Model Developed by

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GitHub: **https://github.com/1umairali/models**

Developed a machine learning-based system for detecting brain tumors from MRI images. The project involved preprocessing image data and extracting relevant features, followed by training and evaluating various machine learning classifiers, including Support Vector Classifier (SVC), Logistic Regression, k-Nearest Neighbors (k-NN), Naives Regression, Random Forest, and Decision Tree. The models were assessed based on accuracy and performance metrics to determine the most effective approach for tumor classification. Demonstrated strong skills in medical image analysis and classical machine learning techniques using Python and scikit-learn.

In [1]:

```
import numpy as np  # for numeric calculation
import pandas as pd  # for data analysis and manupulation
import matplotlib.pyplot as plt  # for data visualization
import seaborn as sns  # for data visualization
```

In [2]:

```
# import dataframe
url = 'https://raw.githubusercontent.com/1umairali/models/main/brain_tumor_detection/brain_dataset.csv'
brain_dataframe = pd.read_csv(url)
brain_dataframe
```

Out[2]:

	Image	Class	Mean	Variance	Standard Deviation	Entropy	Skewness	Kurtosis	Contrast	Energy	ASM	Homogeneity
0	Image1	0	6.535339	619.587845	24.891522	0.109059	4.276477	18.900575	98.613971	0.293314	0.086033	0.530941
1	Image2	0	8.749969	805.957634	28.389393	0.266538	3.718116	14.464618	63.858816	0.475051	0.225674	0.651352
2	Image3	1	7.341095	1143.808219	33.820234	0.001467	5.061750	26.479563	81.867206	0.031917	0.001019	0.268275
3	Image4	1	5.958145	959.711985	30.979219	0.001477	5.677977	33.428845	151.229741	0.032024	0.001026	0.243851
4	Image5	0	7.315231	729.540579	27.010009	0.146761	4.283221	19.079108	174.988756	0.343849	0.118232	0.501140
...	...	...	...	...	...	...	...	...	...	...	...	...
3757	Image3758	0	21.234512	1208.850174	34.768523	0.063774	2.082079	4.647310	158.437600	0.220666	0.048693	0.487131
3758	Image3759	0	20.435349	1227.151440	35.030721	0.066763	2.144625	4.882034	161.158675	0.225931	0.051045	0.502712
3759	Image3760	0	18.011520	1151.582765	33.934978	0.068396	2.308349	5.579498	167.130118	0.228930	0.052409	0.492269
3760	Image3761	0	13.330429	945.732779	30.752769	0.087872	2.732822	7.757570	223.812932	0.261527	0.068397	0.480064
3761	Image3762	0	6.110138	480.884025	21.929068	0.118171	4.110669	17.538826	239.251388	0.306224	0.093773	0.494333

3762 rows × 15 columns

In [3]:

```
# Head (first six rows) of brain dataframe
brain_dataframe.head(6)
```

Out[3]:

	Image	Class	Mean	Variance	Standard Deviation	Entropy	Skewness	Kurtosis	Contrast	Energy	ASM	Homogeneity	Dissimi
0	Image1	0	6.535339	619.587845	24.891522	0.109059	4.276477	18.900575	98.613971	0.293314	0.086033	0.530941	4.47
1	Image2	0	8.749969	805.957634	28.389393	0.266538	3.718116	14.464618	63.858816	0.475051	0.225674	0.651352	3.22
2	Image3	1	7.341095	1143.808219	33.820234	0.001467	5.061750	26.479563	81.867206	0.031917	0.001019	0.268275	5.98
3	Image4	1	5.958145	959.711985	30.979219	0.001477	5.677977	33.428845	151.229741	0.032024	0.001026	0.243851	7.70
4	Image5	0	7.315231	729.540579	27.010009	0.146761	4.283221	19.079108	174.988756	0.343849	0.118232	0.501140	6.83
5	Image6	0	7.524109	607.395258	24.645390	0.214086	3.729886	14.471736	105.077882	0.421587	0.177736	0.598169	4.19

In [4]:

```
# Tail (last six rows) of brain dataframe
brain_dataframe.tail(6)
```

Out[4]:

	Image	Class	Mean	Variance	Standard Deviation	Entropy	Skewness	Kurtosis	Contrast	Energy	ASM	Homogeneity
3756	Image3757	0	20.976822	1144.456066	33.829810	0.062252	2.106235	4.798339	166.395916	0.217934	0.047495	0.488449
3757	Image3758	0	21.234512	1208.850174	34.768523	0.063774	2.082079	4.647310	158.437600	0.220666	0.048693	0.487131
3758	Image3759	0	20.435349	1227.151440	35.030721	0.066763	2.144625	4.882034	161.158675	0.225931	0.051045	0.502712
3759	Image3760	0	18.011520	1151.582765	33.934978	0.068396	2.308349	5.579498	167.130118	0.228930	0.052409	0.492269
3760	Image3761	0	13.330429	945.732779	30.752769	0.087872	2.732822	7.757570	223.812932	0.261527	0.068397	0.480064
3761	Image3762	0	6.110138	480.884025	21.929068	0.118171	4.110669	17.538826	239.251388	0.306224	0.093773	0.494333

In [5]:

```
# Information of brain dataframe
brain_dataframe.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3762 entries, 0 to 3761
Data columns (total 15 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   Image               3762 non-null   object 
 1   Class               3762 non-null   int64  
 2   Mean                3762 non-null   float64
 3   Variance            3762 non-null   float64
 4   Standard Deviation  3762 non-null   float64
 5   Entropy             3762 non-null   float64
 6   Skewness            3762 non-null   float64
 7   Kurtosis            3762 non-null   float64
 8   Contrast            3762 non-null   float64
 9   Energy              3762 non-null   float64
 10  ASM                 3762 non-null   float64
 11  Homogeneity         3762 non-null   float64
 12  Dissimilarity       3762 non-null   float64
 13  Correlation         3762 non-null   float64
 14  Coarseness          3762 non-null   float64
dtypes: float64(13), int64(1), object(1)
memory usage: 441.0+ KB
```

