Artificial Neural network

```
In [1]: #!pip install tensorflow
In [2]: # Importing necessary libraries
         import pandas as pd
         from sklearn.metrics import accuracy score, confusion matrix
         from sklearn.model_selection import train_test_split, cross_val_score
         # Create your first MLP in Keras
         from keras.models import Sequential
         from keras.layers import Dense
         import numpy as np
         import matplotlib.pyplot as plt
         import warnings
         warnings.filterwarnings('ignore')
In [3]: forest data = pd.read csv('forestfires.csv')
         forest data
Out[3]:
               month day FFMC
                                   DMC
                                           DC
                                                 ISI temp
                                                           RH
                                                                wind rain ... monthfeb monthjan me
             0
                        fri
                             86.2
                                    26.2
                                          94.3
                                                 5.1
                                                       8.2
                                                            51
                                                                  6.7
                                                                       0.0
                                                                                      0
                                                                                                0
                  mar
             1
                             90.6
                                    35.4
                                         669.1
                                                 6.7
                                                      18.0
                                                            33
                                                                  0.9
                                                                       0.0
                                                                                      0
                                                                                                0
                  oct
                       tue
                                                                           ...
             2
                             90.6
                                    43.7
                                         686.9
                                                 6.7
                                                      14.6
                                                                  1.3
                                                                                                0
                  oct
                        sat
                                                            33
                                                                       0.0
             3
                        fri
                             91.7
                                    33.3
                                          77.5
                                                 9.0
                                                       8.3
                                                            97
                                                                  4.0
                                                                       0.2
                                                                                                0
                  mar
                                                                                      0
                                    51.3 102.2
             4
                  mar
                       sun
                             89.3
                                                 9.6
                                                      11.4
                                                            99
                                                                  1.8
                                                                       0.0
                                                                                      0
                                                                                                0
                   ...
                                                  ...
                                                        ...
                                                                        ...
           512
                             81.6
                                    56.7
                                         665.6
                                                 1.9
                                                      27.8
                                                            32
                                                                  2.7
                                                                       0.0 ...
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                  aug
                       sun
           513
                                         665.6
                                                      21.9
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                                                                  5.8
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                  aug
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           516
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                       tue
                             79.5
                                     3.0 106.7
                                                 1.1
                                                      11.8
                                                            31
                                                                  4.5
                                                                       0.0 ...
                                                                                                0
```

In [4]:	forest_data.:	isna().sum()	
Out[4]:	month	0	
	day	0	
	FFMC	0	
	DMC	0	
	DC	0	
	ISI	0	
	temp	0	
	RH	0	
	wind	0	
	rain	0	
	area	0	
	dayfri	0	
	daymon	0	
	daysat	0	
	daysun	0	
	daythu	0	
	daytue	0	
	daywed	0	
	monthapr	0	_
	·	^	~

In [5]: forest_data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 517 entries, 0 to 516
Data columns (total 31 columns):

pata #	Columns (total	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					
	es: float64(8),							
memoi	memory usage: 125.3+ KB							

localhost:8888/notebooks/Data science assignment_16/Assignment_16.1(Artificial Neural Network).ipynb

In [6]: forest_data.describe().T

Out[6]:

	count	mean	std	min	25%	50%	75%	max
FFMC	517.0	90.644681	5.520111	18.7	90.2	91.60	92.90	96.20
DMC	517.0	110.872340	64.046482	1.1	68.6	108.30	142.40	291.30
DC	517.0	547.940039	248.066192	7.9	437.7	664.20	713.90	860.60
ISI	517.0	9.021663	4.559477	0.0	6.5	8.40	10.80	56.10
temp	517.0	18.889168	5.806625	2.2	15.5	19.30	22.80	33.30
RH	517.0	44.288201	16.317469	15.0	33.0	42.00	53.00	100.00
wind	517.0	4.017602	1.791653	0.4	2.7	4.00	4.90	9.40
rain	517.0	0.021663	0.295959	0.0	0.0	0.00	0.00	6.40
area	517.0	12.847292	63.655818	0.0	0.0	0.52	6.57	1090.84
dayfri	517.0	0.164410	0.371006	0.0	0.0	0.00	0.00	1.00
daymon	517.0	0.143133	0.350548	0.0	0.0	0.00	0.00	1.00
daysat	517.0	0.162476	0.369244	0.0	0.0	0.00	0.00	1.00
daysun	517.0	0.183752	0.387657	0.0	0.0	0.00	0.00	1.00
daythu	517.0	0.117988	0.322907	0.0	0.0	0.00	0.00	1.00
daytue	517.0	0.123791	0.329662	0.0	0.0	0.00	0.00	1.00
daywed	517.0	0.104449	0.306138	0.0	0.0	0.00	0.00	1.00
monthapr	517.0	0.017408	0.130913	0.0	0.0	0.00	0.00	1.00
monthaug	517.0	0.355899	0.479249	0.0	0.0	0.00	1.00	1.00
monthdec	517.0	0.017408	0.130913	0.0	0.0	0.00	0.00	1.00
monthfeb	517.0	0.038685	0.193029	0.0	0.0	0.00	0.00	1.00
monthjan	517.0	0.003868	0.062137	0.0	0.0	0.00	0.00	1.00
monthjul	517.0	0.061896	0.241199	0.0	0.0	0.00	0.00	1.00
monthjun	517.0	0.032882	0.178500	0.0	0.0	0.00	0.00	1.00
monthmar	517.0	0.104449	0.306138	0.0	0.0	0.00	0.00	1.00
monthmay	517.0	0.003868	0.062137	0.0	0.0	0.00	0.00	1.00
monthnov	517.0	0.001934	0.043980	0.0	0.0	0.00	0.00	1.00
monthoct	517.0	0.029014	0.168007	0.0	0.0	0.00	0.00	1.00
monthsep	517.0	0.332689	0.471632	0.0	0.0	0.00	1.00	1.00

In [7]: forest_data_corr = forest_data.corr()
 forest_data_corr

Out[7]:

	FFMC	DMC	DC	ISI	temp	RH	wind	rain	
FFMC	1.000000	0.382619	0.330512	0.531805	0.431532	-0.300995	-0.028485	0.056702	_
DMC	0.382619	1.000000	0.682192	0.305128	0.469594	0.073795	-0.105342	0.074790	
DC	0.330512	0.682192	1.000000	0.229154	0.496208	-0.039192	-0.203466	0.035861	
ISI	0.531805	0.305128	0.229154	1.000000	0.394287	-0.132517	0.106826	0.067668	
temp	0.431532	0.469594	0.496208	0.394287	1.000000	-0.527390	-0.227116	0.069491	
RH	-0.300995	0.073795	-0.039192	-0.132517	-0.527390	1.000000	0.069410	0.099751	-
wind	-0.028485	-0.105342	-0.203466	0.106826	-0.227116	0.069410	1.000000	0.061119	
rain	0.056702	0.074790	0.035861	0.067668	0.069491	0.099751	0.061119	1.000000	-
area	0.040122	0.072994	0.049383	0.008258	0.097844	-0.075519	0.012317	-0.007366	
dayfri	0.019306	-0.012010	-0.004220	0.046695	-0.071949	0.064506	0.118090	-0.004261	-
daymon	-0.059396	-0.107921	-0.052993	-0.158601	-0.136529	0.009376	-0.063881	-0.029945	-
daysat	-0.019637	-0.003653	-0.035189	-0.038585	0.034899	-0.023869	-0.063799	-0.032271	
daysun	-0.089517	0.025355	-0.001431	-0.003243	0.014403	0.136220	0.027981	-0.017872	-
daythu	0.071730	0.087672	0.051859	-0.022406	0.051432	-0.123061	-0.062553	-0.026798	
daytue	0.011225	0.000016	0.028368	0.068610	0.035630	-0.014211	0.053396	0.139311	-
daywed	0.093908	0.017939	0.024803	0.125415	0.090580	-0.087508	-0.019965	-0.020744	-
monthapr	-0.117199	-0.197543	-0.268211	-0.106478	-0.157051	0.021235	0.048266	-0.009752	-
monthaug	0.228103	0.497928	0.279361	0.334639	0.351404	0.054761	0.028577	0.093101	-
monthdec	-0.137044	-0.176301	-0.105642	-0.162322	-0.329648	-0.047714	0.269702	-0.009752	
monthfeb	-0.281535	-0.317899	-0.399277	-0.249777	-0.320015	0.140430	-0.029431	-0.014698	-
monthjan	-0.454771	-0.105647	-0.115064	-0.103588	-0.146520	0.170923	-0.070245	-0.004566	-
monthjul	0.031833	-0.001946	-0.100887	0.020982	0.142588	0.013185	-0.040645	-0.013390	
monthjun	-0.040634	-0.050403	-0.186183	0.111516	0.051015	0.009382	0.012124	-0.013510	-
monthmar	-0.074327	-0.407404	-0.650427	-0.143520	-0.341797	-0.089836	0.181433	-0.020744	-
monthmay	-0.037230	-0.081980	-0.114209	-0.060493	-0.045540	0.086822	0.015054	-0.004566	
monthnov	-0.088964	-0.074218	-0.078380	-0.076559	-0.053798	-0.035885	0.011864	-0.003225	-
monthoct	-0.005998	-0.187632	0.093279	-0.071154	-0.053513	-0.072334	-0.053850	-0.012665	-
monthsep	0.076609	0.110907	0.531857	-0.068877	0.088006	-0.062596	-0.181476	-0.051733	

