CS 559-B Homework 3

Student Information:

- Full name: Thanapoom Phatthanaphan
- CWID: 20011296

Importing the necessary libraries

In [1]:
```
import numpy as np
import pandas as pd
```

Problem 1

In [2]:
```
# Given data points
X = np.array([
    [5.9, 3.2],
    [4.6, 2.9],
    [6.2, 2.8],
    [4.7, 3.2],
    [5.5, 4.2],
    [5.0, 3.0],
    [4.9, 3.1],
    [6.7, 3.1],
    [5.1, 3.8],
    [6.0, 3.0]
])

# Initial cluster centers
mean_1 = np.array([6.2, 3.2])
mean_2 = np.array([6.6, 3.7])
mean_3 = np.array([6.5, 3.0])

# Perform k-means clustering for one iteration
def kmeans_iteration(X, mean_1, mean_2, mean_3):

    # Assign each data point to the nearest cluster by calculating the Eucl
    distances = np.column_stack([
        np.linalg.norm(X - mean_1, axis=1),
        np.linalg.norm(X - mean_2, axis=1),
        np.linalg.norm(X - mean_3, axis=1)
    ])
    print(distances)
    # Find the minimum distance of each point to each cluster
    labels = np.argmin(distances, axis=1)

    # Update cluster centers
    mean_1 = np.mean(X[labels == 0], axis=0)
    mean_2 = np.mean(X[labels == 1], axis=0)
    mean_3 = np.mean(X[labels == 2], axis=0)

    return mean_1, mean_2, mean_3
```

Problem 1.1 : [10pt] What is the center of the first cluster (red) after one iteration? (Answer in the format of [x1,x2], round results to three decimal places, same as part (2) and (3))

In [3]:
```
# The first iteration of k-means clustering
mean_1_after_one_iteration, mean_2_after_one_iteration, mean_3_after_one_ite

# The result of the center of the first cluster (red) after one iteration wi
print(f"The center of the first cluster (red) after one iteration: {np.round
```

```
[[0.3        0.86023253 0.63245553]
 [1.62788206 2.15406592 1.90262976]
 [0.4        0.98488578 0.36055513]
 [1.5        1.96468827 1.81107703]
 [1.22065556 1.2083046  1.56204994]
 [1.21655251 1.74642492 1.5       ]
 [1.30384048 1.80277564 1.60312195]
 [0.50990195 0.60827625 0.2236068 ]
 [1.25299641 1.50332964 1.61245155]
 [0.28284271 0.92195445 0.5       ]]
The center of the first cluster (red) after one iteration: [5.171 3.171]
```

Problem 1.2 : [5pt] What's the center of the second cluster (green) after two iteration?

In [4]:
```
# The second iteration of k-means clustering
mean_1_after_two_iteration, mean_2_after_two_iteration, mean_3_after_two_ite

# The result of the center of the second cluster (green) after two iteration
print(f"The center of the second cluster (green) after two iteration: {np.ro
```

```
[[0.72913144 1.07703296 0.6041523 ]
 [0.63261685 1.58113883 1.85067555]
 [1.09358053 1.56524758 0.29154759]
 [0.47229358 1.28062485 1.76776695]
 [1.079777   0.         1.57003185]
 [0.24243661 1.3        1.45086181]
 [0.28066975 1.25299641 1.55724115]
 [1.53023941 1.62788206 0.29154759]
 [0.63261685 0.56568542 1.59530561]
 [0.84611959 1.3        0.45276926]]
The center of the second cluster (green) after two iteration: [5.3 4. ]
```

Problem 1.3 : [5pt] What's the center of the third cluster (blue) when the clustering converges?

In [5]:
```
# Iterate k-means clustering until convergence
curr_iteration_count = 2
while True:
    curr_mean_1, curr_mean_2, curr_mean_3 = mean_1_after_two_iteration, mean
    new_mean_1, new_mean_2, new_mean_3 = kmeans_iteration(X, curr_mean_1, cu
    if np.mean(new_mean_1) == np.mean(curr_mean_1) and np.mean(new_mean_2) =
        break
    curr_iteration_count += 1

# The result of the center of the third cluster (blue) when the clustering c
print(f"The center of the second cluster (green) after two iteration: {np.ro
```

```
[[1.11018017 1.         0.3473111 ]
 [0.25       1.30384048 1.60487538]
 [1.42214627 1.5        0.225     ]
 [0.18027756 1.         1.51017383]
 [1.3462912  0.28284271 1.36770794]
 [0.20615528 1.04403065 1.20026039]
 [0.1118034  0.98488578 1.30216166]
 [1.90065778 1.6643317  0.50559371]
 [0.80777472 0.28284271 1.34559466]
 [1.20104121 1.22065556 0.20155644]]
The center of the second cluster (green) after two iteration: [6.2   3.025]
```

Problem 1.4 : [5pt] How many iterations are required for the clusters to converge?