In [6]:

```
# show image columns
print(brain_dataframe['Image'])
```

```
0           Image1
1           Image2
2           Image3
3           Image4
4           Image5
           ...    
3757    Image3758
3758    Image3759
3759    Image3760
3760    Image3761
3761    Image3762
Name: Image, Length: 3762, dtype: object
```

image column is object dtype. contains only images name. if we drop that column it will not impact dataframe or result

```python
In [7]: # drop Image column.
brain_df2 = brain_dataframe.drop(['Image'], axis = 1)
brain_df2
```

Out[7]:

	Class	Mean	Variance	Standard Deviation	Entropy	Skewness	Kurtosis	Contrast	Energy	ASM	Homogeneity	Dissimilarit
0	0	6.535339	619.587845	24.891522	0.109059	4.276477	18.900575	98.613971	0.293314	0.086033	0.530941	4.47334
1	0	8.749969	805.957634	28.389393	0.266538	3.718116	14.464618	63.858816	0.475051	0.225674	0.651352	3.22007
2	1	7.341095	1143.808219	33.820234	0.001467	5.061750	26.479563	81.867206	0.031917	0.001019	0.268275	5.98180
3	1	5.958145	959.711985	30.979219	0.001477	5.677977	33.428845	151.229741	0.032024	0.001026	0.243851	7.70091
4	0	7.315231	729.540579	27.010009	0.146761	4.283221	19.079108	174.988756	0.343849	0.118232	0.501140	6.83468
...	...	...	...	...	...	...	...	...	...	...	...	.
3757	0	21.234512	1208.850174	34.768523	0.063774	2.082079	4.647310	158.437600	0.220666	0.048693	0.487131	5.21173
3758	0	20.435349	1227.151440	35.030721	0.066763	2.144625	4.882034	161.158675	0.225931	0.051045	0.502712	5.08312
3759	0	18.011520	1151.582765	33.934978	0.068396	2.308349	5.579498	167.130118	0.228930	0.052409	0.492269	5.10370
3760	0	13.330429	945.732779	30.752769	0.087872	2.732822	7.757570	223.812932	0.261527	0.068397	0.480064	6.43978
3761	0	6.110138	480.884025	21.929068	0.118171	4.110669	17.538826	239.251388	0.306224	0.093773	0.494333	6.78732

3762 rows × 14 columns

In [8]:
```
# Numerical distribution of data
brain_df2.describe()
```

Out[8]:

	Class	Mean	Variance	Standard Deviation	Entropy	Skewness	Kurtosis	Contrast	Energy	ASM
count	3762.000000	3762.000000	3762.000000	3762.000000	3762.000000	3762.000000	3762.000000	3762.000000	3762.000000	3762.000000
mean	0.447368	9.488890	711.101063	25.182271	0.073603	4.102727	24.389071	127.961459	0.204705	0.058632
std	0.497288	5.728022	467.466896	8.773526	0.070269	2.560940	56.434747	109.499601	0.129352	0.058300
min	0.000000	0.078659	3.145628	1.773592	0.000882	1.886014	3.942402	3.194733	0.024731	0.000612
25%	0.000000	4.982395	363.225459	19.058475	0.006856	2.620203	7.252852	72.125208	0.069617	0.004847
50%	0.000000	8.477531	622.580417	24.951560	0.066628	3.422210	12.359088	106.737418	0.225496	0.050849
75%	1.000000	13.212723	966.954319	31.095889	0.113284	4.651737	22.640304	161.059006	0.298901	0.089342
max	1.000000	33.239975	2910.581879	53.949809	0.394539	36.931294	1371.640060	3382.574163	0.589682	0.347725

In [9]:
```
# check sum of null values in each columns
brain_df2.isnull().sum()
```

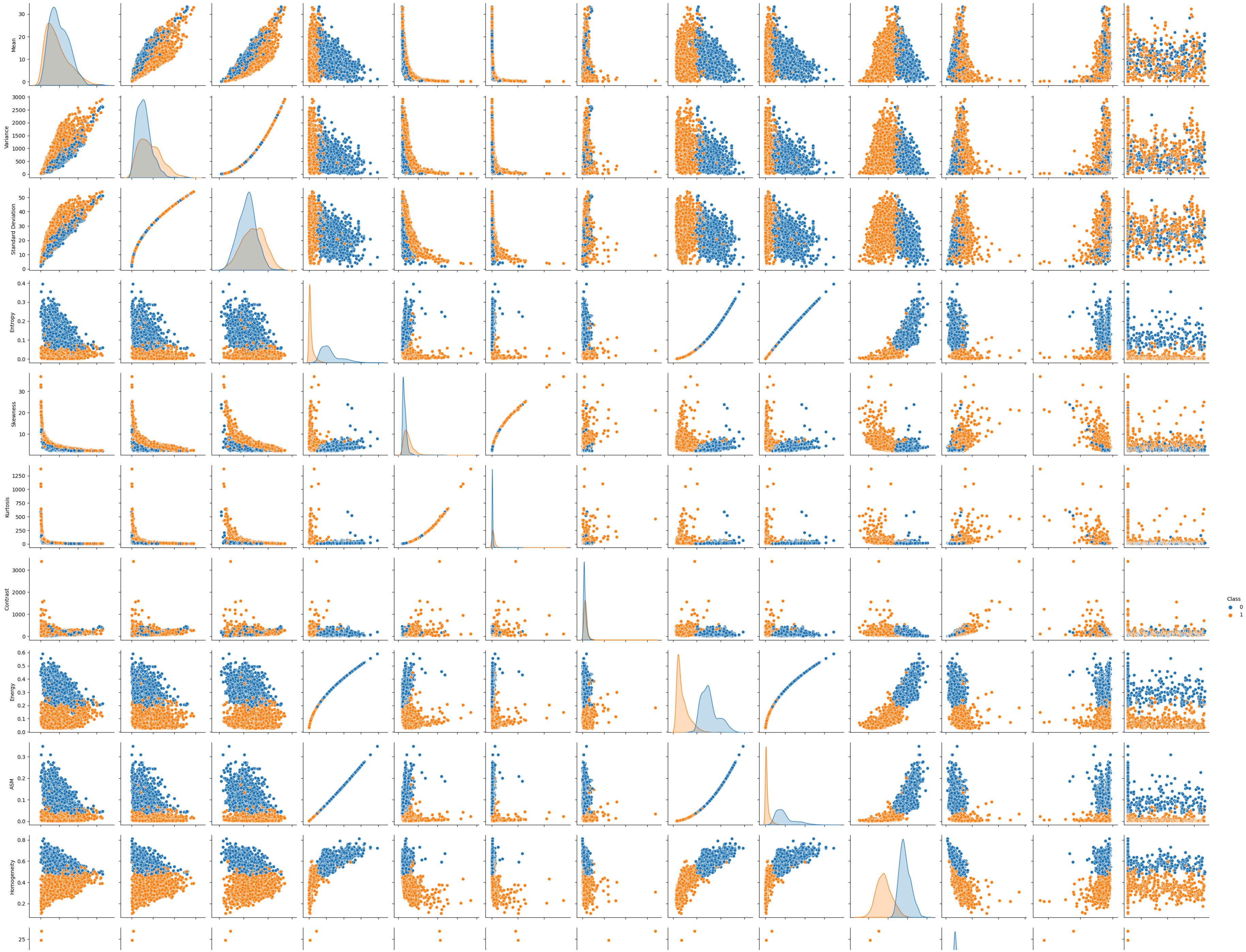
Out[9]:
```
Class                 0
Mean                  0
Variance              0
Standard Deviation    0
Entropy               0
Skewness              0
Kurtosis              0
Contrast              0
Energy                0
ASM                   0
Homogeneity           0
Dissimilarity         0
Correlation           0
Coarseness            0
dtype: int64
```