28 rows × 28 columns

```
In [8]: import seaborn as sns
plt.figure(figsize=(20,16))
sns.heatmap(forest_data_corr, annot = True)
None
```

```
- 1.0
FFMC - 1 0.38 0.33 0.53 0.43 0.3 0.03 0.03 0.04 0.019 0.059 0.02 0.09 0.072 0.011 0.094 0.12 0.23 0.14 0.28 0.45 0.032 0.041 0.074 0.037 0.089 0.006 0.07
                   0.08 0.1 0.68 0.31 0.47 0.074 0.11 0.075 0.073 0.012 0.11 0.00370.025 0.0881.6e-050.018 0.2 0.5 0.18 0.32 0.11 0.0019 0.05 0.41 0.082 0.074 0.19 0.11
                   0.33 0.68 1 0.23 0.5 0.039 0.2 0.036 0.0490 00420.053 0.0350 0.0140 052 0.028 0.025 0.27 0.28 0.11 0.4 0.12 0.1 0.19 0.65 0.11 0.078 0.093 0.53
                   053 031 023 1 039 0.13 0.11 0.0680.0083.0047 0.16 0.0390.00320.022.0.069 0.13 0.11 0.33 0.16 0.25 0.1 0.021 0.11 0.14 0.06 0.077 0.071 0.069
                   043 047 0.5 0.39 1 0.53 0.23 0.069 0.098 0.072 0.14 0.035 0.014 0.051 0.036 0.091 0.16 0.35 0.33 0.32 0.15 0.14 0.051 0.34 0.0460.054 0.054 0.054
                  0.3 0.074 0.039 0.13 0.53 1 0.069 0.1 0.076 0.065 0.0094 0.024 0.14 0.12 0.014 0.088 0.021 0.055 0.048 0.14 0.17 0.013 0.0094 0.09 0.087 0.036 0.072 0.065
                   0.028 -0.11 -0.2 0.11 -0.23 0.069 1 0.061 0.012 0.12 -0.064 -0.064 0.028 -0.063 0.053 -0.02 0.048 0.029 0.27 -0.029 -0.07 -0.041 0.012 0.18 0.015 0.012 -0.054 -0.18
                   0.057 0.075 0.036 0.068 0.069 0.1 0.061 1 0.0074) 0.043-0.03 -0.032-0.018-0.027 0.14 -0.0210.00980.093-0.00980.0150.00460.013-0.014-0.0210.00440.00320.013-0.052
                   0.04 0.073 0.049 0.0083 0.098 0.076 0.012 0.0074 1 -0.053 -0.021 0.088 -0.02 0.02 0.00130 0.110 0.083 0.0420 0.01 0.021 0.0130 0.061 0.02 0.0460 0.0630 0.00890 0.17 0.057
                    019-0.0120.00420.047-0.072.0065-012-0.00430.053 1 0.18 0.2 0.21 0.16 0.17 0.15 0.019 0.01 0.019 0.046-0.028-0.049 0.006 0.036 0.056 0.02 0.046 0.011
                     059 -0.11 -0.053 -0.16 -0.14 0.00940.064 -0.03 -0.021 -0.18 -0.18 -0.19 -0.15 -0.15 -0.15 -0.12 -0.13 -0.11 -0.0390.025 -0.013 0.018 0.077 -0.025 -0.018 0.061 -0.04
                   0.09 0.0250 0.0140 0.0320 0.014 0.014 0.028 0.018 0.02 0.21 0.19 0.21 1 0.17 0.18 0.16 0.051 0.065 0.0250 0.0840 0.51 0.018 0.025 0.048 0.03 0.0210.00730 0.49
                    072 0088 0052 -0.022 0051 -0.12 -0.063-0.027 002 -0.16 -0.15 -0.16 -0.15 -0.16 -0.17 1 -0.14 -0.12 0.043 0.0540 00280 042-0.023-0.0190 00020 027-0.023-0.016-0.063 0.005
                                                                                                                                                                                                                                                                                                                                                                                                                                                                           0.2
                   01116-050028 0069 0036 0.014 0053 014 0.0013 0.17 0.15 0.17 0.18 0.14 1 0.13 0.05 0.0640 00510.014 0.023 0.05 0.0690 0.032 0.023 0.12 0.005 0.02
                   0.094 0.018 0.025 0.13 0.091 0.088 0.02 0.021 0.011 0.15 0.14 0.15 0.16 0.12 0.13 1 0.00290.0760.00290.0360.021 0.009 0.043 0.034 0.0210.015 0.016 0.053
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                                                                                                                                                                                                                                                                                                                                                                                                                                                                           0.0
                   0.23 0.5 0.28 0.33 0.35 0.055 0.029 0.093 0.094 0.1 0.13 0.0098 0.065 0.054 0.064 0.076 0.099 1 0.099 0.15 0.046 0.19 0.14 0.25 0.046 0.033 0.13 0.52
                   0.14 | 0.18 | 0.11 | 0.16 | 0.33 | 0.048 | 0.27 | 0.00980 001 | 0.019 | 0.11 | 0.059 | 0.0250 | 0.0250 | 0.0250 | 0.0250 | 0.018 | 0.099 | 1 | 0.0270 | 0.00830 | 0.034 | 0.025 | 0.0450 | 0.04830 | 0.0590 | 0.23 | 0.094
                  .0.28 .0.32 .0.4 .0.25 .0.32 <mark>0.14 .</mark>0.029 .0.15 .0.021 .0.0460.0039 .0.02 .0.00840.042-0.014-0.036-0.027 .0.15 .0.027 1 .0.013 -0.052 -0.037 -0.069 .0.0130.00880 .035 -0.14
               0.45 0.11 0.12 0.1 0.15 0.17 0.070.00460.0130.028-0.0250.057 0.051 0.023-0.023-0.023-0.0230.00830.0460.00830.013 1 0.016-0.011-0.0210.00330.00270.011-0.044
                   0324 0019 0.1 0021 0.14 0013 0.041 0.0130 00610 0490 013 0.061 0.018 0.019 0.05 0.0090 034 0.19 0.034 0.052 0.016 1 0.047 0.088 0.0160 011 0.044 0.18
                   0.041 - 0.05 - 0.19 = 0.11 - 0.0510.00940.012 - 0.014 - 0.02 - 0.006 - 0.018 - 0.022 - 0.025 - 0.0020 - 0.069 - 0.043 - 0.025 - 0.14 - 0.025 - 0.037 - 0.011 - 0.047 = 1 + 0.063 - 0.0110 - 0.0810 - 0.032 - 0.13 + 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 0.033 - 
                   0.074 0.41 0.65 0.14 0.34 0.09 0.18 0.021-0.046 0.036 0.077 0.021 0.048 0.027 0.032 0.034 0.045 0.25 0.045 0.069 0.021 0.088 0.063 1 0.021 0.015 0.059 0.24
                   0.037 - 0.082 - 0.11 - 0.06 - 0.046 - 0.087 - 0.0150 .0046 .0063 0.056 - 0.025 0.057 - 0.03 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 - 0.023 
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                    .006 \cdot 0.19 \cdot 0.093 \cdot 0.071 \cdot 0.054 \cdot 0.072 \cdot 0.054 \cdot 0.013 \cdot 0.017 \cdot 0.046 \cdot 0.061 \cdot 0.0180 \cdot 0.0073 \cdot 0.063 \cdot 0.005 \cdot 0.016 \cdot 0.023 \cdot 0.13 \cdot 0.023 \cdot 0.035 \cdot 0.011 \cdot 0.044 \cdot 0.032 \cdot 0.059 \cdot 0.0110 \cdot 0.0076 \cdot 1.008 \cdot 0.008 \cdot 0.0
                   0077 0.11 0.53 0.069 0.088 0.063 0.18 0.052 0.057 0.11 0.04 0.033 0.049 0.009 0.029 0.053 0.094 0.52 0.094 0.14 0.044 0.18 0.13 0.24 0.044 0.031 0.12
```

```
In [9]: from sklearn.metrics import classification_report
    from sklearn import preprocessing
    label_encoder = preprocessing.LabelEncoder()
    forest_data['size_category']= label_encoder.fit_transform(forest_data['size_category'])
```

