## **Question 1**

## Iris Dataset

```
# Import required libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import sklearn
# Import necessary modules
from sklearn.model selection import train test split
from sklearn.metrics import mean squared error
from math import sqrt
# Keras specific
import keras
from keras.models import Sequential
from keras.layers import Dense
from keras.utils import to categorical
df = pd.read_csv('sample_data/iris.data')
print(df.shape)
df.describe()
(150, 5)
            s len
                        s wid
                                     p len
                                                 p wid
                   150.000000
       150.000000
                                150.000000
                                            150.000000
count
         5.843333
                     3.054000
                                  3.758667
                                              1.198667
mean
         0.828066
                     0.433594
                                  1.764420
                                              0.763161
std
min
         4.300000
                     2.000000
                                  1.000000
                                              0.100000
25%
         5.100000
                     2.800000
                                  1.600000
                                              0.300000
50%
         5.800000
                     3.000000
                                 4.350000
                                              1.300000
75%
         6.400000
                     3.300000
                                  5.100000
                                              1.800000
         7.900000
                     4.400000
                                  6.900000
                                              2.500000
max
target column = ['class']
predictors = list(set(list(df.columns))-set(target column))
df[predictors] = df[predictors]/df[predictors].max()
df.describe()
            s len
                        s wid
                                     p len
                                                 p wid
       150.000000
                   150.000000
                                150.000000
                                            150.000000
count
                                  0.544734
                                              0.479467
         0.739662
                     0.694091
mean
std
         0.104818
                     0.098544
                                  0.255713
                                              0.305264
                     0.454545
                                  0.144928
         0.544304
                                              0.040000
min
25%
         0.645570
                     0.636364
                                  0.231884
                                              0.120000
50%
         0.734177
                     0.681818
                                  0.630435
                                              0.520000
```

```
75%
       0.810127
                           0.739130
                                     0.720000
                 0.750000
       1.000000
                 1.000000
                           1.000000
                                     1.000000
max
X = df[predictors].values
df['class'].replace(['Iris-setosa', 'Iris-virginica', 'Iris-
versicolor'l.
                    [0, 1, 2], inplace=True)
y = df[target column].values
X train, X test, y train, y test = train test split(X, y,
test size=0.30, random state=40)
print(X train.shape); print(X test.shape)
(105, 4)
(45, 4)
# one hot encode outputs
y train = to categorical(y train)
y_test = to_categorical(y_test)
count classes = y test.shape[1]
print(count classes)
3
model = Sequential()
model.add(Dense(500, activation='relu', input dim=4))
model.add(Dense(100, activation='sigmoid'))
model.add(Dense(50, activation='sigmoid'))
model.add(Dense(3, activation='softmax'))
# Compile the model
model.compile(optimizer='adam',
           loss='categorical crossentropy',
           metrics=['accuracy'])
# build the model
md = model.fit(X_train, y_train, epochs=100, validation_split=0.2)
Epoch 1/100
accuracy: 0.3214 - val loss: 1.1312 - val accuracy: 0.4286
Epoch 2/100
accuracy: 0.3214 - val loss: 1.1135 - val accuracy: 0.5238
Epoch 3/100
accuracy: 0.4405 - val loss: 1.1298 - val accuracy: 0.2381
Epoch 4/100
accuracy: 0.3571 - val loss: 1.1418 - val accuracy: 0.2381
```

```
Epoch 5/100
accuracy: 0.4286 - val loss: 1.1305 - val accuracy: 0.5714
Epoch 6/100
accuracy: 0.6667 - val loss: 1.1117 - val accuracy: 0.5714
Epoch 7/100
accuracy: 0.6310 - val loss: 1.0889 - val accuracy: 0.5714
Epoch 8/100
accuracy: 0.6786 - val_loss: 1.0623 - val_accuracy: 0.5714
Epoch 9/100
accuracy: 0.6786 - val loss: 1.0429 - val accuracy: 0.5714
Epoch 10/100
accuracy: 0.6786 - val_loss: 1.0245 - val_accuracy: 0.4762
Epoch 11/100
accuracy: 0.5000 - val loss: 1.0026 - val accuracy: 0.4762
Epoch 12/100
accuracy: 0.5595 - val loss: 0.9812 - val accuracy: 0.7619
Epoch 13/100
accuracy: 0.7024 - val loss: 0.9641 - val accuracy: 0.5714
Epoch 14/100
accuracy: 0.7500 - val_loss: 0.9453 - val_accuracy: 0.5714
Epoch 15/100
accuracy: 0.6786 - val loss: 0.9303 - val accuracy: 0.5714
Epoch 16/100
accuracy: 0.6786 - val loss: 0.9090 - val accuracy: 0.5714
Epoch 17/100
accuracy: 0.6786 - val loss: 0.8809 - val accuracy: 0.5714
Epoch 18/100
accuracy: 0.6786 - val loss: 0.8455 - val accuracy: 0.5714
Epoch 19/100
accuracy: 0.6786 - val loss: 0.8048 - val accuracy: 0.5714
Epoch 20/100
accuracy: 0.6905 - val loss: 0.7572 - val accuracy: 0.5714
Epoch 21/100
```

```
accuracy: 0.7500 - val loss: 0.7150 - val accuracy: 0.5714
Epoch 22/100
accuracy: 0.7857 - val loss: 0.6795 - val accuracy: 0.6667
Epoch 23/100
accuracy: 0.7976 - val loss: 0.6496 - val accuracy: 0.6190
Epoch 24/100
accuracy: 0.7976 - val loss: 0.6229 - val accuracy: 0.6190
Epoch 25/100
accuracy: 0.7976 - val loss: 0.5995 - val accuracy: 0.6190
Epoch 26/100
accuracy: 0.8214 - val loss: 0.5724 - val accuracy: 0.7619
Epoch 27/100
accuracy: 0.8214 - val loss: 0.5499 - val accuracy: 0.8095
Epoch 28/100
accuracy: 0.8571 - val loss: 0.5252 - val accuracy: 0.9524
Epoch 29/100
accuracy: 0.9167 - val loss: 0.5024 - val accuracy: 0.9524
Epoch 30/100
accuracy: 0.9167 - val loss: 0.4904 - val accuracy: 0.9524
Epoch 31/100
accuracy: 0.8929 - val loss: 0.4826 - val accuracy: 0.9524
Epoch 32/100
accuracy: 0.8810 - val loss: 0.4635 - val accuracy: 0.9524
Epoch 33/100
accuracy: 0.9405 - val loss: 0.4407 - val accuracy: 0.9524
Epoch 34/100
accuracy: 0.9643 - val loss: 0.4232 - val accuracy: 0.9524
Epoch 35/100
accuracy: 0.9643 - val loss: 0.4131 - val accuracy: 0.9524
Epoch 36/100
accuracy: 0.9643 - val_loss: 0.4003 - val_accuracy: 0.9524
Epoch 37/100
accuracy: 0.9643 - val loss: 0.3821 - val accuracy: 0.9524
Epoch 38/100
```

