```
In [1]: #Import required libraries
       from keras.datasets import mnist
       from keras.models import Sequential, load model
       from keras.utils import to categorical
       from keras import layers, models, optimizers
       from keras.preprocessing.image import ImageDataGenerator
       import numpy as np
       import matplotlib.pyplot as plt
       from pathlib import Path
       import pandas as pd
       import os
In [2]: # Instantiating a small convnet for dogs vs. cats classification
      model = models.Sequential()
      model.add(layers.Conv2D(32, (3, 3), activation='relu', input shape=(28, 28, 1)))
      model.add(layers.MaxPooling2D((2, 2)))
      model.add(layers.Conv2D(64, (3, 3), activation='relu'))
      model.add(layers.MaxPooling2D((2, 2)))
      model.add(layers.Conv2D(64, (3, 3), activation='relu'))
       #Display architecture of the convnet
      model.summary()
      Model: "sequential"
       Layer (type)
                              Output Shape
      ______
       conv2d (Conv2D)
                              (None, 26, 26, 32) 320
       max pooling2d (MaxPooling2D (None, 13, 13, 32)
       conv2d 1 (Conv2D) (None, 11, 11, 64) 18496
       max pooling2d 1 (MaxPooling (None, 5, 5, 64)
       2D)
                              (None, 3, 3, 64)
       conv2d 2 (Conv2D)
                                                     36928
      ______
      Total params: 55,744
      Trainable params: 55,744
      Non-trainable params: 0
In [3]: # Adding a classifier on top of the convnet
      model.add(layers.Flatten())
      model.add(layers.Dense(64, activation='relu'))
      model.add(layers.Dense(10, activation='softmax'))
      model.summary()
      Model: "sequential"
       Layer (type)
                              Output Shape
      ______
       conv2d (Conv2D)
                              (None, 26, 26, 32)
       max pooling2d (MaxPooling2D (None, 13, 13, 32) 0
       conv2d 1 (Conv2D) (None, 11, 11, 64) 18496
```

max pooling2d 1 (MaxPooling (None, 5, 5, 64)

```
conv2d 2 (Conv2D)
                                  (None, 3, 3, 64)
                                                           36928
        flatten (Flatten)
                                   (None, 576)
                                                            36928
        dense (Dense)
                                   (None, 64)
        dense 1 (Dense)
                                   (None, 10)
                                                            650
       ______
       Total params: 93,322
       Trainable params: 93,322
       Non-trainable params: 0
In [4]: # Training the convnet on MNIST images
       (train images, train labels), (test images, test labels) = mnist.load data()
In [5]: train_images.shape, train_labels.shape, test_images.shape, test_labels.shape
       ((60000, 28, 28), (60000,), (10000, 28, 28), (10000,))
       # First 10 training labels
       for i in range(10):
          plt.subplot(4,3,i+1)
          plt.tight layout()
           plt.imshow(train images[i], cmap='gray')
           plt.title("Digit: {}".format(train labels[i]))
       plt.show()
           Diait: 5
                                                             Digit: 4
                                    Diait: 0
           Diait: 1
           Digit: 1
                                                             Diait: 1
        20
           0
                25
                                                                  25
                                         25
                                                             0
           Digit: 4
                25
```

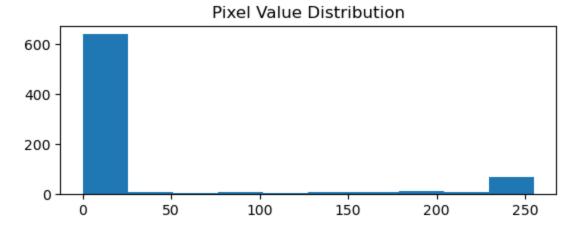
2D)

Out[5]:

In [6]:

In [7]: plt.subplot(2,1,2) plt.hist(train images[0].reshape(784))

```
plt.title("Pixel Value Distribution")
plt.show()
```



```
train images = train images.reshape((60000, 28, 28, 1))
In [8]:
        train images = train images.astype('float32') / 255
        test images = test images.reshape((10000, 28, 28, 1))
        test images = test images.astype('float32') / 255
        train labels = to categorical(train labels)
        test labels = to categorical(test labels)
        model.compile(optimizer='rmsprop',
        loss='categorical crossentropy',
        metrics=['accuracy'])
        # Training the model and saving metrics in history
       history = model.fit(train images, train labels,batch size=64,epochs=15,verbose=2,validat
       Epoch 1/15
        938/938 - 58s - loss: 0.1818 - accuracy: 0.9431 - val loss: 0.1332 - val accuracy: 0.952
       9 - 58s/epoch - 62ms/step
       Epoch 2/15
       938/938 - 55s - loss: 0.0489 - accuracy: 0.9847 - val loss: 0.0351 - val accuracy: 0.989
       0 - 55s/epoch - 59ms/step
       Epoch 3/15
       938/938 - 55s - loss: 0.0340 - accuracy: 0.9889 - val loss: 0.0319 - val accuracy: 0.989
       7 - 55s/epoch - 58ms/step
       Epoch 4/15
       938/938 - 50s - loss: 0.0248 - accuracy: 0.9923 - val loss: 0.0322 - val accuracy: 0.991
       3 - 50s/epoch - 53ms/step
       Epoch 5/15
       938/938 - 39s - loss: 0.0199 - accuracy: 0.9937 - val loss: 0.0284 - val accuracy: 0.990
       9 - 39s/epoch - 41ms/step
       Epoch 6/15
       938/938 - 41s - loss: 0.0154 - accuracy: 0.9954 - val loss: 0.0459 - val accuracy: 0.988
       1 - 41s/epoch - 44ms/step
       Epoch 7/15
       938/938 - 37s - loss: 0.0130 - accuracy: 0.9960 - val loss: 0.0248 - val accuracy: 0.993
       4 - 37s/epoch - 40ms/step
       Epoch 8/15
       938/938 - 29s - loss: 0.0102 - accuracy: 0.9968 - val loss: 0.0270 - val accuracy: 0.992
       7 - 29s/epoch - 31ms/step
       Epoch 9/15
       938/938 - 29s - loss: 0.0079 - accuracy: 0.9974 - val loss: 0.0321 - val accuracy: 0.992
       0 - 29s/epoch - 31ms/step
       Epoch 10/15
       938/938 - 37s - loss: 0.0068 - accuracy: 0.9978 - val loss: 0.0329 - val accuracy: 0.992
       2 - 37s/epoch - 39ms/step
       Epoch 11/15
```

