Q1-advertising

April 17, 2021

0.0.1 PROBLEM STATEMENT for ANN:

In this assignment you will be working with a dummy advertising data set, indicating whether or not a particular internet user clicked on an Advertisement on a company website. you will try to create a model that will predict whether or not they will click on an ad based on the features of that user.

This data set contains the following features:

- 'Daily Time Spent on Site': consumer time on site in minutes
- 'Age': customer age in years
- 'Area Income': Avg. Income of geographical area of consumer
- 'Daily Internet Usage': Avg. minutes a day consumer is on the internet
- 'Ad Topic Line': Headline of the advertisement
- 'City': City of consumer
- 'Male': Whether or not consumer was male
- 'Country': Country of consumer
- 'Timestamp': Time at which consumer clicked on Ad or closed window
- 'Clicked on Ad': 0 or 1 indicated clicking on Ad

For the dataset (Advertising dataset), implement the ANN classifier using Keras in Python. [5M]

Dataset: Advertising Dataset.csv

0.1 1. Import the libraries and Load the dataset and Remove/replace missing values

```
[35]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from tensorflow.keras.layers import Dropout
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report,confusion_matrix
from tensorflow.keras.callbacks import EarlyStopping
from tensorflow.keras.models import Sequential
```

```
from tensorflow.keras.layers import Dense, Dropout, Activation
    from sklearn.preprocessing import MinMaxScaler
    import warnings
    warnings.filterwarnings('ignore')
    %matplotlib inline
[2]: adf=pd.read_csv('advertising-1.csv',na_values='?')
[3]: adf.info()
    <class 'pandas.core.frame.DataFrame'>
    RangeIndex: 1000 entries, 0 to 999
    Data columns (total 10 columns):
     #
         Column
                                   Non-Null Count Dtype
                                   -----
                                                   ____
         Daily Time Spent on Site 1000 non-null
                                                   float64
     0
     1
         Age
                                   1000 non-null
                                                   int64
     2
        Area Income
                                   1000 non-null
                                                   float64
        Daily Internet Usage
                                   1000 non-null
                                                   float64
     4
         Ad Topic Line
                                   1000 non-null
                                                   object
     5
                                   1000 non-null
         City
                                                   object
     6
         Male
                                   1000 non-null
                                                   int64
     7
         Country
                                   1000 non-null
                                                   object
     8
         Timestamp
                                   1000 non-null
                                                   object
     9
         Clicked on Ad
                                   1000 non-null
                                                   int64
    dtypes: float64(3), int64(3), object(4)
    memory usage: 78.2+ KB
[4]: print(adf.columns)
    print ("Shape of Data :" , adf.shape)
    print ("\nFeatures :" ,adf.columns.tolist())
    print ("\nMissing values : ", adf.isnull().sum().values.sum())
    print ("\nUnique values : ", adf.nunique(),'\n')
    adf.head()
    Index(['Daily Time Spent on Site', 'Age', 'Area Income',
           'Daily Internet Usage', 'Ad Topic Line', 'City', 'Male', 'Country',
           'Timestamp', 'Clicked on Ad'],
          dtype='object')
    Shape of Data : (1000, 10)
    Features: ['Daily Time Spent on Site', 'Age', 'Area Income', 'Daily Internet
    Usage', 'Ad Topic Line', 'City', 'Male', 'Country', 'Timestamp', 'Clicked on
    Ad']
    Missing values: 0
```

```
Unique values :
                       Daily Time Spent on Site
                                                     900
                                    43
    Age
                                 1000
    Area Income
    Daily Internet Usage
                                  966
    Ad Topic Line
                                 1000
                                  969
    City
    Male
                                    2
    Country
                                  237
    Timestamp
                                 1000
    Clicked on Ad
                                     2
    dtype: int64
[4]:
        Daily Time Spent on Site
                                        Area Income
                                   Age
                                                     Daily Internet Usage
                            68.95
                                    35
                                            61833.90
                                                                     256.09
     1
                            80.23
                                    31
                                                                     193.77
                                            68441.85
     2
                            69.47
                                    26
                                            59785.94
                                                                     236.50
     3
                                    29
                            74.15
                                            54806.18
                                                                     245.89
     4
                            68.37
                                    35
                                           73889.99
                                                                     225.58
                                 Ad Topic Line
                                                                           Country \
                                                           City Male
     0
           Cloned 5thgeneration orchestration
                                                    Wrightburgh
                                                                    0
                                                                           Tunisia
     1
           Monitored national standardization
                                                      West Jodi
                                                                     1
                                                                             Nauru
     2
             Organic bottom-line service-desk
                                                       Davidton
                                                                    0
                                                                       San Marino
     3
       Triple-buffered reciprocal time-frame
                                                West Terrifurt
                                                                     1
                                                                             Italy
                Robust logistical utilization
     4
                                                   South Manuel
                                                                    0
                                                                           Iceland
                  Timestamp
                             Clicked on Ad
       2016-03-27 00:53:11
     1 2016-04-04 01:39:02
                                          0
     2 2016-03-13 20:35:42
                                          0
     3 2016-01-10 02:31:19
                                          0
```

