

Course Name

Neural Networks and Deep Learning (COMP-8610)

Document Type

Assignment 3

Professor

Dr. Alioune Ngom

Team - Members	Student ID	Contribution
Manjinder Singh	110097177	33.33%
Harbhajan Singh	110100089	33.33%
Navjot Makkar	110100116	33.33%

NN&DL_Assignment_3

June 11, 2023

```
[]: from google.colab import drive drive.mount('/content/drive')
```

Mounted at /content/drive

```
[]: cd /content/drive/MyDrive/Assignment_3
```

/content/drive/MyDrive/Assignment_3

```
[]: !ls
```

```
Assignment_3.ipynb MNIST_Dataset train-images-idx3-ubyte.gz
Assignment_3_Main.ipynb t10k-images-idx3-ubyte.gz train-labels-idx1-ubyte.gz
Assignment 3 old.ipynb t10k-labels-idx1-ubyte.gz
```

1 Que 1:

Download the benchmark dataset, MNIST, from http://yann.lecun.com/exdb/mnist/. Implement multi-class classification for recognizing handwritten digits (also known as multiclass logistic regression —this is simply a feedforward neural network with k output neurons, with one output neuron for each class, and each output neuron oi returns the probability that the input datapoint xj is in class i) and try it on MNIST.

Comments: No need to implement almost anything in DL by your own (this is true in general); the software framework (ie, the DL platform) typically provides implementations for all the things discussed in class, such as the learning algorithms, the regularizations methods, the cross-validation methods, etc.

Use your favorite deep learning platform. A few candidates: 1. Marvin from http://marvin.is/2. Caffe from http://caffe.berkeleyvision.org) 3. TensorFlow from https://www.tensorflow.org 4. Pylearn2 from http://deeplearning.net/software/pylearn2/5. Theano, Torch, Lasagne, etc. See more platforms at http://deeplearning.net/software_links/.

Read the tutorial about your selected platform (eg, for TensorFlow: https://www.tensorflow.org/tutorials), try it on MNIST; note that the first few examples in the tutorials are typically on MNIST or other simple image datasets, so you can follow the steps.

Comments: MNIST is a standard dataset for machine learning and also deep learning. It's good to try it on one shallow neural network (with one output neuron; eg, for recognizing a character A from a not-A character) before trying it on a deep neural network with multiple outputs. Downloading

the dataset from other places in preprocessed format is allowed, but practicing how to read the dataset prepares you for other new datasets you may be interested in (thus, please, read the MNIST website carefully).

1.1 Que 1: Part 1

1. Try the basic minibatch SGD as your learning algorithm. It is recommended to try different initializations, different batch sizes, and different learning rates, in order to get a sense about how to tune the hyperparameters (batch size, and, learning rate). Remember to create and use validation dataset!. it will be very useful for you to read Chapter-11 of the textbook.

```
def read_mnist_images(filename):
    with gzip.open(filename, 'rb') as f:
        data = np.frombuffer(f.read(), np.uint8, offset=16)
    return data.reshape(-1, 784)

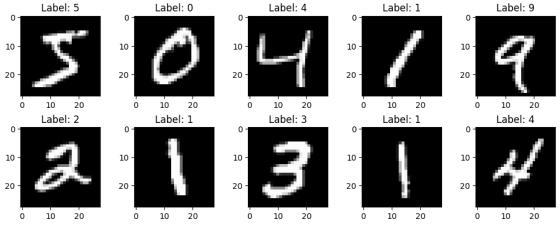
def read_mnist_labels(filename):
    with gzip.open(filename, 'rb') as f:
        data = np.frombuffer(f.read(), np.uint8, offset=8)
    return data
```

```
[]: # Create MNIST folder in Google Drive
!mkdir -p '/content/drive/MyDrive/Assignment_3/MNIST_Dataset'
```

```
[]:  # Set the Google Drive folder as the working directory os.chdir('/content/drive/MyDrive/Assignment_3/MNIST_Dataset')
```

```
[]: # Download MNIST dataset download_mnist()
```

```
# Read training and testing images and labels
     train_images = read_mnist_images('train-images-idx3-ubyte.gz')
     train_labels = read_mnist_labels('train-labels-idx1-ubyte.gz')
     test_images = read_mnist_images('t10k-images-idx3-ubyte.gz')
     test_labels = read_mnist_labels('t10k-labels-idx1-ubyte.gz')
[]: print("Size of Training Images Dataset : ", len(train_images))
     print("Size of Training Images Dataset : ", len(test_labels))
    Size of Training Images Dataset :
    Size of Training Images Dataset :
                                       10000
[]: train_images[1].shape
[]: (784,)
[]: # Display some training images
     fig, axs = plt.subplots(2, 5, figsize=(10, 4))
     axs = axs.flatten()
     for i in range(10):
         img = train_images[i].reshape(28, 28)
         axs[i].imshow(img, cmap='gray')
        axs[i].set_title(f"Label: {train_labels[i]}")
     plt.tight_layout()
     plt.show()
```