In [10]: forest_data=forest_data.drop(columns=['month','day'],axis=1)
forest_data

Out[10]:

	FFMC	DMC	DC	ISI	temp	RH	wind	rain	area	dayfri	 monthfeb	monthjan	mon
0	86.2	26.2	94.3	5.1	8.2	51	6.7	0.0	0.00	1	 0	0	
1	90.6	35.4	669.1	6.7	18.0	33	0.9	0.0	0.00	0	 0	0	
2	90.6	43.7	686.9	6.7	14.6	33	1.3	0.0	0.00	0	 0	0	
3	91.7	33.3	77.5	9.0	8.3	97	4.0	0.2	0.00	1	 0	0	
4	89.3	51.3	102.2	9.6	11.4	99	1.8	0.0	0.00	0	 0	0	
512	81.6	56.7	665.6	1.9	27.8	32	2.7	0.0	6.44	0	 0	0	
513	81.6	56.7	665.6	1.9	21.9	71	5.8	0.0	54.29	0	 0	0	
514	81.6	56.7	665.6	1.9	21.2	70	6.7	0.0	11.16	0	 0	0	
515	94.4	146.0	614.7	11.3	25.6	42	4.0	0.0	0.00	0	 0	0	
516	79.5	3.0	106.7	1.1	11.8	31	4.5	0.0	0.00	0	 0	0	

517 rows × 29 columns

In [11]: forest_data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 517 entries, 0 to 516
Data columns (total 29 columns):
```

# Column Non-Null Count Dtype	Data	columns (total	29 columns):					
DMC 517 non-null floated 1517 non-null int64 floated 1517 non-null int64 floated 1517 non-null floated 1517 non-null floated 1517 non-null floated 1517 non-null int64 float	#	Column	Non-Null Count	Dtype				
DMC 517 non-null floated 1517 non-null int64 floated 1517 non-null int64 floated 1517 non-null floated 1517 non-null floated 1517 non-null floated 1517 non-null int64 float								
2 DC 517 non-null floated temp 517 non-null floated wind 517 non-null int64 6 wind 517 non-null floated wind 517 non-null int64 floated wind 517 non-null int64 floated wind wind wind wind wind wind wind win								
3 ISI 517 non-null floated temp 517 non-null floated wind 517 non-null int64 6 wind 517 non-null floated 7 rain 517 non-null floated 8 area 517 non-null floated 9 dayfri 517 non-null int64 10 daymon 517 non-null int64 11 daysat 517 non-null int64 12 daysun 517 non-null int64 13 daythu 517 non-null int64 14 daytue 517 non-null int64 15 daywed 517 non-null int64 16 monthapr 517 non-null int64 17 monthaug 517 non-null int64 18 monthdec 517 non-null int64 19 monthfeb 517 non-null int64 20 monthjan 517 non-null int64 21 monthjul 517 non-null int64 22 monthjun 517 non-null int64 23 monthmar 517 non-null int64 24 monthmay 517 non-null int64 25 monthnov 517 non-null int64 26 monthoct 517 non-null int64 27 monthsep 517 non-null int64 28 size_category 517 non-null int64 28 size_category 517 non-null int64 20 domestic floated (8), int32(1), int64(20)								
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23 monthmar 517 non-null int64 24 monthmay 517 non-null int64 25 monthnov 517 non-null int64 26 monthoct 517 non-null int64 27 monthsep 517 non-null int64 28 size_category 517 non-null int32 dtypes: float64(8), int32(1), int64(20)	21	3	517 non-null	int64				
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25 monthnov 517 non-null int64 26 monthoct 517 non-null int64 27 monthsep 517 non-null int64 28 size_category 517 non-null int32 dtypes: float64(8), int32(1), int64(20)	23	monthmar	517 non-null	int64				
26 monthoct 517 non-null int64 27 monthsep 517 non-null int64 28 size_category 517 non-null int32 dtypes: float64(8), int32(1), int64(20)	24	monthmay	517 non-null	int64				
27 monthsep 517 non-null int64 28 size_category 517 non-null int32 dtypes: float64(8), int32(1), int64(20)	25	monthnov	517 non-null	int64				
28 size_category 517 non-null int32 dtypes: float64(8), int32(1), int64(20)	26	monthoct	517 non-null	int64				
dtypes: float64(8), int32(1), int64(20)	27	monthsep	517 non-null	int64				
* * * * * * * * * * * * * * * * * * * *	28	size_category	517 non-null	int32				
memory usage: 115.2 KB	dtype	es: float64(8),	int32(1), int64(20)					
	memor	ry usage: 115.2	KB					

```
In [12]: x = forest_data.iloc[:,0:-1]
y = forest_data['size_category']
```

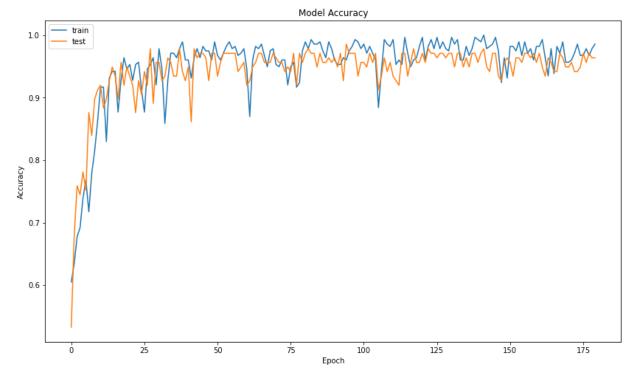
```
In [13]: x
Out[13]:
                                                                      dayfri ... monthdec
                 FFMC
                        DMC
                                DC
                                                                                          monthfeb mor
                                      ISI
                                         temp
                                                RH wind
                                                           rain
                                                                 area
              0
                  86.2
                         26.2
                               94.3
                                     5.1
                                           8.2
                                                51
                                                      6.7
                                                           0.0
                                                                 0.00
                                                                                        0
                                                                                                  0
              1
                  90.6
                         35.4
                              669.1
                                     6.7
                                           18.0
                                                33
                                                      0.9
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                                                                          0
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                                                                                                  0
              2
                  90.6
                         43.7
                              686.9
                                           14.6
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                                                                                                  0
                                     6.7
                                                      1.3
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              4
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                  89.3
                                     9.6
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                                                99
                                                      1.8
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                                                                          0
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            512
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                                     1.9
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                                                      2.7
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            513
                  81.6
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                              665.6
                                           21.9
                                                           0.0
                                                                                        0
                                                                                                  0
                                     1.9
                                                      5.8
                                                               54.29
            514
                  81.6
                         56.7
                              665.6
                                     1.9
                                          21.2
                                                70
                                                      6.7
                                                           0.0
                                                                11.16
                                                                                        0
                                                                                                  0
            515
                  94.4 146.0 614.7
                                    11.3
                                          25.6
                                                42
                                                           0.0
                                                                 0.00
                                                                                        0
                                                                                                  0
                                                      4.0
                                                                          n
            516
                  79.5
                         3.0
                             106.7
                                     1.1
                                           11.8
                                                31
                                                      4.5
                                                           0.0
                                                                 0.00
                                                                          0
                                                                                        0
                                                                                                  0
           517 rows × 28 columns
In [14]: y
Out[14]:
          0
                   1
           1
                   1
           2
                   1
           3
                   1
                   1
           4
                  . .
           512
                   0
           513
                   0
           514
                   0
           515
                   1
           516
           Name: size category, Length: 517, dtype: int32
In [15]: from sklearn.model selection import train test split
           x_train,x_test,y_train,y_test = train_test_split(x,y, test_size=0.20)
          Artificial neural network model - backpropagation
          #create model
In [16]:
           model = Sequential()
           model.add(Dense(42, input dim =28, activation = 'relu'))
           model.add(Dense(28,activation='relu'))
           model.add(Dense(1, activation='sigmoid'))
In [17]: #Complile model
```

model.compile(loss = 'binary_crossentropy', optimizer = 'adam', metrics=['accura

