ADVANCED MACHINE LEARNING
Assignment 1: Neural Networks

Code:

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras import layers
import matplotlib.pyplot as plt
```

```
imdb = keras.datasets.imdb
```

```
(train_data, train_labels), (test_data, test_labels) = imdb.load_data(num_words=10000)
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb.npz
17464789/17464789 [==============================] - 0s 0us/step
```

```
print("Training entries: {}, labels: {}".format(len(train_data), len(train_labels)))
```

```
Training entries: 25000, labels: 25000
```

```
word_index=imdb.get_word_index()
reverse_word_index=dict(
                    [(value,key) for (key,value) in word_index.items()])
decoded_review = "".join(
    [reverse_word_index.get(i-3,"?") for i in train_data[0]])
```

```
Downloading data from https://storage.googleapis.com/tensorflow/tf-keras-datasets/imdb_word_index.json
1641221/1641221 [==============================] - 0s 0us/step
```

```
def vectorize_sequences(sequences, dimension=10000):
    results=np.zeros((len(sequences),dimension))
    for i,sequence in enumerate(sequences):
        for j in sequence:
            results[i,j]=1.
    return results
x_train=vectorize_sequences(train_data)
x_test=vectorize_sequences(test_data)
```

```
x_train[0]
```

```
array([0., 1., 1., ..., 0., 0., 0.])
```

```
y_train=np.asarray(train_labels).astype("float32")
y_test=np.asarray(test_labels).astype("float32")
```

```
model=keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dense(16, activation = "relu"),
    layers.Dense(1, activation="sigmoid")
])
```

```
model.compile(optimizer="adam",
              loss="binary_crossentropy",
               metrics=["accuracy"])
```

```
#creating validation set
x_val=x_train[:10000]
partial_x_train=x_train[10000:]
y_val=y_train[:10000]
partial_y_train=y_train[10000:]
```

```
history= model.fit(partial_x_train,
                   partial_y_train,
                   epochs=20,
                   batch_size=512,
                   validation_data=(x_val,y_val))
```

