Implementing Feed-forward neural networks with Keras and TensorFlow

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In [23]: import numpy as np
          import matplotlib.pyplot as plt
          import tensorflow as tf
          from tensorflow.keras.datasets import mnist
          from tensorflow.keras.models import Sequential
          from tensorflow.keras.layers import Dense,Input
          from tensorflow.keras.optimizers import SGD
          from tensorflow.keras.utils import to_categorical
          from tensorflow.keras.utils import plot_model
In [24]: # Load MNIST data
          (x_train, y_train), (x_test, y_test) = mnist.load_data()
          # Preprocess data
          x_{train} = x_{train.reshape((x_{train.shape[0], 28 * 28)).astype('float32') / 255)}
          x_{\text{test}} = x_{\text{test}} \cdot \text{reshape}((x_{\text{test}} \cdot \text{shape}[0], 28 * 28)) \cdot \text{astype}('float32') / 255
          # One-hot encode labels
          y_train = to_categorical(y_train, 10)
          y_test = to_categorical(y_test, 10)
In [25]: # Define the network architecture
          model = Sequential([
              Input(shape=(28 * 28,)), # Define the input shape here
               Dense(512, activation='relu'),
              Dense(256, activation='relu'),
              Dense(10, activation='softmax')
          ])
In [26]: # Compile the model
          model.compile(optimizer=SGD(),
                         loss='categorical_crossentropy',
                         metrics=['accuracy'])
          # Train the model
          history = model.fit(x_train, y_train,
                                epochs=20,
                                batch_size=32,
                                validation_split=0.2)
```

```
Epoch 1/20
1500/1500
                              - 5s 3ms/step - accuracy: 0.7532 - loss: 0.9979 - val_accuracy: 0.9118 - val_loss: 0.31
31
Epoch 2/20
1500/1500
                               5s 3ms/step - accuracy: 0.9129 - loss: 0.3045 - val_accuracy: 0.9302 - val_loss: 0.24
Epoch 3/20
1500/1500
                              - 5s 4ms/step - accuracy: 0.9306 - loss: 0.2419 - val_accuracy: 0.9386 - val_loss: 0.21
Epoch 4/20
1500/1500
                              - 5s 3ms/step - accuracy: 0.9401 - loss: 0.2056 - val_accuracy: 0.9479 - val_loss: 0.18
Epoch 5/20
                               5s 3ms/step - accuracy: 0.9477 - loss: 0.1812 - val_accuracy: 0.9531 - val_loss: 0.16
1500/1500
87
Epoch 6/20
1500/1500
                             - 4s 3ms/step - accuracy: 0.9556 - loss: 0.1618 - val_accuracy: 0.9563 - val_loss: 0.15
47
Epoch 7/20
                               4s 3ms/step - accuracy: 0.9600 - loss: 0.1420 - val_accuracy: 0.9594 - val_loss: 0.14
1500/1500
Epoch 8/20
1500/1500
                               5s 3ms/step - accuracy: 0.9635 - loss: 0.1303 - val_accuracy: 0.9628 - val_loss: 0.13
Epoch 9/20
1500/1500
                               6s 4ms/step - accuracy: 0.9684 - loss: 0.1133 - val_accuracy: 0.9647 - val_loss: 0.12
Epoch 10/20
                               5s 3ms/step - accuracy: 0.9719 - loss: 0.1036 - val_accuracy: 0.9668 - val_loss: 0.11
1500/1500
83
Epoch 11/20
1500/1500
                              - 5s 4ms/step - accuracy: 0.9740 - loss: 0.0969 - val_accuracy: 0.9684 - val_loss: 0.11
31
Epoch 12/20
1500/1500
                               5s 3ms/step - accuracy: 0.9753 - loss: 0.0889 - val_accuracy: 0.9680 - val_loss: 0.11
Epoch 13/20
1500/1500
                               5s 3ms/step - accuracy: 0.9788 - loss: 0.0813 - val_accuracy: 0.9693 - val_loss: 0.10
Epoch 14/20
                              - 5s    3ms/step - accuracy: 0.9802 - loss: 0.0765 - val_accuracy: 0.9705 - val_loss: 0.10
1500/1500
Epoch 15/20
1500/1500
                               6s 4ms/step - accuracy: 0.9822 - loss: 0.0690 - val_accuracy: 0.9721 - val_loss: 0.09
Epoch 16/20
1500/1500
                              - 6s 4ms/step - accuracy: 0.9829 - loss: 0.0634 - val_accuracy: 0.9718 - val_loss: 0.09
Epoch 17/20
1500/1500
                               6s 4ms/step - accuracy: 0.9843 - loss: 0.0608 - val_accuracy: 0.9722 - val_loss: 0.09
58
Epoch 18/20
1500/1500
                              - 5s 3ms/step - accuracy: 0.9854 - loss: 0.0569 - val_accuracy: 0.9738 - val_loss: 0.09
Epoch 19/20
                              - 5s 3ms/step - accuracy: 0.9858 - loss: 0.0538 - val_accuracy: 0.9744 - val_loss: 0.08
1500/1500
Epoch 20/20
1500/1500
                               6s 4ms/step - accuracy: 0.9872 - loss: 0.0489 - val_accuracy: 0.9733 - val_loss: 0.09
```

In [27]: model.summary()

Model: "sequential_2"

Layer (type)	Output Shape	Param #
dense_6 (Dense)	(None, 512)	401,920
dense_7 (Dense)	(None, 256)	131,328
dense_8 (Dense)	(None, 10)	2,570

Total params: 535,820 (2.04 MB)

Trainable params: 535,818 (2.04 MB)

Non-trainable params: 0 (0.00 B)

Optimizer params: 2 (12.00 B)

```
In [28]: # Evaluate the model on test data
    test_loss, test_accuracy = model.evaluate(x_test, y_test)
    print(f'Test Loss: {test_loss:.4f}')
    print(f'Test Accuracy: {test_accuracy:.4f}')
```

313/313 — **1s** 2ms/step - accuracy: 0.9695 - loss: 0.1002 Test Loss: 0.0863

Test Accuracy: 0.9732

In [29]: #plotting the model plot_model(model,to_file='C:/Users/tmbha/Downloads/DLprac2_model.png',show_shapes=True,show_layer_names=True,show_l Out[29]: dense_6 (Dense) Activation: relu Input shape: (None, 784) Output shape: (None, 512) dense_7 (Dense) Activation: relu Input shape: (None, 512) Output shape: (None, 256) dense_8 (Dense) Activation: softmax Output shape: (None, 10) Input shape: (None, 256) In [30]: # Plotting

```
plt.figure(figsize=(14, 6))
# Plot training & validation loss
plt.subplot(1, 2, 1)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()
# Plot training & validation accuracy
plt.subplot(1, 2, 2)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title('Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```