1.1.1 Data Preprocessing

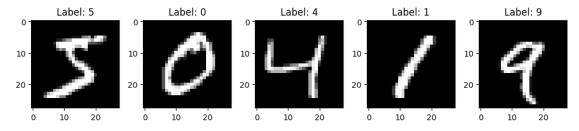
```
[]: # Step 2: Data preprocessing
  train_images = train_images / 255.0

test_images = test_images / 255.0

# Showing images after preprocessing
  fig, axs = plt.subplots(1, 5, figsize=(10, 4))
  axs = axs.flatten()

for i in range(5):
    img = train_images[i].reshape(28, 28)
    axs[i].imshow(img, cmap='gray')
    axs[i].set_title(f"Label: {train_labels[i]}")

plt.tight_layout()
  plt.show()
```



```
[]: # Step 2: Prepare the data
num_classes = 10
num_features = train_images.shape[1]
num_samples = train_images.shape[0]
```

```
[]: import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import SGD
from tensorflow.keras.wrappers.scikit_learn import KerasClassifier
```

```
[23]: # Preprocess the MNIST dataset
  input_dim = train_images.shape[1]
  x_train = train_images.reshape(-1, 784)
  x_test = test_images.reshape(-1, 784)
  y_train = tf.keras.utils.to_categorical(train_labels, num_classes=10)
  y_test = tf.keras.utils.to_categorical(test_labels, num_classes=10)
```

```
# Create a validation dataset
    x_train, x_val, y_train, y_val = train_test_split(x_train, y_train, test_size=0.
     []: # Define a function to create your model with the desired architecture
    def create_model(learning_rate, hidden_units):
        model = Sequential()
        model.add(Dense(hidden_units, activation='relu', input_shape=(input_dim,)))
        model.add(Dense(num_classes, activation='sigmoid'))
        optimizer = SGD(learning_rate=learning_rate)
        model.compile(loss='categorical_crossentropy', optimizer=optimizer,__
     →metrics=['accuracy'])
        return model
    # Create the KerasClassifier wrapper
    model = KerasClassifier(build_fn=create_model, epochs=11, batch_size=64,__
     ⇔verbose=1)
    # Define the hyperparameters grid
    param_grid = {
        'learning_rate': [0.001, 0.01, 0.1],
        'hidden_units': [32, 64, 128]
    }
    # Perform grid search cross-validation
    grid = GridSearchCV(estimator=model, param grid=param grid, cv=5)
    grid_result = grid.fit(x_train, y_train)
    print("\n\n")
    # Print the best hyperparameters and accuracy
    print("Best Hyperparameters: ", grid_result.best_params_)
    print("Best Accuracy: ", grid_result.best_score_)
    <ipython-input-16-bb1ba6c3502e>:11: DeprecationWarning: KerasClassifier is
   deprecated, use Sci-Keras (https://github.com/adriangb/scikeras) instead. See
   https://www.adriangb.com/scikeras/stable/migration.html for help migrating.
     model = KerasClassifier(build fn=create model, epochs=11, batch_size=64,
   verbose=1)
   Epoch 1/11
   accuracy: 0.2839
   Epoch 2/11
   accuracy: 0.6174
   Epoch 3/11
   675/675 [============ ] - 1s 2ms/step - loss: 1.3518 -
```

```
accuracy: 0.7499
Epoch 4/11
675/675 [============ ] - 1s 2ms/step - loss: 1.0960 -
accuracy: 0.7933
Epoch 5/11
accuracy: 0.8138
Epoch 6/11
accuracy: 0.8291
Epoch 7/11
675/675 [============= ] - 1s 2ms/step - loss: 0.7202 -
accuracy: 0.8399
Epoch 8/11
accuracy: 0.8481
Epoch 9/11
accuracy: 0.8534
Epoch 10/11
accuracy: 0.8585
Epoch 11/11
accuracy: 0.8629
169/169 [============= ] - Os 2ms/step - loss: 0.5447 -
accuracy: 0.8634
Epoch 1/11
accuracy: 0.3253
Epoch 2/11
accuracy: 0.5901
Epoch 3/11
accuracy: 0.6912
Epoch 4/11
accuracy: 0.7501
Epoch 5/11
accuracy: 0.7856
Epoch 6/11
675/675 [=========== ] - 1s 2ms/step - loss: 0.8113 -
accuracy: 0.8069
Epoch 7/11
accuracy: 0.8214
```

```
Epoch 8/11
accuracy: 0.8322
Epoch 9/11
accuracy: 0.8400
Epoch 10/11
accuracy: 0.8476
Epoch 11/11
675/675 [============ ] - 1s 2ms/step - loss: 0.5749 -
accuracy: 0.8536
accuracy: 0.8571
Epoch 1/11
accuracy: 0.2753
Epoch 2/11
675/675 [============ ] - 1s 2ms/step - loss: 1.7394 -
accuracy: 0.5300
Epoch 3/11
accuracy: 0.6708
Epoch 4/11
675/675 [============ ] - 1s 2ms/step - loss: 1.1685 -
accuracy: 0.7523
Epoch 5/11
675/675 [============ ] - 1s 2ms/step - loss: 0.9916 -
accuracy: 0.7916
Epoch 6/11
675/675 [===========] - 2s 3ms/step - loss: 0.8661 -
accuracy: 0.8117
Epoch 7/11
675/675 [============] - 3s 4ms/step - loss: 0.7760 -
accuracy: 0.8258
Epoch 8/11
accuracy: 0.8347
Epoch 9/11
675/675 [============= ] - 2s 2ms/step - loss: 0.6586 -
accuracy: 0.8411
Epoch 10/11
accuracy: 0.8471
Epoch 11/11
675/675 [=========== ] - 1s 2ms/step - loss: 0.5869 -
accuracy: 0.8518
```

```
accuracy: 0.8555
Epoch 1/11
accuracy: 0.2748
Epoch 2/11
accuracy: 0.5704
Epoch 3/11
accuracy: 0.6673
Epoch 4/11
675/675 [============ ] - 2s 3ms/step - loss: 1.1790 -
accuracy: 0.7269
Epoch 5/11
accuracy: 0.7686
Epoch 6/11
accuracy: 0.7944
Epoch 7/11
accuracy: 0.8119
Epoch 8/11
accuracy: 0.8248
Epoch 9/11
accuracy: 0.8348
Epoch 10/11
accuracy: 0.8427
Epoch 11/11
accuracy: 0.8490
169/169 [============= ] - Os 2ms/step - loss: 0.6071 -
accuracy: 0.8476
Epoch 1/11
accuracy: 0.2593
Epoch 2/11
675/675 [============ ] - 1s 2ms/step - loss: 1.8125 -
accuracy: 0.5514
Epoch 3/11
675/675 [============ ] - 1s 2ms/step - loss: 1.4598 -
accuracy: 0.7019
Epoch 4/11
accuracy: 0.7581
```

```
Epoch 5/11
accuracy: 0.7913
Epoch 6/11
accuracy: 0.8148
Epoch 7/11
accuracy: 0.8294
Epoch 8/11
675/675 [============ ] - 2s 3ms/step - loss: 0.7037 -
accuracy: 0.8404
Epoch 9/11
accuracy: 0.8483
Epoch 10/11
675/675 [===========] - 1s 2ms/step - loss: 0.6106 -
accuracy: 0.8549
Epoch 11/11
accuracy: 0.8607
accuracy: 0.8668
Epoch 1/11
675/675 [============ ] - 2s 2ms/step - loss: 1.1842 -
accuracy: 0.6800
Epoch 2/11
675/675 [============ ] - 1s 2ms/step - loss: 0.5282 -
accuracy: 0.8640
Epoch 3/11
675/675 [=========== ] - 1s 2ms/step - loss: 0.4213 -
accuracy: 0.8867
Epoch 4/11
675/675 [============ ] - 2s 2ms/step - loss: 0.3756 -
accuracy: 0.8958
Epoch 5/11
accuracy: 0.9025
Epoch 6/11
675/675 [============ ] - 2s 3ms/step - loss: 0.3293 -
accuracy: 0.9067
Epoch 7/11
accuracy: 0.9104
Epoch 8/11
675/675 [===========] - 1s 2ms/step - loss: 0.3030 -
accuracy: 0.9139
Epoch 9/11
```

```
accuracy: 0.9167
Epoch 10/11
675/675 [============ ] - 1s 2ms/step - loss: 0.2840 -
accuracy: 0.9202
Epoch 11/11
accuracy: 0.9223
accuracy: 0.9205
Epoch 1/11
675/675 [============ ] - 2s 2ms/step - loss: 1.2126 -
accuracy: 0.6791
Epoch 2/11
accuracy: 0.8691
Epoch 3/11
675/675 [============ ] - 2s 3ms/step - loss: 0.4155 -
accuracy: 0.8864
Epoch 4/11
accuracy: 0.8968
Epoch 5/11
accuracy: 0.9032
Epoch 6/11
accuracy: 0.9084
Epoch 7/11
accuracy: 0.9118
Epoch 8/11
accuracy: 0.9152
Epoch 9/11
675/675 [============ ] - 1s 2ms/step - loss: 0.2892 -
accuracy: 0.9183
Epoch 10/11
accuracy: 0.9206
Epoch 11/11
675/675 [============= ] - 1s 2ms/step - loss: 0.2726 -
accuracy: 0.9225
accuracy: 0.9215
Epoch 1/11
accuracy: 0.7380
```

```
Epoch 2/11
accuracy: 0.8737
Epoch 3/11
accuracy: 0.8908
Epoch 4/11
accuracy: 0.9010
Epoch 5/11
675/675 [============ ] - 1s 2ms/step - loss: 0.3381 -
accuracy: 0.9066
Epoch 6/11
675/675 [===========] - 1s 2ms/step - loss: 0.3200 -
accuracy: 0.9114
Epoch 7/11
675/675 [===========] - 1s 2ms/step - loss: 0.3061 -
accuracy: 0.9147
Epoch 8/11
accuracy: 0.9179
Epoch 9/11
accuracy: 0.9207
Epoch 10/11
accuracy: 0.9230
Epoch 11/11
accuracy: 0.9248
169/169 [=========== ] - Os 2ms/step - loss: 0.2661 -
accuracy: 0.9254
Epoch 1/11
675/675 [============ ] - 2s 2ms/step - loss: 1.2580 -
accuracy: 0.6683
Epoch 2/11
accuracy: 0.8632
Epoch 3/11
675/675 [============ ] - 1s 2ms/step - loss: 0.4251 -
accuracy: 0.8852
Epoch 4/11
accuracy: 0.8945
Epoch 5/11
675/675 [===========] - 1s 2ms/step - loss: 0.3498 -
accuracy: 0.9007
Epoch 6/11
```

```
accuracy: 0.9056
Epoch 7/11
675/675 [============ ] - 2s 3ms/step - loss: 0.3141 -
accuracy: 0.9098
Epoch 8/11
accuracy: 0.9136
Epoch 9/11
675/675 [============= ] - 1s 2ms/step - loss: 0.2901 -
accuracy: 0.9163
Epoch 10/11
accuracy: 0.9195
Epoch 11/11
accuracy: 0.9220
accuracy: 0.9179
Epoch 1/11
accuracy: 0.7120
Epoch 2/11
accuracy: 0.8631
Epoch 3/11
accuracy: 0.8878
Epoch 4/11
accuracy: 0.8985
Epoch 5/11
accuracy: 0.9053
Epoch 6/11
accuracy: 0.9102
Epoch 7/11
accuracy: 0.9145
Epoch 8/11
675/675 [============ ] - 1s 2ms/step - loss: 0.2945 -
accuracy: 0.9178
Epoch 9/11
accuracy: 0.9197
Epoch 10/11
```

```
accuracy: 0.9220
Epoch 11/11
675/675 [============ ] - 1s 2ms/step - loss: 0.2668 -
accuracy: 0.9251
accuracy: 0.9255
Epoch 1/11
accuracy: 0.8703
Epoch 2/11
675/675 [=========== ] - 1s 2ms/step - loss: 0.2712 -
accuracy: 0.9222
Epoch 3/11
675/675 [=========== ] - 1s 2ms/step - loss: 0.2270 -
accuracy: 0.9353
Epoch 4/11
accuracy: 0.9434
Epoch 5/11
accuracy: 0.9505
Epoch 6/11
accuracy: 0.9563
Epoch 7/11
accuracy: 0.9588
Epoch 8/11
accuracy: 0.9626
Epoch 9/11
accuracy: 0.9647
Epoch 10/11
accuracy: 0.9672
Epoch 11/11
accuracy: 0.9691
169/169 [============ ] - Os 2ms/step - loss: 0.1434 -
accuracy: 0.9592
Epoch 1/11
accuracy: 0.8743
Epoch 2/11
675/675 [===========] - 1s 2ms/step - loss: 0.2631 -
accuracy: 0.9235
Epoch 3/11
```

```
accuracy: 0.9389
Epoch 4/11
675/675 [============ ] - 2s 3ms/step - loss: 0.1876 -
accuracy: 0.9467
Epoch 5/11
accuracy: 0.9520
Epoch 6/11
675/675 [============ ] - 1s 2ms/step - loss: 0.1518 -
accuracy: 0.9550
Epoch 7/11
accuracy: 0.9587
Epoch 8/11
accuracy: 0.9618
Epoch 9/11
675/675 [============ ] - 1s 2ms/step - loss: 0.1209 -
accuracy: 0.9638
Epoch 10/11
accuracy: 0.9665
Epoch 11/11
accuracy: 0.9683
accuracy: 0.9581
Epoch 1/11
accuracy: 0.8773
Epoch 2/11
accuracy: 0.9278
Epoch 3/11
accuracy: 0.9406
Epoch 4/11
accuracy: 0.9499
Epoch 5/11
675/675 [============ ] - 1s 2ms/step - loss: 0.1563 -
accuracy: 0.9547
Epoch 6/11
accuracy: 0.9587
Epoch 7/11
```

```
accuracy: 0.9619
Epoch 8/11
675/675 [============= ] - 2s 3ms/step - loss: 0.1201 -
accuracy: 0.9652
Epoch 9/11
accuracy: 0.9681
Epoch 10/11
accuracy: 0.9697
Epoch 11/11
675/675 [============ ] - 1s 2ms/step - loss: 0.0983 -
accuracy: 0.9713
accuracy: 0.9611
Epoch 1/11
accuracy: 0.8738
Epoch 2/11
accuracy: 0.9231
Epoch 3/11
accuracy: 0.9366
Epoch 4/11
accuracy: 0.9454
Epoch 5/11
accuracy: 0.9515
Epoch 6/11
accuracy: 0.9557
Epoch 7/11
accuracy: 0.9584
Epoch 8/11
accuracy: 0.9628
Epoch 9/11
accuracy: 0.9648
Epoch 10/11
accuracy: 0.9669
Epoch 11/11
accuracy: 0.9681
```

```
accuracy: 0.9568
Epoch 1/11
675/675 [============ ] - 2s 3ms/step - loss: 0.4585 -
accuracy: 0.8710
Epoch 2/11
accuracy: 0.9259
Epoch 3/11
675/675 [============ ] - 1s 2ms/step - loss: 0.2129 -
accuracy: 0.9393
Epoch 4/11
accuracy: 0.9475
Epoch 5/11
accuracy: 0.9539
Epoch 6/11
675/675 [============ ] - 2s 3ms/step - loss: 0.1441 -
accuracy: 0.9591
Epoch 7/11
accuracy: 0.9623
Epoch 8/11
accuracy: 0.9656
Epoch 9/11
675/675 [============ ] - 1s 2ms/step - loss: 0.1135 -
accuracy: 0.9671
Epoch 10/11
accuracy: 0.9688
Epoch 11/11
accuracy: 0.9707
accuracy: 0.9608
Epoch 1/11
accuracy: 0.3171
Epoch 2/11
675/675 [============ ] - 2s 2ms/step - loss: 1.6371 -
accuracy: 0.5908
Epoch 3/11
accuracy: 0.7126
Epoch 4/11
675/675 [============ ] - 2s 3ms/step - loss: 1.0656 -
```

```
accuracy: 0.7716
Epoch 5/11
675/675 [============ ] - 2s 3ms/step - loss: 0.9068 -
accuracy: 0.8036
Epoch 6/11
accuracy: 0.8234
Epoch 7/11
accuracy: 0.8367
Epoch 8/11
675/675 [============] - 2s 2ms/step - loss: 0.6639 -
accuracy: 0.8464
Epoch 9/11
accuracy: 0.8531
Epoch 10/11
accuracy: 0.8581
Epoch 11/11
accuracy: 0.8628
accuracy: 0.8640
Epoch 1/11
accuracy: 0.3148
Epoch 2/11
accuracy: 0.6170
Epoch 3/11
accuracy: 0.7211
Epoch 4/11
accuracy: 0.7730
Epoch 5/11
accuracy: 0.8003
Epoch 6/11
accuracy: 0.8178
Epoch 7/11
675/675 [===========] - 2s 2ms/step - loss: 0.7230 -
accuracy: 0.8305
Epoch 8/11
accuracy: 0.8403
```

```
Epoch 9/11
accuracy: 0.8480
Epoch 10/11
accuracy: 0.8538
Epoch 11/11
accuracy: 0.8596
accuracy: 0.8631
Epoch 1/11
accuracy: 0.3389
Epoch 2/11
accuracy: 0.6017
Epoch 3/11
675/675 [============ ] - 1s 2ms/step - loss: 1.3072 -
accuracy: 0.7150
Epoch 4/11
accuracy: 0.7719
Epoch 5/11
accuracy: 0.8033
Epoch 6/11
675/675 [============ ] - 2s 3ms/step - loss: 0.8112 -
accuracy: 0.8202
Epoch 7/11
675/675 [===========] - 2s 2ms/step - loss: 0.7338 -
accuracy: 0.8327
Epoch 8/11
675/675 [============ ] - 2s 2ms/step - loss: 0.6760 -
accuracy: 0.8417
Epoch 9/11
accuracy: 0.8487
Epoch 10/11
675/675 [============= ] - 1s 2ms/step - loss: 0.5955 -
accuracy: 0.8543
Epoch 11/11
accuracy: 0.8593
169/169 [============ ] - 1s 3ms/step - loss: 0.5501 -
accuracy: 0.8630
Epoch 1/11
675/675 [============] - 3s 3ms/step - loss: 2.1824 -
```

```
accuracy: 0.2367
Epoch 2/11
accuracy: 0.6232
Epoch 3/11
accuracy: 0.7326
Epoch 4/11
accuracy: 0.7773
Epoch 5/11
675/675 [============ ] - 2s 2ms/step - loss: 0.9579 -
accuracy: 0.8011
Epoch 6/11
accuracy: 0.8172
Epoch 7/11
accuracy: 0.8276
Epoch 8/11
accuracy: 0.8360
Epoch 9/11
accuracy: 0.8435
Epoch 10/11
accuracy: 0.8496
Epoch 11/11
accuracy: 0.8549
169/169 [============ ] - Os 2ms/step - loss: 0.5808 -
accuracy: 0.8555
Epoch 1/11
accuracy: 0.2950
Epoch 2/11
accuracy: 0.6154
Epoch 3/11
675/675 [============] - 2s 2ms/step - loss: 1.3001 -
accuracy: 0.7327
Epoch 4/11
675/675 [===========] - 2s 3ms/step - loss: 1.0629 -
accuracy: 0.7806
Epoch 5/11
675/675 [============ ] - 2s 3ms/step - loss: 0.9063 -
accuracy: 0.8047
```

```
Epoch 6/11
accuracy: 0.8219
Epoch 7/11
accuracy: 0.8340
Epoch 8/11
accuracy: 0.8420
Epoch 9/11
675/675 [============ ] - 2s 2ms/step - loss: 0.6222 -
accuracy: 0.8500
Epoch 10/11
accuracy: 0.8562
Epoch 11/11
accuracy: 0.8609
169/169 [============ ] - 1s 2ms/step - loss: 0.5406 -
accuracy: 0.8646
Epoch 1/11
accuracy: 0.7384
Epoch 2/11
675/675 [============ ] - 2s 2ms/step - loss: 0.4832 -
accuracy: 0.8757
Epoch 3/11
675/675 [============ ] - 2s 2ms/step - loss: 0.3981 -
accuracy: 0.8924
Epoch 4/11
675/675 [===========] - 2s 2ms/step - loss: 0.3595 -
accuracy: 0.9013
Epoch 5/11
675/675 [============ ] - 2s 2ms/step - loss: 0.3352 -
accuracy: 0.9070
Epoch 6/11
accuracy: 0.9115
Epoch 7/11
675/675 [============] - 2s 2ms/step - loss: 0.3019 -
accuracy: 0.9157
Epoch 8/11
accuracy: 0.9193
Epoch 9/11
675/675 [=========== ] - 2s 3ms/step - loss: 0.2782 -
accuracy: 0.9228
Epoch 10/11
```

```
accuracy: 0.9257
Epoch 11/11
675/675 [============ ] - 2s 2ms/step - loss: 0.2597 -
accuracy: 0.9283
accuracy: 0.9277
Epoch 1/11
accuracy: 0.7363
Epoch 2/11
675/675 [============ ] - 2s 3ms/step - loss: 0.4906 -
accuracy: 0.8730
Epoch 3/11
accuracy: 0.8920
Epoch 4/11
675/675 [============ ] - 2s 3ms/step - loss: 0.3560 -
accuracy: 0.9017
Epoch 5/11
accuracy: 0.9077
Epoch 6/11
accuracy: 0.9123
Epoch 7/11
accuracy: 0.9160
Epoch 8/11
accuracy: 0.9201
Epoch 9/11
accuracy: 0.9232
Epoch 10/11
accuracy: 0.9268
Epoch 11/11
accuracy: 0.9288
accuracy: 0.9254
Epoch 1/11
accuracy: 0.7234
Epoch 2/11
accuracy: 0.8732
```

```
Epoch 3/11
accuracy: 0.8912
Epoch 4/11
accuracy: 0.8998
Epoch 5/11
accuracy: 0.9055
Epoch 6/11
675/675 [============ ] - 2s 2ms/step - loss: 0.3175 -
accuracy: 0.9102
Epoch 7/11
accuracy: 0.9150
Epoch 8/11
accuracy: 0.9183
Epoch 9/11
accuracy: 0.9202
Epoch 10/11
accuracy: 0.9234
Epoch 11/11
accuracy: 0.9256
169/169 [============= ] - 1s 2ms/step - loss: 0.2663 -
accuracy: 0.9252
Epoch 1/11
accuracy: 0.7332
Epoch 2/11
675/675 [============] - 2s 2ms/step - loss: 0.4871 -
accuracy: 0.8754
Epoch 3/11
accuracy: 0.8933
Epoch 4/11
675/675 [============= ] - 2s 2ms/step - loss: 0.3555 -
accuracy: 0.9025
Epoch 5/11
accuracy: 0.9082
Epoch 6/11
675/675 [===========] - 2s 2ms/step - loss: 0.3124 -
accuracy: 0.9120
Epoch 7/11
```

```
accuracy: 0.9155
Epoch 8/11
675/675 [============ ] - 2s 3ms/step - loss: 0.2855 -
accuracy: 0.9194
Epoch 9/11
accuracy: 0.9229
Epoch 10/11
675/675 [============ ] - 2s 2ms/step - loss: 0.2655 -
accuracy: 0.9253
Epoch 11/11
accuracy: 0.9284
accuracy: 0.9226
Epoch 1/11
675/675 [============] - 2s 2ms/step - loss: 1.0614 -
accuracy: 0.7369
Epoch 2/11
accuracy: 0.8742
Epoch 3/11
accuracy: 0.8912
Epoch 4/11
accuracy: 0.9011
Epoch 5/11
accuracy: 0.9073
Epoch 6/11
accuracy: 0.9120
Epoch 7/11
accuracy: 0.9159
Epoch 8/11
accuracy: 0.9193
Epoch 9/11
675/675 [============ ] - 2s 2ms/step - loss: 0.2753 -
accuracy: 0.9224
Epoch 10/11
accuracy: 0.9251
Epoch 11/11
```

```
accuracy: 0.9282
accuracy: 0.9259
Epoch 1/11
accuracy: 0.8767
Epoch 2/11
accuracy: 0.9330
Epoch 3/11
675/675 [============ ] - 2s 2ms/step - loss: 0.1880 -
accuracy: 0.9458
Epoch 4/11
675/675 [===========] - 2s 2ms/step - loss: 0.1554 -
accuracy: 0.9560
Epoch 5/11
675/675 [============= ] - 2s 2ms/step - loss: 0.1326 -
accuracy: 0.9619
Epoch 6/11
accuracy: 0.9677
Epoch 7/11
accuracy: 0.9705
Epoch 8/11
accuracy: 0.9738
Epoch 9/11
accuracy: 0.9770
Epoch 10/11
accuracy: 0.9782
Epoch 11/11
accuracy: 0.9803
accuracy: 0.9676
Epoch 1/11
675/675 [============ ] - 2s 2ms/step - loss: 0.4289 -
accuracy: 0.8800
Epoch 2/11
accuracy: 0.9292
Epoch 3/11
675/675 [===========] - 2s 2ms/step - loss: 0.1951 -
accuracy: 0.9438
Epoch 4/11
```

```
accuracy: 0.9533
Epoch 5/11
675/675 [============ ] - 2s 3ms/step - loss: 0.1429 -
accuracy: 0.9589
Epoch 6/11
accuracy: 0.9638
Epoch 7/11
675/675 [============= ] - 2s 2ms/step - loss: 0.1135 -
accuracy: 0.9680
Epoch 8/11
accuracy: 0.9703
Epoch 9/11
accuracy: 0.9732
Epoch 10/11
675/675 [============ ] - 2s 2ms/step - loss: 0.0871 -
accuracy: 0.9750
Epoch 11/11
accuracy: 0.9769
accuracy: 0.9652
Epoch 1/11
accuracy: 0.8811
Epoch 2/11
accuracy: 0.9299
Epoch 3/11
accuracy: 0.9442
Epoch 4/11
675/675 [============ ] - 2s 2ms/step - loss: 0.1652 -
accuracy: 0.9524
Epoch 5/11
accuracy: 0.9588
Epoch 6/11
accuracy: 0.9636
Epoch 7/11
accuracy: 0.9674
Epoch 8/11
675/675 [============ ] - 2s 3ms/step - loss: 0.1012 -
```

```
accuracy: 0.9708
Epoch 9/11
675/675 [============ ] - 2s 3ms/step - loss: 0.0925 -
accuracy: 0.9735
Epoch 10/11
accuracy: 0.9756
Epoch 11/11
accuracy: 0.9779
accuracy: 0.9648
Epoch 1/11
675/675 [============ ] - 2s 2ms/step - loss: 0.4281 -
accuracy: 0.8808
Epoch 2/11
accuracy: 0.9319
Epoch 3/11
accuracy: 0.9452
Epoch 4/11
accuracy: 0.9546
Epoch 5/11
accuracy: 0.9611
Epoch 6/11
accuracy: 0.9656
Epoch 7/11
accuracy: 0.9693
Epoch 8/11
accuracy: 0.9720
Epoch 9/11
accuracy: 0.9748
Epoch 10/11
accuracy: 0.9775
Epoch 11/11
accuracy: 0.9797
169/169 [=========== ] - Os 2ms/step - loss: 0.1179 -
accuracy: 0.9677
Epoch 1/11
```

```
accuracy: 0.8797
Epoch 2/11
675/675 [============ ] - 2s 3ms/step - loss: 0.2461 -
accuracy: 0.9281
Epoch 3/11
accuracy: 0.9453
Epoch 4/11
675/675 [============ ] - 2s 3ms/step - loss: 0.1592 -
accuracy: 0.9547
Epoch 5/11
accuracy: 0.9611
Epoch 6/11
675/675 [===========] - 2s 2ms/step - loss: 0.1192 -
accuracy: 0.9666
Epoch 7/11
675/675 [============ ] - 2s 2ms/step - loss: 0.1071 -
accuracy: 0.9706
Epoch 8/11
accuracy: 0.9733
Epoch 9/11
accuracy: 0.9755
Epoch 10/11
675/675 [============ ] - 2s 3ms/step - loss: 0.0807 -
accuracy: 0.9780
Epoch 11/11
accuracy: 0.9794
accuracy: 0.9662
Epoch 1/11
675/675 [============ ] - 2s 3ms/step - loss: 2.0628 -
accuracy: 0.3666
Epoch 2/11
accuracy: 0.6562
Epoch 3/11
675/675 [============ ] - 3s 4ms/step - loss: 1.2372 -
accuracy: 0.7482
Epoch 4/11
675/675 [============ ] - 2s 4ms/step - loss: 1.0131 -
accuracy: 0.7895
Epoch 5/11
```

```
accuracy: 0.8114
Epoch 6/11
675/675 [============ ] - 2s 3ms/step - loss: 0.7673 -
accuracy: 0.8257
Epoch 7/11
accuracy: 0.8365
Epoch 8/11
accuracy: 0.8451
Epoch 9/11
675/675 [============ ] - 2s 3ms/step - loss: 0.6026 -
accuracy: 0.8521
Epoch 10/11
accuracy: 0.8578
Epoch 11/11
675/675 [============] - 3s 4ms/step - loss: 0.5431 -
accuracy: 0.8629
accuracy: 0.8633
Epoch 1/11
accuracy: 0.3593
Epoch 2/11
accuracy: 0.6874
Epoch 3/11
accuracy: 0.7620
Epoch 4/11
accuracy: 0.8017
Epoch 5/11
accuracy: 0.8254
Epoch 6/11
accuracy: 0.8388
Epoch 7/11
accuracy: 0.8493
Epoch 8/11
accuracy: 0.8559
Epoch 9/11
accuracy: 0.8615
```

```
Epoch 10/11
accuracy: 0.8663
Epoch 11/11
accuracy: 0.8700
accuracy: 0.8727
Epoch 1/11
675/675 [============ ] - 2s 3ms/step - loss: 2.0326 -
accuracy: 0.3794
Epoch 2/11
accuracy: 0.6726
Epoch 3/11
accuracy: 0.7595
Epoch 4/11
675/675 [============ ] - 2s 3ms/step - loss: 0.9973 -
accuracy: 0.8017
Epoch 5/11
accuracy: 0.8224
Epoch 6/11
accuracy: 0.8360
Epoch 7/11
675/675 [===========] - 3s 4ms/step - loss: 0.6829 -
accuracy: 0.8454
Epoch 8/11
675/675 [=========== ] - 2s 3ms/step - loss: 0.6311 -
accuracy: 0.8524
Epoch 9/11
675/675 [============ ] - 2s 3ms/step - loss: 0.5912 -
accuracy: 0.8582
Epoch 10/11
accuracy: 0.8628
Epoch 11/11
accuracy: 0.8671
169/169 [============ ] - Os 2ms/step - loss: 0.5189 -
accuracy: 0.8702
Epoch 1/11
accuracy: 0.3671
Epoch 2/11
```

```
accuracy: 0.6666
Epoch 3/11
675/675 [============ ] - 2s 3ms/step - loss: 1.2252 -
accuracy: 0.7535
Epoch 4/11
accuracy: 0.7949
Epoch 5/11
accuracy: 0.8191
Epoch 6/11
675/675 [============] - 3s 4ms/step - loss: 0.7655 -
accuracy: 0.8344
Epoch 7/11
accuracy: 0.8443
Epoch 8/11
675/675 [============] - 2s 3ms/step - loss: 0.6418 -
accuracy: 0.8520
Epoch 9/11
accuracy: 0.8578
Epoch 10/11
accuracy: 0.8630
Epoch 11/11
accuracy: 0.8673
169/169 [============ ] - 1s 3ms/step - loss: 0.5411 -
accuracy: 0.8676
Epoch 1/11
accuracy: 0.2780
Epoch 2/11
accuracy: 0.6351
Epoch 3/11
accuracy: 0.7383
Epoch 4/11
accuracy: 0.7851
Epoch 5/11
675/675 [=========== ] - 2s 3ms/step - loss: 0.8919 -
accuracy: 0.8115
Epoch 6/11
accuracy: 0.8291
```

```
Epoch 7/11
accuracy: 0.8411
Epoch 8/11
accuracy: 0.8507
Epoch 9/11
accuracy: 0.8575
Epoch 10/11
675/675 [============ ] - 2s 3ms/step - loss: 0.5732 -
accuracy: 0.8629
Epoch 11/11
accuracy: 0.8682
accuracy: 0.8671
Epoch 1/11
675/675 [============ ] - 3s 3ms/step - loss: 1.0147 -
accuracy: 0.7592
Epoch 2/11
accuracy: 0.8750
Epoch 3/11
accuracy: 0.8924
Epoch 4/11
675/675 [============ ] - 2s 3ms/step - loss: 0.3536 -
accuracy: 0.9016
Epoch 5/11
675/675 [=========== ] - 2s 3ms/step - loss: 0.3278 -
accuracy: 0.9083
Epoch 6/11
675/675 [============] - 3s 4ms/step - loss: 0.3089 -
accuracy: 0.9134
Epoch 7/11
accuracy: 0.9178
Epoch 8/11
675/675 [============ ] - 2s 3ms/step - loss: 0.2801 -
accuracy: 0.9218
Epoch 9/11
accuracy: 0.9253
Epoch 10/11
675/675 [=========== ] - 2s 3ms/step - loss: 0.2587 -
accuracy: 0.9279
Epoch 11/11
```

```
accuracy: 0.9305
accuracy: 0.9289
Epoch 1/11
accuracy: 0.7593
Epoch 2/11
accuracy: 0.8787
Epoch 3/11
675/675 [============] - 3s 4ms/step - loss: 0.3856 -
accuracy: 0.8945
Epoch 4/11
accuracy: 0.9041
Epoch 5/11
accuracy: 0.9108
Epoch 6/11
accuracy: 0.9153
Epoch 7/11
accuracy: 0.9191
Epoch 8/11
accuracy: 0.9234
Epoch 9/11
accuracy: 0.9263
Epoch 10/11
675/675 [============ ] - 3s 4ms/step - loss: 0.2543 -
accuracy: 0.9293
Epoch 11/11
accuracy: 0.9317
accuracy: 0.9301
Epoch 1/11
accuracy: 0.7581
Epoch 2/11
675/675 [===========] - 2s 3ms/step - loss: 0.4702 -
accuracy: 0.8791
Epoch 3/11
675/675 [============ ] - 2s 3ms/step - loss: 0.3891 -
accuracy: 0.8943
```

```
Epoch 4/11
accuracy: 0.9033
Epoch 5/11
accuracy: 0.9099
Epoch 6/11
accuracy: 0.9137
Epoch 7/11
675/675 [===========] - 2s 3ms/step - loss: 0.2947 -
accuracy: 0.9179
Epoch 8/11
accuracy: 0.9218
Epoch 9/11
675/675 [=========== ] - 2s 3ms/step - loss: 0.2713 -
accuracy: 0.9246
Epoch 10/11
accuracy: 0.9279
Epoch 11/11
accuracy: 0.9293
accuracy: 0.9271
Epoch 1/11
675/675 [===========] - 3s 3ms/step - loss: 1.0089 -
accuracy: 0.7618
Epoch 2/11
accuracy: 0.8786
Epoch 3/11
675/675 [============] - 2s 3ms/step - loss: 0.3840 -
accuracy: 0.8946
Epoch 4/11
accuracy: 0.9039
Epoch 5/11
675/675 [============ ] - 2s 4ms/step - loss: 0.3195 -
accuracy: 0.9104
Epoch 6/11
accuracy: 0.9147
Epoch 7/11
675/675 [===========] - 3s 4ms/step - loss: 0.2857 -
accuracy: 0.9194
Epoch 8/11
```

```
accuracy: 0.9233
Epoch 9/11
675/675 [============ ] - 2s 3ms/step - loss: 0.2622 -
accuracy: 0.9263
Epoch 10/11
accuracy: 0.9286
Epoch 11/11
675/675 [============ ] - 2s 3ms/step - loss: 0.2440 -
accuracy: 0.9314
169/169 [============ ] - Os 2ms/step - loss: 0.2637 -
accuracy: 0.9250
Epoch 1/11
accuracy: 0.7600
Epoch 2/11
675/675 [===========] - 3s 4ms/step - loss: 0.4617 -
accuracy: 0.8806
Epoch 3/11
accuracy: 0.8956
Epoch 4/11
accuracy: 0.9034
Epoch 5/11
accuracy: 0.9088
Epoch 6/11
accuracy: 0.9136
Epoch 7/11
accuracy: 0.9166
Epoch 8/11
accuracy: 0.9198
Epoch 9/11
accuracy: 0.9227
Epoch 10/11
675/675 [============ ] - 2s 3ms/step - loss: 0.2644 -
accuracy: 0.9250
Epoch 11/11
accuracy: 0.9281
accuracy: 0.9273
```