```
Epoch 1/20
30/30 [==============================] - 4s 90ms/step - loss: 0.5546 - accuracy: 0.7721 - val_loss: 0.4042 - val_accuracy: 0.8549
Epoch 2/20
30/30 [==============================] - 2s 82ms/step - loss: 0.2993 - accuracy: 0.8993 - val_loss: 0.2994 - val_accuracy: 0.8825
Epoch 3/20
30/30 [==============================] - 2s 66ms/step - loss: 0.2022 - accuracy: 0.9337 - val_loss: 0.2754 - val_accuracy: 0.8903
Epoch 4/20
30/30 [==============================] - 2s 56ms/step - loss: 0.1482 - accuracy: 0.9536 - val_loss: 0.2804 - val_accuracy: 0.8865
Epoch 5/20
30/30 [==============================] - 2s 57ms/step - loss: 0.1125 - accuracy: 0.9685 - val_loss: 0.3024 - val_accuracy: 0.8825
Epoch 6/20
30/30 [==============================] - 2s 56ms/step - loss: 0.0862 - accuracy: 0.9790 - val_loss: 0.3186 - val_accuracy: 0.8831
Epoch 7/20
30/30 [==============================] - 1s 48ms/step - loss: 0.0651 - accuracy: 0.9862 - val_loss: 0.3423 - val_accuracy: 0.8781
Epoch 8/20
30/30 [==============================] - 1s 42ms/step - loss: 0.0489 - accuracy: 0.9912 - val_loss: 0.3743 - val_accuracy: 0.8796
Epoch 9/20
30/30 [==============================] - 2s 60ms/step - loss: 0.0364 - accuracy: 0.9957 - val_loss: 0.4023 - val_accuracy: 0.8771
Epoch 10/20
30/30 [==============================] - 2s 74ms/step - loss: 0.0275 - accuracy: 0.9974 - val_loss: 0.4268 - val_accuracy: 0.8762
Epoch 11/20
30/30 [==============================] - 1s 48ms/step - loss: 0.0203 - accuracy: 0.9988 - val_loss: 0.4596 - val_accuracy: 0.8739
Epoch 12/20
30/30 [==============================] - 1s 45ms/step - loss: 0.0150 - accuracy: 0.9995 - val_loss: 0.4912 - val_accuracy: 0.8733
Epoch 13/20
30/30 [==============================] - 2s 56ms/step - loss: 0.0111 - accuracy: 0.9998 - val_loss: 0.5185 - val_accuracy: 0.8713
```

Using TensorFlow and Keras, this code builds a neural network to categorize movie reviews as good or bad based on IMDB data. It begins by loading the IMDB dataset Keras gave, which consists of preprocessed movie reviews in the form of sequences of numbers, with each integer representing a word from a dictionary of the 10,000 most commonly occurring terms. The method then vectorizes these sequences, transforming them into a binary matrix where each row represents a review, and each column represents a dictionary term. The presence of a term in a review is indicated by setting the matrix entry to 1. The labels (positive and negative sentiment) have also been prepared for training and testing.

A basic neural network model is then defined using Keras' Sequential API. It is made up of three dense (completely associated) layers, each having 16 units and ReLU activation functions, except the output layer, which has a single unit and a sigmoid activation function for binary classification. The model is constructed using the Adam optimizer and the binary cross-entropy loss function, with accuracy as the metric. To avoid overfitting, a validation set is formed by dividing a portion of the training data. The model is trained on training data and verified on validation data for 20 epochs using a batch size of 512.

Following training, the model is evaluated against test data, and its performance metrics (loss and accuracy) are printed. The test accuracy is found to be approximately 85.58%. Finally, the model is used to predict the sentiment of the test data.

1. **You used two hidden layers. Try using one or three hidden layers and see how doing so affects validation and test accuracy.**

Code:

```
[ ] model3=keras.Sequential([
        layers.Dense(32, activation="relu"),
        layers.Dense(32, activation = "relu"),
        layers.Dense(1, activation="sigmoid")
    ])

model3.compile(optimizer="adam",
               loss="binary_crossentropy",
               metrics=["accuracy"])
history3= model3.fit(partial_x_train,
                     partial_y_train,
                     epochs=20,
                     batch_size=512,
                     validation_data=(x_val,y_val))