In [6]:
```python
print("The number of iterations for the clusters to converge:", curr_iterat
```

```
The number of iterations for the clusters to converge: 2 iterations
```

Problem 5

Importing the necessary libraries

In [7]:
```python
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder
import matplotlib.pyplot as plt
```

Importing the Iris plant dataset

In [8]:
```python
!pip install ucimlrepo
```

```
Requirement already satisfied: ucimlrepo in /usr/local/lib/python3.10/dist-
packages (0.0.3)
```

In [9]:
```python
from ucimlrepo import fetch_ucirepo

# fetch dataset
iris = fetch_ucirepo(id=53)

# data (as pandas dataframes)
X = iris.data.features
y = iris.data.targets
```

In [10]:
```python
# metadata
iris.metadata
```

Out[10]:

```
{'uci_id': 53,
 'name': 'Iris',
 'repository_url': 'https://archive.ics.uci.edu/dataset/53/iris',
 'data_url': 'https://archive.ics.uci.edu/static/public/53/data.csv',
 'abstract': 'A small classic dataset from Fisher, 1936. One of the earlies
t known datasets used for evaluating classification methods.\n',
 'area': 'Biology',
 'tasks': ['Classification'],
 'characteristics': ['Tabular'],
 'num_instances': 150,
 'num_features': 4,
 'feature_types': ['Real'],
 'demographics': [],
 'target_col': ['class'],
 'index_col': None,
 'has_missing_values': 'no',
 'missing_values_symbol': None,
 'year_of_dataset_creation': 1936,
 'last_updated': 'Tue Sep 12 2023',
 'dataset_doi': '10.24432/C56C76',
 'creators': ['R. A. Fisher'],
 'intro_paper': {'title': 'The Iris data set: In search of the source of vi
rginica',
  'authors': 'A. Unwin, K. Kleinman',
  'published_in': 'Significance, 2021',
  'year': 2021,
  'url': 'https://www.semanticscholar.org/paper/4599862ea877863669a6a8e63a3
c707a787d5d7e',
  'doi': '1740-9713.01589'},
 'additional_info': {'summary': 'This is one of the earliest datasets used
in the literature on classification methods and widely used in statistics a
nd machine learning.  The data set contains 3 classes of 50 instances each,
where each class refers to a type of iris plant.  One class is linearly sep
arable from the other 2; the latter are not linearly separable from each ot
her.\n\nPredicted attribute: class of iris plant.\n\nThis is an exceedingly
simple domain.\n\nThis data differs from the data presented in Fishers arti
cle (identified by Steve Chadwick,  spchadwick@espeedaz.net ).  The 35th sa
mple should be: 4.9,3.1,1.5,0.2,"Iris-setosa" where the error is in the fou
rth feature. The 38th sample: 4.9,3.6,1.4,0.1,"Iris-setosa" where the error
s are in the second and third features.  ',
  'purpose': 'N/A',
  'funded_by': None,
  'instances_represent': 'Each instance is a plant',
  'recommended_data_splits': None,
  'sensitive_data': None,
  'preprocessing_description': None,
  'variable_info': None,
  'citation': None}}
```


In [11]:
```
# variable information
iris.variables
```

Out[11]:

	name	role	type	demographic	description	units	missing_values
0	sepal length	Feature	Continuous	None	None	cm	no
1	sepal width	Feature	Continuous	None	None	cm	no
2	petal length	Feature	Continuous	None	None	cm	no
3	petal width	Feature	Continuous	None	None	cm	no
4	class	Target	Categorical	None	class of iris plant: Iris Setosa, Iris Versico...	None	no

In [12]:

```
X # features
```

Out[12]:

	sepal length	sepal width	petal length	petal width
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2
...	...	...	...	...
145	6.7	3.0	5.2	2.3
146	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8