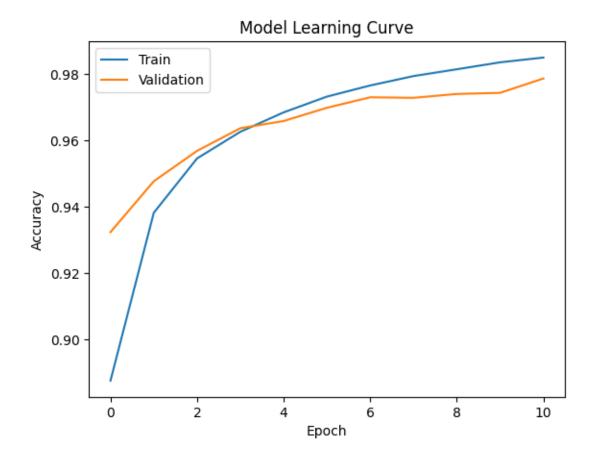
```
Epoch 1/11
accuracy: 0.8858
Epoch 2/11
accuracy: 0.9348
Epoch 3/11
accuracy: 0.9497
Epoch 4/11
675/675 [===========] - 2s 3ms/step - loss: 0.1434 -
accuracy: 0.9601
Epoch 5/11
accuracy: 0.9652
Epoch 6/11
675/675 [===========] - 2s 3ms/step - loss: 0.1052 -
accuracy: 0.9700
Epoch 7/11
accuracy: 0.9738
Epoch 8/11
accuracy: 0.9770
Epoch 9/11
accuracy: 0.9796
Epoch 10/11
accuracy: 0.9817
Epoch 11/11
accuracy: 0.9838
169/169 [============= ] - Os 2ms/step - loss: 0.1043 -
accuracy: 0.9705
Epoch 1/11
accuracy: 0.8829
Epoch 2/11
675/675 [============ ] - 2s 3ms/step - loss: 0.2268 -
accuracy: 0.9357
Epoch 3/11
accuracy: 0.9504
Epoch 4/11
675/675 [===========] - 3s 4ms/step - loss: 0.1438 -
accuracy: 0.9590
Epoch 5/11
```

```
accuracy: 0.9655
Epoch 6/11
675/675 [============ ] - 2s 3ms/step - loss: 0.1059 -
accuracy: 0.9704
Epoch 7/11
accuracy: 0.9740
Epoch 8/11
675/675 [============ ] - 2s 3ms/step - loss: 0.0837 -
accuracy: 0.9765
Epoch 9/11
accuracy: 0.9797
Epoch 10/11
accuracy: 0.9812
Epoch 11/11
675/675 [============ ] - 3s 4ms/step - loss: 0.0616 -
accuracy: 0.9823
accuracy: 0.9719
Epoch 1/11
accuracy: 0.8840
Epoch 2/11
accuracy: 0.9344
Epoch 3/11
accuracy: 0.9500
Epoch 4/11
675/675 [===========] - 3s 4ms/step - loss: 0.1461 -
accuracy: 0.9574
Epoch 5/11
675/675 [============ ] - 2s 4ms/step - loss: 0.1227 -
accuracy: 0.9660
Epoch 6/11
accuracy: 0.9700
Epoch 7/11
675/675 [============ ] - 2s 3ms/step - loss: 0.0933 -
accuracy: 0.9734
Epoch 8/11
accuracy: 0.9773
Epoch 9/11
```

```
accuracy: 0.9798
Epoch 10/11
675/675 [===========] - 2s 3ms/step - loss: 0.0668 -
accuracy: 0.9817
Epoch 11/11
accuracy: 0.9840
accuracy: 0.9735
Epoch 1/11
accuracy: 0.8834
Epoch 2/11
accuracy: 0.9352
Epoch 3/11
accuracy: 0.9506
Epoch 4/11
accuracy: 0.9592
Epoch 5/11
accuracy: 0.9666
Epoch 6/11
accuracy: 0.9712
Epoch 7/11
accuracy: 0.9740
Epoch 8/11
accuracy: 0.9773
Epoch 9/11
accuracy: 0.9795
Epoch 10/11
accuracy: 0.9822
Epoch 11/11
accuracy: 0.9840
accuracy: 0.9686
Epoch 1/11
675/675 [===========] - 2s 3ms/step - loss: 0.4147 -
accuracy: 0.8861
Epoch 2/11
```

```
accuracy: 0.9354
Epoch 3/11
675/675 [============ ] - 3s 4ms/step - loss: 0.1780 -
accuracy: 0.9493
Epoch 4/11
accuracy: 0.9589
Epoch 5/11
675/675 [============ ] - 3s 4ms/step - loss: 0.1235 -
accuracy: 0.9655
Epoch 6/11
accuracy: 0.9705
Epoch 7/11
accuracy: 0.9744
Epoch 8/11
675/675 [============ ] - 2s 3ms/step - loss: 0.0836 -
accuracy: 0.9766
Epoch 9/11
accuracy: 0.9801
Epoch 10/11
accuracy: 0.9811
Epoch 11/11
675/675 [============ ] - 2s 3ms/step - loss: 0.0614 -
accuracy: 0.9834
accuracy: 0.9711
Epoch 1/11
844/844 [============= ] - 4s 4ms/step - loss: 0.3869 -
accuracy: 0.8926
Epoch 2/11
accuracy: 0.9414
Epoch 3/11
accuracy: 0.9552
Epoch 4/11
844/844 [============= ] - 3s 3ms/step - loss: 0.1283 -
accuracy: 0.9639
Epoch 5/11
accuracy: 0.9694
Epoch 6/11
844/844 [============== ] - 4s 4ms/step - loss: 0.0947 -
```

```
accuracy: 0.9735
   Epoch 7/11
   844/844 [=========== ] - 3s 3ms/step - loss: 0.0833 -
   accuracy: 0.9770
   Epoch 8/11
   accuracy: 0.9797
   Epoch 9/11
   844/844 [======
                            =======] - 3s 3ms/step - loss: 0.0666 -
   accuracy: 0.9815
   Epoch 10/11
   844/844 [=========== ] - 2s 3ms/step - loss: 0.0604 -
   accuracy: 0.9830
   Epoch 11/11
   accuracy: 0.9852
   Best Hyperparameters: {'hidden_units': 128, 'learning_rate': 0.1}
   Best Accuracy: 0.9711111068725586
[]: # Get the best model from the grid search
    best_model = grid_result.best_estimator_
    # Get the training history
    history = best_model.fit(x_train, y_train, epochs=11, batch_size=64, verbose=0,_
     →validation_data=(x_val, y_val))
    # Plot the learning curve
    plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])
    plt.title('Model Learning Curve')
    plt.ylabel('Accuracy')
    plt.xlabel('Epoch')
    plt.legend(['Train', 'Validation'], loc='upper left')
    plt.show()
    print("\n\n")
    # Print the best hyperparameters and accuracy
    print("Best Hyperparameters: ", grid_result.best_params_)
    print("Best Accuracy: ", grid_result.best_score_)
```



Best Hyperparameters: {'hidden_units': 128, 'learning_rate': 0.1}

Best Accuracy: 0.9711111068725586

In this experiment, our objective was to construct a simple neural network comprising only one hidden layer. To optimize its performance, we employed GridSearchCV to explore various values for the learning rate and the number of neurons in the hidden layer. In addition, we selected 'accuracy' as the evaluation metric and utilized cross-entropy categorical loss as our loss function, which is suitable for multiclass classification scenarios.

To facilitate learning, we employed mini-batch stochastic gradient descent (SGD) as our chosen learning algorithm, employing a batch size of 64. Furthermore, we integrated a validation set to conduct ongoing validation during the training process. In the results, we can see the best accuracy achieved is 97.1% with hidden units as 128 and learning rate of 0.1.

1.2 Que 1: Part 2

2. It is recommended to try, at least, another optimization method of your choice (SGD with

momentum, RMSProp, RMSProp with momentum, AdaGrad, AdaDelta, or Adam) and compare its performances to those of the basic minibatch SGD on the MNIST dataset. Which methods you want to try and how many you want to try and compare is up to you and up to the amount of time you have left to complete the assignment. Remember, this is a research course. You may want to read Chapter-8 also.

```
[]: import matplotlib.pyplot as plt
     from tensorflow.keras.optimizers import SGD, RMSprop, Adagrad, Adadelta, Adam
     learning_rates = [0.001, 0.01, 0.1]
     optimizers = [
         ('SGD', SGD),
         ('RMSprop', RMSprop),
         ('Adagrad', Adagrad),
         ('Adadelta', Adadelta),
         ('Adam', Adam)
     # Find the best learning rate and optimizer based on model accuracy
     best_accuracy = 0.0
     best_learning_rate = None
     best_optimizer = None
     # Define the model architecture
     model = Sequential()
     model.add(Dense(128, activation='relu', input_shape=(784,)))
     model.add(Dense(10, activation='sigmoid'))
     # Train and plot accuracy for different learning rates and optimizers
     fig, axs = plt.subplots(3, len(optimizers), figsize=(12, 12))
     for i, lr in enumerate(learning_rates):
         for j, (optimizer_name, optimizer_class) in enumerate(optimizers):
             optimizer = optimizer_class(learning_rate=lr)
             model.compile(loss='categorical_crossentropy', optimizer=optimizer,_
      →metrics=['accuracy'])
             history = model.fit(x_train, y_train, batch_size=64, epochs=11,__
      →validation_split=0.2, verbose=0)
             accuracy = history.history['val_accuracy'][-1]
             if accuracy > best_accuracy:
                 best_accuracy = accuracy
                 best_learning_rate = lr
                 best_optimizer = optimizer_name
             # Plot accuracy
             axs[i, j].plot(history.history['val_accuracy'])
```

```
# Set plot labels
    axs[i, j].set_title(f'Optimizer: {optimizer_name}\nLearning Rate: {lr}')
    axs[i, j].set_xlabel('Epochs')
    axs[i, j].set_ylabel('Validation Accuracy')

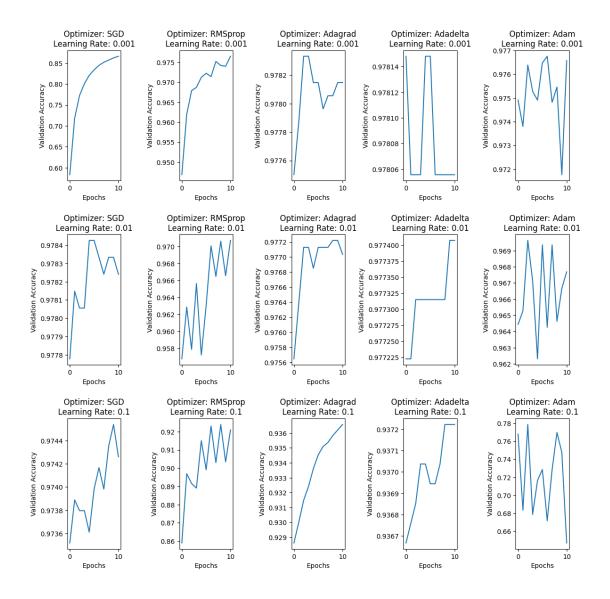
# Set layout and spacing between subplots
plt.tight_layout(pad=2.0)

# Print the best learning rate and optimizer
print(f'Best Learning Rate: {best_learning_rate}')
print(f'Best Optimizer: {best_optimizer}')
print(f'Best Accuracy: {best_accuracy}')

print("\n\n")
# Show the plots
plt.show()
```

Best Learning Rate: 0.01
Best Optimizer: SGD

Best Accuracy: 0.9782407283782959



In our experiment, we investigated the performance of various optimization algorithms by testing them with three different learning rate values: 0.1, 0.01, and 0.001. To ensure a fair comparison, we kept the batch size, number of epochs, loss function, number of layers, and hidden units consistent across all methods.

By analyzing the plots of validation accuracy versus epochs for each optimization algorithm, we can draw some conclusions.

Firstly, both SGD and RMSProp consistently outperformed Adagrad and Adadelta. This observation suggests that SGD and RMSProp were more effective in finding the optimal parameters for our neural network. The reason behind their superior performance could be attributed to their ability to adapt the learning rate based on the gradients of the parameters.

On the other hand, the performance of Adam exhibited high variation in the plots. This variation could be attributed to a couple of factors. One possibility is that we trained the neural network for a relatively small number of epochs, which might not have been sufficient for Adam to converge to a stable solution. Additionally, Adam incorporates adaptive learning rates and momentum, which can introduce additional complexity in optimization, especially in scenarios with simple data.

Despite the variations observed with Adam, it is worth noting that all the optimization algorithms achieved an accuracy of over 90 percent. This outcome suggests that the dataset used in our experiment was relatively simple, allowing all the algorithms to achieve satisfactory results. It is important to consider that more complex datasets may require further fine-tuning of hyperparameters and choice of optimization algorithm to achieve optimal performance.

Overall, through these iterations we achieved 97.8% as a best accuracy and optimizer was "SGD" with learning rate 0.01.