```
In [18]: #Fit the model
               = model.fit(x train,y train, validation split=0.33,epochs=180,batch siz
       history
       Epoch 1/180
       cy: 0.6051 - val_loss: 2.5061 - val_accuracy: 0.5328
       Epoch 2/180
       y: 0.6341 - val_loss: 1.3441 - val_accuracy: 0.6788
       Epoch 3/180
       28/28 [============== ] - 0s 8ms/step - loss: 1.3318 - accurac
       y: 0.6775 - val loss: 2.0934 - val accuracy: 0.7591
       Epoch 4/180
       28/28 [============= ] - 0s 7ms/step - loss: 2.1458 - accurac
       y: 0.6920 - val_loss: 0.8428 - val_accuracy: 0.7445
       Epoch 5/180
       28/28 [============== ] - 0s 7ms/step - loss: 0.8388 - accurac
       y: 0.7391 - val_loss: 0.6515 - val_accuracy: 0.7810
       Epoch 6/180
       y: 0.7681 - val_loss: 0.6501 - val_accuracy: 0.7518
       Epoch 7/180
       20/20 5
                                                        0 0000
In [24]: #evalute the model
       score = model.evaluate(x,v)
       print("%s; %.2f%%" % (model.metrics names[1], scores[1]*100))
       17/17 [=============== ] - 0s 3ms/step - loss: 0.0913 - accuracy:
       0.9691
       accuracy; 96.91%
In [25]: # Visualizing training history
       # list all data in history
       history.history.keys()
Out[25]: dict keys(['loss', 'accuracy', 'val loss', 'val accuracy'])
```

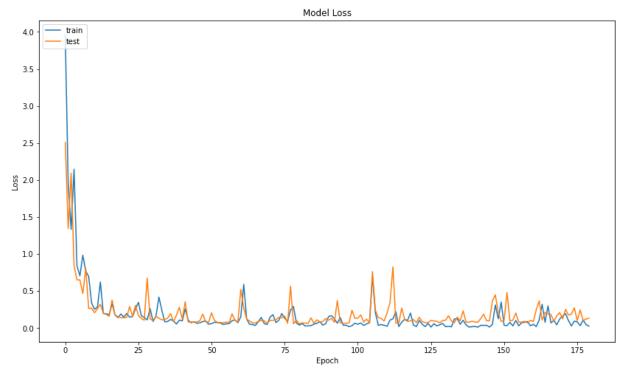
```
In [26]: # summarize history for accuracy
from matplotlib import pyplot as plt

plt.figure(figsize=(14,8))
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model Accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(['train','test'], loc='upper left')
plt.show()
```



```
In [27]: # summarize history for Loss

plt.figure(figsize=(14,8))
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model Loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



hyper parameter tuning

```
In [28]: X =forest_data.iloc[:,0:-1]
Y =forest_data['size_category']

In [31]: #standardization
from sklearn.preprocessing import StandardScaler
a = StandardScaler()
a.fit(X)
X_standardized = a.transform(X)
```

In [32]: pd.DataFrame(X_standardized).describe().T

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())()	I スノー	١ ٠
out	J Z	

	count	mean	std	min	25%	50%	75%	max
0	517.0	-1.754024e-15	1.000969	-13.045818	-0.080635	0.173229	0.408960	1.007353
1	517.0	3.070830e-16	1.000969	-1.715608	-0.660665	-0.040203	0.492739	2.819865
2	517.0	7.387171e-17	1.000969	-2.179108	-0.444828	0.469119	0.669663	1.261610
3	517.0	-3.865380e-17	1.000969	-1.980578	-0.553595	-0.136477	0.390409	10.335381
4	517.0	2.005703e-16	1.000969	-2.876943	-0.584238	0.070821	0.674164	2.484195
5	517.0	3.362881e-16	1.000969	-1.796637	-0.692456	-0.140366	0.534411	3.417549
6	517.0	-2.676776e-16	1.000969	-2.021098	-0.736124	-0.009834	0.492982	3.007063
7	517.0	-2.841054e-16	1.000969	-0.073268	-0.073268	-0.073268	-0.073268	21.572284
8	517.0	-1.274502e-16	1.000969	-0.202020	-0.202020	-0.193843	-0.098709	16.951110
9	517.0	4.874674e-17	1.000969	-0.443576	-0.443576	-0.443576	-0.443576	2.254407
10	517.0	-1.868267e-16	1.000969	-0.408709	-0.408709	-0.408709	-0.408709	2.446730
11	517.0	-2.238699e-16	1.000969	-0.440449	-0.440449	-0.440449	-0.440449	2.270410
12	517.0	-6.098711e-17	1.000969	-0.474467	-0.474467	-0.474467	-0.474467	2.107630
13	517.0	-1.004999e-16	1.000969	-0.365748	-0.365748	-0.365748	-0.365748	2.734120
14	517.0	2.405125e-17	1.000969	-0.375873	-0.375873	-0.375873	-0.375873	2.660475
15	517.0	-3.843906e-17	1.000969	-0.341512	-0.341512	-0.341512	-0.341512	2.928152
16	517.0	-1.344293e-16	1.000969	-0.133103	-0.133103	-0.133103	-0.133103	7.512952
17	517.0	2.473843e-16	1.000969	-0.743339	-0.743339	-0.743339	1.345282	1.345282
18	517.0	7.179943e-16	1.000969	-0.133103	-0.133103	-0.133103	-0.133103	7.512952
19	517.0	-1.933764e-16	1.000969	-0.200603	-0.200603	-0.200603	-0.200603	4.984977
20	517.0	-2.260174e-17	1.000969	-0.062318	-0.062318	-0.062318	-0.062318	16.046807
21	517.0	1.352883e-17	1.000969	-0.256865	-0.256865	-0.256865	-0.256865	3.893103
22	517.0	1.169277e-16	1.000969	-0.184391	-0.184391	-0.184391	-0.184391	5.423261
23	517.0	2.265542e-16	1.000969	-0.341512	-0.341512	-0.341512	-0.341512	2.928152
24	517.0	-2.596515e-16	1.000969	-0.062318	-0.062318	-0.062318	-0.062318	16.046807
25	517.0	1.443075e-16	1.000969	-0.044023	-0.044023	-0.044023	-0.044023	22.715633
26	517.0	6.253326e-16	1.000969	-0.172860	-0.172860	-0.172860	-0.172860	5.785038
27	517.0	4.024290e-16	1.000969	-0.706081	-0.706081	-0.706081	1.416268	1.416268