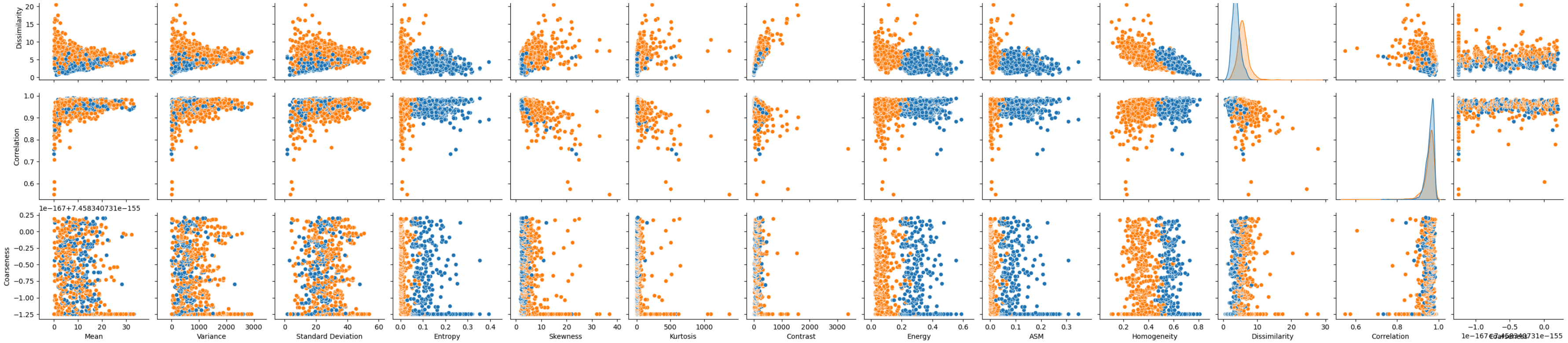
Data Visualization

In [10]:
```
# Pairplot of brain dataframe
sns.pairplot(brain_df2, hue = 'Class')
```

```
C:\Users\Umair Ali\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and
will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Umair Ali\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and
will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Umair Ali\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and
will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Umair Ali\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and
will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Umair Ali\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and
will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Umair Ali\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and
will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Umair Ali\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and
will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Umair Ali\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and
will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Umair Ali\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and
will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Umair Ali\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and
will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Umair Ali\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and
will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Umair Ali\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and
will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\Users\Umair Ali\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and