150 rows × 4 columns

In [13]:

```
y # target
```

Out[13]:

	class
0	Iris-setosa
1	Iris-setosa
2	Iris-setosa
3	Iris-setosa
4	Iris-setosa
...	...
145	Iris-virginica
146	Iris-virginica
147	Iris-virginica
148	Iris-virginica
149	Iris-virginica

150 rows × 1 columns

Problem 5.1 : [20pt] Properly split the data to training and testing set, and report the training, testing accuracy. You can use sigmoid activation function and select any reasonable size of hidden units. Note that for this part, you need to implement the forward/backward function yourself without using the deep learning package. However, you can use the deep learning package, e.g., tensorflow, pytorch, matconvnet etc, to compare with your own results.

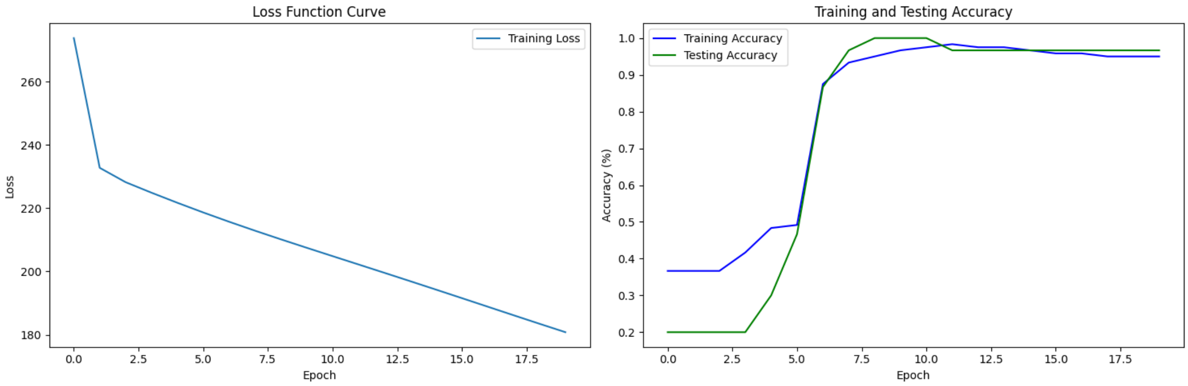
In [14]:

```
# One-hot encode the target variable
encoder = OneHotEncoder(sparse=False)
y_one_hot = encoder.fit_transform(y)

# Split the data into training (80%) and testing sets (20%)
X_train, X_test, y_train, y_test = train_test_split(X, y_one_hot, test_size=

# Define neural network parameters
input_size = X_train.shape[1]
hidden_size = 32
output_size = y_train.shape[1]
learning_rate = 0.01
epochs = 20

# Initialize weights and biases
np.random.seed(42)
weights_input_hidden = np.random.randn(input_size, hidden_size) / np.sqrt(in
biases_hidden = np.zeros((1, hidden_size))
weights_hidden_output = np.random.randn(hidden_size, output_size) / np.sqrt(
biases_output = np.zeros((1, output_size))

# Sigmoid activation function and its derivative
def sigmoid(x):
    return 1 / (1 + np.exp(-x))

def sigmoid_derivative(x):
    return x * (1 - x)

# Lists to store training loss, training and testing accuracies
training_loss_history = []
```

```
training_accuracy_history = []
testing_accuracy_history = []

# Training the neural network
for epoch in range(epochs):

    # Forward pass
    hidden_input = np.dot(X_train, weights_input_hidden) + biases_hidden
    hidden_output = sigmoid(hidden_input)
    final_input = np.dot(hidden_output, weights_hidden_output) + biases_outp
    final_output = sigmoid(final_input)

    # Compute loss
    loss = -np.sum(y_train * np.log(final_output) + (1 - y_train) * np.log(1

    # Backward pass
    d_loss = final_output - y_train
    d_final_input = d_loss * sigmoid_derivative(final_output)
    d_hidden_output = np.dot(d_final_input, weights_hidden_output.T)
    d_hidden_input = d_hidden_output * sigmoid_derivative(hidden_output)

