

# Neural Network

PREDICT THE BURNED AREA OF FOREST FIRES WITH NEURAL NETWORKS

## Import Necessary Libraries

```
In [1]: 1 import pandas as pd
        2 import numpy as np
        3 from matplotlib import pyplot as plt
        4 import seaborn as sns
        5 from sklearn import preprocessing
        6 from sklearn.model_selection import train_test_split
        7 import warnings
        8 warnings.filterwarnings('ignore')
```

## Import data

```
In [2]: 1 forest_data = pd.read_csv('forestfires.csv')
        2 forest_data.head(7)
```

Out[2]:

	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	...	monthfeb	monthjan	monthjul	monthjun	monthmar	monthmay	monthnov	monthoct	m
0	mar	fri	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	...	0	0	0	0	1	0	0	0	
1	oct	tue	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	...	0	0	0	0	0	0	0	1	
2	oct	sat	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	...	0	0	0	0	0	0	0	1	
3	mar	fri	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	...	0	0	0	0	1	0	0	0	
4	mar	sun	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	...	0	0	0	0	1	0	0	0	
5	aug	sun	92.3	85.3	488.0	14.7	22.2	29	5.4	0.0	...	0	0	0	0	0	0	0	0	
6	aug	mon	92.3	88.9	495.6	8.5	24.1	27	3.1	0.0	...	0	0	0	0	0	0	0	0	

7 rows × 31 columns

## Data Understanding

```
In [3]: 1 forest_data.shape
```

Out[3]: (517, 31)

```
In [4]: 1 forest_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 517 entries, 0 to 516
Data columns (total 31 columns):
#   Column                Non-Null Count  Dtype
---  ---
0   month                 517 non-null    object
1   day                   517 non-null    object
2   FFMC                  517 non-null    float64
3   DMC                   517 non-null    float64
4   DC                    517 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 non-null    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  monthnov               517 non-null    int64
28  monthoct               517 non-null    int64
29  monthsep               517 non-null    int64
30  size_category          517 non-null    object
dtypes: float64(8), int64(20), object(3)
memory usage: 125.3+ KB
```

Data Preprocessing

Check for Duplicate Values

```
In [5]: 1 forest_data = forest_data.drop_duplicates()
        2 forest_data.head()
```

Out[5]:

	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	...	monthfeb	monthjan	monthjul	monthjun	monthmar	monthmay	monthnov	monthoct	mor
0	mar	fri	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	...	0	0	0	0	1	0	0	0	
1	oct	tue	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	...	0	0	0	0	0	0	0	1	
2	oct	sat	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	...	0	0	0	0	0	0	0	1	
3	mar	fri	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	...	0	0	0	0	1	0	0	0	
4	mar	sun	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	...	0	0	0	0	1	0	0	0	

5 rows × 31 columns

Removing unnecessary Features

```
In [6]: 1 forest_data = forest_data.drop(forest_data.columns[10:30], axis = 1)
        2 forest_data.head()
```

Out[6]:

	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	size_category
0	mar	fri	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	small
1	oct	tue	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	small
2	oct	sat	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	small
3	mar	fri	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	small
4	mar	sun	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	small

```
In [7]: 1 forest_data.shape
        2
```

Out[7]: (509, 11)

## Label Encoding

```
In [8]: 1 label_encoder = preprocessing.LabelEncoder()
        2 label_encoder
```

Out[8]: LabelEncoder()

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.  
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
In [9]: 1 forest_data['size_category'] = label_encoder.fit_transform(forest_data['size_category'])
```

```
In [10]: 1 forest_data.head()
```

Out[10]:

	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	size_category
0	mar	fri	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	1
1	oct	tue	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	1
2	oct	sat	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	1
3	mar	fri	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	1
4	mar	sun	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	1

## Converting categorical values of days and months into intergers