will be removed in a future version. Convert inf values to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```

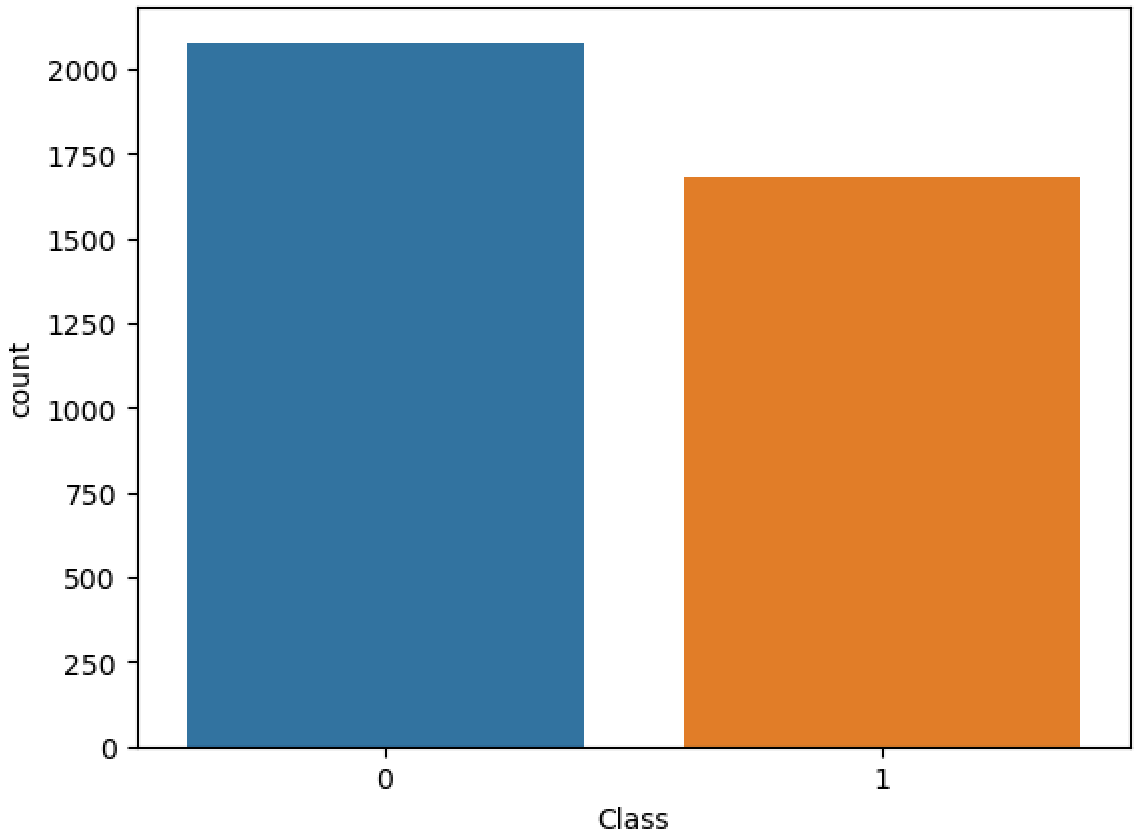
Out[10]:
```
<seaborn.axisgrid.PairGrid at 0x21f83af1dd0>
```


Mean
Variance
Standard Deviation
Entropy
Skewness
Kurtosis
Contrast
Energy
ASM
Homogeneity
Class
0
1



In [11]:
```python
# Count the class columns
# 0 = Non tumor / no cancer
# 1 = Tumor / has cancer
sns.countplot(x=brain_df2["Class"])
```

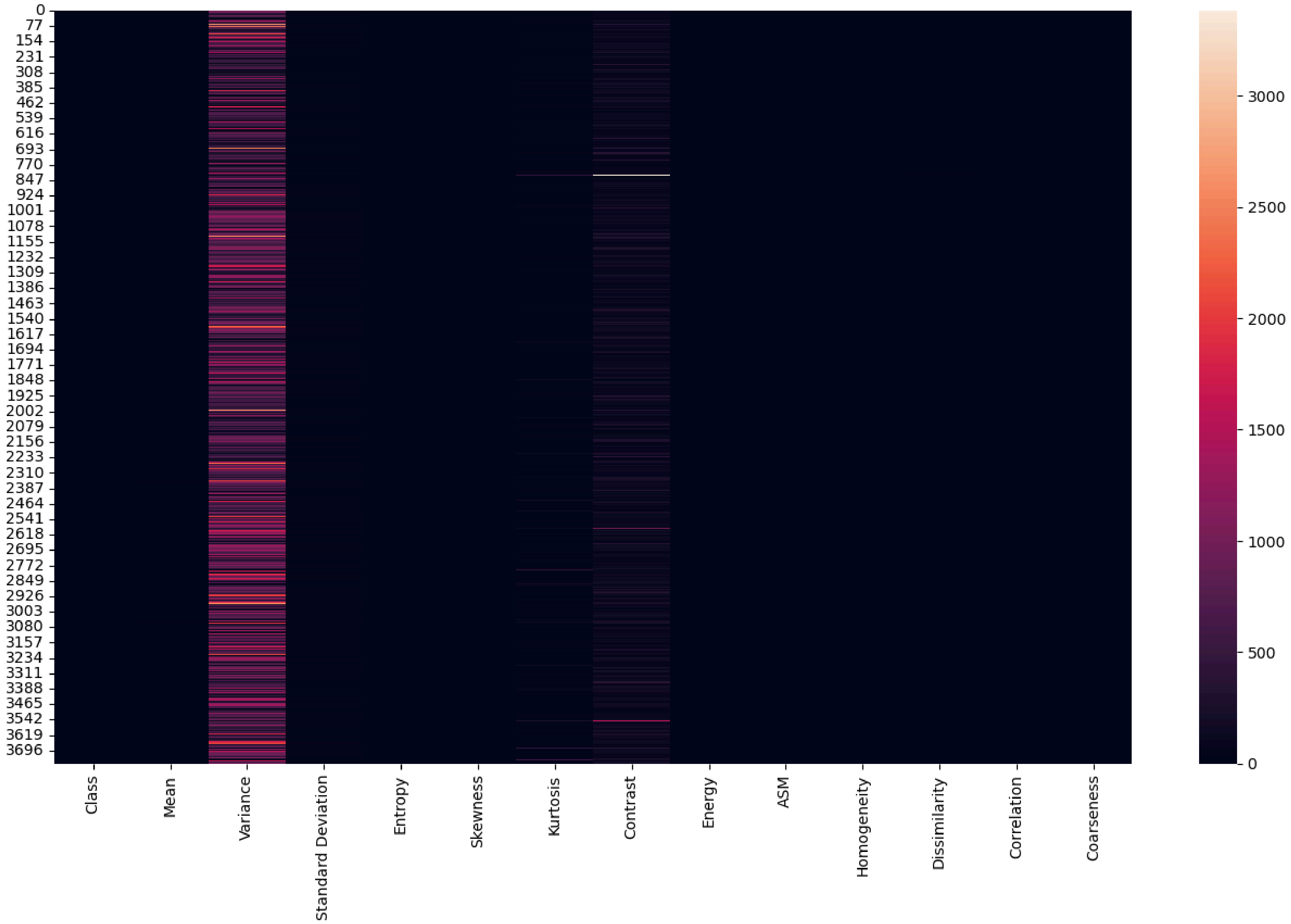
Out[11]: <Axes: xlabel='Class', ylabel='count'>



Heatmap

In [12]:
```
# heatmap of DataFrame
plt.figure(figsize=(16,9))
sns.heatmap(brain_df2)
```

Out[12]: `<Axes: >`



0
77
154
231
308
385
462
539
616
693
770
847
924
1001
1078
1155
1232
1309
1386
1463
1540
1617
1694
1771
1848
1925
2002
2079
2156
2233
2310
2387
2464
2541
2618
2695
2772
2849
2926
3003
3080
3157
3234
3311
3388
3465
3542
3619
3696
Class
Mean
Variance
Standard Deviation
Entropy
Skewness
Kurtosis
Contrast
Energy
ASM
Homogeneity
Dissimilarity
Correlation
Coarseness
3000
2500
2000
1500
1000
500
0

Heatmap of a correlation Matrix

In [13]:
```
# correlation matrix
brain_df2.corr()
```

Out[13]:

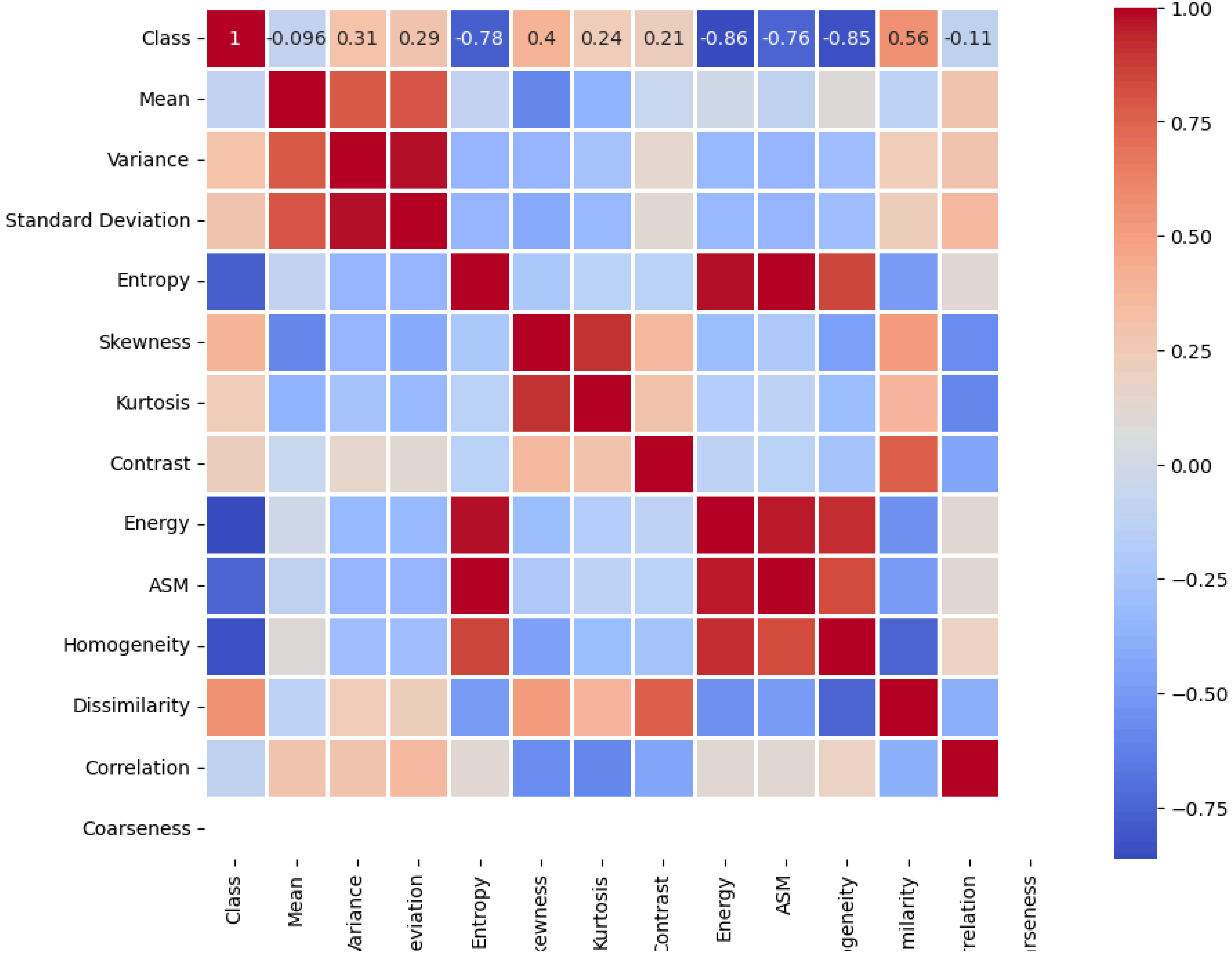
	Class	Mean	Variance	Standard Deviation	Entropy	Skewness	Kurtosis	Contrast	Energy	ASM	Homogeneity
Class	1.000000	-0.095729	0.308818	0.285568	-0.778180	0.402644	0.239844	0.212643	-0.862413	-0.758255	-0.847529
Mean	-0.095729	1.000000	0.783027	0.790984	-0.099729	-0.601593	-0.358163	-0.050974	-0.014863	-0.109393	0.095556
Variance	0.308818	0.783027	1.000000	0.975699	-0.344432	-0.347399	-0.248312	0.135494	-0.335470	-0.341061	-0.290527