• No Missing Values Observed

4 2016-06-03 03:36:18

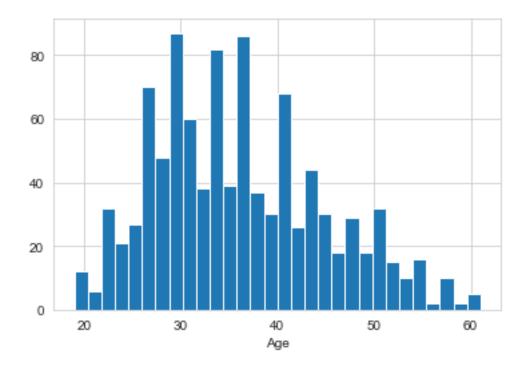
0.1.1 1.1 Exploratory Data Analysis

1.1.1 Create Histogram of the AGE

```
[5]: sns.set_style('whitegrid')
adf['Age'].hist(bins=30)
plt.xlabel('Age')
```

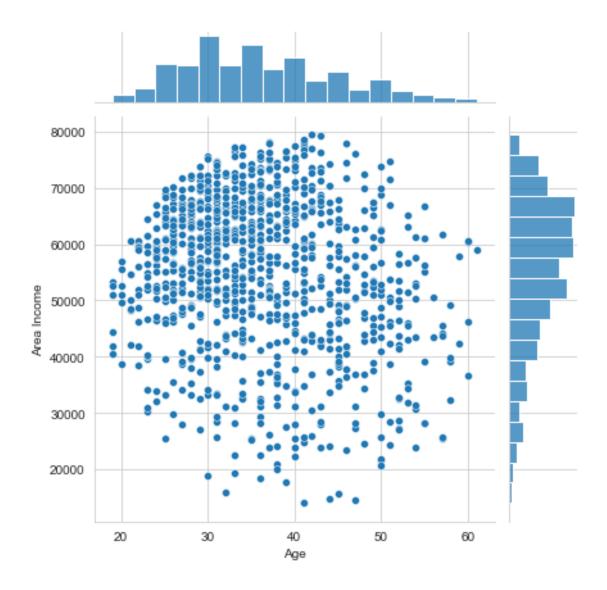
0

[5]: Text(0.5, 0, 'Age')



Most of the internet users Age in between 28 - 40 ###### 1.1.2 Joint plot - Area Income Vs. Age

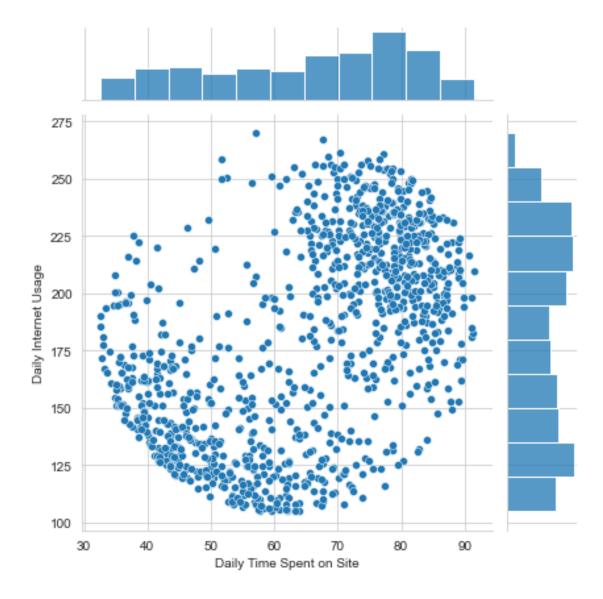
- [6]: sns.jointplot(x='Age',y='Area Income',data=adf)
- [6]: <seaborn.axisgrid.JointGrid at 0x15fab533a58>



1.1.3 jointplot showing the Daily Time spent on site vs. Daily Internet Usage

[7]: sns.jointplot(x='Daily Time Spent on Site', y='Daily Internet Usage', data= adf)

[7]: <seaborn.axisgrid.JointGrid at 0x15fab6ae978>

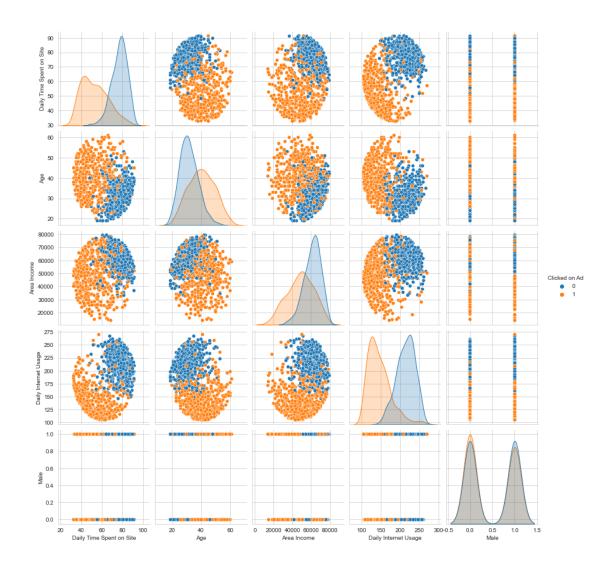


We can see from the plot the users who spend more time on internet tend to spend more time on the website

1.1.4 Pair Plot to see the relationship of all features considering if they have Clicked on Ad on Not

```
[8]: sns.pairplot(adf, hue='Clicked on Ad')
```

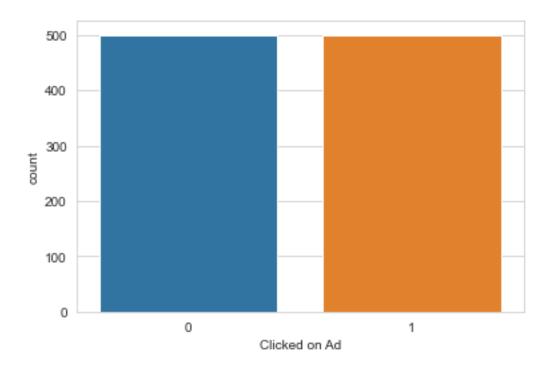
[8]: <seaborn.axisgrid.PairGrid at 0x15fab7f1e80>



1.1.5 Target Class Distribution

```
[9]: sns.set_style('whitegrid')
sns.countplot(x='Clicked on Ad', data=adf)
```

[9]: <AxesSubplot:xlabel='Clicked on Ad', ylabel='count'>



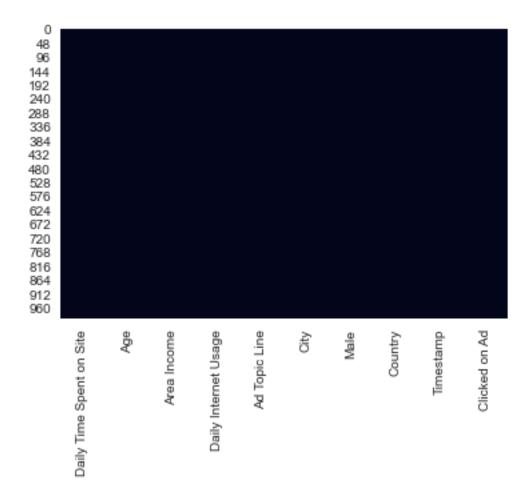
Above graph shows that the Target class for "Clicked & Not Clicked on Ad" are equally distributed

0.1.2 1.2 Cleaning the Data

1.2.1 Check if there are any missing values

```
[10]: sns.heatmap(adf.isnull(), cbar=False)
```

[10]: <AxesSubplot:>



There are no missing values in the given data

1.2.2 Identify and Convert Categorical Values to Numberical Values

[11]: adf.dtypes

```
[11]: Daily Time Spent on Site
                                   float64
      Age
                                      int64
      Area Income
                                   float64
                                   float64
      Daily Internet Usage
      Ad Topic Line
                                    object
      City
                                    object
      Male
                                     int64
      Country
                                    object
      Timestamp
                                    object
      Clicked on Ad
                                      int64
      dtype: object
```

Here, we have some non numerical values such as "City", "Ad Topic Line", "Country", "Times-

tamp". Since we cannot use them as an input to the machine learning model, we replace them with numerical codes.

```
[12]: adf['City Codes']= adf['City'].astype('category').cat.codes
adf['Country Codes'] = adf['Country'].astype('category').cat.codes
adf[['City Codes','Country Codes']].head()
```

```
[12]:
         City Codes
                      Country Codes
                 961
                 903
                                  147
      1
      2
                 111
                                  184
                 939
      3
                                  103
      4
                 805
                                   96
```

```
[13]: adf['Month'] = adf['Timestamp'].apply(lambda x: x.split('-')[1])
adf['Hour'] = adf['Timestamp'].apply(lambda x: x.split(':')[0].split(' ')[1])
adf[['Month','Hour']].head()
```

```
[13]: Month Hour
```

- 0 03 00
- 1 04 01
- 2 03 20
- 3 01 02
- 4 06 03

1.2.3 Droping Extra Features

- We have already converted the non numerical data to numerical values.
- Dropping the remaining non-numerical columns.

```
[14]: adf_updata = adf.drop(labels=['Ad Topic Line','City','Country','Timestamp'], 

⇔axis=1)
adf_updata.head()
```

```
[14]:
         Daily Time Spent on Site
                                    Age Area Income Daily Internet Usage
                                                                              Male
                                                                                    \
                             68.95
                                     35
                                             61833.90
                                                                      256.09
                                                                                  0
      0
                             80.23
                                                                      193.77
      1
                                     31
                                             68441.85
                                                                                  1
      2
                             69.47
                                             59785.94
                                                                      236.50
                                                                                  0
                                     26
      3
                             74.15
                                      29
                                             54806.18
                                                                      245.89
                                                                                  1
                             68.37
                                     35
                                             73889.99
                                                                      225.58
                                                                                  0
```

	Clicked on Ad	City Codes	Country	Codes	Month	Hour
0	0	961		215	03	00
1	0	903		147	04	01
2	0	111		184	03	20
3	0	939		103	01	02
4	0	805		96	06	03

```
[15]: adf_updata.columns
```

0.2 2. Split features and labels

here, we have taken the class label 'Clicked on Ad' as 'y' (Lower case - y, because it is one dimentional data) and all remaining features as 'X'

0.3 3. Split train and test data

```
[17]: from sklearn.model_selection import train_test_split
```

```
[18]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, u →random_state=42)
```

0.4 4. Implement ANN Classifier using Keras

0.4.1 4.1 Normalizing the Data

Used MinMaxScaler to normalize the feature data X_train and X_test. We don't want data leakage from the test set, so we only fit on the X_train data

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

```
[20]: X_train.shape
```

[20]: (700, 9)

```
[21]: X_train
```

```
...,
[0.99898011, 0.61904762, 0.57909566, ..., 0.42975207, 0.5, 0.30434783],
[0.40897501, 0.54761905, 0.89615916, ..., 0.39772727, 0.16666667, 0.43478261],
[0.97416284, 0.5, 0.69626269, ..., 0.88739669, 1., 0.60869565]])
```

0.4.2 4.2 Creating the Model

4.2.1 TRAIL - 01

- Considering 8 & 4 multiplying with number of class labels (0,1), and final output as 1 neuron.
- it is a binary classification problem we have given the activation function as 'sigmoid' for the output.
- ran it for 600 epochs

```
[22]: model = Sequential()
  model.add(Dense(units=16,activation='relu'))
  model.add(Dense(units=8,activation='relu'))
  model.add(Dense(units=1,activation='sigmoid'))
# For a binary classification problem
  model.compile(loss='binary_crossentropy', optimizer='adam')
```

```
Epoch 1/600
val loss: 0.6807
Epoch 2/600
0.6463
Epoch 3/600
0.6141
Epoch 4/600
0.5804
Epoch 5/600
0.5423
Epoch 6/600
```

```
0.5007
Epoch 7/600
0.4528
Epoch 8/600
0.4050
Epoch 9/600
0.3588
Epoch 10/600
0.3172
Epoch 11/600
0.2852
Epoch 12/600
0.2570
Epoch 13/600
0.2358
Epoch 14/600
0.2190
Epoch 15/600
0.2090
Epoch 16/600
0.1984
Epoch 17/600
0.1912
Epoch 18/600
0.1838
Epoch 19/600
0.1805
Epoch 20/600
0.1760
Epoch 21/600
0.1732
Epoch 22/600
```

```
0.1719
Epoch 23/600
0.1701
Epoch 24/600
Epoch 25/600
0.1666
Epoch 26/600
0.1635
Epoch 27/600
0.1626
Epoch 28/600
0.1620
Epoch 29/600
0.1631
Epoch 30/600
0.1595
Epoch 31/600
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Epoch 32/600
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Epoch 33/600
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Epoch 37/600
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Epoch 51/600
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Epoch 52/600
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Epoch 53/600
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Epoch 54/600
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Epoch 55/600
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Epoch 64/600
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Epoch 65/600
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Epoch 66/600
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Epoch 67/600
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Epoch 68/600
0.1466
Epoch 69/600
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Epoch 70/600
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0.1476
Epoch 71/600
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Epoch 80/600
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Epoch 81/600
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Epoch 106/600
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Epoch 107/600
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Epoch 117/600
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Epoch 131/600
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Epoch 132/600
0.1548
Epoch 133/600
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Epoch 134/600
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Epoch 135/600
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Epoch 136/600
Epoch 137/600
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Epoch 138/600
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Epoch 139/600
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Epoch 149/600
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Epoch 179/600
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Epoch 180/600
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Epoch 181/600
0.1643
Epoch 182/600
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```
loss: 0.0594 - val_loss: 0.1656
Epoch 183/600
0.1652
Epoch 184/600
Epoch 185/600
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Epoch 186/600
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Epoch 187/600
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Epoch 263/600
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Epoch 267/600
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Epoch 273/600
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Epoch 274/600
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```

```
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0.1811
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Epoch 305/600
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Epoch 308/600
0.1829
Epoch 309/600
0.1836
Epoch 310/600
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0.1821
Epoch 311/600
0.1799
Epoch 312/600
Epoch 313/600
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Epoch 314/600
0.1824
Epoch 315/600
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Epoch 316/600
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Epoch 318/600
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Epoch 319/600
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Epoch 321/600
0.1841
Epoch 322/600
0.1832
Epoch 323/600
0.1848
Epoch 324/600
0.1846
Epoch 325/600
0.1840
Epoch 326/600
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0.1841
Epoch 327/600
0.1847
Epoch 328/600
Epoch 329/600
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Epoch 330/600
0.1873
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Epoch 334/600
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Epoch 335/600
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Epoch 337/600
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Epoch 338/600
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Epoch 339/600
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Epoch 341/600
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Epoch 342/600
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Epoch 347/600
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Epoch 349/600
0.1896
Epoch 350/600
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Epoch 351/600
0.1882
Epoch 352/600
0.1870
Epoch 353/600
0.1877
Epoch 354/600
0.1890
Epoch 355/600
0.1900
Epoch 356/600
0.1889
Epoch 357/600
0.1900
Epoch 358/600
```

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0.1901
Epoch 359/600
0.1908
Epoch 360/600
Epoch 361/600
0.1926
Epoch 362/600
0.1891
Epoch 363/600
0.1901
Epoch 364/600
0.1909
Epoch 365/600
0.1885
Epoch 366/600
0.1838
Epoch 367/600
0.1876
Epoch 368/600
0.1880
Epoch 369/600
0.1894
Epoch 370/600
0.1898
Epoch 371/600
0.1883
Epoch 372/600
22/22 [============= ] - Os 13ms/step - loss: 0.0220 - val_loss:
0.1897
Epoch 373/600
0.1931
Epoch 374/600
```

```
0.1900
Epoch 375/600
Epoch 376/600
Epoch 377/600
0.1899
Epoch 378/600
0.1895
Epoch 379/600
0.1917
Epoch 380/600
0.1931
Epoch 381/600
0.1932
Epoch 382/600
0.1893
Epoch 383/600
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Epoch 384/600
0.1936
Epoch 385/600
0.1948
Epoch 386/600
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Epoch 387/600
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Epoch 388/600
0.1934
Epoch 389/600
0.1918
Epoch 390/600
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0.1917
Epoch 391/600
Epoch 392/600
Epoch 393/600
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Epoch 394/600
0.1925
Epoch 395/600
0.1928
Epoch 396/600
0.1951
Epoch 397/600
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Epoch 398/600
0.1921
Epoch 399/600
0.1939
Epoch 400/600
0.1935
Epoch 401/600
0.1927
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0.1938
Epoch 403/600
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Epoch 404/600
0.1949
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0.1922
Epoch 406/600
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```
0.1991
Epoch 407/600
0.1952
Epoch 408/600
Epoch 409/600
0.1948
Epoch 410/600
0.1956
Epoch 411/600
0.1935
Epoch 412/600
0.1935
Epoch 413/600
0.1924
Epoch 414/600
0.1954
Epoch 415/600
0.1941
Epoch 416/600
0.1934
Epoch 417/600
0.1961
Epoch 418/600
0.1958
Epoch 419/600
0.1941
Epoch 420/600
0.1935
Epoch 421/600
0.1959
Epoch 422/600
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0.1966
Epoch 423/600
0.1950
Epoch 424/600
Epoch 425/600
0.1944
Epoch 426/600
0.1977
Epoch 427/600
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Epoch 428/600
0.1980
Epoch 429/600
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Epoch 430/600
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Epoch 431/600
0.1958
Epoch 432/600
0.1951
Epoch 433/600
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Epoch 434/600
0.1967
Epoch 435/600
0.1948
Epoch 436/600
0.1969
Epoch 437/600
0.1965
Epoch 438/600
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0.1973
Epoch 439/600
0.1963
Epoch 440/600
Epoch 441/600
0.1986
Epoch 442/600
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Epoch 443/600
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Epoch 444/600
0.1968
Epoch 445/600
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Epoch 446/600
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Epoch 447/600
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Epoch 449/600
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Epoch 450/600
0.1970
Epoch 451/600
0.1978
Epoch 452/600
0.1988
Epoch 453/600
0.1990
Epoch 454/600
```

```
0.2004
Epoch 455/600
0.1976
Epoch 456/600
Epoch 457/600
0.1971
Epoch 458/600
0.1999
Epoch 459/600
0.1974
Epoch 460/600
0.2018
Epoch 461/600
0.1999
Epoch 462/600
0.1961
Epoch 463/600
0.2010
Epoch 464/600
0.1999
Epoch 465/600
0.1982
Epoch 466/600
0.2010
Epoch 467/600
0.1997
Epoch 468/600
0.1975
Epoch 469/600
0.2004
Epoch 470/600
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0.1997
Epoch 471/600
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0.2044
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0.2000
Epoch 476/600
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Epoch 477/600
0.2020
Epoch 478/600
0.2013
Epoch 479/600
0.2007
Epoch 480/600
0.1977
Epoch 481/600
0.2011
Epoch 482/600
0.2021
Epoch 483/600
0.1986
Epoch 484/600
0.2028
Epoch 485/600
0.1996
Epoch 486/600
```

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0.2019
Epoch 487/600
Epoch 488/600
0.2012
Epoch 489/600
0.2009
Epoch 490/600
0.2020
Epoch 491/600
0.2024
Epoch 492/600
0.2001
Epoch 493/600
0.1995
Epoch 494/600
0.2021
Epoch 495/600
0.2000
Epoch 496/600
0.2022
Epoch 497/600
0.2038
Epoch 498/600
0.2032
Epoch 499/600
0.2026
Epoch 500/600
0.2001
Epoch 501/600
0.2022
Epoch 502/600
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```
0.2017
Epoch 503/600
0.2046
Epoch 504/600
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Epoch 508/600
0.2016
Epoch 509/600
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Epoch 512/600
0.2013
Epoch 513/600
0.2032
Epoch 514/600
0.2025
Epoch 515/600
0.2044
Epoch 516/600
0.2005
Epoch 517/600
0.2025
Epoch 518/600
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0.2043
Epoch 519/600
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Epoch 520/600
0.2017
Epoch 521/600
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Epoch 524/600
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Epoch 531/600
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Epoch 532/600
0.2026
Epoch 533/600
0.2027
Epoch 534/600
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Epoch 536/600
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Epoch 537/600
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Epoch 538/600
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Epoch 539/600
0.2034
Epoch 540/600
0.2026
Epoch 541/600
0.2023
Epoch 542/600
0.2056
Epoch 543/600
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Epoch 544/600
0.2028
Epoch 545/600
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Epoch 546/600
0.2060
Epoch 547/600
0.2040
Epoch 548/600
0.2029
Epoch 549/600
0.2040
Epoch 550/600
```

```
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Epoch 551/600
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Epoch 552/600
0.2070
Epoch 553/600
0.2078
Epoch 554/600
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Epoch 555/600
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Epoch 556/600
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Epoch 557/600
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Epoch 558/600
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Epoch 559/600
0.2036
Epoch 560/600
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Epoch 561/600
0.2043
Epoch 562/600
0.2095
Epoch 563/600
0.2030
Epoch 564/600
0.2066
Epoch 565/600
0.2058
Epoch 566/600
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0.2049
Epoch 567/600
0.2049
Epoch 568/600
0.2088
Epoch 569/600
0.2055
Epoch 570/600
0.2064
Epoch 571/600
0.2060
Epoch 572/600
0.2077
Epoch 573/600
0.2053
Epoch 574/600
0.2086
Epoch 575/600
0.2061
Epoch 576/600
0.2052
Epoch 577/600
0.2087
Epoch 578/600
0.2087
Epoch 579/600
0.2071
Epoch 580/600
0.2092
Epoch 581/600
0.2050
Epoch 582/600
```

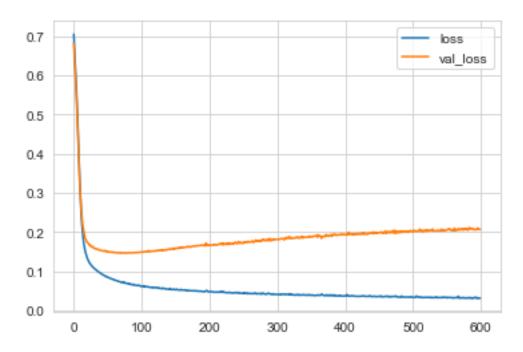
```
0.2050
Epoch 583/600
0.2074
Epoch 584/600
Epoch 585/600
0.2069
Epoch 586/600
0.2091
Epoch 587/600
0.2090
Epoch 588/600
0.2092
Epoch 589/600
0.2076
Epoch 590/600
0.2058
Epoch 591/600
0.2068
Epoch 592/600
0.2067
Epoch 593/600
0.2060
Epoch 594/600
0.2055
Epoch 595/600
0.2076
Epoch 596/600
0.2101
Epoch 597/600
0.2064
Epoch 598/600
```

[23]: <tensorflow.python.keras.callbacks.History at 0x15fae9e7ac8>

Analyze the Loss - Model History

```
[24]: model_loss = pd.DataFrame(model.history.history)
model_loss.plot()
```

[24]: <AxesSubplot:>



The above plot interpretes that we have trained our data alot! leads to "Over fitting".

• Let's use early stopping to track the val_loss and stop training once it begins increasing to a limit. #### 4.2.2 TRAIL -02 #### Using Early Stopping: Stop training when a monitored quantity has stopped improving.

```
[25]: model = Sequential()
  model.add(Dense(units=16,activation='relu'))
  model.add(Dense(units=8,activation='relu'))
  model.add(Dense(units=1,activation='sigmoid'))
```

```
model.compile(loss='binary_crossentropy', optimizer='adam')
[26]: early_stop = EarlyStopping(monitor='val_loss', mode='min', verbose=1,__
  →patience=25)
[27]: model.fit(x=X_train,
     y=y_train,
     epochs=600,
     validation_data=(X_test, y_test), verbose=1,
     callbacks=[early_stop]
     )
 Epoch 1/600
 0.6965
 Epoch 2/600
 0.6721
 Epoch 3/600
 0.6506
 Epoch 4/600
 0.6263
 Epoch 5/600
 0.5961
 Epoch 6/600
 0.5581
 Epoch 7/600
 0.5107
 Epoch 8/600
 0.4524
 Epoch 9/600
 0.3921
 Epoch 10/600
 0.3436
 Epoch 11/600
 0.3055
 Epoch 12/600
```

```
0.2751
Epoch 13/600
0.2551
Epoch 14/600
0.2390
Epoch 15/600
0.2284
Epoch 16/600
0.2215
Epoch 17/600
0.2138
Epoch 18/600
0.2107
Epoch 19/600
0.2041
Epoch 20/600
0.2009
Epoch 21/600
0.1994
Epoch 22/600
0.1957
Epoch 23/600
0.1933
Epoch 24/600
0.1913
Epoch 25/600
0.1900
Epoch 26/600
0.1884
Epoch 27/600
0.1866
Epoch 28/600
```

```
0.1853
Epoch 29/600
0.1850
Epoch 30/600
Epoch 31/600
0.1817
Epoch 32/600
0.1807
Epoch 33/600
0.1799
Epoch 34/600
0.1794
Epoch 35/600
0.1782
Epoch 36/600
0.1772
Epoch 37/600
0.1758
Epoch 38/600
0.1755
Epoch 39/600
0.1746
Epoch 40/600
0.1733
Epoch 41/600
0.1726
Epoch 42/600
0.1714
Epoch 43/600
0.1706
Epoch 44/600
```

```
0.1702
Epoch 45/600
0.1700
Epoch 46/600
Epoch 47/600
0.1688
Epoch 48/600
0.1672
Epoch 49/600
0.1665
Epoch 50/600
0.1662
Epoch 51/600
0.1658
Epoch 52/600
0.1651
Epoch 53/600
0.1640
Epoch 54/600
0.1634
Epoch 55/600
0.1633
Epoch 56/600
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Epoch 57/600
0.1621
Epoch 58/600
0.1617
Epoch 59/600
0.1613
Epoch 60/600
```

```
0.1603
Epoch 61/600
0.1606
Epoch 62/600
0.1595
Epoch 63/600
0.1592
Epoch 64/600
0.1587
Epoch 65/600
0.1586
Epoch 66/600
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Epoch 67/600
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Epoch 68/600
0.1573
Epoch 69/600
0.1570
Epoch 70/600
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Epoch 71/600
0.1562
Epoch 72/600
0.1599
Epoch 73/600
0.1556
Epoch 74/600
0.1553
Epoch 75/600
0.1545
Epoch 76/600
```

```
0.1543
Epoch 77/600
0.1542
Epoch 78/600
Epoch 79/600
0.1533
Epoch 80/600
0.1537
Epoch 81/600
0.1531
Epoch 82/600
0.1528
Epoch 83/600
0.1522
Epoch 84/600
0.1525
Epoch 85/600
0.1529
Epoch 86/600
0.1522
Epoch 87/600
0.1531
Epoch 88/600
0.1520
Epoch 89/600
0.1516
Epoch 90/600
0.1520
Epoch 91/600
0.1521
Epoch 92/600
```

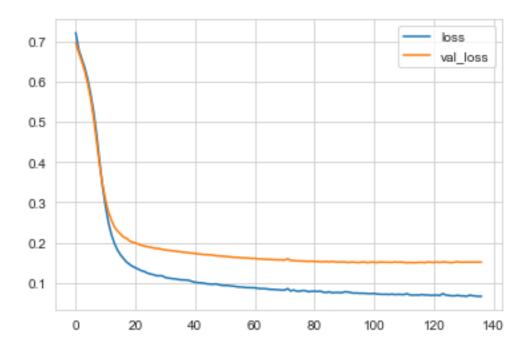
```
0.1507
Epoch 93/600
0.1509
Epoch 94/600
Epoch 95/600
0.1504
Epoch 96/600
0.1504
Epoch 97/600
0.1516
Epoch 98/600
0.1513
Epoch 99/600
0.1501
Epoch 100/600
0.1516
Epoch 101/600
0.1511
Epoch 102/600
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Epoch 103/600
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Epoch 104/600
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Epoch 105/600
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Epoch 106/600
0.1509
Epoch 107/600
0.1506
Epoch 108/600
```

```
0.1518
Epoch 109/600
0.1510
Epoch 110/600
Epoch 111/600
0.1506
Epoch 112/600
0.1500
Epoch 113/600
0.1505
Epoch 114/600
0.1500
Epoch 115/600
0.1500
Epoch 116/600
0.1506
Epoch 117/600
0.1508
Epoch 118/600
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Epoch 119/600
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Epoch 120/600
0.1510
Epoch 121/600
0.1505
Epoch 122/600
0.1518
Epoch 123/600
0.1505
Epoch 124/600
```

```
Epoch 125/600
 Epoch 126/600
 Epoch 127/600
 0.1502
 Epoch 128/600
 0.1513
 Epoch 129/600
 0.1524
 Epoch 130/600
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 Epoch 131/600
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 Epoch 132/600
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 Epoch 133/600
 0.1515
 Epoch 134/600
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 Epoch 135/600
 0.1513
 Epoch 136/600
 0.1516
 Epoch 137/600
 0.1513
 Epoch 00137: early stopping
[27]: <tensorflow.python.keras.callbacks.History at 0x15fae878cf8>
[28]: model_loss = pd.DataFrame(model.history.history)
 model_loss.plot()
```

0.1520

[28]: <AxesSubplot:>



Training Stopped at 168th Epoch. We can see our traing & Val_loss are started decreasing and become constant after 125th Epoch! Let's add "Dropout Layers" to prevent over fitting * Dropout layers essentially turn off a percent of neurons randomly

4.2.3 TRAIL - 03

We have given Dropout rate = 0.5, that means Half the neurons in the layer are going to be turned off randomly for each batch or epoch of the training.

```
[29]: model = Sequential()
model.add(Dense(units=16,activation='relu'))
model.add(Dropout(0.5))

model.add(Dense(units=8,activation='relu'))
model.add(Dropout(0.5))

model.add(Dense(units=1,activation='sigmoid'))
model.compile(loss='binary_crossentropy', optimizer='adam')
```

) Epoch 1/600 0.6809 Epoch 2/600 0.6747 Epoch 3/600 0.6674 Epoch 4/600 0.6588 Epoch 5/600 0.6489 Epoch 6/600 0.6367 Epoch 7/600 0.6243 Epoch 8/600 0.6109 Epoch 9/600 0.6001 Epoch 10/600 0.5864 Epoch 11/600 0.5750 Epoch 12/600 0.5544 Epoch 13/600 0.5330 Epoch 14/600 0.5104 Epoch 15/600

0.4839

```
Epoch 16/600
0.4554
Epoch 17/600
0.4298
Epoch 18/600
0.4129
Epoch 19/600
0.3915
Epoch 20/600
0.3662
Epoch 21/600
0.3424
Epoch 22/600
0.3204
Epoch 23/600
0.3098
Epoch 24/600
0.2985
Epoch 25/600
0.2818
Epoch 26/600
0.2690
Epoch 27/600
0.2572
Epoch 28/600
0.2517
Epoch 29/600
0.2404
Epoch 30/600
0.2341
Epoch 31/600
0.2254
```

```
Epoch 32/600
0.2193
Epoch 33/600
0.2175
Epoch 34/600
0.2133
Epoch 35/600
0.2111
Epoch 36/600
0.2075
Epoch 37/600
0.2045
Epoch 38/600
0.2016
Epoch 39/600
0.2003
Epoch 40/600
0.1956
Epoch 41/600
0.1950
Epoch 42/600
0.1935
Epoch 43/600
0.1924
Epoch 44/600
0.1903
Epoch 45/600
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Epoch 46/600
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```

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Epoch 48/600
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Epoch 61/600
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Epoch 63/600
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Epoch 64/600
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Epoch 80/600
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Epoch 81/600
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Epoch 95/600
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Epoch 96/600
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Epoch 104/600
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Epoch 106/600
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Epoch 107/600
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Epoch 108/600
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Epoch 109/600
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Epoch 111/600
0.1696
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Epoch 112/600
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Epoch 113/600
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Epoch 123/600
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Epoch 124/600
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Epoch 125/600
0.1674
Epoch 126/600
0.1701
Epoch 127/600
0.1659
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Epoch 128/600
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Epoch 129/600
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Epoch 140/600
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Epoch 142/600
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Epoch 143/600
0.1625
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Epoch 144/600
0.1641
Epoch 145/600
0.1610
Epoch 146/600
0.1638
Epoch 147/600
0.1673
Epoch 148/600
0.1696
Epoch 149/600
0.1690
Epoch 150/600
0.1664
Epoch 151/600
0.1677
Epoch 152/600
22/22 [============== ] - Os 19ms/step - loss: 0.1651 - val_loss:
0.1702
Epoch 153/600
0.1680
Epoch 154/600
0.1684
Epoch 155/600
0.1713
Epoch 156/600
0.1660
Epoch 157/600
0.1684
Epoch 158/600
0.1736
Epoch 159/600
0.1702
```

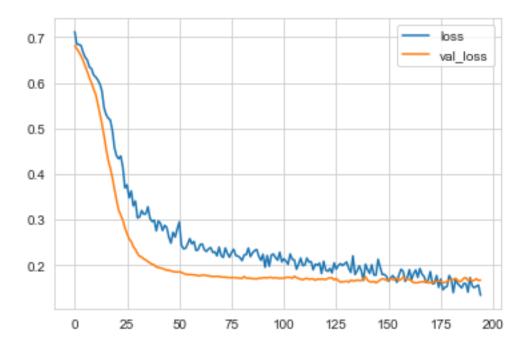
```
Epoch 160/600
0.1695
Epoch 161/600
0.1680
Epoch 162/600
0.1649
Epoch 163/600
0.1612
Epoch 164/600
0.1613
Epoch 165/600
0.1613
Epoch 166/600
0.1625
Epoch 167/600
0.1636
Epoch 168/600
0.1626
Epoch 169/600
0.1660
Epoch 170/600
0.1607
Epoch 171/600
0.1618
Epoch 172/600
0.1613
Epoch 173/600
0.1639
Epoch 174/600
0.1636
Epoch 175/600
0.1660
```

```
Epoch 176/600
0.1639
Epoch 177/600
0.1614
Epoch 178/600
0.1620
Epoch 179/600
0.1634
Epoch 180/600
0.1671
Epoch 181/600
0.1669
Epoch 182/600
0.1679
Epoch 183/600
0.1709
Epoch 184/600
0.1666
Epoch 185/600
0.1631
Epoch 186/600
0.1658
Epoch 187/600
0.1711
Epoch 188/600
0.1723
Epoch 189/600
0.1659
Epoch 190/600
0.1688
Epoch 191/600
0.1656
```

```
Epoch 192/600
  0.1664
  Epoch 193/600
  22/22 [=======
              ========] - Os 11ms/step - loss: 0.1618 - val_loss:
  0.1700
  Epoch 194/600
  0.1659
  Epoch 195/600
  0.1671
  Epoch 00195: early stopping
[30]: <tensorflow.python.keras.callbacks.History at 0x15fb2485be0>
```

```
[31]: model_loss = pd.DataFrame(model.history.history)
      model_loss.plot()
```

[31]: <AxesSubplot:>



From the plot we can see that, Training loss and Validation loss are both quickly going down and eventually flattening nearly at the same rate. This is much improved than the earlier.

0.5 5. Calculate Accuracy Measures

```
[32]: predictions = model.predict_classes(X_test)
```

[33]: print(classification_report(y_test,predictions))

	precision	recall	f1-score	support
0	0.93	0.97	0.95	146
1	0.97	0.93	0.95	154
accuracy			0.95	300
macro avg	0.95	0.95	0.95	300
weighted avg	0.95	0.95	0.95	300

[34]: print(confusion_matrix(y_test,predictions))

[[141 5] [11 143]]

${\it Justification}:$

- Initially we have trained the data by giving same inputs for 600 epochs and we observed over fitting.
- Then we applied *Early Stopping* method which stoped training when a monitored quantity has stopped improving after 168th Epoch, for this we have given the parameter patience=25 which run for extra 25 epoch even after identifying the best val_loss.
- Finally we have applied *Dropout rate* to get more precise output, with this configuration we got an accuracy of 95%.