2 Que 2:

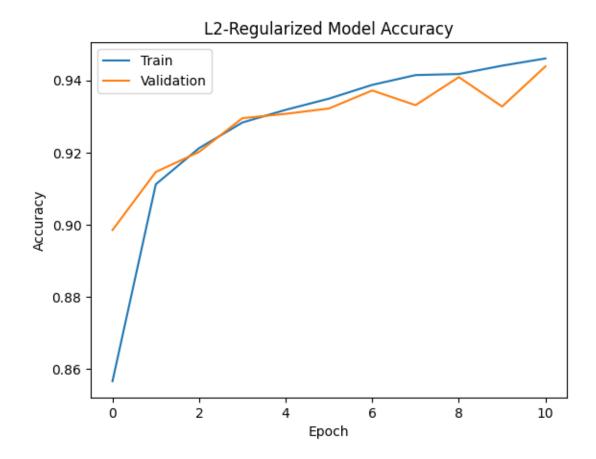
Consider the L2-regularized multiclass logistic regression. That is, add to the logistic regression loss a regularization term that represents the L2-norm of the parameters. More precisely, the regularization term is

```
(w, b) = i(wi2 + bi2)
```

where {wi, bi} are all the parameters in the logistic regression, and R is the regularization hyperparameter. Typically, is about C/n where n is the number of data points and C is some constant in [0.01,100] (need to tune C). Run the regularized multiclass logistic regression on MNIST, using the basic minibatch SGD, and compare its results to those of the basic minibatch SGD with nonregularized loss, in Question #1.

```
[25]: import numpy as np
     import matplotlib.pyplot as plt
     from tensorflow.keras.datasets import mnist
     from tensorflow.keras.models import Sequential
     from tensorflow.keras.layers import Dense, InputLayer
     from tensorflow.keras.optimizers import SGD
     from sklearn.preprocessing import OneHotEncoder
     # Define the logistic regression model architecture with L2 regularization
     model = Sequential()
     model.add(Dense(128, activation='relu', input_shape=(784,),_
       →kernel_regularizer='12'))
     model.add(Dense(10, activation='sigmoid'))
     # Compile the model
     model.compile(loss='categorical_crossentropy', optimizer=SGD(learning_rate=0.
       # Train the model with L2 regularization
     history = model.fit(x_train, y_train, batch_size=128, epochs=11,__
       ⇔validation_split=0.2, verbose=1)
```

```
# Evaluate the model on the testing set
_, test_accuracy = model.evaluate(x_test, y_test, verbose=0)
print("\n")
# Plot the training and validation accuracies
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('L2-Regularized Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(['Train', 'Validation'])
plt.show()
print("\n\n")
# Print the accuracy
print(f'Test Accuracy (L2-Regularized): {test_accuracy}')
Epoch 1/11
338/338 [============ ] - 2s 5ms/step - loss: 1.8499 -
accuracy: 0.8566 - val_loss: 1.0354 - val_accuracy: 0.8985
accuracy: 0.9112 - val_loss: 0.5689 - val_accuracy: 0.9146
338/338 [=========== ] - 2s 5ms/step - loss: 0.4855 -
accuracy: 0.9212 - val_loss: 0.4373 - val_accuracy: 0.9202
Epoch 4/11
accuracy: 0.9283 - val_loss: 0.3874 - val_accuracy: 0.9295
Epoch 5/11
accuracy: 0.9319 - val_loss: 0.3551 - val_accuracy: 0.9307
Epoch 6/11
accuracy: 0.9350 - val_loss: 0.3500 - val_accuracy: 0.9322
Epoch 7/11
338/338 [============ ] - 1s 4ms/step - loss: 0.3320 -
accuracy: 0.9388 - val_loss: 0.3371 - val_accuracy: 0.9372
Epoch 8/11
338/338 [============ ] - 1s 4ms/step - loss: 0.3207 -
accuracy: 0.9415 - val_loss: 0.3377 - val_accuracy: 0.9331
Epoch 9/11
accuracy: 0.9418 - val_loss: 0.3129 - val_accuracy: 0.9409
Epoch 10/11
338/338 [============ ] - 1s 4ms/step - loss: 0.3057 -
accuracy: 0.9441 - val_loss: 0.3383 - val_accuracy: 0.9328
```



Test Accuracy (L2-Regularized): 0.9488000273704529

We applied L2 regularization to the same model that was used in the previous question. L2 regularization is a technique commonly employed to prevent overfitting in neural networks by adding a penalty term to the loss function based on the magnitudes of the model's weights.

After incorporating L2 regularization, we observed a slight decrease in the training accuracy compared to the previous result. The training accuracy now stands at 94.62% instead of the previous 97.1%. This drop in training accuracy can be attributed to the regularization term penalizing the weights and encouraging them to be smaller. While we achieved 94.88% as a test accuracy with L2-Regularization.

However, an interesting observation is that the validation accuracy is now closer to the training

accuracy after the addition of L2 regularization. This outcome suggests that the regularization helped in reducing overfitting and improving the generalization capability of the model. When the validation accuracy is closer to the training accuracy, it indicates that the model's performance on unseen data is more aligned with its performance on the training data.

Overall, although the training accuracy decreased slightly due to the L2 regularization, the improved alignment between the training and validation accuracies implies that the model is now less likely to overfit and more capable of generalizing well to unseen data.

3 Que 3:

Build a three-layer feedforward neural network:

```
x \rightarrow h1 \rightarrow h2 \rightarrow o
```

The hidden layers h1 and h2 have width 500. Train the network for 250 epochs1 and test the classification error. Do not use regularizations. Plot the cross-entropy loss on the batches and also plot the classification error on the validation data.

Comments: 1Each epoch is a pass over the training data. Suppose you use batches of size b, and the training data set has n points, then an epoch consists of n/b batches. Note that you can divide the data set into batches, and then round robin over the batches. You can also randomly sample say 64 points for each batch. Either way is OK, and typically there is no performance difference between them. When these batches are randomly sampled, it is possible that some point are not in any of them, but we still call these batches a pass over the data.