Standard Deviation	0.285568	0.790984	0.975699	1.000000	-0.345127	-0.425428	-0.329798	0.117981	-0.331103	-0.342530	-0.288801
Entropy	-0.778180	-0.099729	-0.344432	-0.345127	1.000000	-0.222222	-0.140125	-0.140769	0.971260	0.999213	0.852019
Skewness	0.402644	-0.601593	-0.347399	-0.425428	-0.222222	1.000000	0.899713	0.349856	-0.295413	-0.209289	-0.470054
Kurtosis	0.239844	-0.358163	-0.248312	-0.329798	-0.140125	0.899713	1.000000	0.296664	-0.172454	-0.133741	-0.307314
Contrast	0.212643	-0.050974	0.135494	0.117981	-0.140769	0.349856	0.296664	1.000000	-0.130708	-0.139276	-0.270119
Energy	-0.862413	-0.014863	-0.335470	-0.331103	0.971260	-0.295413	-0.172454	-0.130708	1.000000	0.961628	0.915988
ASM	-0.758255	-0.109393	-0.341061	-0.342530	0.999213	-0.209289	-0.133741	-0.139276	0.961628	1.000000	0.837139
Homogeneity	-0.847529	0.095556	-0.290527	-0.288801	0.852019	-0.470054	-0.307314	-0.270119	0.915988	0.837139	1.000000
Dissimilarity	0.556319	-0.113864	0.235487	0.224773	-0.502363	0.511931	0.375939	0.761497	-0.545774	-0.491813	-0.746675
Correlation	-0.108601	0.293693	0.288037	0.354161	0.122080	-0.570919	-0.589211	-0.427443	0.123680	0.121054	0.198639
Coarseness	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

we checked in information 'Coarseness' column is float datatype. contains 0 values which is not empty....... but in corelation matrix it contain NaN values...... we have to remove that column. it will not impact the result...... lets confirm in Heatmap and Barplot of Correlation Matrix

In [14]:
```
# Heatmap of Correlation matrix of Brain DataFrame
plt.figure(figsize=(10,8))
sns.heatmap(brain_df2.corr(), annot = True, cmap ='coolwarm', linewidths=2)
```