Tuning of hyperparameters - Batch size and Epochs

In [35]: !pip install keras

Requirement already satisfied: keras in e:\anaconda\lib\site-packages (2.7.0)

```
In [36]: from sklearn.model_selection import GridSearchCV
    from keras.models import Sequential
    from keras.layers import Dense
    from keras.wrappers.scikit_learn import KerasClassifier
    from tensorflow.keras.optimizers import Adam
```

```
In [37]: # create model
def create_model():
    model = Sequential()
    model.add(Dense(12, input_dim=28, kernel_initializer='uniform', activation='r
    model.add(Dense(8, kernel_initializer='uniform', activation='relu'))
    model.add(Dense(1, kernel_initializer='uniform', activation='sigmoid'))

adam=Adam(lr=0.01)
    model.compile(loss='binary_crossentropy', optimizer=adam, metrics=['accuracy'
    return model
```

```
In [38]: #create the model
       model = KerasClassifier(build fn= create model, verbose = 0)
       #Define the grid search parameters
       batch size = [10, 20, 40]
       epochs = [10,50,100]
       # Make a dictionary of thr grid of the search parameters
       param grid = dict(batch size = batch size,epochs = epochs)
       # build and fit the GridSearchCV
       grid = GridSearchCV(estimator = model,param_grid= param_grid, verbose = 10)
       grid result = grid.fit(X standardized,Y)
       Fitting 5 folds for each of 9 candidates, totalling 45 fits
       [CV 1/5; 1/9] START batch_size=10, epochs=1
       0..........
       [CV 1/5; 1/9] END .....batch size=10, epochs=10; total time=
                                                                      5.9
       [CV 2/5; 1/9] START batch_size=10, epochs=1
       0...........
       [CV 2/5; 1/9] END .....batch size=10, epochs=10; total time=
                                                                      5.2
       [CV 3/5; 1/9] START batch size=10, epochs=1
       0..........
       [CV 3/5; 1/9] END ......batch_size=10, epochs=10; total time=
                                                                      5.0
       [CV 4/5; 1/9] START batch size=10, epochs=1
       0.........
       [CV 4/5; 1/9] END ......batch size=10, epochs=10; total time=
                                                                      5.0
       [CV 5/5; 1/9] START batch_size=10, epochs=1
       0...........
       [CV 5/5; 1/9] END ......batch size=10, epochs=10; total time=
                                                                      5.0
       [CV 1/5; 2/9] START batch_size=10, epochs=5
       0..........
       [CV 1/5; 2/9] END ......batch_size=10, epochs=50; total time= 11.9
       [CV 2/5; 2/9] START batch size=10, epochs=5
       0...........
       [CV 2/5; 2/9] END .....batch_size=10, epochs=50; total time= 11.9
       [CV 3/5; 2/9] START batch size=10, epochs=5
       0...........
       [CV 3/5; 2/9] END .....batch_size=10, epochs=50; total time= 11.8
       [CV 4/5; 2/9] START batch size=10, epochs=5
       0...........
       [CV 4/5; 2/9] END .....batch size=10, epochs=50; total time= 11.8
       [CV 5/5; 2/9] START batch_size=10, epochs=5
       0..........
       [CV 5/5; 2/9] END .....batch size=10, epochs=50; total time= 11.8
       [CV 1/5; 3/9] START batch size=10, epochs=10
       0..........
       [CV 1/5; 3/9] END .....batch_size=10, epochs=100; total time= 21.6
```

```
[CV 2/5; 3/9] START batch size=10, epochs=10
0......
[CV 2/5; 3/9] END ......batch size=10, epochs=100; total time= 20.5
[CV 3/5; 3/9] START batch size=10, epochs=10
0..........
[CV 3/5; 3/9] END ......batch size=10, epochs=100; total time= 20.6
[CV 4/5; 3/9] START batch_size=10, epochs=10
[CV 4/5; 3/9] END .....batch size=10, epochs=100; total time= 20.3
[CV 5/5; 3/9] START batch size=10, epochs=10
0...........
[CV 5/5; 3/9] END ......batch_size=10, epochs=100; total time=
[CV 1/5; 4/9] START batch size=20, epochs=1
0..........
[CV 1/5; 4/9] END .....batch size=20, epochs=10; total time=
                                                            4.2
[CV 2/5; 4/9] START batch_size=20, epochs=1
0...........
[CV 2/5; 4/9] END ......batch size=20, epochs=10; total time=
                                                            4.3
[CV 3/5; 4/9] START batch_size=20, epochs=1
0..........
[CV 3/5; 4/9] END .....batch_size=20, epochs=10; total time=
                                                            4.2
[CV 4/5; 4/9] START batch size=20, epochs=1
0.......
[CV 4/5; 4/9] END .....batch_size=20, epochs=10; total time=
                                                            4.2
[CV 5/5; 4/9] START batch_size=20, epochs=1
[CV 5/5; 4/9] END ......batch size=20, epochs=10; total time=
                                                            4.2
[CV 1/5; 5/9] START batch_size=20, epochs=5
0...........
[CV 1/5; 5/9] END ......batch_size=20, epochs=50; total time=
                                                            7.7
[CV 2/5; 5/9] START batch size=20, epochs=5
0..........
[CV 2/5; 5/9] END .....batch_size=20, epochs=50; total time=
                                                            7.7
[CV 3/5; 5/9] START batch size=20, epochs=5
[CV 3/5; 5/9] END .....batch_size=20, epochs=50; total time=
                                                            8.7
[CV 4/5; 5/9] START batch_size=20, epochs=5
0......
[CV 4/5; 5/9] END .....batch_size=20, epochs=50; total time=
                                                            7.6
[CV 5/5; 5/9] START batch_size=20, epochs=5
   [CV 5/5; 5/9] END ......batch_size=20, epochs=50; total time=
                                                            7.6
[CV 1/5; 6/9] START batch size=20, epochs=10
```

```
0...........
[CV 1/5; 6/9] END .....batch_size=20, epochs=100; total time= 12.1
[CV 2/5; 6/9] START batch size=20, epochs=10
0......
[CV 2/5; 6/9] END ......batch_size=20, epochs=100; total time= 12.0
[CV 3/5; 6/9] START batch_size=20, epochs=10
0......
[CV 3/5; 6/9] END ......batch_size=20, epochs=100; total time= 12.5
[CV 4/5; 6/9] START batch_size=20, epochs=10
0...........
[CV 4/5; 6/9] END ......batch_size=20, epochs=100; total time= 12.1
[CV 5/5; 6/9] START batch_size=20, epochs=10
0...........
[CV 5/5; 6/9] END .....batch_size=20, epochs=100; total time= 12.0
[CV 1/5; 7/9] START batch_size=40, epochs=1
0..........
[CV 1/5; 7/9] END .....batch_size=40, epochs=10; total time=
                                                                   3.9
[CV 2/5; 7/9] START batch_size=40, epochs=1
0.....
[CV 2/5; 7/9] END ......batch_size=40, epochs=10; total time=
                                                                   3.8
[CV 3/5; 7/9] START batch size=40, epochs=1
0...........
[CV 3/5; 7/9] END .....batch_size=40, epochs=10; total time=
                                                                   3.8
[CV 4/5; 7/9] START batch size=40, epochs=1
0.........
WARNING:tensorflow:5 out of the last 16 calls to <function Model.make test func
tion.<locals>.test function at 0x000001FA0DC29B80> triggered tf.function retrac
ing. Tracing is expensive and the excessive number of tracings could be due to
(1) creating @tf.function repeatedly in a loop, (2) passing tensors with differ
ent shapes, (3) passing Python objects instead of tensors. For (1), please defi
ne your @tf.function outside of the loop. For (2), @tf.function has experimenta
1 relax shapes=True option that relaxes argument shapes that can avoid unnecess
ary retracing. For (3), please refer to https://www.tensorflow.org/guide/functi
on#controlling retracing (https://www.tensorflow.org/guide/function#controlling
_retracing) and https://www.tensorflow.org/api_docs/python/tf/function (http
s://www.tensorflow.org/api docs/python/tf/function) for more details.
[CV 4/5; 7/9] END .....batch size=40, epochs=10; total time=
                                                                   3.8
[CV 5/5; 7/9] START batch_size=40, epochs=1
0..........
WARNING:tensorflow:5 out of the last 13 calls to <function Model.make_test_func
tion.<locals>.test_function at 0x000001FA0DB23D30> triggered tf.function retrac
ing. Tracing is expensive and the excessive number of tracings could be due to
(1) creating @tf.function repeatedly in a loop, (2) passing tensors with diffe
rent shapes, (3) passing Python objects instead of tensors. For (1), please def
ine your @tf.function outside of the loop. For (2), @tf.function has experiment
al relax shapes=True option that relaxes argument shapes that can avoid unneces
sary retracing. For (3), please refer to https://www.tensorflow.org/guide/funct
ion#controlling retracing (https://www.tensorflow.org/guide/function#controllin
```

```
g retracing) and https://www.tensorflow.org/api docs/python/tf/function (http
s://www.tensorflow.org/api_docs/python/tf/function) for more details.
[CV 5/5; 7/9] END .....batch_size=40, epochs=10; total time=
                                                            3.8
[CV 1/5; 8/9] START batch size=40, epochs=5
0......
[CV 1/5; 8/9] END .....batch size=40, epochs=50; total time=
                                                            6.7
[CV 2/5; 8/9] START batch_size=40, epochs=5
0...........
[CV 2/5; 8/9] END .....batch size=40, epochs=50; total time=
                                                            5.7
[CV 3/5; 8/9] START batch size=40, epochs=5
0...........
[CV 3/5; 8/9] END .....batch_size=40, epochs=50; total time=
                                                            5.7
[CV 4/5; 8/9] START batch size=40, epochs=5
0..........
[CV 4/5; 8/9] END .....batch size=40, epochs=50; total time=
                                                            5.8
[CV 5/5; 8/9] START batch size=40, epochs=5
0..........
[CV 5/5; 8/9] END .....batch size=40, epochs=50; total time=
                                                            6.1
[CV 1/5; 9/9] START batch_size=40, epochs=10
0...........
[CV 1/5; 9/9] END ......batch size=40, epochs=100; total time=
                                                            8.1
[CV 2/5; 9/9] START batch size=40, epochs=10
0.....
[CV 2/5; 9/9] END ......batch size=40, epochs=100; total time=
                                                            8.2
[CV 3/5; 9/9] START batch size=40, epochs=10
0......
[CV 3/5; 9/9] END ......batch_size=40, epochs=100; total time=
                                                            8.2
[CV 4/5; 9/9] START batch_size=40, epochs=10
0.......
[CV 4/5; 9/9] END ......batch size=40, epochs=100; total time=
                                                            8.2
[CV 5/5; 9/9] START batch_size=40, epochs=10
0.........
[CV 5/5; 9/9] END ......batch size=40, epochs=100; total time=
                                                            8.2
```

```
In [39]: # summarize the results
         print('Best : {}, using {}'.format(grid_result.best_score_,grid_result.best_paran
         means = grid result.cv results ['mean test score']
         stds = grid result.cv results ['std test score']
         # Summarize the results
         params = grid_result.cv_results_['params']
         for mean, stdev, param in zip(means, stds, params ):
             print('{},{} with: {}'.format(mean, stdev, param))
         Best: 0.9148058295249939, using {'batch size': 10, 'epochs': 100}
         0.8645071029663086,0.04543507484343193 with: {'batch size': 10, 'epochs': 10}
         0.9109783411026001,0.0500215105010093 with: {'batch_size': 10, 'epochs': 50}
         0.9148058295249939,0.04465227790273617 with: {'batch size': 10, 'epochs': 100}
         0.8547796845436096,0.07583689529403034 with: {'batch size': 20, 'epochs': 10}
         0.9070575118064881,0.04912849167571362 with: {'batch size': 20, 'epochs': 50}
         0.8954816937446595,0.05699809270164309 with: {'batch size': 20, 'epochs': 100}
         0.7635922431945801,0.15143452693911913 with: {'batch size': 40, 'epochs': 10}
         0.9109783411026001,0.04412957120431605 with: {'batch_size': 40, 'epochs': 50}
         0.9051157593727112,0.04906203215779241 with: {'batch size': 40, 'epochs': 100}
```