    # Update weights and biases
    weights_hidden_output -= learning_rate * np.dot(hidden_output.T, d_final
    biases_output -= learning_rate * np.sum(d_final_input, axis=0, keepdims=
    weights_input_hidden -= learning_rate * np.dot(X_train.T, d_hidden_input
    biases_hidden -= learning_rate * np.sum(d_hidden_input, axis=0, keepdims

    # Store training loss
    training_loss_history.append(loss)

    # Calculate training accuracy
    hidden_layer_train = sigmoid(np.dot(X_train, weights_input_hidden) + bia
    output_layer_train = sigmoid(np.dot(hidden_layer_train, weights_hidden_o

    # Convert probabilities to class labels
    predicted_labels_train = np.argmax(output_layer_train, axis=1)
    accuracy_train = np.mean(predicted_labels_train == np.argmax(y_train, ax
    training_accuracy_history.append(accuracy_train)

    # Testing the neural network
    hidden_layer_test = sigmoid(np.dot(X_test, weights_input_hidden) + biase
    output_layer_test = sigmoid(np.dot(hidden_layer_test, weights_hidden_out

    # Convert probabilities to class labels
    predicted_labels_test = np.argmax(output_layer_test, axis=1)
    accuracy_test = np.mean(predicted_labels_test == np.argmax(y_test, axis=
    testing_accuracy_history.append(accuracy_test)

# Plot the loss function curve and training/testing accuracy
plt.figure(figsize=(15, 5))

# Loss Function Curve
plt.subplot(1, 2, 1)
plt.plot(training_loss_history, label='Training Loss')
plt.title('Loss Function Curve')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

# Training and Testing Accuracy
plt.subplot(1, 2, 2)
plt.plot(training_accuracy_history, label='Training Accuracy', color='blue')
plt.plot(testing_accuracy_history, label='Testing Accuracy', color='green')
plt.title('Training and Testing Accuracy')
```

```
plt.xlabel('Epoch')
plt.ylabel('Accuracy (%)')
plt.legend()

plt.tight_layout()
plt.show()

print("\nAfter 20 epochs")
print("Training accuracy:", round(accuracy_train * 100, 1), '%')
print("Testing accuracy:", round(accuracy_test * 100, 1), '%')
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/preprocessing/_encoders.py:868: FutureWarning: `sparse` was renamed to `sparse_output` in version 1.2 and will be removed in 1.4. `sparse_output` is ignored unless you leave `sparse` to its default value.
  warnings.warn(
```




```
After 20 epochs
Training accuracy: 95.0 %
Testing accuracy: 96.7 %
```

