Activity 1.2 : Training Neural Networks

Objective(s):

This activity aims to demonstrate how to train neural networks using keras

Intended Learning Outcomes (ILOs):

- Demonstrate how to build and train neural networks
- Demonstrate how to evaluate and plot the model using training and validation loss

Resources:

- Jupyter Notebook

CI Pima Diabetes Dataset

- pima-indians-diabetes.csv

Procedures

Load the necessary libraries

```
from __future__ import absolute_import, division, print_function

import warnings
warnings.filterwarnings("ignore")

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import confusion_matrix, precision_recall_curve, roc_auc_score, roc_cur
from sklearn.ensemble import RandomForestClassifier

import seaborn as sns

%matplotlib inline
```

```
## Import Keras objects for Deep Learning

from keras.models  import Sequential
from keras.layers import Input, Dense, Flatten, Dropout, BatchNormalization
from keras.optimizers import Adam, SGD, RMSprop
```

Load the dataset

```
filepath = "pima-indians-diabetes.csv"
names = ["times_pregnant", "glucose_tolerance_test", "blood_pressure", "skin_thickness", "ir
         "bmi", "pedigree_function", "age", "has_diabetes"]
diabetes_df = pd.read_csv(filepath, names=names)
```

Check the top 5 samples of the data

```
print(diabetes_df.shape)
diabetes_df.sample(5)
```

```
(768, 9)
```

	times_pregnant	glucose_tolerance_test	blood_pressure	skin_thickness	insulin	b
662	8	167	106	46	231	37
324	2	112	75	32	0	35
494	3	80	0	0	0	(
278	5	114	74	0	0	24
353	1	90	62	12	43	27

```
diabetes_df.dtypes
```

```
times_pregnant               int64
glucose_tolerance_test       int64
blood_pressure               int64
skin_thickness               int64
insulin                      int64
bmi                        float64
pedigree_function          float64
age                          int64
has_diabetes                 int64
dtype: object
```

```
X = diabetes_df.iloc[:, :-1].values
y = diabetes_df["has_diabetes"].values
```

Split the data to Train, and Test (75%, 25%)

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, random_state=11111
```

```
np.mean(y), np.mean(1-y)
```

```
     (0.3489583333333333, 0.6510416666666666)
```

Build a single hidden layer neural network using 12 nodes. Use the sequential model with single layer network and input shape to 8.

Normalize the data

```
normalizer = StandardScaler()
X_train_norm = normalizer.fit_transform(X_train)
X_test_norm = normalizer.transform(X_test)
```

Define the model:

- Input size is 8-dimensional
- 1 hidden layer, 12 hidden nodes, sigmoid activation
- Final layer with one node and sigmoid activation (standard for binary classification)

```
model_1 = Sequential([
    Dense(12, input_shape=(8,), activation="relu"),
    Dense(1, activation="sigmoid")
])
```

View the model summary

```
model_1.summary()
```

```
     Model: "sequential"
     _________________________________________________________________
      Layer (type)                Output Shape              Param #   
     =================================================================
      dense (Dense)               (None, 12)                108       
                                                                      
      dense_1 (Dense)             (None, 1)                 13        
                                                                      
     =================================================================
Total params: 121 (484.00 Byte)
Trainable params: 121 (484.00 Byte)
Non-trainable params: 0 (0.00 Byte)
```

Train the model

- Compile the model with optimizer, loss function and metrics
- Use the fit function to return the run history.