Tuning of Hyperparameters:- Learning rate and Drop out rate

```
In [40]: from keras.layers import Dropout
         # Defining the model
         def create model(learning rate, dropout rate):
             model = Sequential()
             model.add(Dense(8,input dim = 28,kernel initializer = 'normal',activation =
             model.add(Dropout(dropout rate))
             model.add(Dense(4,input dim = 28,kernel initializer = 'normal',activation =
             model.add(Dropout(dropout rate))
             model.add(Dense(1,activation = 'sigmoid'))
             adam = Adam(lr = learning rate)
             model.compile(loss = 'binary crossentropy',optimizer = adam,metrics = ['accur
             return model
         # Create the model
         model = KerasClassifier(build fn = create model, verbose = 0, batch size = 40, epoch
         # Define the grid search parameters
         learning rate = [0.001, 0.01, 0.1]
         dropout_rate = [0.0, 0.1, 0.2]
         # Make a dictionary of the grid search parameters
         param_grids = dict(learning_rate = learning_rate, dropout_rate = dropout_rate)
         # Build and fit the GridSearchCV
         grid = GridSearchCV(estimator = model,param grid = param grids,verbose = 10)
         grid result = grid.fit(X standardized,Y)
         Fitting 5 folds for each of 9 candidates, totalling 45 fits
         [CV 1/5; 1/9] START dropout rate=0.0, learning rate=0.00
         1........
         [CV 1/5; 1/9] END .....dropout rate=0.0, learning rate=0.001; total time=
         [CV 2/5; 1/9] START dropout rate=0.0, learning rate=0.00
         [CV 2/5; 1/9] END .....dropout rate=0.0, learning rate=0.001; total time=
         3.9s
         [CV 3/5; 1/9] START dropout_rate=0.0, learning_rate=0.00
         [CV 3/5; 1/9] END .....dropout rate=0.0, learning rate=0.001; total time=
         3.8s
         [CV 4/5; 1/9] START dropout rate=0.0, learning rate=0.00
         1......
         [CV 4/5; 1/9] END .....dropout_rate=0.0, learning_rate=0.001; total time=
         3.8s
         [CV 5/5; 1/9] START dropout rate=0.0, learning rate=0.00
         1.....
```

```
In [41]: # Summarize the results
         print('Best : {}, using {}'.format(grid_result.best_score_,grid_result.best_paran
         means = grid_result.cv_results_['mean_test_score']
         stds = grid result.cv results ['std test score']
         params = grid_result.cv_results_['params']
         for mean, stdev, param in zip(means, stds, params):
           print('{},{} with: {}'.format(mean, stdev, param))
         Best : 0.7714152336120605, using {'dropout_rate': 0.0, 'learning_rate': 0.01}
         0.728659451007843,0.1510055827692834 with: {'dropout rate': 0.0, 'learning rat
         e': 0.001}
         0.7714152336120605,0.14136657433344296 with: {'dropout_rate': 0.0, 'learning_ra
         te': 0.01}
         0.744772219657898,0.056601793865556374 with: {'dropout rate': 0.0, 'learning ra
         te': 0.1}
         0.7305825233459473,0.15435061319000673 with: {'dropout rate': 0.1, 'learning ra
         te': 0.001}
         0.7577669858932495,0.1485473087246425 with: {'dropout rate': 0.1, 'learning rat
         e': 0.01}
         0.7305825233459473,0.15435061319000673 with: {'dropout rate': 0.1, 'learning ra
         te': 0.1}
         0.7305825233459473,0.15435061319000673 with: {'dropout rate': 0.2, 'learning ra
         te': 0.001}
         0.75,0.15082954673425533 with: {'dropout_rate': 0.2, 'learning_rate': 0.01}
         0.7383495092391967,0.15354239422184465 with: {'dropout_rate': 0.2, 'learning_ra
         te': 0.1}
```

uning of Hyperparameters:- Activation Function and Kernel Initializer

```
In [42]: from keras.layers import Dropout
         # Defining the model
         def create model(activation function,init):
             model = Sequential()
             model.add(Dense(8,input dim = 28,kernel initializer = init,activation = activ
             model.add(Dropout(0.1))
             model.add(Dense(4,input dim = 28,kernel initializer = init,activation = activ
             model.add(Dropout(0.1))
             model.add(Dense(1,activation = 'sigmoid'))
             adam = Adam(lr = 0.001)
             model.compile(loss = 'binary_crossentropy',optimizer = adam,metrics = ['accur
             return model
         # Create the model
         model = KerasClassifier(build fn = create model, verbose = 0, batch size = 40, epoc∤
         # Define the grid search parameters
         activation function = ['softmax', 'relu', 'tanh', 'linear']
         init = ['uniform', 'normal', 'zero']
         # Make a dictionary of the grid search parameters
         param grids = dict(activation function = activation function,init = init)
         # Build and fit the GridSearchCV
         grid = GridSearchCV(estimator = model,param grid = param grids,verbose = 10)
         grid result = grid.fit(X standardized,Y)
         Fitting 5 folds for each of 12 candidates, totalling 60 fits
         [CV 1/5; 1/12] START activation_function=softmax, init=unifor
         [CV 1/5; 1/12] END activation function=softmax, init=uniform; total time=
         5.3s
         [CV 2/5; 1/12] START activation function=softmax, init=unifor
         [CV 2/5; 1/12] END activation function=softmax, init=uniform; total time=
         4.2s
         [CV 3/5; 1/12] START activation function=softmax, init=unifor
         m......
         [CV 3/5; 1/12] END activation_function=softmax, init=uniform; total time=
         4.3s
         [CV 4/5; 1/12] START activation function=softmax, init=unifor
         [CV 4/5; 1/12] END activation function=softmax, init=uniform; total time=
         [CV 5/5; 1/12] START activation_function=softmax, init=unifor
         FOV E/E 4/401 END
                              . .
```

```
In [43]: # Summarize the results
         print('Best : {}, using {}'.format(grid_result.best_score_,grid_result.best_paran
         means = grid result.cv results ['mean test score']
         stds = grid result.cv results ['std test score']
         params = grid result.cv results ['params']
         for mean, stdev, param in zip(means, stds, params):
           print('{},{} with: {}'.format(mean, stdev, param))
         Best : 0.7442120909690857, using {'activation_function': 'linear', 'init': 'uni
         form'}
         0.7305825233459473,0.15435061319000673 with: {'activation function': 'softmax',
         'init': 'uniform'}
         0.5305825233459472,0.2757845556417363 with: {'activation function': 'softmax',
          'init': 'normal'}
         0.7305825233459473,0.15435061319000673 with: {'activation function': 'softmax',
          'init': 'zero'}
         0.7325242757797241,0.15178268966445949 with: {'activation function': 'relu', 'i
         nit': 'uniform'}
         0.7325242757797241,0.15178268966445949 with: {'activation function': 'relu', 'i
         nit': 'normal'}
         0.7305825233459473,0.15435061319000673 with: {'activation function': 'relu', 'i
         nit': 'zero'}
         0.7383868575096131,0.1343536254145011 with: {'activation function': 'tanh', 'in
         it': 'uniform'}
         0.7267923831939698,0.13622830288028945 with: {'activation function': 'tanh', 'i
         nit': 'normal'}
         0.7305825233459473,0.15435061319000673 with: {'activation function': 'tanh', 'i
         nit': 'zero'}
         0.7442120909690857,0.1263171221477866 with: {'activation function': 'linear',
         'init': 'uniform'}
         0.7383495211601258,0.14611891933450738 with: {'activation_function': 'linear',
         'init': 'normal'}
         0.7305825233459473,0.15435061319000673 with: {'activation function': 'linear',
         'init': 'zero'}
```