```
C:\Users\Umair Ali\anaconda3\Lib\site-packages\seaborn\matrix.py:260: FutureWarning: Format strings passed to MaskedConstant ar
e ignored, but in future may error or produce different behavior
  annotation = ("{:" + self.fmt + "}").format(val)
```

Out[14]:
```
<Axes: >
```


Class
Mean
Variance
Standard Deviation
Entropy
Skewness
Kurtosis
Contrast
Energy
ASM
Homogeneity
Dissimilarity
Correlation
Coarseness
1
-0.096
0.31
0.29
-0.78
0.4
0.24
0.21
-0.86
-0.76
-0.85
0.56
-0.11
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75

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In [15]:
```python
# drop coarseness column from brain_df2
brain_df3 = brain_df2.drop(['Coarseness'], axis=1)
```

Split Dataframe in Train and Test

In [16]:
```python
# drop dependent (Class) column, it will assign to y
X = brain_df3.drop(['Class'], axis = 1)
X.head(6)
```

Out[16]:

	Mean	Variance	Standard Deviation	Entropy	Skewness	Kurtosis	Contrast	Energy	ASM	Homogeneity	Dissimilarity	Correlati
0	6.535339	619.587845	24.891522	0.109059	4.276477	18.900575	98.613971	0.293314	0.086033	0.530941	4.473346	0.9819
1	8.749969	805.957634	28.389393	0.266538	3.718116	14.464618	63.858816	0.475051	0.225674	0.651352	3.220072	0.9888
2	7.341095	1143.808219	33.820234	0.001467	5.061750	26.479563	81.867206	0.031917	0.001019	0.268275	5.981800	0.9780
3	5.958145	959.711985	30.979219	0.001477	5.677977	33.428845	151.229741	0.032024	0.001026	0.243851	7.700919	0.9641
4	7.315231	729.540579	27.010009	0.146761	4.283221	19.079108	174.988756	0.343849	0.118232	0.501140	6.834689	0.9727
5	7.524109	607.395258	24.645390	0.214086	3.729886	14.471736	105.077882	0.421587	0.177736	0.598169	4.193146	0.9764

In [17]:
```python
# output variable
# assign Class column to y
y = brain_df3['Class']
y.head(6)
```

Out[17]:
```
0    0
1    0
2    1
3    1
4    0
5    0
Name: Class, dtype: int64
```

In [18]:
```
# split dataset into train and test
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state= 5)
```

In [19]:
```
X_train
```

Out[19]:

	Mean	Variance	Standard Deviation	Entropy	Skewness	Kurtosis	Contrast	Energy	ASM	Homogeneity	Dissimilarity	Corı
2021	7.885529	681.803866	26.111374	0.133134	3.806777	14.939540	277.900762	0.326207	0.106411	0.546301	6.445886	0
1286	6.639282	207.782336	14.414657	0.102582	2.607407	7.151179	33.038741	0.282621	0.079875	0.638838	2.064030	0
1106	3.186020	314.159477	17.724544	0.179837	6.354288	43.889536	165.700313	0.383583	0.147136	0.569095	4.329943	0
3688	7.752167	850.780349	29.168139	0.000954	4.667157	23.797444	162.713111	0.025726	0.000662	0.255565	7.630112	0
1781	15.907272	859.296845	29.313765	0.093459	2.257804	5.399814	111.219504	0.269897	0.072845	0.543017	3.945097	0
...	...	...	...	...	...	...	...	...	...	...	...	
3190	19.755035	1511.266702	38.875014	0.098117	2.359856	5.823204	155.330111	0.276962	0.076708	0.564342	4.108485	0
3046	17.384506	1151.899226	33.939641	0.007915	2.516995	6.645917	119.718675	0.075044	0.005632	0.381815	5.310392	0
1725	9.873734	647.095405	25.438070	0.203971	2.936003	8.936402	116.379595	0.410201	0.168265	0.653499	3.168139	0
2254	4.993439	837.608629	28.941469	0.001184	6.201616	39.682251	98.674332	0.028656	0.000821	0.218662	6.251872	0
2915	14.946762	1063.536983	32.611915	0.144926	2.589608	7.070669	140.031810	0.341421	0.116569	0.579450	4.088308	0

3009 rows × 12 columns

In [20]:
```
X_test
```

Out[20]:

	Mean	Variance	Standard Deviation	Entropy	Skewness	Kurtosis	Contrast	Energy	ASM	Homogeneity	Dissimilarity	Corre
1829	14.244751	677.906461	26.036637	0.064730	2.245463	5.280704	68.194040	0.221802	0.049196	0.573020	3.171980	0.9
142	6.439590	711.402252	26.672125	0.003683	4.945783	26.258025	191.833333	0.050998	0.002601	0.252045	8.161609	0.9
2934	18.273666	960.554970	30.992821	0.053945	2.113554	4.673078	135.033939	0.201307	0.040524	0.550705	3.961433	0.9
1648	8.556091	557.147920	23.603981	0.187408	3.215624	10.791892	87.087468	0.392090	0.153735	0.626582	3.201900	0.9
1178	6.661285	761.907895	27.602679	0.004002	4.637791	22.559937	81.489763	0.052887	0.002797	0.370518	4.495690	0.9
...	...	...	...	...	...	...	...	...	...	...	...	
3044	2.566971	254.252713	15.945304	0.001956	6.762827	47.224837	43.256424	0.036846	0.001358	0.317558	4.147622	0.9
2743	11.161804	736.299788	27.134845	0.071535	2.928248	8.891376	147.695042	0.234516	0.054998	0.510246	5.120198	0.9
3413	7.838409	300.574737	17.337091	0.134217	2.797981	8.655661	51.790533	0.327457	0.107228	0.616866	2.620355	0.9
1619	4.232285	153.173766	12.376339	0.095976	3.288243	11.029013	35.134788	0.271702	0.073822	0.639419	2.224797	0.9
3220	8.853958	573.067789	23.938834	0.006357	3.228923	10.874134	90.170569	0.067020	0.004492	0.391093	4.633593	0.9

753 rows × 12 columns

In [21]:
```
y_train
```

Out[21]:
```
2021    0
1286    0
1106    1
3688    1
1781    0
       ..
3190    0
3046    1
1725    0
2254    1
2915    0
Name: Class, Length: 3009, dtype: int64
```

In [22]:
```
y_test
```

Out[22]:
```
1829    0
142     1
2934    0
1648    0
1178    1
       ..
3044    1
2743    0
3413    0
1619    0
3220    1
Name: Class, Length: 753, dtype: int64
```

Feature Scaling

In [23]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train_sc = sc.fit_transform(X_train)
X_test_sc = sc.transform(X_test)
```

