```
In [5]:
from keras.models import Sequential
from keras.layers import Dense
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
                                                                                                      In [2]:
!pip install keras
Collecting keras
  Downloading Keras-2.4.3-py2.py3-none-any.whl (36 kB)
Requirement already satisfied: pyyaml in c:\users\acer\anaconda3\lib\site-packages (from keras) (5.3.1)
Requirement already satisfied: numpy>=1.9.1 in c:\users\acer\anaconda3\lib\site-packages (from keras) (1.
Requirement already satisfied: scipy>=0.14 in c:\users\acer\anaconda3\lib\site-packages (from keras) (1.5
.2)
Requirement already satisfied: h5py in c:\users\acer\anaconda3\lib\site-packages (from keras) (2.10.0)
Requirement already satisfied: six in c:\users\acer\anaconda3\lib\site-packages (from h5py->keras) (1.15.
Installing collected packages: keras
Successfully installed keras-2.4.3
4
                                                                                                       •
                                                                                                      In [4]:
!pip install tensorflow
Collecting tensorflow
 Downloading tensorflow-2.5.0-cp38-cp38-win amd64.whl (422.6 MB)
Collecting gast == 0.4.0
 Downloading gast-0.4.0-py3-none-any.whl (9.8 kB)
Collecting tensorflow-estimator<2.6.0,>=2.5.0rc0
  Downloading tensorflow estimator-2.5.0-py2.py3-none-any.whl (462 kB)
Requirement already satisfied: typing-extensions \sim 3.7.4 in c:\users\acer\anaconda3\lib\site-packages (fro
m tensorflow) (3.7.4.3)
Collecting keras-nightly~=2.5.0.dev
  Downloading keras nightly-2.5.0.dev2021032900-py2.py3-none-any.whl (1.2 MB)
Collecting h5py\sim=3.1.0
  Downloading h5py-3.1.0-cp38-cp38-win_amd64.whl (2.7 MB)
Collecting opt-einsum~=3.3.0
  Downloading opt einsum-3.3.0-py3-none-any.whl (65 kB)
Collecting wrapt~=1.12.1
 Downloading wrapt-1.12.1.tar.gz (27 kB)
Collecting grpcio~=1.34.0
  Downloading grpcio-1.34.1-cp38-cp38-win amd64.whl (2.9 MB)
Collecting tensorboard~=2.5
  Downloading tensorboard-2.5.0-py3-none-any.whl (6.0 MB)
Collecting keras-preprocessing~=1.1.2
  Downloading Keras Preprocessing-1.1.2-py2.py3-none-any.whl (42 kB)
Requirement already satisfied: numpy~=1.19.2 in c:\users\acer\anaconda3\lib\site-packages (from tensorflo
w) (1.19.2)
Collecting google-pasta~=0.2
 Downloading google pasta-0.2.0-py3-none-any.whl (57 kB)
Requirement already satisfied: protobuf>=3.9.2 in c:\users\acer\anaconda3\lib\site-packages (from tensorf
low) (3.14.0)
Collecting termcolor~=1.1.0
  Downloading termcolor-1.1.0.tar.gz (3.9 kB)
Collecting flatbuffers~=1.12.0
  Downloading flatbuffers-1.12-py2.py3-none-any.whl (15 kB)
Requirement already satisfied: wheel~=0.35 in c:\users\acer\anaconda3\lib\site-packages (from tensorflow)
(0.35.1)
Collecting astunparse~=1.6.3
  Downloading astunparse-1.6.3-py2.py3-none-any.whl (12 kB)
Requirement already satisfied: six~=1.15.0 in c:\users\acer\anaconda3\lib\site-packages (from tensorflow)
(1.15.0)
Collecting absl-py~=0.10
  Downloading absl py-0.13.0-py3-none-any.whl (132 kB)
Requirement already satisfied: requests<3,>=2.21.0 in c:\users\acer\anaconda3\lib\site-packages (from ten
sorboard~=2.5->tensorflow) (2.24.0)
Requirement already satisfied: google-auth<2,>=1.6.3 in c:\users\acer\anaconda3\lib\site-packages (from t
ensorboard~=2.5->tensorflow) (1.25.0)
Collecting google-auth-oauthlib<0.5,>=0.4.1
  Downloading google auth oauthlib-0.4.4-py2.py3-none-any.whl (18 kB)
Collecting tensorboard-plugin-wit>=1.6.0
 Downloading tensorboard_plugin_wit-1.8.0-py3-none-any.whl (781 kB)
Requirement already satisfied: setuptools>=41.0.0 in c:\users\acer\anaconda3\lib\site-packages (from tens
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orboard~=2.5->tensorflow) (50.3.1.post20201107) Collecting tensorboard-data-server<0.7.0,>=0.6.0

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Collecting markdown>=2.6.8
      Downloading Markdown-3.3.4-py3-none-any.whl (97 kB)
Requirement already satisfied: werkzeug>=0.11.15 in c:\users\acer\anaconda3\lib\site-packages (from tenso
rboard~=2.5->tensorflow) (1.0.1)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in
c:\users\acer\anaconda3\lib\site-packages (from requests<3,>=2.21.0->tensorboard\sim=2.5->tensorflow)
(1.25.11)
Requirement already satisfied: idna<3,>=2.5 in c:\users\acer\anaconda3\lib\site-packages (from requests<3
,>=2.21.0->tensorboard\sim=2.5->tensorflow) (2.10)
Requirement already satisfied: certifi>=2017.4.17 in c:\users\acer\anaconda3\lib\site-packages (from requ
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Requirement already satisfied: chardet<4,>=3.0.2 in c:\users\acer\anaconda3\lib\site-packages (from reque
sts<3,>=2.21.0->tensorboard~=2.5->tensorflow) (3.0.4)
Requirement already satisfied: pyasn1-modules>=0.2.1 in c:\users\acer\anaconda3\lib\site-packages (from g
oogle-auth<2,>=1.6.3->tensorboard~=2.5->tensorflow) (0.2.8)
Requirement already satisfied: rsa<5,>=3.1.4; python version >= "3.6" in
\verb|c:|users|| acer| anaconda3| lib| site-packages (from google-auth<2,>=1.6.3-> tensorboard = 2.5-> tensorflow)| acer| library | librar
(4.7.2)
Requirement already satisfied: cachetools<5.0,>=2.0.0 in c:\users\acer\anaconda3\lib\site-packages (from
google-auth<2,>=1.6.3->tensorboard~=2.5->tensorflow) (4.2.2)
Collecting requests-oauthlib>=0.7.0
      Downloading requests oauthlib-1.3.0-py2.py3-none-any.whl (23 kB)
Requirement already satisfied: pyasn1<0.5.0,>=0.4.6 in c:\users\acer\anaconda3\lib\site-packages (from py
asn1-modules>=0.2.1-\\sqoogle-auth<2,>=1.6.3-\\tensorboard~=2.5-\\tensorflow)~(0.4.8)
Collecting oauthlib>=3.0.0
      Downloading oauthlib-3.1.1-py2.py3-none-any.whl (146 kB)
Building wheels for collected packages: wrapt, termcolor
      Building wheel for wrapt (setup.py): started
      Building wheel for wrapt (setup.py): finished with status 'done'
      Created wheel for wrapt: filename=wrapt-1.12.1-py3-none-any.whl size=19558
Stored in directory:
\verb|c:|users|| acer| appdata \\ | ocal| pip| cache| wheels \\ | 5f| fd \\ | 9e| b6cf \\ | 5890494cb \\ | 6ef \\ | 05266f \\ | 05
      Building wheel for termcolor (setup.py): started
      Building wheel for termcolor (setup.py): finished with status 'done'
      Created wheel for termcolor: filename=termcolor-1.1.0-py3-none-any.whl size=4835
\verb|sha| 256 = 13047748e5152c6967c11a7b50c066349739dff1f223052cdf5a9011807901ae| | 1807901ae| | 18079001ae| | 1807901ae| |
      Stored in directory:
\verb|c:|users|| acer|| appdata|| local|| pip|| cache|| wheels|| a0|| 16|| 9c|| 5473df82468f958445479c59e784896fa24f4a5fc024b0f501|| acer|| appdata|| acer|| a
Successfully built wrapt termcolor
Installing collected packages: gast, tensorflow-estimator, keras-nightly, h5py, opt-einsum, wrapt,
grpcio, oauthlib, requests-oauthlib, google-auth-oauthlib, tensorboard-plugin-wit, absl-py, tensorboard-
data-server, markdown, tensorboard, keras-preprocessing, google-pasta, termcolor, flatbuffers, astunparse
, tensorflow
      Attempting uninstall: h5py
             Found existing installation: h5py 2.10.0
             Uninstalling h5py-2.10.0:
                  Successfully uninstalled h5py-2.10.0
      Attempting uninstall: wrapt
             Found existing installation: wrapt 1.11.2
             Uninstalling wrapt-1.11.2:
                  Successfully uninstalled wrapt-1.11.2
Successfully installed absl-py-0.13.0 astunparse-1.6.3 flatbuffers-1.12 gast-0.4.0 google-auth-oauthlib-
.1.2 markdown-3.3.4 oauthlib-3.1.1 opt-einsum-3.3.0 requests-oauthlib-1.3.0 tensorboard-2.5.0
tensorboard-data-server-0.6.1 tensorboard-plugin-wit-1.8.0 tensorflow-2.5.0 tensorflow-estimator-2.5.0 t
ermcolor-1.1.0 wrapt-1.12.1
4
                                                                                                                                                                                                                                                                                                                          In [6]:
```

df = pd.read csv('/Users/acer/Sandesh Pal/Data Science Assgn/Neural Network/forestfires.csv')

In [7]:

```
Out[7]:
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```

517 rows × 31 columns

#Checking for null values & data types
df.info()

RangeIndex: 517 entries, 0 to 516
Data columns (total 31 columns):

	Column		-Null Count	Dtype
0			non-null	object
1	4		non-null	object
2			non-null	float64
3	DMC		non-null	float64
4	DC		non-null	float64
5	ISI	517	non-null	float64
6	temp	517	non-null	float64
7	RH	517	non-null	int64
8	wind	517	non-null	float64
9	rain	517		float64
10	area	517	non-null	float64
11	dayfri	517	non-null	int64
12	daymon	517	non-null	int64
13	daysat	517	non-null	int64
14	daysun	517	non-null	int64
15	daythu	517	non-null	int64
16	daytue	517	non-null	int64
17	daywed	517	non-null	int64
18	monthapr	517	non-null	int64
19	monthaug	517	non-null	int64
20	monthdec	517	non-null	int64
21	monthfeb	517	non-null	int64
22	monthjan	517	non-null	int64
23	monthjul	517	non-null	int64
24	monthjun	517	non-null	int64
25	monthmar	517	non-null	int64
26	monthmay	517	non-null	int64
27				int64
28	monthoct	517	non-null	int64
29	monthsep	517	non-null	int64
30	size_category	517	non-null	object
dtype	es: float64(8),	int64(20), object(3)		

In [9]:

In [8]:

#Scaling the data (leaving out the target variable, and the taking only the numerical data for input) dfl=df.iloc[:,2:30]

In [10]:

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

In [11]:

sc.fit(df1)
df norm = sc.transform(df1)

memory usage: 125.3+ KB

```
array([[-8.05959472e-01, -1.32332557e+00, -1.83047676e+00, ...,
         -4.40225453e-02, -1.72859706e-01, -7.06081245e-01],
        [-8.10203395e-03, -1.17954077e+00, 4.88890915e-01, ...,
        -4.40225453e-02, 5.78503817e+00, -7.06081245e-01], [-8.10203395e-03, -1.04982188e+00, 5.60715454e-01, ..., -4.40225453e-02, 5.78503817e+00, -7.06081245e-01],
        [-1.64008316e+00, -8.46647711e-01, 4.74768113e-01, ...,
         -4.40225453e-02, -1.72859706e-01, -7.06081245e-01],
        [ 6.80956663e-01, 5.49002541e-01, 2.69382214e-01, ..., -4.40225453e-02, -1.72859706e-01, -7.06081245e-01],
        [-2.02087875e+00, -1.68591332e+00, -1.78044169e+00, ...,
           2.27156334e+01, -1.72859706e-01, -7.06081245e-01]])
                                                                                                                            In [12]:
from sklearn.decomposition import PCA
pca = PCA(n components = 28)
pca values = pca.fit transform(df norm)
pca values
                                                                                                                           Out[12]:
array([[ 3.76670947e+00, -1.32025451e+00, -8.43971398e-01, ...,
        -6.53345819e-02, 1.02062582e-14, 8.43633968e-16], [ 3.90786263e-01, 8.31061522e-01, -1.10136513e+00, ...,
           3.42618601e-02, 4.71409252e-15, 2.25999472e-16],
        [ 6.90415596e-01, 1.17774562e+00, -1.22199841e+00, ...,
          2.63235187e-02, 4.28072464e-15, 1.86480662e-16],
        [ 9.21634000e-01, -2.64543072e-01, 2.71921606e+00, ...,
          -2.97865814e-01, 3.40869735e-16, 4.52552927e-17],
        [-1.62054896e+00, -9.78838231e-01, 3.31987355e-01, ...,
          3.91949863e-02, 2.86075370e-16, 1.07765779e-16],
        [ 4.07590654e+00, -3.67440726e-01, -2.47151775e-01, ..., -2.50420726e-02, -4.56772859e-17, 6.90662122e-17]])
                                                                                                                            In [13]:
# The amount of variance that each PCA explains is
var = pca.explained variance ratio
var
                                                                                                                           Out[13]:
array([1.35522746e-01, 6.85788793e-02, 6.23572652e-02, 5.32713255e-02,
        4.75942360e-02, 4.68009902e-02, 4.37490015e-02, 4.28025164e-02,
        4.08875728e-02, 4.01633268e-02, 3.92926854e-02, 3.83232321e-02, 3.64221503e-02, 3.63217289e-02, 3.57856782e-02, 3.50087806e-02, 3.35447704e-02, 3.24777366e-02, 3.04490902e-02, 3.00246758e-02,
        2.37167400e-02, 2.08329788e-02, 1.18357869e-02, 8.88449559e-03,
        4.55347471e-03, 7.98135931e-04, 2.67271490e-32, 1.28276240e-33])
                                                                                                                            In [14]:
# Cumulative variance
var1 = np.cumsum(np.round(var,decimals = 4)*100)
var1
                                                                                                                           Out[14]:
array([13.55, 20.41, 26.65, 31.98, 36.74, 41.42, 45.79, 50.07, 54.16,
        58.18, 62.11, 65.94, 69.58, 73.21, 76.79, 80.29, 83.64, 86.89, 89.93, 92.93, 95.3, 97.38, 98.56, 99.45, 99.91, 99.99, 99.99,
        99.99])
                                                                                                                            In [15]:
# Variance plot for PCA components obtained
plt.figure(figsize=(12,4))
plt.plot(var1,color="red");
```

Out[11]:

```
100
 80
 60
 40
 20
                                  10
                                                15
                                                              20
                                                                            25
                                                                                                      In [17]:
finalDf = pd.concat([pd.DataFrame(pca_values[:,0:24],columns=['pc1','pc2','pc3','pc4','pc5','pc6','pc7',
 'pc8', 'pc9', 'pc10', 'pc11', 'pc12', 'pc13', 'pc14',
 'pc15', 'pc16', 'pc17', 'pc18', 'pc19', 'pc20', 'pc21',
 'pc22', 'pc23', 'pc24']),
 df[['size category']]], axis = 1)
finalDf.size category.replace(('large','small'),(1,0),inplace=True)
                                                                                                     Out[17]:
                                       pc5
                                                                            pc10 ...
                                                                                               pc17
        pc1
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                               pc4
                                                      pc7
                                                              pc8
                                                                     pc9
                                                                                        pc16
                                                                                                       pc18
                                              pc6
  0 3.766709 1.320255 0.843971 1.994738 1.453359 0.693985 0.308104 0.019764 0.010161 0.437314 ... -0.197543 0.021839 0.688958
  2 0.690416 1.177746 1.221998 2.442038 1.090630 0.390801 1.586675 2.159336 0.090580 0.260888 ... -2.545144 0.658411 0.423618
  3 3.359951 1.161443 0.385728 2.118328 1.949601 1.027664 0.179422 0.250227 0.620329 1.343189 ... -0.040887 0.017843 0.332572
  4 2.974329 0.842626 1.327788 0.038086 1.124763 0.574676 0.777155 0.303635 0.861126 2.024719 ... 0.844431 1.014944 0.618231
    513 0.794366 0.083966 2.670485 0.284995 0.223323 0.904232 0.014849 0.107226 1.340049 0.147246 ... 0.342367 0.485571 0.580150
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    1.620549 0.978838 0.331987 1.256638 0.408164 0.735698 0.815510 1.398344 0.076379 0.005814 ... -0.011739 1.035533 0.774382
516 4.075907 0.367441 0.247152 0.979966 6.792273 5.943666 1.639583 8.121827 0.627980 4.953722 ... 10.467443 7.333036 0.377340
517 rows × 25 columns
                                                                                                      In [18]:
# split into input (X) and output (Y) variables
array = finalDf.values
X = array[:,0:24]
Y = array[:,24]
                                                                                                      In [19]:
X.reshape(-1,1)
Y.reshape (-1,1)
                                                                                                     Out[19]:
array([[0.],
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                                                                       In [20]:
# create model
model = Sequential()
model.add(Dense(12, input dim=24, activation='relu'))
model.add(Dense(8,activation='relu'))
model.add(Dense(1,activation='sigmoid'))
                                                                       In [21]:
# Compile model
model.compile(loss='binary crossentropy', optimizer='adam', metrics=['accuracy'])
# Fit the model
model.fit(X, Y, validation split=0.3, epochs=150, batch size=10)
815 - val_accuracy: 0.5513
Epoch 2/150
0.7765 - val_accuracy: 0.6410
Epoch 3/150
37/37 [=========== ] - 0s 2ms/step - loss: 0.5862 - accuracy: 0.7249 - val loss:
0.7721 - val accuracy: 0.6667
Epoch 4/150
0.7695 - val_accuracy: 0.6731
Epoch 5/150
37/37 [========== 0.5654 - accuracy: 0.7394 - val loss:
0.7646 - val accuracy: 0.6859
Epoch 6/150
0.7576 - val accuracy: 0.6731
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Epoch 7/150
37/37 [========= 0.5212 - accuracy: 0.7672 - val loss:
0.7517 - val accuracy: 0.6795
Epoch 8/150
37/37 [========== 0.7605 - val loss: 0.5252 - accuracy: 0.7605 - val loss:
0.7485 - val accuracy: 0.6795
Epoch 9/150
37/37 [========== ] - 0s 3ms/step - loss: 0.5080 - accuracy: 0.7533 - val loss:
0.7456 - val accuracy: 0.6795
Epoch 10/150
37/37 [========== 0.7782 - val loss: 0.4716 - accuracy: 0.7782 - val loss:
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Epoch 11/150
37/37 [========= 0.7828 - 0.7828 - accuracy: 0.7828 - val loss:
0.7370 - val accuracy: 0.6859
Epoch 12/150
37/37 [=========== 0.7788 - val loss: 0.4699 - accuracy: 0.7788 - val loss:
0.7313 - val_accuracy: 0.6859
Epoch 13/150
37/37 [========== 0.7949 - val loss: 0.4486 - accuracy: 0.7949 - val loss:
0.7266 - val accuracy: 0.6859
Epoch 14/150
37/37 [========= 0.7949 - val loss: 0.4466 - accuracy: 0.7949 - val loss:
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Epoch 15/150
37/37 [========== 0.7976 - val loss: 0.4579 - accuracy: 0.7976 - val loss:
0.7239 - val_accuracy: 0.6859
Epoch 16/150
0.7238 - val accuracy: 0.6987
Epoch 17/150
0.7173 - val accuracy: 0.6987
Epoch 18/150
0.7221 - val accuracy: 0.7051
Epoch 19/150
37/37 [=========== ] - 0s 2ms/step - loss: 0.4012 - accuracy: 0.8177 - val loss:
0.7220 - val accuracy: 0.7051
Epoch 20/150
0.7169 - val accuracy: 0.7051
Epoch 21/150
0.7244 - val accuracy: 0.7115
Epoch 22/150
37/37 [========== 0.8135 - val loss: 0.4023 - accuracy: 0.8135 - val loss:
0.7211 - val accuracy: 0.7051
Epoch 23/150
37/37 [========== 0.8533 - val loss: 0.3636 - accuracy: 0.8533 - val loss:
0.7319 - val_accuracy: 0.7179
Epoch 24/150
37/37 [========== 0.8348 - val loss: 0.3787 - accuracy: 0.8348 - val loss:
0.7305 - val accuracy: 0.7179
Epoch 25/150
0.7300 - val accuracy: 0.7179
Epoch 26/150
37/37 [============ ] - 0s 3ms/step - loss: 0.3772 - accuracy: 0.8289 - val_loss:
0.7255 - val_accuracy: 0.7308
Epoch 27/150
0.7296 - val accuracy: 0.7308
Epoch 28/150
37/37 [=========== ] - 0s 2ms/step - loss: 0.3370 - accuracy: 0.8403 - val loss:
0.7362 - val accuracy: 0.7308
Epoch 29/150
37/37 [=========== ] - 0s 2ms/step - loss: 0.3520 - accuracy: 0.8370 - val loss:
0.7358 - val accuracy: 0.7308
Epoch 30/150
0.7346 - val_accuracy: 0.7372
Epoch 31/150
37/37 [========== 0.8349 - val loss: 0.3599 - accuracy: 0.8349 - val loss:
0.7386 - val_accuracy: 0.7372
Epoch 32/150
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0.7443 - val accuracy: 0.7372
Epoch 33/150
37/37 [========== 0.8893 - val loss: 0.3135 - accuracy: 0.8893 - val loss:
0.7418 - val accuracy: 0.7564
Epoch 34/150
37/37 [=========== ] - 0s 2ms/step - loss: 0.3350 - accuracy: 0.8610 - val loss:
0.7502 - val accuracy: 0.7564
Epoch 35/150
37/37 [=========== ] - 0s 2ms/step - loss: 0.3728 - accuracy: 0.8245 - val loss:
0.7497 - val accuracy: 0.7564
Epoch 36/150
0.7424 - val_accuracy: 0.7564
Epoch 37/150
37/37 [========== 0.8558 - val loss: 0.3414 - accuracy: 0.8558 - val loss:
0.7554 - val_accuracy: 0.7628
Epoch 38/150
37/37 [============ ] - Os 2ms/step - loss: 0.3134 - accuracy: 0.8548 - val loss:
0.7635 - val accuracy: 0.7628
Epoch 39/150
37/37 [========== 0.8441 - val loss: 0.3510 - accuracy: 0.8441 - val loss:
0.7666 - val accuracy: 0.7564
Epoch 40/150
37/37 [=========== ] - 0s 2ms/step - loss: 0.3292 - accuracy: 0.8523 - val loss:
0.7724 - val accuracy: 0.7564
Epoch 41/150
37/37 [========== 0.8760 - val loss: 0.2824 - accuracy: 0.8760 - val loss:
0.7775 - val accuracy: 0.7628
Epoch 42/150
37/37 [=========== 0.9004 - val loss: 0.2733 - accuracy: 0.9004 - val loss:
0.7747 - val accuracy: 0.7628
Epoch 43/150
37/37 [========== 0.8834 - val loss: 0.2929 - accuracy: 0.8834 - val loss:
0.7822 - val accuracy: 0.7628
Epoch 44/150
37/37 [========== ] - 0s 3ms/step - loss: 0.2884 - accuracy: 0.8937 - val loss:
0.7857 - val accuracy: 0.7628
Epoch 45/150
37/37 [=========== ] - 0s 5ms/step - loss: 0.2983 - accuracy: 0.8870 - val loss:
0.7914 - val accuracy: 0.7692
Epoch 46/150
37/37 [========== 0.9096 - val loss: 0.2652 - accuracy: 0.9096 - val loss:
0.7842 - val_accuracy: 0.7564
Epoch 47/150
37/37 [========== 0.9045 - val loss: 0.2641 - accuracy: 0.9045 - val loss:
0.7916 - val_accuracy: 0.7692
Epoch 48/150
37/37 [============ 0.9219 - 0s 2ms/step - loss: 0.2655 - accuracy: 0.9219 - val loss:
0.7962 - val_accuracy: 0.7692
Epoch 49/150
37/37 [========== 0.9183 - val loss: 0.2773 - accuracy: 0.9183 - val loss:
0.8030 - val_accuracy: 0.7628
Epoch 50/150
37/37 [========== 0.8988 - val loss: 0.2625 - accuracy: 0.8988 - val loss:
0.8114 - val accuracy: 0.7628
Epoch 51/150
37/37 [========== 0.9135 - val loss: 0.2566 - accuracy: 0.9135 - val loss:
0.8174 - val accuracy: 0.7628
Epoch 52/150
37/37 [========== 0.8956 - val loss: 0.2781 - accuracy: 0.8956 - val loss:
0.8227 - val accuracy: 0.7564
Epoch 53/150
0.8248 - val_accuracy: 0.7564
Epoch 54/150
37/37 [========== ] - 0s 6ms/step - loss: 0.2598 - accuracy: 0.9096 - val loss:
0.8316 - val accuracy: 0.7564
Epoch 55/150
37/37 [=========== ] - 0s 3ms/step - loss: 0.2027 - accuracy: 0.9465 - val loss:
0.8312 - val accuracy: 0.7500
Epoch 56/150
0.8415 - val accuracy: 0.7692
Epoch 57/150
0.8457 - val_accuracy: 0.7692
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Epoch 58/150

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0.8545 - val accuracy: 0.7628
Epoch 59/150
37/37 [========== 0.9202 - val loss: 0.2196 - accuracy: 0.9202 - val loss:
0.8616 - val accuracy: 0.7628
Epoch 60/150
37/37 [========== 0.9178 - 0.9178 - val loss: 0.2226 - accuracy: 0.9178 - val loss:
0.8626 - val accuracy: 0.7692
Epoch 61/150
37/37 [========== 0.9279 - 0s 2ms/step - loss: 0.2168 - accuracy: 0.9279 - val loss:
0.8729 - val accuracy: 0.7885
Epoch 62/150
37/37 [========== 0.9022 - val loss: 0.2374 - accuracy: 0.9022 - val loss:
0.8783 - val accuracy: 0.7821
Epoch 63/150
37/37 [========== 0.9237 - val loss: 0.2141 - accuracy: 0.9237 - val loss:
0.8822 - val accuracy: 0.7821
Epoch 64/150
0.8892 - val accuracy: 0.7756
Epoch 65/150
37/37 [=========== 0.9330 - val loss: 0.1944 - accuracy: 0.9330 - val loss:
0.8864 - val accuracy: 0.7692
Epoch 66/150
0.8938 - val accuracy: 0.7628
Epoch 67/150
0.8993 - val accuracy: 0.7692
Epoch 68/150
37/37 [=========== 0.8992 - val loss: 0.2092 - accuracy: 0.8992 - val loss:
0.9015 - val accuracy: 0.7821
Epoch 69/150
37/37 [=========== ] - 0s 3ms/step - loss: 0.1848 - accuracy: 0.9416 - val loss:
0.9052 - val accuracy: 0.7756
Epoch 70/150
37/37 [=========== ] - 0s 3ms/step - loss: 0.1696 - accuracy: 0.9474 - val loss:
0.9128 - val accuracy: 0.7564
Epoch 71/150
37/37 [========== ] - 0s 3ms/step - loss: 0.1936 - accuracy: 0.9335 - val loss:
0.9087 - val accuracy: 0.7821
Epoch 72/150
37/37 [========== 0.9324 - val loss: 0.1887 - accuracy: 0.9324 - val loss:
0.9205 - val accuracy: 0.7756
Epoch 73/150
37/37 [========== 0.9461 - val loss: 0.1628 - accuracy: 0.9461 - val loss:
0.9296 - val accuracy: 0.7628
Epoch 74/150
0.9358 - val accuracy: 0.7692
Epoch 75/150
37/37 [========== 0.9279 - 0s 3ms/step - loss: 0.1901 - accuracy: 0.9279 - val loss:
0.9400 - val accuracy: 0.7628
Epoch 76/150
37/37 [============ ] - 0s 3ms/step - loss: 0.1621 - accuracy: 0.9280 - val loss:
0.9501 - val accuracy: 0.7564
Epoch 77/150
37/37 [=========== 0.9565 - val loss: 0.1585 - accuracy: 0.9565 - val loss:
0.9523 - val accuracy: 0.7564
Epoch 78/150
0.9603 - val accuracy: 0.7500
Epoch 79/150
0.9681 - val accuracy: 0.7564
Epoch 80/150
0.9812 - val accuracy: 0.7692
Epoch 81/150
37/37 [=========== ] - 0s 2ms/step - loss: 0.1553 - accuracy: 0.9479 - val loss:
0.9791 - val_accuracy: 0.7628
Epoch 82/150
37/37 [========== 0.9415 - val loss: 0.1574 - accuracy: 0.9415 - val loss:
0.9838 - val_accuracy: 0.7500
Epoch 83/150
1.0002 - val accuracy: 0.7500
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var accaracy. 0.7000
Epoch 84/150
37/37 [========== 0.9380 - val loss: 0.1670 - accuracy: 0.9380 - val loss:
0.9912 - val accuracy: 0.7564
Epoch 85/150
37/37 [============ 0.9375 - val loss: 0.1650 - accuracy: 0.9375 - val loss:
1.0017 - val_accuracy: 0.7628
Epoch 86/150
37/37 [=========== 0.9570 - val loss: 0.1402 - accuracy: 0.9570 - val loss:
1.0066 - val_accuracy: 0.7628
Epoch 87/150
37/37 [============ ] - 0s 2ms/step - loss: 0.1581 - accuracy: 0.9498 - val loss:
1.0121 - val accuracy: 0.7564
Epoch 88/150
37/37 [========== 0.9611 - val_loss: 0.1542 - accuracy: 0.9611 - val_loss:
1.0117 - val accuracy: 0.7628
Epoch 89/150
37/37 [=========== 0.9719 - 0s 3ms/step - loss: 0.1122 - accuracy: 0.9719 - val loss:
1.0182 - val_accuracy: 0.7372
Epoch 90/150
37/37 [========== 0.9549 - 0s 2ms/step - loss: 0.1464 - accuracy: 0.9549 - val loss:
1.0221 - val accuracy: 0.7628
Epoch 91/150
1.0276 - val accuracy: 0.7500
Epoch 92/150
37/37 [=========== ] - 0s 2ms/step - loss: 0.1395 - accuracy: 0.9555 - val loss:
1.0271 - val accuracy: 0.7692
Epoch 93/150
37/37 [=========== 0.9693 - val loss: 0.1148 - accuracy: 0.9693 - val loss:
1.0407 - val_accuracy: 0.7628
Epoch 94/150
37/37 [========== 0.9732 - val loss: 0.1118 - accuracy: 0.9732 - val loss:
1.0429 - val accuracy: 0.7500
Epoch 95/150
37/37 [========== 0.9544 - val loss: 0.1353 - accuracy: 0.9544 - val loss:
1.0431 - val accuracy: 0.7564
Epoch 96/150
37/37 [=========== 0.9530 - val loss: 0.1233 - accuracy: 0.9530 - val loss:
1.0554 - val_accuracy: 0.7564
Epoch 97/150
37/37 [=========== ] - 0s 3ms/step - loss: 0.1196 - accuracy: 0.9713 - val loss:
1.0474 - val_accuracy: 0.7436
Epoch 98/150
37/37 [========== 0.9395 - val loss: 0.1426 - accuracy: 0.9395 - val loss:
1.0601 - val accuracy: 0.7436
Epoch 99/150
37/37 [=========== 0.9640 - val loss: 0.1222 - accuracy: 0.9640 - val loss:
1.0618 - val accuracy: 0.7500
Epoch 100/150
1.0674 - val_accuracy: 0.7436
Epoch 101/150
37/37 [========== 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9429 - 0.9
1.0619 - val accuracy: 0.7500
Epoch 102/150
37/37 [============ ] - 0s 2ms/step - loss: 0.1217 - accuracy: 0.9515 - val loss:
1.0735 - val accuracy: 0.7564
Epoch 103/150
37/37 [========== 0.9555 - val loss: 0.1234 - accuracy: 0.9555 - val loss:
1.0854 - val_accuracy: 0.7500
Epoch 104/150
37/37 [=========== ] - 0s 3ms/step - loss: 0.1202 - accuracy: 0.9559 - val loss:
1.0878 - val accuracy: 0.7500
Epoch 105/150
37/37 [========== 0.9690 - val loss: 0.1006 - accuracy: 0.9690 - val loss:
1.0975 - val accuracy: 0.7436
Epoch 106/150
37/37 [========== 0.946 - accuracy: 0.9682 - val loss:
1.1053 - val_accuracy: 0.7564
Epoch 107/150
37/37 [========== 0.9530 - val loss: 0.1073 - accuracy: 0.9530 - val loss:
1.1002 - val accuracy: 0.7628
Epoch 108/150
37/37 [========== 0.9648 - val loss: 0.0922 - accuracy: 0.9648 - val loss:
1.1247 - val accuracy: 0.7500
Epoch 109/150
```

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                           os zms/scep toss. O.tour accuracy. O.your var toss.
1.1169 - val_accuracy: 0.7500
Epoch 110/150
37/37 [========== 0.9702 - 0.9702 - val loss: 0.0893 - accuracy: 0.9702 - val loss:
1.1137 - val accuracy: 0.7500
Epoch 111/150
37/37 [============ 0.9754 - val loss: 0.0831 - accuracy: 0.9754 - val loss:
1.1261 - val_accuracy: 0.7436
Epoch 112/150
37/37 [========== 0.9697 - val loss: 0.0876 - accuracy: 0.9697 - val loss:
1.1241 - val accuracy: 0.7500
Epoch 113/150
1.1466 - val accuracy: 0.7308
Epoch 114/150
37/37 [========== 0.9715 - val loss: 0.0922 - accuracy: 0.9715 - val loss:
1.1446 - val accuracy: 0.7308
Epoch 115/150
1.1503 - val accuracy: 0.7500
Epoch 116/150
37/37 [=========== 0.9694 - val loss: 0.0908 - accuracy: 0.9694 - val loss:
1.1690 - val accuracy: 0.7244
Epoch 117/150
37/37 [========== ] - 0s 3ms/step - loss: 0.0771 - accuracy: 0.9789 - val loss:
1.1739 - val accuracy: 0.7244
Epoch 118/150
37/37 [========== ] - 0s 2ms/step - loss: 0.0949 - accuracy: 0.9730 - val loss:
1.1685 - val accuracy: 0.7564
Epoch 119/150
37/37 [========== 0.9752 - 0.9752 - val loss: 0.0850 - accuracy: 0.9752 - val loss:
1.1686 - val accuracy: 0.7500
Epoch 120/150
1.1864 - val_accuracy: 0.7372
Epoch 121/150
1.1904 - val accuracy: 0.7308
Epoch 122/150
37/37 [========== 0.9811 - val loss: 0.0745 - accuracy: 0.9811 - val loss:
1.1797 - val_accuracy: 0.7372
Epoch 123/150
37/37 [========== 0.9711 - val loss: 0.0775 - accuracy: 0.9711 - val loss:
1.1874 - val accuracy: 0.7500
Epoch 124/150
37/37 [========== 0.9680 - val_loss: 0.0828 - accuracy: 0.9680 - val_loss:
1.2064 - val accuracy: 0.7179
Epoch 125/150
37/37 [============ ] - 0s 2ms/step - loss: 0.0886 - accuracy: 0.9569 - val loss:
1.1995 - val accuracy: 0.7372
Epoch 126/150
1.2139 - val accuracy: 0.7244
Epoch 127/150
37/37 [========== 0.9815 - val loss: 0.0580 - accuracy: 0.9815 - val loss:
1.2113 - val accuracy: 0.7372
Epoch 128/150
37/37 [============ ] - 0s 3ms/step - loss: 0.0632 - accuracy: 0.9848 - val loss:
1.2125 - val accuracy: 0.7372
Epoch 129/150
1.2300 - val accuracy: 0.7244
Epoch 130/150
1.2279 - val accuracy: 0.7308
Epoch 131/150
1.2449 - val accuracy: 0.7436
Epoch 132/150
37/37 [=========== 0.935 - val loss: 0.0570 - accuracy: 0.9935 - val loss:
1.2479 - val accuracy: 0.7500
Epoch 133/150
37/37 [========== 0.9810 - val loss: 0.0650 - accuracy: 0.9810 - val loss:
1.2506 - val accuracy: 0.7372
Epoch 134/150
37/37 [============ ] - 0s 2ms/step - loss: 0.0709 - accuracy: 0.9850 - val_loss:
1.2543 - val accuracy: 0.7436
Fnoch 135/150
```

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THUCII TOO/ TOU
37/37 [========== 0.9729 - 0.9729 - val loss: 0.0654 - accuracy: 0.9729 - val loss:
1.2564 - val accuracy: 0.7564
Epoch 136/150
1.2796 - val accuracy: 0.7308
Epoch 137/150
37/37 [============ ] - 0s 3ms/step - loss: 0.0609 - accuracy: 0.9871 - val loss:
1.2845 - val accuracy: 0.7436
Epoch 138/150
1.2927 - val accuracy: 0.7436
Epoch 139/150
37/37 [============ ] - 0s 2ms/step - loss: 0.0532 - accuracy: 0.9887 - val loss:
1.2956 - val accuracy: 0.7500
Epoch 140/150
37/37 [========== 0.9946 - val loss: 0.0524 - accuracy: 0.9946 - val loss:
1.3027 - val accuracy: 0.7436
Epoch 141/150
1.2955 - val accuracy: 0.7500
Epoch 142/150
37/37 [=========== 0.9755 - val loss: 0.0610 - accuracy: 0.9755 - val loss:
1.3188 - val accuracy: 0.7372
Epoch 143/150
37/37 [=========== ] - 0s 3ms/step - loss: 0.0449 - accuracy: 0.9928 - val loss:
1.3178 - val accuracy: 0.7436
Epoch 144/150
37/37 [========== ] - 0s 2ms/step - loss: 0.0641 - accuracy: 0.9847 - val loss:
1.3323 - val accuracy: 0.7372
Epoch 145/150
37/37 [========== 0.9927 - val loss: 0.0402 - accuracy: 0.9927 - val loss:
1.3477 - val accuracy: 0.7436
Epoch 146/150
37/37 [========== 0.9960 - val loss: 0.0417 - accuracy: 0.9960 - val loss:
1.3394 - val accuracy: 0.7372
Epoch 147/150
1.3574 - val accuracy: 0.7436
Epoch 148/150
37/37 [========== 0.954 - 0.9954 - val loss: 0.0484 - accuracy: 0.9954 - val loss:
1.3598 - val accuracy: 0.7308
Epoch 149/150
1.3606 - val accuracy: 0.7308
Epoch 150/150
37/37 [=========== 0.93ms/step - loss: 0.0372 - accuracy: 0.9917 - val loss:
1.4027 - val accuracy: 0.7244
                                                                       Out[21]:
<keras.callbacks.History at 0x2197c40b160>
                                                                        In [22]:
# evaluate the model
scores = model.evaluate(X, Y)
print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
17/17 [============] - 0s 1ms/step - loss: 0.4524 - accuracy: 0.9149
accuracy: 91.49%
                                                                         In [ ]:
```