Epoch 1/20
30/30 [==============================] - 5s 102ms/step - loss: 0.5157 - accuracy: 0.7907 - val_loss: 0.3410 - val_accuracy: 0.8715
Epoch 2/20
30/30 [==============================] - 2s 61ms/step - loss: 0.2403 - accuracy: 0.9149 - val_loss: 0.2768 - val_accuracy: 0.8902
Epoch 3/20
30/30 [==============================] - 2s 70ms/step - loss: 0.1547 - accuracy: 0.9473 - val_loss: 0.2874 - val_accuracy: 0.8859
Epoch 4/20
30/30 [==============================] - 2s 64ms/step - loss: 0.1074 - accuracy: 0.9671 - val_loss: 0.3193 - val_accuracy: 0.8818
Epoch 5/20
30/30 [==============================] - 2s 67ms/step - loss: 0.0736 - accuracy: 0.9825 - val_loss: 0.3494 - val_accuracy: 0.8783
Epoch 6/20
30/30 [==============================] - 2s 76ms/step - loss: 0.0509 - accuracy: 0.9899 - val_loss: 0.3873 - val_accuracy: 0.8782
Epoch 7/20
30/30 [==============================] - 3s 86ms/step - loss: 0.0334 - accuracy: 0.9953 - val_loss: 0.4332 - val_accuracy: 0.8745
Epoch 8/20
30/30 [==============================] - 2s 68ms/step - loss: 0.0229 - accuracy: 0.9977 - val_loss: 0.4735 - val_accuracy: 0.8753
Epoch 9/20
30/30 [==============================] - 2s 64ms/step - loss: 0.0143 - accuracy: 0.9991 - val_loss: 0.5101 - val_accuracy: 0.8732
Epoch 10/20
30/30 [==============================] - 2s 67ms/step - loss: 0.0096 - accuracy: 0.9997 - val_loss: 0.5456 - val_accuracy: 0.8713
Epoch 11/20
30/30 [==============================] - 2s 67ms/step - loss: 0.0064 - accuracy: 0.9998 - val_loss: 0.5765 - val_accuracy: 0.8690
Epoch 12/20
30/30 [==============================] - 2s 76ms/step - loss: 0.0044 - accuracy: 1.0000 - val_loss: 0.6023 - val_accuracy: 0.8696
Epoch 13/20
30/30 [==============================] - 3s 86ms/step - loss: 0.0033 - accuracy: 1.0000 - val_loss: 0.6243 - val_accuracy: 0.8694
Epoch 14/20
30/30 [==============================] - 2s 69ms/step - loss: 0.0026 - accuracy: 1.0000 - val_loss: 0.6450 - val_accuracy: 0.8689
Epoch 15/20
30/30 [==============================] - 2s 63ms/step - loss: 0.0021 - accuracy: 1.0000 - val_loss: 0.6632 - val_accuracy: 0.8690
Epoch 16/20
30/30 [==============================] - 2s 69ms/step - loss: 0.0017 - accuracy: 1.0000 - val_loss: 0.6796 - val_accuracy: 0.8681
Epoch 17/20
30/30 [==============================] - 2s 70ms/step - loss: 0.0014 - accuracy: 1.0000 - val_loss: 0.6946 - val_accuracy: 0.8673
Epoch 18/20
30/30 [==============================] - 3s 87ms/step - loss: 0.0012 - accuracy: 1.0000 - val_loss: 0.7083 - val_accuracy: 0.8676
Epoch 19/20
30/30 [==============================] - 7s 224ms/step - loss: 0.0011 - accuracy: 1.0000 - val_loss: 0.7214 - val_accuracy: 0.8675
```

```
[ ] results3=model3.evaluate(x_test,y_test)

782/782 [==============================] - 3s 4ms/step - loss: 0.7907 - accuracy: 0.8567
```

The updated code defines and trains two new models. The first new model, model2, adds an additional hidden layer to the neural network, resulting in three hidden layers rather than two. Model2's architecture consists of three dense layers, each with 16 units and ReLU activation functions, and a final output layer with a sigmoid activation function for binary classification. Similarly, it is built using the Adam optimizer, the binary cross-entropy loss function, and accuracy as the metric. This model is then trained using the same training and validation data for 20 epochs with a batch size of 512. Following training, it is evaluated using test data, and performance metrics are calculated.

When compared to the previous model, model2 has a test accuracy of about 85.90%, which is slightly higher than the initial model's test accuracy of about 85.58%. Interestingly, model2 has a higher training accuracy of 100% than the original model, which may indicate overfitting. However, the validation accuracy for model2 is comparable to the previous model, implying that the additional hidden layer may not significantly improve generalization performance. Overall, the main change in this code is the addition of an extra hidden layer to the neural network architecture, which results in a slight increase in test accuracy but no significant changes in validation accuracy.

2. **Try using layers with more hidden units or fewer hidden units: 32 units, 64 units, and so on.**

Code:

2. Try using layers with more hidden units or fewer hidden units: 32 units, 64 units, and so on.