ML Model Building

In [24]:
```
from sklearn.metrics import confusion_matrix, classification_report, accuracy_score
```

Support Vector Classifier

Train with original data

In [25]:
```
from sklearn.svm import SVC
svc_classifier = SVC()
svc_classifier.fit(X_train, y_train)
y_pred_svc = svc_classifier.predict(X_test)
accuracy_score(y_test, y_pred_svc)
```

Out[25]:
```
0.7861885790172642
```

Train with scaled data

In [26]:
```
svc_classifier2 = SVC()
svc_classifier2.fit(X_train_sc, y_train)
y_pred_svc_sc = svc_classifier2.predict(X_test_sc)
accuracy_score(y_test, y_pred_svc_sc)
```

Out[26]:
```
0.9774236387782205
```

Logistic Regression

Train with original data

In [27]:
```
from sklearn.linear_model import LogisticRegression
lr_classifier = LogisticRegression(random_state=51, penalty = 'l2')
lr_classifier.fit(X_train, y_train)
y_pred_lr = lr_classifier.predict(X_test)
accuracy_score(y_test, y_pred_lr)
```

```
C:\Users\Umair Ali\anaconda3\Lib\site-packages\sklearn\linear_model\_logistic.py:458: ConvergenceWarning: lbfgs failed to conve
rge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

Out[27]:
```
0.9096945551128818
```

Train with scaled data

In [28]:
```
lr_classifier2 = LogisticRegression(random_state=51, penalty = 'l2')
lr_classifier2.fit(X_train_sc, y_train)
y_pred_lr_sc = lr_classifier2.predict(X_test_sc)
accuracy_score(y_test, y_pred_lr_sc)
```

Out[28]:
```
0.9787516600265604
```

KNN - K-Nearesr Neighbor Classifier

Train with original data

In [29]:
```
from sklearn.neighbors import KNeighborsClassifier
knn_classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
knn_classifier.fit(X_train, y_train)
y_pred_knn = knn_classifier.predict(X_test)
accuracy_score(y_test, y_pred_knn)
```

Out[29]:
```
0.8061088977423638
```

Train with scaled data

In [30]:
```
knn_classifier2 = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
knn_classifier2.fit(X_train_sc, y_train)
```