```
model_1.compile(SGD(lr = .003), "binary_crossentropy", metrics=["accuracy"])
run_hist_1 = model_1.fit(X_train_norm, y_train, validation_data=(X_test_norm, y_test), epoch
```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use
Epoch 1/200
18/18 [==============================] - 1s 16ms/step - loss: 0.7618 - accuracy: 0.529
Epoch 2/200
18/18 [==============================] - 0s 4ms/step - loss: 0.7237 - accuracy: 0.5712
Epoch 3/200
18/18 [==============================] - 0s 4ms/step - loss: 0.6941 - accuracy: 0.6024
Epoch 4/200
18/18 [==============================] - 0s 5ms/step - loss: 0.6702 - accuracy: 0.6181
Epoch 5/200
18/18 [==============================] - 0s 6ms/step - loss: 0.6507 - accuracy: 0.6181
Epoch 6/200
18/18 [==============================] - 0s 6ms/step - loss: 0.6343 - accuracy: 0.6215
Epoch 7/200
18/18 [==============================] - 0s 5ms/step - loss: 0.6203 - accuracy: 0.6285
Epoch 8/200
18/18 [==============================] - 0s 5ms/step - loss: 0.6083 - accuracy: 0.6458
Epoch 9/200
18/18 [==============================] - 0s 5ms/step - loss: 0.5976 - accuracy: 0.6545
Epoch 10/200
18/18 [==============================] - 0s 6ms/step - loss: 0.5884 - accuracy: 0.6667
Epoch 11/200
18/18 [==============================] - 0s 5ms/step - loss: 0.5800 - accuracy: 0.6719
Epoch 12/200
18/18 [==============================] - 0s 6ms/step - loss: 0.5725 - accuracy: 0.6788
Epoch 13/200
18/18 [==============================] - 0s 5ms/step - loss: 0.5657 - accuracy: 0.6840
Epoch 14/200
18/18 [==============================] - 0s 5ms/step - loss: 0.5594 - accuracy: 0.6858
Epoch 15/200
18/18 [==============================] - 0s 6ms/step - loss: 0.5537 - accuracy: 0.6927
Epoch 16/200
18/18 [==============================] - 0s 5ms/step - loss: 0.5485 - accuracy: 0.6944
Epoch 17/200
18/18 [==============================] - 0s 5ms/step - loss: 0.5436 - accuracy: 0.6962
Epoch 18/200
18/18 [==============================] - 0s 4ms/step - loss: 0.5391 - accuracy: 0.6997
Epoch 19/200
18/18 [==============================] - 0s 5ms/step - loss: 0.5348 - accuracy: 0.7049
```

```
Epoch 20/200
18/18 [==============================] - 0s 8ms/step - loss: 0.5309 - accuracy: 0.704
Epoch 21/200
18/18 [==============================] - 0s 6ms/step - loss: 0.5271 - accuracy: 0.708
Epoch 22/200
18/18 [==============================] - 0s 6ms/step - loss: 0.5238 - accuracy: 0.706
Epoch 23/200
18/18 [==============================] - 0s 6ms/step - loss: 0.5206 - accuracy: 0.706
Epoch 24/200
18/18 [==============================] - 0s 6ms/step - loss: 0.5173 - accuracy: 0.706
Epoch 25/200
18/18 [==============================] - 0s 5ms/step - loss: 0.5145 - accuracy: 0.708
Epoch 26/200
18/18 [==============================] - 0s 5ms/step - loss: 0.5116 - accuracy: 0.711
Epoch 27/200
18/18 [==============================] - 0s 6ms/step - loss: 0.5090 - accuracy: 0.720
Epoch 28/200
18/18 [==============================] - 0s 5ms/step - loss: 0.5064 - accuracy: 0.725
```

```
## Like we did for the Random Forest, we generate two kinds of predictions
#  One is a hard decision, the other is a probabilitistic score.

y_pred_class_nn_1 = model_1.predict(X_test_norm)
y_pred_prob_nn_1 = model_1.predict(X_test_norm)
```

```
6/6 [==============================] - 0s 2ms/step
6/6 [==============================] - 0s 2ms/step
```

```
# Let's check out the outputs to get a feel for how keras apis work.
y_pred_class_nn_1[:10]
```

```
array([[0.65582037],
       [0.6507114 ],
       [0.32304847],
       [0.21720952],
       [0.1633364 ],
       [0.4551786 ],
       [0.02752979],
       [0.38203385],
       [0.89780146],
       [0.17257361]], dtype=float32)
```

```
y_pred_prob_nn_1[:10]
```

```
array([[0.65582037],
       [0.6507114 ],
       [0.32304847],
       [0.21720952],
       [0.1633364 ],
       [0.4551786 ],
       [0.02752979],
       [0.38203385],
        [0.89780146],
        [0.17257361]], dtype=float32)
```

Create the plot_roc function

```
rf = RandomForestClassifier(n_estimators=200)
rf.fit(X_train, y_train)
```

```
▾         RandomForestClassifier
RandomForestClassifier(n_estimators=200)
```

```
def plot_roc(y_test, y_pred, model_name):
    fpr, tpr, thr = roc_curve(y_test, y_pred)
    fig, ax = plt.subplots(figsize=(8, 8))
    ax.plot(fpr, tpr, 'k-')
    ax.plot([0, 1], [0, 1], 'k--', linewidth=.5)  # roc curve for random model
    ax.grid(True)
    ax.set(title='ROC Curve for {} on PIMA diabetes problem'.format(model_name),
           xlim=[-0.01, 1.01], ylim=[-0.01, 1.01])
```

Evaluate the model performance and plot the ROC CURVE

```
y_pred_class_rf = rf.predict(X_test)
y_pred_prob_rf = rf.predict_proba(X_test)
```