Problem 5.2 : [10pt] Try different design of the neural network, compare with part (1), and report findings. This is an open-ended question, you can change the previous model in several ways, e.g., (1) change the activation function to be tanh, ReLU etc, or (2) try to build more complex neural network by introducing more layers, or many other options. Note that for this part, you are allowed to use deep learning packages.

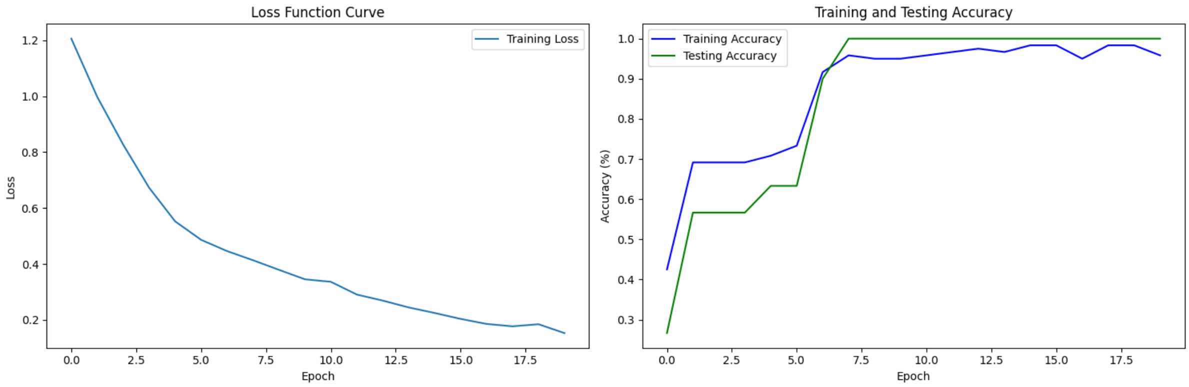
In [15]:
```
# Define neural network model using TensorFlow
model = tf.keras.Sequential([
    tf.keras.layers.Dense(32, activation='tanh', input_shape=(X_train.shape
    tf.keras.layers.Dense(16, activation='tanh', input_shape=(X_train.shape
    tf.keras.layers.Dense(3, activation='softmax')
])

# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['a

# Lists to store training loss, training, and testing accuracies
training_loss_history = []
training_accuracy_history = []
testing_accuracy_history = []

# Train the model
for epoch in range(20):

    history = model.fit(X_train, y_train, epochs=2, batch_size=8, verbose=1

    # Store training loss
    training_loss_history.append(history.history['loss'][0])

    # Calculate training accuracy
```

```
    predicted_labels_train = np.argmax(model.predict(X_train), axis=1)
    accuracy_train = np.mean(predicted_labels_train == np.argmax(y_train, ax
    training_accuracy_history.append(accuracy_train)

    # Evaluate the model on the testing set
    _, accuracy_test = model.evaluate(X_test, y_test, verbose=0)
    testing_accuracy_history.append(accuracy_test)

# Plot the loss function curve and training/testing accuracy
plt.figure(figsize=(15, 5))

# Loss Function Curve
plt.subplot(1, 2, 1)
plt.plot(training_loss_history, label='Training Loss')
plt.title('Loss Function Curve')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend()

# Training and Testing Accuracy
plt.subplot(1, 2, 2)
plt.plot(training_accuracy_history, label='Training Accuracy', color='blue')
plt.plot(testing_accuracy_history, label='Testing Accuracy', color='green')
plt.title('Training and Testing Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy (%)')
plt.legend()

plt.tight_layout()
plt.show()

print("\nAfter 20 epochs")
print("Training accuracy:", round(accuracy_train * 100, 1), '%')
print("Testing accuracy:", round(accuracy_test * 100, 1), '%')
```

```
Epoch 1/2
15/15 [==============================] - 2s 4ms/step - loss: 1.2057 - accur
acy: 0.3083
Epoch 2/2
15/15 [==============================] - 0s 3ms/step - loss: 1.0610 - accur
acy: 0.3750
4/4 [==============================] - 0s 4ms/step
Epoch 1/2
15/15 [==============================] - 0s 3ms/step - loss: 0.9972 - accur
acy: 0.6417
Epoch 2/2
15/15 [==============================] - 0s 3ms/step - loss: 0.9102 - accur
acy: 0.6917
4/4 [==============================] - 0s 3ms/step
Epoch 1/2
15/15 [==============================] - 0s 3ms/step - loss: 0.8266 - accur
acy: 0.6917
Epoch 2/2
15/15 [==============================] - 0s 3ms/step - loss: 0.7513 - accur
acy: 0.6917
4/4 [==============================] - 0s 3ms/step
Epoch 1/2
15/15 [==============================] - 0s 3ms/step - loss: 0.6725 - accur
acy: 0.6917
Epoch 2/2
15/15 [==============================] - 0s 3ms/step - loss: 0.6074 - accur
acy: 0.6917
4/4 [==============================] - 0s 3ms/step
Epoch 1/2
15/15 [==============================] - 0s 3ms/step - loss: 0.5525 - accur
acy: 0.6917
Epoch 2/2
15/15 [==============================] - 0s 3ms/step - loss: 0.5109 - accur
acy: 0.6917
4/4 [==============================] - 0s 3ms/step
Epoch 1/2
15/15 [==============================] - 0s 4ms/step - loss: 0.4865 - accur
acy: 0.8417
Epoch 2/2
15/15 [==============================] - 0s 3ms/step - loss: 0.4692 - accur
acy: 0.8000
4/4 [==============================] - 0s 2ms/step
Epoch 1/2
15/15 [==============================] - 0s 3ms/step - loss: 0.4463 - accur
acy: 0.9000
Epoch 2/2
15/15 [==============================] - 0s 3ms/step - loss: 0.4282 - accur
acy: 0.9167
4/4 [==============================] - 0s 3ms/step
Epoch 1/2
15/15 [==============================] - 0s 3ms/step - loss: 0.4135 - accur
acy: 0.9500
Epoch 2/2
15/15 [==============================] - 0s 5ms/step - loss: 0.3964 - accur
acy: 0.9417
4/4 [==============================] - 0s 5ms/step
Epoch 1/2
15/15 [==============================] - 0s 5ms/step - loss: 0.3792 - accur
acy: 0.9417
Epoch 2/2
15/15 [==============================] - 0s 5ms/step - loss: 0.3662 - accur
acy: 0.9833
4/4 [==============================] - 0s 3ms/step
Epoch 1/2
```

```
15/15 [==============================] - 0s 5ms/step - loss: 0.3454 - accur
acy: 0.9417
Epoch 2/2
15/15 [==============================] - 0s 5ms/step - loss: 0.3302 - accur
acy: 0.9417
4/4 [==============================] - 0s 5ms/step
Epoch 1/2
15/15 [==============================] - 0s 7ms/step - loss: 0.3364 - accur
acy: 0.9500
Epoch 2/2
15/15 [==============================] - 0s 6ms/step - loss: 0.3250 - accur
acy: 0.9000
4/4 [==============================] - 0s 3ms/step
Epoch 1/2
15/15 [==============================] - 0s 5ms/step - loss: 0.2908 - accur
acy: 0.9667
Epoch 2/2
15/15 [==============================] - 0s 6ms/step - loss: 0.2876 - accur
acy: 0.9333
4/4 [==============================] - 0s 15ms/step
Epoch 1/2
15/15 [==============================] - 0s 11ms/step - loss: 0.2692 - accu
racy: 0.9667
Epoch 2/2
15/15 [==============================] - 0s 13ms/step - loss: 0.2595 - accu
racy: 0.9667
4/4 [==============================] - 0s 7ms/step
Epoch 1/2
15/15 [==============================] - 0s 11ms/step - loss: 0.2447 - accu
racy: 0.9667
Epoch 2/2
15/15 [==============================] - 0s 6ms/step - loss: 0.2449 - accur
acy: 0.9500
4/4 [==============================] - 0s 5ms/step
Epoch 1/2
15/15 [==============================] - 0s 5ms/step - loss: 0.2249 - accur
acy: 0.9667
Epoch 2/2
15/15 [==============================] - 0s 6ms/step - loss: 0.2184 - accur
acy: 0.9583
4/4 [==============================] - 0s 4ms/step
Epoch 1/2
15/15 [==============================] - 0s 7ms/step - loss: 0.2038 - accur
acy: 0.9833
Epoch 2/2
15/15 [==============================] - 0s 5ms/step - loss: 0.1965 - accur
acy: 0.9583
4/4 [==============================] - 0s 4ms/step
Epoch 1/2
15/15 [==============================] - 0s 6ms/step - loss: 0.1858 - accur
acy: 0.9750
Epoch 2/2
15/15 [==============================] - 0s 9ms/step - loss: 0.1903 - accur
acy: 0.9667
4/4 [==============================] - 0s 4ms/step
Epoch 1/2
15/15 [==============================] - 0s 5ms/step - loss: 0.1773 - accur
acy: 0.9500
Epoch 2/2
15/15 [==============================] - 0s 6ms/step - loss: 0.1699 - accur
acy: 0.9667
4/4 [==============================] - 0s 5ms/step
Epoch 1/2
15/15 [==============================] - 0s 5ms/step - loss: 0.1848 - accur
```

```
acy: 0.9333
Epoch 2/2
15/15 [==============================] - 0s 5ms/step - loss: 0.1650 - accur
acy: 0.9667
4/4 [==============================] - 0s 3ms/step
Epoch 1/2
15/15 [==============================] - 0s 7ms/step - loss: 0.1531 - accur
acy: 0.9667
Epoch 2/2
15/15 [==============================] - 0s 6ms/step - loss: 0.1539 - accur
acy: 0.9667
4/4 [==============================] - 0s 5ms/step
```




```
After 20 epochs
Training accuracy: 95.8 %
Testing accuracy: 100.0 %
```

Conclusion

In part 2 (Problem 5.2), I used TensorFlow to build the neural network containing 2 hidden layers with 32 and 16 hidden units respectively and using tanh as the activation function instead of sigmoid. I also used optimizer "Adam" for parameters tuning. For training step, I trained and updated the parameters in each batch not the entire training dataset.

The result displays as shown in the above graph. The training loss is better by gradually decreasing, and the training and testing accuracies increase faster than the previous method and the final accuracies are a little bit higher.