```
y_pred_knn_sc = knn_classifier2.predict(X_test_sc)
accuracy_score(y_test, y_pred_knn_sc)
```

Out[30]: 0.9774236387782205

Naive Bayes Classifier

Train with original data

In [31]:
```
from sklearn.naive_bayes import GaussianNB
nb_classifier = GaussianNB()
nb_classifier.fit(X_train, y_train)
y_pred_nb = nb_classifier.predict(X_test)
accuracy_score(y_test, y_pred_nb)
```

Out[31]: 0.953519256308101

Train with scaled data

In [32]:
```
nb_classifier2 = GaussianNB()
nb_classifier2.fit(X_train_sc, y_train)
y_pred_nb_sc = nb_classifier2.predict(X_test_sc)
accuracy_score(y_test, y_pred_nb_sc)
```

Out[32]: 0.9548472775564409

Decision Tree Classifier

Train with original data

In [33]:
```
from sklearn.tree import DecisionTreeClassifier
dt_classifier = DecisionTreeClassifier(criterion = 'entropy', random_state = 51)
dt_classifier.fit(X_train, y_train)
y_pred_dt = dt_classifier.predict(X_test)
accuracy_score(y_test, y_pred_dt)
```

Out[33]: 0.9814077025232404

Train with scaled data

In [34]:
```
dt_classifier2 = DecisionTreeClassifier(criterion = 'entropy', random_state = 51)
dt_classifier2.fit(X_train_sc, y_train)
y_pred_dt_sc = dt_classifier2.predict(X_test_sc)
accuracy_score(y_test, y_pred_dt_sc)
```

Out[34]: 0.9814077025232404

Random Forest Classifier

Train with original data

In [35]:
```
from sklearn.ensemble import RandomForestClassifier
rf_classifier = RandomForestClassifier(n_estimators = 20, criterion = 'entropy', random_state = 51)
rf_classifier.fit(X_train, y_train)
y_pred_rf = rf_classifier.predict(X_test)
accuracy_score(y_test, y_pred_rf)
```

Out[35]: 0.9827357237715804

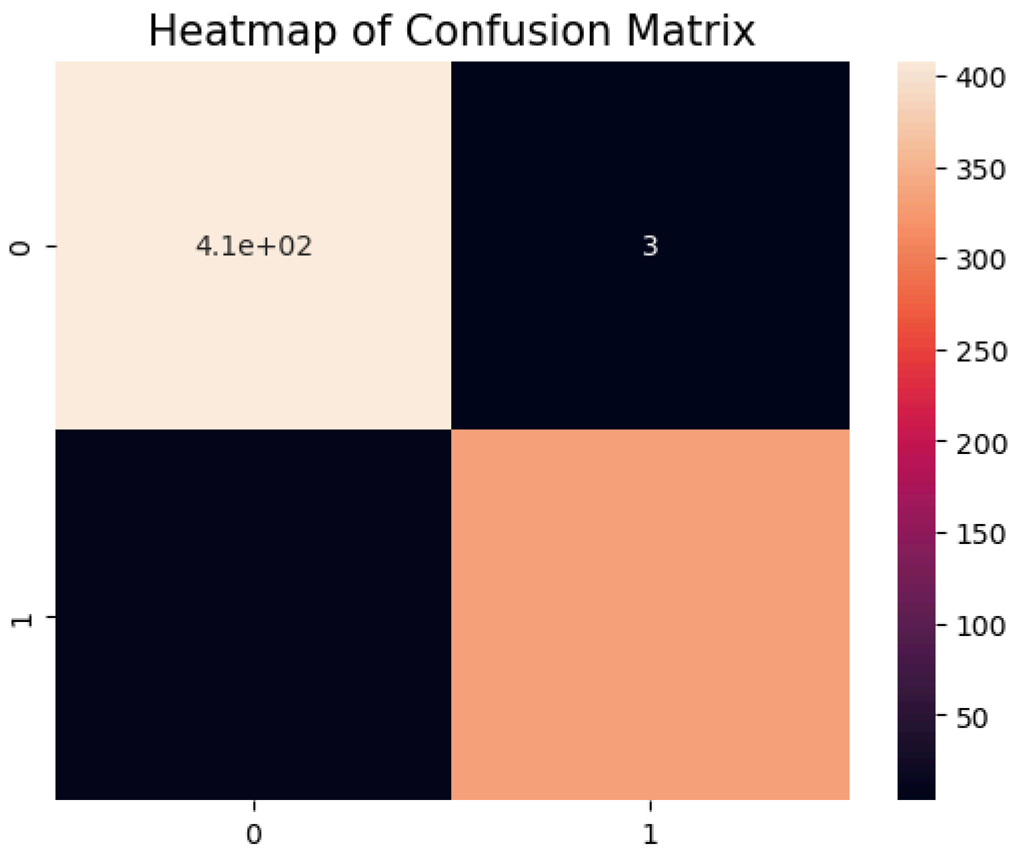
Train with scaled data

In [36]:
```
rf_classifier2 = RandomForestClassifier(n_estimators = 20, criterion = 'entropy', random_state = 51)
rf_classifier2.fit(X_train_sc, y_train)
y_pred_rf_sc = rf_classifier2.predict(X_test_sc)
accuracy_score(y_test, y_pred_rf_sc)
```

Out[36]: 0.9827357237715804

Confusion Matrix

In [37]:
```
cm = confusion_matrix(y_test, y_pred_rf_sc)
plt.title('Heatmap of Confusion Matrix', fontsize = 15)
sns.heatmap(cm, annot = True)
plt.show()
```



Classification Report Of model

In [38]:
```
print(classification_report(y_test, y_pred_rf_sc))
```

```
              precision    recall  f1-score   support

           0       0.98      0.99      0.98       411
           1       0.99      0.97      0.98       342

    accuracy                           0.98       753
   macro avg       0.98      0.98      0.98       753
weighted avg       0.98      0.98      0.98       753
```

Cross-validation of the ML model

In [39]:
```
# Cross validation
from sklearn.model_selection import cross_val_score
cross_validation = cross_val_score(estimator = rf_classifier2, X = X_train_sc,y = y_train, cv = 10)
print("Cross validation accuracy of SVC model = ", cross_validation)
print("\nCross validation mean accuracy of SVC model = ", cross_validation.mean())
```

```
Cross validation accuracy of SVC model =  [0.98671096 0.99335548 0.99003322 0.97009967 0.9833887  0.97674419
 0.99335548 0.99003322 0.99335548 0.99666667]

Cross validation mean accuracy of SVC model =  0.9873743078626799
```

Test Model

In [45]:
```
# we have one patient data
patient1 = [17.99,10.38,122.8,1001.0,0.1184,0.2776,0.3001,
            0.1471,0.2419,0.07871,1.095,0.9053]
```

In [41]:
```
# convert list into array and scale
patient1_sc = sc.transform(np.array([patient1]))
patient1_sc
```

```
C:\Users\Umair Ali\anaconda3\Lib\site-packages\sklearn\base.py:439: UserWarning: X does not have valid feature names, but Stand
ardScaler was fitted with feature names
  warnings.warn(
```

Out[41]:
```
array([[ 1.49256979e+00, -1.49381108e+00,  1.11029758e+01,
          1.40960224e+04, -1.54791906e+00, -4.16334494e-01,
         -1.13805522e+00, -4.48064734e-01,  3.09915646e+00,
         -3.10934480e+00, -1.93429813e+00, -1.84574993e+00]])
```

In [42]:
```
# predict patient1_sc scale data
# zero mean malignant patient has cancer
predict = rf_classifier2.predict(patient1_sc)
predict
```

Out[42]:
```
array([0], dtype=int64)
```

In [43]:
```
# write if else statement to print result in clear format
if predict[0] == 0:
    print ('Patient has *** NO *** Tumor / Cancer')
else:
    print ('Patient *** HAS *** Tumor / Cancer')
```

```
Patient has *** NO *** Tumor / Cancer
```

In [44]:
```
# confusion matrix
print('Confusion matrix of Random Forest model: \n',confusion_matrix(y_test, y_pred_rf_sc),'\n')

# show the accuracy
print('Accuracy of Random Forest model = ',accuracy_score(y_test, y_pred_rf_sc))
```

```
Confusion matrix of Random Forest model:
 [[408   3]
 [ 10 332]]

Accuracy of Random Forest model =  0.9827357237715804
```