Comments: you can also use another dataset, CIFAR-10 or CIFAR-100. Or you can pick your own dataset.

```
[]: import numpy as np
     import matplotlib.pyplot as plt
     from tensorflow.keras.datasets import mnist
     from tensorflow.keras.models import Sequential
     from tensorflow.keras.layers import Dense
     from tensorflow.keras.optimizers import SGD
     from sklearn.preprocessing import OneHotEncoder
     from sklearn.metrics import accuracy_score
     # Define the three-layer feedforward neural network
     model = Sequential()
     model.add(Dense(500, activation='relu', input shape=(784,)))
     model.add(Dense(500, activation='relu'))
     model.add(Dense(10, activation='sigmoid'))
     # Compile the model
     model.compile(loss='categorical_crossentropy', optimizer=SGD(learning_rate=0.
      ⇔01), metrics=['accuracy'])
     # Train the model
```

```
history = model.fit(x_train, y_train, batch_size=64, epochs=250,__
 ⇒validation_split=0.2, verbose=1)
# Evaluate the model on the testing set
_, test_accuracy = model.evaluate(x_test, y_test, verbose=0)
print("\n")
# Plot the cross-entropy loss on the batches
plt.plot(history.history['loss'])
plt.title('Cross-Entropy Loss on Batches')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.show()
print("\n")
# Plot the classification error on the validation data
plt.plot(1 - np.array(history.history['val_accuracy']))
plt.title('Classification Error on Validation Data')
plt.xlabel('Epoch')
plt.ylabel('Error')
plt.show()
print("\n\n")
# Print the test accuracy
print(f'Test Accuracy: {test_accuracy}')
Epoch 1/250
accuracy: 0.7875 - val_loss: 0.4505 - val_accuracy: 0.8779
Epoch 2/250
675/675 [============ ] - 8s 11ms/step - loss: 0.3909 -
accuracy: 0.8938 - val_loss: 0.3414 - val_accuracy: 0.9004
Epoch 3/250
accuracy: 0.9090 - val_loss: 0.3014 - val_accuracy: 0.9111
Epoch 4/250
accuracy: 0.9179 - val loss: 0.2765 - val accuracy: 0.9182
Epoch 5/250
675/675 [============ ] - 7s 10ms/step - loss: 0.2635 -
accuracy: 0.9257 - val_loss: 0.2545 - val_accuracy: 0.9285
Epoch 6/250
675/675 [=========== ] - 6s 9ms/step - loss: 0.2439 -
accuracy: 0.9312 - val_loss: 0.2393 - val_accuracy: 0.9319
Epoch 7/250
accuracy: 0.9358 - val_loss: 0.2276 - val_accuracy: 0.9352
```

```
Epoch 8/250
accuracy: 0.9401 - val_loss: 0.2151 - val_accuracy: 0.9385
Epoch 9/250
675/675 [============= ] - 7s 10ms/step - loss: 0.2002 -
accuracy: 0.9439 - val_loss: 0.2035 - val_accuracy: 0.9415
Epoch 10/250
accuracy: 0.9471 - val_loss: 0.1958 - val_accuracy: 0.9421
Epoch 11/250
accuracy: 0.9497 - val_loss: 0.1855 - val_accuracy: 0.9452
Epoch 12/250
accuracy: 0.9525 - val_loss: 0.1780 - val_accuracy: 0.9487
Epoch 13/250
accuracy: 0.9555 - val_loss: 0.1710 - val_accuracy: 0.9503
Epoch 14/250
accuracy: 0.9573 - val_loss: 0.1660 - val_accuracy: 0.9497
Epoch 15/250
675/675 [============= ] - 8s 11ms/step - loss: 0.1459 -
accuracy: 0.9594 - val_loss: 0.1581 - val_accuracy: 0.9542
Epoch 16/250
675/675 [============= ] - 6s 9ms/step - loss: 0.1392 -
accuracy: 0.9614 - val_loss: 0.1555 - val_accuracy: 0.9564
Epoch 17/250
675/675 [============= ] - 8s 12ms/step - loss: 0.1330 -
accuracy: 0.9637 - val_loss: 0.1500 - val_accuracy: 0.9559
Epoch 18/250
accuracy: 0.9651 - val_loss: 0.1464 - val_accuracy: 0.9574
Epoch 19/250
675/675 [============= ] - 8s 12ms/step - loss: 0.1220 -
accuracy: 0.9670 - val_loss: 0.1400 - val_accuracy: 0.9597
Epoch 20/250
accuracy: 0.9685 - val_loss: 0.1373 - val_accuracy: 0.9593
Epoch 21/250
accuracy: 0.9699 - val_loss: 0.1345 - val_accuracy: 0.9604
Epoch 22/250
accuracy: 0.9714 - val_loss: 0.1316 - val_accuracy: 0.9608
Epoch 23/250
accuracy: 0.9727 - val_loss: 0.1289 - val_accuracy: 0.9619
```

```
Epoch 24/250
accuracy: 0.9732 - val_loss: 0.1242 - val_accuracy: 0.9632
Epoch 25/250
675/675 [============= ] - 7s 11ms/step - loss: 0.0960 -
accuracy: 0.9746 - val_loss: 0.1221 - val_accuracy: 0.9637
Epoch 26/250
accuracy: 0.9755 - val_loss: 0.1218 - val_accuracy: 0.9637
Epoch 27/250
675/675 [============= ] - 7s 10ms/step - loss: 0.0890 -
accuracy: 0.9764 - val_loss: 0.1190 - val_accuracy: 0.9639
Epoch 28/250
675/675 [=========== ] - 7s 10ms/step - loss: 0.0856 -
accuracy: 0.9778 - val_loss: 0.1155 - val_accuracy: 0.9656
Epoch 29/250
accuracy: 0.9780 - val_loss: 0.1146 - val_accuracy: 0.9641
Epoch 30/250
accuracy: 0.9789 - val_loss: 0.1105 - val_accuracy: 0.9671
Epoch 31/250
675/675 [============= ] - 7s 11ms/step - loss: 0.0772 -
accuracy: 0.9799 - val_loss: 0.1097 - val_accuracy: 0.9670
Epoch 32/250
675/675 [============ ] - 7s 10ms/step - loss: 0.0745 -
accuracy: 0.9803 - val_loss: 0.1094 - val_accuracy: 0.9667
Epoch 33/250
675/675 [=========== ] - 7s 10ms/step - loss: 0.0718 -
accuracy: 0.9814 - val_loss: 0.1078 - val_accuracy: 0.9683
Epoch 34/250
675/675 [============= ] - 7s 10ms/step - loss: 0.0695 -
accuracy: 0.9822 - val_loss: 0.1039 - val_accuracy: 0.9692
Epoch 35/250
accuracy: 0.9823 - val_loss: 0.1047 - val_accuracy: 0.9679
Epoch 36/250
675/675 [============= ] - 8s 11ms/step - loss: 0.0651 -
accuracy: 0.9837 - val_loss: 0.1015 - val_accuracy: 0.9700
Epoch 37/250
675/675 [============ ] - 6s 9ms/step - loss: 0.0629 -
accuracy: 0.9847 - val_loss: 0.1006 - val_accuracy: 0.9695
Epoch 38/250
675/675 [=========== ] - 8s 12ms/step - loss: 0.0609 -
accuracy: 0.9848 - val_loss: 0.1007 - val_accuracy: 0.9694
Epoch 39/250
accuracy: 0.9856 - val_loss: 0.0997 - val_accuracy: 0.9698
```

```
Epoch 40/250
accuracy: 0.9860 - val_loss: 0.0980 - val_accuracy: 0.9700
Epoch 41/250
accuracy: 0.9862 - val_loss: 0.0971 - val_accuracy: 0.9710
Epoch 42/250
accuracy: 0.9870 - val_loss: 0.0955 - val_accuracy: 0.9706
Epoch 43/250
accuracy: 0.9876 - val_loss: 0.0956 - val_accuracy: 0.9702
Epoch 44/250
675/675 [=========== ] - 8s 12ms/step - loss: 0.0501 -
accuracy: 0.9881 - val_loss: 0.0952 - val_accuracy: 0.9702
Epoch 45/250
675/675 [============] - 6s 9ms/step - loss: 0.0486 -
accuracy: 0.9883 - val_loss: 0.0933 - val_accuracy: 0.9708
Epoch 46/250
675/675 [============ ] - 8s 11ms/step - loss: 0.0472 -
accuracy: 0.9891 - val_loss: 0.0930 - val_accuracy: 0.9711
Epoch 47/250
accuracy: 0.9891 - val_loss: 0.0926 - val_accuracy: 0.9709
Epoch 48/250
675/675 [============ ] - 7s 11ms/step - loss: 0.0444 -
accuracy: 0.9900 - val_loss: 0.0916 - val_accuracy: 0.9702
Epoch 49/250
675/675 [=========== ] - 6s 10ms/step - loss: 0.0431 -
accuracy: 0.9901 - val_loss: 0.0909 - val_accuracy: 0.9714
Epoch 50/250
accuracy: 0.9907 - val_loss: 0.0898 - val_accuracy: 0.9720
Epoch 51/250
675/675 [============= ] - 7s 10ms/step - loss: 0.0406 -
accuracy: 0.9907 - val_loss: 0.0899 - val_accuracy: 0.9726
Epoch 52/250
accuracy: 0.9911 - val_loss: 0.0901 - val_accuracy: 0.9706
Epoch 53/250
675/675 [============ ] - 8s 11ms/step - loss: 0.0383 -
accuracy: 0.9918 - val_loss: 0.0890 - val_accuracy: 0.9716
Epoch 54/250
675/675 [=========== ] - 9s 13ms/step - loss: 0.0371 -
accuracy: 0.9918 - val_loss: 0.0890 - val_accuracy: 0.9719
Epoch 55/250
accuracy: 0.9923 - val_loss: 0.0882 - val_accuracy: 0.9722
```

```
Epoch 56/250
675/675 [============= ] - 7s 10ms/step - loss: 0.0349 -
accuracy: 0.9925 - val_loss: 0.0885 - val_accuracy: 0.9724
Epoch 57/250
675/675 [============= ] - 7s 11ms/step - loss: 0.0340 -
accuracy: 0.9928 - val_loss: 0.0875 - val_accuracy: 0.9725
Epoch 58/250
accuracy: 0.9929 - val_loss: 0.0863 - val_accuracy: 0.9729
Epoch 59/250
accuracy: 0.9934 - val_loss: 0.0850 - val_accuracy: 0.9729
Epoch 60/250
accuracy: 0.9938 - val_loss: 0.0853 - val_accuracy: 0.9738
Epoch 61/250
675/675 [============ ] - 8s 11ms/step - loss: 0.0305 -
accuracy: 0.9937 - val_loss: 0.0854 - val_accuracy: 0.9731
Epoch 62/250
accuracy: 0.9941 - val_loss: 0.0853 - val_accuracy: 0.9729
Epoch 63/250
675/675 [============= ] - 8s 12ms/step - loss: 0.0287 -
accuracy: 0.9946 - val_loss: 0.0843 - val_accuracy: 0.9731
Epoch 64/250
675/675 [============ ] - 6s 9ms/step - loss: 0.0281 -
accuracy: 0.9944 - val_loss: 0.0839 - val_accuracy: 0.9728
Epoch 65/250
675/675 [=========== ] - 8s 12ms/step - loss: 0.0273 -
accuracy: 0.9949 - val_loss: 0.0837 - val_accuracy: 0.9735
Epoch 66/250
accuracy: 0.9951 - val_loss: 0.0840 - val_accuracy: 0.9737
Epoch 67/250
675/675 [============= ] - 8s 11ms/step - loss: 0.0258 -
accuracy: 0.9956 - val_loss: 0.0835 - val_accuracy: 0.9739
Epoch 68/250
accuracy: 0.9956 - val_loss: 0.0833 - val_accuracy: 0.9730
Epoch 69/250
675/675 [============ ] - 8s 11ms/step - loss: 0.0247 -
accuracy: 0.9955 - val_loss: 0.0823 - val_accuracy: 0.9736
Epoch 70/250
accuracy: 0.9959 - val_loss: 0.0822 - val_accuracy: 0.9744
Epoch 71/250
accuracy: 0.9961 - val_loss: 0.0833 - val_accuracy: 0.9732
```

```
Epoch 72/250
675/675 [============= ] - 6s 10ms/step - loss: 0.0226 -
accuracy: 0.9962 - val_loss: 0.0828 - val_accuracy: 0.9742
Epoch 73/250
675/675 [============= ] - 7s 10ms/step - loss: 0.0221 -
accuracy: 0.9966 - val_loss: 0.0820 - val_accuracy: 0.9743
Epoch 74/250
accuracy: 0.9969 - val_loss: 0.0815 - val_accuracy: 0.9744
Epoch 75/250
accuracy: 0.9967 - val_loss: 0.0833 - val_accuracy: 0.9727
Epoch 76/250
accuracy: 0.9970 - val_loss: 0.0824 - val_accuracy: 0.9746
Epoch 77/250
675/675 [============ ] - 8s 12ms/step - loss: 0.0199 -
accuracy: 0.9972 - val_loss: 0.0819 - val_accuracy: 0.9742
Epoch 78/250
accuracy: 0.9971 - val_loss: 0.0816 - val_accuracy: 0.9746
Epoch 79/250
accuracy: 0.9976 - val_loss: 0.0824 - val_accuracy: 0.9744
Epoch 80/250
675/675 [============= ] - 8s 11ms/step - loss: 0.0185 -
accuracy: 0.9977 - val_loss: 0.0824 - val_accuracy: 0.9745
Epoch 81/250
accuracy: 0.9978 - val_loss: 0.0813 - val_accuracy: 0.9754
Epoch 82/250
accuracy: 0.9978 - val_loss: 0.0816 - val_accuracy: 0.9747
Epoch 83/250
accuracy: 0.9980 - val_loss: 0.0810 - val_accuracy: 0.9744
Epoch 84/250
675/675 [============= ] - 8s 12ms/step - loss: 0.0168 -
accuracy: 0.9979 - val_loss: 0.0825 - val_accuracy: 0.9747
Epoch 85/250
675/675 [============ ] - 6s 9ms/step - loss: 0.0164 -
accuracy: 0.9982 - val_loss: 0.0804 - val_accuracy: 0.9747
Epoch 86/250
675/675 [=========== ] - 8s 12ms/step - loss: 0.0160 -
accuracy: 0.9981 - val_loss: 0.0810 - val_accuracy: 0.9749
Epoch 87/250
accuracy: 0.9983 - val_loss: 0.0811 - val_accuracy: 0.9746
```

```
Epoch 88/250
675/675 [============= ] - 8s 11ms/step - loss: 0.0152 -
accuracy: 0.9982 - val_loss: 0.0807 - val_accuracy: 0.9744
Epoch 89/250
accuracy: 0.9983 - val_loss: 0.0816 - val_accuracy: 0.9744
Epoch 90/250
accuracy: 0.9984 - val_loss: 0.0808 - val_accuracy: 0.9751
Epoch 91/250
accuracy: 0.9985 - val_loss: 0.0805 - val_accuracy: 0.9751
Epoch 92/250
675/675 [=========== ] - 7s 10ms/step - loss: 0.0139 -
accuracy: 0.9987 - val_loss: 0.0806 - val_accuracy: 0.9746
Epoch 93/250
675/675 [============ ] - 7s 10ms/step - loss: 0.0136 -
accuracy: 0.9986 - val_loss: 0.0810 - val_accuracy: 0.9755
Epoch 94/250
accuracy: 0.9987 - val_loss: 0.0807 - val_accuracy: 0.9757
Epoch 95/250
675/675 [============ ] - 8s 11ms/step - loss: 0.0129 -
accuracy: 0.9988 - val_loss: 0.0818 - val_accuracy: 0.9759
Epoch 96/250
675/675 [============ ] - 6s 9ms/step - loss: 0.0127 -
accuracy: 0.9988 - val_loss: 0.0806 - val_accuracy: 0.9751
Epoch 97/250
675/675 [============= ] - 8s 12ms/step - loss: 0.0124 -
accuracy: 0.9987 - val_loss: 0.0807 - val_accuracy: 0.9748
Epoch 98/250
accuracy: 0.9988 - val_loss: 0.0803 - val_accuracy: 0.9756
Epoch 99/250
675/675 [============= ] - 8s 12ms/step - loss: 0.0119 -
accuracy: 0.9989 - val_loss: 0.0804 - val_accuracy: 0.9754
Epoch 100/250
accuracy: 0.9989 - val_loss: 0.0811 - val_accuracy: 0.9759
Epoch 101/250
accuracy: 0.9989 - val_loss: 0.0810 - val_accuracy: 0.9753
Epoch 102/250
accuracy: 0.9990 - val_loss: 0.0804 - val_accuracy: 0.9759
Epoch 103/250
accuracy: 0.9991 - val_loss: 0.0810 - val_accuracy: 0.9755
```

```
Epoch 104/250
accuracy: 0.9991 - val_loss: 0.0808 - val_accuracy: 0.9752
Epoch 105/250
accuracy: 0.9991 - val_loss: 0.0806 - val_accuracy: 0.9757
Epoch 106/250
accuracy: 0.9991 - val_loss: 0.0808 - val_accuracy: 0.9757
Epoch 107/250
accuracy: 0.9993 - val_loss: 0.0809 - val_accuracy: 0.9756
Epoch 108/250
accuracy: 0.9993 - val_loss: 0.0812 - val_accuracy: 0.9754
Epoch 109/250
accuracy: 0.9992 - val_loss: 0.0807 - val_accuracy: 0.9756
Epoch 110/250
675/675 [============ ] - 8s 12ms/step - loss: 0.0093 -
accuracy: 0.9993 - val_loss: 0.0808 - val_accuracy: 0.9757
Epoch 111/250
accuracy: 0.9994 - val_loss: 0.0805 - val_accuracy: 0.9755
Epoch 112/250
675/675 [============= ] - 8s 12ms/step - loss: 0.0091 -
accuracy: 0.9993 - val_loss: 0.0808 - val_accuracy: 0.9762
Epoch 113/250
accuracy: 0.9993 - val_loss: 0.0808 - val_accuracy: 0.9758
Epoch 114/250
accuracy: 0.9994 - val_loss: 0.0808 - val_accuracy: 0.9757
Epoch 115/250
accuracy: 0.9995 - val_loss: 0.0814 - val_accuracy: 0.9756
Epoch 116/250
accuracy: 0.9995 - val_loss: 0.0813 - val_accuracy: 0.9759
Epoch 117/250
accuracy: 0.9995 - val_loss: 0.0812 - val_accuracy: 0.9759
Epoch 118/250
675/675 [=========== ] - 8s 12ms/step - loss: 0.0080 -
accuracy: 0.9995 - val_loss: 0.0808 - val_accuracy: 0.9760
Epoch 119/250
accuracy: 0.9995 - val_loss: 0.0810 - val_accuracy: 0.9756
```

```
Epoch 120/250
675/675 [============= ] - 8s 11ms/step - loss: 0.0077 -
accuracy: 0.9996 - val_loss: 0.0808 - val_accuracy: 0.9764
Epoch 121/250
675/675 [============= ] - 8s 12ms/step - loss: 0.0076 -
accuracy: 0.9995 - val_loss: 0.0812 - val_accuracy: 0.9761
Epoch 122/250
accuracy: 0.9995 - val_loss: 0.0811 - val_accuracy: 0.9758
Epoch 123/250
accuracy: 0.9996 - val_loss: 0.0813 - val_accuracy: 0.9756
Epoch 124/250
accuracy: 0.9996 - val_loss: 0.0810 - val_accuracy: 0.9763
Epoch 125/250
accuracy: 0.9997 - val_loss: 0.0814 - val_accuracy: 0.9757
Epoch 126/250
675/675 [============ ] - 8s 12ms/step - loss: 0.0069 -
accuracy: 0.9997 - val_loss: 0.0817 - val_accuracy: 0.9760
Epoch 127/250
accuracy: 0.9997 - val_loss: 0.0814 - val_accuracy: 0.9762
Epoch 128/250
675/675 [============ ] - 7s 11ms/step - loss: 0.0067 -
accuracy: 0.9997 - val_loss: 0.0815 - val_accuracy: 0.9759
Epoch 129/250
675/675 [=========== ] - 7s 10ms/step - loss: 0.0066 -
accuracy: 0.9997 - val_loss: 0.0818 - val_accuracy: 0.9762
Epoch 130/250
accuracy: 0.9997 - val_loss: 0.0817 - val_accuracy: 0.9759
Epoch 131/250
accuracy: 0.9997 - val_loss: 0.0819 - val_accuracy: 0.9763
Epoch 132/250
accuracy: 0.9998 - val_loss: 0.0820 - val_accuracy: 0.9758
Epoch 133/250
accuracy: 0.9998 - val_loss: 0.0821 - val_accuracy: 0.9761
Epoch 134/250
accuracy: 0.9997 - val_loss: 0.0821 - val_accuracy: 0.9758
Epoch 135/250
accuracy: 0.9997 - val_loss: 0.0817 - val_accuracy: 0.9760
```

```
Epoch 136/250
accuracy: 0.9997 - val_loss: 0.0819 - val_accuracy: 0.9761
Epoch 137/250
accuracy: 0.9997 - val_loss: 0.0820 - val_accuracy: 0.9757
Epoch 138/250
accuracy: 0.9998 - val_loss: 0.0818 - val_accuracy: 0.9761
Epoch 139/250
675/675 [============= ] - 8s 12ms/step - loss: 0.0056 -
accuracy: 0.9998 - val_loss: 0.0819 - val_accuracy: 0.9765
Epoch 140/250
accuracy: 0.9997 - val_loss: 0.0820 - val_accuracy: 0.9761
Epoch 141/250
675/675 [============ ] - 8s 12ms/step - loss: 0.0054 -
accuracy: 0.9998 - val_loss: 0.0820 - val_accuracy: 0.9760
Epoch 142/250
accuracy: 0.9998 - val_loss: 0.0823 - val_accuracy: 0.9761
Epoch 143/250
accuracy: 0.9998 - val_loss: 0.0825 - val_accuracy: 0.9761
Epoch 144/250
675/675 [============ ] - 8s 12ms/step - loss: 0.0051 -
accuracy: 0.9999 - val_loss: 0.0826 - val_accuracy: 0.9757
Epoch 145/250
accuracy: 0.9998 - val_loss: 0.0826 - val_accuracy: 0.9760
Epoch 146/250
675/675 [============= ] - 8s 12ms/step - loss: 0.0050 -
accuracy: 0.9999 - val_loss: 0.0824 - val_accuracy: 0.9759
Epoch 147/250
accuracy: 0.9999 - val_loss: 0.0826 - val_accuracy: 0.9764
Epoch 148/250
accuracy: 0.9999 - val_loss: 0.0826 - val_accuracy: 0.9761
Epoch 149/250
accuracy: 0.9999 - val_loss: 0.0828 - val_accuracy: 0.9758
Epoch 150/250
accuracy: 0.9999 - val_loss: 0.0829 - val_accuracy: 0.9760
Epoch 151/250
accuracy: 0.9999 - val_loss: 0.0828 - val_accuracy: 0.9761
```

```
Epoch 152/250
675/675 [============== ] - 8s 12ms/step - loss: 0.0045 -
accuracy: 0.9999 - val_loss: 0.0830 - val_accuracy: 0.9756
Epoch 153/250
accuracy: 0.9999 - val_loss: 0.0831 - val_accuracy: 0.9760
Epoch 154/250
accuracy: 0.9999 - val_loss: 0.0833 - val_accuracy: 0.9761
Epoch 155/250
accuracy: 0.9999 - val_loss: 0.0833 - val_accuracy: 0.9758
Epoch 156/250
675/675 [=========== ] - 8s 12ms/step - loss: 0.0043 -
accuracy: 0.9999 - val_loss: 0.0832 - val_accuracy: 0.9759
Epoch 157/250
675/675 [===========] - 6s 9ms/step - loss: 0.0042 -
accuracy: 0.9999 - val_loss: 0.0831 - val_accuracy: 0.9763
Epoch 158/250
675/675 [============ ] - 8s 11ms/step - loss: 0.0042 -
accuracy: 0.9999 - val_loss: 0.0835 - val_accuracy: 0.9760
Epoch 159/250
675/675 [============= ] - 6s 10ms/step - loss: 0.0041 -
accuracy: 0.9999 - val_loss: 0.0834 - val_accuracy: 0.9761
Epoch 160/250
675/675 [============ ] - 7s 10ms/step - loss: 0.0041 -
accuracy: 0.9999 - val_loss: 0.0836 - val_accuracy: 0.9762
Epoch 161/250
675/675 [=========== ] - 7s 10ms/step - loss: 0.0040 -
accuracy: 0.9999 - val_loss: 0.0836 - val_accuracy: 0.9761
Epoch 162/250
675/675 [============= ] - 7s 10ms/step - loss: 0.0040 -
accuracy: 0.9999 - val_loss: 0.0834 - val_accuracy: 0.9759
Epoch 163/250
675/675 [============= ] - 7s 11ms/step - loss: 0.0039 -
accuracy: 0.9999 - val_loss: 0.0837 - val_accuracy: 0.9761
Epoch 164/250
675/675 [============= ] - 7s 10ms/step - loss: 0.0039 -
accuracy: 1.0000 - val_loss: 0.0839 - val_accuracy: 0.9761
Epoch 165/250
accuracy: 0.9999 - val_loss: 0.0835 - val_accuracy: 0.9756
Epoch 166/250
675/675 [=========== ] - 7s 10ms/step - loss: 0.0038 -
accuracy: 1.0000 - val_loss: 0.0838 - val_accuracy: 0.9761
Epoch 167/250
accuracy: 0.9999 - val_loss: 0.0838 - val_accuracy: 0.9763
```

```
Epoch 168/250
675/675 [============= ] - 7s 10ms/step - loss: 0.0037 -
accuracy: 1.0000 - val_loss: 0.0841 - val_accuracy: 0.9760
Epoch 169/250
675/675 [============= ] - 7s 11ms/step - loss: 0.0036 -
accuracy: 1.0000 - val_loss: 0.0842 - val_accuracy: 0.9763
Epoch 170/250
accuracy: 1.0000 - val_loss: 0.0845 - val_accuracy: 0.9756
Epoch 171/250
675/675 [============= ] - 8s 12ms/step - loss: 0.0035 -
accuracy: 1.0000 - val_loss: 0.0844 - val_accuracy: 0.9763
Epoch 172/250
accuracy: 1.0000 - val_loss: 0.0841 - val_accuracy: 0.9760
Epoch 173/250
675/675 [============ ] - 8s 12ms/step - loss: 0.0034 -
accuracy: 1.0000 - val_loss: 0.0845 - val_accuracy: 0.9757
Epoch 174/250
accuracy: 1.0000 - val_loss: 0.0846 - val_accuracy: 0.9762
Epoch 175/250
675/675 [============= ] - 8s 12ms/step - loss: 0.0033 -
accuracy: 1.0000 - val_loss: 0.0848 - val_accuracy: 0.9761
Epoch 176/250
675/675 [============ ] - 6s 9ms/step - loss: 0.0033 -
accuracy: 1.0000 - val_loss: 0.0844 - val_accuracy: 0.9757
Epoch 177/250
675/675 [=========== ] - 8s 12ms/step - loss: 0.0033 -
accuracy: 1.0000 - val_loss: 0.0847 - val_accuracy: 0.9761
Epoch 178/250
accuracy: 1.0000 - val_loss: 0.0846 - val_accuracy: 0.9761
Epoch 179/250
675/675 [============= ] - 8s 12ms/step - loss: 0.0032 -
accuracy: 1.0000 - val_loss: 0.0845 - val_accuracy: 0.9761
Epoch 180/250
accuracy: 1.0000 - val_loss: 0.0849 - val_accuracy: 0.9760
Epoch 181/250
675/675 [============== ] - 8s 13ms/step - loss: 0.0031 -
accuracy: 1.0000 - val_loss: 0.0848 - val_accuracy: 0.9763
Epoch 182/250
accuracy: 1.0000 - val_loss: 0.0849 - val_accuracy: 0.9757
Epoch 183/250
accuracy: 1.0000 - val_loss: 0.0850 - val_accuracy: 0.9757
```

```
Epoch 184/250
accuracy: 1.0000 - val_loss: 0.0851 - val_accuracy: 0.9758
Epoch 185/250
675/675 [============= ] - 7s 11ms/step - loss: 0.0030 -
accuracy: 1.0000 - val_loss: 0.0851 - val_accuracy: 0.9760
Epoch 186/250
accuracy: 1.0000 - val_loss: 0.0850 - val_accuracy: 0.9761
Epoch 187/250
675/675 [============ ] - 8s 11ms/step - loss: 0.0029 -
accuracy: 1.0000 - val_loss: 0.0851 - val_accuracy: 0.9761
Epoch 188/250
accuracy: 1.0000 - val_loss: 0.0850 - val_accuracy: 0.9761
Epoch 189/250
675/675 [============= ] - 8s 12ms/step - loss: 0.0029 -
accuracy: 1.0000 - val_loss: 0.0855 - val_accuracy: 0.9761
Epoch 190/250
675/675 [============ ] - 7s 10ms/step - loss: 0.0028 -
accuracy: 1.0000 - val_loss: 0.0853 - val_accuracy: 0.9761
Epoch 191/250
675/675 [============= ] - 7s 11ms/step - loss: 0.0028 -
accuracy: 1.0000 - val_loss: 0.0853 - val_accuracy: 0.9758
Epoch 192/250
675/675 [============ ] - 7s 10ms/step - loss: 0.0028 -
accuracy: 1.0000 - val_loss: 0.0854 - val_accuracy: 0.9763
Epoch 193/250
675/675 [=========== ] - 7s 10ms/step - loss: 0.0028 -
accuracy: 1.0000 - val_loss: 0.0857 - val_accuracy: 0.9757
Epoch 194/250
accuracy: 1.0000 - val_loss: 0.0856 - val_accuracy: 0.9761
Epoch 195/250
accuracy: 1.0000 - val_loss: 0.0856 - val_accuracy: 0.9761
Epoch 196/250
675/675 [============= ] - 7s 11ms/step - loss: 0.0027 -
accuracy: 1.0000 - val_loss: 0.0857 - val_accuracy: 0.9762
Epoch 197/250
accuracy: 1.0000 - val_loss: 0.0856 - val_accuracy: 0.9765
Epoch 198/250
accuracy: 1.0000 - val_loss: 0.0859 - val_accuracy: 0.9764
Epoch 199/250
accuracy: 1.0000 - val_loss: 0.0859 - val_accuracy: 0.9763
```

```
Epoch 200/250
accuracy: 1.0000 - val_loss: 0.0860 - val_accuracy: 0.9758
Epoch 201/250
accuracy: 1.0000 - val_loss: 0.0861 - val_accuracy: 0.9759
Epoch 202/250
accuracy: 1.0000 - val_loss: 0.0859 - val_accuracy: 0.9768
Epoch 203/250
accuracy: 1.0000 - val_loss: 0.0863 - val_accuracy: 0.9761
Epoch 204/250
accuracy: 1.0000 - val_loss: 0.0861 - val_accuracy: 0.9760
Epoch 205/250
675/675 [===========] - 6s 9ms/step - loss: 0.0024 -
accuracy: 1.0000 - val_loss: 0.0862 - val_accuracy: 0.9765
Epoch 206/250
675/675 [=========== ] - 8s 12ms/step - loss: 0.0024 -
accuracy: 1.0000 - val_loss: 0.0865 - val_accuracy: 0.9765
Epoch 207/250
675/675 [============= ] - 8s 12ms/step - loss: 0.0024 -
accuracy: 1.0000 - val_loss: 0.0863 - val_accuracy: 0.9762
Epoch 208/250
675/675 [============ ] - 8s 12ms/step - loss: 0.0024 -
accuracy: 1.0000 - val_loss: 0.0863 - val_accuracy: 0.9762
Epoch 209/250
accuracy: 1.0000 - val_loss: 0.0863 - val_accuracy: 0.9761
Epoch 210/250
accuracy: 1.0000 - val_loss: 0.0864 - val_accuracy: 0.9761
Epoch 211/250
accuracy: 1.0000 - val_loss: 0.0865 - val_accuracy: 0.9765
Epoch 212/250
accuracy: 1.0000 - val_loss: 0.0866 - val_accuracy: 0.9763
Epoch 213/250
accuracy: 1.0000 - val_loss: 0.0868 - val_accuracy: 0.9763
Epoch 214/250
accuracy: 1.0000 - val_loss: 0.0866 - val_accuracy: 0.9766
Epoch 215/250
accuracy: 1.0000 - val_loss: 0.0867 - val_accuracy: 0.9763
```

```
Epoch 216/250
675/675 [============= ] - 8s 11ms/step - loss: 0.0022 -
accuracy: 1.0000 - val_loss: 0.0867 - val_accuracy: 0.9764
Epoch 217/250
675/675 [============= ] - 7s 10ms/step - loss: 0.0022 -
accuracy: 1.0000 - val_loss: 0.0868 - val_accuracy: 0.9763
Epoch 218/250
accuracy: 1.0000 - val_loss: 0.0871 - val_accuracy: 0.9762
Epoch 219/250
accuracy: 1.0000 - val_loss: 0.0872 - val_accuracy: 0.9764
Epoch 220/250
accuracy: 1.0000 - val_loss: 0.0872 - val_accuracy: 0.9763
Epoch 221/250
675/675 [============ ] - 7s 11ms/step - loss: 0.0021 -
accuracy: 1.0000 - val_loss: 0.0870 - val_accuracy: 0.9764
Epoch 222/250
675/675 [============ ] - 7s 10ms/step - loss: 0.0021 -
accuracy: 1.0000 - val_loss: 0.0870 - val_accuracy: 0.9764
Epoch 223/250
675/675 [============= ] - 8s 11ms/step - loss: 0.0021 -
accuracy: 1.0000 - val_loss: 0.0872 - val_accuracy: 0.9767
Epoch 224/250
675/675 [============ ] - 6s 9ms/step - loss: 0.0021 -
accuracy: 1.0000 - val_loss: 0.0872 - val_accuracy: 0.9766
Epoch 225/250
675/675 [=========== ] - 8s 12ms/step - loss: 0.0020 -
accuracy: 1.0000 - val_loss: 0.0874 - val_accuracy: 0.9769
Epoch 226/250
accuracy: 1.0000 - val_loss: 0.0876 - val_accuracy: 0.9760
Epoch 227/250
accuracy: 1.0000 - val_loss: 0.0874 - val_accuracy: 0.9765
Epoch 228/250
accuracy: 1.0000 - val_loss: 0.0875 - val_accuracy: 0.9763
Epoch 229/250
accuracy: 1.0000 - val_loss: 0.0875 - val_accuracy: 0.9765
Epoch 230/250
accuracy: 1.0000 - val_loss: 0.0875 - val_accuracy: 0.9764
Epoch 231/250
accuracy: 1.0000 - val_loss: 0.0876 - val_accuracy: 0.9764
```

```
Epoch 232/250
accuracy: 1.0000 - val_loss: 0.0877 - val_accuracy: 0.9765
Epoch 233/250
675/675 [============= ] - 8s 11ms/step - loss: 0.0019 -
accuracy: 1.0000 - val_loss: 0.0879 - val_accuracy: 0.9764
Epoch 234/250
accuracy: 1.0000 - val_loss: 0.0877 - val_accuracy: 0.9764
Epoch 235/250
675/675 [============== ] - 8s 11ms/step - loss: 0.0019 -
accuracy: 1.0000 - val_loss: 0.0878 - val_accuracy: 0.9763
Epoch 236/250
accuracy: 1.0000 - val_loss: 0.0879 - val_accuracy: 0.9764
Epoch 237/250
675/675 [============ ] - 7s 11ms/step - loss: 0.0019 -
accuracy: 1.0000 - val_loss: 0.0879 - val_accuracy: 0.9763
Epoch 238/250
675/675 [============ ] - 7s 10ms/step - loss: 0.0018 -
accuracy: 1.0000 - val_loss: 0.0880 - val_accuracy: 0.9765
Epoch 239/250
accuracy: 1.0000 - val_loss: 0.0881 - val_accuracy: 0.9765
Epoch 240/250
675/675 [============ ] - 7s 10ms/step - loss: 0.0018 -
accuracy: 1.0000 - val_loss: 0.0879 - val_accuracy: 0.9767
Epoch 241/250
accuracy: 1.0000 - val_loss: 0.0881 - val_accuracy: 0.9765
Epoch 242/250
675/675 [============= ] - 8s 11ms/step - loss: 0.0018 -
accuracy: 1.0000 - val_loss: 0.0882 - val_accuracy: 0.9769
Epoch 243/250
accuracy: 1.0000 - val_loss: 0.0883 - val_accuracy: 0.9765
Epoch 244/250
accuracy: 1.0000 - val_loss: 0.0883 - val_accuracy: 0.9763
Epoch 245/250
accuracy: 1.0000 - val_loss: 0.0883 - val_accuracy: 0.9765
Epoch 246/250
accuracy: 1.0000 - val_loss: 0.0884 - val_accuracy: 0.9763
Epoch 247/250
accuracy: 1.0000 - val_loss: 0.0885 - val_accuracy: 0.9766
```

```
Epoch 248/250 675/675 [=====
```