```
model3=keras.Sequential([
    layers.Dense(32, activation="relu"),
    layers.Dense(32, activation = "relu"),
    layers.Dense(1, activation="sigmoid")
])
```

```
model3.compile(optimizer="adam",
             loss="binary_crossentropy",
              metrics=["accuracy"])
history3= model3.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val,y_val))
```

```
Epoch 1/20
30/30 [==============================] - 5s 102ms/step - loss: 0.5157 - accuracy: 0.7907 - val_loss: 0.3410 - val_accuracy: 0.8715
Epoch 2/20
30/30 [==============================] - 2s 61ms/step - loss: 0.2403 - accuracy: 0.9149 - val_loss: 0.2768 - val_accuracy: 0.8902
Epoch 3/20
30/30 [==============================] - 2s 70ms/step - loss: 0.1547 - accuracy: 0.9473 - val_loss: 0.2874 - val_accuracy: 0.8859
Epoch 4/20
30/30 [==============================] - 2s 64ms/step - loss: 0.1074 - accuracy: 0.9671 - val_loss: 0.3193 - val_accuracy: 0.8818
Epoch 5/20
30/30 [==============================] - 2s 67ms/step - loss: 0.0736 - accuracy: 0.9825 - val_loss: 0.3494 - val_accuracy: 0.8783
Epoch 6/20
30/30 [==============================] - 2s 76ms/step - loss: 0.0509 - accuracy: 0.9899 - val_loss: 0.3873 - val_accuracy: 0.8782
Epoch 7/20
30/30 [==============================] - 3s 86ms/step - loss: 0.0334 - accuracy: 0.9953 - val_loss: 0.4332 - val_accuracy: 0.8745
Epoch 8/20
30/30 [==============================] - 2s 68ms/step - loss: 0.0229 - accuracy: 0.9977 - val_loss: 0.4735 - val_accuracy: 0.8753
Epoch 9/20
30/30 [==============================] - 2s 64ms/step - loss: 0.0143 - accuracy: 0.9991 - val_loss: 0.5101 - val_accuracy: 0.8732
Epoch 10/20
30/30 [==============================] - 2s 67ms/step - loss: 0.0096 - accuracy: 0.9997 - val_loss: 0.5456 - val_accuracy: 0.8713
Epoch 11/20
30/30 [==============================] - 2s 67ms/step - loss: 0.0064 - accuracy: 0.9998 - val_loss: 0.5765 - val_accuracy: 0.8690
Epoch 12/20
30/30 [==============================] - 2s 76ms/step - loss: 0.0044 - accuracy: 1.0000 - val_loss: 0.6023 - val_accuracy: 0.8696
Epoch 13/20
30/30 [==============================] - 3s 86ms/step - loss: 0.0033 - accuracy: 1.0000 - val_loss: 0.6243 - val_accuracy: 0.8694
Epoch 14/20
30/30 [==============================] - 2s 69ms/step - loss: 0.0026 - accuracy: 1.0000 - val_loss: 0.6450 - val_accuracy: 0.8689
Epoch 15/20
30/30 [==============================] - 2s 63ms/step - loss: 0.0021 - accuracy: 1.0000 - val_loss: 0.6632 - val_accuracy: 0.8690
Epoch 16/20
30/30 [==============================] - 2s 69ms/step - loss: 0.0017 - accuracy: 1.0000 - val_loss: 0.6796 - val_accuracy: 0.8681
Epoch 17/20
30/30 [==============================] - 2s 70ms/step - loss: 0.0014 - accuracy: 1.0000 - val_loss: 0.6946 - val_accuracy: 0.8673
```

```
results3=model3.evaluate(x_test,y_test)
```

```
782/782 [==============================] - 3s 4ms/step - loss: 0.7907 - accuracy: 0.8567
```

Model 3 is defined with a different architecture than the initial model. model3 has two hidden layers, each with 32 units and ReLU activation functions, followed by a final output layer that uses a sigmoid activation function for binary classification. The model is built using the Adam optimizer, a binary cross-entropy loss function, and accuracy as the metric. Similarly, it is trained using the same training and validation data for 20 epochs with a batch size of 512. Model3's performance metrics are calculated after it has been trained and evaluated using test data.

When compared to the initial model, model3 has a test accuracy of approximately 85.67%, which is slightly lower than the initial model's test accuracy of approximately 85.58%. However, the difference in accuracy is minimal. Interestingly, model3 has a higher training accuracy of 100%, indicating possible overfitting, similar to model2. The validation accuracy for model3 remains comparable to the initial model, indicating that changing the number of hidden units had no significant effect on generalization performance. Overall, the main change in this code is the number of hidden units in the neural network architecture, which results in slightly different test accuracy but no significant changes in validation accuracy.

3. Try using the mse loss function instead of binary_crossentropy.

Code:

```
[ ] model.compile(optimizer="adam",
                  loss="mse",
                  metrics=["accuracy"])
    history4= model.fit(partial_x_train,
                        partial_y_train,
                        epochs=20,
                        batch_size=512,
                        validation_data=(x_val,y_val))

    Epoch 1/20
    30/30 [==============================] - 4s 87ms/step - loss: 2.0590e-04 - accuracy: 0.9999 - val_loss: 0.1160 - val_accuracy: 0.8659
    Epoch 2/20
    30/30 [==============================] - 2s 60ms/step - loss: 1.9826e-04 - accuracy: 0.9999 - val_loss: 0.1171 - val_accuracy: 0.8646
    Epoch 3/20
    30/30 [==============================] - 2s 58ms/step - loss: 1.5706e-04 - accuracy: 1.0000 - val_loss: 0.1179 - val_accuracy: 0.8638
    Epoch 4/20
    30/30 [==============================] - 2s 58ms/step - loss: 8.0067e-05 - accuracy: 1.0000 - val_loss: 0.1191 - val_accuracy: 0.8641
    Epoch 5/20
    30/30 [==============================] - 3s 84ms/step - loss: 4.3442e-05 - accuracy: 1.0000 - val_loss: 0.1197 - val_accuracy: 0.8640
    Epoch 6/20
    30/30 [==============================] - 1s 50ms/step - loss: 2.2530e-05 - accuracy: 1.0000 - val_loss: 0.1202 - val_accuracy: 0.8632
    Epoch 7/20
    30/30 [==============================] - 1s 49ms/step - loss: 1.4919e-05 - accuracy: 1.0000 - val_loss: 0.1204 - val_accuracy: 0.8621
    Epoch 8/20
    30/30 [==============================] - 2s 58ms/step - loss: 1.2111e-05 - accuracy: 1.0000 - val_loss: 0.1205 - val_accuracy: 0.8618
    Epoch 9/20
    30/30 [==============================] - 2s 60ms/step - loss: 1.0152e-05 - accuracy: 1.0000 - val_loss: 0.1207 - val_accuracy: 0.8623
    Epoch 10/20
    30/30 [==============================] - 2s 59ms/step - loss: 8.8359e-06 - accuracy: 1.0000 - val_loss: 0.1207 - val_accuracy: 0.8621
    Epoch 11/20
    30/30 [==============================] - 2s 52ms/step - loss: 7.8295e-06 - accuracy: 1.0000 - val_loss: 0.1208 - val_accuracy: 0.8622
    Epoch 12/20
    30/30 [==============================] - 2s 70ms/step - loss: 7.0037e-06 - accuracy: 1.0000 - val_loss: 0.1209 - val_accuracy: 0.8618
    Epoch 13/20
    30/30 [==============================] - 2s 67ms/step - loss: 6.3278e-06 - accuracy: 1.0000 - val_loss: 0.1210 - val_accuracy: 0.8621
    Epoch 14/20
    30/30 [==============================] - 2s 61ms/step - loss: 5.7782e-06 - accuracy: 1.0000 - val_loss: 0.1210 - val_accuracy: 0.8619
    Epoch 15/20
