy: 0.9833  
Epoch 23/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0286 -  
accuracy: 0.9999 - val\_loss: 0.0741 - val\_accuracy: 0.9844  
Epoch 24/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0278 -  
accuracy: 0.9998 - val\_loss: 0.0734 - val\_accuracy: 0.9839  
Epoch 25/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0265 -  
accuracy: 0.9999 - val\_loss: 0.0727 - val\_accuracy: 0.9843  
Epoch 26/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0258 -  
accuracy: 1.0000 - val\_loss: 0.0721 - val\_accuracy: 0.9838  
Epoch 27/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0247 -  
accuracy: 0.9999 - val\_loss: 0.0729 - val\_accuracy: 0.9836  
Epoch 28/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0241 -  
accuracy: 1.0000 - val\_loss: 0.0707 - val\_accuracy: 0.9846  
Epoch 29/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0235 -  
accuracy: 1.0000 - val\_loss: 0.0716 - val\_accuracy: 0.9847  
Epoch 30/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0229 -  
accuracy: 0.9999 - val\_loss: 0.0705 - val\_accuracy: 0.9842  
Epoch 31/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0222 -  
accuracy: 0.9999 - val\_loss: 0.0696 - val\_accuracy: 0.9852  
Epoch 32/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0218 -  
accuracy: 1.0000 - val\_loss: 0.0699 - val\_accuracy: 0.9842  
Epoch 33/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0212 -  
accuracy: 1.0000 - val\_loss: 0.0690 - val\_accuracy: 0.9844  
Epoch 34/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0209 -  
accuracy: 1.0000 - val\_loss: 0.0686 - val\_accuracy: 0.9842

Epoch 35/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0203 - accuracy: 1.0000 - val\_loss: 0.0682 - val\_accuracy: 0.9850

Epoch 36/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0199 - accuracy: 1.0000 - val\_loss: 0.0685 - val\_accuracy: 0.9845

Epoch 37/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0196 - accuracy: 1.0000 - val\_loss: 0.0676 - val\_accuracy: 0.9844

Epoch 38/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0192 - accuracy: 1.0000 - val\_loss: 0.0677 - val\_accuracy: 0.9843

Epoch 39/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0189 - accuracy: 1.0000 - val\_loss: 0.0669 - val\_accuracy: 0.9842

Epoch 40/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0184 - accuracy: 1.0000 - val\_loss: 0.0667 - val\_accuracy: 0.9842

Epoch 1/40  
469/469 [=====] - 6s 12ms/step - loss: 0.7834 - accuracy: 0.8321 - val\_loss: 0.2770 - val\_accuracy: 0.9455

Epoch 2/40  
469/469 [=====] - 5s 11ms/step - loss: 0.2579 - accuracy: 0.9473 - val\_loss: 0.1999 - val\_accuracy: 0.9598

Epoch 3/40  
469/469 [=====] - 5s 11ms/step - loss: 0.1820 - accuracy: 0.9646 - val\_loss: 0.1621 - val\_accuracy: 0.9682

Epoch 4/40  
469/469 [=====] - 5s 12ms/step - loss: 0.1480 - accuracy: 0.9733 - val\_loss: 0.1427 - val\_accuracy: 0.9732

Epoch 5/40  
469/469 [=====] - 5s 11ms/step - loss: 0.1217 - accuracy: 0.9791 - val\_loss: 0.1268 - val\_accuracy: 0.9761

Epoch 6/40  
469/469 [=====] - 5s 11ms/step - loss: 0.1043 - accuracy: 0.9843 - val\_loss: 0.1172 - val\_accuracy: 0.9775

Epoch 7/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0891 - accuracy: 0.9884 - val\_loss: 0.1108 - val\_accuracy: 0.9780

Epoch 8/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0800 - accuracy: 0.9904 - val\_loss: 0.1027 - val\_accuracy: 0.9793

Epoch 9/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0714 - accuracy: 0.9919 - val\_loss: 0.0987 - val\_accuracy: 0.9806

Epoch 10/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0645 - accuracy: 0.9940 - val\_loss: 0.0955 - val\_accuracy: 0.9798

Epoch 11/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0588 - accuracy: 0.9952 - val\_loss: 0.0918 - val\_accuracy: 0.9811

Epoch 12/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0539 - accuracy: 0.9963 - val\_loss: 0.0904 - val\_accuracy: 0.9804

Epoch 13/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0488 - accuracy: 0.9976 - val\_loss: 0.0890 - val\_accuracy: 0.9817

Epoch 14/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0461 - accuracy: 0.9979 - val\_loss: 0.0859 - val\_accuracy: 0.9819

Epoch 15/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0430 - accuracy: 0.9984 - val\_loss: 0.0833 - val\_accuracy: 0.9830

Epoch 16/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0396 - accuracy: 0.9990 - val\_loss: 0.0830 - val\_accuracy: 0.9823

Epoch 17/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0371 - accuracy: 0.9994 - val\_loss: 0.0808 - val\_accuracy: 0.9827

Epoch 18/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0353 - accuracy: 0.9995 - val\_loss: 0.0808 - val\_accuracy: 0.9824

Epoch 19/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0341 - accuracy: 0.9996 - val\_loss: 0.0794 - val\_accuracy: 0.9826

Epoch 20/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0321 - accuracy: 0.9998 - val\_loss: 0.0784 - val\_accuracy: 0.9824

Epoch 21/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0307 - accuracy: 0.9998 - val\_loss: 0.0784 - val\_accuracy: 0.9825

Epoch 22/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0295 - accuracy: 0.9998 - val\_loss: 0.0772 - val\_accuracy: 0.9818

Epoch 23/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0286 - accuracy: 0.9999 - val\_loss: 0.0778 - val\_accuracy: 0.9820

Epoch 24/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0275 - accuracy: 0.9999 - val\_loss: 0.0759 - val\_accuracy: 0.9829

Epoch 25/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0261 - accuracy: 1.0000 - val\_loss: 0.0762 - val\_accuracy: 0.9818

Epoch 26/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0255 - accuracy: 0.9999 - val\_loss: 0.0749 - val\_accuracy: 0.9830

Epoch 27/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0246 -  
accuracy: 1.0000 - val\_loss: 0.0746 - val\_accuracy: 0.9823  
Epoch 28/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0241 -  
accuracy: 1.0000 - val\_loss: 0.0744 - val\_accuracy: 0.9825  
Epoch 29/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0233 -  
accuracy: 1.0000 - val\_loss: 0.0739 - val\_accuracy: 0.9821  
Epoch 30/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0228 -  
accuracy: 1.0000 - val\_loss: 0.0727 - val\_accuracy: 0.9823  
Epoch 31/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0222 -  
accuracy: 1.0000 - val\_loss: 0.0729 - val\_accuracy: 0.9826  
Epoch 32/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0216 -  
accuracy: 1.0000 - val\_loss: 0.0724 - val\_accuracy: 0.9821  
Epoch 33/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0212 -  
accuracy: 1.0000 - val\_loss: 0.0721 - val\_accuracy: 0.9822  
Epoch 34/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0207 -  
accuracy: 1.0000 - val\_loss: 0.0718 - val\_accuracy: 0.9820  
Epoch 35/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0204 -  
accuracy: 1.0000 - val\_loss: 0.0711 - val\_accuracy: 0.9823  
Epoch 36/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0199 -  
accuracy: 1.0000 - val\_loss: 0.0714 - val\_accuracy: 0.9823  
Epoch 37/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0195 -  
accuracy: 1.0000 - val\_loss: 0.0711 - val\_accuracy: 0.9826  
Epoch 38/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0192 -  
accuracy: 1.0000 - val\_loss: 0.0710 - val\_accuracy: 0.9822  
Epoch 39/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0188 -  
accuracy: 1.0000 - val\_loss: 0.0703 - val\_accuracy: 0.9826  
Epoch 40/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0184 -  
accuracy: 1.0000 - val\_loss: 0.0699 - val\_accuracy: 0.9825  
Epoch 1/40  
469/469 [=====] - 6s 12ms/step - loss: 0.7910 -  
accuracy: 0.8232 - val\_loss: 0.2805 - val\_accuracy: 0.9424  
Epoch 2/40  
469/469 [=====] - 5s 12ms/step - loss: 0.2557 -  
accuracy: 0.9484 - val\_loss: 0.1954 - val\_accuracy: 0.9603

Epoch 3/40  
469/469 [=====] - 5s 12ms/step - loss: 0.1814 - accuracy: 0.9647 - val\_loss: 0.1642 - val\_accuracy: 0.9661

Epoch 4/40  
469/469 [=====] - 5s 11ms/step - loss: 0.1441 - accuracy: 0.9755 - val\_loss: 0.1415 - val\_accuracy: 0.9723

Epoch 5/40  
469/469 [=====] - 5s 12ms/step - loss: 0.1214 - accuracy: 0.9803 - val\_loss: 0.1281 - val\_accuracy: 0.9752

Epoch 6/40  
469/469 [=====] - 5s 12ms/step - loss: 0.1038 - accuracy: 0.9839 - val\_loss: 0.1167 - val\_accuracy: 0.9776

Epoch 7/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0913 - accuracy: 0.9875 - val\_loss: 0.1142 - val\_accuracy: 0.9778

Epoch 8/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0799 - accuracy: 0.9902 - val\_loss: 0.1019 - val\_accuracy: 0.9798

Epoch 9/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0718 - accuracy: 0.9927 - val\_loss: 0.0993 - val\_accuracy: 0.9800

Epoch 10/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0648 - accuracy: 0.9942 - val\_loss: 0.0958 - val\_accuracy: 0.9805

Epoch 11/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0582 - accuracy: 0.9957 - val\_loss: 0.0925 - val\_accuracy: 0.9804

Epoch 12/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0534 - accuracy: 0.9967 - val\_loss: 0.0899 - val\_accuracy: 0.9820

Epoch 13/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0487 - accuracy: 0.9976 - val\_loss: 0.0866 - val\_accuracy: 0.9810

Epoch 14/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0458 - accuracy: 0.9981 - val\_loss: 0.0857 - val\_accuracy: 0.9826

Epoch 15/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0423 - accuracy: 0.9987 - val\_loss: 0.0847 - val\_accuracy: 0.9822

Epoch 16/40  
469/469 [=====] - 7s 14ms/step - loss: 0.0394 - accuracy: 0.9990 - val\_loss: 0.0846 - val\_accuracy: 0.9816

Epoch 17/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0371 - accuracy: 0.9994 - val\_loss: 0.0811 - val\_accuracy: 0.9826

Epoch 18/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0355 - accuracy: 0.9994 - val\_loss: 0.0805 - val\_accuracy: 0.9825

Epoch 19/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0336 -  
accuracy: 0.9996 - val\_loss: 0.0789 - val\_accuracy: 0.9833  
Epoch 20/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0324 -  
accuracy: 0.9996 - val\_loss: 0.0808 - val\_accuracy: 0.9821  
Epoch 21/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0309 -  
accuracy: 0.9998 - val\_loss: 0.0773 - val\_accuracy: 0.9832  
Epoch 22/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0292 -  
accuracy: 0.9999 - val\_loss: 0.0770 - val\_accuracy: 0.9832  
Epoch 23/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0285 -  
accuracy: 0.9998 - val\_loss: 0.0761 - val\_accuracy: 0.9829  
Epoch 24/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0272 -  
accuracy: 1.0000 - val\_loss: 0.0762 - val\_accuracy: 0.9832  
Epoch 25/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0261 -  
accuracy: 1.0000 - val\_loss: 0.0751 - val\_accuracy: 0.9832  
Epoch 26/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0257 -  
accuracy: 0.9999 - val\_loss: 0.0750 - val\_accuracy: 0.9833  
Epoch 27/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0248 -  
accuracy: 0.9999 - val\_loss: 0.0748 - val\_accuracy: 0.9829  
Epoch 28/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0239 -  
accuracy: 1.0000 - val\_loss: 0.0740 - val\_accuracy: 0.9839  
Epoch 29/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0236 -  
accuracy: 1.0000 - val\_loss: 0.0734 - val\_accuracy: 0.9828  
Epoch 30/40  
469/469 [=====] - 5s 11ms/step - loss: 0.0228 -  
accuracy: 1.0000 - val\_loss: 0.0737 - val\_accuracy: 0.9833  
Epoch 31/40  
469/469 [=====] - 5s 12ms/step - loss: 0.0221 -  
accuracy: 1.0000 - val\_loss: 0.0725 - val\_accuracy: 0.9835  
Epoch 32/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0217 -  
accuracy: 1.0000 - val\_loss: 0.0728 - val\_accuracy: 0.9832  
Epoch 33/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0212 -  
accuracy: 1.0000 - val\_loss: 0.0718 - val\_accuracy: 0.9834  
Epoch 34/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0208 -  
accuracy: 1.0000 - val\_loss: 0.0715 - val\_accuracy: 0.9835

Epoch 35/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0203 - accuracy: 1.0000 - val\_loss: 0.0723 - val\_accuracy: 0.9833

Epoch 36/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0199 - accuracy: 1.0000 - val\_loss: 0.0716 - val\_accuracy: 0.9832

Epoch 37/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0194 - accuracy: 1.0000 - val\_loss: 0.0708 - val\_accuracy: 0.9837

Epoch 38/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0191 - accuracy: 1.0000 - val\_loss: 0.0708 - val\_accuracy: 0.9832

Epoch 39/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0188 - accuracy: 1.0000 - val\_loss: 0.0705 - val\_accuracy: 0.9837

Epoch 40/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0184 - accuracy: 1.0000 - val\_loss: 0.0707 - val\_accuracy: 0.9829