accuracy: 1.0000 - val_loss: 0.0885 - val_accuracy: 0.9766

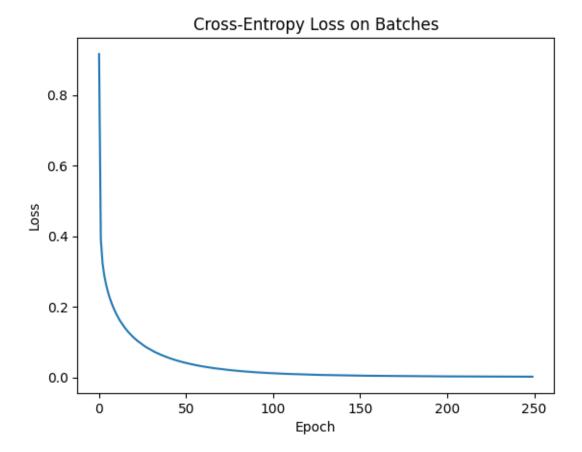
Epoch 249/250

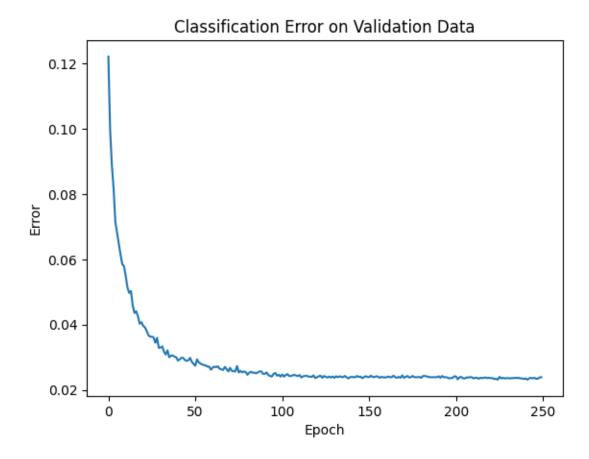
675/675 [=============] - 6s 9ms/step - loss: 0.0017 -

accuracy: 1.0000 - val_loss: 0.0888 - val_accuracy: 0.9762

Epoch 250/250

accuracy: 1.0000 - val_loss: 0.0885 - val_accuracy: 0.9761





Test Accuracy: 0.9799000024795532

In this experiment, we constructed a three-layer neural network with a higher number of neurons in each layer compared to previous models. We also increased the training duration to 250 epochs.

After training the model, we obtained 100% accuracy while training and test accuracy of 97.99%, indicating that it was able to perfectly fit the training data. This exceptional performance suggests that the model had sufficient capacity to capture the complex patterns present in the training dataset. Also this 100% accuracy waqs acheivable due to simplicity of the data and actually it was achieved by 170 epochs only.

Furthermore, the model achieved an accuracy of 97.6% on the validation set. This result demonstrates that the model generalized well to unseen data, as it performed with high accuracy on samples it had not been exposed to during training. This validates the model's ability to capture the underlying patterns in the data and make accurate predictions.

For the purpose of comparison, we employed the SGD optimizer with a learning rate of 0.01 and a batch size of 64, consistent with the previous questions. This allows us to evaluate the impact of the increased model complexity and training duration while keeping other factors constant.

4 Que 4:

Repeat Question #3 but train the network with the following regularizations:

L2-norm, dropout, and early-stopping. Compare with the results of Question #3.