Tuning of Hyperparameter :-Number of Neurons in activation layer

```
In [44]: # Defining the model
        def create model(neuron1, neuron2):
           model = Sequential()
           model.add(Dense(neuron1,input dim = 28,kernel initializer = 'uniform',activat
           model.add(Dropout(0.1))
           model.add(Dense(neuron2,input_dim = neuron1,kernel_initializer = 'uniform',ad
           model.add(Dropout(0.1))
           model.add(Dense(1,activation = 'sigmoid'))
           adam = Adam(lr = 0.001)
           model.compile(loss = 'binary_crossentropy',optimizer = adam,metrics = ['accur
           return model
        # Create the model
        model = KerasClassifier(build fn = create model, verbose = 0, batch size = 40, epoch
        # Define the grid search parameters
        neuron1 = [4,8,16]
        neuron2 = [2,4,8]
        # Make a dictionary of the grid search parameters
        param grids = dict(neuron1 = neuron1, neuron2 = neuron2)
       # Build and fit the GridSearchCV
        grid = GridSearchCV(estimator = model,param grid = param grids,verbose = 10)
        grid_result = grid.fit(X_standardized,Y)
        Fitting 5 folds for each of 9 candidates, totalling 45 fits
        [CV 1/5; 1/9] START neuron1=4, neuron2=
        2............
        [CV 1/5; 1/9] END .....neuron1=4, neuron2=2; total time=
                                                                        4.1
        [CV 2/5; 1/9] START neuron1=4, neuron2=
        [CV 2/5; 1/9] END .....neuron1=4, neuron2=2; total time=
                                                                        4.3
        [CV 3/5; 1/9] START neuron1=4, neuron2=
        2.....
        [CV 3/5; 1/9] END .....neuron1=4, neuron2=2; total time=
                                                                        4.1
        [CV 4/5; 1/9] START neuron1=4, neuron2=
        2.....
        [CV 4/5; 1/9] END .....neuron1=4, neuron2=2; total time=
                                                                        4.1
        [CV 5/5; 1/9] START neuron1=4, neuron2=
        [CV 5/5; 1/9] END .....neuron1=4, neuron2=2; total time=
                                                                        4.3
        [CV 1/5; 2/9] START neuron1=4, neuron2=
        4............
        [CV 1/5; 2/9] END .....neuron1=4, neuron2=4; total time=
                                                                        4.2
```

```
[CV 2/5; 2/9] START neuron1=4, neuron2=
4...........
[CV 2/5; 2/9] END .....neuron1=4, neuron2=4; total time=
                                                      4.1
[CV 3/5; 2/9] START neuron1=4, neuron2=
4......
[CV 3/5; 2/9] END .....neuron1=4, neuron2=4; total time=
                                                      5.1
[CV 4/5; 2/9] START neuron1=4, neuron2=
   [CV 4/5; 2/9] END .....neuron1=4, neuron2=4; total time=
                                                      4.1
[CV 5/5; 2/9] START neuron1=4, neuron2=
4............
[CV 5/5; 2/9] END .....neuron1=4, neuron2=4; total time=
                                                      4.3
[CV 1/5; 3/9] START neuron1=4, neuron2=
8......
[CV 1/5; 3/9] END .....neuron1=4, neuron2=8; total time=
                                                      4.3
[CV 2/5; 3/9] START neuron1=4, neuron2=
8...........
[CV 2/5; 3/9] END .....neuron1=4, neuron2=8; total time=
                                                      4.6
[CV 3/5; 3/9] START neuron1=4, neuron2=
[CV 3/5; 3/9] END .....neuron1=4, neuron2=8; total time=
                                                      4.3
[CV 4/5; 3/9] START neuron1=4, neuron2=
8......
[CV 4/5; 3/9] END .....neuron1=4, neuron2=8; total time=
                                                      4.3
[CV 5/5; 3/9] START neuron1=4, neuron2=
         [CV 5/5; 3/9] END .....neuron1=4, neuron2=8; total time=
                                                      4.1
[CV 1/5; 4/9] START neuron1=8, neuron2=
2.............
[CV 1/5; 4/9] END .....neuron1=8, neuron2=2; total time=
                                                      4.1
[CV 2/5; 4/9] START neuron1=8, neuron2=
2.............
[CV 2/5; 4/9] END .....neuron1=8, neuron2=2; total time=
                                                      4.1
[CV 3/5; 4/9] START neuron1=8, neuron2=
2.............
[CV 3/5; 4/9] END .....neuron1=8, neuron2=2; total time=
                                                      4.1
[CV 4/5; 4/9] START neuron1=8, neuron2=
2............
[CV 4/5; 4/9] END .....neuron1=8, neuron2=2; total time=
                                                      5.0
[CV 5/5; 4/9] START neuron1=8, neuron2=
      [CV 5/5; 4/9] END .....neuron1=8, neuron2=2; total time=
                                                      4.1
[CV 1/5; 5/9] START neuron1=8, neuron2=
```

```
4............
[CV 1/5; 5/9] END .....neuron1=8, neuron2=4; total time=
                                                     4.1
[CV 2/5; 5/9] START neuron1=8, neuron2=
4......
[CV 2/5; 5/9] END .....neuron1=8, neuron2=4; total time=
                                                     4.1
[CV 3/5; 5/9] START neuron1=8, neuron2=
4...........
[CV 3/5; 5/9] END .....neuron1=8, neuron2=4; total time=
                                                     4.1
[CV 4/5; 5/9] START neuron1=8, neuron2=
4...........
[CV 4/5; 5/9] END .....neuron1=8, neuron2=4; total time=
                                                     4.1
[CV 5/5; 5/9] START neuron1=8, neuron2=
4............
[CV 5/5; 5/9] END .....neuron1=8, neuron2=4; total time=
                                                     4.1
[CV 1/5; 6/9] START neuron1=8, neuron2=
8......
[CV 1/5; 6/9] END .....neuron1=8, neuron2=8; total time=
                                                     4.1
[CV 2/5; 6/9] START neuron1=8, neuron2=
8.....
[CV 2/5; 6/9] END .....neuron1=8, neuron2=8; total time=
                                                     4.2
[CV 3/5; 6/9] START neuron1=8, neuron2=
8..........
[CV 3/5; 6/9] END .....neuron1=8, neuron2=8; total time=
                                                     4.1
[CV 4/5; 6/9] START neuron1=8, neuron2=
8..........
[CV 4/5; 6/9] END .....neuron1=8, neuron2=8; total time=
                                                     4.1
[CV 5/5; 6/9] START neuron1=8, neuron2=
8.....
[CV 5/5; 6/9] END .....neuron1=8, neuron2=8; total time=
                                                     5.0
[CV 1/5; 7/9] START neuron1=16, neuron2=
2.............
[CV 1/5; 7/9] END .....neuron1=16, neuron2=2; total time=
                                                     4.1
[CV 2/5; 7/9] START neuron1=16, neuron2=
[CV 2/5; 7/9] END .....neuron1=16, neuron2=2; total time=
                                                     4.1
[CV 3/5; 7/9] START neuron1=16, neuron2=
2.............
[CV 3/5; 7/9] END .....neuron1=16, neuron2=2; total time=
                                                     4.1
[CV 4/5; 7/9] START neuron1=16, neuron2=
2.............
[CV 4/5; 7/9] END .....neuron1=16, neuron2=2; total time=
                                                     4.3
[CV 5/5; 7/9] START neuron1=16, neuron2=
```

```
[CV 5/5; 7/9] END .....neuron1=16, neuron2=2; total time=
                                                       4.3
[CV 1/5; 8/9] START neuron1=16, neuron2=
4............
[CV 1/5; 8/9] END .....neuron1=16, neuron2=4; total time=
                                                       4.3
[CV 2/5; 8/9] START neuron1=16, neuron2=
4...........
[CV 2/5; 8/9] END .....neuron1=16, neuron2=4; total time=
                                                       4.3
[CV 3/5; 8/9] START neuron1=16, neuron2=
4.....
[CV 3/5; 8/9] END .....neuron1=16, neuron2=4; total time=
                                                       4.2
[CV 4/5; 8/9] START neuron1=16, neuron2=
4............
[CV 4/5; 8/9] END .....neuron1=16, neuron2=4; total time=
                                                       4.2
[CV 5/5; 8/9] START neuron1=16, neuron2=
4..........
[CV 5/5; 8/9] END .....neuron1=16, neuron2=4; total time=
                                                       4.1
[CV 1/5; 9/9] START neuron1=16, neuron2=
8......
[CV 1/5; 9/9] END .....neuron1=16, neuron2=8; total time=
                                                       5.0
[CV 2/5; 9/9] START neuron1=16, neuron2=
8...........
[CV 2/5; 9/9] END .....neuron1=16, neuron2=8; total time=
                                                       4.1
[CV 3/5; 9/9] START neuron1=16, neuron2=
8..........
[CV 3/5; 9/9] END .....neuron1=16, neuron2=8; total time=
                                                       4.1
[CV 4/5; 9/9] START neuron1=16, neuron2=
8......
[CV 4/5; 9/9] END .....neuron1=16, neuron2=8; total time=
                                                       4.1
[CV 5/5; 9/9] START neuron1=16, neuron2=
8......
                                                       4.3
[CV 5/5; 9/9] END .....neuron1=16, neuron2=8; total time=
```

```
In [45]: # Summarize the results
         print('Best : {}, using {}'.format(grid_result.best_score_,grid_result.best_paran
         means = grid result.cv results ['mean test score']
         stds = grid result.cv results ['std test score']
         params = grid_result.cv_results_['params']
         for mean, stdev, param in zip(means, stds, params):
           print('{},{} with: {}'.format(mean, stdev, param))
         Best : 0.7597460746765137, using {'neuron1': 8, 'neuron2': 2}
         0.7519417405128479,0.13090965185428644 with: {'neuron1': 4, 'neuron2': 2}
         0.7442681074142456,0.11234521971869296 with: {'neuron1': 4, 'neuron2': 4}
         0.7481329202651977,0.11386488121195477 with: {'neuron1': 4, 'neuron2': 8}
         0.7597460746765137,0.1141448059440758 with: {'neuron1': 8, 'neuron2': 2}
         0.7365011215209961,0.12116406906444306 with: {'neuron1': 8, 'neuron2': 4}
         0.7422890305519104,0.12394596970524079 with: {'neuron1': 8, 'neuron2': 8}
         0.7423450469970703,0.11163950404768495 with: {'neuron1': 16, 'neuron2': 2}
         0.7443054556846619,0.10033954316259028 with: {'neuron1': 16, 'neuron2': 4}
         0.7481702923774719,0.10204383026701777 with: {'neuron1': 16, 'neuron2': 8}
```