Epoch 1/40  
469/469 [=====] - 6s 13ms/step - loss: 0.7085 - accuracy: 0.8134 - val\_loss: 0.2311 - val\_accuracy: 0.9384

Epoch 2/40  
469/469 [=====] - 6s 12ms/step - loss: 0.2171 - accuracy: 0.9423 - val\_loss: 0.1672 - val\_accuracy: 0.9573

Epoch 3/40  
469/469 [=====] - 6s 12ms/step - loss: 0.1552 - accuracy: 0.9599 - val\_loss: 0.1348 - val\_accuracy: 0.9654

Epoch 4/40  
469/469 [=====] - 6s 12ms/step - loss: 0.1222 - accuracy: 0.9696 - val\_loss: 0.1167 - val\_accuracy: 0.9691

Epoch 5/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0999 - accuracy: 0.9755 - val\_loss: 0.1037 - val\_accuracy: 0.9722

Epoch 6/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0822 - accuracy: 0.9812 - val\_loss: 0.0926 - val\_accuracy: 0.9754

Epoch 7/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0724 - accuracy: 0.9841 - val\_loss: 0.0872 - val\_accuracy: 0.9772

Epoch 8/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0608 - accuracy: 0.9875 - val\_loss: 0.0830 - val\_accuracy: 0.9779

Epoch 9/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0545 - accuracy: 0.9889 - val\_loss: 0.0780 - val\_accuracy: 0.9796

Epoch 10/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0475 - accuracy: 0.9917 - val\_loss: 0.0750 - val\_accuracy: 0.9804

Epoch 11/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0422 -  
accuracy: 0.9931 - val\_loss: 0.0738 - val\_accuracy: 0.9803  
Epoch 12/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0370 -  
accuracy: 0.9943 - val\_loss: 0.0704 - val\_accuracy: 0.9813  
Epoch 13/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0333 -  
accuracy: 0.9959 - val\_loss: 0.0710 - val\_accuracy: 0.9814  
Epoch 14/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0305 -  
accuracy: 0.9967 - val\_loss: 0.0687 - val\_accuracy: 0.9818  
Epoch 15/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0283 -  
accuracy: 0.9978 - val\_loss: 0.0665 - val\_accuracy: 0.9825  
Epoch 16/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0252 -  
accuracy: 0.9981 - val\_loss: 0.0669 - val\_accuracy: 0.9816  
Epoch 17/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0240 -  
accuracy: 0.9985 - val\_loss: 0.0672 - val\_accuracy: 0.9827  
Epoch 18/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0215 -  
accuracy: 0.9989 - val\_loss: 0.0638 - val\_accuracy: 0.9823  
Epoch 19/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0206 -  
accuracy: 0.9991 - val\_loss: 0.0651 - val\_accuracy: 0.9824  
Epoch 20/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0188 -  
accuracy: 0.9995 - val\_loss: 0.0631 - val\_accuracy: 0.9827  
Epoch 21/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0179 -  
accuracy: 0.9995 - val\_loss: 0.0644 - val\_accuracy: 0.9829  
Epoch 22/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0172 -  
accuracy: 0.9996 - val\_loss: 0.0628 - val\_accuracy: 0.9833  
Epoch 23/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0165 -  
accuracy: 0.9995 - val\_loss: 0.0623 - val\_accuracy: 0.9830  
Epoch 24/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0156 -  
accuracy: 0.9998 - val\_loss: 0.0628 - val\_accuracy: 0.9833  
Epoch 25/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0147 -  
accuracy: 0.9999 - val\_loss: 0.0624 - val\_accuracy: 0.9828  
Epoch 26/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0145 -  
accuracy: 0.9999 - val\_loss: 0.0617 - val\_accuracy: 0.9832



Epoch 27/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0138 -  
accuracy: 0.9999 - val\_loss: 0.0611 - val\_accuracy: 0.9831  
Epoch 28/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0133 -  
accuracy: 0.9999 - val\_loss: 0.0603 - val\_accuracy: 0.9830  
Epoch 29/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0127 -  
accuracy: 0.9999 - val\_loss: 0.0614 - val\_accuracy: 0.9832  
Epoch 30/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0123 -  
accuracy: 1.0000 - val\_loss: 0.0611 - val\_accuracy: 0.9833  
Epoch 31/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0119 -  
accuracy: 1.0000 - val\_loss: 0.0603 - val\_accuracy: 0.9829  
Epoch 32/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0116 -  
accuracy: 1.0000 - val\_loss: 0.0608 - val\_accuracy: 0.9826  
Epoch 33/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0114 -  
accuracy: 1.0000 - val\_loss: 0.0601 - val\_accuracy: 0.9829  
Epoch 34/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0109 -  
accuracy: 1.0000 - val\_loss: 0.0596 - val\_accuracy: 0.9832  
Epoch 35/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0108 -  
accuracy: 1.0000 - val\_loss: 0.0605 - val\_accuracy: 0.9830  
Epoch 36/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0105 -  
accuracy: 1.0000 - val\_loss: 0.0593 - val\_accuracy: 0.9836  
Epoch 37/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0103 -  
accuracy: 1.0000 - val\_loss: 0.0596 - val\_accuracy: 0.9831  
Epoch 38/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0100 -  
accuracy: 1.0000 - val\_loss: 0.0589 - val\_accuracy: 0.9830  
Epoch 39/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0099 -  
accuracy: 1.0000 - val\_loss: 0.0592 - val\_accuracy: 0.9829  
Epoch 40/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0096 -  
accuracy: 1.0000 - val\_loss: 0.0587 - val\_accuracy: 0.9837  
Epoch 1/40  
469/469 [=====] - 6s 12ms/step - loss: 0.7151 -  
accuracy: 0.8115 - val\_loss: 0.2396 - val\_accuracy: 0.9330  
Epoch 2/40  
469/469 [=====] - 6s 12ms/step - loss: 0.2193 -  
accuracy: 0.9431 - val\_loss: 0.1649 - val\_accuracy: 0.9565

Epoch 3/40  
469/469 [=====] - 6s 12ms/step - loss: 0.1543 -  
accuracy: 0.9607 - val\_loss: 0.1327 - val\_accuracy: 0.9658  
Epoch 4/40  
469/469 [=====] - 6s 12ms/step - loss: 0.1194 -  
accuracy: 0.9706 - val\_loss: 0.1152 - val\_accuracy: 0.9699  
Epoch 5/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0975 -  
accuracy: 0.9757 - val\_loss: 0.1060 - val\_accuracy: 0.9727  
Epoch 6/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0840 -  
accuracy: 0.9805 - val\_loss: 0.0948 - val\_accuracy: 0.9763  
Epoch 7/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0706 -  
accuracy: 0.9841 - val\_loss: 0.0896 - val\_accuracy: 0.9754  
Epoch 8/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0614 -  
accuracy: 0.9873 - val\_loss: 0.0850 - val\_accuracy: 0.9777  
Epoch 9/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0536 -  
accuracy: 0.9892 - val\_loss: 0.0813 - val\_accuracy: 0.9790  
Epoch 10/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0487 -  
accuracy: 0.9909 - val\_loss: 0.0749 - val\_accuracy: 0.9800  
Epoch 11/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0428 -  
accuracy: 0.9929 - val\_loss: 0.0759 - val\_accuracy: 0.9796  
Epoch 12/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0372 -  
accuracy: 0.9949 - val\_loss: 0.0734 - val\_accuracy: 0.9800  
Epoch 13/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0341 -  
accuracy: 0.9952 - val\_loss: 0.0721 - val\_accuracy: 0.9804  
Epoch 14/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0299 -  
accuracy: 0.9971 - val\_loss: 0.0702 - val\_accuracy: 0.9808  
Epoch 15/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0286 -  
accuracy: 0.9970 - val\_loss: 0.0680 - val\_accuracy: 0.9821  
Epoch 16/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0258 -  
accuracy: 0.9980 - val\_loss: 0.0680 - val\_accuracy: 0.9820  
Epoch 17/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0242 -  
accuracy: 0.9982 - val\_loss: 0.0699 - val\_accuracy: 0.9810  
Epoch 18/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0221 -  
accuracy: 0.9989 - val\_loss: 0.0676 - val\_accuracy: 0.9813

Epoch 19/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0206 -  
accuracy: 0.9993 - val\_loss: 0.0670 - val\_accuracy: 0.9814  
Epoch 20/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0187 -  
accuracy: 0.9995 - val\_loss: 0.0668 - val\_accuracy: 0.9817  
Epoch 21/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0179 -  
accuracy: 0.9996 - val\_loss: 0.0660 - val\_accuracy: 0.9821  
Epoch 22/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0172 -  
accuracy: 0.9997 - val\_loss: 0.0650 - val\_accuracy: 0.9830  
Epoch 23/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0164 -  
accuracy: 0.9997 - val\_loss: 0.0640 - val\_accuracy: 0.9826  
Epoch 24/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0155 -  
accuracy: 0.9998 - val\_loss: 0.0646 - val\_accuracy: 0.9821  
Epoch 25/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0149 -  
accuracy: 0.9999 - val\_loss: 0.0650 - val\_accuracy: 0.9825  
Epoch 26/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0142 -  
accuracy: 0.9999 - val\_loss: 0.0646 - val\_accuracy: 0.9825  
Epoch 27/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0135 -  
accuracy: 0.9999 - val\_loss: 0.0641 - val\_accuracy: 0.9823  
Epoch 28/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0131 -  
accuracy: 1.0000 - val\_loss: 0.0652 - val\_accuracy: 0.9820  
Epoch 29/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0129 -  
accuracy: 1.0000 - val\_loss: 0.0632 - val\_accuracy: 0.9825  
Epoch 30/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0122 -  
accuracy: 0.9999 - val\_loss: 0.0635 - val\_accuracy: 0.9821  
Epoch 31/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0120 -  
accuracy: 0.9999 - val\_loss: 0.0636 - val\_accuracy: 0.9825  
Epoch 32/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0116 -  
accuracy: 0.9999 - val\_loss: 0.0637 - val\_accuracy: 0.9825  
Epoch 33/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0113 -  
accuracy: 1.0000 - val\_loss: 0.0633 - val\_accuracy: 0.9824  
Epoch 34/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0110 -  
accuracy: 1.0000 - val\_loss: 0.0634 - val\_accuracy: 0.9822

Epoch 35/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0108 - accuracy: 1.0000 - val\_loss: 0.0629 - val\_accuracy: 0.9824

Epoch 36/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0105 - accuracy: 1.0000 - val\_loss: 0.0630 - val\_accuracy: 0.9822

Epoch 37/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0103 - accuracy: 1.0000 - val\_loss: 0.0632 - val\_accuracy: 0.9828

Epoch 38/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0101 - accuracy: 1.0000 - val\_loss: 0.0628 - val\_accuracy: 0.9826

Epoch 39/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0098 - accuracy: 1.0000 - val\_loss: 0.0625 - val\_accuracy: 0.9825

Epoch 40/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0096 - accuracy: 1.0000 - val\_loss: 0.0625 - val\_accuracy: 0.9828

Epoch 1/40  
469/469 [=====] - 6s 13ms/step - loss: 0.7149 - accuracy: 0.8163 - val\_loss: 0.2383 - val\_accuracy: 0.9371

Epoch 2/40  
469/469 [=====] - 6s 12ms/step - loss: 0.2190 - accuracy: 0.9434 - val\_loss: 0.1656 - val\_accuracy: 0.9562

Epoch 3/40  
469/469 [=====] - 6s 12ms/step - loss: 0.1572 - accuracy: 0.9601 - val\_loss: 0.1375 - val\_accuracy: 0.9630

Epoch 4/40  
469/469 [=====] - 6s 12ms/step - loss: 0.1231 - accuracy: 0.9704 - val\_loss: 0.1150 - val\_accuracy: 0.9690

Epoch 5/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0994 - accuracy: 0.9759 - val\_loss: 0.1017 - val\_accuracy: 0.9737

Epoch 6/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0849 - accuracy: 0.9807 - val\_loss: 0.0973 - val\_accuracy: 0.9740

Epoch 7/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0726 - accuracy: 0.9837 - val\_loss: 0.0896 - val\_accuracy: 0.9769

Epoch 8/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0623 - accuracy: 0.9871 - val\_loss: 0.0818 - val\_accuracy: 0.9785

Epoch 9/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0542 - accuracy: 0.9895 - val\_loss: 0.0777 - val\_accuracy: 0.9793

Epoch 10/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0499 - accuracy: 0.9903 - val\_loss: 0.0796 - val\_accuracy: 0.9782

Epoch 11/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0427 - accuracy: 0.9933 - val\_loss: 0.0747 - val\_accuracy: 0.9802

Epoch 12/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0385 - accuracy: 0.9947 - val\_loss: 0.0716 - val\_accuracy: 0.9805

Epoch 13/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0335 - accuracy: 0.9959 - val\_loss: 0.0747 - val\_accuracy: 0.9801

Epoch 14/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0315 - accuracy: 0.9964 - val\_loss: 0.0704 - val\_accuracy: 0.9817

Epoch 15/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0280 - accuracy: 0.9978 - val\_loss: 0.0710 - val\_accuracy: 0.9815

Epoch 16/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0260 - accuracy: 0.9978 - val\_loss: 0.0673 - val\_accuracy: 0.9815

Epoch 17/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0232 - accuracy: 0.9990 - val\_loss: 0.0675 - val\_accuracy: 0.9825

Epoch 18/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0224 - accuracy: 0.9989 - val\_loss: 0.0668 - val\_accuracy: 0.9826

Epoch 19/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0208 - accuracy: 0.9992 - val\_loss: 0.0659 - val\_accuracy: 0.9828