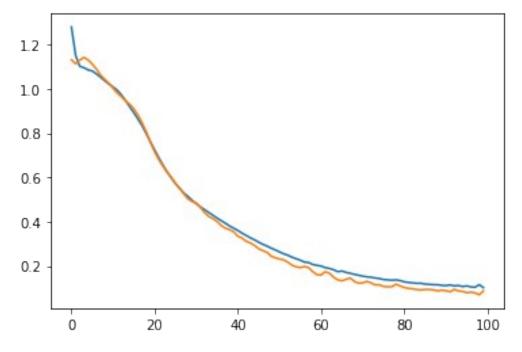
```
accuracy: 0.9643 - val loss: 0.3698 - val accuracy: 0.9524
Epoch 39/100
accuracy: 0.9643 - val loss: 0.3637 - val accuracy: 0.9524
Epoch 40/100
accuracy: 0.9643 - val_loss: 0.3537 - val_accuracy: 0.9524
Epoch 41/100
accuracy: 0.9643 - val loss: 0.3333 - val accuracy: 0.9524
Epoch 42/100
accuracy: 0.9643 - val loss: 0.3256 - val accuracy: 0.9524
Epoch 43/100
accuracy: 0.9643 - val loss: 0.3107 - val accuracy: 0.9524
Epoch 44/100
accuracy: 0.9643 - val loss: 0.3034 - val accuracy: 0.9524
Epoch 45/100
accuracy: 0.9643 - val_loss: 0.2918 - val_accuracy: 0.9524
Epoch 46/100
accuracy: 0.9643 - val loss: 0.2771 - val accuracy: 0.9524
Epoch 47/100
accuracy: 0.9643 - val loss: 0.2684 - val accuracy: 0.9524
Epoch 48/100
accuracy: 0.9643 - val loss: 0.2612 - val accuracy: 0.9524
Epoch 49/100
accuracy: 0.9643 - val loss: 0.2433 - val accuracy: 0.9524
Epoch 50/100
accuracy: 0.9524 - val loss: 0.2364 - val accuracy: 0.9524
Epoch 51/100
accuracy: 0.9643 - val loss: 0.2307 - val accuracy: 0.9524
Epoch 52/100
accuracy: 0.9643 - val loss: 0.2268 - val accuracy: 0.9524
Epoch 53/100
accuracy: 0.9643 - val loss: 0.2164 - val accuracy: 0.9524
Epoch 54/100
accuracy: 0.9643 - val_loss: 0.2030 - val_accuracy: 0.9524
```

```
Epoch 55/100
accuracy: 0.9524 - val loss: 0.1953 - val accuracy: 0.9524
Epoch 56/100
accuracy: 0.9524 - val loss: 0.1918 - val accuracy: 0.9524
Epoch 57/100
accuracy: 0.9643 - val loss: 0.1971 - val accuracy: 0.9524
Epoch 58/100
accuracy: 0.9643 - val loss: 0.1914 - val accuracy: 0.9524
Epoch 59/100
accuracy: 0.9643 - val loss: 0.1735 - val accuracy: 0.9524
Epoch 60/100
accuracy: 0.9643 - val_loss: 0.1599 - val_accuracy: 1.0000
Epoch 61/100
accuracy: 0.9762 - val_loss: 0.1587 - val_accuracy: 0.9524
Epoch 62/100
accuracy: 0.9524 - val loss: 0.1735 - val accuracy: 0.9524
Epoch 63/100
accuracy: 0.9643 - val loss: 0.1661 - val accuracy: 0.9524
Epoch 64/100
accuracy: 0.9643 - val_loss: 0.1487 - val_accuracy: 0.9524
Epoch 65/100
accuracy: 0.9524 - val loss: 0.1367 - val accuracy: 1.0000
Epoch 66/100
accuracy: 0.9762 - val loss: 0.1322 - val accuracy: 1.0000
Epoch 67/100
accuracy: 0.9643 - val loss: 0.1389 - val accuracy: 0.9524
Epoch 68/100
accuracy: 0.9643 - val loss: 0.1448 - val accuracy: 0.9524
Epoch 69/100
accuracy: 0.9643 - val loss: 0.1296 - val accuracy: 0.9524
Epoch 70/100
accuracy: 0.9524 - val loss: 0.1214 - val accuracy: 0.9524
Epoch 71/100
```

```
accuracy: 0.9643 - val loss: 0.1231 - val accuracy: 0.9524
Epoch 72/100
accuracy: 0.9524 - val_loss: 0.1297 - val accuracy: 0.9524
Epoch 73/100
accuracy: 0.9643 - val loss: 0.1225 - val accuracy: 0.9524
Epoch 74/100
accuracy: 0.9524 - val loss: 0.1139 - val accuracy: 0.9524
Epoch 75/100
accuracy: 0.9524 - val loss: 0.1142 - val accuracy: 0.9524
Epoch 76/100
accuracy: 0.9524 - val loss: 0.1062 - val accuracy: 0.9524
Epoch 77/100
accuracy: 0.9643 - val loss: 0.1051 - val accuracy: 0.9524
Epoch 78/100
accuracy: 0.9643 - val loss: 0.1058 - val accuracy: 0.9524
Epoch 79/100
accuracy: 0.9524 - val loss: 0.1172 - val accuracy: 0.9524
Epoch 80/100
accuracy: 0.9643 - val loss: 0.1086 - val accuracy: 0.9524
Epoch 81/100
accuracy: 0.9524 - val loss: 0.1023 - val_accuracy: 0.9524
Epoch 82/100
accuracy: 0.9524 - val loss: 0.0980 - val accuracy: 0.9524
Epoch 83/100
accuracy: 0.9524 - val loss: 0.0957 - val accuracy: 0.9524
Epoch 84/100
accuracy: 0.9524 - val loss: 0.0929 - val accuracy: 0.9524
Epoch 85/100
accuracy: 0.9643 - val loss: 0.0912 - val accuracy: 0.9524
Epoch 86/100
accuracy: 0.9643 - val_loss: 0.0933 - val_accuracy: 0.9524
Epoch 87/100
accuracy: 0.9524 - val loss: 0.0931 - val accuracy: 0.9524
Epoch 88/100
```

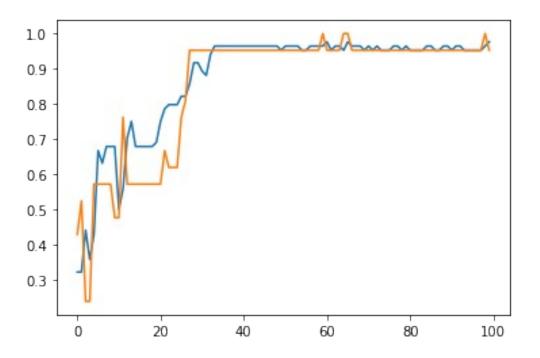
```
accuracy: 0.9524 - val loss: 0.0913 - val accuracy: 0.9524
Epoch 89/100
accuracy: 0.9643 - val loss: 0.0868 - val accuracy: 0.9524
Epoch 90/100
accuracy: 0.9643 - val loss: 0.0902 - val accuracy: 0.9524
Epoch 91/100
accuracy: 0.9524 - val loss: 0.0875 - val accuracy: 0.9524
Epoch 92/100
accuracy: 0.9643 - val loss: 0.0824 - val accuracy: 0.9524
Epoch 93/100
accuracy: 0.9643 - val loss: 0.0938 - val accuracy: 0.9524
Epoch 94/100
accuracy: 0.9524 - val loss: 0.0867 - val accuracy: 0.9524
Epoch 95/100
accuracy: 0.9524 - val loss: 0.0842 - val accuracy: 0.9524
Epoch 96/100
accuracy: 0.9524 - val loss: 0.0787 - val accuracy: 0.9524
Epoch 97/100
accuracy: 0.9524 - val loss: 0.0811 - val accuracy: 0.9524
Epoch 98/100
accuracy: 0.9524 - val loss: 0.0778 - val accuracy: 0.9524
Epoch 99/100
accuracy: 0.9643 - val loss: 0.0690 - val accuracy: 1.0000
Epoch 100/100
accuracy: 0.9762 - val loss: 0.0870 - val accuracy: 0.9524
pred train= model.predict(X train)
scores = model.evaluate(X_train, y_train, verbose=0)
print('Accuracy on training data: {}% \n Error on training data:
{}'.format(scores[1], 1 - scores[1]))
pred test= model.predict(X test)
scores2 = model.evaluate(X_test, y_test, verbose=0)
print('Accuracy on test data: {}% \n Error on test data:
{}'.format(scores2[1], 1 - scores2[1]))
4/4 [======= ] - Os 4ms/step
Accuracy on training data: 0.9523809552192688%
```

[<matplotlib.lines.Line2D at 0x7fdbf596b9d0>]



plt.plot(md.history['accuracy'])
plt.plot(md.history['val\_accuracy'])

[<matplotlib.lines.Line2D at 0x7fdbf59ea340>]



## **Question 2**

```
Breast Cancer Dataset
```

```
df2 = pd.read csv('sample data/wdbc.data', header=None)
print(df2.shape)
df2.drop(df2.columns[0], axis=1, inplace=True)
df2.replace(('M', 'B'), (1, 0), inplace=True)
df2.head()
df2.describe()
(569, 32)
                1
                            2
                                                                        \
       569.000000
                    569.000000
                                 569,000000
                                             569.000000
                                                           569.000000
count
         0.372583
                     14.127292
                                  19.289649
                                              91.969033
                                                           654.889104
mean
         0.483918
                      3.524049
                                   4.301036
                                              24.298981
                                                           351.914129
std
min
         0.000000
                      6.981000
                                   9.710000
                                              43.790000
                                                           143.500000
25%
         0.000000
                     11.700000
                                  16.170000
                                              75.170000
                                                           420.300000
                                              86.240000
                                                           551.100000
50%
         0.000000
                     13.370000
                                  18.840000
         1.000000
                     15.780000
                                  21.800000
                                              104.100000
                                                           782.700000
75%
                                  39.280000
                                              188.500000
                                                          2501.000000
         1.000000
                     28.110000
max
                            7
                                                      9
                6
                                         8
                                                                   10
count
       569.000000
                    569.000000
                                569.000000
                                             569.000000
                                                          569.000000
                      0.104341
                                   0.088799
mean
         0.096360
                                               0.048919
                                                            0.181162
```

```
0.014064
                                   0.079720
                                               0.038803
                                                            0.027414
std
                      0.052813
min
         0.052630
                      0.019380
                                   0.000000
                                               0.000000
                                                            0.106000
25%
         0.086370
                      0.064920
                                   0.029560
                                               0.020310
                                                            0.161900
50%
         0.095870
                      0.092630
                                   0.061540
                                               0.033500
                                                            0.179200
         0.105300
                                   0.130700
                                               0.074000
75%
                      0.130400
                                                            0.195700
         0.163400
                      0.345400
                                   0.426800
                                               0.201200
                                                            0.304000
max
                22
                            23
                                         24
                                                       25
                                                                    26
                                                                        \
       569.000000
                    569.000000
                                 569.000000
                                              569.000000
                                                           569.000000
count
                                 107.261213
        16.269190
                     25.677223
                                              880.583128
                                                             0.132369
mean
         4.833242
                      6.146258
                                  33.602542
                                              569.356993
                                                             0.022832
std
                                  50.410000
min
         7.930000
                     12.020000
                                              185.200000
                                                             0.071170
25%
        13.010000
                     21.080000
                                 84.110000
                                              515.300000
                                                             0.116600
50%
        14.970000
                     25.410000
                                 97.660000
                                              686.500000
                                                             0.131300
                     29.720000
                                 125,400000
        18.790000
                                             1084.000000
75%
                                                             0.146000
                     49.540000
                                 251.200000
max
        36.040000
                                             4254.000000
                                                             0.222600
                27
                            28
                                         29
                                                      30
                                                                   31
       569.000000
                    569.000000
                                 569.000000
                                             569.000000
                                                          569.000000
count
         0.254265
                      0.272188
                                   0.114606
                                               0.290076
                                                            0.083946
mean
         0.157336
                      0.208624
                                   0.065732
                                               0.061867
                                                            0.018061
std
min
         0.027290
                      0.000000
                                   0.000000
                                               0.156500
                                                            0.055040
25%
         0.147200
                      0.114500
                                   0.064930
                                               0.250400
                                                            0.071460
         0.211900
                      0.226700
                                   0.099930
                                               0.282200
                                                            0.080040
50%
75%
         0.339100
                      0.382900
                                   0.161400
                                               0.317900
                                                            0.092080
         1.058000
                      1.252000
                                   0.291000
                                               0.663800
                                                            0.207500
max
[8 rows x 31 columns]
X = df2.drop(df2.columns[[0]],axis = 1)
v = df2.iloc[:,0].values
from sklearn.model selection import train test split
X train,X test,y train,y test =
train test split(X,y,test_size=0.3,random_state=0)
print(X train.shape); print(X test.shape)
(398, 30)
(171, 30)
model = Sequential()
model.add(Dense(500, activation='sigmoid', input_dim=30))
model.add(Dense(100, activation='sigmoid'))
model.add(Dense(50, activation='sigmoid'))
model.add(Dense(1, activation='sigmoid'))
```

```
# Compile the model
model.compile(optimizer='adam',
       loss='binary crossentropy',
       metrics=['accuracy'])
# build the model
md = model.fit(X train, y train, epochs=100, validation split=0.2)
Epoch 1/100
accuracy: 0.6006 - val loss: 0.6463 - val accuracy: 0.6000
Epoch 2/100
accuracy: 0.7107 - val loss: 0.5563 - val accuracy: 0.8125
Epoch 3/100
accuracy: 0.8711 - val loss: 0.4555 - val accuracy: 0.8750
Epoch 4/100
accuracy: 0.8931 - val loss: 0.3644 - val accuracy: 0.8875
Epoch 5/100
accuracy: 0.9025 - val loss: 0.3162 - val accuracy: 0.9125
Epoch 6/100
accuracy: 0.9088 - val_loss: 0.3011 - val_accuracy: 0.8875
Epoch 7/100
accuracy: 0.9088 - val loss: 0.2756 - val accuracy: 0.9000
Epoch 8/100
accuracy: 0.9182 - val loss: 0.3355 - val accuracy: 0.8750
Epoch 9/100
accuracy: 0.9119 - val loss: 0.2995 - val accuracy: 0.8750
Epoch 10/100
accuracy: 0.9151 - val loss: 0.2790 - val accuracy: 0.8875
Epoch 11/100
accuracy: 0.9088 - val_loss: 0.2960 - val_accuracy: 0.8875
Epoch 12/100
accuracy: 0.9182 - val loss: 0.3129 - val accuracy: 0.8750
Epoch 13/100
accuracy: 0.9214 - val loss: 0.2570 - val accuracy: 0.9250
Epoch 14/100
```

```
accuracy: 0.9214 - val loss: 0.2444 - val accuracy: 0.9125
Epoch 15/100
accuracy: 0.9182 - val loss: 0.3122 - val accuracy: 0.8875
Epoch 16/100
accuracy: 0.9057 - val loss: 0.2554 - val accuracy: 0.9250
Epoch 17/100
accuracy: 0.9182 - val loss: 0.2439 - val accuracy: 0.9000
Epoch 18/100
accuracy: 0.9277 - val loss: 0.2600 - val accuracy: 0.9000
Epoch 19/100
accuracy: 0.9214 - val loss: 0.2612 - val accuracy: 0.9000
Epoch 20/100
accuracy: 0.9151 - val loss: 0.2528 - val accuracy: 0.9000
Epoch 21/100
accuracy: 0.9245 - val loss: 0.2421 - val accuracy: 0.9125
Epoch 22/100
accuracy: 0.9245 - val loss: 0.2625 - val accuracy: 0.8875
Epoch 23/100
accuracy: 0.9277 - val loss: 0.2730 - val accuracy: 0.8875
Epoch 24/100
accuracy: 0.9214 - val loss: 0.2851 - val_accuracy: 0.9000
Epoch 25/100
accuracy: 0.9308 - val loss: 0.2333 - val accuracy: 0.9125
Epoch 26/100
accuracy: 0.9182 - val loss: 0.2562 - val accuracy: 0.9125
Epoch 27/100
accuracy: 0.9088 - val loss: 0.2779 - val accuracy: 0.9000
Epoch 28/100
accuracy: 0.9151 - val loss: 0.2384 - val accuracy: 0.9125
Epoch 29/100
accuracy: 0.9214 - val_loss: 0.2309 - val_accuracy: 0.9125
Epoch 30/100
accuracy: 0.9088 - val loss: 0.2359 - val accuracy: 0.9250
Epoch 31/100
```

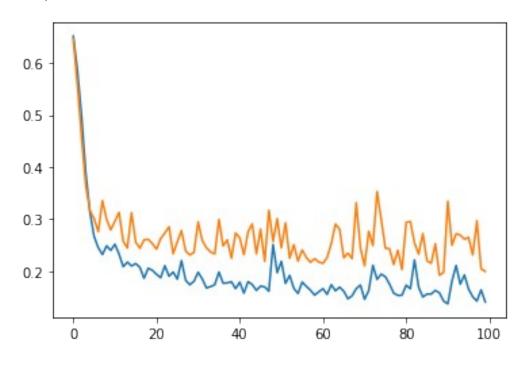
```
accuracy: 0.9214 - val loss: 0.2946 - val accuracy: 0.9000
Epoch 32/100
accuracy: 0.9277 - val loss: 0.2586 - val accuracy: 0.9000
Epoch 33/100
accuracy: 0.9308 - val loss: 0.2447 - val accuracy: 0.9000
Epoch 34/100
accuracy: 0.9340 - val loss: 0.2366 - val accuracy: 0.9125
Epoch 35/100
accuracy: 0.9308 - val loss: 0.2331 - val accuracy: 0.9125
Epoch 36/100
accuracy: 0.9308 - val loss: 0.2992 - val accuracy: 0.9000
Epoch 37/100
accuracy: 0.9277 - val loss: 0.2483 - val accuracy: 0.9125
Epoch 38/100
accuracy: 0.9182 - val loss: 0.2599 - val accuracy: 0.9000
Epoch 39/100
accuracy: 0.9245 - val loss: 0.2249 - val_accuracy: 0.9125
Epoch 40/100
accuracy: 0.9277 - val loss: 0.2732 - val accuracy: 0.9125
Epoch 41/100
accuracy: 0.9245 - val loss: 0.2639 - val accuracy: 0.9000
Epoch 42/100
accuracy: 0.9403 - val loss: 0.2314 - val accuracy: 0.9250
Epoch 43/100
accuracy: 0.9340 - val loss: 0.2753 - val accuracy: 0.9125
Epoch 44/100
accuracy: 0.9308 - val loss: 0.2906 - val accuracy: 0.9000
Epoch 45/100
accuracy: 0.9371 - val loss: 0.2329 - val accuracy: 0.9125
Epoch 46/100
accuracy: 0.9245 - val loss: 0.2806 - val accuracy: 0.8750
Epoch 47/100
accuracy: 0.9403 - val loss: 0.2185 - val accuracy: 0.9250
```

```
Epoch 48/100
accuracy: 0.9277 - val loss: 0.3169 - val accuracy: 0.9000
Epoch 49/100
accuracy: 0.8899 - val loss: 0.2568 - val accuracy: 0.9125
Epoch 50/100
accuracy: 0.9277 - val loss: 0.3008 - val accuracy: 0.8750
Epoch 51/100
accuracy: 0.9182 - val_loss: 0.2447 - val_accuracy: 0.9250
Epoch 52/100
accuracy: 0.9151 - val loss: 0.2926 - val accuracy: 0.9000
Epoch 53/100
accuracy: 0.9182 - val_loss: 0.2247 - val_accuracy: 0.9250
Epoch 54/100
accuracy: 0.9308 - val_loss: 0.2506 - val_accuracy: 0.9250
Epoch 55/100
10/10 [============== ] - Os 12ms/step - loss: 0.1569 -
accuracy: 0.9308 - val loss: 0.2190 - val accuracy: 0.9250
Epoch 56/100
accuracy: 0.9214 - val loss: 0.2405 - val accuracy: 0.9125
Epoch 57/100
accuracy: 0.9214 - val_loss: 0.2262 - val_accuracy: 0.9125
Epoch 58/100
accuracy: 0.9340 - val loss: 0.2168 - val accuracy: 0.9125
Epoch 59/100
accuracy: 0.9403 - val_loss: 0.2239 - val_accuracy: 0.9125
Epoch 60/100
10/10 [============== ] - Os 12ms/step - loss: 0.1602 -
accuracy: 0.9340 - val loss: 0.2174 - val accuracy: 0.9250
Epoch 61/100
accuracy: 0.9277 - val loss: 0.2148 - val accuracy: 0.9125
Epoch 62/100
accuracy: 0.9371 - val loss: 0.2261 - val accuracy: 0.9125
Epoch 63/100
accuracy: 0.9277 - val loss: 0.2525 - val accuracy: 0.9125
Epoch 64/100
```

```
accuracy: 0.9497 - val loss: 0.2904 - val accuracy: 0.9000
Epoch 65/100
10/10 [============== ] - Os 10ms/step - loss: 0.1691 -
accuracy: 0.9277 - val_loss: 0.2804 - val accuracy: 0.9125
Epoch 66/100
accuracy: 0.9308 - val loss: 0.2254 - val accuracy: 0.9125
Epoch 67/100
accuracy: 0.9403 - val loss: 0.2342 - val accuracy: 0.9125
Epoch 68/100
accuracy: 0.9277 - val loss: 0.2239 - val accuracy: 0.9250
Epoch 69/100
10/10 [============= ] - Os 12ms/step - loss: 0.1662 -
accuracy: 0.9182 - val loss: 0.3314 - val accuracy: 0.8875
Epoch 70/100
accuracy: 0.9214 - val loss: 0.2448 - val accuracy: 0.9250
Epoch 71/100
accuracy: 0.9371 - val loss: 0.2099 - val accuracy: 0.9125
Epoch 72/100
accuracy: 0.9245 - val loss: 0.2765 - val accuracy: 0.8875
Epoch 73/100
accuracy: 0.9057 - val loss: 0.2489 - val accuracy: 0.9000
Epoch 74/100
accuracy: 0.9151 - val loss: 0.3529 - val accuracy: 0.8875
Epoch 75/100
10/10 [============= ] - Os 9ms/step - loss: 0.1941 -
accuracy: 0.9214 - val loss: 0.2996 - val accuracy: 0.9000
Epoch 76/100
accuracy: 0.9151 - val loss: 0.2440 - val accuracy: 0.9250
Epoch 77/100
accuracy: 0.9182 - val loss: 0.2427 - val accuracy: 0.9250
Epoch 78/100
accuracy: 0.9371 - val loss: 0.2125 - val accuracy: 0.9250
Epoch 79/100
accuracy: 0.9277 - val_loss: 0.2401 - val_accuracy: 0.9125
Epoch 80/100
accuracy: 0.9371 - val loss: 0.2027 - val accuracy: 0.9125
Epoch 81/100
```

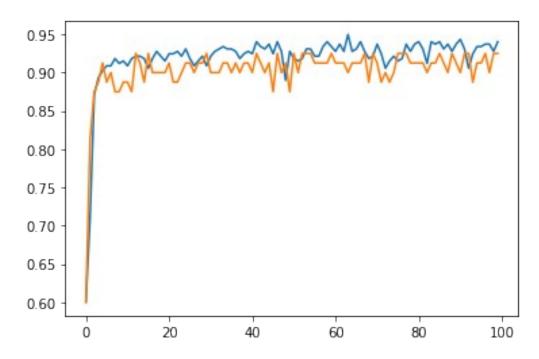
```
accuracy: 0.9403 - val loss: 0.2937 - val accuracy: 0.9125
Epoch 82/100
accuracy: 0.9308 - val loss: 0.2952 - val accuracy: 0.9125
Epoch 83/100
accuracy: 0.9119 - val loss: 0.2537 - val accuracy: 0.9000
Epoch 84/100
accuracy: 0.9403 - val loss: 0.2326 - val accuracy: 0.9125
Epoch 85/100
accuracy: 0.9371 - val loss: 0.2721 - val accuracy: 0.9125
Epoch 86/100
accuracy: 0.9403 - val loss: 0.2197 - val accuracy: 0.9250
Epoch 87/100
accuracy: 0.9308 - val loss: 0.2150 - val accuracy: 0.9125
Epoch 88/100
accuracy: 0.9371 - val loss: 0.2526 - val accuracy: 0.9000
Epoch 89/100
accuracy: 0.9277 - val loss: 0.1919 - val accuracy: 0.9250
Epoch 90/100
accuracy: 0.9371 - val loss: 0.1974 - val accuracy: 0.9125
Epoch 91/100
accuracy: 0.9434 - val loss: 0.3343 - val accuracy: 0.9000
Epoch 92/100
accuracy: 0.9308 - val loss: 0.2495 - val accuracy: 0.9250
Epoch 93/100
accuracy: 0.9057 - val loss: 0.2719 - val accuracy: 0.9250
Epoch 94/100
accuracy: 0.9245 - val loss: 0.2692 - val accuracy: 0.8875
Epoch 95/100
accuracy: 0.9340 - val loss: 0.2613 - val accuracy: 0.9125
Epoch 96/100
accuracy: 0.9340 - val loss: 0.2647 - val accuracy: 0.9125
Epoch 97/100
accuracy: 0.9371 - val loss: 0.2308 - val accuracy: 0.9250
```

```
Epoch 98/100
accuracy: 0.9371 - val loss: 0.2967 - val accuracy: 0.9000
Epoch 99/100
accuracy: 0.9277 - val loss: 0.2045 - val accuracy: 0.9250
Epoch 100/100
accuracy: 0.9403 - val loss: 0.1992 - val accuracy: 0.9250
pred train= model.predict(X train)
scores = model.evaluate(X_train, y_train, verbose=0)
print('Accuracy on training data: {}% \n Error on training data:
{}'.format(scores[1], 1 - scores[1]))
pred test= model.predict(X test)
scores2 = model.evaluate(X test, y test, verbose=0)
print('Accuracy on test data: {}% \n Error on test data:
{}'.format(scores2[1], 1 - scores2[1]))
13/13 [======== ] - Os 2ms/step
Accuracy on training data: 0.9396985173225403%
Error on training data: 0.06030148267745972
6/6 [======= ] - 0s 2ms/step
Accuracy on test data: 0.9181286692619324%
Error on test data: 0.08187133073806763
plt.plot(md.history['loss'])
plt.plot(md.history['val_loss'])
[<matplotlib.lines.Line2D at 0x7fdbf526ab50>]
```



```
plt.plot(md.history['accuracy'])
plt.plot(md.history['val accuracy'])
```

[<matplotlib.lines.Line2D at 0x7fdbf5407d60>]



## **Question 3**

```
Bank Dataset
```

3

4

47

33

blue-collar

unknown

married

single

```
df3 = pd.read csv('sample data/bank-full.csv', delimiter=';')
print(df3.shape)
df3.head()
(45211, 17)
                                 education default
                                                     balance housing loan
                  iob
                       marital
   age
0
    58
          management
                       married
                                  tertiary
                                                        2143
                                                 no
                                                                  yes
                                                                        no
    44
          technician
                                                          29
1
                        single
                                 secondary
                                                                  yes
                                                 no
                                                                        no
2
                                                           2
    33
        entrepreneur
                       married
                                 secondary
                                                 no
                                                                  yes
                                                                       yes
```

contact day month duration campaign pdays previous poutcome

unknown

unknown

1506

1

yes

no

no

no

no

no

```
У
0
   unknown
                              261
                                                              0 unknown
               5
                                           1
                                                  - 1
                   may
no
1
   unknown
               5
                              151
                                           1
                                                  -1
                                                                 unknown
                   may
no
2
   unknown
               5
                   may
                               76
                                           1
                                                  -1
                                                                 unknown
no
3
  unknown
               5
                               92
                                           1
                                                  -1
                                                                 unknown
                   may
no
4 unknown
               5
                              198
                                           1
                                                  -1
                                                                 unknown
                   may
no
df3.housing.replace(('yes', 'no'), (1, 0), inplace=True)
df3.default.replace(('yes', 'no'), (1, 0), inplace=True)
df3.loan.replace(('yes', 'no'), (1, 0), inplace=True)
df3.y.replace(('yes', 'no'), (1, 0), inplace=True)
df3.contact.replace(('unknown', 'telephone', 'cellular'), (0, 1, 2),
inplace=True)
df3.marital.replace(('married', 'divorced', 'single'), (0, 1, 2),
inplace=True)
df3.education.replace(('unknown', 'primary', 'secondary', 'tertiary'),
(0, 1, 2, 3), inplace=True)
df3.poutcome.replace(('unknown', 'other', 'failure', 'success'), (0,
1, 2, 3, ), inplace=True)
df3.month.replace(('jan', 'feb', 'mar', 'apr', 'may', 'jun', 'jul',
'aug', 'sep', 'oct', 'nov', 'dec'), (1,2,3,4,5,6,7,8,9,10,11,12),
inplace=True)
df3.job.replace(("admin.", "unknown", "unemployed", "management", "housema
id", "entrepreneur", "student", "blue-collar", "self-
employed", "retired", "technician", "services"),
(1,2,3,4,5,6,7,8,9,10,11,12), inplace=True)
df3.head()
        job marital education default balance housing loan
   age
contact \
0
    58
          4
                    0
                                 3
                                          0
                                                 2143
                                                              1
                                                                     0
0
1
                    2
                                2
                                                   29
    44
                                          0
                                                              1
                                                                     0
          11
0
2
    33
                    0
                                 2
                                          0
                                                    2
                                                              1
                                                                     1
           6
0
3
    47
           8
                    0
                                 0
                                                 1506
                                                              1
                                          0
                                                                     0
0
4
    33
           2
                    2
                                0
                                          0
                                                    1
                                                              0
                                                                    0
0
   day
        month
               duration campaign pdays previous poutcome
                                                                   У
0
     5
             5
                      261
                                   1
                                         - 1
                                                     0
                                                                0
                                                                   0
     5
             5
                                   1
                                         - 1
                                                     0
1
                      151
                                                                0
                                                                   0
     5
             5
2
                       76
                                   1
                                         -1
                                                     0
                                                                0
                                                                   0
```

3 4	5 5	5 5	92 1 198 1	-1 -1	0 0 0 0 0 0	
<pre>target_column = ['y'] predictors = list(set(list(df3.columns))-set(target_column)) df3.describe()</pre>						
-l - C	unt 45 211.000 an 018027 d 133049 n 000000 % 0000000 %	age	job	marital	education	
cou		211.000000	45211.000000	45211.000000	45211.000000	
mea		000 40.936210	7.018159	0.680963	2.060516	
std		10.618762	3.543218	0.884908	0.778704	
min		18.000000	1.000000	0.000000	0.000000	
25%		33.000000	4.000000	0.000000	2.000000	
50%		39.000000	8.000000	0.000000	2.000000	
75% 0.0 max		48.000000	11.000000	2.000000	3.000000	
		95.000000	12.000000	2.000000	3.000000	
	,	balance	housing	loan	contact	
day cou	nt 4	5211.000000	45211.000000	45211.000000	45211.000000	
mea	.806419	1362.272058	0.555838	0.160226	1.359758	
std		3044.765829	0.496878	0.366820	0.897951	
min	-	8019.000000	0.000000	0.000000	0.00000	
25%		72.000000	0.000000	0.000000	0.00000	
50%		448.000000	1.000000	0.000000	2.000000	
75% 21. max		1428.000000	1.000000	0.000000	2.000000	
	.000000 × 10 .000000	2127.000000	1.000000	1.000000	2.000000	
		month	duration	campaign	pdays	
cou		\ 211.000000	45211.000000	45211.000000	45211.000000	
	11.000 n	6.144655	258.163080	2.763841	40.197828	

```
0.580323
           2.408034
                        257.527812
                                        3.098021
std
                                                     100.128746
2.303441
           1.000000
                          0.000000
                                        1.000000
                                                      -1.000000
min
0.000000
25%
           5.000000
                        103,000000
                                        1.000000
                                                      -1.000000
0.000000
50%
           6.000000
                        180.000000
                                        2.000000
                                                      -1.000000
0.000000
75%
           8,000000
                        319.000000
                                        3.000000
                                                      -1.000000
0.000000
          12.000000
                       4918.000000
                                                     871.000000
max
                                       63.000000
275.000000
           poutcome
       45211.000000
                     45211.000000
count
           0.357767
                          0.116985
mean
           0.804435
                          0.321406
std
           0.000000
                          0.000000
min
25%
           0.000000
                          0.000000
           0.000000
                          0.00000
50%
75%
           0.000000
                          0.000000
           3,000000
                          1.000000
max
X = df3[predictors].values
y = df3[target column].values
X train, X test, y train, y test = train test split(X, y,
test_size=0.30, random state=40)
print(X train.shape);print(X test.shape)
(31647, 16)
(13564, 16)
model = Sequential()
model.add(Dense(16, activation='sigmoid', input dim=16))
model.add(Dense(32, activation='sigmoid'))
model.add(Dense(1, activation='sigmoid'))
model.summary()
```

Model: "sequential 6"

Layer (type) Output Shape Para	am # 
dense_20 (Dense) (None, 16) 272	
dense_21 (Dense) (None, 32) 544	
dense_22 (Dense) (None, 1) 33	

\_\_\_\_\_\_

Total params: 849

Trainable params: 849 Non-trainable params: 0

# Compile the model model.compile(optimizer='adam',loss='binary crossentropy',metrics=['ac curacy']) md = model.fit(X train,y train,epochs=100,validation split=0.2) Epoch 1/100 - accuracy: 0.8840 - val loss: 0.3336 - val accuracy: 0.8809 Epoch 2/100 - accuracy: 0.8840 - val loss: 0.3019 - val accuracy: 0.8809 Epoch 3/100 - accuracy: 0.8838 - val\_loss: 0.2994 - val\_accuracy: 0.8809 Epoch 4/100 - accuracy: 0.8841 - val loss: 0.3013 - val accuracy: 0.8817 Epoch 5/100 792/792 [============] - 2s 2ms/step - loss: 0.2939 - accuracy: 0.8834 - val loss: 0.2960 - val accuracy: 0.8809 Epoch 6/100 792/792 [============= ] - 2s 2ms/step - loss: 0.2927 - accuracy: 0.8842 - val loss: 0.2929 - val accuracy: 0.8826 Epoch 7/100 - accuracy: 0.8828 - val\_loss: 0.2948 - val\_accuracy: 0.8821 Epoch 8/100 - accuracy: 0.8847 - val loss: 0.2886 - val accuracy: 0.8826 Epoch 9/100 - accuracy: 0.8843 - val loss: 0.2864 - val accuracy: 0.8828 Epoch 10/100 792/792 [============= ] - 2s 2ms/step - loss: 0.2845 - accuracy: 0.8846 - val loss: 0.2847 - val accuracy: 0.8831 Epoch 11/100 792/792 [============= ] - 2s 2ms/step - loss: 0.2845 - accuracy: 0.8858 - val\_loss: 0.2859 - val\_accuracy: 0.8853 Epoch 12/100 - accuracy: 0.8863 - val loss: 0.2841 - val accuracy: 0.8859 Epoch 13/100 792/792 [============= ] - 2s 2ms/step - loss: 0.2834 - accuracy: 0.8882 - val loss: 0.2837 - val accuracy: 0.8858 Epoch 14/100 

```
- accuracy: 0.8864 - val loss: 0.2840 - val accuracy: 0.8867
Epoch 15/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2793
- accuracy: 0.8881 - val_loss: 0.2804 - val accuracy: 0.8859
Epoch 16/100
- accuracy: 0.8888 - val loss: 0.2820 - val accuracy: 0.8847
Epoch 17/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2780
- accuracy: 0.8886 - val loss: 0.2793 - val accuracy: 0.8845
Epoch 18/100
- accuracy: 0.8875 - val loss: 0.2794 - val accuracy: 0.8836
Epoch 19/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2739
- accuracy: 0.8873 - val loss: 0.2778 - val accuracy: 0.8820
Epoch 20/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2753
- accuracy: 0.8880 - val loss: 0.2762 - val accuracy: 0.8870
Epoch 21/100
- accuracy: 0.8884 - val loss: 0.2751 - val accuracy: 0.8900
Epoch 22/100
- accuracy: 0.8884 - val loss: 0.2741 - val accuracy: 0.8883
Epoch 23/100
- accuracy: 0.8888 - val loss: 0.2725 - val accuracy: 0.8874
Epoch 24/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2757
- accuracy: 0.8868 - val loss: 0.2758 - val accuracy: 0.8833
Epoch 25/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2760
- accuracy: 0.8871 - val loss: 0.2721 - val accuracy: 0.8850
Epoch 26/100
- accuracy: 0.8860 - val loss: 0.2796 - val accuracy: 0.8866
Epoch 27/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2763
- accuracy: 0.8876 - val loss: 0.2774 - val accuracy: 0.8806
Epoch 28/100
- accuracy: 0.8879 - val loss: 0.2716 - val accuracy: 0.8889
Epoch 29/100
- accuracy: 0.8869 - val_loss: 0.2711 - val_accuracy: 0.8807
Epoch 30/100
- accuracy: 0.8866 - val loss: 0.2761 - val accuracy: 0.8821
Epoch 31/100
```

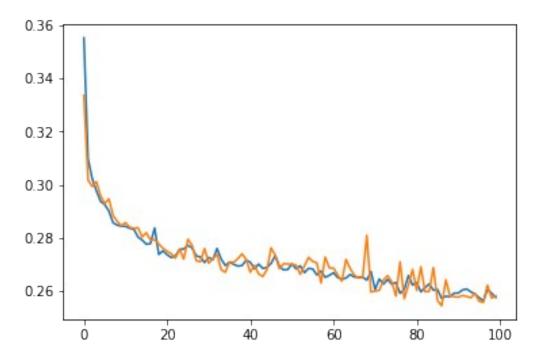
```
792/792 [============== ] - 2s 2ms/step - loss: 0.2728
- accuracy: 0.8877 - val loss: 0.2706 - val accuracy: 0.8902
Epoch 32/100
- accuracy: 0.8890 - val loss: 0.2723 - val accuracy: 0.8874
Epoch 33/100
- accuracy: 0.8884 - val loss: 0.2739 - val accuracy: 0.8886
Epoch 34/100
- accuracy: 0.8888 - val loss: 0.2681 - val accuracy: 0.8874
Epoch 35/100
- accuracy: 0.8888 - val loss: 0.2672 - val accuracy: 0.8874
Epoch 36/100
- accuracy: 0.8878 - val loss: 0.2711 - val accuracy: 0.8902
Epoch 37/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2702
- accuracy: 0.8886 - val loss: 0.2709 - val accuracy: 0.8894
Epoch 38/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2695
- accuracy: 0.8891 - val loss: 0.2722 - val accuracy: 0.8888
Epoch 39/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2697
- accuracy: 0.8915 - val loss: 0.2741 - val accuracy: 0.8837
Epoch 40/100
- accuracy: 0.8892 - val loss: 0.2720 - val accuracy: 0.8885
Epoch 41/100
792/792 [============== ] - 2s 2ms/step - loss: 0.2710
- accuracy: 0.8890 - val loss: 0.2672 - val accuracy: 0.8886
Epoch 42/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2685
- accuracy: 0.8903 - val loss: 0.2698 - val accuracy: 0.8880
Epoch 43/100
- accuracy: 0.8901 - val loss: 0.2666 - val accuracy: 0.8863
Epoch 44/100
792/792 [============== ] - 2s 2ms/step - loss: 0.2686
- accuracy: 0.8892 - val loss: 0.2656 - val accuracy: 0.8875
Epoch 45/100
792/792 [============= ] - 3s 4ms/step - loss: 0.2690
- accuracy: 0.8881 - val loss: 0.2682 - val accuracy: 0.8891
Epoch 46/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2705
- accuracy: 0.8892 - val loss: 0.2764 - val accuracy: 0.8858
Epoch 47/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2735
- accuracy: 0.8880 - val loss: 0.2735 - val accuracy: 0.8848
```

```
Epoch 48/100
- accuracy: 0.8892 - val loss: 0.2685 - val accuracy: 0.8837
Epoch 49/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2681
- accuracy: 0.8884 - val_loss: 0.2704 - val_accuracy: 0.8894
Epoch 50/100
- accuracy: 0.8886 - val loss: 0.2703 - val accuracy: 0.8885
Epoch 51/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2703
- accuracy: 0.8887 - val loss: 0.2702 - val accuracy: 0.8878
Epoch 52/100
- accuracy: 0.8876 - val loss: 0.2699 - val accuracy: 0.8866
Epoch 53/100
- accuracy: 0.8875 - val_loss: 0.2664 - val_accuracy: 0.8882
Epoch 54/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2670
- accuracy: 0.8888 - val_loss: 0.2695 - val_accuracy: 0.8897
Epoch 55/100
792/792 [============== ] - 2s 2ms/step - loss: 0.2686
- accuracy: 0.8893 - val loss: 0.2728 - val accuracy: 0.8888
Epoch 56/100
- accuracy: 0.8901 - val_loss: 0.2712 - val_accuracy: 0.8847
Epoch 57/100
- accuracy: 0.8899 - val_loss: 0.2707 - val_accuracy: 0.8893
Epoch 58/100
- accuracy: 0.8898 - val loss: 0.2632 - val accuracy: 0.8837
Epoch 59/100
792/792 [============= ] - 2s 3ms/step - loss: 0.2653
- accuracy: 0.8910 - val loss: 0.2729 - val accuracy: 0.8888
Epoch 60/100
- accuracy: 0.8900 - val loss: 0.2688 - val accuracy: 0.8809
Epoch 61/100
- accuracy: 0.8900 - val loss: 0.2688 - val accuracy: 0.8929
Epoch 62/100
- accuracy: 0.8899 - val loss: 0.2662 - val accuracy: 0.8918
Epoch 63/100
- accuracy: 0.8915 - val loss: 0.2638 - val accuracy: 0.8926
Epoch 64/100
```

```
- accuracy: 0.8907 - val loss: 0.2720 - val accuracy: 0.8856
Epoch 65/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2663
- accuracy: 0.8906 - val_loss: 0.2686 - val accuracy: 0.8855
Epoch 66/100
- accuracy: 0.8916 - val loss: 0.2661 - val accuracy: 0.8866
Epoch 67/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2654
- accuracy: 0.8854 - val loss: 0.2651 - val accuracy: 0.8874
Epoch 68/100
- accuracy: 0.8907 - val loss: 0.2652 - val accuracy: 0.8888
Epoch 69/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2642
- accuracy: 0.8903 - val loss: 0.2811 - val accuracy: 0.8874
Epoch 70/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2675
- accuracy: 0.8887 - val loss: 0.2598 - val accuracy: 0.8893
Epoch 71/100
- accuracy: 0.8901 - val loss: 0.2601 - val accuracy: 0.8869
Epoch 72/100
- accuracy: 0.8889 - val loss: 0.2604 - val accuracy: 0.8889
Epoch 73/100
- accuracy: 0.8885 - val loss: 0.2643 - val accuracy: 0.8878
Epoch 74/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2645
- accuracy: 0.8885 - val loss: 0.2659 - val accuracy: 0.8866
Epoch 75/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2627
- accuracy: 0.8880 - val loss: 0.2636 - val accuracy: 0.8853
Epoch 76/100
- accuracy: 0.8884 - val loss: 0.2582 - val accuracy: 0.8902
Epoch 77/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2593
- accuracy: 0.8906 - val loss: 0.2711 - val accuracy: 0.8874
Epoch 78/100
- accuracy: 0.8920 - val loss: 0.2572 - val accuracy: 0.8893
Epoch 79/100
- accuracy: 0.8889 - val_loss: 0.2624 - val_accuracy: 0.8897
Epoch 80/100
- accuracy: 0.8886 - val loss: 0.2683 - val accuracy: 0.8883
Epoch 81/100
```

```
- accuracy: 0.8896 - val loss: 0.2603 - val accuracy: 0.8864
Epoch 82/100
- accuracy: 0.8905 - val loss: 0.2692 - val accuracy: 0.8834
Epoch 83/100
- accuracy: 0.8888 - val loss: 0.2599 - val accuracy: 0.8883
Epoch 84/100
- accuracy: 0.8875 - val loss: 0.2600 - val accuracy: 0.8855
Epoch 85/100
- accuracy: 0.8900 - val loss: 0.2689 - val accuracy: 0.8872
Epoch 86/100
- accuracy: 0.8883 - val loss: 0.2566 - val accuracy: 0.8875
Epoch 87/100
- accuracy: 0.8895 - val loss: 0.2546 - val accuracy: 0.8915
Epoch 88/100
792/792 [============== ] - 2s 2ms/step - loss: 0.2582
- accuracy: 0.8907 - val loss: 0.2643 - val accuracy: 0.8880
Epoch 89/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2580
- accuracy: 0.8915 - val loss: 0.2583 - val accuracy: 0.8907
Epoch 90/100
- accuracy: 0.8900 - val loss: 0.2580 - val accuracy: 0.8863
Epoch 91/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2594
- accuracy: 0.8899 - val loss: 0.2578 - val accuracy: 0.8894
Epoch 92/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2605
- accuracy: 0.8902 - val loss: 0.2585 - val accuracy: 0.8897
Epoch 93/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2609
- accuracy: 0.8909 - val loss: 0.2581 - val accuracy: 0.8924
Epoch 94/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2598
- accuracy: 0.8900 - val loss: 0.2576 - val accuracy: 0.8904
Epoch 95/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2590
- accuracy: 0.8920 - val loss: 0.2593 - val accuracy: 0.8878
Epoch 96/100
792/792 [============= ] - 2s 2ms/step - loss: 0.2576
- accuracy: 0.8895 - val loss: 0.2563 - val accuracy: 0.8840
Epoch 97/100
792/792 [============== ] - 2s 2ms/step - loss: 0.2564
- accuracy: 0.8892 - val loss: 0.2558 - val accuracy: 0.8888
```

```
Epoch 98/100
- accuracy: 0.8905 - val loss: 0.2623 - val accuracy: 0.8924
Epoch 99/100
- accuracy: 0.8918 - val loss: 0.2575 - val accuracy: 0.8889
Epoch 100/100
- accuracy: 0.8896 - val loss: 0.2583 - val accuracy: 0.8855
pred train= model.predict(X train)
scores = model.evaluate(X_train, y_train, verbose=0)
print('Accuracy on training data: {}% \n Error on training data:
{}'.format(scores[1], 1 - scores[1]))
pred test= model.predict(X test)
scores2 = model.evaluate(X test, y test, verbose=0)
print('Accuracy on test data: {}% \n Error on test data:
{} '.format(scores2[1], 1 - scores2[1]))
989/989 [========= ] - 3s 3ms/step
Accuracy on training data: 0.8889310359954834%
Error on training data: 0.1110689640045166
Accuracy on test data: 0.8850634098052979%
Error on test data: 0.11493659019470215
plt.plot(md.history['loss'])
plt.plot(md.history['val_loss'])
[<matplotlib.lines.Line2D at 0x7fdbee8edc70>]
```



plt.plot(md.history['accuracy'])
plt.plot(md.history['val\_accuracy'])

[<matplotlib.lines.Line2D at 0x7fdbef849730>]