Training model with optimum values of Hyperparameters

```
In [46]: from sklearn.metrics import classification report, accuracy score
         # Defining the model
         def create model():
             model = Sequential()
             model.add(Dense(16,input dim = 28,kernel initializer = 'uniform',activation =
             model.add(Dropout(0.1))
             model.add(Dense(4,input_dim = 16,kernel_initializer = 'uniform',activation =
             model.add(Dropout(0.1))
             model.add(Dense(1,activation = 'sigmoid'))
             adam = Adam(1r = 0.001) #sqd = SGD(lr=learning rate, momentum=momentum, decay
             model.compile(loss = 'binary crossentropy',optimizer = adam,metrics = ['accur
             return model
         # Create the model
         model = KerasClassifier(build fn = create model, verbose = 0, batch size = 40, epoch
         # Fitting the model
         model.fit(X standardized,Y)
         # Predicting using trained model
         y predict = model.predict(X standardized)
         # Printing the metrics
         print(accuracy_score(Y,y_predict))
```

0.7794970986460348

Hyperparameters all at once-

• The hyperparameter optimization was carried out by taking 2 hyperparameters at once. We may have missed the best values. The performance can be further improved by finding the optimum values of hyperparameters all at once given by the code snippet below.*

```
In [47]: def create_model(learning_rate, dropout_rate, activation_function, init, neuron1, neur
             model = Sequential()
             model.add(Dense(neuron1,input_dim = 28,kernel_initializer = init,activation =
             model.add(Dropout(dropout rate))
             model.add(Dense(neuron2,input dim = neuron1,kernel initializer = init,activat
             model.add(Dropout(dropout rate))
             model.add(Dense(1,activation = 'sigmoid'))
             adam = Adam(lr = learning_rate)
             model.compile(loss = 'binary crossentropy',optimizer = adam,metrics = ['accur
             return model
In [48]: # Create the model
         model = KerasClassifier(build fn = create model, verbose = 0)
In [49]: # Define the grid search parameters
         batch size = [10, 20, 40]
         epochs = [10,50,100]
         learning rate = [0.001, 0.01, 0.1]
         dropout rate = [0.0, 0.1, 0.2]
         activation_function = ['softmax','relu','tanh','linear']
         init = ['uniform', 'normal', 'zero']
         neuron1 = [4,8,16]
         neuron2 = [2,4,8]
In [50]: # Make a dictionary of the grid search parameters
         param grids = dict(batch size = batch size,epochs = epochs,learning rate = learni
                             activation function = activation function, init = init, neuron1
```

```
In [51]: # Build and fit the GridSearchCV

grid = GridSearchCV(estimator = model,param_grid = param_grids,verbose = 10)
grid_result = grid.fit(X_standardized,Y)

# Summarize the results
print('Best : {}, using {}'.format(grid_result.best_score_,grid_result.best_param means = grid_result.cv_results_['mean_test_score']
stds = grid_result.cv_results_['std_test_score']
params = grid_result.cv_results_['params']
for mean, stdev, param in zip(means, stds, params):
    print('{},{} with: {}'.format(mean, stdev, param))
```

Fitting 5 folds for each of 8748 candidates, totalling 43740 fits [CV 1/5; 1/8748] START activation_function=softmax, batch_size=10, dropout_ra te=0.0, epochs=10, init=uniform, learning rate=0.001, neuron1=4, neuron2=2 [CV 1/5; 1/8748] END activation function=softmax, batch size=10, dropout rate =0.0, epochs=10, init=uniform, learning rate=0.001, neuron1=4, neuron2=2; tot al time= 5.2s [CV 2/5; 1/8748] START activation function=softmax, batch size=10, dropout ra te=0.0, epochs=10, init=uniform, learning_rate=0.001, neuron1=4, neuron2=2 [CV 2/5; 1/8748] END activation function=softmax, batch size=10, dropout rate =0.0, epochs=10, init=uniform, learning rate=0.001, neuron1=4, neuron2=2; tot al time= 6.1s [CV 3/5; 1/8748] START activation function=softmax, batch size=10, dropout ra te=0.0, epochs=10, init=uniform, learning rate=0.001, neuron1=4, neuron2=2 [CV 3/5; 1/8748] END activation_function=softmax, batch_size=10, dropout_rate =0.0, epochs=10, init=uniform, learning rate=0.001, neuron1=4, neuron2=2; tot al time= [CV 4/5; 1/8748] START activation function=softmax, batch size=10, dropout ra te=0.0, epochs=10, init=uniform, learning_rate=0.001, neuron1=4, neuron2=2 [CV 4/5; 1/8748] END activation_function=softmax, batch_size=10, dropout_rate

In []: