

# 2020\_1127\_DNN\_Classification

November 27, 2020

## 1 Classifying Pulsars from the High Time Resolution Universe Survey (HTRU2) - Deep Neural Network (DNN) Classification

### 1.1 Overview & Citation

In this code notebook, we attempt to classify pulsars from the High Time Resolution Universe Survey, South (HTRU2) dataset using deep neural network (DNN) classification. The dataset was retrieved from the UC Irvine Machine Learning Repository at the following link: <https://archive.ics.uci.edu/ml/datasets/HTRU2#>.

The dataset was donated to the UCI Repository by Dr. Robert Lyon of The University of Manchester, United Kingdom. The two papers requested for citation in the description are listed below:

- R. J. Lyon, B. W. Stappers, S. Cooper, J. M. Brooke, J. D. Knowles, Fifty Years of Pulsar Candidate Selection: From simple filters to a new principled real-time classification approach, Monthly Notices of the Royal Astronomical Society 459 (1), 1104-1123, DOI: 10.1093/mnras/stw656
- R. J. Lyon, HTRU2, DOI: 10.6084/m9.figshare.3080389.v1.

### 1.2 Import the Relevant Libraries

```
[108]: # Data Manipulation
import numpy as np
import pandas as pd

# Data Visualization
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
sns.set()

# Data Preprocessing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler

# ANN Modeling in TensorFlow & Keras
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Activation
```

```

from tensorflow.keras.optimizers import Adam
from tensorflow.keras.layers import Dropout

# Model Evaluation
from sklearn.metrics import classification_report, confusion_matrix

```

## 1.3 Data Preprocessing

### 1.3.1 Import & Check the Data

```

[109]: df = pd.read_csv('2020_1125_Pulsar_Data.csv')
       pulsar_data = df.copy()

```

```

[110]: pulsar_data.head()

```

```

[110]:      IP_Mean  IP_StdDev  IP_Kurtosis  IP_Skewness  DM_Mean  DM_StdDev  \
0  140.562500  55.683782   -0.234571   -0.699648   3.199833   19.110426
1  102.507812  58.882430    0.465318   -0.515088   1.677258   14.860146
2  103.015625  39.341649    0.323328    1.051164   3.121237   21.744669
3  136.750000  57.178449   -0.068415   -0.636238   3.642977   20.959280
4   88.726562  40.672225    0.600866    1.123492   1.178930   11.468720

      DM_Kurtosis  DM_Skewness  Class
0     7.975532    74.242225     0
1    10.576487   127.393580     0
2     7.735822    63.171909     0
3     6.896499    53.593661     0
4    14.269573   252.567306     0

```

### 1.3.2 Train Test Split

```

[111]: X = pulsar_data.drop('Class',axis=1)
       y = pulsar_data['Class']

```

```

[112]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,
       ↪random_state=42)

```

### 1.3.3 Scale the Data

```

[113]: scaler = MinMaxScaler()
       X_train= scaler.fit_transform(X_train)
       X_test = scaler.transform(X_test)

```

## 1.4 Model 1 - DNN with 2 Hidden Layers

### 1.4.1 Construct the Deep Neural Network

```
[115]: # Determine number of starting nodes by finding the shape of X_train
X_train.shape
```

```
[115]: (13423, 8)
```

```
[133]: model = Sequential()

# Input Layer
model.add(Dense(8,activation='relu')) # All layers utilize rectified linear
↪ units (relu)

# Hidden Layers
model.add(Dense(8,activation='relu'))
model.add(Dense(8,activation='relu'))

# Output Layer (Sigmoid for Binary Classification)
model.add(Dense(1,activation='sigmoid'))

model.compile(loss='binary_crossentropy', optimizer='adam')
```

### 1.4.2 Train the Model on the Test Data

```
[134]: model.fit(x=X_train, y=y_train, epochs=200, validation_data=(X_test, y_test),
↪ verbose=1)
```

```
Epoch 1/200
420/420 [=====] - 0s 737us/step - loss: 0.3329 -
val_loss: 0.1499
Epoch 2/200
420/420 [=====] - 0s 588us/step - loss: 0.1032 -
val_loss: 0.0866
Epoch 3/200
420/420 [=====] - 0s 600us/step - loss: 0.0874 -
val_loss: 0.0840
Epoch 4/200
420/420 [=====] - 0s 616us/step - loss: 0.0850 -
val_loss: 0.0838
Epoch 5/200
420/420 [=====] - 0s 589us/step - loss: 0.0842 -
val_loss: 0.0831
Epoch 6/200
420/420 [=====] - 0s 586us/step - loss: 0.0836 -
val_loss: 0.0833
Epoch 7/200
```

```

420/420 [=====] - 0s 589us/step - loss: 0.0830 -
val_loss: 0.0814
Epoch 8/200
420/420 [=====] - 0s 593us/step - loss: 0.0823 -
val_loss: 0.0814
Epoch 9/200
420/420 [=====] - 0s 589us/step - loss: 0.0817 -
val_loss: 0.0806
Epoch 10/200
420/420 [=====] - 0s 590us/step - loss: 0.0811 -
val_loss: 0.0803
Epoch 11/200
420/420 [=====] - 0s 586us/step - loss: 0.0805 -
val_loss: 0.0817
Epoch 12/200
420/420 [=====] - 0s 590us/step - loss: 0.0804 -
val_loss: 0.0797
Epoch 13/200
420/420 [=====] - 0s 589us/step - loss: 0.0798 -
val_loss: 0.0794
Epoch 14/200
420/420 [=====] - 0s 582us/step - loss: 0.0796 -
val_loss: 0.0808
Epoch 15/200
420/420 [=====] - 0s 615us/step - loss: 0.0795 -
val_loss: 0.0793
Epoch 16/200
420/420 [=====] - 0s 581us/step - loss: 0.0790 -
val_loss: 0.0786
Epoch 17/200
420/420 [=====] - 0s 585us/step - loss: 0.0786 -
val_loss: 0.0785
Epoch 18/200
420/420 [=====] - 0s 587us/step - loss: 0.0783 -
val_loss: 0.0783
Epoch 19/200
420/420 [=====] - 0s 587us/step - loss: 0.0778 -
val_loss: 0.0784
Epoch 20/200
420/420 [=====] - 0s 590us/step - loss: 0.0776 -
val_loss: 0.0784
Epoch 21/200
420/420 [=====] - 0s 586us/step - loss: 0.0778 -
val_loss: 0.0788
Epoch 22/200
420/420 [=====] - 0s 588us/step - loss: 0.0776 -
val_loss: 0.0805
Epoch 23/200

```

420/420 [=====] - 0s 585us/step - loss: 0.0770 -  
val\_loss: 0.0799  
Epoch 24/200  
420/420 [=====] - 0s 588us/step - loss: 0.0770 -  
val\_loss: 0.0775  
Epoch 25/200  
420/420 [=====] - 0s 594us/step - loss: 0.0766 -  
val\_loss: 0.0772  
Epoch 26/200  
420/420 [=====] - 0s 584us/step - loss: 0.0763 -  
val\_loss: 0.0774  
Epoch 27/200  
420/420 [=====] - 0s 593us/step - loss: 0.0762 -  
val\_loss: 0.0787  
Epoch 28/200  
420/420 [=====] - 0s 591us/step - loss: 0.0761 -  
val\_loss: 0.0771  
Epoch 29/200  
420/420 [=====] - 0s 593us/step - loss: 0.0754 -  
val\_loss: 0.0794  
Epoch 30/200  
420/420 [=====] - 0s 590us/step - loss: 0.0755 -  
val\_loss: 0.0767  
Epoch 31/200  
420/420 [=====] - 0s 588us/step - loss: 0.0754 -  
val\_loss: 0.0764  
Epoch 32/200  
420/420 [=====] - 0s 590us/step - loss: 0.0751 -  
val\_loss: 0.0775  
Epoch 33/200  
420/420 [=====] - 0s 590us/step - loss: 0.0747 -  
val\_loss: 0.0765  
Epoch 34/200  
420/420 [=====] - 0s 586us/step - loss: 0.0746 -  
val\_loss: 0.0761  
Epoch 35/200  
420/420 [=====] - 0s 592us/step - loss: 0.0746 -  
val\_loss: 0.0777  
Epoch 36/200  
420/420 [=====] - 0s 596us/step - loss: 0.0745 -  
val\_loss: 0.0760  
Epoch 37/200  
420/420 [=====] - 0s 596us/step - loss: 0.0741 -  
val\_loss: 0.0801  
Epoch 38/200  
420/420 [=====] - 0s 587us/step - loss: 0.0738 -  
val\_loss: 0.0770  
Epoch 39/200

```
420/420 [=====] - 0s 595us/step - loss: 0.0742 -  
val_loss: 0.0767  
Epoch 40/200  
420/420 [=====] - 0s 592us/step - loss: 0.0738 -  
val_loss: 0.0752  
Epoch 41/200  
420/420 [=====] - 0s 590us/step - loss: 0.0735 -  
val_loss: 0.0752  
Epoch 42/200  
420/420 [=====] - 0s 595us/step - loss: 0.0731 -  
val_loss: 0.0753  
Epoch 43/200  
420/420 [=====] - 0s 594us/step - loss: 0.0730 -  
val_loss: 0.0753  
Epoch 44/200  
420/420 [=====] - 0s 616us/step - loss: 0.0727 -  
val_loss: 0.0782  
Epoch 45/200  
420/420 [=====] - 0s 582us/step - loss: 0.0731 -  
val_loss: 0.0759  
Epoch 46/200  
420/420 [=====] - 0s 587us/step - loss: 0.0727 -  
val_loss: 0.0755  
Epoch 47/200  
420/420 [=====] - 0s 595us/step - loss: 0.0723 -  
val_loss: 0.0750  
Epoch 48/200  
420/420 [=====] - 0s 624us/step - loss: 0.0729 -  
val_loss: 0.0753  
Epoch 49/200  
420/420 [=====] - 0s 615us/step - loss: 0.0723 -  
val_loss: 0.0767  
Epoch 50/200  
420/420 [=====] - 0s 585us/step - loss: 0.0726 -  
val_loss: 0.0747  
Epoch 51/200  
420/420 [=====] - 0s 595us/step - loss: 0.0724 -  
val_loss: 0.0756  
Epoch 52/200  
420/420 [=====] - 0s 591us/step - loss: 0.0724 -  
val_loss: 0.0741  
Epoch 53/200  
420/420 [=====] - 0s 597us/step - loss: 0.0719 -  
val_loss: 0.0739  
Epoch 54/200  
420/420 [=====] - 0s 617us/step - loss: 0.0716 -  
val_loss: 0.0748  
Epoch 55/200
```

420/420 [=====] - 0s 602us/step - loss: 0.0718 -  
val\_loss: 0.0738  
Epoch 56/200  
420/420 [=====] - 0s 585us/step - loss: 0.0715 -  
val\_loss: 0.0740  
Epoch 57/200  
420/420 [=====] - 0s 585us/step - loss: 0.0717 -  
val\_loss: 0.0735  
Epoch 58/200  
420/420 [=====] - 0s 585us/step - loss: 0.0711 -  
val\_loss: 0.0738  
Epoch 59/200  
420/420 [=====] - 0s 583us/step - loss: 0.0714 -  
val\_loss: 0.0736  
Epoch 60/200  
420/420 [=====] - 0s 589us/step - loss: 0.0714 -  
val\_loss: 0.0745  
Epoch 61/200  
420/420 [=====] - 0s 584us/step - loss: 0.0714 -  
val\_loss: 0.0737  
Epoch 62/200  
420/420 [=====] - 0s 580us/step - loss: 0.0708 -  
val\_loss: 0.0732  
Epoch 63/200  
420/420 [=====] - 0s 583us/step - loss: 0.0712 -  
val\_loss: 0.0739  
Epoch 64/200  
420/420 [=====] - 0s 588us/step - loss: 0.0707 -  
val\_loss: 0.0732  
Epoch 65/200  
420/420 [=====] - 0s 583us/step - loss: 0.0712 -  
val\_loss: 0.0732  
Epoch 66/200  
420/420 [=====] - 0s 584us/step - loss: 0.0710 -  
val\_loss: 0.0753  
Epoch 67/200  
420/420 [=====] - 0s 589us/step - loss: 0.0710 -  
val\_loss: 0.0748  
Epoch 68/200  
420/420 [=====] - 0s 586us/step - loss: 0.0705 -  
val\_loss: 0.0735  
Epoch 69/200  
420/420 [=====] - 0s 589us/step - loss: 0.0706 -  
val\_loss: 0.0733  
Epoch 70/200  
420/420 [=====] - 0s 600us/step - loss: 0.0702 -  
val\_loss: 0.0738  
Epoch 71/200

420/420 [=====] - 0s 584us/step - loss: 0.0706 -  
val\_loss: 0.0728  
Epoch 72/200  
420/420 [=====] - 0s 584us/step - loss: 0.0702 -  
val\_loss: 0.0730  
Epoch 73/200  
420/420 [=====] - 0s 592us/step - loss: 0.0702 -  
val\_loss: 0.0729  
Epoch 74/200  
420/420 [=====] - 0s 589us/step - loss: 0.0696 -  
val\_loss: 0.0728  
Epoch 75/200  
420/420 [=====] - 0s 587us/step - loss: 0.0698 -  
val\_loss: 0.0784  
Epoch 76/200  
420/420 [=====] - 0s 589us/step - loss: 0.0696 -  
val\_loss: 0.0750  
Epoch 77/200  
420/420 [=====] - 0s 588us/step - loss: 0.0698 -  
val\_loss: 0.0725  
Epoch 78/200  
420/420 [=====] - 0s 585us/step - loss: 0.0693 -  
val\_loss: 0.0779  
Epoch 79/200  
420/420 [=====] - 0s 595us/step - loss: 0.0698 -  
val\_loss: 0.0725  
Epoch 80/200  
420/420 [=====] - 0s 585us/step - loss: 0.0699 -  
val\_loss: 0.0738  
Epoch 81/200  
420/420 [=====] - 0s 581us/step - loss: 0.0701 -  
val\_loss: 0.0722  
Epoch 82/200  
420/420 [=====] - 0s 575us/step - loss: 0.0700 -  
val\_loss: 0.0723  
Epoch 83/200  
420/420 [=====] - 0s 579us/step - loss: 0.0693 -  
val\_loss: 0.0720  
Epoch 84/200  
420/420 [=====] - 0s 582us/step - loss: 0.0695 -  
val\_loss: 0.0727  
Epoch 85/200  
420/420 [=====] - 0s 580us/step - loss: 0.0693 -  
val\_loss: 0.0728  
Epoch 86/200  
420/420 [=====] - 0s 576us/step - loss: 0.0691 -  
val\_loss: 0.0719  
Epoch 87/200



420/420 [=====] - 0s 580us/step - loss: 0.0697 -  
val\_loss: 0.0727  
Epoch 88/200  
420/420 [=====] - 0s 581us/step - loss: 0.0689 -  
val\_loss: 0.0759  
Epoch 89/200  
420/420 [=====] - 0s 579us/step - loss: 0.0692 -  
val\_loss: 0.0752  
Epoch 90/200  
420/420 [=====] - 0s 585us/step - loss: 0.0698 -  
val\_loss: 0.0719  
Epoch 91/200  
420/420 [=====] - 0s 579us/step - loss: 0.0696 -  
val\_loss: 0.0723  
Epoch 92/200  
420/420 [=====] - 0s 583us/step - loss: 0.0692 -  
val\_loss: 0.0735  
Epoch 93/200  
420/420 [=====] - 0s 583us/step - loss: 0.0688 -  
val\_loss: 0.0735  
Epoch 94/200  
420/420 [=====] - 0s 582us/step - loss: 0.0690 -  
val\_loss: 0.0721  
Epoch 95/200  
420/420 [=====] - 0s 596us/step - loss: 0.0682 -  
val\_loss: 0.0736  
Epoch 96/200  
420/420 [=====] - 0s 576us/step - loss: 0.0690 -  
val\_loss: 0.0719  
Epoch 97/200  
420/420 [=====] - 0s 587us/step - loss: 0.0693 -  
val\_loss: 0.0747  
Epoch 98/200  
420/420 [=====] - 0s 583us/step - loss: 0.0688 -  
val\_loss: 0.0716  
Epoch 99/200  
420/420 [=====] - 0s 578us/step - loss: 0.0686 -  
val\_loss: 0.0717  
Epoch 100/200  
420/420 [=====] - 0s 578us/step - loss: 0.0687 -  
val\_loss: 0.0713  
Epoch 101/200  
420/420 [=====] - 0s 583us/step - loss: 0.0688 -  
val\_loss: 0.0723  
Epoch 102/200  
420/420 [=====] - 0s 581us/step - loss: 0.0686 -  
val\_loss: 0.0715  
Epoch 103/200

420/420 [=====] - 0s 582us/step - loss: 0.0684 -  
val\_loss: 0.0732  
Epoch 104/200  
420/420 [=====] - 0s 587us/step - loss: 0.0685 -  
val\_loss: 0.0712  
Epoch 105/200  
420/420 [=====] - 0s 582us/step - loss: 0.0685 -  
val\_loss: 0.0717  
Epoch 106/200  
420/420 [=====] - 0s 580us/step - loss: 0.0682 -  
val\_loss: 0.0713  
Epoch 107/200  
420/420 [=====] - 0s 586us/step - loss: 0.0683 -  
val\_loss: 0.0712  
Epoch 108/200  
420/420 [=====] - 0s 576us/step - loss: 0.0688 -  
val\_loss: 0.0710  
Epoch 109/200  
420/420 [=====] - 0s 579us/step - loss: 0.0685 -  
val\_loss: 0.0713  
Epoch 110/200  
420/420 [=====] - 0s 581us/step - loss: 0.0687 -  
val\_loss: 0.0713  
Epoch 111/200  
420/420 [=====] - 0s 579us/step - loss: 0.0688 -  
val\_loss: 0.0722  
Epoch 112/200  
420/420 [=====] - 0s 598us/step - loss: 0.0682 -  
val\_loss: 0.0715  
Epoch 113/200  
420/420 [=====] - 0s 587us/step - loss: 0.0686 -  
val\_loss: 0.0709  
Epoch 114/200  
420/420 [=====] - 0s 583us/step - loss: 0.0682 -  
val\_loss: 0.0728  
Epoch 115/200  
420/420 [=====] - 0s 585us/step - loss: 0.0684 -  
val\_loss: 0.0709  
Epoch 116/200  
420/420 [=====] - 0s 586us/step - loss: 0.0684 -  
val\_loss: 0.0735  
Epoch 117/200  
420/420 [=====] - 0s 581us/step - loss: 0.0683 -  
val\_loss: 0.0725  
Epoch 118/200  
420/420 [=====] - 0s 579us/step - loss: 0.0688 -  
val\_loss: 0.0712  
Epoch 119/200

420/420 [=====] - 0s 580us/step - loss: 0.0687 -  
val\_loss: 0.0727  
Epoch 120/200  
420/420 [=====] - 0s 595us/step - loss: 0.0678 -  
val\_loss: 0.0709  
Epoch 121/200  
420/420 [=====] - 0s 587us/step - loss: 0.0680 -  
val\_loss: 0.0735  
Epoch 122/200  
420/420 [=====] - 0s 580us/step - loss: 0.0685 -  
val\_loss: 0.0713  
Epoch 123/200  
420/420 [=====] - 0s 583us/step - loss: 0.0681 -  
val\_loss: 0.0744  
Epoch 124/200  
420/420 [=====] - 0s 583us/step - loss: 0.0680 -  
val\_loss: 0.0709  
Epoch 125/200  
420/420 [=====] - 0s 588us/step - loss: 0.0683 -  
val\_loss: 0.0713  
Epoch 126/200  
420/420 [=====] - 0s 582us/step - loss: 0.0682 -  
val\_loss: 0.0716  
Epoch 127/200  
420/420 [=====] - 0s 584us/step - loss: 0.0678 -  
val\_loss: 0.0835  
Epoch 128/200  
420/420 [=====] - 0s 586us/step - loss: 0.0682 -  
val\_loss: 0.0721  
Epoch 129/200  
420/420 [=====] - 0s 580us/step - loss: 0.0686 -  
val\_loss: 0.0712  
Epoch 130/200  
420/420 [=====] - 0s 581us/step - loss: 0.0679 -  
val\_loss: 0.0712  
Epoch 131/200  
420/420 [=====] - 0s 581us/step - loss: 0.0681 -  
val\_loss: 0.0753  
Epoch 132/200  
420/420 [=====] - 0s 586us/step - loss: 0.0681 -  
val\_loss: 0.0708  
Epoch 133/200  
420/420 [=====] - 0s 578us/step - loss: 0.0677 -  
val\_loss: 0.0707  
Epoch 134/200  
420/420 [=====] - 0s 587us/step - loss: 0.0683 -  
val\_loss: 0.0714  
Epoch 135/200

420/420 [=====] - 0s 586us/step - loss: 0.0682 -  
val\_loss: 0.0722  
Epoch 136/200  
420/420 [=====] - 0s 594us/step - loss: 0.0683 -  
val\_loss: 0.0708  
Epoch 137/200  
420/420 [=====] - 0s 591us/step - loss: 0.0681 -  
val\_loss: 0.0706  
Epoch 138/200  
420/420 [=====] - 0s 578us/step - loss: 0.0681 -  
val\_loss: 0.0712  
Epoch 139/200  
420/420 [=====] - 0s 584us/step - loss: 0.0677 -  
val\_loss: 0.0715  
Epoch 140/200  
420/420 [=====] - 0s 586us/step - loss: 0.0681 -  
val\_loss: 0.0708  
Epoch 141/200  
420/420 [=====] - 0s 579us/step - loss: 0.0680 -  
val\_loss: 0.0707  
Epoch 142/200  
420/420 [=====] - 0s 583us/step - loss: 0.0676 -  
val\_loss: 0.0715  
Epoch 143/200  
420/420 [=====] - 0s 582us/step - loss: 0.0678 -  
val\_loss: 0.0717  
Epoch 144/200  
420/420 [=====] - 0s 580us/step - loss: 0.0681 -  
val\_loss: 0.0710  
Epoch 145/200  
420/420 [=====] - 0s 584us/step - loss: 0.0681 -  
val\_loss: 0.0705  
Epoch 146/200  
420/420 [=====] - 0s 581us/step - loss: 0.0679 -  
val\_loss: 0.0710  
Epoch 147/200  
420/420 [=====] - 0s 590us/step - loss: 0.0677 -  
val\_loss: 0.0710  
Epoch 148/200  
420/420 [=====] - 0s 588us/step - loss: 0.0679 -  
val\_loss: 0.0708  
Epoch 149/200  
420/420 [=====] - 0s 584us/step - loss: 0.0681 -  
val\_loss: 0.0703  
Epoch 150/200  
420/420 [=====] - 0s 581us/step - loss: 0.0676 -  
val\_loss: 0.0713  
Epoch 151/200

420/420 [=====] - 0s 587us/step - loss: 0.0678 -  
val\_loss: 0.0706  
Epoch 152/200  
420/420 [=====] - 0s 591us/step - loss: 0.0677 -  
val\_loss: 0.0707  
Epoch 153/200  
420/420 [=====] - 0s 603us/step - loss: 0.0680 -  
val\_loss: 0.0703  
Epoch 154/200  
420/420 [=====] - 0s 592us/step - loss: 0.0678 -  
val\_loss: 0.0715  
Epoch 155/200  
420/420 [=====] - 0s 607us/step - loss: 0.0674 -  
val\_loss: 0.0723  
Epoch 156/200  
420/420 [=====] - 0s 600us/step - loss: 0.0677 -  
val\_loss: 0.0703  
Epoch 157/200  
420/420 [=====] - 0s 627us/step - loss: 0.0680 -  
val\_loss: 0.0706  
Epoch 158/200  
420/420 [=====] - 0s 619us/step - loss: 0.0677 -  
val\_loss: 0.0702  
Epoch 159/200  
420/420 [=====] - 0s 603us/step - loss: 0.0676 -  
val\_loss: 0.0709  
Epoch 160/200  
420/420 [=====] - 0s 591us/step - loss: 0.0677 -  
val\_loss: 0.0707  
Epoch 161/200  
420/420 [=====] - 0s 600us/step - loss: 0.0677 -  
val\_loss: 0.0706  
Epoch 162/200  
420/420 [=====] - 0s 584us/step - loss: 0.0678 -  
val\_loss: 0.0722  
Epoch 163/200  
420/420 [=====] - 0s 580us/step - loss: 0.0678 -  
val\_loss: 0.0705  
Epoch 164/200  
420/420 [=====] - 0s 578us/step - loss: 0.0680 -  
val\_loss: 0.0749  
Epoch 165/200  
420/420 [=====] - 0s 584us/step - loss: 0.0681 -  
val\_loss: 0.0710  
Epoch 166/200  
420/420 [=====] - 0s 581us/step - loss: 0.0677 -  
val\_loss: 0.0709  
Epoch 167/200

420/420 [=====] - 0s 579us/step - loss: 0.0683 -  
val\_loss: 0.0704  
Epoch 168/200  
420/420 [=====] - 0s 586us/step - loss: 0.0674 -  
val\_loss: 0.0705  
Epoch 169/200  
420/420 [=====] - 0s 577us/step - loss: 0.0680 -  
val\_loss: 0.0708  
Epoch 170/200  
420/420 [=====] - 0s 583us/step - loss: 0.0675 -  
val\_loss: 0.0705  
Epoch 171/200  
420/420 [=====] - 0s 575us/step - loss: 0.0677 -  
val\_loss: 0.0707  
Epoch 172/200  
420/420 [=====] - 0s 579us/step - loss: 0.0677 -  
val\_loss: 0.0709  
Epoch 173/200  
420/420 [=====] - 0s 586us/step - loss: 0.0675 -  
val\_loss: 0.0707  
Epoch 174/200  
420/420 [=====] - 0s 585us/step - loss: 0.0676 -  
val\_loss: 0.0720  
Epoch 175/200  
420/420 [=====] - 0s 585us/step - loss: 0.0681 -  
val\_loss: 0.0711  
Epoch 176/200  
420/420 [=====] - 0s 588us/step - loss: 0.0672 -  
val\_loss: 0.0711  
Epoch 177/200  
420/420 [=====] - 0s 597us/step - loss: 0.0676 -  
val\_loss: 0.0711  
Epoch 178/200  
420/420 [=====] - 0s 599us/step - loss: 0.0682 -  
val\_loss: 0.0701  
Epoch 179/200  
420/420 [=====] - 0s 583us/step - loss: 0.0676 -  
val\_loss: 0.0707  
Epoch 180/200  
420/420 [=====] - 0s 581us/step - loss: 0.0679 -  
val\_loss: 0.0709  
Epoch 181/200  
420/420 [=====] - 0s 588us/step - loss: 0.0675 -  
val\_loss: 0.0738  
Epoch 182/200  
420/420 [=====] - 0s 597us/step - loss: 0.0671 -  
val\_loss: 0.0712  
Epoch 183/200

420/420 [=====] - 0s 587us/step - loss: 0.0680 -  
val\_loss: 0.0723  
Epoch 184/200  
420/420 [=====] - 0s 588us/step - loss: 0.0675 -  
val\_loss: 0.0706  
Epoch 185/200  
420/420 [=====] - 0s 587us/step - loss: 0.0678 -  
val\_loss: 0.0704  
Epoch 186/200  
420/420 [=====] - 0s 584us/step - loss: 0.0680 -  
val\_loss: 0.0732  
Epoch 187/200  
420/420 [=====] - 0s 585us/step - loss: 0.0680 -  
val\_loss: 0.0710  
Epoch 188/200  
420/420 [=====] - 0s 583us/step - loss: 0.0679 -  
val\_loss: 0.0703  
Epoch 189/200  
420/420 [=====] - 0s 585us/step - loss: 0.0674 -  
val\_loss: 0.0707  
Epoch 190/200  
420/420 [=====] - 0s 583us/step - loss: 0.0677 -  
val\_loss: 0.0750  
Epoch 191/200  
420/420 [=====] - 0s 591us/step - loss: 0.0678 -  
val\_loss: 0.0703  
Epoch 192/200  
420/420 [=====] - 0s 581us/step - loss: 0.0676 -  
val\_loss: 0.0703  
Epoch 193/200  
420/420 [=====] - 0s 586us/step - loss: 0.0676 -  
val\_loss: 0.0728  
Epoch 194/200  
420/420 [=====] - 0s 588us/step - loss: 0.0676 -  
val\_loss: 0.0717  
Epoch 195/200  
420/420 [=====] - 0s 582us/step - loss: 0.0679 -  
val\_loss: 0.0718  
Epoch 196/200  
420/420 [=====] - 0s 591us/step - loss: 0.0675 -  
val\_loss: 0.0712  
Epoch 197/200  
420/420 [=====] - 0s 593us/step - loss: 0.0676 -  
val\_loss: 0.0704  
Epoch 198/200  
420/420 [=====] - 0s 588us/step - loss: 0.0684 -  
val\_loss: 0.0706  
Epoch 199/200

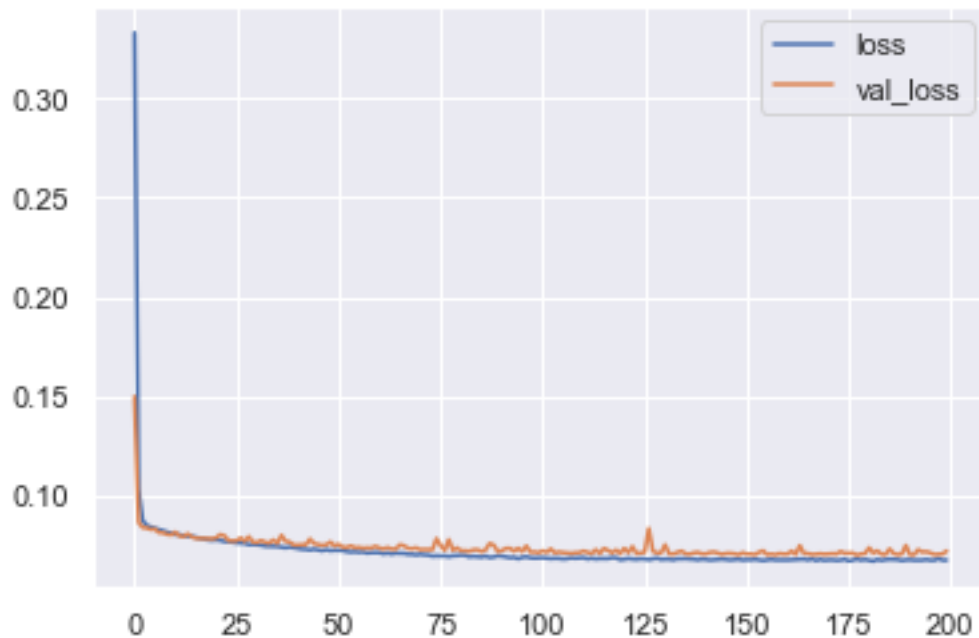
```
420/420 [=====] - 0s 582us/step - loss: 0.0676 -  
val_loss: 0.0707  
Epoch 200/200  
420/420 [=====] - 0s 588us/step - loss: 0.0676 -  
val_loss: 0.0722
```

```
[134]: <tensorflow.python.keras.callbacks.History at 0x7fe8f7f80460>
```

### 1.4.3 Visualize the Loss Function

```
[135]: losses = pd.DataFrame(model.history.history)  
losses.plot()
```

```
[135]: <matplotlib.axes._subplots.AxesSubplot at 0x7fe8fc57ea00>
```



Our validation loss remains relatively stable with the actual loss, so overfitting is minimal.

### 1.4.4 Test the Model

```
[136]: #y_pred = np.argmax(model.predict(X_test), axis=-1)  
y_pred = model.predict_classes(X_test)
```



### 1.4.5 Model Evaluation

```
[137]: confusion = confusion_matrix(y_test,y_pred)
print(f'CONFUSION MATRIX:
      ↪\n\n{confusion[0][0]}\t{confusion[0][1]}\n{confusion[1][0]}\t{confusion[1][1]}\n')
```

CONFUSION MATRIX:

```
4034    36
56      349
```

```
[139]: print(f"CLASSIFICATION REPORT:\n\n{classification_report(y_test,y_pred)}")
```

CLASSIFICATION REPORT:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	4070
1	0.91	0.86	0.88	405
accuracy			0.98	4475
macro avg	0.95	0.93	0.94	4475
weighted avg	0.98	0.98	0.98	4475

## 1.5 Model Optimization

### 1.5.1 Iterating Through the Models

Let's experiment with the number of hidden layers in our network. We'll iterate from 2 to 50 hidden layers, each containing 8 units

```
[145]: results = []
for i in range(2,51):
    model_loop = Sequential()

    # Input and hidden layers
    for j in range(0,(i+1)):
        model_loop.add(Dense(8,activation='relu'))

    # Output layer
    model_loop.add(Dense(1,activation='sigmoid'))

    # Compile layers
    model_loop.compile(loss='binary_crossentropy', optimizer='adam')

    # We will reduce epochs to 100 to reduce run time.
    # 100 was chosen based on previous loss function visualization.
    model_loop.fit(x=X_train,y=y_train.values,
```

```

validation_data=(X_test,y_test.values),
batch_size=128,epochs=100,verbose=0)

# Model evaluation
predictions_loop = model_loop.predict_classes(X_test)

# Calculate statistics for each iteration
confusion = confusion_matrix(y_test,predictions_loop)

tp = confusion[1][1]
tn = confusion[0][0]
fp = confusion[0][1]
fn = confusion[1][0]

total = tp+tn+fp+fn
accuracy = (tp+tn)/total
precision = tp/(tp+fp)
recall = tp/(tp+fn)
f1_score = 2*precision*recall/(precision+recall)

# Append results to the list for future reference
results.append([i,accuracy,precision,recall,f1_score])

# Print classification report after each iteration
print(f"CLASSIFICATION REPORT FOR {i} HIDDEN LAYERS:
→\n\n{classification_report(y_test,predictions_loop)}")

```

CLASSIFICATION REPORT FOR 2 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	0.99	0.99	4070
1	0.93	0.83	0.88	405
accuracy			0.98	4475
macro avg	0.96	0.91	0.93	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 3 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	0.99	0.99	4070
1	0.94	0.83	0.88	405
accuracy			0.98	4475
macro avg	0.96	0.91	0.93	4475

weighted avg	0.98	0.98	0.98	4475
--------------	------	------	------	------

CLASSIFICATION REPORT FOR 4 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	4070
1	0.91	0.86	0.89	405
accuracy			0.98	4475
macro avg	0.95	0.93	0.94	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 5 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	0.99	0.99	4070
1	0.92	0.84	0.88	405
accuracy			0.98	4475
macro avg	0.95	0.92	0.93	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 6 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	0.99	0.99	4070
1	0.93	0.84	0.88	405
accuracy			0.98	4475
macro avg	0.96	0.92	0.93	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 7 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	1.00	0.99	4070
1	0.94	0.82	0.88	405
accuracy			0.98	4475
macro avg	0.96	0.91	0.93	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 8 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	0.99	0.99	4070
1	0.92	0.84	0.88	405
accuracy			0.98	4475
macro avg	0.95	0.92	0.93	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 9 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	4070
1	0.91	0.86	0.89	405
accuracy			0.98	4475
macro avg	0.95	0.93	0.94	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 10 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	0.99	0.99	4070
1	0.93	0.84	0.88	405
accuracy			0.98	4475
macro avg	0.96	0.92	0.94	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 11 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	4070
1	0.91	0.86	0.88	405
accuracy			0.98	4475
macro avg	0.95	0.93	0.94	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 12 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	0.99	0.99	4070
1	0.94	0.82	0.88	405

accuracy			0.98	4475
macro avg	0.96	0.91	0.93	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 13 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	0.99	0.99	4070
1	0.94	0.83	0.88	405

accuracy			0.98	4475
macro avg	0.96	0.91	0.94	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 14 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	1.00	0.99	4070
1	0.95	0.82	0.88	405

accuracy			0.98	4475
macro avg	0.96	0.91	0.94	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 15 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	0.99	0.99	4070
1	0.93	0.82	0.87	405

accuracy			0.98	4475
macro avg	0.96	0.91	0.93	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 16 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	4070
1	0.91	0.85	0.88	405

accuracy			0.98	4475
macro avg	0.95	0.92	0.93	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 17 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	0.99	0.99	4070
1	0.93	0.83	0.88	405
accuracy			0.98	4475
macro avg	0.96	0.91	0.93	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 18 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	1.00	0.99	4070
1	0.95	0.82	0.88	405
accuracy			0.98	4475
macro avg	0.96	0.91	0.93	4475
weighted avg	0.98	0.98	0.98	4475

<ipython-input-145-31c4091dd8c8>:34: RuntimeWarning: invalid value encountered in long\_scalars

```
precision = tp/(tp+fp)
/opt/anaconda3/lib/python3.8/site-
packages/sklearn/metrics/_classification.py:1221: UndefinedMetricWarning:
Precision and F-score are ill-defined and being set to 0.0 in labels with no
predicted samples. Use `zero_division` parameter to control this behavior.
_warn_prf(average, modifier, msg_start, len(result))
```

CLASSIFICATION REPORT FOR 19 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405
accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 20 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070

1	0.00	0.00	0.00	405
accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 21 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405
accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 22 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405
accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 23 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405
accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 24 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	4070
1	0.92	0.86	0.89	405
accuracy			0.98	4475
macro avg	0.95	0.92	0.94	4475

weighted avg	0.98	0.98	0.98	4475
--------------	------	------	------	------

CLASSIFICATION REPORT FOR 25 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	0.99	0.99	4070
1	0.92	0.85	0.88	405
accuracy			0.98	4475
macro avg	0.95	0.92	0.94	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 26 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	0.99	0.99	4070
1	0.93	0.84	0.88	405
accuracy			0.98	4475
macro avg	0.96	0.92	0.94	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 27 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	4070
1	0.91	0.85	0.88	405
accuracy			0.98	4475
macro avg	0.95	0.92	0.93	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 28 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405
accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 29 HIDDEN LAYERS:



	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405
accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 30 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	4070
1	0.92	0.85	0.88	405
accuracy			0.98	4475
macro avg	0.95	0.92	0.94	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 31 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	4070
1	0.90	0.87	0.88	405
accuracy			0.98	4475
macro avg	0.94	0.93	0.94	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 32 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	1.00	0.99	4070
1	0.95	0.83	0.88	405
accuracy			0.98	4475
macro avg	0.96	0.91	0.94	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 33 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	0.99	0.99	4070
1	0.94	0.81	0.87	405

accuracy			0.98	4475
macro avg	0.96	0.90	0.93	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 34 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405
accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 35 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	1.00	0.99	4070
1	0.96	0.80	0.88	405
accuracy			0.98	4475
macro avg	0.97	0.90	0.93	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 36 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405
accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 37 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.98	0.99	0.99	4070
1	0.92	0.85	0.88	405
accuracy			0.98	4475
macro avg	0.95	0.92	0.94	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 38 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.99	0.99	0.99	4070
1	0.93	0.85	0.89	405
accuracy			0.98	4475
macro avg	0.96	0.92	0.94	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 39 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405
accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 40 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405
accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 41 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405
accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 42 HIDDEN LAYERS:

	precision	recall	f1-score	support
--	-----------	--------	----------	---------

0	0.98	0.99	0.99	4070
1	0.92	0.85	0.88	405
accuracy			0.98	4475
macro avg	0.95	0.92	0.94	4475
weighted avg	0.98	0.98	0.98	4475

CLASSIFICATION REPORT FOR 43 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405
accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 44 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405
accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 45 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405
accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 46 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405

accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 47 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405

accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 48 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405

accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 49 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405

accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

CLASSIFICATION REPORT FOR 50 HIDDEN LAYERS:

	precision	recall	f1-score	support
0	0.91	1.00	0.95	4070
1	0.00	0.00	0.00	405

accuracy			0.91	4475
macro avg	0.45	0.50	0.48	4475
weighted avg	0.83	0.91	0.87	4475

### 1.5.2 Cleaning the Results

Display the results in a pandas dataframe

```
[152]: results_df = pd.  
↳ DataFrame(columns=['Hidden_Layers', 'Accuracy', 'Precision', 'Recall', 'F1-Score'], data=results  
results_df
```

```
[152]:
```

	Hidden_Layers	Accuracy	Precision	Recall	F1-Score
0	2	0.978771	0.928177	0.829630	0.876141
1	3	0.979665	0.936111	0.832099	0.881046
2	4	0.979888	0.913386	0.859259	0.885496
3	5	0.979218	0.921622	0.841975	0.880000
4	6	0.979218	0.926230	0.837037	0.879377
5	7	0.979218	0.943182	0.819753	0.877147
6	8	0.978994	0.921409	0.839506	0.878553
7	9	0.980112	0.911458	0.864198	0.887199
8	10	0.979888	0.929155	0.841975	0.883420
9	11	0.979218	0.906250	0.859259	0.882129
10	12	0.979218	0.940678	0.822222	0.877470
11	13	0.979888	0.936288	0.834568	0.882507
12	14	0.979888	0.946176	0.824691	0.881266
13	15	0.978547	0.930362	0.824691	0.874346
14	16	0.978994	0.912467	0.849383	0.879795
15	17	0.978771	0.928177	0.829630	0.876141
16	18	0.979665	0.946023	0.822222	0.879789
17	19	0.909497	NaN	0.000000	NaN
18	20	0.909497	NaN	0.000000	NaN
19	21	0.909497	NaN	0.000000	NaN
20	22	0.909497	NaN	0.000000	NaN
21	23	0.909497	NaN	0.000000	NaN
22	24	0.980112	0.917989	0.856790	0.886335
23	25	0.979441	0.919571	0.846914	0.881748
24	26	0.979665	0.931319	0.837037	0.881664
25	27	0.979218	0.914894	0.849383	0.880922
26	28	0.909497	NaN	0.000000	NaN
27	29	0.909497	NaN	0.000000	NaN
28	30	0.979665	0.917553	0.851852	0.883483
29	31	0.979441	0.900256	0.869136	0.884422
30	32	0.980335	0.946479	0.829630	0.884211
31	33	0.978324	0.937500	0.814815	0.871863
32	34	0.909497	NaN	0.000000	NaN
33	35	0.979218	0.958824	0.804938	0.875168
34	36	0.909497	NaN	0.000000	NaN
35	37	0.979888	0.924528	0.846914	0.884021
36	38	0.981006	0.932432	0.851852	0.890323
37	39	0.909497	NaN	0.000000	NaN
38	40	0.909497	NaN	0.000000	NaN

39	41	0.909497	NaN	0.000000	NaN
40	42	0.979441	0.919571	0.846914	0.881748
41	43	0.909497	NaN	0.000000	NaN
42	44	0.909497	NaN	0.000000	NaN
43	45	0.909497	NaN	0.000000	NaN
44	46	0.909497	NaN	0.000000	NaN
45	47	0.909497	NaN	0.000000	NaN
46	48	0.909497	NaN	0.000000	NaN
47	49	0.909497	NaN	0.000000	NaN
48	50	0.909497	NaN	0.000000	NaN

There appear to be many null values. Let's remove them.

```
[155]: cleaned_results = results_df.dropna()
cleaned_results
```

```
[155]:
```

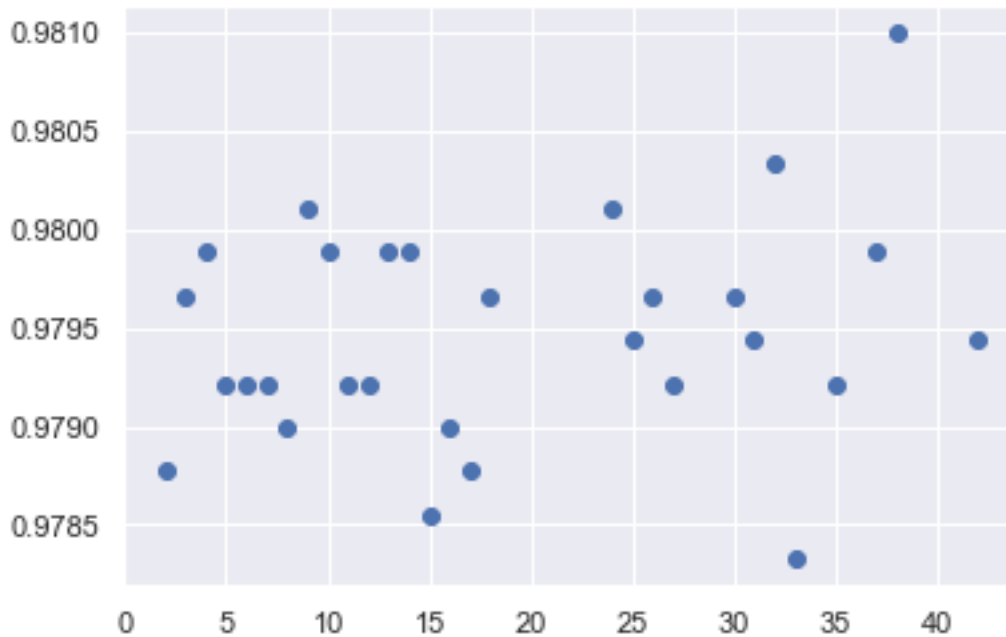
	Hidden_Layers	Accuracy	Precision	Recall	F1-Score
0	2	0.978771	0.928177	0.829630	0.876141
1	3	0.979665	0.936111	0.832099	0.881046
2	4	0.979888	0.913386	0.859259	0.885496
3	5	0.979218	0.921622	0.841975	0.880000
4	6	0.979218	0.926230	0.837037	0.879377
5	7	0.979218	0.943182	0.819753	0.877147
6	8	0.978994	0.921409	0.839506	0.878553
7	9	0.980112	0.911458	0.864198	0.887199
8	10	0.979888	0.929155	0.841975	0.883420
9	11	0.979218	0.906250	0.859259	0.882129
10	12	0.979218	0.940678	0.822222	0.877470
11	13	0.979888	0.936288	0.834568	0.882507
12	14	0.979888	0.946176	0.824691	0.881266
13	15	0.978547	0.930362	0.824691	0.874346
14	16	0.978994	0.912467	0.849383	0.879795
15	17	0.978771	0.928177	0.829630	0.876141
16	18	0.979665	0.946023	0.822222	0.879789
22	24	0.980112	0.917989	0.856790	0.886335
23	25	0.979441	0.919571	0.846914	0.881748
24	26	0.979665	0.931319	0.837037	0.881664
25	27	0.979218	0.914894	0.849383	0.880922
28	30	0.979665	0.917553	0.851852	0.883483
29	31	0.979441	0.900256	0.869136	0.884422
30	32	0.980335	0.946479	0.829630	0.884211
31	33	0.978324	0.937500	0.814815	0.871863
33	35	0.979218	0.958824	0.804938	0.875168
35	37	0.979888	0.924528	0.846914	0.884021
36	38	0.981006	0.932432	0.851852	0.890323
40	42	0.979441	0.919571	0.846914	0.881748

### 1.5.3 Visualizing the Iterations

Let's visualize the performance by number of hidden layers.

```
[161]: # Visualizing Accuracy  
plt.scatter(x=cleaned_results['Hidden_Layers'],y=cleaned_results['Accuracy'])
```

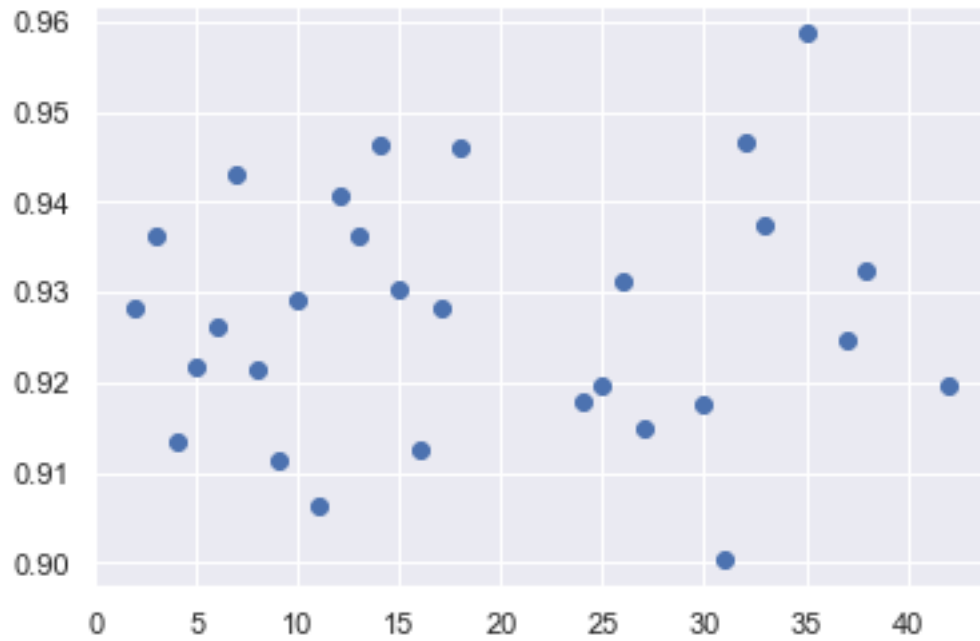
```
[161]: <matplotlib.collections.PathCollection at 0x7fe8e9781340>
```



```
[163]: # Visualizing Precision  
plt.scatter(x=cleaned_results['Hidden_Layers'],y=cleaned_results['Precision'])
```