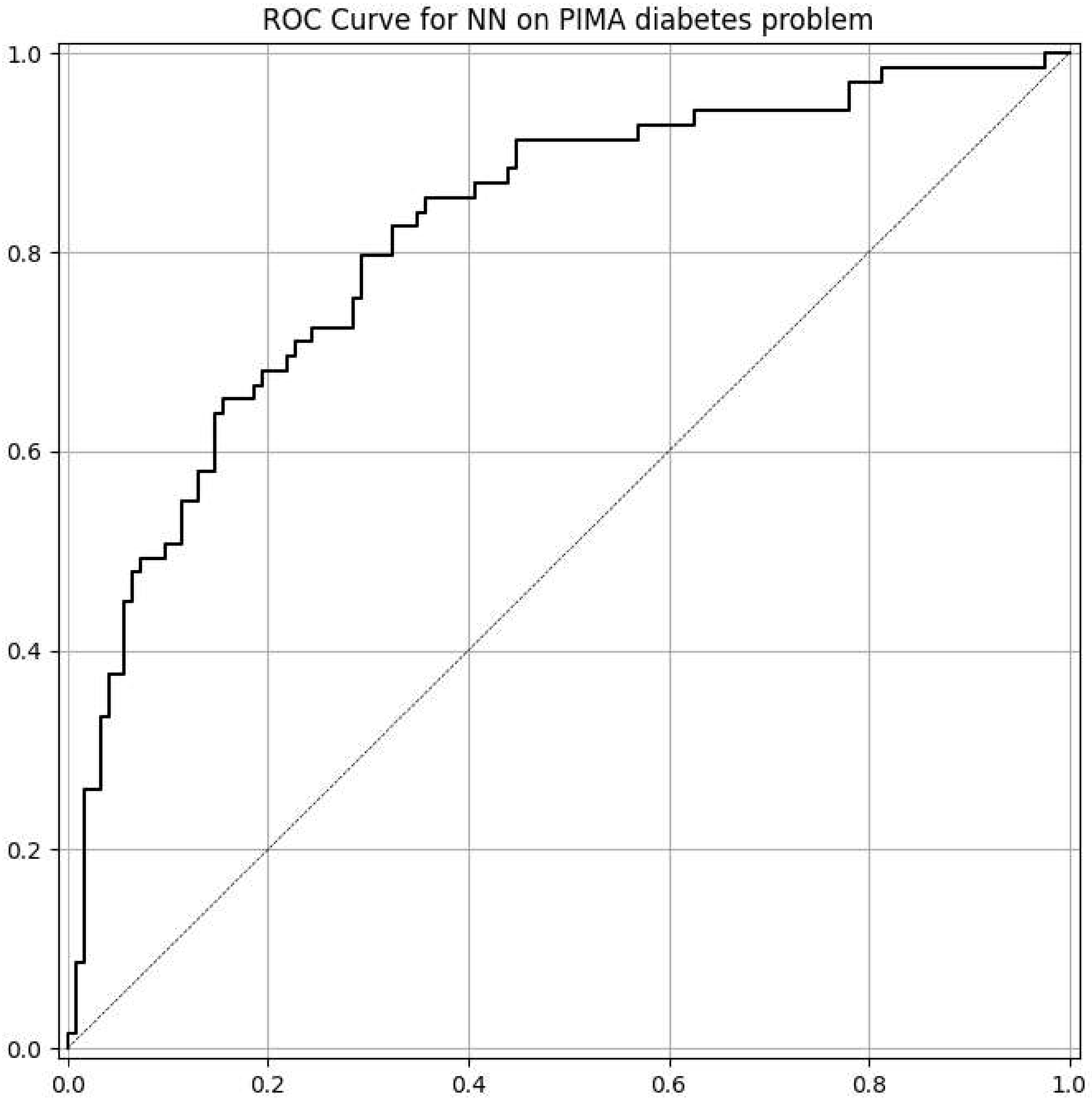
```
print('accuracy is {:.3f}'.format(accuracy_score(y_test,y_pred_class_rf)))
print('roc-auc is {:.3f}'.format(roc_auc_score(y_test,y_pred_prob_rf[:,1])))
```

```
accuracy is 0.760
roc-auc is 0.818
```

```
print('accuracy is {:.3f}'.format(accuracy_score(y_test,y_pred_class_rf)))
print('roc-auc is {:.3f}'.format(roc_auc_score(y_test,y_pred_prob_rf[:,1])))

plot_roc(y_test, y_pred_prob_nn_1, 'NN')
```

```
accuracy is 0.760
roc-auc is 0.818
```



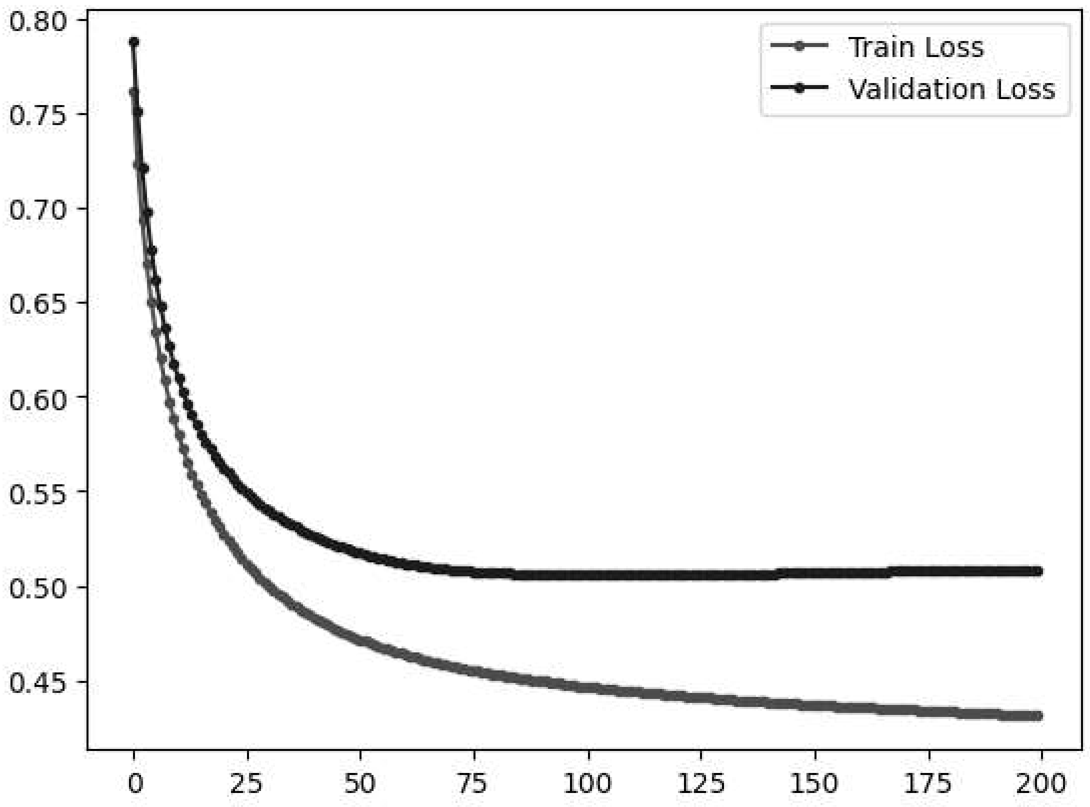
Plot the training loss and the validation loss over the different epochs and see how it looks

```
run_hist_1.history.keys()
```

```
dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

```
fig, ax = plt.subplots()
ax.plot(run_hist_1.history["loss"],'r', marker='.', label="Train Loss")
ax.plot(run_hist_1.history["val_loss"],'b', marker='.', label="Validation Loss")
ax.legend()
```

```
<matplotlib.legend.Legend at 0x7ce35e04a7a0>
```



What is your interpretation about the result of the train and validation loss?

type your answer here

My interpretation on the results of train and validation loss is that the model should have further training, thus adding more epoch may result into better or worse. Also, the results shows it is underfitting since the both losses is high creating wider gap each epoch.

Supplementary Activity

- Build a model with two hidden layers, each with 6 nodes
- Use the "relu" activation function for the hidden layers, and "sigmoid" for the final layer
- Use a learning rate of .003 and train for 1500 epochs
- Graph the trajectory of the loss functions, accuracy on both train and test set

- Plot the roc curve for the predictions
- Use different learning rates, numbers of epochs, and network structures.
- Plot the results of training and validation loss using different learning rates, number of epocgs and network structures
- Interpret your result

```
#Build a model with two hidden layers, each with 6 nodes
#Use the "relu" activation function for the hidden layers, and "sigmoid" for the final layer
model_supple = Sequential([
    Dense(6, input_shape=(8,), activation="sigmoid"),
    Dense(2, activation="relu")
])
```

```
model_supple.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_2 (Dense)             (None, 6)                 54

 dense_3 (Dense)             (None, 2)                 14

=================================================================
Total params: 68 (272.00 Byte)
Trainable params: 68 (272.00 Byte)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

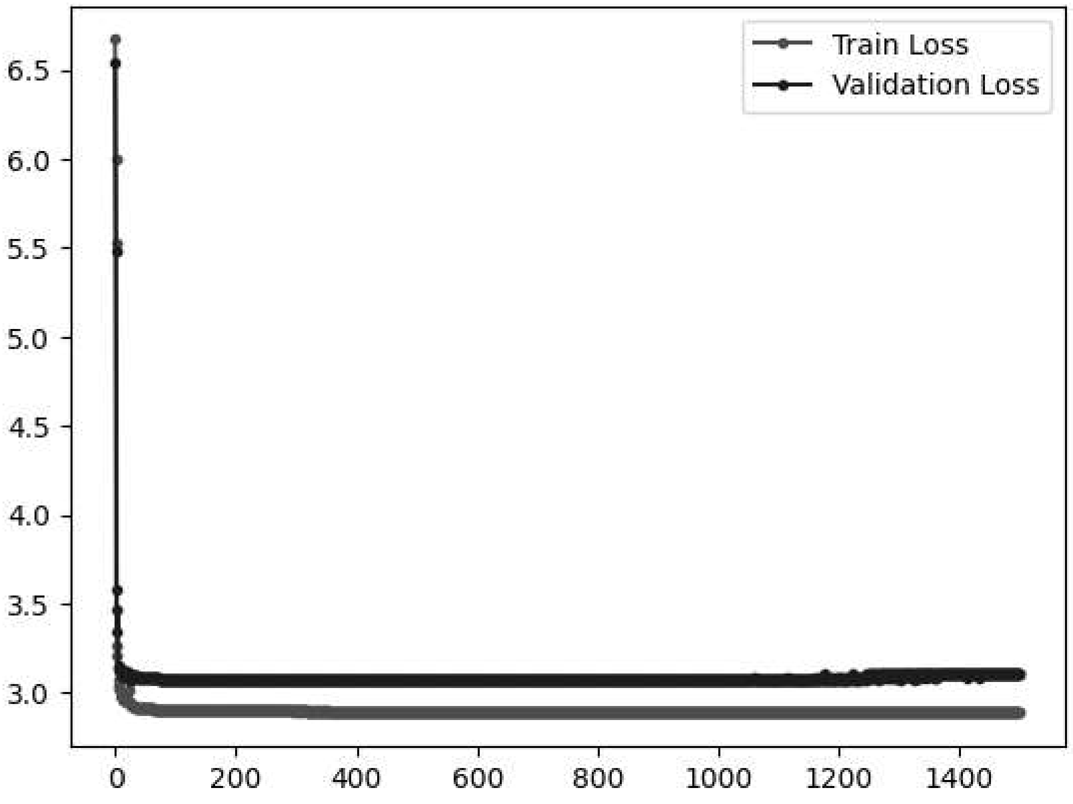
```
model_supple.compile(SGD(lr = .003), "binary_crossentropy", metrics=["accuracy"])
run_hist_1 = model_supple.fit(X_train_norm, y_train, validation_data=(X_test_norm, y_test),
```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use
Epoch 1/1500
18/18 [==============================] - 1s 13ms/step - loss: 6.6705 - accuracy: 0.654
Epoch 2/1500
18/18 [==============================] - 0s 4ms/step - loss: 6.0002 - accuracy: 0.6545
Epoch 3/1500
18/18 [==============================] - 0s 4ms/step - loss: 5.5249 - accuracy: 0.6528
Epoch 4/1500
18/18 [==============================] - 0s 4ms/step - loss: 3.2684 - accuracy: 0.6545
Epoch 5/1500
18/18 [==============================] - 0s 4ms/step - loss: 3.2098 - accuracy: 0.6545
Epoch 6/1500
18/18 [==============================] - 0s 5ms/step - loss: 3.0724 - accuracy: 0.6545
Epoch 7/1500
18/18 [==============================] - 0s 5ms/step - loss: 3.0379 - accuracy: 0.6545
Epoch 8/1500
18/18 [==============================] - 0s 4ms/step - loss: 3.0258 - accuracy: 0.6545
Epoch 9/1500
18/18 [==============================] - 0s 4ms/step - loss: 3.0175 - accuracy: 0.6545
```

```
Epoch 10/1500
18/18 [==============================] - 0s 4ms/step - loss: 2.9997 - accuracy: 0.6545
Epoch 11/1500
18/18 [==============================] - 0s 5ms/step - loss: 2.9832 - accuracy: 0.6545
Epoch 12/1500
18/18 [==============================] - 0s 4ms/step - loss: 2.9775 - accuracy: 0.6545
Epoch 13/1500
18/18 [==============================] - 0s 4ms/step - loss: 2.9723 - accuracy: 0.6545
Epoch 14/1500
18/18 [==============================] - 0s 4ms/step - loss: 2.9684 - accuracy: 0.6545
Epoch 15/1500
18/18 [==============================] - 0s 4ms/step - loss: 2.9649 - accuracy: 0.6545
Epoch 16/1500
18/18 [==============================] - 0s 3ms/step - loss: 2.9615 - accuracy: 0.6545
Epoch 17/1500
18/18 [==============================] - 0s 4ms/step - loss: 2.9589 - accuracy: 0.6545
Epoch 18/1500
18/18 [==============================] - 0s 4ms/step - loss: 2.9567 - accuracy: 0.6545
Epoch 19/1500
18/18 [==============================] - 0s 4ms/step - loss: 2.9541 - accuracy: 0.6545
Epoch 20/1500
18/18 [==============================] - 0s 4ms/step - loss: 2.9524 - accuracy: 0.6545
Epoch 21/1500
18/18 [==============================] - 0s 4ms/step - loss: 2.9504 - accuracy: 0.6545
Epoch 22/1500
18/18 [==============================] - 0s 4ms/step - loss: 2.9487 - accuracy: 0.6545
Epoch 23/1500
18/18 [==============================] - 0s 5ms/step - loss: 2.9472 - accuracy: 0.6545
Epoch 24/1500
18/18 [==============================] - 0s 4ms/step - loss: 2.9456 - accuracy: 0.6545
Epoch 25/1500
18/18 [==============================] - 0s 4ms/step - loss: 3.0134 - accuracy: 0.6545
Epoch 26/1500
18/18 [==============================] - 0s 4ms/step - loss: 2.9322 - accuracy: 0.6545
Epoch 27/1500
18/18 [==============================] - 0s 4ms/step - loss: 2.9265 - accuracy: 0.6545
Epoch 28/1500
18/18 [==============================] - 0s 4ms/step - loss: 2.9249 - accuracy: 0.6545
```

```
fig, ax = plt.subplots()
ax.plot(run_hist_1.history["loss"],'r', marker='.', label="Train Loss")
ax.plot(run_hist_1.history["val_loss"],'b', marker='.', label="Validation Loss")
ax.legend()
```

```
<matplotlib.legend.Legend at 0x7ce35defc6a0>
```

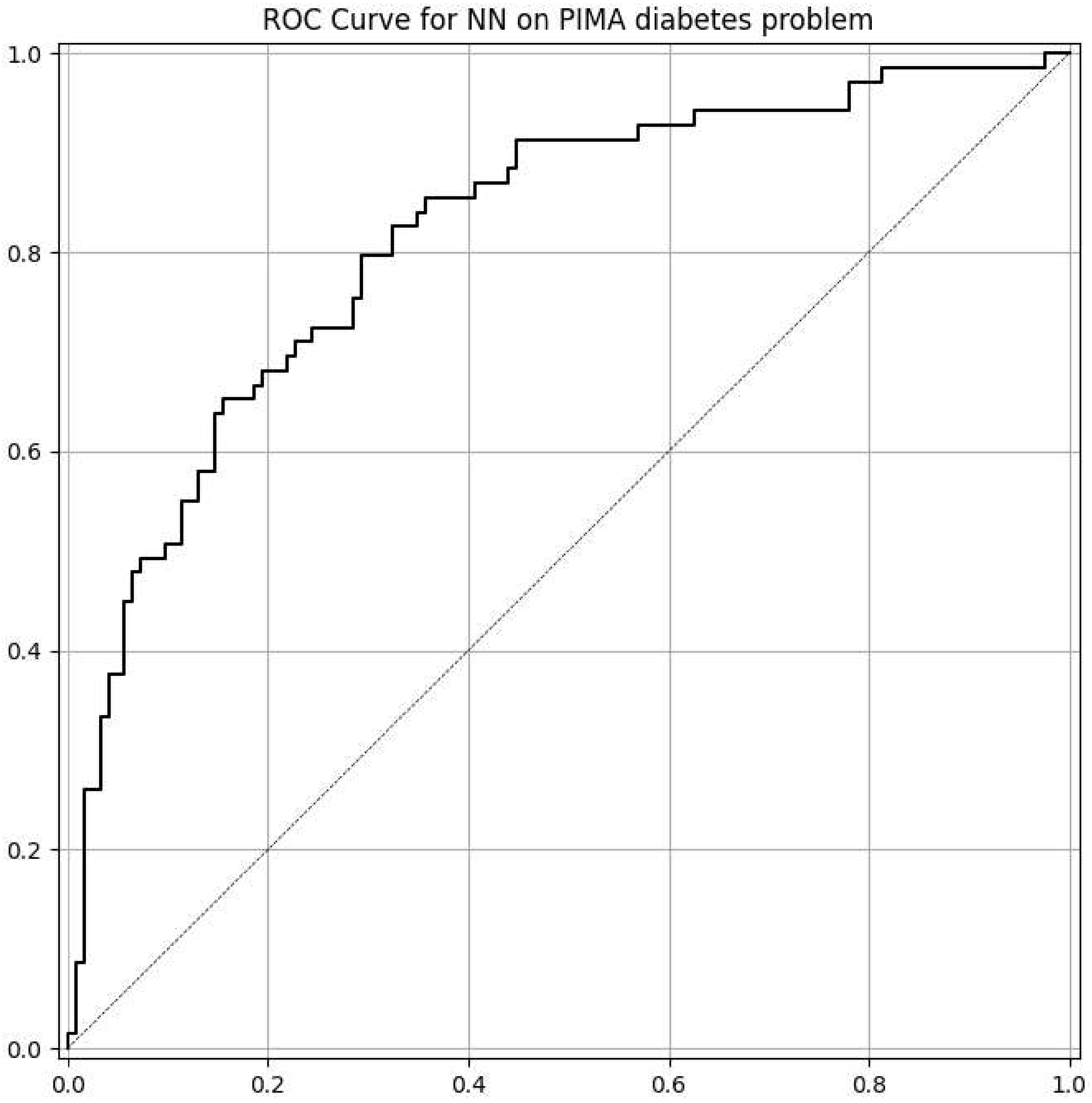


- Interpret results The results shows in the graph that the model is underfitting since the gap between the two losses are high. It shows that under 200 epoch the model are good fit indicating that having 200 epoch is enough.

```
#Plot the roc curve for the predictions
print('accuracy is {:.3f}'.format(accuracy_score(y_test,y_pred_class_rf)))
print('roc-auc is {:.3f}'.format(roc_auc_score(y_test,y_pred_prob_rf[:,1])))

plot_roc(y_test, y_pred_prob_nn_1, 'NN')
```

```
accuracy is 0.760
roc-auc is 0.818
```



```
#Use different learning rates, numbers of epochs, and network structures.
model_2 = Sequential([
    Dense(10, input_shape=(8,), activation="tanh"),
    Dense(1, activation="sigmoid")
])
```

```
model_2.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
```

```
=================================================================
 dense_4 (Dense)             (None, 10)                90

 dense_5 (Dense)             (None, 1)                 11

=================================================================
Total params: 101 (404.00 Byte)
Trainable params: 101 (404.00 Byte)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

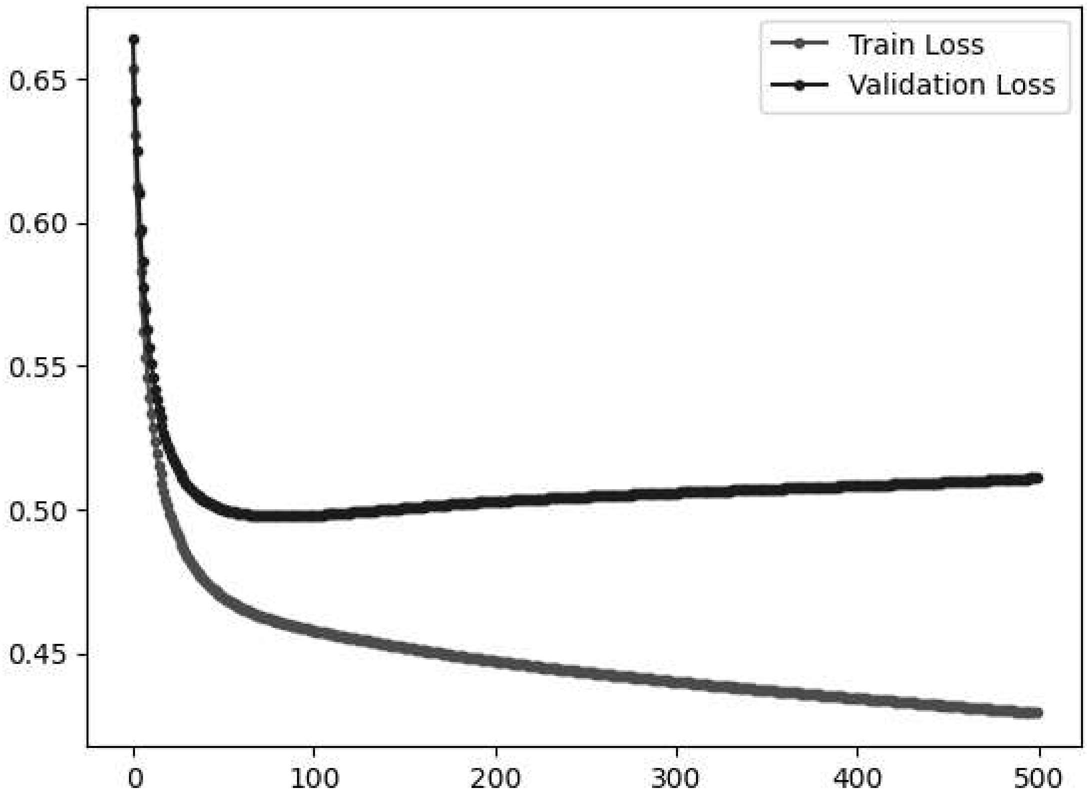
```
#Plot the results of training and validation loss using different learning rates, number of
model_2.compile(SGD(lr = .005), "binary_crossentropy", metrics=["accuracy"])
run_hist_2 = model_2.fit(X_train_norm, y_train, validation_data=(X_test_norm, y_test), epoch
```

```
WARNING:absl:`lr` is deprecated in Keras optimizer, please use `learning_rate` or use 
Epoch 1/500
18/18 [==============================] - 1s 13ms/step - loss: 0.6533 - accuracy: 0.631
Epoch 2/500
18/18 [==============================] - 0s 5ms/step - loss: 0.6307 - accuracy: 0.6806
Epoch 3/500
18/18 [==============================] - 0s 4ms/step - loss: 0.6120 - accuracy: 0.7101
Epoch 4/500
18/18 [==============================] - 0s 5ms/step - loss: 0.5962 - accuracy: 0.7222
Epoch 5/500
18/18 [==============================] - 0s 4ms/step - loss: 0.5831 - accuracy: 0.7361
Epoch 6/500
18/18 [==============================] - 0s 4ms/step - loss: 0.5716 - accuracy: 0.7344
Epoch 7/500
18/18 [==============================] - 0s 4ms/step - loss: 0.5618 - accuracy: 0.7413
Epoch 8/500
18/18 [==============================] - 0s 4ms/step - loss: 0.5533 - accuracy: 0.7448
Epoch 9/500
18/18 [==============================] - 0s 4ms/step - loss: 0.5458 - accuracy: 0.7500
Epoch 10/500
18/18 [==============================] - 0s 4ms/step - loss: 0.5392 - accuracy: 0.7517
Epoch 11/500
18/18 [==============================] - 0s 4ms/step - loss: 0.5334 - accuracy: 0.7483
Epoch 12/500
18/18 [==============================] - 0s 4ms/step - loss: 0.5282 - accuracy: 0.7483
Epoch 13/500
