Activity 9: Neural Networks

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App Physics 157 WFY-FX-2

```
# importing necessary codes
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.model_selection import train_test_split as split
from google.colab import drive
```

Part 1: Sine Function Appproximation

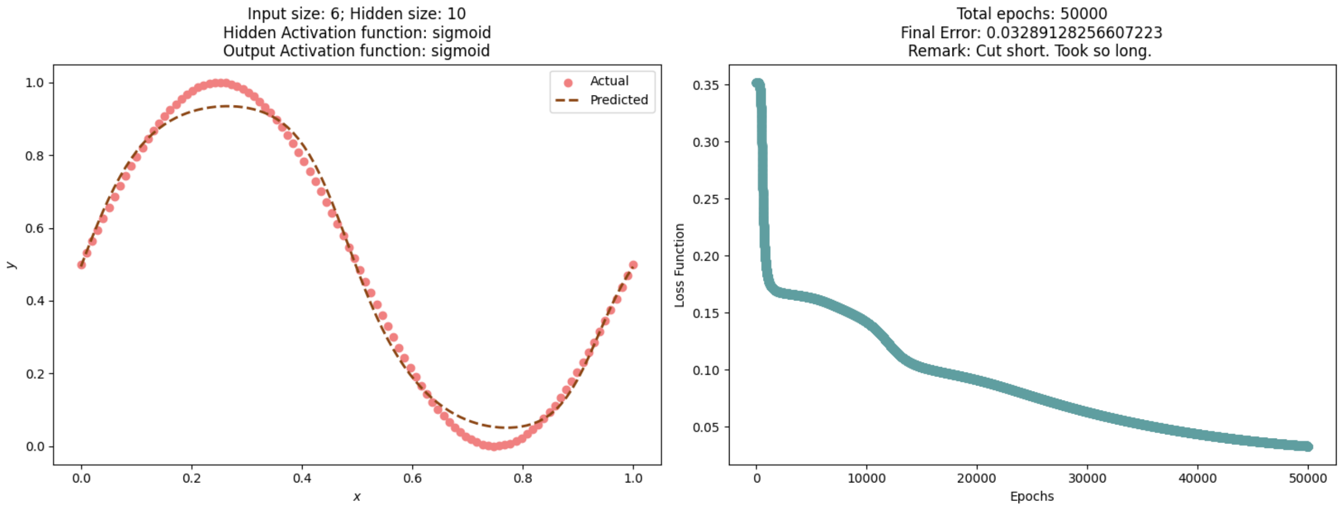
```
#all the necessary functions
def model(x):
  '''normalized sine function that will be used for approximation'''
  output = np.sin(2*np.pi*x)
  output = (output - np.min(output))/(np.max(output) - np.min(output))
  output = np.reshape(output, (len(x), 1))
  return output

def tanh(a, derivative = False):
  '''getting the hyperbolic tangent function and its derivative '''
  if derivative == False:
      output = np.tanh(a)
  else:
      output = 1 + (np.tanh(a))**2
  return output

def sigmoid(a, derivative = False):
  '''getting the sigmoid function and its derivative '''
  if derivative == False:
      output = 1/(1 + np.exp(-a))
  else:
      s = sigmoid(a)
      output = s*(1 - s)
  return output


def linear(x, derivative = False):
  '''getting the linear function and its derivative '''
  if derivative == False:
      output = x
  else:
      output = 1
  return output

def rectified_linear(x, derivative = False):
    '''getting the rectified linear function and its derivative '''
    if derivative == False:
        output = np.maximum(0,x)
    else:
        output = np.maximum(0,1)
    return output
```

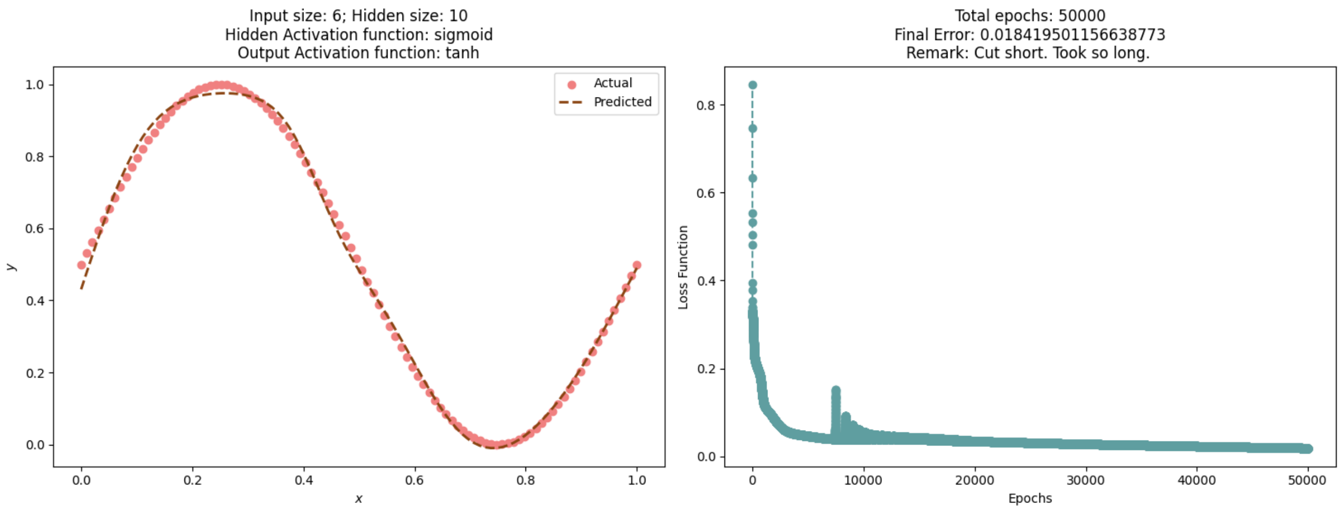
```
def x_vectors(x, n):
    vectors = []
    for i in range(n):
        vectors.append(x**i)
    vecs = np.dstack(np.split(np.array(vectors), n))
    vecs = np.reshape(vecs, (vecs.shape[1], vecs.shape[2]))
    return vecs

def initialize_weights(input_size, hidden_size, output_size, factor = 0.01):
    omega0 = np.random.randn(hidden_size,input_size)*factor
    omega1 = np.random.randn(output_size, hidden_size)*factor
    weights = {'omega0': omega0, 'omega1': omega1,}
    return weights

def compute_loss():
  '''calculates the loss function through root mean squared error'''
  pass


def training(x, validation, weights_biases, learning_rate, afunc_hidden, afunc_o
    omega_h = weights_biases['omega0'].copy()
    omega_o = weights_biases['omega1'].copy()
    loss = []
    max_epoch = 50000
    epoch_counter = 1

    while True:
        # Getting outputs of the hidden layer
        aji = np.dot(x, omega_h.T)
        hidden_layer = afunc_hidden(aji )

        # Getting output
        ak = np.dot(hidden_layer, omega_o.T)
        output_layer = afunc_out(ak )

        # RMSE
        error = output_layer - validation
        current_loss = np.sqrt(np.mean(error**2))
        loss.append(current_loss)

        # For debugging
        if error_tracker == True:
            if epoch_counter%100 == 0:
                print('RMSE at epoch', epoch_counter, ': ', current_loss)

        # Breaks if RMSE is lesser than the threshold or if the maximum number o
        if current_loss < error_threshold:
            break
```

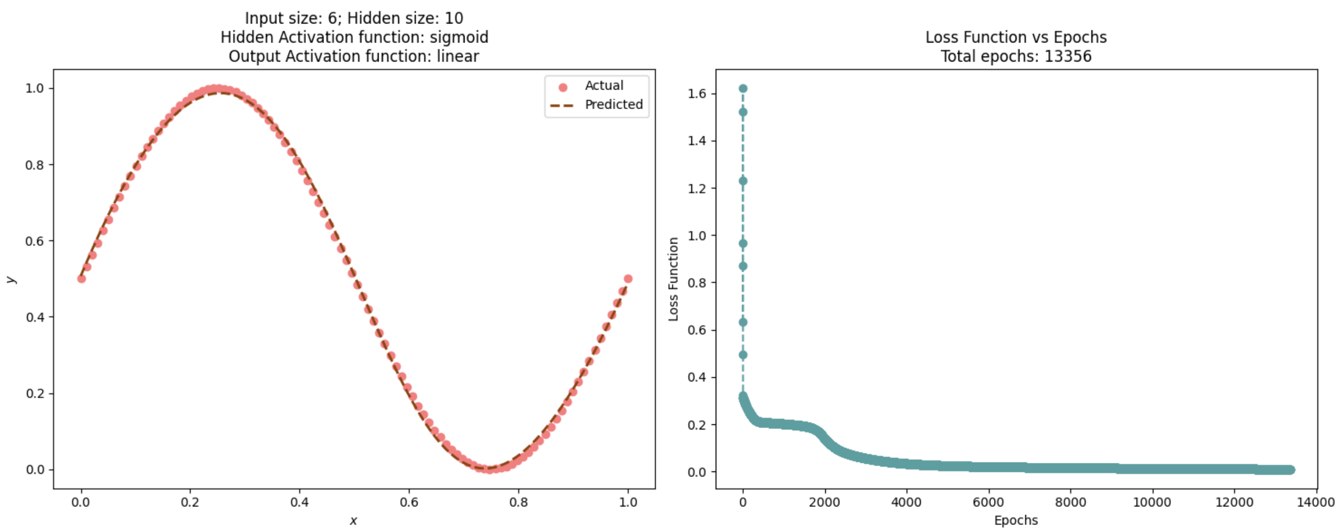
```
        elif epoch_counter >= max_epoch:
            break
        # Solving for the error of the output
        delta_output = afunc_out((ak ), derivative = True)*error

        # Solving for the error of the hidden units
        delta_hidden = afunc_hidden(aji , derivative = True)*np.dot(delta_output

        # Solving for the error derivatives
        E_hidden_derivative = np.dot(x.T, delta_hidden).T
        E_output_derivative = np.dot(hidden_layer.T,delta_output).T

        # updating weights
        omega_h += -learning_rate*E_hidden_derivative
        omega_o += -learning_rate*E_output_derivative

        epoch_counter +=1

    return output_layer, np.array(loss), omega_h, omega_o
```

```
def create_plots(x, predictions, validation,  RMSE, input_size, hidden_size, afu
    epochs = np.arange(1, len(loss)+1, 1)
    fig, ax = plt.subplots(1,2, figsize = (15,6))
    ax[0].scatter(x, validation, label = 'Actual', color = 'lightcoral')
    ax[0].plot(x, predictions, linestyle = '--', lw = 2, color = 'saddlebrown',
    ax[0].set_xlabel('$x$')
    ax[0].set_ylabel('$y$')
    ax[0].set_title(
                'Input size: ' + str(input_size) +
                '; Hidden size: ' + str(hidden_size) +
                '\nHidden Activation function: ' + str(afunc_h.__name__) +
                '\nOutput Activation function: ' + str(afunc_o.__name__),
                loc = 'center')
    ax[0].legend()

    ax[1].plot(epochs, loss, linestyle = '--', marker = 'o', color = 'cadetblue'
    ax[1].set_xlabel('Epochs')
    ax[1].set_ylabel('Loss Function')

    if RMSE[len(loss)-1] >= error_threshold:
        ax[1].set_title(
                '\nTotal epochs: ' + str(len(RMSE))+
                '\nFinal Error: ' + str(RMSE[len(RMSE)-1])+
                '\nRemark: Cut short. Took so long. ',
                loc = 'center'
        )
    else:
        ax[1].set_title('Loss Function vs Epochs' +
                '\nTotal epochs: ' + str(len(RMSE)),
                loc = 'center'
        )

    plt.tight_layout()
    plt.show()


input_size = 6
hidden_size = 10
learning_rate = 0.01
x = np.linspace(0, 1, 100)
x_vec = x_vectors(x, input_size)
error_threshold = 0.01
weights = initialize_weights(input_size, hidden_size, 1)
validation = model(x)


activation_function = [[sigmoid, sigmoid], [sigmoid, tanh], [sigmoid, linear], [
                       [tanh, sigmoid], [tanh, tanh], [tanh, linear], [tanh, rec
```

```
                          [linear, sigmoid], [linear, tanh], [linear, linear], [lin
                          [rectified_linear, sigmoid], [rectified_linear, tanh], [r
]

for i in activation_function:
    z, loss, omega_h, omega_o = training(x_vec, validation, weights, learning_ra
    create_plots(x, z, validation,  loss, input_size, hidden_size, i[0], i[1], l
```

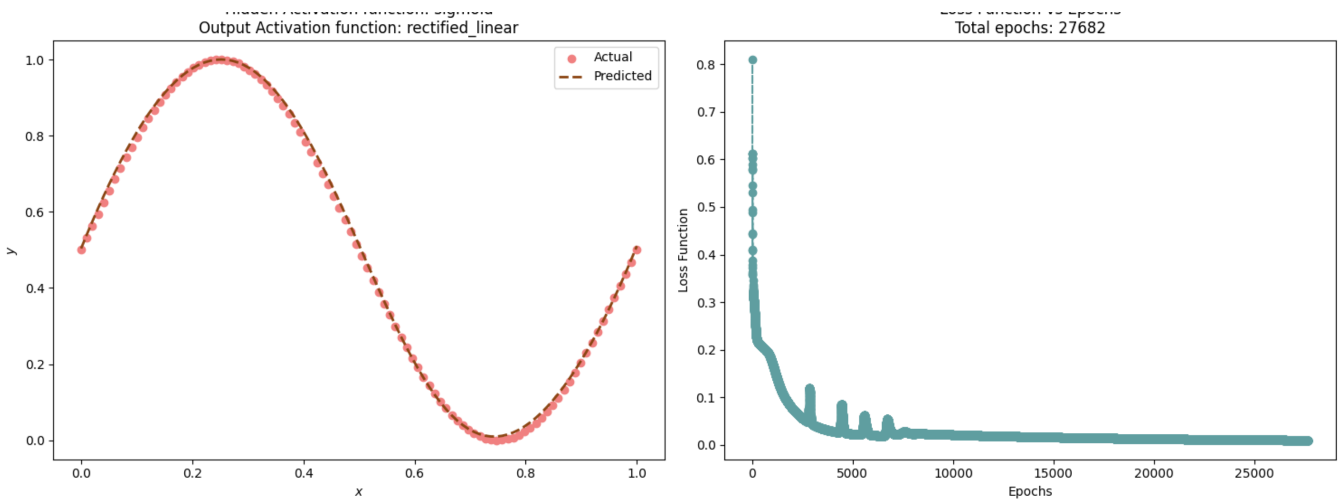






Input size: 6; Hidden size: 10
Hidden Activation function: sigmoid

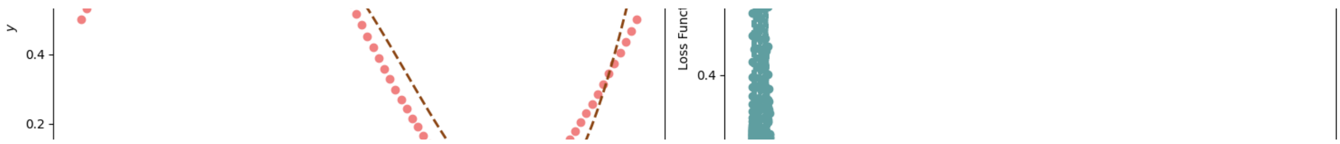
Loss Function vs Epochs



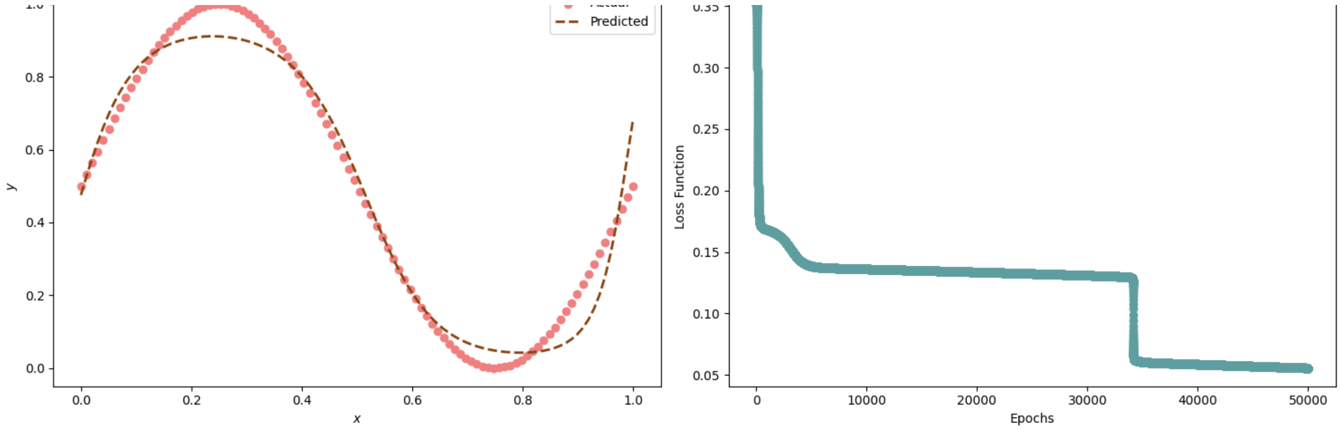
Part 2: Fruit Classification

The dataset used was converted from an initial .mat file to .csv file. The same file was used for Perceptron algorithm

```
data_path = '/content/drive/MyDrive/'
def Extract(filename1, filename2, features):
    df1 = pd.read_csv(data_path + filename1)
    df2 = pd.read_csv(data_path + filename2)

    df1_features = df1.loc[:,features]
    df2_features = df2.loc[:,features]

    return df1_features, df2_features

def vectorize(data):
    output = data.copy()
    return np.array(output)

def normalize(data_in1, data_in2):
    data_1 = data_in1.copy()
    data_2 = data_in2.copy()

    data_1.iloc[:,1] *= 1/255
    data_2.iloc[:,1] *= 1/255

    return data_1, data_2
```

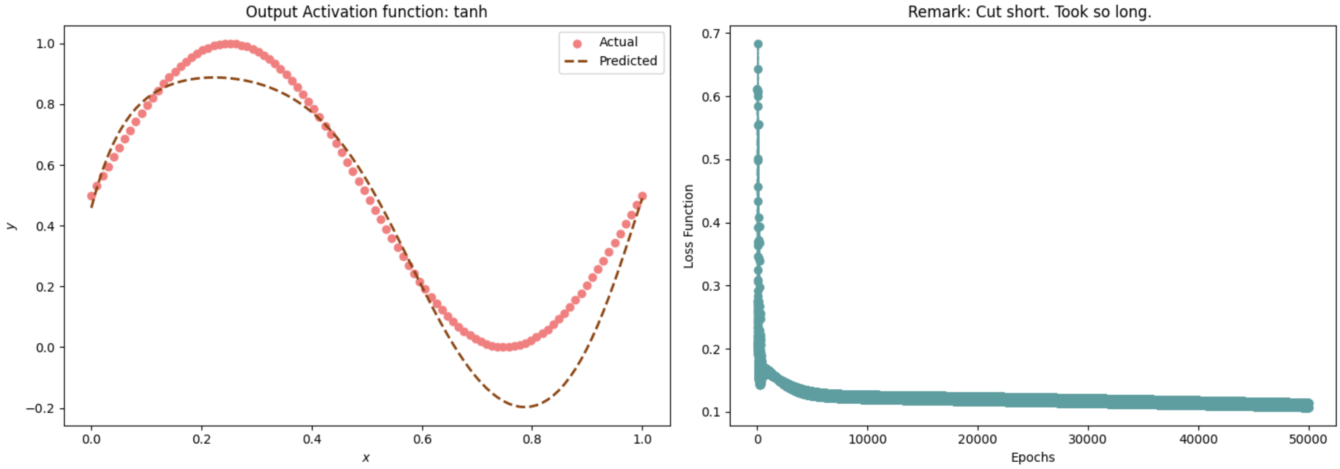


```
# Loading the data
BananaD, AppleD = Extract('Banana.csv', 'Apple.csv', ['Feature1', 'Feature2'])
norm_BananaD, norm_AppleD = normalize(BananaD, AppleD)

# Vectorizing
BananaV = vectorize(norm_BananaD)
AppleV = vectorize(norm_AppleD)

# Splitting the data into training and testing
BananaTrain, BananaTest, AppleTrain, AppleTest = split(BananaV, AppleV, train_si

# For validation
Bananavalidation = np.tile(1, (len(BananaTrain), 1))
Applevalidation = np.tile(0, (len(AppleTrain), 1))

#Compilation
Combined_train = np.concatenate((BananaTrain, AppleTrain))
Combined_validation = np.concatenate((Bananavalidation, Applevalidation))
```



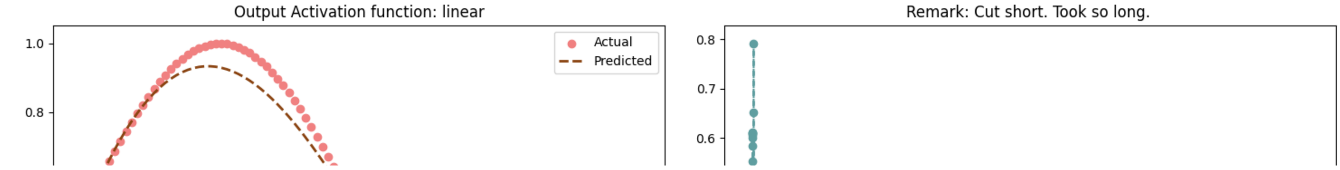
Input size: 6; Hidden size: 10
Hidden Activation function: linear
Output Activation function: tanh

Total epochs: 50000
Final Error: 0.11403996586960043
Remark: Cut short. Took so long.



Input size: 6; Hidden size: 10
Hidden Activation function: linear
Output Activation function: linear

Total epochs: 50000
Final Error: 0.05656959820498719
Remark: Cut short. Took so long.



```
def Classification(testing, validation, label1, label2, textlabel1, textlabel2,

    # Getting outputs of the hidden layer
    z_j = np.dot(testing, omega_0.T)
    hidden_layer = afunc_hidden(z_j )

    # Getting output
    a_k = np.dot(hidden_layer, omega_1.T)
    output_layer = afunc_out(a_k)

    # Rounding off to the nearest integer
    output_layer = (np.rint(output_layer)).astype(int)

    # Making the dataframe
    images = []
    for i in range(1, len(testing) + 1):
        images.append('Test Img '+str(i))

    df = pd.DataFrame({ 'Test image': images,
                        'Actual' : real_classification
    })
    df.insert(len(df.iloc[0]),'Prediction', None)

    df.loc[output_layer[:,0] == label1,'Prediction'] = textlabel1
    df.loc[output_layer[:,0] == label2,'Prediction'] = textlabel2

    accuracy = (len(df[df['Prediction'] == real_classification]))/len(df)

    return df, accuracy
```


```
input_size = len(Combined_train[0])

hidden_size = 10
learning_rate = 0.01
error_threshold = 0.01
weights = initialize_weights(input_size, hidden_size, 1)

#The corresponding hidden and output functions used were based on the results of
#so it is only intuitive to use it in this part.
functions = [[sigmoid, linear], [sigmoid, rectified_linear], [rectified_linear,
                       [sigmoid, sigmoid], [sigmoid, tanh]
]

for i in functions:
    z, loss, omega_h, omega_o = training(Combined_train, Combined_validation, we
    Bananaclassifications, Bananaaccuracy = Classification(BananaTest, Bananaval
```

```
Appleclassifications, Appleaccuracy = Classification(AppleTest, Applevalidat
print('Banana Classification')
display(Bananaclassifications)
print('------------------')
print('Apple Classification')
display(Appleclassifications)
print('Hidden layer function:', i[0].__name__)
print('Output layer function:', i[1].__name__)
print('------------------')
print('Summary:')
print('Banana Accuracy: ', Bananaaccuracy*100,'%')
print('Apple Accuracy: ', Appleaccuracy*100,'%')
print('------------------')
```

```
Banana Classification
```

	Test image	Actual	Prediction
0	Test Img 1	Banana	Banana
1	Test Img 2	Banana	Banana
2	Test Img 3	Banana	Banana
3	Test Img 4	Banana	Banana
4	Test Img 5	Banana	Banana
5	Test Img 6	Banana	Banana
6	Test Img 7	Banana	Banana
7	Test Img 8	Banana	Banana
8	Test Img 9	Banana	Banana
9	Test Img 10	Banana	Banana
10	Test Img 11	Banana	Banana
11	Test Img 12	Banana	Banana
12	Test Img 13	Banana	Banana
13	Test Img 14	Banana	Banana
14	Test Img 15	Banana	Banana
15	Test Img 16	Banana	Banana
16	Test Img 17	Banana	Banana
17	Test Img 18	Banana	Banana
18	Test Img 19	Banana	Banana
19	Test Img 20	Banana	Banana

19	Test Img 20	Banana	Banana
20	Test Img 21	Banana	Banana
21	Test Img 22	Banana	Banana
22	Test Img 23	Banana	Banana
23	Test Img 24	Banana	Banana
24	Test Img 25	Banana	Banana

```
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Apple Classification
```

	Test image	Actual	Prediction
0	Test Img 1	Apple	Apple
1	Test Img 2	Apple	Apple
2	Test Img 3	Apple	Apple
3	Test Img 4	Apple	Apple
4	Test Img 5	Apple	Apple
5	Test Img 6	Apple	Apple
6	Test Img 7	Apple	Apple
7	Test Img 8	Apple	Apple
8	Test Img 9	Apple	Apple
9	Test Img 10	Apple	Apple
10	Test Img 11	Apple	Apple
11	Test Img 12	Apple	Apple
12	Test Img 13	Apple	Apple
13	Test Img 14	Apple	Apple
14	Test Img 15	Apple	Apple
15	Test Img 16	Apple	Apple
16	Test Img 17	Apple	Apple
17	Test Img 18	Apple	Apple