```
In [11]: 1 forest_data.month.replace(('jan','feb','mar','apr','may','jun','jul','aug','sep','oct','nov','dec'),
        2                               (1,2,3,4,5,6,7,8,9,10,11,12), inplace = True)
        3 forest_data.day.replace(('mon','tue','wed','thu','fri','sat','sun'),(1,2,3,4,5,6,7),inplace = True)
```

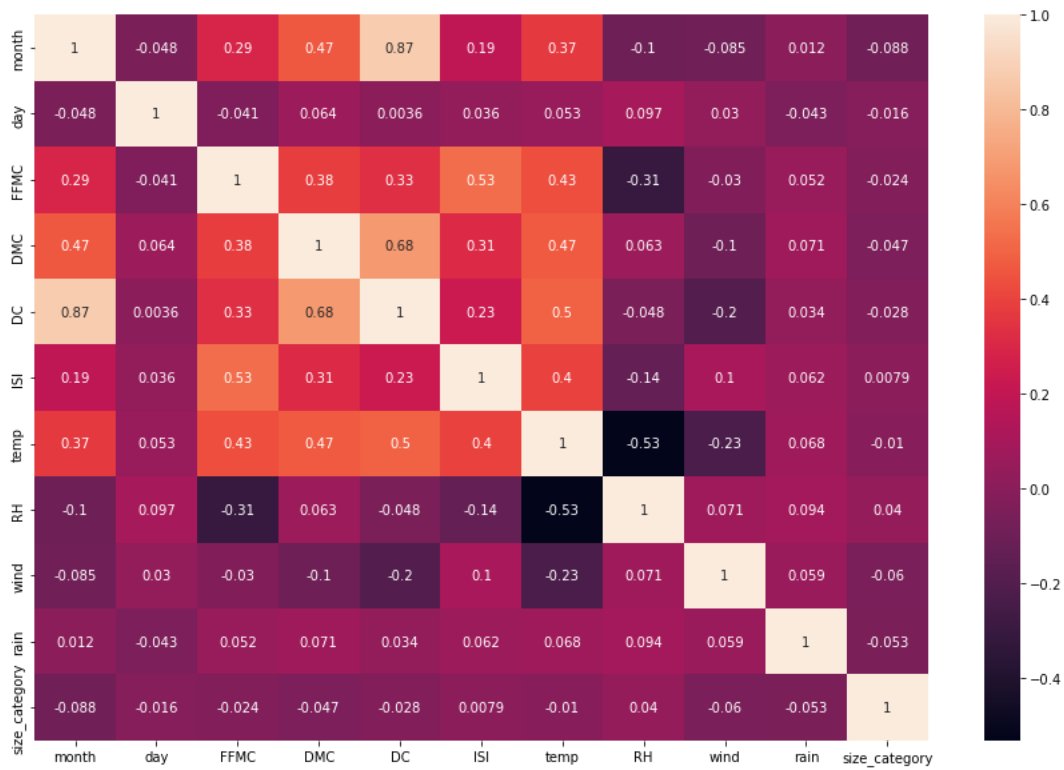
```
In [12]: 1 forest_data.head()
```

Out[12]:

	month	day	FFMC	DMC	DC	ISI	temp	RH	wind	rain	size_category
0	3	5	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	1
1	10	2	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	1
2	10	6	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	1
3	3	5	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	1
4	3	7	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	1

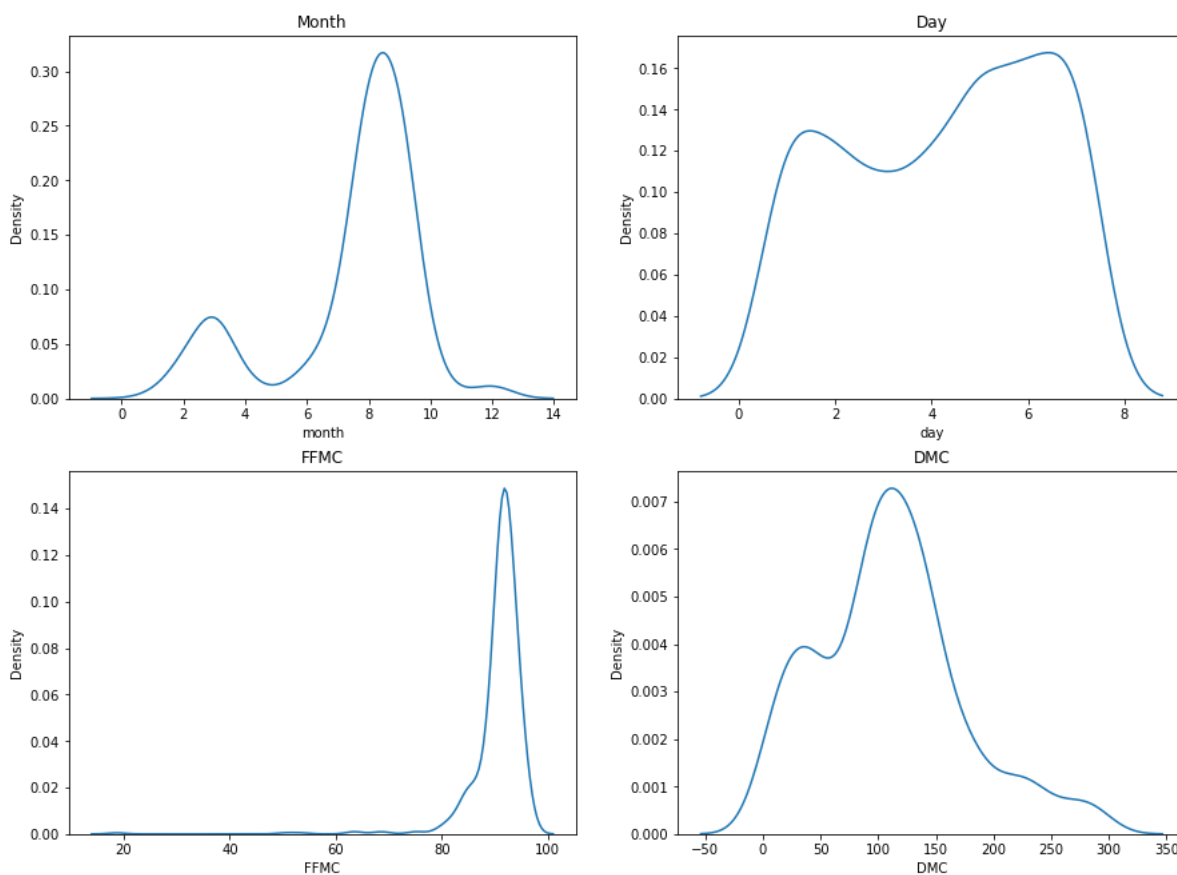
## Correlation Analysis

```
In [13]: 1 plt.figure(figsize= (15,10))
2 sns.heatmap(forest_data.corr(),annot= True)
3 plt.show()
```

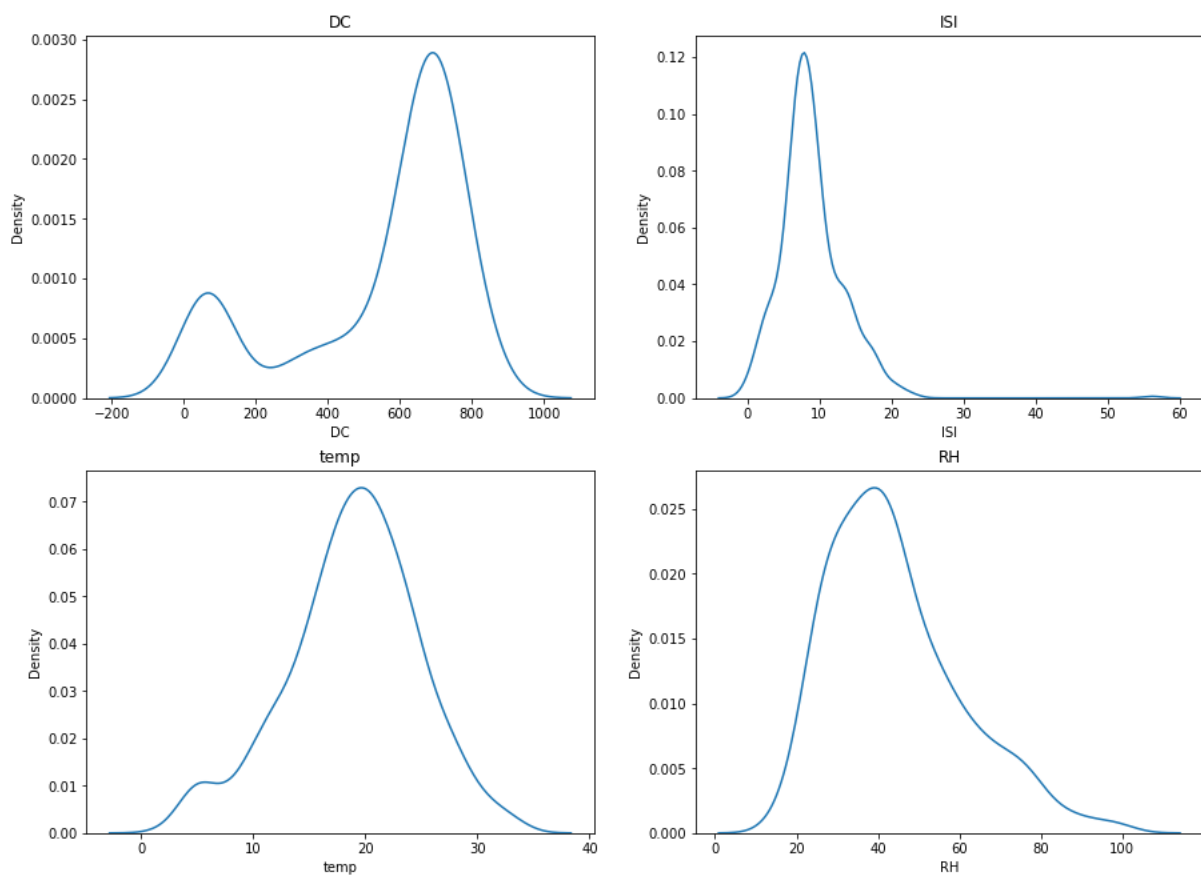


## Visualization of Independent variables

```
In [14]: 1 Normality_fig,Axes2=plt.subplots(2,2)
2
3 Normality_fig.set_figheight(11)
4 Normality_fig.set_figwidth(15)
5
6 sns.kdeplot(x="month",data=forest_data,ax=Axes2[0,0])
7 Axes2[0,0].set_title("Month")
8
9 sns.kdeplot(x="day",data=forest_data,ax=Axes2[0,1])
10 Axes2[0,1].set_title("Day")
11
12 sns.kdeplot(x="FFMC",data=forest_data,ax=Axes2[1,0])
13 Axes2[1,0].set_title("FFMC")
14
15 sns.kdeplot(x="DMC",data=forest_data,ax=Axes2[1,1])
16 Axes2[1,1].set_title("DMC")
17
18 plt.show()
```

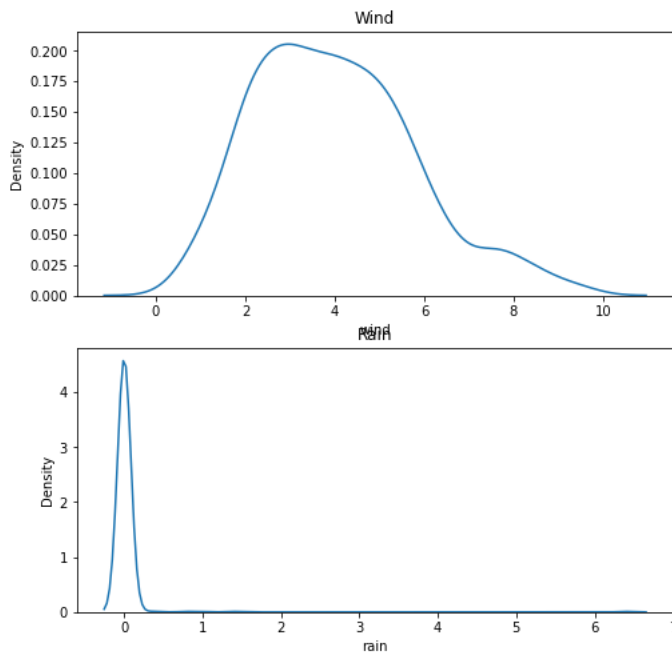


```
In [15]: 1 Normality_fig,Axes2=plt.subplots(2,2)
2
3 Normality_fig.set_figheight(11)
4 Normality_fig.set_figwidth(15)
5
6 sns.kdeplot(x="DC",data=forest_data,ax=Axes2[0,0])
7 Axes2[0,0].set_title("DC")
8
9 sns.kdeplot(x="ISI",data=forest_data,ax=Axes2[0,1])
10 Axes2[0,1].set_title("ISI")
11
12 sns.kdeplot(x="temp",data=forest_data,ax=Axes2[1,0])
13 Axes2[1,0].set_title("temp")
14
15 sns.kdeplot(x="RH",data=forest_data,ax=Axes2[1,1])
16 Axes2[1,1].set_title("RH")
17
18 plt.show()
```



```
In [16]: 1 Normality_fig,Axes2=plt.subplots(2)
2 Normality_fig.set_figheight(8)
3 Normality_fig.set_figwidth(8)
4 sns.kdeplot(x="wind",data=forest_data,ax=Axes2[0])
5 Axes2[0].set_title("Wind")
6 sns.kdeplot(x="rain",data=forest_data,ax=Axes2[1])
7 Axes2[1].set_title("Rain")
```

```
Out[16]: Text(0.5, 1.0, 'Rain')
```



## Extracting the independent and dependent variables

```
In [17]: 1 X = forest_data.iloc[:,0:10].values
2 X
```

```
Out[17]: array([[ 3. ,  5. , 86.2, ..., 51. ,  6.7,  0. ],
 [10. ,  2. , 90.6, ..., 33. ,  0.9,  0. ],
 [10. ,  6. , 90.6, ..., 33. ,  1.3,  0. ],
 ...,
 [ 8. ,  7. , 81.6, ..., 70. ,  6.7,  0. ],
 [ 8. ,  6. , 94.4, ..., 42. ,  4. ,  0. ],
 [11. ,  2. , 79.5, ..., 31. ,  4.5,  0. ]])
```

```
In [18]: 1 y = forest_data.iloc[:, -1].values
```

## Normalizing data

```
In [19]: 1 def norm_func(i):
2         X = (i-i.min())/(i.max()-i.min())
3         return (X)
```

```
In [20]: 1 X_norm = norm_func(X)
```

## Train Test Split

```
In [21]: 1 X_train,X_test,y_train,y_test = train_test_split(X_norm,y, test_size=0.2,stratify=y)
```

## Applying Neural Network

```
In [22]: 1 import warnings
2 warnings.filterwarnings('ignore')
```

In [23]: 1 pip install keras

Requirement already satisfied: keras in c:\users\admin\anaconda3\lib\site-packages (2.9.0)  
Note: you may need to restart the kernel to use updated packages.

WARNING: Ignoring invalid distribution -tatsmodels (c:\users\admin\anaconda3\lib\site-packages)  
WARNING: Ignoring invalid distribution -tatsmodels (c:\users\admin\anaconda3\lib\site-packages)  
WARNING: Ignoring invalid distribution -tatsmodels (c:\users\admin\anaconda3\lib\site-packages)  
WARNING: Ignoring invalid distribution -tatsmodels (c:\users\admin\anaconda3\lib\site-packages)  
WARNING: Ignoring invalid distribution -tatsmodels (c:\users\admin\anaconda3\lib\site-packages)  
WARNING: Ignoring invalid distribution -tatsmodels (c:\users\admin\anaconda3\lib\site-packages)

In [24]: 1 pip install tensorflow

Requirement already satisfied: tensorflow in c:\users\admin\anaconda3\lib\site-packages (2.9.1)  
Requirement already satisfied: termcolor>=1.1.0 in c:\users\admin\anaconda3\lib\site-packages (from tensorflow) (1.1.0)  
Requirement already satisfied: keras-preprocessing>=1.1.1 in c:\users\admin\anaconda3\lib\site-packages (from tensorflow) (1.1.2)  
Requirement already satisfied: protobuf<3.20,>=3.9.2 in c:\users\admin\anaconda3\lib\site-packages (from tensorflow) (3.19.4)  
Requirement already satisfied: tensorflow-estimator<2.10.0,>=2.9.0rc0 in c:\users\admin\anaconda3\lib\site-packages (from tensorflow) (2.9.0)  
Requirement already satisfied: flatbuffers<2,>=1.12 in c:\users\admin\anaconda3\lib\site-packages (from tensorflow) (1.12)  
Requirement already satisfied: keras<2.10.0,>=2.9.0rc0 in c:\users\admin\anaconda3\lib\site-packages (from tensorflow) (2.9.0)  
Requirement already satisfied: libclang>=13.0.0 in c:\users\admin\anaconda3\lib\site-packages (from tensorflow) (14.0.6)  
Requirement already satisfied: grpcio<2.0,>=1.24.3 in c:\users\admin\anaconda3\lib\site-packages (from tensorflow) (1.47.0)  
Requirement already satisfied: wrapt>=1.11.0 in c:\users\admin\anaconda3\lib\site-packages (from tensorflow) (1.12.1)  
Requirement already satisfied: absl-py>=1.0.0 in c:\users\admin\anaconda3\lib\site-packages (from tensorflow) (1.2.0)  
Requirement already satisfied: tensorboard<2.10,>=2.9 in c:\users\admin\anaconda3\lib\site-packages (from tensorflow) (2.9.1)  
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in c:\users\admin\anaconda3\lib\site-packages (from tensorflow) (0.26.0)  
Requirement already satisfied: setuptools in c:\users\admin\anaconda3\lib\site-packages (from tensorflow) (58.0.4)  
Requirement already satisfied: gast<0.4.0,>=0.2.1 in c:\users\admin\anaconda3\lib\site-packages (from tensorflow) (0.4.0)  
Requirement already satisfied: google-auth<2.14.0,>=2.1.0 in c:\users\admin\anaconda3\lib\site-packages (from tensorflow) (2.14.0)

In [25]: 1 import keras.models  
2 import tensorflow  
3 from tensorflow.keras.models import Sequential  
4 from keras.layers import Dense

In [26]: 1 model = Sequential()

In [27]: 1 # fix random seed for reproducibility  
2 seed =123  
3 np.random.seed(seed)

In [28]: 1 model.add(Dense(12, input\_dim = 10, kernel\_initializer='uniform', activation = 'relu'))  
2 model.add(Dense(8, kernel\_initializer='uniform', activation = 'relu'))  
3 model.add(Dense(1, kernel\_initializer='uniform', activation = 'linear'))

In [29]: 1 model.compile(loss='mse', optimizer = 'adam', metrics=['accuracy'])

In [30]: 1 model.fit(X\_train,y\_train, validation\_split=0.33,epochs=100,batch\_size =10)

Epoch 1/100  
28/28 [=====] - 2s 19ms/step - loss: 0.7048 - accuracy: 0.2721 - val\_loss: 0.6822 - val\_accuracy: 0.2667  
Epoch 2/100  
28/28 [=====] - 0s 6ms/step - loss: 0.6465 - accuracy: 0.2721 - val\_loss: 0.6117 - val\_accuracy: 0.2667  
Epoch 3/100  
28/28 [=====] - 0s 6ms/step - loss: 0.5646 - accuracy: 0.2721 - val\_loss: 0.5081 - val\_accuracy: 0.2667  
Epoch 4/100  
28/28 [=====] - 0s 6ms/step - loss: 0.4476 - accuracy: 0.2721 - val\_loss: 0.3796 - val\_accuracy: 0.2667  
Epoch 5/100  
28/28 [=====] - 0s 5ms/step - loss: 0.3207 - accuracy: 0.2831 - val\_loss: 0.2656 - val\_accuracy: 0.3852  
Epoch 6/100  
28/28 [=====] - 0s 5ms/step - loss: 0.2335 - accuracy: 0.6140 - val\_loss: 0.2121 - val\_accuracy: 0.6667  
Epoch 7/100  
28/28 [=====] - 0s 5ms/step - loss: 0.2076 - accuracy: 0.7316 - val\_loss: 0.2041 - val\_accuracy: 0.7333

In [31]: 1 model.evaluate(X\_test,y\_test)

4/4 [=====] - 0s 5ms/step - loss: 0.2021 - accuracy: 0.7255

Out[31]: [0.20208163559436798, 0.7254902124404907]



```
In [32]: 1 scores = model.evaluate(X_train, y_train)
2 print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

13/13 [=====] - 0s 2ms/step - loss: 0.1965 - accuracy: 0.7297  
accuracy: 72.97%

```
In [33]: 1 scores = model.evaluate(X_test, y_test)
2 print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```

4/4 [=====] - 0s 3ms/step - loss: 0.2021 - accuracy: 0.7255  
accuracy: 72.55%

**Validation accuracy is less**

## Tuning the number of layers in the model

```
In [34]: 1 model=Sequential()
```

```
In [35]: 1 model.add(Dense(28, input_dim=10, kernel_initializer='uniform', activation='relu'))
2 model.add(Dense(20, kernel_initializer='uniform', activation='relu'))
3 model.add(Dense(5, kernel_initializer='uniform', activation='linear'))
```

```
In [36]: 1 model.compile(loss='mse', optimizer = 'adam', metrics=['accuracy'])
```

```
In [37]: 1 model.fit(X_train,y_train, validation_split=0.33,epochs=100,batch_size=50)
```

Epoch 1/100  
6/6 [=====] - 1s 74ms/step - loss: 0.7239 - accuracy: 0.7243 - val\_loss: 0.7221 - val\_accuracy: 0.7333  
Epoch 2/100  
6/6 [=====] - 0s 14ms/step - loss: 0.7122 - accuracy: 0.7279 - val\_loss: 0.7096 - val\_accuracy: 0.7333  
Epoch 3/100  
6/6 [=====] - 0s 13ms/step - loss: 0.6993 - accuracy: 0.7279 - val\_loss: 0.6947 - val\_accuracy: 0.7333  
Epoch 4/100  
6/6 [=====] - 0s 16ms/step - loss: 0.6834 - accuracy: 0.7279 - val\_loss: 0.6763 - val\_accuracy: 0.7333  
Epoch 5/100  
6/6 [=====] - 0s 14ms/step - loss: 0.6635 - accuracy: 0.7279 - val\_loss: 0.6532 - val\_accuracy: 0.7333  
Epoch 6/100  
6/6 [=====] - 0s 14ms/step - loss: 0.6393 - accuracy: 0.7279 - val\_loss: 0.6239 - val\_accuracy: 0.7333  
Epoch 7/100  
6/6 [=====] - 0s 14ms/step - loss: 0.6255 - accuracy: 0.7279 - val\_loss: 0.6077 - val\_accuracy: 0.7333

```
In [38]: 1 model.evaluate(X_train,y_train)
```

13/13 [=====] - 0s 3ms/step - loss: 0.1970 - accuracy: 0.0958

Out[38]: [0.19699284434318542, 0.09582309424877167]

```
In [39]: 1 model.evaluate(X_test,y_test)
```

4/4 [=====] - 0s 3ms/step - loss: 0.2035 - accuracy: 0.0882

Out[39]: [0.20350773632526398, 0.0882352963089943]

## Trying different values

```
In [40]: 1 model=Sequential()
```

```
In [41]: 1 model.add(Dense(20, input_dim = 10, kernel_initializer = 'uniform', activation = 'relu'))
2 model.add(Dense(10, kernel_initializer = 'uniform', activation = 'relu'))
3 model.add(Dense(2, kernel_initializer = 'uniform', activation = 'linear'))
```

```
In [42]: 1 model.compile(loss = 'mse', optimizer = 'adam', metrics = ['accuracy'])
```

```
In [43]: 1 model.fit(X_train,y_train, validation_split = 0.33, epochs = 250, batch_size = 10)
```

```
Epoch 1/250
28/28 [=====] - 1s 20ms/step - loss: 0.7056 - accuracy: 0.4118 - val_loss: 0.6796 - val_accuracy: 0.2667
Epoch 2/250
28/28 [=====] - 0s 5ms/step - loss: 0.6332 - accuracy: 0.2721 - val_loss: 0.5784 - val_accuracy: 0.2667
Epoch 3/250
28/28 [=====] - 0s 5ms/step - loss: 0.4987 - accuracy: 0.2721 - val_loss: 0.3975 - val_accuracy: 0.2667
Epoch 4/250
28/28 [=====] - 0s 6ms/step - loss: 0.3160 - accuracy: 0.2721 - val_loss: 0.2309 - val_accuracy: 0.2667
Epoch 5/250
28/28 [=====] - 0s 6ms/step - loss: 0.2120 - accuracy: 0.2721 - val_loss: 0.2053 - val_accuracy: 0.2667
Epoch 6/250
28/28 [=====] - 0s 6ms/step - loss: 0.2078 - accuracy: 0.2721 - val_loss: 0.2052 - val_accuracy: 0.2667
Epoch 7/250
28/28 [=====] - 0s 6ms/step - loss: 0.2055 - accuracy: 0.2721 - val_loss: 0.2042 - val_accuracy: 0.2667
```

```
In [44]: 1 model.evaluate(X_train,y_train)
```

```
13/13 [=====] - 0s 4ms/step - loss: 0.1945 - accuracy: 0.4988
```

```
Out[44]: [0.19451133906841278, 0.498771488665344]
```

the accuracy has not improved with variations in layers

## Applying Varried activation methods

```
In [45]: 1 model = Sequential()
```

```
In [46]: 1 model.add(Dense(20, input_dim = 10, kernel_initializer = 'uniform', activation = 'relu'))
2 model.add(Dense(10, kernel_initializer = 'uniform', activation = 'linear'))
3 model.add(Dense(2, kernel_initializer = 'uniform', activation = 'sigmoid'))
```

```
In [47]: 1 model.compile(loss='mse', optimizer='adam', metrics=['accuracy'])
```

```
In [48]: 1 model.fit(X_train,y_train, validation_split = 0.33, epochs = 250, batch_size = 10)
```

```
Epoch 1/250
28/28 [=====] - 2s 23ms/step - loss: 0.2481 - accuracy: 0.3566 - val_loss: 0.2453 - val_accuracy: 0.6000
Epoch 2/250
28/28 [=====] - 0s 7ms/step - loss: 0.2409 - accuracy: 0.7022 - val_loss: 0.2344 - val_accuracy: 0.7333
Epoch 3/250
28/28 [=====] - 0s 7ms/step - loss: 0.2249 - accuracy: 0.7279 - val_loss: 0.2149 - val_accuracy: 0.7333
Epoch 4/250
28/28 [=====] - 0s 6ms/step - loss: 0.2072 - accuracy: 0.7279 - val_loss: 0.1995 - val_accuracy: 0.7333
Epoch 5/250
28/28 [=====] - 0s 8ms/step - loss: 0.1997 - accuracy: 0.7279 - val_loss: 0.1971 - val_accuracy: 0.7333
Epoch 6/250
28/28 [=====] - 0s 6ms/step - loss: 0.1992 - accuracy: 0.7279 - val_loss: 0.1970 - val_accuracy: 0.7333
Epoch 7/250
28/28 [=====] - 0s 6ms/step - loss: 0.1980 - accuracy: 0.7279 - val_loss: 0.1960 - val_accuracy: 0.7333
```

```
In [49]: 1 model.evaluate(X_train,y_train)
```

```
13/13 [=====] - 0s 3ms/step - loss: 0.1954 - accuracy: 0.4054
```

```
Out[49]: [0.19535548985004425, 0.4054054021835327]
```

no improvement is seen

In [50]:

1 model=Sequential()

In [51]:

1 model.add(Dense(20, input\_dim = 10, kernel\_initializer = 'uniform', activation = 'linear'))  
2 model.add(Dense(10, kernel\_initializer = 'uniform', activation = 'relu'))  
3 model.add(Dense(2, kernel\_initializer = 'uniform', activation = 'sigmoid'))

In [52]:

1 model.compile(loss = 'mse', optimizer = 'adam', metrics = ['accuracy'])

In [53]:

1 model.fit(X\_train,y\_train, validation\_split = 0.33, epochs = 250, batch\_size = 10)

Epoch 1/250  
28/28 [=====] - 1s 14ms/step - loss: 0.2480 - accuracy: 0.7169 - val\_loss: 0.2453 - val\_accuracy: 0.7333  
Epoch 2/250  
28/28 [=====] - 0s 4ms/step - loss: 0.2410 - accuracy: 0.7279 - val\_loss: 0.2351 - val\_accuracy: 0.7333  
Epoch 3/250  
28/28 [=====] - 0s 4ms/step - loss: 0.2270 - accuracy: 0.7279 - val\_loss: 0.2164 - val\_accuracy: 0.7333  
Epoch 4/250  
28/28 [=====] - 0s 4ms/step - loss: 0.2088 - accuracy: 0.7279 - val\_loss: 0.2011 - val\_accuracy: 0.7333  
Epoch 5/250  
28/28 [=====] - 0s 4ms/step - loss: 0.2001 - accuracy: 0.7279 - val\_loss: 0.1978 - val\_accuracy: 0.7333  
Epoch 6/250  
28/28 [=====] - 0s 5ms/step - loss: 0.1998 - accuracy: 0.7279 - val\_loss: 0.1973 - val\_accuracy: 0.7333  
Epoch 7/250  
28/28 [=====] - 0s 5ms/step - loss: 0.1993 - accuracy: 0.7279 - val\_loss: 0.1973 - val\_accuracy: 0.7333

In [54]:

1 model.evaluate(X\_train,y\_train)

13/13 [=====] - 0s 3ms/step - loss: 0.1954 - accuracy: 0.6314

Out[54]:

[0.19544364511966705, 0.6314496397972107]

No improvement is seen.

Data Optimization

In [55]:

1 forest = pd.read\_csv('forestfires.csv')

Label encoding the "Size category"feature.

In [56]:

1 forest.loc[forest.size\_category=='small','size\_category']=0  
2 forest.loc[forest.size\_category=='large','size\_category']=1

Taking dummy columns of day and month and dropping the "day" and "month" feature

In [57]:

1 forest.drop(['month','day'],axis=1,inplace=True)

In [58]:

1 forest.head()

Out[58]:

	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area	dayfri	...	monthfeb	monthjan	monthjul	monthjun	monthmar	monthmay	monthnov	monthoct	mor
0	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	0.0	1	...	0	0	0	0	1	0	0	0	
1	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	0.0	0	...	0	0	0	0	0	0	0	1	
2	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	0.0	0	...	0	0	0	0	0	0	0	1	
3	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	0.0	1	...	0	0	0	0	1	0	0	0	
4	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	0.0	0	...	0	0	0	0	1	0	0	0	

5 rows × 29 columns

localhost:8888/notebooks/Assignment-16-(Neural Networks) new %5BForest Fires%5D.ipynb

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## Dependant and Independent variables

```
In [59]: 1 x=forest.iloc[:, :-1]
          2 y=forest.iloc[:, -1]
          3
          4 y=y.astype('float')
```

## Scaling the Data

```
In [60]: 1 ss=preprocessing.StandardScaler()
          2 x=ss.fit_transform(x)
```

## Train Test Split

```
In [61]: 1 X_train,X_test,y_train,y_test = train_test_split(x,y, test_size=0.2,stratify=y)
```

```
In [62]: 1 X_train.shape
```

```
Out[62]: (413, 28)
```

```
In [63]: 1 y_train.shape
```

```
Out[63]: (413,)
```

```
In [64]: 1 X_test.shape
```

```
Out[64]: (104, 28)
```

```
In [65]: 1 y_test.shape
```

```
Out[65]: (104,)
```

## Building New Model with loss function binary\_crossentropy

```
In [66]: 1 model=Sequential()
          2 model.add(Dense(28, activation='relu'))
          3 model.add(Dense(28, activation='relu'))
          4 model.add(Dense(1, activation='sigmoid'))
```

```
In [67]: 1 model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
```

```
In [68]: 1 history=model.fit(X_train, y_train, validation_split=0.33, epochs=250, batch_size=50)
```

```
Epoch 1/250
6/6 [=====] - 2s 107ms/step - loss: 0.7537 - accuracy: 0.3986 - val_loss: 0.7092 - val_accuracy: 0.4453
Epoch 2/250
6/6 [=====] - 0s 14ms/step - loss: 0.6788 - accuracy: 0.4819 - val_loss: 0.6581 - val_accuracy: 0.5912
Epoch 3/250
6/6 [=====] - 0s 52ms/step - loss: 0.6258 - accuracy: 0.6413 - val_loss: 0.6244 - val_accuracy: 0.7226
Epoch 4/250
6/6 [=====] - 0s 25ms/step - loss: 0.5897 - accuracy: 0.7572 - val_loss: 0.6019 - val_accuracy: 0.7080
Epoch 5/250
6/6 [=====] - 0s 21ms/step - loss: 0.5638 - accuracy: 0.7717 - val_loss: 0.5872 - val_accuracy: 0.7299
Epoch 6/250
6/6 [=====] - 0s 20ms/step - loss: 0.5470 - accuracy: 0.7717 - val_loss: 0.5770 - val_accuracy: 0.7299
Epoch 7/250
6/6 [=====] - 0s 17ms/step - loss: 0.5324 - accuracy: 0.7700 - val_loss: 0.5701 - val_accuracy: 0.7300
```

```
In [69]: 1 model.evaluate(X_train,y_train)
```

```
13/13 [=====] - 0s 4ms/step - loss: 0.2452 - accuracy: 0.9516
```

```
Out[69]: [0.2451915442943573, 0.9515738487243652]
```

```
In [70]: 1 model.evaluate(X_test,y_test)
```

```
4/4 [=====] - 0s 4ms/step - loss: 1.0461 - accuracy: 0.8846
```

```
Out[70]: [1.0460717678070068, 0.8846153616905212]
```

**accuracy has improved**

## Visualize training history

```
In [71]: 1 history = model.fit(X_train,y_train, validation_split = 0.33, epochs = 100, batch_size = 10)
```

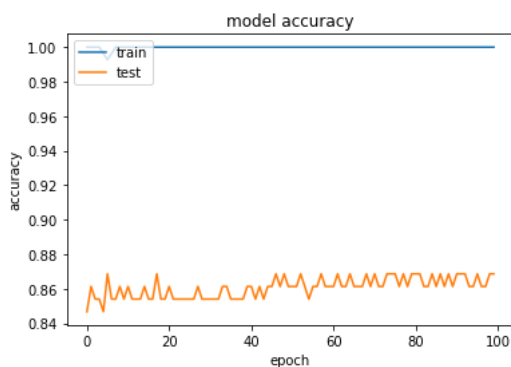
```
Epoch 1/100
28/28 [=====] - 0s 12ms/step - loss: 0.0080 - accuracy: 1.0000 - val_loss: 0.7431 - val_accuracy: 0.8467
Epoch 2/100
28/28 [=====] - 0s 7ms/step - loss: 0.0078 - accuracy: 1.0000 - val_loss: 0.7365 - val_accuracy: 0.8613
Epoch 3/100
28/28 [=====] - 0s 7ms/step - loss: 0.0087 - accuracy: 1.0000 - val_loss: 0.8001 - val_accuracy: 0.8540
Epoch 4/100
28/28 [=====] - 0s 12ms/step - loss: 0.0092 - accuracy: 1.0000 - val_loss: 0.7557 - val_accuracy: 0.8540
Epoch 5/100
28/28 [=====] - 0s 9ms/step - loss: 0.0164 - accuracy: 0.9964 - val_loss: 0.6941 - val_accuracy: 0.8467
Epoch 6/100
28/28 [=====] - 0s 9ms/step - loss: 0.0194 - accuracy: 0.9928 - val_loss: 0.7655 - val_accuracy: 0.8686
Epoch 7/100
28/28 [=====] - 0s 7ms/step - loss: 0.0081 - accuracy: 0.9964 - val_loss: 0.7370 - val_accuracy: 0.8613
```

```
In [72]: 1 # List all data in history
2 model.history.history.keys()
```

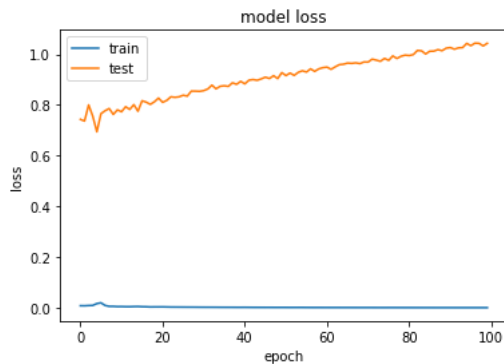
```
Out[72]: dict_keys(['loss', 'accuracy', 'val_loss', 'val_accuracy'])
```

## summarize history for accuracy and Loss

```
In [73]: 1 plt.plot(history.history['accuracy'])
2 plt.plot(history.history['val_accuracy'])
3 plt.title('model accuracy')
4 plt.ylabel('accuracy')
5 plt.xlabel('epoch')
6 plt.legend(['train', 'test'], loc = 'upper left')
7 plt.show()
```



```
In [74]: 1 plt.plot(history.history['loss'])
2 plt.plot(history.history['val_loss'])
3 plt.title('model loss')
4 plt.ylabel('loss')
5 plt.xlabel('epoch')
6 plt.legend(['train', 'test'], loc = 'upper left')
7 plt.show()
```



### Tuning of Hyperparameters

```
In [75]: 1 from sklearn.model_selection import GridSearchCV, KFold
2 from keras.wrappers.scikit_learn import KerasClassifier
3 from keras.optimizers import Adam
4 from tensorflow.keras.models import load_model
```

### Defining a Function for the Model

```
In [76]: 1 def create_model():
2     model_2 = Sequential()
3     model_2.add(Dense(10, input_dim = 10, kernel_initializer = 'uniform', activation = 'relu'))
4     model_2.add(Dense(11, kernel_initializer = 'uniform', activation = 'relu'))
5     model_2.add(Dense(1, kernel_initializer = 'uniform', activation = 'linear'))
6
7     adam = Adam(lr = 0.01)
8     model_2.compile(loss = 'mse', optimizer = adam, metrics = ['accuracy'])
9     return model_2
```

```
In [77]: 1 model_1 = KerasClassifier(build_fn = create_model, verbose = 0)
```

```
In [78]: 1 validation_split = [0.33, 0.2, 0.4, 0.37]
2 batch_size = [10, 20, 40]
3 epochs = [10, 50, 100]
```

### Gridsearch CV

```
In [79]: 1 param_grid = dict(batch_size = batch_size, epochs = epochs, validation_split=validation_split)
```

```
In [80]: 1 grid = GridSearchCV(estimator = model_1, param_grid = param_grid,cv = KFold(),verbose = 10)
2 grid_result = grid.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 36 candidates, totalling 180 fits
[CV 1/5; 1/36] START batch_size=10, epochs=10, validation_split=0.33;.....
[CV 1/5; 1/36] END batch_size=10, epochs=10, validation_split=0.33; score=0.988 total time= 3.5s
[CV 2/5; 1/36] START batch_size=10, epochs=10, validation_split=0.33;.....
[CV 2/5; 1/36] END batch_size=10, epochs=10, validation_split=0.33; score=1.000 total time= 1.6s
[CV 3/5; 1/36] START batch_size=10, epochs=10, validation_split=0.33;.....
[CV 3/5; 1/36] END batch_size=10, epochs=10, validation_split=0.33; score=1.000 total time= 2.0s
[CV 4/5; 1/36] START batch_size=10, epochs=10, validation_split=0.33;.....
[CV 4/5; 1/36] END batch_size=10, epochs=10, validation_split=0.33; score=0.963 total time= 1.9s
[CV 5/5; 1/36] START batch_size=10, epochs=10, validation_split=0.33;.....
[CV 5/5; 1/36] END batch_size=10, epochs=10, validation_split=0.33; score=0.890 total time= 2.3s
[CV 1/5; 2/36] START batch_size=10, epochs=10, validation_split=0.2;.....
[CV 1/5; 2/36] END batch_size=10, epochs=10, validation_split=0.2; score=0.988 total time= 1.9s
[CV 2/5; 2/36] START batch_size=10, epochs=10, validation_split=0.2;.....
[CV 2/5; 2/36] END batch_size=10, epochs=10, validation_split=0.2; score=1.000 total time= 1.7s
[CV 3/5; 2/36] START batch_size=10, epochs=10, validation_split=0.2;.....
[CV 3/5; 2/36] END batch_size=10, epochs=10, validation_split=0.2; score=1.000 total time= 1.8s
[CV 4/5; 2/36] START batch_size=10, epochs=10, validation_split=0.2;.....
[CV 4/5; 2/36] END batch_size=10, epochs=10, validation_split=0.2; score=1.000 total time= 3.2s
```

```
In [81]: 1 grid_result.best_params_
```

```
Out[81]: {'batch_size': 10, 'epochs': 10, 'validation_split': 0.4}
```

## Creating the Final Model with Best Parameters

```
In [82]: 1 model_2 = Sequential()
2 model_2.add(Dense(10,input_dim = 10, kernel_initializer = 'uniform', activation = 'relu'))
3 model_2.add(Dense(11,kernel_initializer = 'uniform', activation = 'relu'))
4 model_2.add(Dense(1,kernel_initializer = 'uniform', activation = 'linear'))
```

```
In [83]: 1 history = model.fit(X_train,y_train, validation_split = 0.33, epochs = 10, batch_size = 10)
```

```
Epoch 1/10
28/28 [=====] - 0s 10ms/step - loss: 1.4118e-09 - accuracy: 1.0000 - val_loss: 1.8696 - val_accuracy: 0.9197
Epoch 2/10
28/28 [=====] - 0s 7ms/step - loss: 1.3692e-09 - accuracy: 1.0000 - val_loss: 1.8715 - val_accuracy: 0.9197
Epoch 3/10
28/28 [=====] - 0s 6ms/step - loss: 1.3791e-09 - accuracy: 1.0000 - val_loss: 1.8692 - val_accuracy: 0.9197
Epoch 4/10
28/28 [=====] - 0s 6ms/step - loss: 1.3667e-09 - accuracy: 1.0000 - val_loss: 1.8708 - val_accuracy: 0.9197
Epoch 5/10
28/28 [=====] - 0s 7ms/step - loss: 1.3977e-09 - accuracy: 1.0000 - val_loss: 1.8726 - val_accuracy: 0.9197
Epoch 6/10
28/28 [=====] - 0s 6ms/step - loss: 1.4252e-09 - accuracy: 1.0000 - val_loss: 1.8719 - val_accuracy: 0.9197
Epoch 7/10
28/28 [=====] - 0s 6ms/step - loss: 1.3793e-09 - accuracy: 1.0000 - val_loss: 1.8712 - val_accuracy: 0.9197
Epoch 8/10
28/28 [=====] - 0s 5ms/step - loss: 1.3962e-09 - accuracy: 1.0000 - val_loss: 1.8731 - val_accuracy: 0.9197
Epoch 9/10
28/28 [=====] - 0s 5ms/step - loss: 1.4249e-09 - accuracy: 1.0000 - val_loss: 1.8748 - val_accuracy: 0.9197
Epoch 10/10
28/28 [=====] - 0s 6ms/step - loss: 1.4518e-09 - accuracy: 1.0000 - val_loss: 1.8706 - val_accuracy: 0.9197
```

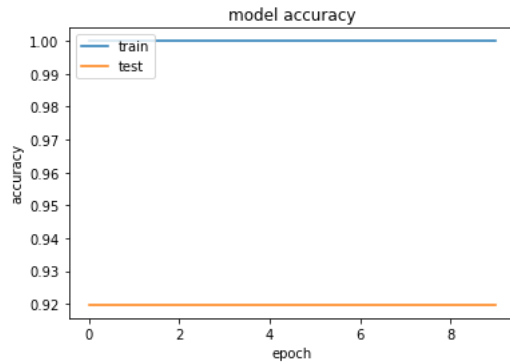
```
In [84]: 1 model.evaluate(X_train,y_train)
```

```
13/13 [=====] - 0s 3ms/step - loss: 0.6205 - accuracy: 0.9734
```

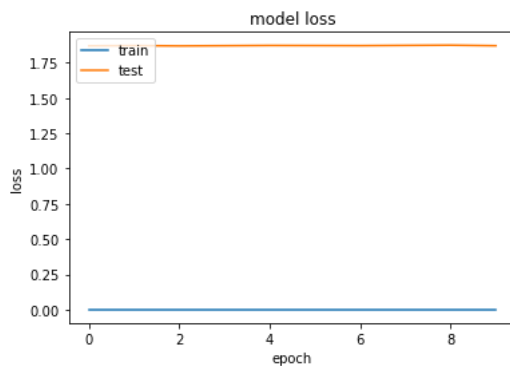
```
Out[84]: [0.6205052733421326, 0.9733656048774719]
```

## Visualizing the Final Model¶

```
In [85]: 1 plt.plot(history.history['accuracy'])
2 plt.plot(history.history['val_accuracy'])
3 plt.title('model accuracy')
4 plt.ylabel('accuracy')
5 plt.xlabel('epoch')
6 plt.legend(['train', 'test'], loc = 'upper left')
7 plt.show()
```



```
In [86]: 1 plt.plot(history.history['loss'])
2 plt.plot(history.history['val_loss'])
3 plt.title('model loss')
4 plt.ylabel('loss')
5 plt.xlabel('epoch')
6 plt.legend(['train', 'test'], loc = 'upper left')
7 plt.show()
```



## The Model is then Deployed.

```
In [ ]: 1
```