18/18 [==============================] - 0s 5ms/step - loss: 0.5235 - accuracy: 0.7517
Epoch 14/500
18/18 [==============================] - 0s 5ms/step - loss: 0.5194 - accuracy: 0.7604
Epoch 15/500
18/18 [==============================] - 0s 4ms/step - loss: 0.5156 - accuracy: 0.7639
Epoch 16/500
18/18 [==============================] - 0s 4ms/step - loss: 0.5122 - accuracy: 0.7656
Epoch 17/500
18/18 [==============================] - 0s 4ms/step - loss: 0.5090 - accuracy: 0.7639
Epoch 18/500
18/18 [==============================] - 0s 4ms/step - loss: 0.5061 - accuracy: 0.7656
Epoch 19/500
18/18 [==============================] - 0s 4ms/step - loss: 0.5036 - accuracy: 0.7691
Epoch 20/500
```

```
18/18 [==============================] - 0s 5ms/step - loss: 0.5011 - accuracy: 0.7708
Epoch 21/500
18/18 [==============================] - 0s 4ms/step - loss: 0.4989 - accuracy: 0.7708
Epoch 22/500
18/18 [==============================] - 0s 4ms/step - loss: 0.4968 - accuracy: 0.7708
Epoch 23/500
18/18 [==============================] - 0s 4ms/step - loss: 0.4949 - accuracy: 0.7726
Epoch 24/500
18/18 [==============================] - 0s 4ms/step - loss: 0.4931 - accuracy: 0.7760
Epoch 25/500
18/18 [==============================] - 0s 4ms/step - loss: 0.4914 - accuracy: 0.7760
Epoch 26/500
18/18 [==============================] - 0s 4ms/step - loss: 0.4899 - accuracy: 0.7778
Epoch 27/500
18/18 [==============================] - 0s 4ms/step - loss: 0.4884 - accuracy: 0.7778
Epoch 28/500
18/18 [==============================] - 0s 4ms/step - loss: 0.4871 - accuracy: 0.7795
```

```python
fig, ax = plt.subplots()
ax.plot(run_hist_2.history["loss"],'r', marker='.', label="Train Loss")
ax.plot(run_hist_2.history["val_loss"],'b', marker='.', label="Validation Loss")
ax.legend()
```

```
<matplotlib.legend.Legend at 0x7ce35dbe9f00>
```



- Interpret your result

It shows that the experimented one is good fit since both are stabilizing as the epoch gets higher. The results shows stablization as the epoch gets further.

Conclusion

To conclude, this activity help me understand on how to train neural networks and how to apply it into deep learning and how to use it in models. Although I experienced some errors, I still tried to solve it and I think I solved it somehow and as the time goes by and everytime I tried to fix the errors I realized what this hands-on activity for and how this works. Lastly, this activity help me to have a better idea how cool deep learning is and how important it is.

Double-click (or enter) to edit

Double-click (or enter) to edit

+ Code + Text