    30/30 [==============================] - 2s 60ms/step - loss: 5.2705e-06 - accuracy: 1.0000 - val_loss: 0.1211 - val_accuracy: 0.8621
    Epoch 16/20
    30/30 [==============================] - 2s 62ms/step - loss: 4.8376e-06 - accuracy: 1.0000 - val_loss: 0.1212 - val_accuracy: 0.8623
    Epoch 17/20
    30/30 [==============================] - 2s 59ms/step - loss: 4.4694e-06 - accuracy: 1.0000 - val_loss: 0.1213 - val_accuracy: 0.8623
    Epoch 18/20
    30/30 [==============================] - 1s 43ms/step - loss: 4.1370e-06 - accuracy: 1.0000 - val_loss: 0.1213 - val_accuracy: 0.8626
    Epoch 19/20
    30/30 [==============================] - 2s 64ms/step - loss: 3.8381e-06 - accuracy: 1.0000 - val_loss: 0.1214 - val_accuracy: 0.8623
    Epoch 20/20
    30/30 [==============================] - 2s 74ms/step - loss: 3.5826e-06 - accuracy: 1.0000 - val_loss: 0.1214 - val_accuracy: 0.8621
```

Instead of binary cross-entropy, the model uses Mean Squared Error (MSE) as its loss function. Additionally, the accuracy metric is kept for evaluation. The model is then trained using the same training and validation data for 20 epochs, with a batch size of 512.

When comparing the performance of this model (let's call it model4) to the first model, several differences can be seen. First, the loss function is converted from binary cross-entropy to MSE. This change in loss function may cause differences in how the model updates its weights during training, particularly in how it handles misclassifications. As a result, model 4 has a significantly lower loss value than the first model, with a final loss of around 3.5826e-06.

However, when we look at the validation accuracy, we see a slight decrease compared to the first model, with a final validation accuracy of approximately 86.21%. This change suggests that, while the model fits the training data very well (as evidenced by the extremely low loss and 100% training accuracy), it may not generalize as well to unseen data. The variation in the loss function appears to have hampered the model's ability to generalize, resulting in a slightly lower validation accuracy than the original model. Overall, model 4 achieves an impressively low loss on the training data, but its performance on the validation set indicates potential overfitting.

4. Try using the tanh activation (an activation that was popular in the early days of neural networks) instead of relu.

Code:

4. Try using the tanh activation (an activation that was popular in the early days of neural networks) instead of relu.

```python
model4=keras.Sequential([
    layers.Dense(16, activation="tanh"),
    layers.Dense(16, activation = "tanh"),
    layers.Dense(1, activation="sigmoid")
])
```

```python
model4.compile(optimizer="adam",
              loss="binary_crossentropy",
               metrics=["accuracy"])
history4= model4.fit(partial_x_train,
                     partial_y_train,
                     epochs=20,
                     batch_size=512,
                     validation_data=(x_val,y_val))
```

```
Epoch 1/20
30/30 [==============================] - 4s 87ms/step - loss: 0.5116 - accuracy: 0.7893 - val_loss: 0.3711 - val_accuracy: 0.8598
Epoch 2/20
30/30 [==============================] - 2s 61ms/step - loss: 0.2716 - accuracy: 0.9076 - val_loss: 0.2840 - val_accuracy: 0.8875
Epoch 3/20
30/30 [==============================] - 2s 72ms/step - loss: 0.1816 - accuracy: 0.9407 - val_loss: 0.2720 - val_accuracy: 0.8886
Epoch 4/20
30/30 [==============================] - 1s 45ms/step - loss: 0.1309 - accuracy: 0.9623 - val_loss: 0.2846 - val_accuracy: 0.8860
Epoch 5/20
30/30 [==============================] - 1s 50ms/step - loss: 0.0964 - accuracy: 0.9756 - val_loss: 0.3031 - val_accuracy: 0.8830
Epoch 6/20
30/30 [==============================] - 1s 42ms/step - loss: 0.0717 - accuracy: 0.9843 - val_loss: 0.3297 - val_accuracy: 0.8786
Epoch 7/20
30/30 [==============================] - 1s 48ms/step - loss: 0.0521 - accuracy: 0.9907 - val_loss: 0.3579 - val_accuracy: 0.8765
Epoch 8/20
30/30 [==============================] - 2s 55ms/step - loss: 0.0377 - accuracy: 0.9946 - val_loss: 0.3884 - val_accuracy: 0.8736
Epoch 9/20
30/30 [==============================] - 1s 44ms/step - loss: 0.0271 - accuracy: 0.9974 - val_loss: 0.4168 - val_accuracy: 0.8727
Epoch 10/20
30/30 [==============================] - 2s 54ms/step - loss: 0.0198 - accuracy: 0.9987 - val_loss: 0.4431 - val_accuracy: 0.8700
Epoch 11/20
30/30 [==============================] - 2s 72ms/step - loss: 0.0147 - accuracy: 0.9995 - val_loss: 0.4664 - val_accuracy: 0.8698
Epoch 12/20
30/30 [==============================] - 2s 62ms/step - loss: 0.0110 - accuracy: 0.9997 - val_loss: 0.4894 - val_accuracy: 0.8682
Epoch 13/20
30/30 [==============================] - 1s 48ms/step - loss: 0.0085 - accuracy: 0.9999 - val_loss: 0.5091 - val_accuracy: 0.8684
Epoch 14/20
30/30 [==============================] - 1s 46ms/step - loss: 0.0068 - accuracy: 0.9999 - val_loss: 0.5276 - val_accuracy: 0.8674
Epoch 15/20
30/30 [==============================] - 1s 49ms/step - loss: 0.0057 - accuracy: 0.9999 - val_loss: 0.5431 - val_accuracy: 0.8678
Epoch 16/20
30/30 [==============================] - 2s 62ms/step - loss: 0.0048 - accuracy: 1.0000 - val_loss: 0.5598 - val_accuracy: 0.8656
```

```python
[ ] results4=model4.evaluate(x_test,y_test)
```

```
782/782 [==============================] - 2s 3ms/step - loss: 0.6603 - accuracy: 0.8550
```

Model4 uses tanh instead of ReLU for both hidden layers. The architecture remains the same, with two hidden layers of 16 units each and tanh activation functions, followed by a final output layer with sigmoid activation function for binary classification. The model is built using the Adam optimizer, a binary cross-entropy loss function, and accuracy as the metric. Similarly, it is trained using the same training and validation data for 20 epochs with a batch size of 512.

There are several differences between the performance of model 4 and the first model, which used ReLU activations. Model4 achieves a relatively high training accuracy of 100%, as does the first model, but its validation accuracy is slightly lower, with a final value of approximately 86.64%. Furthermore, model4's test accuracy is slightly lower than the first model, with a final accuracy of around 85.50%. This suggests that the choice of activation function influenced the model's ability to generalize to previously unseen data, with the tanh activation function performing slightly worse in terms of validation and test accuracy than ReLU. Overall, while both models achieve similar training accuracies, the first model with ReLU activations has slightly better generalization performance on the validation and test sets than model 4 with tanh activations.

5. Use any technique we studied in class, and these include regularization, dropout, etc., to get your model to perform better on validation.

Code:

5. Use any technique we studied in class, and these include regularization, dropout, etc., to get your model to perform better on validation.

```
model5=keras.Sequential([
    layers.Dense(16, activation="relu"),
    layers.Dropout(0.2),
    layers.Dense(16, activation = "relu"),
    layers.Dropout(0.2),
    layers.Dense(1, activation="sigmoid")
])
```

```
model5.compile(optimizer="adam",
             loss="binary_crossentropy",
              metrics=["accuracy"])
history5= model5.fit(partial_x_train,
                    partial_y_train,
                    epochs=20,
                    batch_size=512,
                    validation_data=(x_val,y_val))
```

```
Epoch 1/20
30/30 [==============================] - 3s 75ms/step - loss: 0.6213 - accuracy: 0.6649 - val_loss: 0.4995 - val_accuracy: 0.8402
Epoch 2/20
30/30 [==============================] - 2s 55ms/step - loss: 0.4463 - accuracy: 0.8314 - val_loss: 0.3601 - val_accuracy: 0.8772
Epoch 3/20
30/30 [==============================] - 1s 43ms/step - loss: 0.3239 - accuracy: 0.8873 - val_loss: 0.2980 - val_accuracy: 0.8880
Epoch 4/20
30/30 [==============================] - 2s 64ms/step - loss: 0.2484 - accuracy: 0.9158 - val_loss: 0.2788 - val_accuracy: 0.8915
Epoch 5/20
30/30 [==============================] - 2s 69ms/step - loss: 0.1981 - accuracy: 0.9361 - val_loss: 0.2783 - val_accuracy: 0.8879
Epoch 6/20
30/30 [==============================] - 2s 61ms/step - loss: 0.1596 - accuracy: 0.9501 - val_loss: 0.2904 - val_accuracy: 0.8879
Epoch 7/20
30/30 [==============================] - 2s 61ms/step - loss: 0.1284 - accuracy: 0.9605 - val_loss: 0.3039 - val_accuracy: 0.8868
Epoch 8/20
30/30 [==============================] - 2s 59ms/step - loss: 0.1023 - accuracy: 0.9716 - val_loss: 0.3233 - val_accuracy: 0.8850
Epoch 9/20
30/30 [==============================] - 2s 52ms/step - loss: 0.0844 - accuracy: 0.9780 - val_loss: 0.3532 - val_accuracy: 0.8797
Epoch 10/20
30/30 [==============================] - 2s 62ms/step - loss: 0.0655 - accuracy: 0.9832 - val_loss: 0.3789 - val_accuracy: 0.8826
Epoch 11/20
30/30 [==============================] - 2s 77ms/step - loss: 0.0567 - accuracy: 0.9867 - val_loss: 0.3952 - val_accuracy: 0.8792
Epoch 12/20
30/30 [==============================] - 2s 60ms/step - loss: 0.0466 - accuracy: 0.9899 - val_loss: 0.4184 - val_accuracy: 0.8793
Epoch 13/20
30/30 [==============================] - 2s 59ms/step - loss: 0.0390 - accuracy: 0.9910 - val_loss: 0.4471 - val_accuracy: 0.8791
Epoch 14/20
30/30 [==============================] - 1s 49ms/step - loss: 0.0311 - accuracy: 0.9935 - val_loss: 0.4841 - val_accuracy: 0.8759
Epoch 15/20
30/30 [==============================] - 2s 57ms/step - loss: 0.0251 - accuracy: 0.9952 - val_loss: 0.4990 - val_accuracy: 0.8771
```

```
[ ] results=model5.evaluate(x_test,y_test)

782/782 [==============================] - 3s 4ms/step - loss: 0.6797 - accuracy: 0.8620
```

Model 5 is characterized by the addition of dropout layers following each dense layer. Dropout is a regularization strategy used in neural networks in order to prevent overfitting by randomly discarding (setting to zero) a proportion of input units during training. To prevent overfitting, a 0.2-rate dropout occurs after each hidden layer. Model5's architecture is identical to the original model, with two 16-unit hidden layers and ReLU activation functions, followed by a final output layer with a sigmoid activation function for binary classification. The Adam optimizer is used to create the model, along with a binary cross-entropy loss function and accuracy as the measure. Similarly, it is trained across 20 epochs using the same training and validation data with a batch size of 512. There are numerous variations in model5's performance compared to the first model. Model5 with dropout layers outperforms the initial model in generalization, with a final validation accuracy of 87.40% vs 86.21% for the initial model. Both models achieve excellent training accuracy. Furthermore, model5 obtains a little higher test accuracy of roughly 86.20% compared to the initial model's test accuracy of about 85.58%. The introduction of dropout layers improves generalization performance by minimizing reliance on individual neurons and pushing the network to acquire stronger characteristics.