Comments: No need to implement them by your own (this is true in general); the software framework (ie, the DL platform) typically provides implementations for all the regularizations methods discussed in class. Early stopping is done in training, so you only need to tune your training code slightly.

```
[]: from tensorflow.keras.layers import Dense, Dropout
     from tensorflow.keras.callbacks import EarlyStopping
     # Define the three-layer feedforward neural network with regularizations
     model = Sequential()
     model.add(Dense(500, activation='relu', input_shape=(784,),_
      →kernel_regularizer='12'))
    model.add(Dropout(0.5))
     model.add(Dense(500, activation='relu', kernel_regularizer='12'))
     model.add(Dropout(0.5))
     model.add(Dense(10, activation='sigmoid'))
     # Compile the model
     model.compile(loss='categorical_crossentropy', optimizer=SGD(learning_rate=0.
      ⇔01), metrics=['accuracy'])
     # Define early stopping callback
     early_stopping = EarlyStopping(monitor='val_loss', patience=10)
     # Train the model with regularizations and early stopping
     history = model.fit(x_train, y_train, batch_size=64, epochs=250,__
      ⇔validation_split=0.2, callbacks=[early_stopping], verbose=1)
     # Evaluate the model on the testing set
     _, test_accuracy = model.evaluate(x_test, y_test, verbose=0)
     print("\n")
     # Plot the cross-entropy loss on the batches
     plt.plot(history.history['loss'])
     plt.title('Cross-Entropy Loss on Batches (with Regularizations)')
     plt.xlabel('Epoch')
     plt.ylabel('Loss')
     plt.show()
     print("\n")
     # Plot the classification error on the validation data
     plt.plot(1 - np.array(history.history['val_accuracy']))
```

```
plt.title('Classification Error on Validation Data (with Regularizations)')
plt.xlabel('Epoch')
plt.ylabel('Error')
plt.show()
print("\n\n")
# Print the test accuracy
print(f'Test Accuracy: {test_accuracy}')
Epoch 1/250
accuracy: 0.5968 - val_loss: 9.1323 - val_accuracy: 0.8585
Epoch 2/250
accuracy: 0.8062 - val_loss: 7.0144 - val_accuracy: 0.8893
Epoch 3/250
accuracy: 0.8498 - val_loss: 5.4540 - val_accuracy: 0.9004
Epoch 4/250
accuracy: 0.8682 - val_loss: 4.2735 - val_accuracy: 0.9064
Epoch 5/250
675/675 [============] - 8s 12ms/step - loss: 3.9040 -
accuracy: 0.8798 - val_loss: 3.3728 - val_accuracy: 0.9111
Epoch 6/250
675/675 [============= ] - 8s 12ms/step - loss: 3.1057 -
accuracy: 0.8882 - val_loss: 2.6870 - val_accuracy: 0.9156
Epoch 7/250
accuracy: 0.8929 - val_loss: 2.1638 - val_accuracy: 0.9194
Epoch 8/250
accuracy: 0.8994 - val_loss: 1.7635 - val_accuracy: 0.9217
Epoch 9/250
accuracy: 0.9025 - val_loss: 1.4568 - val_accuracy: 0.9227
Epoch 10/250
accuracy: 0.9066 - val_loss: 1.2230 - val_accuracy: 0.9253
Epoch 11/250
675/675 [=========== ] - 10s 15ms/step - loss: 1.1903 -
accuracy: 0.9090 - val_loss: 1.0430 - val_accuracy: 0.9273
Epoch 12/250
675/675 [============= ] - 7s 11ms/step - loss: 1.0329 -
accuracy: 0.9110 - val loss: 0.9052 - val accuracy: 0.9297
Epoch 13/250
```

```
accuracy: 0.9140 - val_loss: 0.7981 - val_accuracy: 0.9324
Epoch 14/250
accuracy: 0.9141 - val_loss: 0.7166 - val_accuracy: 0.9319
Epoch 15/250
accuracy: 0.9184 - val_loss: 0.6525 - val_accuracy: 0.9340
Epoch 16/250
675/675 [============= ] - 9s 13ms/step - loss: 0.6809 -
accuracy: 0.9182 - val_loss: 0.6043 - val_accuracy: 0.9340
Epoch 17/250
675/675 [============ ] - 7s 11ms/step - loss: 0.6333 -
accuracy: 0.9211 - val_loss: 0.5639 - val_accuracy: 0.9369
Epoch 18/250
accuracy: 0.9223 - val_loss: 0.5338 - val_accuracy: 0.9387
Epoch 19/250
675/675 [=========== ] - 7s 11ms/step - loss: 0.5680 -
accuracy: 0.9248 - val_loss: 0.5128 - val_accuracy: 0.9344
Epoch 20/250
accuracy: 0.9254 - val_loss: 0.4891 - val_accuracy: 0.9395
Epoch 21/250
accuracy: 0.9258 - val_loss: 0.4750 - val_accuracy: 0.9396
Epoch 22/250
accuracy: 0.9266 - val_loss: 0.4614 - val_accuracy: 0.9409
accuracy: 0.9277 - val_loss: 0.4509 - val_accuracy: 0.9408
Epoch 24/250
675/675 [============= ] - 7s 11ms/step - loss: 0.4897 -
accuracy: 0.9293 - val_loss: 0.4420 - val_accuracy: 0.9418
Epoch 25/250
accuracy: 0.9306 - val loss: 0.4334 - val accuracy: 0.9444
Epoch 26/250
accuracy: 0.9314 - val_loss: 0.4277 - val_accuracy: 0.9439
Epoch 27/250
675/675 [============ ] - 10s 15ms/step - loss: 0.4684 -
accuracy: 0.9311 - val_loss: 0.4221 - val_accuracy: 0.9449
Epoch 28/250
accuracy: 0.9312 - val_loss: 0.4172 - val_accuracy: 0.9445
Epoch 29/250
```

```
accuracy: 0.9322 - val_loss: 0.4123 - val_accuracy: 0.9452
Epoch 30/250
accuracy: 0.9337 - val_loss: 0.4084 - val_accuracy: 0.9464
Epoch 31/250
accuracy: 0.9337 - val_loss: 0.4058 - val_accuracy: 0.9463
Epoch 32/250
675/675 [============= ] - 9s 13ms/step - loss: 0.4439 -
accuracy: 0.9346 - val_loss: 0.4018 - val_accuracy: 0.9463
Epoch 33/250
675/675 [=========== ] - 8s 12ms/step - loss: 0.4433 -
accuracy: 0.9354 - val_loss: 0.3992 - val_accuracy: 0.9476
Epoch 34/250
accuracy: 0.9362 - val_loss: 0.3953 - val_accuracy: 0.9469
Epoch 35/250
accuracy: 0.9377 - val_loss: 0.3931 - val_accuracy: 0.9480
Epoch 36/250
675/675 [============= ] - 8s 11ms/step - loss: 0.4321 -
accuracy: 0.9372 - val_loss: 0.3931 - val_accuracy: 0.9469
Epoch 37/250
accuracy: 0.9382 - val_loss: 0.3895 - val_accuracy: 0.9473
Epoch 38/250
675/675 [============= ] - 7s 11ms/step - loss: 0.4264 -
accuracy: 0.9381 - val_loss: 0.3849 - val_accuracy: 0.9508
accuracy: 0.9383 - val_loss: 0.3838 - val_accuracy: 0.9501
Epoch 40/250
accuracy: 0.9392 - val_loss: 0.3814 - val_accuracy: 0.9511
Epoch 41/250
accuracy: 0.9398 - val loss: 0.3792 - val accuracy: 0.9503
Epoch 42/250
accuracy: 0.9406 - val_loss: 0.3778 - val_accuracy: 0.9503
Epoch 43/250
accuracy: 0.9401 - val_loss: 0.3771 - val_accuracy: 0.9497
Epoch 44/250
accuracy: 0.9413 - val_loss: 0.3733 - val_accuracy: 0.9517
Epoch 45/250
```

```
accuracy: 0.9417 - val_loss: 0.3720 - val_accuracy: 0.9503
Epoch 46/250
accuracy: 0.9414 - val_loss: 0.3699 - val_accuracy: 0.9525
Epoch 47/250
675/675 [============= ] - 7s 11ms/step - loss: 0.4062 -
accuracy: 0.9423 - val_loss: 0.3673 - val_accuracy: 0.9515
Epoch 48/250
675/675 [============ ] - 9s 13ms/step - loss: 0.4031 -
accuracy: 0.9436 - val_loss: 0.3670 - val_accuracy: 0.9512
Epoch 49/250
675/675 [============= ] - 8s 12ms/step - loss: 0.4026 -
accuracy: 0.9431 - val_loss: 0.3651 - val_accuracy: 0.9524
Epoch 50/250
675/675 [============= ] - 8s 12ms/step - loss: 0.3986 -
accuracy: 0.9443 - val_loss: 0.3644 - val_accuracy: 0.9519
Epoch 51/250
675/675 [============ ] - 9s 14ms/step - loss: 0.3991 -
accuracy: 0.9433 - val_loss: 0.3628 - val_accuracy: 0.9527
Epoch 52/250
accuracy: 0.9444 - val_loss: 0.3617 - val_accuracy: 0.9519
Epoch 53/250
675/675 [============= ] - 12s 17ms/step - loss: 0.3963 -
accuracy: 0.9440 - val_loss: 0.3591 - val_accuracy: 0.9536
Epoch 54/250
accuracy: 0.9445 - val_loss: 0.3579 - val_accuracy: 0.9542
675/675 [============= ] - 7s 11ms/step - loss: 0.3915 -
accuracy: 0.9452 - val_loss: 0.3556 - val_accuracy: 0.9544
Epoch 56/250
accuracy: 0.9454 - val_loss: 0.3558 - val_accuracy: 0.9526
Epoch 57/250
675/675 [============= ] - 8s 11ms/step - loss: 0.3901 -
accuracy: 0.9443 - val loss: 0.3538 - val accuracy: 0.9538
Epoch 58/250
accuracy: 0.9460 - val_loss: 0.3522 - val_accuracy: 0.9551
Epoch 59/250
accuracy: 0.9455 - val_loss: 0.3507 - val_accuracy: 0.9551
Epoch 60/250
accuracy: 0.9455 - val_loss: 0.3509 - val_accuracy: 0.9533
Epoch 61/250
675/675 [=========== ] - 10s 15ms/step - loss: 0.3845 -
```

```
accuracy: 0.9471 - val_loss: 0.3498 - val_accuracy: 0.9553
Epoch 62/250
accuracy: 0.9472 - val_loss: 0.3484 - val_accuracy: 0.9556
Epoch 63/250
accuracy: 0.9468 - val_loss: 0.3466 - val_accuracy: 0.9543
Epoch 64/250
accuracy: 0.9473 - val_loss: 0.3470 - val_accuracy: 0.9542
Epoch 65/250
675/675 [=========== ] - 9s 14ms/step - loss: 0.3799 -
accuracy: 0.9457 - val_loss: 0.3454 - val_accuracy: 0.9556
Epoch 66/250
675/675 [============= ] - 8s 12ms/step - loss: 0.3765 -
accuracy: 0.9474 - val_loss: 0.3439 - val_accuracy: 0.9545
Epoch 67/250
675/675 [=========== ] - 8s 12ms/step - loss: 0.3769 -
accuracy: 0.9462 - val_loss: 0.3421 - val_accuracy: 0.9556
Epoch 68/250
accuracy: 0.9480 - val_loss: 0.3414 - val_accuracy: 0.9557
Epoch 69/250
accuracy: 0.9474 - val_loss: 0.3404 - val_accuracy: 0.9567
Epoch 70/250
accuracy: 0.9483 - val_loss: 0.3399 - val_accuracy: 0.9557
675/675 [============= ] - 8s 11ms/step - loss: 0.3710 -
accuracy: 0.9479 - val_loss: 0.3387 - val_accuracy: 0.9573
Epoch 72/250
accuracy: 0.9481 - val_loss: 0.3388 - val_accuracy: 0.9567
Epoch 73/250
675/675 [============ ] - 8s 11ms/step - loss: 0.3699 -
accuracy: 0.9488 - val loss: 0.3374 - val accuracy: 0.9555
Epoch 74/250
accuracy: 0.9489 - val_loss: 0.3358 - val_accuracy: 0.9567
Epoch 75/250
675/675 [============= ] - 8s 13ms/step - loss: 0.3680 -
accuracy: 0.9485 - val_loss: 0.3357 - val_accuracy: 0.9570
Epoch 76/250
675/675 [============= ] - 8s 12ms/step - loss: 0.3682 -
accuracy: 0.9484 - val_loss: 0.3349 - val_accuracy: 0.9561
Epoch 77/250
```

```
accuracy: 0.9498 - val_loss: 0.3343 - val_accuracy: 0.9562
Epoch 78/250
accuracy: 0.9489 - val_loss: 0.3313 - val_accuracy: 0.9570
Epoch 79/250
accuracy: 0.9497 - val_loss: 0.3312 - val_accuracy: 0.9575
Epoch 80/250
accuracy: 0.9498 - val_loss: 0.3307 - val_accuracy: 0.9580
Epoch 81/250
675/675 [============= ] - 8s 11ms/step - loss: 0.3616 -
accuracy: 0.9503 - val_loss: 0.3304 - val_accuracy: 0.9579
Epoch 82/250
accuracy: 0.9503 - val_loss: 0.3299 - val_accuracy: 0.9570
Epoch 83/250
accuracy: 0.9494 - val_loss: 0.3288 - val_accuracy: 0.9582
Epoch 84/250
accuracy: 0.9498 - val_loss: 0.3283 - val_accuracy: 0.9576
Epoch 85/250
accuracy: 0.9499 - val_loss: 0.3294 - val_accuracy: 0.9566
Epoch 86/250
accuracy: 0.9515 - val_loss: 0.3263 - val_accuracy: 0.9583
accuracy: 0.9498 - val_loss: 0.3253 - val_accuracy: 0.9587
Epoch 88/250
675/675 [============ ] - 8s 11ms/step - loss: 0.3581 -
accuracy: 0.9499 - val_loss: 0.3244 - val_accuracy: 0.9576
Epoch 89/250
accuracy: 0.9508 - val_loss: 0.3237 - val_accuracy: 0.9574
Epoch 90/250
accuracy: 0.9509 - val_loss: 0.3245 - val_accuracy: 0.9589
Epoch 91/250
accuracy: 0.9518 - val_loss: 0.3229 - val_accuracy: 0.9581
Epoch 92/250
accuracy: 0.9516 - val_loss: 0.3232 - val_accuracy: 0.9585
Epoch 93/250
```

```
accuracy: 0.9518 - val_loss: 0.3212 - val_accuracy: 0.9590
Epoch 94/250
accuracy: 0.9511 - val_loss: 0.3204 - val_accuracy: 0.9587
Epoch 95/250
accuracy: 0.9509 - val_loss: 0.3200 - val_accuracy: 0.9593
Epoch 96/250
675/675 [============ ] - 9s 13ms/step - loss: 0.3521 -
accuracy: 0.9513 - val_loss: 0.3183 - val_accuracy: 0.9585
Epoch 97/250
675/675 [============ ] - 8s 12ms/step - loss: 0.3472 -
accuracy: 0.9532 - val_loss: 0.3197 - val_accuracy: 0.9581
Epoch 98/250
accuracy: 0.9515 - val_loss: 0.3179 - val_accuracy: 0.9591
Epoch 99/250
675/675 [============= ] - 10s 14ms/step - loss: 0.3473 -
accuracy: 0.9518 - val_loss: 0.3173 - val_accuracy: 0.9593
Epoch 100/250
675/675 [============= ] - 7s 11ms/step - loss: 0.3499 -
accuracy: 0.9511 - val_loss: 0.3171 - val_accuracy: 0.9602
Epoch 101/250
accuracy: 0.9525 - val_loss: 0.3160 - val_accuracy: 0.9589
Epoch 102/250
accuracy: 0.9518 - val_loss: 0.3159 - val_accuracy: 0.9593
Epoch 103/250
accuracy: 0.9525 - val_loss: 0.3138 - val_accuracy: 0.9600
Epoch 104/250
accuracy: 0.9517 - val_loss: 0.3205 - val_accuracy: 0.9585
Epoch 105/250
675/675 [============= ] - 8s 12ms/step - loss: 0.3444 -
accuracy: 0.9526 - val loss: 0.3143 - val accuracy: 0.9594
Epoch 106/250
accuracy: 0.9518 - val_loss: 0.3125 - val_accuracy: 0.9606
Epoch 107/250
675/675 [============ ] - 7s 11ms/step - loss: 0.3419 -
accuracy: 0.9532 - val_loss: 0.3128 - val_accuracy: 0.9597
Epoch 108/250
675/675 [============= ] - 9s 13ms/step - loss: 0.3428 -
accuracy: 0.9529 - val_loss: 0.3128 - val_accuracy: 0.9589
Epoch 109/250
```

```
accuracy: 0.9534 - val_loss: 0.3110 - val_accuracy: 0.9603
Epoch 110/250
accuracy: 0.9532 - val_loss: 0.3104 - val_accuracy: 0.9597
Epoch 111/250
accuracy: 0.9539 - val_loss: 0.3102 - val_accuracy: 0.9601
Epoch 112/250
675/675 [============ ] - 10s 15ms/step - loss: 0.3399 -
accuracy: 0.9525 - val_loss: 0.3104 - val_accuracy: 0.9604
Epoch 113/250
675/675 [============ ] - 9s 14ms/step - loss: 0.3386 -
accuracy: 0.9535 - val_loss: 0.3089 - val_accuracy: 0.9606
Epoch 114/250
675/675 [============= ] - 7s 11ms/step - loss: 0.3385 -
accuracy: 0.9529 - val_loss: 0.3096 - val_accuracy: 0.9595
Epoch 115/250
675/675 [=========== ] - 9s 13ms/step - loss: 0.3384 -
accuracy: 0.9545 - val_loss: 0.3109 - val_accuracy: 0.9584
Epoch 116/250
accuracy: 0.9529 - val_loss: 0.3090 - val_accuracy: 0.9604
Epoch 117/250
accuracy: 0.9542 - val_loss: 0.3087 - val_accuracy: 0.9600
Epoch 118/250
accuracy: 0.9529 - val_loss: 0.3072 - val_accuracy: 0.9592
675/675 [============ ] - 8s 12ms/step - loss: 0.3358 -
accuracy: 0.9546 - val_loss: 0.3063 - val_accuracy: 0.9606
Epoch 120/250
accuracy: 0.9540 - val_loss: 0.3091 - val_accuracy: 0.9580
Epoch 121/250
accuracy: 0.9532 - val loss: 0.3067 - val accuracy: 0.9598
Epoch 122/250
accuracy: 0.9541 - val_loss: 0.3058 - val_accuracy: 0.9604
Epoch 123/250
675/675 [============ ] - 7s 11ms/step - loss: 0.3327 -
accuracy: 0.9545 - val_loss: 0.3074 - val_accuracy: 0.9590
Epoch 124/250
675/675 [============ ] - 9s 13ms/step - loss: 0.3334 -
accuracy: 0.9551 - val_loss: 0.3055 - val_accuracy: 0.9606
Epoch 125/250
```

```
accuracy: 0.9536 - val_loss: 0.3042 - val_accuracy: 0.9603
Epoch 126/250
675/675 [============= ] - 8s 12ms/step - loss: 0.3331 -
accuracy: 0.9538 - val_loss: 0.3047 - val_accuracy: 0.9604
Epoch 127/250
accuracy: 0.9551 - val_loss: 0.3028 - val_accuracy: 0.9607
Epoch 128/250
accuracy: 0.9551 - val_loss: 0.3022 - val_accuracy: 0.9613
Epoch 129/250
accuracy: 0.9548 - val_loss: 0.3018 - val_accuracy: 0.9622
Epoch 130/250
accuracy: 0.9556 - val_loss: 0.3028 - val_accuracy: 0.9613
Epoch 131/250
675/675 [============ ] - 8s 12ms/step - loss: 0.3295 -
accuracy: 0.9556 - val_loss: 0.3011 - val_accuracy: 0.9603
Epoch 132/250
675/675 [============ ] - 10s 15ms/step - loss: 0.3311 -
accuracy: 0.9542 - val_loss: 0.3002 - val_accuracy: 0.9619
Epoch 133/250
675/675 [============ ] - 12s 18ms/step - loss: 0.3308 -
accuracy: 0.9545 - val_loss: 0.2998 - val_accuracy: 0.9621
Epoch 134/250
accuracy: 0.9550 - val_loss: 0.2993 - val_accuracy: 0.9624
Epoch 135/250
accuracy: 0.9547 - val_loss: 0.2990 - val_accuracy: 0.9622
Epoch 136/250
675/675 [============ ] - 11s 16ms/step - loss: 0.3286 -
accuracy: 0.9550 - val_loss: 0.3001 - val_accuracy: 0.9618
Epoch 137/250
accuracy: 0.9552 - val_loss: 0.2987 - val_accuracy: 0.9616
Epoch 138/250
accuracy: 0.9557 - val_loss: 0.2971 - val_accuracy: 0.9630
Epoch 139/250
675/675 [============= ] - 10s 15ms/step - loss: 0.3276 -
accuracy: 0.9553 - val_loss: 0.2993 - val_accuracy: 0.9613
Epoch 140/250
accuracy: 0.9553 - val_loss: 0.2970 - val_accuracy: 0.9628
Epoch 141/250
```

```
accuracy: 0.9556 - val_loss: 0.2970 - val_accuracy: 0.9629
Epoch 142/250
accuracy: 0.9564 - val_loss: 0.2968 - val_accuracy: 0.9625
Epoch 143/250
accuracy: 0.9559 - val_loss: 0.2970 - val_accuracy: 0.9625
Epoch 144/250
accuracy: 0.9558 - val_loss: 0.2957 - val_accuracy: 0.9631
Epoch 145/250
675/675 [=========== ] - 8s 12ms/step - loss: 0.3236 -
accuracy: 0.9558 - val_loss: 0.2970 - val_accuracy: 0.9620
Epoch 146/250
675/675 [============= ] - 9s 14ms/step - loss: 0.3241 -
accuracy: 0.9557 - val_loss: 0.2976 - val_accuracy: 0.9619
Epoch 147/250
675/675 [=========== ] - 7s 11ms/step - loss: 0.3234 -
accuracy: 0.9557 - val_loss: 0.2950 - val_accuracy: 0.9627
Epoch 148/250
accuracy: 0.9553 - val_loss: 0.2947 - val_accuracy: 0.9629
Epoch 149/250
675/675 [============= ] - 8s 12ms/step - loss: 0.3237 -
accuracy: 0.9551 - val_loss: 0.2937 - val_accuracy: 0.9622
Epoch 150/250
accuracy: 0.9557 - val_loss: 0.2935 - val_accuracy: 0.9620
accuracy: 0.9567 - val_loss: 0.2928 - val_accuracy: 0.9624
Epoch 152/250
675/675 [============ ] - 8s 13ms/step - loss: 0.3200 -
accuracy: 0.9563 - val_loss: 0.2928 - val_accuracy: 0.9618
Epoch 153/250
accuracy: 0.9566 - val loss: 0.2921 - val accuracy: 0.9633
Epoch 154/250
accuracy: 0.9563 - val_loss: 0.2955 - val_accuracy: 0.9609
Epoch 155/250
accuracy: 0.9561 - val_loss: 0.2922 - val_accuracy: 0.9622
Epoch 156/250
675/675 [=========== ] - 14s 21ms/step - loss: 0.3197 -
accuracy: 0.9568 - val_loss: 0.2911 - val_accuracy: 0.9631
Epoch 157/250
675/675 [=========== ] - 10s 15ms/step - loss: 0.3194 -
```