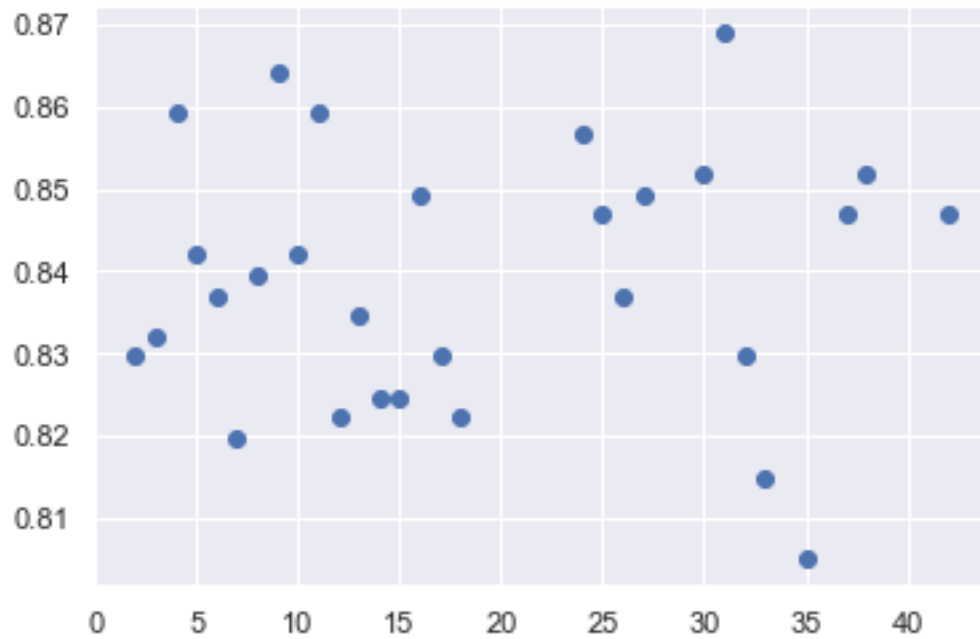
```
[163]: <matplotlib.collections.PathCollection at 0x7fe8e0483760>
```





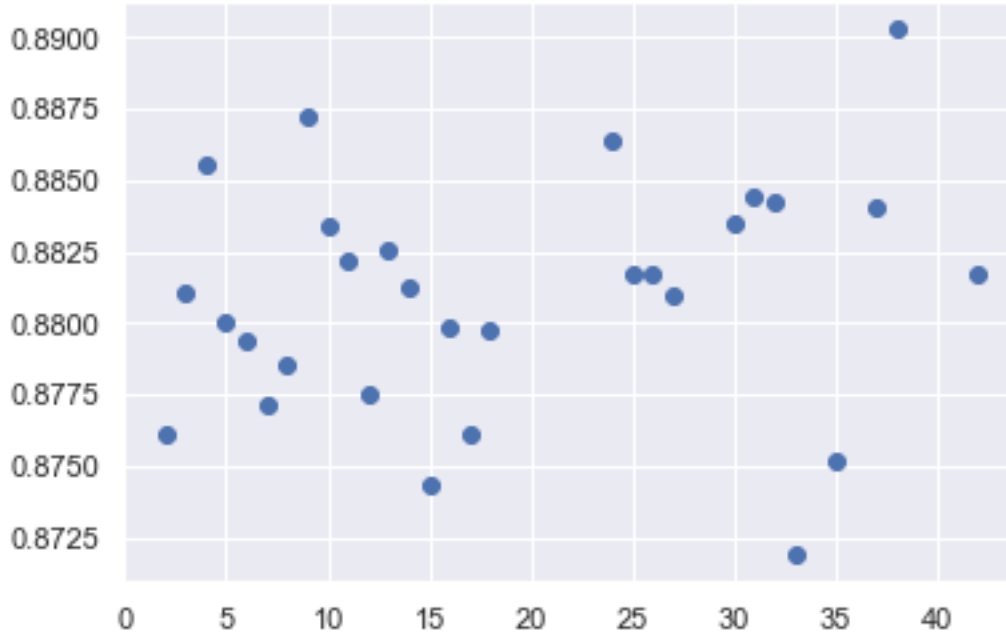
```
[164]: # Visualizing Recall  
plt.scatter(x=cleaned_results['Hidden_Layers'],y=cleaned_results['Recall'])
```

```
[164]: <matplotlib.collections.PathCollection at 0x7fe8fe99a130>
```



```
[165]: # Visualizing F1-Score
plt.scatter(x=cleaned_results['Hidden_Layers'],y=cleaned_results['F1-Score'])
```

```
[165]: <matplotlib.collections.PathCollection at 0x7fe8fe936850>
```



#### 1.5.4 Analyzing the Results

```
[162]: cleaned_results.describe()
```

```
[162]:
```

	Hidden_Layers	Accuracy	Precision	Recall	F1-Score
count	29.000000	29.000000	29.000000	29.000000	29.000000
mean	18.965517	0.979480	0.927520	0.839251	0.880956
std	12.040060	0.000567	0.013611	0.015649	0.004102
min	2.000000	0.978324	0.900256	0.804938	0.871863
25%	9.000000	0.979218	0.917989	0.829630	0.878553
50%	16.000000	0.979441	0.928177	0.839506	0.881266
75%	30.000000	0.979888	0.936288	0.849383	0.883483
max	42.000000	0.981006	0.958824	0.869136	0.890323

```
[181]: # Display Top 5 Models by Accuracy
cleaned_results.sort_values(by='Accuracy',ascending=False).
↳drop(['Precision','Recall','F1-Score'],axis=1)[:5]
```

```
[181]:
```

	Hidden_Layers	Accuracy
36	38	0.981006

30	32	0.980335
7	9	0.980112
22	24	0.980112
11	13	0.979888

```
[178]: # Display Top 5 Models by Precision
cleaned_results.sort_values(by='Precision',ascending=False).
↳drop(['Accuracy','Recall','F1-Score'],axis=1)[:5]
```

```
[178]: Hidden_Layers Precision
33          35    0.958824
30          32    0.946479
12          14    0.946176
16          18    0.946023
5           7    0.943182
```

```
[183]: # Display Top 5 Models by Recall
cleaned_results.sort_values(by='Recall',ascending=False).
↳drop(['Accuracy','Precision','F1-Score'],axis=1)[:5]
```

```
[183]: Hidden_Layers Recall
29          31 0.869136
7           9 0.864198
2           4 0.859259
9           11 0.859259
22          24 0.856790
```

```
[182]: # Display Top 5 Models by F1-Score
cleaned_results.sort_values(by='F1-Score',ascending=False).
↳drop(['Accuracy','Precision','Recall'],axis=1)[:5]
```

```
[182]: Hidden_Layers F1-Score
36          38 0.890323
7           9 0.887199
22          24 0.886335
2           4 0.885496
29          31 0.884422
```

## 1.6 Conclusions

The best performing models for each category below (number of hidden layers in parentheses) were:  
 \* Accuracy = 0.981 from Model(38) \* Precision = 0.959 from Model(35) \* Recall = 0.869 from Model(31) \* F1-Score = 0.890 from Model(38)

The objective of this project is to find a model that can correctly identify pulsars, which account for only approximately 10% of the dataset. Therefore, the most important metric is recall for this exercise. The model with the best recall had 31 hidden layers. Its evaluation metrics are saved below for future comparison with the other models:

```
[1]: with open("2020_1127_DNN_Results.csv","w") as file:
      file.write('Model,Accuracy,Precision,Recall,F1-Score\n')
      file.write('DNN,0.98,0.90,0.87,0.88\n')
```