Epoch 20/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0191 - accuracy: 0.9995 - val\_loss: 0.0661 - val\_accuracy: 0.9828

Epoch 21/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0183 - accuracy: 0.9996 - val\_loss: 0.0656 - val\_accuracy: 0.9819

Epoch 22/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0172 - accuracy: 0.9998 - val\_loss: 0.0638 - val\_accuracy: 0.9829

Epoch 23/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0166 - accuracy: 0.9995 - val\_loss: 0.0642 - val\_accuracy: 0.9834

Epoch 24/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0157 - accuracy: 0.9997 - val\_loss: 0.0635 - val\_accuracy: 0.9833

Epoch 25/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0148 - accuracy: 0.9999 - val\_loss: 0.0633 - val\_accuracy: 0.9826

Epoch 26/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0144 - accuracy: 0.9998 - val\_loss: 0.0634 - val\_accuracy: 0.9833

Epoch 27/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0139 - accuracy: 0.9999 - val\_loss: 0.0627 - val\_accuracy: 0.9833

Epoch 28/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0133 - accuracy: 1.0000 - val\_loss: 0.0636 - val\_accuracy: 0.9831

Epoch 29/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0129 - accuracy: 1.0000 - val\_loss: 0.0626 - val\_accuracy: 0.9833

Epoch 30/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0125 - accuracy: 0.9999 - val\_loss: 0.0622 - val\_accuracy: 0.9828

Epoch 31/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0121 - accuracy: 1.0000 - val\_loss: 0.0621 - val\_accuracy: 0.9835

Epoch 32/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0118 - accuracy: 0.9999 - val\_loss: 0.0619 - val\_accuracy: 0.9833

Epoch 33/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0115 - accuracy: 1.0000 - val\_loss: 0.0619 - val\_accuracy: 0.9833

Epoch 34/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0111 - accuracy: 1.0000 - val\_loss: 0.0624 - val\_accuracy: 0.9828

Epoch 35/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0109 - accuracy: 1.0000 - val\_loss: 0.0618 - val\_accuracy: 0.9832

Epoch 36/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0107 - accuracy: 1.0000 - val\_loss: 0.0616 - val\_accuracy: 0.9830

Epoch 37/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0105 - accuracy: 1.0000 - val\_loss: 0.0616 - val\_accuracy: 0.9823

Epoch 38/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0101 - accuracy: 1.0000 - val\_loss: 0.0618 - val\_accuracy: 0.9833

Epoch 39/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0100 - accuracy: 1.0000 - val\_loss: 0.0608 - val\_accuracy: 0.9833

Epoch 40/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0098 - accuracy: 1.0000 - val\_loss: 0.0612 - val\_accuracy: 0.9833

Epoch 1/40  
469/469 [=====] - 6s 13ms/step - loss: 0.6972 - accuracy: 0.8161 - val\_loss: 0.2785 - val\_accuracy: 0.9197

Epoch 2/40  
469/469 [=====] - 6s 12ms/step - loss: 0.2165 - accuracy: 0.9406 - val\_loss: 0.1625 - val\_accuracy: 0.9566

Epoch 3/40  
469/469 [=====] - 6s 12ms/step - loss: 0.1480 - accuracy: 0.9598 - val\_loss: 0.1320 - val\_accuracy: 0.9635

Epoch 4/40  
469/469 [=====] - 6s 12ms/step - loss: 0.1151 - accuracy: 0.9695 - val\_loss: 0.1169 - val\_accuracy: 0.9686

Epoch 5/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0982 - accuracy: 0.9748 - val\_loss: 0.1034 - val\_accuracy: 0.9715

Epoch 6/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0811 - accuracy: 0.9791 - val\_loss: 0.0910 - val\_accuracy: 0.9742

Epoch 7/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0682 - accuracy: 0.9836 - val\_loss: 0.0838 - val\_accuracy: 0.9763

Epoch 8/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0602 - accuracy: 0.9853 - val\_loss: 0.0799 - val\_accuracy: 0.9783

Epoch 9/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0516 - accuracy: 0.9889 - val\_loss: 0.0760 - val\_accuracy: 0.9797

Epoch 10/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0456 - accuracy: 0.9909 - val\_loss: 0.0807 - val\_accuracy: 0.9769

Epoch 11/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0397 - accuracy: 0.9924 - val\_loss: 0.0742 - val\_accuracy: 0.9800

Epoch 12/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0364 - accuracy: 0.9936 - val\_loss: 0.0708 - val\_accuracy: 0.9800

Epoch 13/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0327 - accuracy: 0.9949 - val\_loss: 0.0665 - val\_accuracy: 0.9813

Epoch 14/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0294 - accuracy: 0.9961 - val\_loss: 0.0661 - val\_accuracy: 0.9825

Epoch 15/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0257 - accuracy: 0.9968 - val\_loss: 0.0655 - val\_accuracy: 0.9815

Epoch 16/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0238 - accuracy: 0.9977 - val\_loss: 0.0655 - val\_accuracy: 0.9815

Epoch 17/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0210 - accuracy: 0.9984 - val\_loss: 0.0663 - val\_accuracy: 0.9814

Epoch 18/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0197 - accuracy: 0.9987 - val\_loss: 0.0628 - val\_accuracy: 0.9825

Epoch 19/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0184 -  
accuracy: 0.9989 - val\_loss: 0.0633 - val\_accuracy: 0.9817

Epoch 20/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0169 -  
accuracy: 0.9992 - val\_loss: 0.0624 - val\_accuracy: 0.9819

Epoch 21/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0163 -  
accuracy: 0.9993 - val\_loss: 0.0613 - val\_accuracy: 0.9823

Epoch 22/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0147 -  
accuracy: 0.9995 - val\_loss: 0.0613 - val\_accuracy: 0.9823

Epoch 23/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0140 -  
accuracy: 0.9996 - val\_loss: 0.0604 - val\_accuracy: 0.9824

Epoch 24/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0133 -  
accuracy: 0.9996 - val\_loss: 0.0607 - val\_accuracy: 0.9832

Epoch 25/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0127 -  
accuracy: 0.9998 - val\_loss: 0.0603 - val\_accuracy: 0.9830

Epoch 26/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0120 -  
accuracy: 0.9998 - val\_loss: 0.0601 - val\_accuracy: 0.9827

Epoch 27/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0114 -  
accuracy: 0.9998 - val\_loss: 0.0609 - val\_accuracy: 0.9833

Epoch 28/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0111 -  
accuracy: 0.9999 - val\_loss: 0.0592 - val\_accuracy: 0.9833

Epoch 29/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0108 -  
accuracy: 1.0000 - val\_loss: 0.0597 - val\_accuracy: 0.9832

Epoch 30/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0102 -  
accuracy: 0.9999 - val\_loss: 0.0597 - val\_accuracy: 0.9832

Epoch 31/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0098 -  
accuracy: 1.0000 - val\_loss: 0.0591 - val\_accuracy: 0.9832

Epoch 32/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0097 -  
accuracy: 1.0000 - val\_loss: 0.0599 - val\_accuracy: 0.9828

Epoch 33/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0093 -  
accuracy: 1.0000 - val\_loss: 0.0590 - val\_accuracy: 0.9833

Epoch 34/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0093 -  
accuracy: 1.0000 - val\_loss: 0.0594 - val\_accuracy: 0.9832



Epoch 35/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0088 - accuracy: 1.0000 - val\_loss: 0.0588 - val\_accuracy: 0.9833

Epoch 36/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0086 - accuracy: 1.0000 - val\_loss: 0.0588 - val\_accuracy: 0.9836

Epoch 37/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0084 - accuracy: 1.0000 - val\_loss: 0.0590 - val\_accuracy: 0.9830

Epoch 38/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0082 - accuracy: 1.0000 - val\_loss: 0.0585 - val\_accuracy: 0.9834

Epoch 39/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0081 - accuracy: 1.0000 - val\_loss: 0.0586 - val\_accuracy: 0.9833

Epoch 40/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0079 - accuracy: 1.0000 - val\_loss: 0.0581 - val\_accuracy: 0.9834

Epoch 1/40  
469/469 [=====] - 7s 13ms/step - loss: 0.6769 - accuracy: 0.8220 - val\_loss: 0.2277 - val\_accuracy: 0.9389

Epoch 2/40  
469/469 [=====] - 6s 12ms/step - loss: 0.2091 - accuracy: 0.9434 - val\_loss: 0.1616 - val\_accuracy: 0.9554

Epoch 3/40  
469/469 [=====] - 6s 13ms/step - loss: 0.1529 - accuracy: 0.9588 - val\_loss: 0.1333 - val\_accuracy: 0.9635

Epoch 4/40  
469/469 [=====] - 6s 12ms/step - loss: 0.1156 - accuracy: 0.9699 - val\_loss: 0.1147 - val\_accuracy: 0.9681

Epoch 5/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0968 - accuracy: 0.9748 - val\_loss: 0.1011 - val\_accuracy: 0.9714

Epoch 6/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0806 - accuracy: 0.9796 - val\_loss: 0.0937 - val\_accuracy: 0.9728

Epoch 7/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0704 - accuracy: 0.9833 - val\_loss: 0.0885 - val\_accuracy: 0.9745

Epoch 8/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0604 - accuracy: 0.9874 - val\_loss: 0.0846 - val\_accuracy: 0.9753

Epoch 9/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0543 - accuracy: 0.9877 - val\_loss: 0.0824 - val\_accuracy: 0.9763

Epoch 10/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0460 - accuracy: 0.9908 - val\_loss: 0.0774 - val\_accuracy: 0.9786

Epoch 11/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0426 - accuracy: 0.9919 - val\_loss: 0.0756 - val\_accuracy: 0.9782

Epoch 12/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0367 - accuracy: 0.9940 - val\_loss: 0.0746 - val\_accuracy: 0.9774

Epoch 13/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0328 - accuracy: 0.9952 - val\_loss: 0.0746 - val\_accuracy: 0.9770

Epoch 14/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0300 - accuracy: 0.9958 - val\_loss: 0.0713 - val\_accuracy: 0.9790

Epoch 15/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0272 - accuracy: 0.9962 - val\_loss: 0.0717 - val\_accuracy: 0.9785

Epoch 16/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0245 - accuracy: 0.9975 - val\_loss: 0.0696 - val\_accuracy: 0.9794

Epoch 17/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0220 - accuracy: 0.9981 - val\_loss: 0.0691 - val\_accuracy: 0.9804

Epoch 18/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0207 - accuracy: 0.9983 - val\_loss: 0.0677 - val\_accuracy: 0.9795

Epoch 19/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0181 - accuracy: 0.9990 - val\_loss: 0.0670 - val\_accuracy: 0.9806

Epoch 20/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0173 - accuracy: 0.9992 - val\_loss: 0.0677 - val\_accuracy: 0.9793

Epoch 21/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0163 - accuracy: 0.9994 - val\_loss: 0.0667 - val\_accuracy: 0.9804

Epoch 22/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0154 - accuracy: 0.9995 - val\_loss: 0.0685 - val\_accuracy: 0.9799

Epoch 23/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0145 - accuracy: 0.9995 - val\_loss: 0.0669 - val\_accuracy: 0.9811

Epoch 24/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0136 - accuracy: 0.9997 - val\_loss: 0.0649 - val\_accuracy: 0.9808

Epoch 25/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0128 - accuracy: 0.9997 - val\_loss: 0.0647 - val\_accuracy: 0.9809

Epoch 26/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0123 - accuracy: 0.9997 - val\_loss: 0.0647 - val\_accuracy: 0.9813

Epoch 27/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0114 - accuracy: 0.9999 - val\_loss: 0.0643 - val\_accuracy: 0.9815

Epoch 28/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0111 - accuracy: 1.0000 - val\_loss: 0.0647 - val\_accuracy: 0.9811

Epoch 29/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0110 - accuracy: 0.9999 - val\_loss: 0.0636 - val\_accuracy: 0.9819

Epoch 30/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0105 - accuracy: 0.9999 - val\_loss: 0.0641 - val\_accuracy: 0.9814

Epoch 31/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0100 - accuracy: 1.0000 - val\_loss: 0.0634 - val\_accuracy: 0.9816

Epoch 32/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0098 - accuracy: 1.0000 - val\_loss: 0.0645 - val\_accuracy: 0.9812

Epoch 33/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0095 - accuracy: 1.0000 - val\_loss: 0.0635 - val\_accuracy: 0.9818

Epoch 34/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0092 - accuracy: 1.0000 - val\_loss: 0.0636 - val\_accuracy: 0.9816

Epoch 35/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0090 - accuracy: 1.0000 - val\_loss: 0.0631 - val\_accuracy: 0.9816

Epoch 36/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0088 - accuracy: 1.0000 - val\_loss: 0.0629 - val\_accuracy: 0.9821

Epoch 37/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0086 - accuracy: 1.0000 - val\_loss: 0.0627 - val\_accuracy: 0.9819

Epoch 38/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0085 - accuracy: 1.0000 - val\_loss: 0.0634 - val\_accuracy: 0.9821

Epoch 39/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0082 - accuracy: 1.0000 - val\_loss: 0.0630 - val\_accuracy: 0.9819

Epoch 40/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0080 - accuracy: 1.0000 - val\_loss: 0.0627 - val\_accuracy: 0.9822

Epoch 1/40  
469/469 [=====] - 6s 12ms/step - loss: 0.6931 - accuracy: 0.8156 - val\_loss: 0.2214 - val\_accuracy: 0.9409

Epoch 2/40  
469/469 [=====] - 6s 12ms/step - loss: 0.2111 - accuracy: 0.9425 - val\_loss: 0.1656 - val\_accuracy: 0.9539

Epoch 3/40  
469/469 [=====] - 6s 12ms/step - loss: 0.1522 -  
accuracy: 0.9596 - val\_loss: 0.1296 - val\_accuracy: 0.9632  
Epoch 4/40  
469/469 [=====] - 6s 12ms/step - loss: 0.1151 -  
accuracy: 0.9699 - val\_loss: 0.1129 - val\_accuracy: 0.9682  
Epoch 5/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0987 -  
accuracy: 0.9747 - val\_loss: 0.1027 - val\_accuracy: 0.9713  
Epoch 6/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0825 -  
accuracy: 0.9788 - val\_loss: 0.0926 - val\_accuracy: 0.9733  
Epoch 7/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0685 -  
accuracy: 0.9841 - val\_loss: 0.0901 - val\_accuracy: 0.9751  
Epoch 8/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0587 -  
accuracy: 0.9870 - val\_loss: 0.0835 - val\_accuracy: 0.9760  
Epoch 9/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0525 -  
accuracy: 0.9884 - val\_loss: 0.0755 - val\_accuracy: 0.9790  
Epoch 10/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0454 -  
accuracy: 0.9907 - val\_loss: 0.0791 - val\_accuracy: 0.9768  
Epoch 11/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0394 -  
accuracy: 0.9926 - val\_loss: 0.0701 - val\_accuracy: 0.9793  
Epoch 12/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0352 -  
accuracy: 0.9943 - val\_loss: 0.0716 - val\_accuracy: 0.9791  
Epoch 13/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0316 -  
accuracy: 0.9951 - val\_loss: 0.0674 - val\_accuracy: 0.9808  
Epoch 14/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0283 -  
accuracy: 0.9960 - val\_loss: 0.0661 - val\_accuracy: 0.9805  
Epoch 15/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0257 -  
accuracy: 0.9972 - val\_loss: 0.0663 - val\_accuracy: 0.9800  
Epoch 16/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0230 -  
accuracy: 0.9978 - val\_loss: 0.0671 - val\_accuracy: 0.9800  
Epoch 17/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0211 -  
accuracy: 0.9985 - val\_loss: 0.0652 - val\_accuracy: 0.9804  
Epoch 18/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0200 -  
accuracy: 0.9988 - val\_loss: 0.0653 - val\_accuracy: 0.9805

Epoch 19/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0178 -  
accuracy: 0.9990 - val\_loss: 0.0649 - val\_accuracy: 0.9808  
Epoch 20/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0165 -  
accuracy: 0.9993 - val\_loss: 0.0646 - val\_accuracy: 0.9813  
Epoch 21/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0159 -  
accuracy: 0.9994 - val\_loss: 0.0633 - val\_accuracy: 0.9816  
Epoch 22/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0148 -  
accuracy: 0.9995 - val\_loss: 0.0640 - val\_accuracy: 0.9812  
Epoch 23/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0140 -  
accuracy: 0.9997 - val\_loss: 0.0623 - val\_accuracy: 0.9823  
Epoch 24/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0132 -  
accuracy: 0.9998 - val\_loss: 0.0639 - val\_accuracy: 0.9815  
Epoch 25/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0123 -  
accuracy: 0.9999 - val\_loss: 0.0624 - val\_accuracy: 0.9824  
Epoch 26/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0120 -  
accuracy: 0.9998 - val\_loss: 0.0640 - val\_accuracy: 0.9814  
Epoch 27/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0115 -  
accuracy: 0.9998 - val\_loss: 0.0630 - val\_accuracy: 0.9818  
Epoch 28/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0113 -  
accuracy: 0.9999 - val\_loss: 0.0635 - val\_accuracy: 0.9819  
Epoch 29/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0108 -  
accuracy: 0.9999 - val\_loss: 0.0633 - val\_accuracy: 0.9818  
Epoch 30/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0105 -  
accuracy: 0.9999 - val\_loss: 0.0624 - val\_accuracy: 0.9821  
Epoch 31/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0100 -  
accuracy: 0.9999 - val\_loss: 0.0625 - val\_accuracy: 0.9824  
Epoch 32/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0097 -  
accuracy: 0.9999 - val\_loss: 0.0624 - val\_accuracy: 0.9818  
Epoch 33/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0094 -  
accuracy: 0.9999 - val\_loss: 0.0619 - val\_accuracy: 0.9827  
Epoch 34/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0091 -  
accuracy: 1.0000 - val\_loss: 0.0622 - val\_accuracy: 0.9827

Epoch 35/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0089 - accuracy: 1.0000 - val\_loss: 0.0620 - val\_accuracy: 0.9822

Epoch 36/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0086 - accuracy: 1.0000 - val\_loss: 0.0621 - val\_accuracy: 0.9821

Epoch 37/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0085 - accuracy: 1.0000 - val\_loss: 0.0615 - val\_accuracy: 0.9820

Epoch 38/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0083 - accuracy: 1.0000 - val\_loss: 0.0618 - val\_accuracy: 0.9826

Epoch 39/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0080 - accuracy: 1.0000 - val\_loss: 0.0621 - val\_accuracy: 0.9827

Epoch 40/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0079 - accuracy: 1.0000 - val\_loss: 0.0621 - val\_accuracy: 0.9822

Epoch 1/40  
469/469 [=====] - 6s 12ms/step - loss: 0.6899 - accuracy: 0.8133 - val\_loss: 0.2392 - val\_accuracy: 0.9304

Epoch 2/40  
469/469 [=====] - 6s 12ms/step - loss: 0.2033 - accuracy: 0.9429 - val\_loss: 0.1544 - val\_accuracy: 0.9548

Epoch 3/40  
469/469 [=====] - 6s 12ms/step - loss: 0.1361 - accuracy: 0.9622 - val\_loss: 0.1228 - val\_accuracy: 0.9632

Epoch 4/40  
469/469 [=====] - 6s 12ms/step - loss: 0.1117 - accuracy: 0.9694 - val\_loss: 0.1084 - val\_accuracy: 0.9687

Epoch 5/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0886 - accuracy: 0.9751 - val\_loss: 0.0955 - val\_accuracy: 0.9720

Epoch 6/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0768 - accuracy: 0.9789 - val\_loss: 0.0932 - val\_accuracy: 0.9729

Epoch 7/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0622 - accuracy: 0.9829 - val\_loss: 0.0802 - val\_accuracy: 0.9756

Epoch 8/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0540 - accuracy: 0.9860 - val\_loss: 0.0790 - val\_accuracy: 0.9760

Epoch 9/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0469 - accuracy: 0.9879 - val\_loss: 0.0755 - val\_accuracy: 0.9773

Epoch 10/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0408 - accuracy: 0.9903 - val\_loss: 0.0756 - val\_accuracy: 0.9769

Epoch 11/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0360 -  
accuracy: 0.9914 - val\_loss: 0.0739 - val\_accuracy: 0.9772  
Epoch 12/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0308 -  
accuracy: 0.9934 - val\_loss: 0.0707 - val\_accuracy: 0.9784  
Epoch 13/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0263 -  
accuracy: 0.9950 - val\_loss: 0.0675 - val\_accuracy: 0.9794  
Epoch 14/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0254 -  
accuracy: 0.9953 - val\_loss: 0.0674 - val\_accuracy: 0.9799  
Epoch 15/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0215 -  
accuracy: 0.9966 - val\_loss: 0.0658 - val\_accuracy: 0.9802  
Epoch 16/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0189 -  
accuracy: 0.9973 - val\_loss: 0.0786 - val\_accuracy: 0.9775  
Epoch 17/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0162 -  
accuracy: 0.9980 - val\_loss: 0.0629 - val\_accuracy: 0.9819  
Epoch 18/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0155 -  
accuracy: 0.9983 - val\_loss: 0.0653 - val\_accuracy: 0.9806  
Epoch 19/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0137 -  
accuracy: 0.9984 - val\_loss: 0.0634 - val\_accuracy: 0.9812  
Epoch 20/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0121 -  
accuracy: 0.9990 - val\_loss: 0.0674 - val\_accuracy: 0.9812  
Epoch 21/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0116 -  
accuracy: 0.9993 - val\_loss: 0.0631 - val\_accuracy: 0.9810  
Epoch 22/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0102 -  
accuracy: 0.9994 - val\_loss: 0.0640 - val\_accuracy: 0.9812  
Epoch 23/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0089 -  
accuracy: 0.9997 - val\_loss: 0.0647 - val\_accuracy: 0.9808  
Epoch 24/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0088 -  
accuracy: 0.9998 - val\_loss: 0.0649 - val\_accuracy: 0.9814  
Epoch 25/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0082 -  
accuracy: 0.9997 - val\_loss: 0.0633 - val\_accuracy: 0.9814  
Epoch 26/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0075 -  
accuracy: 0.9999 - val\_loss: 0.0631 - val\_accuracy: 0.9818

Epoch 27/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0071 -  
accuracy: 0.9999 - val\_loss: 0.0645 - val\_accuracy: 0.9819  
Epoch 28/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0070 -  
accuracy: 0.9999 - val\_loss: 0.0635 - val\_accuracy: 0.9815  
Epoch 29/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0065 -  
accuracy: 0.9998 - val\_loss: 0.0638 - val\_accuracy: 0.9819  
Epoch 30/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0063 -  
accuracy: 0.9999 - val\_loss: 0.0624 - val\_accuracy: 0.9824  
Epoch 31/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0059 -  
accuracy: 0.9999 - val\_loss: 0.0638 - val\_accuracy: 0.9818  
Epoch 32/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0056 -  
accuracy: 1.0000 - val\_loss: 0.0640 - val\_accuracy: 0.9817  
Epoch 33/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0054 -  
accuracy: 1.0000 - val\_loss: 0.0634 - val\_accuracy: 0.9824  
Epoch 34/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0053 -  
accuracy: 1.0000 - val\_loss: 0.0636 - val\_accuracy: 0.9823  
Epoch 35/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0052 -  
accuracy: 1.0000 - val\_loss: 0.0631 - val\_accuracy: 0.9823  
Epoch 36/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0050 -  
accuracy: 1.0000 - val\_loss: 0.0645 - val\_accuracy: 0.9819  
Epoch 37/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0049 -  
accuracy: 1.0000 - val\_loss: 0.0635 - val\_accuracy: 0.9826  
Epoch 38/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0047 -  
accuracy: 1.0000 - val\_loss: 0.0639 - val\_accuracy: 0.9821  
Epoch 39/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0047 -  
accuracy: 1.0000 - val\_loss: 0.0637 - val\_accuracy: 0.9825  
Epoch 40/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0045 -  
accuracy: 1.0000 - val\_loss: 0.0641 - val\_accuracy: 0.9822  
Epoch 1/40  
469/469 [=====] - 6s 12ms/step - loss: 0.7016 -  
accuracy: 0.8064 - val\_loss: 0.2393 - val\_accuracy: 0.9318  
Epoch 2/40  
469/469 [=====] - 6s 12ms/step - loss: 0.2144 -  
accuracy: 0.9390 - val\_loss: 0.1512 - val\_accuracy: 0.9557



Epoch 3/40  
469/469 [=====] - 6s 12ms/step - loss: 0.1442 -  
accuracy: 0.9593 - val\_loss: 0.1245 - val\_accuracy: 0.9630  
Epoch 4/40  
469/469 [=====] - 6s 12ms/step - loss: 0.1102 -  
accuracy: 0.9685 - val\_loss: 0.1109 - val\_accuracy: 0.9678  
Epoch 5/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0910 -  
accuracy: 0.9739 - val\_loss: 0.0924 - val\_accuracy: 0.9724  
Epoch 6/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0752 -  
accuracy: 0.9798 - val\_loss: 0.0885 - val\_accuracy: 0.9730  
Epoch 7/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0593 -  
accuracy: 0.9850 - val\_loss: 0.0802 - val\_accuracy: 0.9757  
Epoch 8/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0563 -  
accuracy: 0.9853 - val\_loss: 0.0753 - val\_accuracy: 0.9760  
Epoch 9/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0472 -  
accuracy: 0.9874 - val\_loss: 0.0751 - val\_accuracy: 0.9771  
Epoch 10/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0418 -  
accuracy: 0.9900 - val\_loss: 0.0703 - val\_accuracy: 0.9784  
Epoch 11/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0348 -  
accuracy: 0.9923 - val\_loss: 0.0734 - val\_accuracy: 0.9781  
Epoch 12/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0308 -  
accuracy: 0.9928 - val\_loss: 0.0724 - val\_accuracy: 0.9779  
Epoch 13/40  
469/469 [=====] - 6s 12ms/step - loss: 0.0268 -  
accuracy: 0.9946 - val\_loss: 0.0656 - val\_accuracy: 0.9803  
Epoch 14/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0229 -  
accuracy: 0.9955 - val\_loss: 0.0709 - val\_accuracy: 0.9781  
Epoch 15/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0208 -  
accuracy: 0.9969 - val\_loss: 0.0637 - val\_accuracy: 0.9805  
Epoch 16/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0178 -  
accuracy: 0.9973 - val\_loss: 0.0648 - val\_accuracy: 0.9811  
Epoch 17/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0159 -  
accuracy: 0.9982 - val\_loss: 0.0623 - val\_accuracy: 0.9806  
Epoch 18/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0146 -  
accuracy: 0.9983 - val\_loss: 0.0637 - val\_accuracy: 0.9809

Epoch 19/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0130 -  
accuracy: 0.9990 - val\_loss: 0.0633 - val\_accuracy: 0.9812  
Epoch 20/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0120 -  
accuracy: 0.9991 - val\_loss: 0.0617 - val\_accuracy: 0.9822  
Epoch 21/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0111 -  
accuracy: 0.9992 - val\_loss: 0.0637 - val\_accuracy: 0.9811  
Epoch 22/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0097 -  
accuracy: 0.9996 - val\_loss: 0.0644 - val\_accuracy: 0.9808  
Epoch 23/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0091 -  
accuracy: 0.9997 - val\_loss: 0.0632 - val\_accuracy: 0.9814  
Epoch 24/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0089 -  
accuracy: 0.9995 - val\_loss: 0.0620 - val\_accuracy: 0.9819  
Epoch 25/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0080 -  
accuracy: 0.9998 - val\_loss: 0.0641 - val\_accuracy: 0.9816  
Epoch 26/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0074 -  
accuracy: 0.9998 - val\_loss: 0.0632 - val\_accuracy: 0.9814  
Epoch 27/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0070 -  
accuracy: 0.9998 - val\_loss: 0.0628 - val\_accuracy: 0.9819  
Epoch 28/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0068 -  
accuracy: 0.9999 - val\_loss: 0.0633 - val\_accuracy: 0.9821  
Epoch 29/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0061 -  
accuracy: 0.9999 - val\_loss: 0.0624 - val\_accuracy: 0.9819  
Epoch 30/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0060 -  
accuracy: 0.9999 - val\_loss: 0.0628 - val\_accuracy: 0.9824  
Epoch 31/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0058 -  
accuracy: 0.9999 - val\_loss: 0.0635 - val\_accuracy: 0.9824  
Epoch 32/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0056 -  
accuracy: 1.0000 - val\_loss: 0.0631 - val\_accuracy: 0.9820  
Epoch 33/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0053 -  
accuracy: 1.0000 - val\_loss: 0.0627 - val\_accuracy: 0.9820  
Epoch 34/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0052 -  
accuracy: 1.0000 - val\_loss: 0.0632 - val\_accuracy: 0.9824

Epoch 35/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0050 -  
accuracy: 1.0000 - val\_loss: 0.0643 - val\_accuracy: 0.9821  
Epoch 36/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0049 -  
accuracy: 1.0000 - val\_loss: 0.0637 - val\_accuracy: 0.9820  
Epoch 37/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0048 -  
accuracy: 1.0000 - val\_loss: 0.0637 - val\_accuracy: 0.9822  
Epoch 38/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0046 -  
accuracy: 1.0000 - val\_loss: 0.0634 - val\_accuracy: 0.9827  
Epoch 39/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0046 -  
accuracy: 1.0000 - val\_loss: 0.0635 - val\_accuracy: 0.9824  
Epoch 40/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0044 -  
accuracy: 1.0000 - val\_loss: 0.0645 - val\_accuracy: 0.9825  
Epoch 1/40  
469/469 [=====] - 7s 13ms/step - loss: 0.6758 -  
accuracy: 0.8157 - val\_loss: 0.2539 - val\_accuracy: 0.9203  
Epoch 2/40  
469/469 [=====] - 6s 13ms/step - loss: 0.2049 -  
accuracy: 0.9411 - val\_loss: 0.1560 - val\_accuracy: 0.9533  
Epoch 3/40  
469/469 [=====] - 6s 13ms/step - loss: 0.1446 -  
accuracy: 0.9593 - val\_loss: 0.1277 - val\_accuracy: 0.9627  
Epoch 4/40  
469/469 [=====] - 6s 13ms/step - loss: 0.1113 -  
accuracy: 0.9679 - val\_loss: 0.0991 - val\_accuracy: 0.9701  
Epoch 5/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0894 -  
accuracy: 0.9746 - val\_loss: 0.0908 - val\_accuracy: 0.9729  
Epoch 6/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0731 -  
accuracy: 0.9802 - val\_loss: 0.0847 - val\_accuracy: 0.9757  
Epoch 7/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0636 -  
accuracy: 0.9827 - val\_loss: 0.0767 - val\_accuracy: 0.9779  
Epoch 8/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0530 -  
accuracy: 0.9858 - val\_loss: 0.0731 - val\_accuracy: 0.9783  
Epoch 9/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0451 -  
accuracy: 0.9882 - val\_loss: 0.0676 - val\_accuracy: 0.9809  
Epoch 10/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0431 -  
accuracy: 0.9888 - val\_loss: 0.0711 - val\_accuracy: 0.9779

Epoch 11/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0357 -  
accuracy: 0.9918 - val\_loss: 0.0651 - val\_accuracy: 0.9806  
Epoch 12/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0294 -  
accuracy: 0.9936 - val\_loss: 0.0649 - val\_accuracy: 0.9797  
Epoch 13/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0278 -  
accuracy: 0.9943 - val\_loss: 0.0623 - val\_accuracy: 0.9806  
Epoch 14/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0237 -  
accuracy: 0.9956 - val\_loss: 0.0599 - val\_accuracy: 0.9815  
Epoch 15/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0214 -  
accuracy: 0.9966 - val\_loss: 0.0596 - val\_accuracy: 0.9813  
Epoch 16/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0188 -  
accuracy: 0.9971 - val\_loss: 0.0582 - val\_accuracy: 0.9813  
Epoch 17/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0160 -  
accuracy: 0.9982 - val\_loss: 0.0664 - val\_accuracy: 0.9791  
Epoch 18/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0146 -  
accuracy: 0.9982 - val\_loss: 0.0587 - val\_accuracy: 0.9823  
Epoch 19/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0129 -  
accuracy: 0.9989 - val\_loss: 0.0593 - val\_accuracy: 0.9817  
Epoch 20/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0126 -  
accuracy: 0.9988 - val\_loss: 0.0586 - val\_accuracy: 0.9824  
Epoch 21/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0109 -  
accuracy: 0.9992 - val\_loss: 0.0588 - val\_accuracy: 0.9829  
Epoch 22/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0099 -  
accuracy: 0.9994 - val\_loss: 0.0579 - val\_accuracy: 0.9829  
Epoch 23/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0091 -  
accuracy: 0.9996 - val\_loss: 0.0590 - val\_accuracy: 0.9828  
Epoch 24/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0085 -  
accuracy: 0.9996 - val\_loss: 0.0577 - val\_accuracy: 0.9836  
Epoch 25/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0082 -  
accuracy: 0.9997 - val\_loss: 0.0581 - val\_accuracy: 0.9835  
Epoch 26/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0078 -  
accuracy: 0.9997 - val\_loss: 0.0582 - val\_accuracy: 0.9831

Epoch 27/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0070 - accuracy: 0.9999 - val\_loss: 0.0598 - val\_accuracy: 0.9834

Epoch 28/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0068 - accuracy: 0.9999 - val\_loss: 0.0590 - val\_accuracy: 0.9827

Epoch 29/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0062 - accuracy: 0.9999 - val\_loss: 0.0592 - val\_accuracy: 0.9831

Epoch 30/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0062 - accuracy: 0.9999 - val\_loss: 0.0588 - val\_accuracy: 0.9836

Epoch 31/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0057 - accuracy: 1.0000 - val\_loss: 0.0592 - val\_accuracy: 0.9830

Epoch 32/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0056 - accuracy: 1.0000 - val\_loss: 0.0588 - val\_accuracy: 0.9839

Epoch 33/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0055 - accuracy: 1.0000 - val\_loss: 0.0589 - val\_accuracy: 0.9834

Epoch 34/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0052 - accuracy: 1.0000 - val\_loss: 0.0586 - val\_accuracy: 0.9837

Epoch 35/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0050 - accuracy: 1.0000 - val\_loss: 0.0592 - val\_accuracy: 0.9834

Epoch 36/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0048 - accuracy: 1.0000 - val\_loss: 0.0592 - val\_accuracy: 0.9840

Epoch 37/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0048 - accuracy: 1.0000 - val\_loss: 0.0595 - val\_accuracy: 0.9839

Epoch 38/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0047 - accuracy: 1.0000 - val\_loss: 0.0587 - val\_accuracy: 0.9836

Epoch 39/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0045 - accuracy: 1.0000 - val\_loss: 0.0591 - val\_accuracy: 0.9842

Epoch 40/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0043 - accuracy: 1.0000 - val\_loss: 0.0592 - val\_accuracy: 0.9840

Epoch 1/40  
469/469 [=====] - 7s 14ms/step - loss: 0.6868 - accuracy: 0.8156 - val\_loss: 0.2120 - val\_accuracy: 0.9365

Epoch 2/40  
469/469 [=====] - 6s 14ms/step - loss: 0.2054 - accuracy: 0.9420 - val\_loss: 0.1646 - val\_accuracy: 0.9507

Epoch 3/40  
469/469 [=====] - 6s 13ms/step - loss: 0.1512 - accuracy: 0.9564 - val\_loss: 0.1280 - val\_accuracy: 0.9606

Epoch 4/40  
469/469 [=====] - 6s 13ms/step - loss: 0.1150 - accuracy: 0.9662 - val\_loss: 0.1040 - val\_accuracy: 0.9690

Epoch 5/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0906 - accuracy: 0.9747 - val\_loss: 0.1050 - val\_accuracy: 0.9671

Epoch 6/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0741 - accuracy: 0.9785 - val\_loss: 0.0872 - val\_accuracy: 0.9734

Epoch 7/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0671 - accuracy: 0.9813 - val\_loss: 0.0779 - val\_accuracy: 0.9760

Epoch 8/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0538 - accuracy: 0.9845 - val\_loss: 0.0752 - val\_accuracy: 0.9764

Epoch 9/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0456 - accuracy: 0.9874 - val\_loss: 0.0700 - val\_accuracy: 0.9775

Epoch 10/40  
469/469 [=====] - 6s 14ms/step - loss: 0.0406 - accuracy: 0.9890 - val\_loss: 0.0733 - val\_accuracy: 0.9768

Epoch 11/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0354 - accuracy: 0.9906 - val\_loss: 0.0663 - val\_accuracy: 0.9789

Epoch 12/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0320 - accuracy: 0.9918 - val\_loss: 0.0697 - val\_accuracy: 0.9781

Epoch 13/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0277 - accuracy: 0.9931 - val\_loss: 0.0673 - val\_accuracy: 0.9797

Epoch 14/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0230 - accuracy: 0.9951 - val\_loss: 0.0650 - val\_accuracy: 0.9787

Epoch 15/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0200 - accuracy: 0.9959 - val\_loss: 0.0621 - val\_accuracy: 0.9796

Epoch 16/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0172 - accuracy: 0.9970 - val\_loss: 0.0634 - val\_accuracy: 0.9807

Epoch 17/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0151 - accuracy: 0.9974 - val\_loss: 0.0671 - val\_accuracy: 0.9787

Epoch 18/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0141 - accuracy: 0.9979 - val\_loss: 0.0637 - val\_accuracy: 0.9801

Epoch 19/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0122 -  
accuracy: 0.9985 - val\_loss: 0.0629 - val\_accuracy: 0.9807  
Epoch 20/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0107 -  
accuracy: 0.9988 - val\_loss: 0.0621 - val\_accuracy: 0.9800  
Epoch 21/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0090 -  
accuracy: 0.9992 - val\_loss: 0.0628 - val\_accuracy: 0.9800  
Epoch 22/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0090 -  
accuracy: 0.9992 - val\_loss: 0.0614 - val\_accuracy: 0.9811  
Epoch 23/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0074 -  
accuracy: 0.9995 - val\_loss: 0.0618 - val\_accuracy: 0.9811  
Epoch 24/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0069 -  
accuracy: 0.9995 - val\_loss: 0.0618 - val\_accuracy: 0.9808  
Epoch 25/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0061 -  
accuracy: 0.9996 - val\_loss: 0.0627 - val\_accuracy: 0.9809  
Epoch 26/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0054 -  
accuracy: 0.9997 - val\_loss: 0.0612 - val\_accuracy: 0.9809  
Epoch 27/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0049 -  
accuracy: 0.9998 - val\_loss: 0.0623 - val\_accuracy: 0.9813  
Epoch 28/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0047 -  
accuracy: 0.9998 - val\_loss: 0.0637 - val\_accuracy: 0.9809  
Epoch 29/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0044 -  
accuracy: 0.9999 - val\_loss: 0.0634 - val\_accuracy: 0.9814  
Epoch 30/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0040 -  
accuracy: 1.0000 - val\_loss: 0.0623 - val\_accuracy: 0.9819  
Epoch 31/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0036 -  
accuracy: 1.0000 - val\_loss: 0.0623 - val\_accuracy: 0.9814  
Epoch 32/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0034 -  
accuracy: 1.0000 - val\_loss: 0.0622 - val\_accuracy: 0.9813  
Epoch 33/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0032 -  
accuracy: 1.0000 - val\_loss: 0.0633 - val\_accuracy: 0.9812  
Epoch 34/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0030 -  
accuracy: 1.0000 - val\_loss: 0.0642 - val\_accuracy: 0.9818

Epoch 35/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0030 - accuracy: 1.0000 - val\_loss: 0.0642 - val\_accuracy: 0.9811

Epoch 36/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0026 - accuracy: 1.0000 - val\_loss: 0.0636 - val\_accuracy: 0.9811

Epoch 37/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0026 - accuracy: 1.0000 - val\_loss: 0.0643 - val\_accuracy: 0.9818

Epoch 38/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0025 - accuracy: 1.0000 - val\_loss: 0.0643 - val\_accuracy: 0.9814

Epoch 39/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0024 - accuracy: 1.0000 - val\_loss: 0.0645 - val\_accuracy: 0.9818

Epoch 40/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0022 - accuracy: 1.0000 - val\_loss: 0.0649 - val\_accuracy: 0.9816

Epoch 1/40  
469/469 [=====] - 7s 14ms/step - loss: 0.6798 - accuracy: 0.8154 - val\_loss: 0.2246 - val\_accuracy: 0.9312

Epoch 2/40  
469/469 [=====] - 6s 13ms/step - loss: 0.2040 - accuracy: 0.9408 - val\_loss: 0.1445 - val\_accuracy: 0.9571

Epoch 3/40  
469/469 [=====] - 6s 13ms/step - loss: 0.1420 - accuracy: 0.9600 - val\_loss: 0.1220 - val\_accuracy: 0.9633

Epoch 4/40  
469/469 [=====] - 6s 13ms/step - loss: 0.1110 - accuracy: 0.9670 - val\_loss: 0.1051 - val\_accuracy: 0.9695

Epoch 5/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0895 - accuracy: 0.9744 - val\_loss: 0.0917 - val\_accuracy: 0.9707

Epoch 6/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0732 - accuracy: 0.9794 - val\_loss: 0.0890 - val\_accuracy: 0.9728

Epoch 7/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0601 - accuracy: 0.9836 - val\_loss: 0.0813 - val\_accuracy: 0.9752

Epoch 8/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0500 - accuracy: 0.9866 - val\_loss: 0.0727 - val\_accuracy: 0.9789

Epoch 9/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0467 - accuracy: 0.9874 - val\_loss: 0.0717 - val\_accuracy: 0.9772

Epoch 10/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0376 - accuracy: 0.9903 - val\_loss: 0.0694 - val\_accuracy: 0.9778



Epoch 11/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0317 -  
accuracy: 0.9921 - val\_loss: 0.0655 - val\_accuracy: 0.9795  
Epoch 12/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0278 -  
accuracy: 0.9939 - val\_loss: 0.0642 - val\_accuracy: 0.9800  
Epoch 13/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0245 -  
accuracy: 0.9945 - val\_loss: 0.0613 - val\_accuracy: 0.9806  
Epoch 14/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0209 -  
accuracy: 0.9960 - val\_loss: 0.0650 - val\_accuracy: 0.9811  
Epoch 15/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0182 -  
accuracy: 0.9967 - val\_loss: 0.0623 - val\_accuracy: 0.9800  
Epoch 16/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0149 -  
accuracy: 0.9976 - val\_loss: 0.0613 - val\_accuracy: 0.9806  
Epoch 17/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0132 -  
accuracy: 0.9978 - val\_loss: 0.0588 - val\_accuracy: 0.9819  
Epoch 18/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0118 -  
accuracy: 0.9983 - val\_loss: 0.0641 - val\_accuracy: 0.9803  
Epoch 19/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0105 -  
accuracy: 0.9988 - val\_loss: 0.0597 - val\_accuracy: 0.9824  
Epoch 20/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0097 -  
accuracy: 0.9991 - val\_loss: 0.0605 - val\_accuracy: 0.9819  
Epoch 21/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0084 -  
accuracy: 0.9994 - val\_loss: 0.0614 - val\_accuracy: 0.9816  
Epoch 22/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0077 -  
accuracy: 0.9994 - val\_loss: 0.0618 - val\_accuracy: 0.9815  
Epoch 23/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0067 -  
accuracy: 0.9996 - val\_loss: 0.0608 - val\_accuracy: 0.9824  
Epoch 24/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0061 -  
accuracy: 0.9996 - val\_loss: 0.0627 - val\_accuracy: 0.9823  
Epoch 25/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0053 -  
accuracy: 0.9998 - val\_loss: 0.0622 - val\_accuracy: 0.9818  
Epoch 26/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0048 -  
accuracy: 0.9999 - val\_loss: 0.0624 - val\_accuracy: 0.9812

Epoch 27/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0043 - accuracy: 0.9999 - val\_loss: 0.0628 - val\_accuracy: 0.9815

Epoch 28/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0041 - accuracy: 0.9999 - val\_loss: 0.0629 - val\_accuracy: 0.9814

Epoch 29/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0038 - accuracy: 0.9999 - val\_loss: 0.0637 - val\_accuracy: 0.9815

Epoch 30/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0036 - accuracy: 0.9999 - val\_loss: 0.0631 - val\_accuracy: 0.9817

Epoch 31/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0033 - accuracy: 1.0000 - val\_loss: 0.0627 - val\_accuracy: 0.9820

Epoch 32/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0031 - accuracy: 1.0000 - val\_loss: 0.0637 - val\_accuracy: 0.9822

Epoch 33/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0030 - accuracy: 1.0000 - val\_loss: 0.0633 - val\_accuracy: 0.9826

Epoch 34/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0028 - accuracy: 1.0000 - val\_loss: 0.0646 - val\_accuracy: 0.9820

Epoch 35/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0027 - accuracy: 1.0000 - val\_loss: 0.0635 - val\_accuracy: 0.9817

Epoch 36/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0025 - accuracy: 1.0000 - val\_loss: 0.0650 - val\_accuracy: 0.9818

Epoch 37/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0024 - accuracy: 1.0000 - val\_loss: 0.0648 - val\_accuracy: 0.9816

Epoch 38/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0023 - accuracy: 1.0000 - val\_loss: 0.0648 - val\_accuracy: 0.9820

Epoch 39/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0023 - accuracy: 0.9999 - val\_loss: 0.0654 - val\_accuracy: 0.9823

Epoch 40/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0021 - accuracy: 1.0000 - val\_loss: 0.0651 - val\_accuracy: 0.9823

Epoch 1/40  
469/469 [=====] - 7s 14ms/step - loss: 0.6800 - accuracy: 0.8162 - val\_loss: 0.2206 - val\_accuracy: 0.9369

Epoch 2/40  
469/469 [=====] - 6s 13ms/step - loss: 0.2095 - accuracy: 0.9385 - val\_loss: 0.1565 - val\_accuracy: 0.9549

Epoch 3/40  
469/469 [=====] - 6s 13ms/step - loss: 0.1456 - accuracy: 0.9587 - val\_loss: 0.1221 - val\_accuracy: 0.9650

Epoch 4/40  
469/469 [=====] - 6s 13ms/step - loss: 0.1124 - accuracy: 0.9688 - val\_loss: 0.1100 - val\_accuracy: 0.9661

Epoch 5/40  
469/469 [=====] - 6s 14ms/step - loss: 0.0904 - accuracy: 0.9738 - val\_loss: 0.0884 - val\_accuracy: 0.9730

Epoch 6/40  
469/469 [=====] - 6s 14ms/step - loss: 0.0723 - accuracy: 0.9802 - val\_loss: 0.0830 - val\_accuracy: 0.9741

Epoch 7/40  
469/469 [=====] - 7s 14ms/step - loss: 0.0632 - accuracy: 0.9823 - val\_loss: 0.0794 - val\_accuracy: 0.9758

Epoch 8/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0541 - accuracy: 0.9849 - val\_loss: 0.0702 - val\_accuracy: 0.9783

Epoch 9/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0465 - accuracy: 0.9876 - val\_loss: 0.0688 - val\_accuracy: 0.9788

Epoch 10/40  
469/469 [=====] - 6s 14ms/step - loss: 0.0399 - accuracy: 0.9891 - val\_loss: 0.0667 - val\_accuracy: 0.9789

Epoch 11/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0339 - accuracy: 0.9915 - val\_loss: 0.0681 - val\_accuracy: 0.9771

Epoch 12/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0305 - accuracy: 0.9926 - val\_loss: 0.0682 - val\_accuracy: 0.9772

Epoch 13/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0251 - accuracy: 0.9942 - val\_loss: 0.0660 - val\_accuracy: 0.9782

Epoch 14/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0224 - accuracy: 0.9951 - val\_loss: 0.0644 - val\_accuracy: 0.9797

Epoch 15/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0198 - accuracy: 0.9956 - val\_loss: 0.0606 - val\_accuracy: 0.9804

Epoch 16/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0168 - accuracy: 0.9971 - val\_loss: 0.0599 - val\_accuracy: 0.9794

Epoch 17/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0146 - accuracy: 0.9976 - val\_loss: 0.0616 - val\_accuracy: 0.9792

Epoch 18/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0134 - accuracy: 0.9981 - val\_loss: 0.0677 - val\_accuracy: 0.9783

Epoch 19/40  
469/469 [=====] - 6s 14ms/step - loss: 0.0117 -  
accuracy: 0.9985 - val\_loss: 0.0605 - val\_accuracy: 0.9805  
Epoch 20/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0098 -  
accuracy: 0.9989 - val\_loss: 0.0579 - val\_accuracy: 0.9825  
Epoch 21/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0089 -  
accuracy: 0.9991 - val\_loss: 0.0611 - val\_accuracy: 0.9802  
Epoch 22/40  
469/469 [=====] - 6s 14ms/step - loss: 0.0080 -  
accuracy: 0.9992 - val\_loss: 0.0592 - val\_accuracy: 0.9807  
Epoch 23/40  
469/469 [=====] - 6s 14ms/step - loss: 0.0072 -  
accuracy: 0.9995 - val\_loss: 0.0607 - val\_accuracy: 0.9811  
Epoch 24/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0065 -  
accuracy: 0.9996 - val\_loss: 0.0588 - val\_accuracy: 0.9807  
Epoch 25/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0058 -  
accuracy: 0.9997 - val\_loss: 0.0585 - val\_accuracy: 0.9809  
Epoch 26/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0051 -  
accuracy: 0.9997 - val\_loss: 0.0604 - val\_accuracy: 0.9811  
Epoch 27/40  
469/469 [=====] - 6s 14ms/step - loss: 0.0049 -  
accuracy: 0.9998 - val\_loss: 0.0595 - val\_accuracy: 0.9814  
Epoch 28/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0042 -  
accuracy: 0.9999 - val\_loss: 0.0604 - val\_accuracy: 0.9809  
Epoch 29/40  
469/469 [=====] - 6s 14ms/step - loss: 0.0041 -  
accuracy: 0.9999 - val\_loss: 0.0598 - val\_accuracy: 0.9809  
Epoch 30/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0037 -  
accuracy: 0.9999 - val\_loss: 0.0598 - val\_accuracy: 0.9813  
Epoch 31/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0035 -  
accuracy: 0.9999 - val\_loss: 0.0608 - val\_accuracy: 0.9817  
Epoch 32/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0033 -  
accuracy: 0.9999 - val\_loss: 0.0602 - val\_accuracy: 0.9815  
Epoch 33/40  
469/469 [=====] - 6s 13ms/step - loss: 0.0030 -  
accuracy: 1.0000 - val\_loss: 0.0608 - val\_accuracy: 0.9809  
Epoch 34/40  
469/469 [=====] - 6s 14ms/step - loss: 0.0029 -  
accuracy: 1.0000 - val\_loss: 0.0608 - val\_accuracy: 0.9812

```

Epoch 35/40
469/469 [=====] - 6s 13ms/step - loss: 0.0030 -
accuracy: 1.0000 - val_loss: 0.0611 - val_accuracy: 0.9808
Epoch 36/40
469/469 [=====] - 6s 13ms/step - loss: 0.0027 -
accuracy: 1.0000 - val_loss: 0.0618 - val_accuracy: 0.9811
Epoch 37/40
469/469 [=====] - 6s 13ms/step - loss: 0.0024 -
accuracy: 1.0000 - val_loss: 0.0622 - val_accuracy: 0.9813
Epoch 38/40
469/469 [=====] - 6s 13ms/step - loss: 0.0023 -
accuracy: 1.0000 - val_loss: 0.0618 - val_accuracy: 0.9815
Epoch 39/40
469/469 [=====] - 6s 13ms/step - loss: 0.0023 -
accuracy: 1.0000 - val_loss: 0.0625 - val_accuracy: 0.9815
Epoch 40/40
469/469 [=====] - 6s 13ms/step - loss: 0.0022 -
accuracy: 1.0000 - val_loss: 0.0622 - val_accuracy: 0.9815

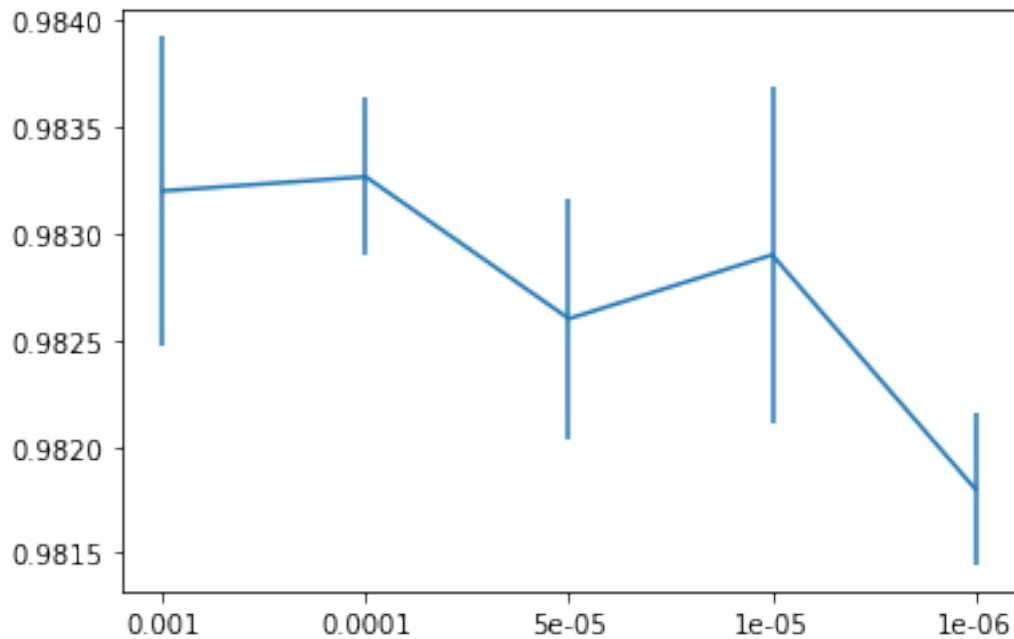
```

```

[ ]: #Plot the final validation accuracy with standard deviation
x = list(map(str, reg_factors))
y = list(map(np.mean, val_accuracys))
e = list(map(np.std, val_accuracys))

plt.errorbar(x, y, yerr=e)
plt.show()

```



How close do you get to Hinton's result? – If you do not get the same results, what factors may influence this? (hint: What information is not given by Hinton on the MNIST database that may influence Model training)

[Answer]

As seen in the graph the highest accuracy we get is around 0.9838. We did not quite get the same result as Hinton, which we believe can be due to us not choosing the most proper regularization factors which is something that is not mentioned in the MNIST database. Maybe by modifying the regularization factors we can get closer or get the same result as Hinton, but since it takes such a long time we just let it be. Another thing that was different was the batch sizes, Hinton had a batch size of 100 while we have 128, maybe this could also be something related to the result. The nr of epochs could be a factor, in the science paper Hinton uses a maxepoch of 50 while we use 40.

#3) 2points. Convolutional layers.

A) Design a model that makes use of at least one convolutional layer—how performant a model can you get? –According to the MNIST database it should be possible reach to 99% accuracy on the validation data. If you choose to use any layers apart from convolutional layers and layers that you used in previous questions, you must describe what they do. If you do not reach 99% accuracy, report your best performance and explain your attempts and thought process.

[Answer]

```
[ ]: #model with convolutional layer
convModel = Sequential()
convModel.add(Conv2D(32, kernel_size=(3, 3),
                    activation='relu',
                    input_shape=(28,28,1)))

convModel.add(Conv2D(64, (3, 3), activation='relu'))
convModel.add(MaxPooling2D(pool_size=(2, 2)))
convModel.add(Dropout(0.25))# helps to prevent overfitting
convModel.add(Flatten())
convModel.add(Dense(128, activation='relu'))
convModel.add(Dropout(0.5))# helps to prevent overfitting
convModel.add(Dense(num_classes, activation='softmax'))

convModel.compile(loss=keras.losses.categorical_crossentropy,
                  optimizer=keras.optimizers.SGD(learning_rate=0.1),
                  metrics=['accuracy'])

fit_info_convModel = convModel.fit(x_train, y_train,
                                   batch_size=batch_size,
                                   epochs=40,
                                   verbose=1,
                                   validation_data=(x_test, y_test))

score = convModel.evaluate(x_test, y_test, verbose=0)
```

```
print("Accuracy: ", score[1])
```

Epoch 1/40

469/469 [=====] - 142s 302ms/step - loss: 0.7713 -  
accuracy: 0.7521 - val\_loss: 0.1057 - val\_accuracy: 0.9681

Epoch 2/40

469/469 [=====] - 140s 299ms/step - loss: 0.1659 -  
accuracy: 0.9511 - val\_loss: 0.0632 - val\_accuracy: 0.9792

Epoch 3/40

469/469 [=====] - 140s 298ms/step - loss: 0.1177 -  
accuracy: 0.9653 - val\_loss: 0.0501 - val\_accuracy: 0.9839

Epoch 4/40

469/469 [=====] - 139s 297ms/step - loss: 0.0922 -  
accuracy: 0.9714 - val\_loss: 0.0431 - val\_accuracy: 0.9853

Epoch 5/40

469/469 [=====] - 139s 297ms/step - loss: 0.0782 -  
accuracy: 0.9768 - val\_loss: 0.0401 - val\_accuracy: 0.9864

Epoch 6/40

469/469 [=====] - 139s 297ms/step - loss: 0.0704 -  
accuracy: 0.9782 - val\_loss: 0.0379 - val\_accuracy: 0.9877

Epoch 7/40

469/469 [=====] - 137s 293ms/step - loss: 0.0605 -  
accuracy: 0.9818 - val\_loss: 0.0392 - val\_accuracy: 0.9877

Epoch 8/40

469/469 [=====] - 137s 293ms/step - loss: 0.0571 -  
accuracy: 0.9825 - val\_loss: 0.0342 - val\_accuracy: 0.9893

Epoch 9/40

469/469 [=====] - 137s 292ms/step - loss: 0.0536 -  
accuracy: 0.9832 - val\_loss: 0.0335 - val\_accuracy: 0.9894

Epoch 10/40

469/469 [=====] - 137s 292ms/step - loss: 0.0513 -  
accuracy: 0.9840 - val\_loss: 0.0314 - val\_accuracy: 0.9898

Epoch 11/40

469/469 [=====] - 137s 292ms/step - loss: 0.0468 -  
accuracy: 0.9857 - val\_loss: 0.0302 - val\_accuracy: 0.9889

Epoch 12/40

469/469 [=====] - 137s 293ms/step - loss: 0.0409 -  
accuracy: 0.9871 - val\_loss: 0.0307 - val\_accuracy: 0.9898

Epoch 13/40

469/469 [=====] - 139s 297ms/step - loss: 0.0380 -  
accuracy: 0.9876 - val\_loss: 0.0273 - val\_accuracy: 0.9911

Epoch 14/40

469/469 [=====] - 140s 299ms/step - loss: 0.0369 -  
accuracy: 0.9878 - val\_loss: 0.0284 - val\_accuracy: 0.9911

Epoch 15/40

469/469 [=====] - 140s 298ms/step - loss: 0.0348 -  
accuracy: 0.9889 - val\_loss: 0.0286 - val\_accuracy: 0.9908

Epoch 16/40  
469/469 [=====] - 140s 300ms/step - loss: 0.0332 -  
accuracy: 0.9891 - val\_loss: 0.0285 - val\_accuracy: 0.9903  
Epoch 17/40  
469/469 [=====] - 140s 298ms/step - loss: 0.0327 -  
accuracy: 0.9894 - val\_loss: 0.0284 - val\_accuracy: 0.9907  
Epoch 18/40  
469/469 [=====] - 139s 296ms/step - loss: 0.0286 -  
accuracy: 0.9907 - val\_loss: 0.0267 - val\_accuracy: 0.9923  
Epoch 19/40  
469/469 [=====] - 137s 293ms/step - loss: 0.0285 -  
accuracy: 0.9911 - val\_loss: 0.0266 - val\_accuracy: 0.9910  
Epoch 20/40  
469/469 [=====] - 138s 294ms/step - loss: 0.0276 -  
accuracy: 0.9912 - val\_loss: 0.0286 - val\_accuracy: 0.9909  
Epoch 21/40  
469/469 [=====] - 137s 292ms/step - loss: 0.0262 -  
accuracy: 0.9916 - val\_loss: 0.0289 - val\_accuracy: 0.9914  
Epoch 22/40  
469/469 [=====] - 140s 298ms/step - loss: 0.0256 -  
accuracy: 0.9922 - val\_loss: 0.0264 - val\_accuracy: 0.9917  
Epoch 23/40  
469/469 [=====] - 140s 298ms/step - loss: 0.0224 -  
accuracy: 0.9923 - val\_loss: 0.0292 - val\_accuracy: 0.9907  
Epoch 24/40  
469/469 [=====] - 141s 301ms/step - loss: 0.0220 -  
accuracy: 0.9926 - val\_loss: 0.0273 - val\_accuracy: 0.9913  
Epoch 25/40  
469/469 [=====] - 140s 299ms/step - loss: 0.0229 -  
accuracy: 0.9923 - val\_loss: 0.0261 - val\_accuracy: 0.9920  
Epoch 26/40  
469/469 [=====] - 140s 298ms/step - loss: 0.0210 -  
accuracy: 0.9929 - val\_loss: 0.0255 - val\_accuracy: 0.9920  
Epoch 27/40  
469/469 [=====] - 138s 295ms/step - loss: 0.0212 -  
accuracy: 0.9928 - val\_loss: 0.0243 - val\_accuracy: 0.9923  
Epoch 28/40  
469/469 [=====] - 137s 293ms/step - loss: 0.0196 -  
accuracy: 0.9932 - val\_loss: 0.0259 - val\_accuracy: 0.9918  
Epoch 29/40  
469/469 [=====] - 137s 293ms/step - loss: 0.0207 -  
accuracy: 0.9932 - val\_loss: 0.0248 - val\_accuracy: 0.9918  
Epoch 30/40  
469/469 [=====] - 137s 293ms/step - loss: 0.0198 -  
accuracy: 0.9933 - val\_loss: 0.0266 - val\_accuracy: 0.9920  
Epoch 31/40  
469/469 [=====] - 137s 293ms/step - loss: 0.0183 -  
accuracy: 0.9939 - val\_loss: 0.0270 - val\_accuracy: 0.9926



```

Epoch 32/40
469/469 [=====] - 137s 293ms/step - loss: 0.0172 -
accuracy: 0.9939 - val_loss: 0.0275 - val_accuracy: 0.9911
Epoch 33/40
469/469 [=====] - 137s 293ms/step - loss: 0.0177 -
accuracy: 0.9944 - val_loss: 0.0268 - val_accuracy: 0.9922
Epoch 34/40
469/469 [=====] - 137s 293ms/step - loss: 0.0189 -
accuracy: 0.9937 - val_loss: 0.0271 - val_accuracy: 0.9920
Epoch 35/40
469/469 [=====] - 137s 292ms/step - loss: 0.0159 -
accuracy: 0.9946 - val_loss: 0.0265 - val_accuracy: 0.9929
Epoch 36/40
469/469 [=====] - 137s 293ms/step - loss: 0.0165 -
accuracy: 0.9941 - val_loss: 0.0287 - val_accuracy: 0.9924
Epoch 37/40
469/469 [=====] - 137s 293ms/step - loss: 0.0153 -
accuracy: 0.9947 - val_loss: 0.0279 - val_accuracy: 0.9924
Epoch 38/40
469/469 [=====] - 140s 299ms/step - loss: 0.0148 -
accuracy: 0.9945 - val_loss: 0.0287 - val_accuracy: 0.9919
Epoch 39/40
469/469 [=====] - 140s 298ms/step - loss: 0.0148 -
accuracy: 0.9950 - val_loss: 0.0288 - val_accuracy: 0.9930
Epoch 40/40
469/469 [=====] - 140s 299ms/step - loss: 0.0153 -
accuracy: 0.9948 - val_loss: 0.0288 - val_accuracy: 0.9926
Accuracy: 0.9926000237464905

```

After creating our convolutional layer we apply a MaxPooling2D layer which reduces the dimensions of the feature maps, thus, reducing the number of parameters to learn and computational load. Maxpooling might also reduce overfitting.

Maxpooling will select the maximum element(higher valued pixels that are the most activated) from each region generated by the convolutional layer and preserve these values in a 2x2 matrix. This makes the model more robust to variations in the position of the features in the input image.

Then we add a dropout layer which is used to prevent overfitting since it drops neurons out of the network during training so other neurons can step in and make the predictions for the missing neurons, the network then becomes less sensitive to specific weights and more generalized.

We then flatten the network, converting a matrix into a single array.

We then add a Dense layer which is a neural network. Our dense layer has 128 units(neurons) which is our batch size.

Another dropout layer is added with probability of 0.5 in order to retain the output of each node in a hidden layer.

And finally at last we have the output layer with 10 units which is the number of possible outputs/predictions classes that we have(0-9).

**B) Discuss the differences and potential benefits of using convolutional layers over fully connected ones for the particular application?**

**[Answer]**

In a fully connected layer each neuron is connected to every neuron in the previous layer where each connection has its own weight. This makes it more of a general principle that does not make any assumptions about the features in the data. Due to the mass of connections it becomes very expensive in terms of computation and memory.

In a convolutional layer each neuron is instead only connected to a few near(local) neurons in the previous layer. Each neuron is applied the same set of weights.

The convolutional layer consists of feature maps that are connected directly to the inputs. The feature maps enable the network to detect different kinds of features of the image.

The weakness of a fully connected network is that if we shift a digit slightly to any direction, the network will no longer recognize the digit. This is something that convolutional networks can handle. Convolutional networks are most used today in networks for image recognition, which makes it a better option for our problem at hand.

Due to the reduction of connections, convolutional layers make it cheaper in terms of computation and memory.

#### 0.0.1 Question 4) Auto-Encoder for denoising

```
[ ]: import numpy as np
def salt_and_pepper(input, noise_level=0.5):
    """
    This applies salt and pepper noise to the input tensor - randomly setting
    ↪ bits to 1 or 0.
    Parameters
    -----
    input : tensor
        The tensor to apply salt and pepper noise to.
    noise_level : float
        The amount of salt and pepper noise to add.
    Returns
    -----
    tensor
        Tensor with salt and pepper noise applied.
    """
    # salt and pepper noise
    a = np.random.binomial(size=input.shape, n=1, p=(1 - noise_level))
    b = np.random.binomial(size=input.shape, n=1, p=0.5)
    c = (a==0) * b
    return input * a + c
```

```
#data preparation
flattened_x_train = x_train.reshape(-1,784)
flattened_x_train_seasoned = salt_and_pepper(flattened_x_train, noise_level=0.4)

flattened_x_test = x_test.reshape(-1,784)
flattened_x_test_seasoned = salt_and_pepper(flattened_x_test, noise_level=0.4)
```

```
[ ]: latent_dim = 96

input_image = keras.Input(shape=(784,))
encoded = Dense(128, activation='relu')(input_image)
encoded = Dense(latent_dim, activation='relu')(encoded)
decoded = Dense(128, activation='relu')(encoded)
decoded = Dense(784, activation='sigmoid')(decoded)

autoencoder = keras.Model(input_image, decoded)
encoder_only = keras.Model(input_image, encoded)

encoded_input = keras.Input(shape=(latent_dim,))
decoder_layer = Sequential(autoencoder.layers[-2:])
decoder = keras.Model(encoded_input, decoder_layer(encoded_input))

autoencoder.compile(optimizer='adam', loss='binary_crossentropy')
```

```
[ ]: fit_info_AE = autoencoder.fit(flattened_x_train_seasoned, flattened_x_train,
                                epochs=32,
                                batch_size=64,
                                shuffle=True,
                                validation_data=(flattened_x_test_seasoned, flattened_x_test))
```

```
Epoch 1/32
938/938 [=====] - 7s 7ms/step - loss: 0.2441 -
val_loss: 0.1544
Epoch 2/32
938/938 [=====] - 6s 7ms/step - loss: 0.1508 -
val_loss: 0.1403
Epoch 3/32
938/938 [=====] - 6s 7ms/step - loss: 0.1386 -
val_loss: 0.1344
Epoch 4/32
938/938 [=====] - 6s 7ms/step - loss: 0.1330 -
val_loss: 0.1307
Epoch 5/32
938/938 [=====] - 6s 7ms/step - loss: 0.1295 -
val_loss: 0.1285
Epoch 6/32
938/938 [=====] - 7s 7ms/step - loss: 0.1275 -
```

```
val_loss: 0.1272
Epoch 7/32
938/938 [=====] - 6s 7ms/step - loss: 0.1253 -
val_loss: 0.1264
Epoch 8/32
938/938 [=====] - 6s 7ms/step - loss: 0.1243 -
val_loss: 0.1260
Epoch 9/32
938/938 [=====] - 7s 7ms/step - loss: 0.1232 -
val_loss: 0.1244
Epoch 10/32
938/938 [=====] - 7s 7ms/step - loss: 0.1221 -
val_loss: 0.1238
Epoch 11/32
938/938 [=====] - 7s 7ms/step - loss: 0.1211 -
val_loss: 0.1237
Epoch 12/32
938/938 [=====] - 7s 7ms/step - loss: 0.1206 -
val_loss: 0.1228
Epoch 13/32
938/938 [=====] - 7s 7ms/step - loss: 0.1201 -
val_loss: 0.1232
Epoch 14/32
938/938 [=====] - 7s 7ms/step - loss: 0.1193 -
val_loss: 0.1220
Epoch 15/32
938/938 [=====] - 7s 7ms/step - loss: 0.1188 -
val_loss: 0.1218
Epoch 16/32
938/938 [=====] - 6s 7ms/step - loss: 0.1187 -
val_loss: 0.1226
Epoch 17/32
938/938 [=====] - 6s 7ms/step - loss: 0.1183 -
val_loss: 0.1220
Epoch 18/32
938/938 [=====] - 6s 7ms/step - loss: 0.1176 -
val_loss: 0.1211
Epoch 19/32
938/938 [=====] - 6s 7ms/step - loss: 0.1175 -
val_loss: 0.1210
Epoch 20/32
938/938 [=====] - 6s 7ms/step - loss: 0.1169 -
val_loss: 0.1208
Epoch 21/32
938/938 [=====] - 6s 7ms/step - loss: 0.1170 -
val_loss: 0.1209
Epoch 22/32
938/938 [=====] - 6s 7ms/step - loss: 0.1167 -
```

```

val_loss: 0.1204
Epoch 23/32
938/938 [=====] - 6s 7ms/step - loss: 0.1167 -
val_loss: 0.1209
Epoch 24/32
938/938 [=====] - 6s 7ms/step - loss: 0.1161 -
val_loss: 0.1204
Epoch 25/32
938/938 [=====] - 6s 7ms/step - loss: 0.1162 -
val_loss: 0.1208
Epoch 26/32
938/938 [=====] - 6s 7ms/step - loss: 0.1158 -
val_loss: 0.1201
Epoch 27/32
938/938 [=====] - 6s 7ms/step - loss: 0.1158 -
val_loss: 0.1206
Epoch 28/32
938/938 [=====] - 6s 7ms/step - loss: 0.1157 -
val_loss: 0.1205
Epoch 29/32
938/938 [=====] - 6s 7ms/step - loss: 0.1154 -
val_loss: 0.1201
Epoch 30/32
938/938 [=====] - 6s 7ms/step - loss: 0.1151 -
val_loss: 0.1200
Epoch 31/32
938/938 [=====] - 6s 7ms/step - loss: 0.1152 -
val_loss: 0.1203
Epoch 32/32
938/938 [=====] - 6s 7ms/step - loss: 0.1150 -
val_loss: 0.1201

```

#4)3points. Auto-Encodersfor denoising.

**A) The notebook implements a simple denoising deep autoencoder model. Explain what the model does: use the data-preparation and model definition code to explain how the goal of the model is achieved. Explain the role of the loss function? Draw a diagram of the model and include it in your report. Train the model with the settings given.**

**[Answer]**

The goal of this model is to be able to recreate the input images as accurate as possible by denoising the images after they have been compressed and added with noise.

The model is constructed by 4 layers(2 encoders & 2 decoders) and one bottleneck(code) layer in between.

In the encoder layers the images will be compressed and added with noise while trying to maintain sufficient information in order for the decoder to be able to recreate the images.

When entering the decoder layers the model tries to recreate the images with the information it received from the encoder. In this process the noise in the images will be removed and thus, the recreated images revealed.

In the first encoder layer the image have a 784 dimensional vector and then enters the second encoder layer where it reduces to a 128 dimensional vector. In between(bottleneck) the 2 types of layers(encoder & decoder) the image reduces to a 96 dimensional vector. When entering the decoder layers it first increases to a 128 dimensional vector and then enters the last layer where it increases to the original 784 dimensional vector(the recreated image).

The model trains by taking images from the mnist database as inputs and adding noise to them and then running them over the autoencoder to compare the output(recreated image) to the original input(original image).

The loss function describes the amount of information loss between the compressed and decompressed image. Thus, comparing the recreated image(denoised image) to the original image(input) to observe the amount of accuracy of the autoencoder. This information helps to update the weights to improve future predictions when back propagating.

**B) Add increasing levels of noise to the test-set using the `salt_and_pepper()`-function (0 to 1). Use matplotlib to visualize a few examples (3-4) in the original, “seasoned” (noisy), and denoised versions. (Hint: for visualization use `imshow()`, use the trained autoencoder from 4A to denoise the noisy digits). At what noise level does it become difficult to identify the seasoned digits for you? At what noise level does the denoising stop working?**

[Answer]

```
[ ]: #noises
noises = [0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1]

#input images
num_images = 3
np.random.seed(42)
random_test_images = np.random.randint(flattened_x_test.shape[0],
    ↳size=num_images)

#encoded and decoded images
encoded_imgs = encoder_only.predict(flattened_x_test)
decoded_imgs = autoencoder.predict(flattened_x_test)

#in order to plot images in row/column format style
fig, ax = plt.subplots(nrows=2*len(random_test_images), ncols=len(noises),
    ↳figsize=(10,10))

for i, image_idx in enumerate(random_test_images):
    #plot original image
```

```

ax[2*i][0].imshow(flattened_x_test[image_idx].reshape(28,28))
ax[2*i][0].axis('off')
for j, noise in enumerate(noises):
    #plot encoded image with varying noises
    ax[2*i][j].imshow(tf.reshape(salt_and_pepper(flattened_x_test[image_idx].
↳reshape(1, -1),
                                                    noise_level=noise)),(28,28)),
↳cmap='gray')
    ax[2*i][j].axis('off')
    #plot reconstructed image
    ax[2*i+1][j].imshow(tf.
↳reshape(autoencoder(salt_and_pepper(flattened_x_test[image_idx].reshape(1,
↳-1),
                                                   
↳noise_level=noise))), (28,28)), cmap='gray')
    ax[2*i+1][j].axis('off')

```



It becomes difficult to identify the digits at noise level 0.7(70%). At the noise level of 0.5(50%) the quality of the recreation images start to decline, so we would say that it is at this point that the denoising stops working.

C)Test whether denoising improves the classification with the best performing model you obtained in questions 2 or 3. Plot the accuracy as a function of noise-level for the seasoned and denoised datasets. Discuss your results.

[Answer]

```
[14]: #score = convModel.evaluate(x_test, y_test, verbose=0)
      #print("Accuracy: ", score[1])

      #lists of accuracy for denoised and seasoned datasets
      autoencoded_accuracy_list = []
      seasoned_accuracy_list    = []

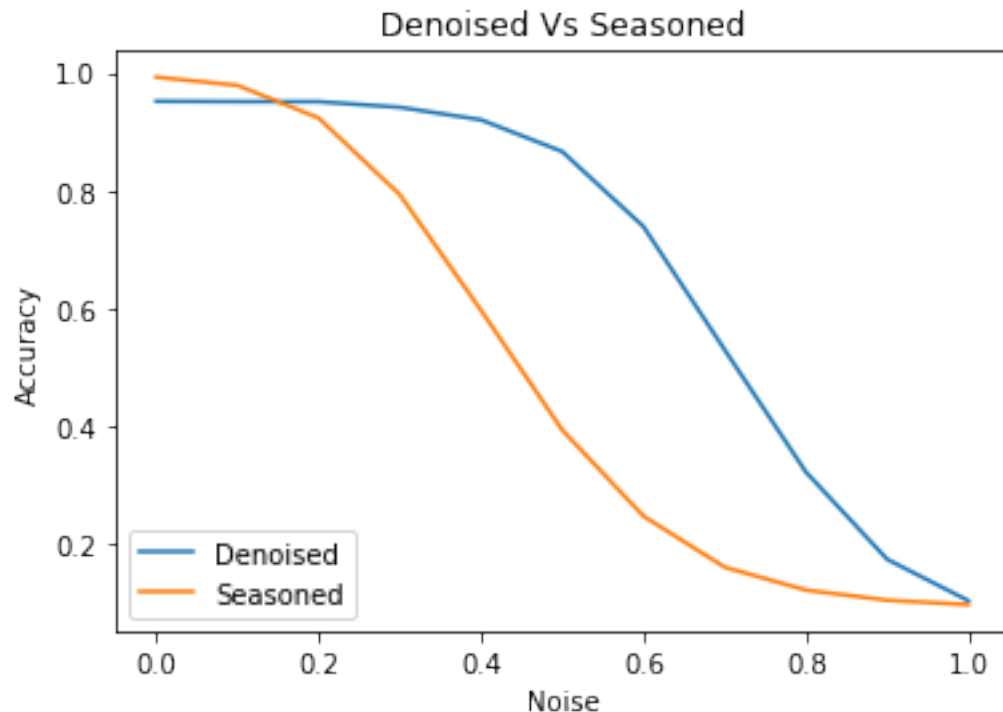
      for i, noise in enumerate(noises):
          #denoised datasets
          x_autoencoded_test = tf.reshape(autoencoder(salt_and_pepper(flattened_x_test,
          ↪noise_level=noise)), (10000, 28, 28, 1))
          #loss and accuracy data
          autoencoded_score    = convModel.evaluate(x_autoencoded_test, y_test,
          ↪verbose=0)
          autoencoded_loss     = autoencoded_score[0]
          autoencoded_accuracy = autoencoded_score[1]
          #add the accuracy to the list
          autoencoded_accuracy_list.append(autoencoded_accuracy)

          #seasoned datasets
          x_seasoned_test = tf.reshape(salt_and_pepper(flattened_x_test,
          ↪noise_level=noise), (10000, 28, 28, 1))
          #loss and accuracy data
          seasoned_score      = convModel.evaluate(x_seasoned_test, y_test, verbose=0)
          seasoned_loss       = seasoned_score[0]
          seasoned_accuracy   = seasoned_score[1]
          #add the accuracy to the list
          seasoned_accuracy_list.append(seasoned_accuracy)

      #plot
      plt.plot(noises, autoencoded_accuracy_list)
      plt.plot(noises, seasoned_accuracy_list)
      plt.title('Denoised Vs Seasoned')
      plt.ylabel('Accuracy')
      plt.xlabel('Noise')
      plt.legend(['Denoised', 'Seasoned'], loc='lower left')
```



```
plt.show()
```



What we can see from the plot is that the convolutional neural network with denoised input improves the classification drastically compared to the convolutional neural network with seasoned(noised) input, after reaching the noise level of around 0.1(10%). What it also shows us is what we mentioned before, that at noise level 0.5(50%) or even before that the accuracy decreases which is an indication that the denoising has stopped working.

**D) Explain how you can use the decoder part of the denoising auto-encoder to generate synthetic“hand-written” digits? –Describe the procedure, implement it and show examples in your report.**

[Answer]

One way could be to train a Generative Adversarial Network(GAN) to generate “fake” hand-written digits. But how we did it here is that we instead of giving the autoencoder the flattened\_x\_test(original image of the digit) values we gave it the flattened\_x\_train\_seasoned which are the “trained” attempts of recreating the digits, which will look more like handwritten, which in this case can be seen in the images plotted.

```
[16]: import random
      encoded_imgs = encoder_only.predict(flattened_x_test)
      decoded_imgs_seasoned = autoencoder.predict(flattened_x_train_seasoned)

      for i in range(10): #4
```

```
plt.subplot(5,10,1+i*2) #2,4
plt.imshow(flattened_x_train_seasoned[i].reshape(28,28), cmap='gray')
plt.axis('off')

plt.subplot(5,10,2+i*2) #2,4
plt.imshow((decoded_imgs_seasoned[i].reshape(28,28)+1)/2, cmap='gray')
plt.axis('off')
plt.show()
```