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938/938 - 37s - loss: 0.0057 - accuracy: 0.9984 - val loss: 0.0340 - val accuracy: 0.992
      9 - 37s/epoch - 39ms/step
      Epoch 12/15
      938/938 - 33s - loss: 0.0046 - accuracy: 0.9984 - val loss: 0.0479 - val accuracy: 0.990
      2 - 33s/epoch - 35ms/step
      Epoch 13/15
      938/938 - 36s - loss: 0.0048 - accuracy: 0.9987 - val loss: 0.0408 - val accuracy: 0.992
      1 - 36s/epoch - 39ms/step
      Epoch 14/15
      938/938 - 34s - loss: 0.0039 - accuracy: 0.9989 - val loss: 0.0460 - val accuracy: 0.991
      6 - 34s/epoch - 36ms/step
      Epoch 15/15
      938/938 - 33s - loss: 0.0029 - accuracy: 0.9991 - val loss: 0.0515 - val accuracy: 0.991
      7 - 33s/epoch - 35ms/step
In [9]: # Evaluate the model on the test data
      results = model.evaluate(test images, test labels)
      print(results)
      test loss, test acc = model.evaluate(test images, test labels)
      test acc, test loss
      [0.051524363458156586, 0.9916999936103821]
      (0.9916999936103821, 0.051524363458156586)
Out[9]:
In [10]: predictions = np.argmax(model.predict(test images), axis=1)
      predictions = list(predictions)
      actuals = list(test labels)
      pred res = pd.DataFrame({'Actual': actuals, 'Predictions': predictions})
      pred res
      313/313 [=========== - 3s 10ms/step
Out[10]:
                          Actual Predictions
        0 [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 1.0, 0.0, ...
        4
      2
      4
      6
      10000 rows × 2 columns
```

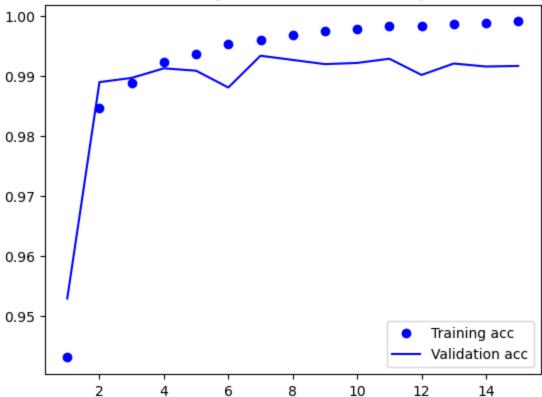
In [11]: acc = history.history['accuracy']
 val_acc = history.history['val_accuracy']

```
loss = history.history['loss']
val_loss = history.history['val_loss']
epochs = range(1, len(acc) + 1)

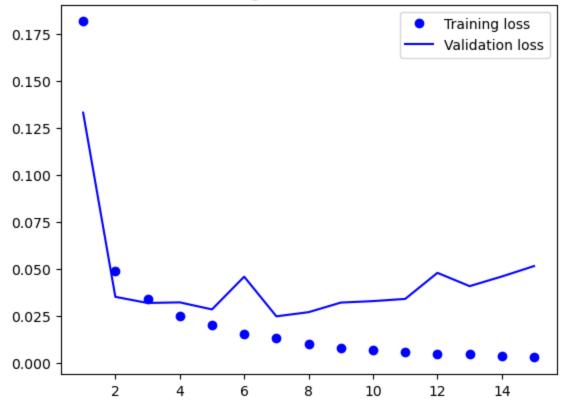
//: # Plotting the results
plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
```

```
In [17]: # Plotting the results
plt.plot(epochs, acc, 'bo', label='Training acc')
plt.plot(epochs, val_acc, 'b', label='Validation acc')
plt.title('Training and validation accuracy')
plt.legend()
plt.figure()
plt.savefig('results/Assignment_6-1_Accuracy.png')
plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()
plt.show()
plt.savefig('results/Assignment_6-1_Loss.png')
```

Training and validation accuracy



Training and validation loss



<Figure size 640x480 with 0 Axes>

```
In [14]: # Get the current directory and add the results folder to the path.
    current_dir = Path(os.getcwd()).absolute()
    results_dir = current_dir.joinpath('results')
    results_dir.mkdir(parents=True, exist_ok=True)
```

```
In [15]: model.save('results/Assignment_6-1_model.h5')
```

```
In [22]: #write metrics to file
with open('results/Assignment_6-1_metrics.txt', 'w') as f:
    f.write('Training Loss: {}'.format(str(history.history['loss'])))
    f.write('\nTraining Accuracy: {}'.format(str(history.history['accuracy'])))
    f.write('\nTest Loss: {}'.format(results[0]))
    f.write('\nTest Accuracy: {}'.format(results[1]))
    predictions = pd.DataFrame(pred_res)
    predictions.to_csv('results/Assignment_6-1_predictions.csv', index=False)
```