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accuracy: 0.9567 - val_loss: 0.2903 - val_accuracy: 0.9631
Epoch 158/250
675/675 [============= ] - 8s 12ms/step - loss: 0.3183 -
accuracy: 0.9571 - val_loss: 0.2923 - val_accuracy: 0.9618
Epoch 159/250
accuracy: 0.9565 - val_loss: 0.2908 - val_accuracy: 0.9626
Epoch 160/250
accuracy: 0.9575 - val_loss: 0.2904 - val_accuracy: 0.9635
Epoch 161/250
675/675 [============= ] - 10s 15ms/step - loss: 0.3176 -
accuracy: 0.9577 - val_loss: 0.2902 - val_accuracy: 0.9624
Epoch 162/250
accuracy: 0.9572 - val_loss: 0.2918 - val_accuracy: 0.9614
Epoch 163/250
675/675 [============= ] - 12s 17ms/step - loss: 0.3162 -
accuracy: 0.9575 - val_loss: 0.2893 - val_accuracy: 0.9634
Epoch 164/250
accuracy: 0.9567 - val_loss: 0.2895 - val_accuracy: 0.9624
Epoch 165/250
accuracy: 0.9565 - val_loss: 0.2923 - val_accuracy: 0.9616
Epoch 166/250
675/675 [============ ] - 7s 11ms/step - loss: 0.3156 -
accuracy: 0.9568 - val_loss: 0.2889 - val_accuracy: 0.9639
accuracy: 0.9569 - val_loss: 0.2884 - val_accuracy: 0.9631
Epoch 168/250
accuracy: 0.9575 - val_loss: 0.2889 - val_accuracy: 0.9637
Epoch 169/250
675/675 [============= ] - 8s 12ms/step - loss: 0.3165 -
accuracy: 0.9559 - val loss: 0.2875 - val accuracy: 0.9635
Epoch 170/250
accuracy: 0.9563 - val_loss: 0.2883 - val_accuracy: 0.9630
Epoch 171/250
accuracy: 0.9567 - val_loss: 0.2889 - val_accuracy: 0.9634
Epoch 172/250
accuracy: 0.9573 - val_loss: 0.2879 - val_accuracy: 0.9634
Epoch 173/250
```

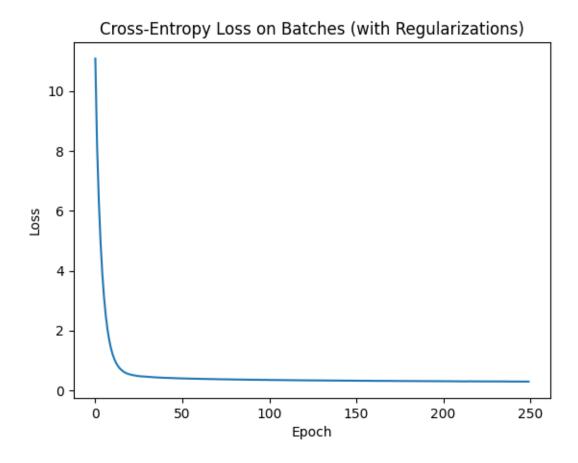
```
accuracy: 0.9563 - val_loss: 0.2869 - val_accuracy: 0.9631
Epoch 174/250
675/675 [============ ] - 10s 15ms/step - loss: 0.3125 -
accuracy: 0.9576 - val_loss: 0.2871 - val_accuracy: 0.9639
Epoch 175/250
accuracy: 0.9574 - val_loss: 0.2858 - val_accuracy: 0.9650
Epoch 176/250
675/675 [============= ] - 7s 11ms/step - loss: 0.3127 -
accuracy: 0.9579 - val_loss: 0.2856 - val_accuracy: 0.9640
Epoch 177/250
675/675 [============ ] - 9s 14ms/step - loss: 0.3112 -
accuracy: 0.9588 - val_loss: 0.2861 - val_accuracy: 0.9631
Epoch 178/250
675/675 [============== ] - 8s 12ms/step - loss: 0.3129 -
accuracy: 0.9566 - val_loss: 0.2871 - val_accuracy: 0.9632
Epoch 179/250
675/675 [============ ] - 9s 13ms/step - loss: 0.3110 -
accuracy: 0.9582 - val_loss: 0.2850 - val_accuracy: 0.9644
Epoch 180/250
accuracy: 0.9578 - val_loss: 0.2858 - val_accuracy: 0.9639
Epoch 181/250
accuracy: 0.9577 - val_loss: 0.2838 - val_accuracy: 0.9636
Epoch 182/250
accuracy: 0.9579 - val_loss: 0.2851 - val_accuracy: 0.9633
675/675 [============== ] - 8s 12ms/step - loss: 0.3086 -
accuracy: 0.9576 - val_loss: 0.2819 - val_accuracy: 0.9643
Epoch 184/250
accuracy: 0.9582 - val_loss: 0.2829 - val_accuracy: 0.9646
Epoch 185/250
accuracy: 0.9576 - val loss: 0.2828 - val accuracy: 0.9640
Epoch 186/250
accuracy: 0.9581 - val_loss: 0.2851 - val_accuracy: 0.9631
Epoch 187/250
accuracy: 0.9581 - val_loss: 0.2839 - val_accuracy: 0.9633
Epoch 188/250
accuracy: 0.9589 - val_loss: 0.2833 - val_accuracy: 0.9635
Epoch 189/250
675/675 [============ ] - 10s 15ms/step - loss: 0.3063 -
```

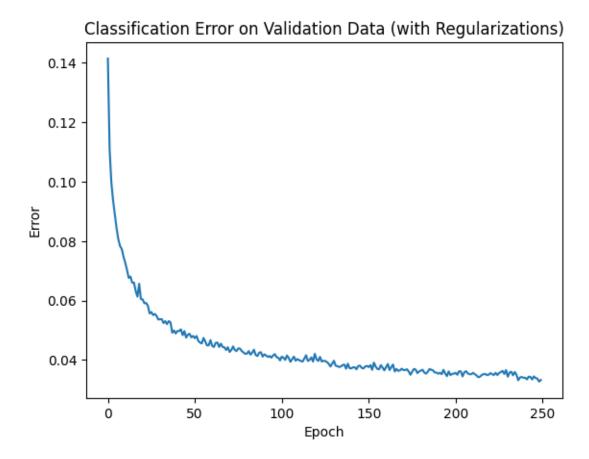
```
accuracy: 0.9590 - val_loss: 0.2813 - val_accuracy: 0.9643
Epoch 190/250
675/675 [=========== ] - 11s 17ms/step - loss: 0.3075 -
accuracy: 0.9591 - val_loss: 0.2805 - val_accuracy: 0.9643
Epoch 191/250
accuracy: 0.9579 - val_loss: 0.2812 - val_accuracy: 0.9646
Epoch 192/250
accuracy: 0.9587 - val_loss: 0.2815 - val_accuracy: 0.9644
Epoch 193/250
675/675 [=========== ] - 8s 11ms/step - loss: 0.3055 -
accuracy: 0.9595 - val_loss: 0.2802 - val_accuracy: 0.9648
Epoch 194/250
accuracy: 0.9581 - val_loss: 0.2805 - val_accuracy: 0.9633
Epoch 195/250
675/675 [=========== ] - 8s 12ms/step - loss: 0.3068 -
accuracy: 0.9584 - val_loss: 0.2797 - val_accuracy: 0.9645
Epoch 196/250
accuracy: 0.9588 - val_loss: 0.2790 - val_accuracy: 0.9655
Epoch 197/250
accuracy: 0.9594 - val_loss: 0.2794 - val_accuracy: 0.9639
Epoch 198/250
accuracy: 0.9578 - val_loss: 0.2802 - val_accuracy: 0.9651
Epoch 199/250
accuracy: 0.9586 - val_loss: 0.2791 - val_accuracy: 0.9647
Epoch 200/250
675/675 [============= ] - 7s 11ms/step - loss: 0.3061 -
accuracy: 0.9583 - val_loss: 0.2787 - val_accuracy: 0.9646
Epoch 201/250
accuracy: 0.9580 - val loss: 0.2790 - val accuracy: 0.9644
Epoch 202/250
accuracy: 0.9573 - val_loss: 0.2783 - val_accuracy: 0.9650
Epoch 203/250
accuracy: 0.9590 - val_loss: 0.2788 - val_accuracy: 0.9638
Epoch 204/250
675/675 [============= ] - 9s 13ms/step - loss: 0.3049 -
accuracy: 0.9580 - val_loss: 0.2800 - val_accuracy: 0.9639
Epoch 205/250
```

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accuracy: 0.9597 - val_loss: 0.2773 - val_accuracy: 0.9656
Epoch 206/250
675/675 [============ ] - 10s 15ms/step - loss: 0.3037 -
accuracy: 0.9588 - val_loss: 0.2770 - val_accuracy: 0.9642
Epoch 207/250
accuracy: 0.9596 - val_loss: 0.2798 - val_accuracy: 0.9638
Epoch 208/250
675/675 [============= ] - 9s 13ms/step - loss: 0.3021 -
accuracy: 0.9584 - val_loss: 0.2773 - val_accuracy: 0.9645
Epoch 209/250
675/675 [=========== ] - 9s 14ms/step - loss: 0.3021 -
accuracy: 0.9590 - val_loss: 0.2768 - val_accuracy: 0.9648
Epoch 210/250
accuracy: 0.9589 - val_loss: 0.2755 - val_accuracy: 0.9648
Epoch 211/250
675/675 [=========== ] - 9s 13ms/step - loss: 0.3023 -
accuracy: 0.9592 - val_loss: 0.2772 - val_accuracy: 0.9644
Epoch 212/250
675/675 [============ ] - 7s 11ms/step - loss: 0.3024 -
accuracy: 0.9583 - val_loss: 0.2766 - val_accuracy: 0.9648
Epoch 213/250
675/675 [============= ] - 9s 13ms/step - loss: 0.3019 -
accuracy: 0.9589 - val_loss: 0.2761 - val_accuracy: 0.9652
Epoch 214/250
accuracy: 0.9596 - val_loss: 0.2763 - val_accuracy: 0.9658
Epoch 215/250
675/675 [============= ] - 7s 11ms/step - loss: 0.2990 -
accuracy: 0.9608 - val_loss: 0.2750 - val_accuracy: 0.9656
Epoch 216/250
accuracy: 0.9590 - val_loss: 0.2753 - val_accuracy: 0.9651
Epoch 217/250
675/675 [============= ] - 7s 11ms/step - loss: 0.3005 -
accuracy: 0.9600 - val_loss: 0.2767 - val_accuracy: 0.9648
Epoch 218/250
accuracy: 0.9586 - val_loss: 0.2742 - val_accuracy: 0.9647
Epoch 219/250
675/675 [============= ] - 9s 13ms/step - loss: 0.2997 -
accuracy: 0.9597 - val_loss: 0.2747 - val_accuracy: 0.9651
Epoch 220/250
675/675 [============ ] - 8s 11ms/step - loss: 0.2990 -
accuracy: 0.9606 - val_loss: 0.2748 - val_accuracy: 0.9650
Epoch 221/250
```

```
accuracy: 0.9575 - val_loss: 0.2756 - val_accuracy: 0.9644
Epoch 222/250
accuracy: 0.9598 - val_loss: 0.2747 - val_accuracy: 0.9648
Epoch 223/250
accuracy: 0.9591 - val_loss: 0.2744 - val_accuracy: 0.9651
Epoch 224/250
675/675 [============ ] - 10s 15ms/step - loss: 0.2994 -
accuracy: 0.9597 - val_loss: 0.2746 - val_accuracy: 0.9644
Epoch 225/250
675/675 [============ ] - 7s 11ms/step - loss: 0.2996 -
accuracy: 0.9590 - val_loss: 0.2750 - val_accuracy: 0.9651
Epoch 226/250
accuracy: 0.9598 - val_loss: 0.2730 - val_accuracy: 0.9644
Epoch 227/250
675/675 [=========== ] - 8s 12ms/step - loss: 0.2975 -
accuracy: 0.9603 - val_loss: 0.2763 - val_accuracy: 0.9641
Epoch 228/250
accuracy: 0.9595 - val_loss: 0.2734 - val_accuracy: 0.9637
Epoch 229/250
675/675 [============ ] - 9s 13ms/step - loss: 0.2968 -
accuracy: 0.9602 - val_loss: 0.2732 - val_accuracy: 0.9647
Epoch 230/250
accuracy: 0.9603 - val_loss: 0.2732 - val_accuracy: 0.9634
accuracy: 0.9594 - val_loss: 0.2717 - val_accuracy: 0.9656
Epoch 232/250
accuracy: 0.9594 - val_loss: 0.2739 - val_accuracy: 0.9643
Epoch 233/250
accuracy: 0.9597 - val loss: 0.2731 - val accuracy: 0.9640
Epoch 234/250
accuracy: 0.9604 - val_loss: 0.2725 - val_accuracy: 0.9652
Epoch 235/250
675/675 [============ ] - 7s 11ms/step - loss: 0.2978 -
accuracy: 0.9596 - val_loss: 0.2731 - val_accuracy: 0.9641
Epoch 236/250
accuracy: 0.9592 - val_loss: 0.2719 - val_accuracy: 0.9650
Epoch 237/250
```

```
accuracy: 0.9607 - val_loss: 0.2700 - val_accuracy: 0.9669
Epoch 238/250
accuracy: 0.9597 - val_loss: 0.2708 - val_accuracy: 0.9659
Epoch 239/250
accuracy: 0.9602 - val_loss: 0.2706 - val_accuracy: 0.9657
Epoch 240/250
675/675 [============ ] - 8s 11ms/step - loss: 0.2953 -
accuracy: 0.9596 - val_loss: 0.2698 - val_accuracy: 0.9660
Epoch 241/250
accuracy: 0.9600 - val_loss: 0.2691 - val_accuracy: 0.9660
Epoch 242/250
675/675 [============ ] - 7s 11ms/step - loss: 0.2941 -
accuracy: 0.9599 - val_loss: 0.2693 - val_accuracy: 0.9666
Epoch 243/250
675/675 [============ ] - 9s 13ms/step - loss: 0.2919 -
accuracy: 0.9609 - val_loss: 0.2699 - val_accuracy: 0.9656
Epoch 244/250
accuracy: 0.9611 - val_loss: 0.2693 - val_accuracy: 0.9657
Epoch 245/250
accuracy: 0.9600 - val_loss: 0.2692 - val_accuracy: 0.9666
Epoch 246/250
accuracy: 0.9594 - val_loss: 0.2698 - val_accuracy: 0.9656
accuracy: 0.9613 - val_loss: 0.2702 - val_accuracy: 0.9661
Epoch 248/250
accuracy: 0.9606 - val_loss: 0.2689 - val_accuracy: 0.9663
Epoch 249/250
675/675 [============ ] - 9s 13ms/step - loss: 0.2944 -
accuracy: 0.9595 - val loss: 0.2690 - val accuracy: 0.9673
Epoch 250/250
accuracy: 0.9609 - val_loss: 0.2672 - val_accuracy: 0.9668
```





Test Accuracy: 0.9688000082969666

In this experiment, we incorporated additional techniques to prevent overfitting and enhance the performance of the model. Firstly, we applied dropout layers with a dropout rate of 0.5 after both hidden layers. Dropout is a regularization technique that randomly sets a fraction of the input units to zero during training, which helps prevent overfitting by reducing interdependencies between neurons.

Additionally, we implemented early stopping based on validation loss values. This technique monitors the validation loss during training and stops the training process if the validation loss does not improve after a certain number of epochs (patience value of 10, in this case). Early stopping helps prevent overfitting by stopping the training process before the model starts to memorize the training data.

We also continued to apply L2 regularization to further control overfitting.

The results of these modifications are promising. The training accuracy achieved was 96.09%, indicating that the model performed well on the training set while preventing overfitting. The final test accuracy of 96.88% indicates that the model generalized well to unseen data and maintained

a high level of accuracy.

By analyzing the plot, we observed a significant decrease in the classification error until around 50 epochs, suggesting that the model quickly learned relevant patterns and improved its performance. After this point, the learning process gradually converged, resulting in a slower decrease in classification error.

In summary, the incorporation of dropout layers, early stopping, and L2 regularization helped control overfitting and improve the model's performance. The achieved accuracy on both training and test sets indicates the model's ability to generalize well and make accurate predictions on unseen data. The plot demonstrates the learning progression, with a significant reduction in classification error followed by a gradual convergence.

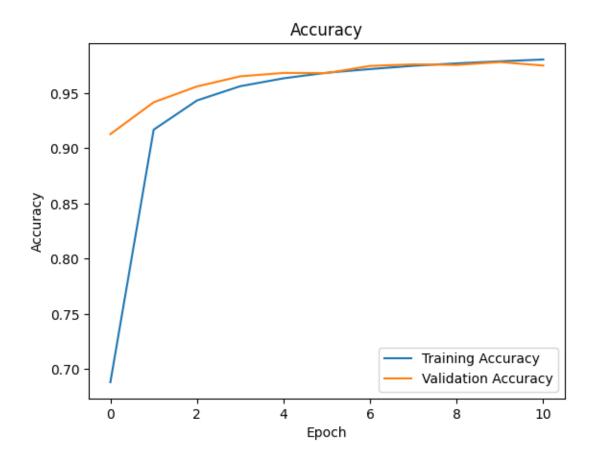
5 Que 5:

Try CNN (convolutional neural networks) on MNIST (or CIFAR or any dataset of your choice). Use the basic minibatch SGD as your learning algorithm, with or without regularizations. You may need to read Chapter-7, Chapter-8 and Chapter-9.

```
[22]: from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense
      # Preprocess the dataset
      x_train = train_images.reshape(-1, 28, 28, 1)
      x_{test} = test_{images.reshape}(-1, 28, 28, 1)
      # Convert labels to categorical
      y_train = tf.keras.utils.to_categorical(train_labels, num_classes=10)
      y_test = tf.keras.utils.to_categorical(test_labels, num_classes=10)
      # Define the CNN architecture
      model = Sequential()
      model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))
      model.add(MaxPooling2D((2, 2)))
      model.add(Conv2D(64, (3, 3), activation='relu'))
      model.add(MaxPooling2D((2, 2)))
      model.add(Flatten())
      model.add(Dense(64, activation='relu'))
      model.add(Dense(10, activation='sigmoid'))
      # Compile the model
      model.compile(loss='categorical crossentropy', optimizer=SGD(learning rate=0.
       ⇔01), metrics=['accuracy'])
      # Train the model
      history = model.fit(x_train, y_train, batch_size=64, epochs=11,__
       →validation_split=0.2, verbose=1)
      # Evaluate the model on the testing set
```

```
_, test_accuracy = model.evaluate(x_test, y_test, verbose=0)
print("\n")
# Plot the accuracy on training and validation data
plt.plot(history.history['accuracy'], label='Training Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
print("\n\n")
# Print the test accuracy
print(f'Test Accuracy: {test_accuracy}')
Epoch 1/11
750/750 [============ ] - 47s 62ms/step - loss: 1.0832 -
accuracy: 0.6881 - val_loss: 0.3104 - val_accuracy: 0.9128
Epoch 2/11
accuracy: 0.9168 - val_loss: 0.2009 - val_accuracy: 0.9416
Epoch 3/11
accuracy: 0.9432 - val_loss: 0.1553 - val_accuracy: 0.9559
Epoch 4/11
accuracy: 0.9561 - val_loss: 0.1227 - val_accuracy: 0.9651
accuracy: 0.9633 - val_loss: 0.1095 - val_accuracy: 0.9682
Epoch 6/11
750/750 [============= ] - 43s 58ms/step - loss: 0.1037 -
accuracy: 0.9684 - val_loss: 0.1057 - val_accuracy: 0.9680
750/750 [============= ] - 45s 60ms/step - loss: 0.0923 -
accuracy: 0.9717 - val_loss: 0.0870 - val_accuracy: 0.9745
accuracy: 0.9746 - val_loss: 0.0822 - val_accuracy: 0.9759
Epoch 9/11
750/750 [============= ] - 46s 62ms/step - loss: 0.0768 -
accuracy: 0.9768 - val loss: 0.0839 - val accuracy: 0.9754
Epoch 10/11
750/750 [============= ] - 47s 63ms/step - loss: 0.0705 -
accuracy: 0.9787 - val_loss: 0.0726 - val_accuracy: 0.9780
```

Epoch 11/11



Test Accuracy: 0.9764000177383423

In this final experiment, we constructed a neural network model using Convolutional Neural Network (CNN) layers, a popular choice for image classification tasks. For comparison purposes, we maintained the same number of layers, 11 epochs, a batch size of 64, and a learning rate of 0.01.

The results of this experiment are highly promising. Within just 11 epochs, the CNN model achieved an accuracy of 97.6% on the test data and 98.03% on train dataset. This high accuracy demonstrates the effectiveness of the CNN architecture in capturing relevant image features and making accurate predictions.

Additionally, the validation accuracy closely aligns with the test accuracy, indicating a low chance of overfitting. When the validation accuracy closely matches the test accuracy, it suggests that the model generalizes well to unseen data and can make reliable predictions on new instances.

The utilization of CNN layers in image classification models allows for the extraction of spatial hierarchies and local patterns present in the images. This enables the model to effectively learn and distinguish features essential for accurate classification.

Overall, the achieved accuracy of 97.6% on the test data, coupled with the similar validation accuracy, demonstrates the robustness and generalization capability of the CNN model. These results highlight the suitability of CNNs for image classification tasks, providing accurate predictions while minimizing the risk of overfitting.

[22]: