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CSE- 1

MACHINE LEARNING

LAB PROGRAM

EXPERIMENT-3

Problem Statement
Estimate the accuracy of decision tree classifier on breast cancer dataset using 5 fold cross validation

Algorithm
In a decision tree, for predicting the class of the given dataset, the algorithm starts from the root node of the tree.
Step-1: Begin the tree with the root node, says R, which contains the complete dataset.

This algorithm compares the values of root attribute with the record (real dataset) attribute and, based on the comparison, follows the branch and jumps to the next node.
Step-2: Find the best attribute in the dataset using Attribute Selection Measure (ASM).

For the next node, the algorithm again compares the attribute value with the other sub-nodes and move further.
Step-3: Divide the S into subsets that contains possible values for the best attributes.
Step-4: Generate the decision tree node, which contains the best attribute.

It continues the process until it reaches the leaf node of the tree.
Step-5: Recursively make new decision trees using the subsets of the dataset created in step -3. Continue this process until a stage is reached where it cannot further classify the nodes and called the final node as a leaf node.

Program Code Snippet

LOADING DATA SET:

```
In [5]: import pandas as pd
        df = pd.read_csv("./data.csv")
        df
```

Out[5]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	...
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	...
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	0.07017	...
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	0.12790	...
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	...
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	...
...	...	...	...	...	...	...	...	...	...	...	...
564	926424	M	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	...
565	926682	M	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	...
566	926954	M	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	...
567	927241	M	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	...
568	92751	B	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	...

569 rows × 33 columns

PREPROCESSING:

In [5]:
```
#to read the last end of data
df.tail()
```

Out[5]:

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	...	te
564	926424	M	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	...	
565	926682	M	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	...	
566	926954	M	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	...	
567	927241	M	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	...	
568	92751	B	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	...	

5 rows × 33 columns

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 33 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   id                       569 non-null    int64
 1   diagnosis                569 non-null    object
 2   radius_mean              569 non-null    float64
 3   texture_mean             569 non-null    float64
 4   perimeter_mean           569 non-null    float64
 5   area_mean                569 non-null    float64
 6   smoothness_mean          569 non-null    float64
 7   compactness_mean         569 non-null    float64
 8   concavity_mean           569 non-null    float64
 9   concave points_mean      569 non-null    float64
 10  symmetry_mean            569 non-null    float64
 11  fractal_dimension_mean   569 non-null    float64
 12  radius_se                569 non-null    float64
 13  texture_se               569 non-null    float64
 14  perimeter_se             569 non-null    float64
 15  area_se                  569 non-null    float64
 16  smoothness_se            569 non-null    float64
 17  compactness_se           569 non-null    float64
 18  concavity_se             569 non-null    float64
 19  concave points_se        569 non-null    float64
 20  symmetry_se              569 non-null    float64
 21  fractal_dimension_se     569 non-null    float64
 22  radius_worst             569 non-null    float64
 23  texture_worst            569 non-null    float64
 24  perimeter_worst          569 non-null    float64
 25  area_worst               569 non-null    float64
 26  smoothness_worst         569 non-null    float64
 27  compactness_worst        569 non-null    float64
 28  concavity_worst          569 non-null    float64
 29  concave points_worst     569 non-null    float64
 30  symmetry_worst           569 non-null    float64
 31  fractal_dimension_worst  569 non-null    float64
 32  Unnamed: 32              0 non-null      float64
dtypes: float64(31), int64(1), object(1)
memory usage: 146.8+ KB
```

In [7]:
```
df.shape
```
Out[7]:
```
(569, 33)
```

In [8]:
```
#print all the columns of dataset
df.columns.values
```
Out[8]:
```
array(['id', 'diagnosis', 'radius_mean', 'texture_mean', 'perimeter_mean',
       'area_mean', 'smoothness_mean', 'compactness_mean',
       'concavity_mean', 'concave points_mean', 'symmetry_mean',
       'fractal_dimension_mean', 'radius_se', 'texture_se',
       'perimeter_se', 'area_se', 'smoothness_se', 'compactness_se',
       'concavity_se', 'concave points_se', 'symmetry_se',
       'fractal_dimension_se', 'radius_worst', 'texture_worst',
       'perimeter_worst', 'area_worst', 'smoothness_worst',
       'compactness_worst', 'concavity_worst', 'concave points_worst',
       'symmetry_worst', 'fractal_dimension_worst', 'Unnamed: 32'],
      dtype=object)
```

In [9]:
```
df.corr()
```
Out[9]:

	id	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	conc points_m
id	1.000000	0.074626	0.099770	0.073159	0.096893	-0.012968	0.000096	0.050080	0.04
radius_mean	0.074626	1.000000	0.323782	0.997855	0.987357	0.170581	0.506124	0.676764	0.822
texture_mean	0.099770	0.323782	1.000000	0.329533	0.321086	-0.023389	0.236702	0.302418	0.293
perimeter_mean	0.073159	0.997855	0.329533	1.000000	0.986507	0.207278	0.556936	0.716136	0.850
area_mean	0.096893	0.987357	0.321086	0.986507	1.000000	0.177028	0.498502	0.685983	0.823
smoothness_mean	-0.012968	0.170581	-0.023389	0.207278	0.177028	1.000000	0.659123	0.521984	0.553
compactness_mean	0.000096	0.506124	0.236702	0.556936	0.498502	0.659123	1.000000	0.883121	0.83
concavity_mean	0.050080	0.676764	0.302418	0.716136	0.685983	0.521984	0.883121	1.000000	0.92
concave points_mean	0.044158	0.822529	0.293464	0.850977	0.823269	0.553695	0.831135	0.921391	1.000
symmetry_mean	-0.022114	0.147741	0.071401	0.183027	0.151293	0.557775	0.602641	0.500667	0.462
fractal_dimension_mean	-0.052511	-0.311631	-0.076437	-0.261477	-0.283110	0.584792	0.565369	0.336783	0.166
radius_se	0.143048	0.679090	0.275869	0.691765	0.732562	0.301467	0.497473	0.631925	0.698
texture_se	-0.007526	-0.097317	0.386358	-0.086761	-0.066280	0.068406	0.046205	0.076218	0.02
perimeter_se	0.137331	0.674172	0.281673	0.693135	0.726628	0.296092	0.548905	0.660391	0.710
area_se	0.177742	0.735864	0.259845	0.744983	0.800086	0.246552	0.455653	0.617427	0.690
smoothness_se	0.096781	-0.222600	0.006614	-0.202694	-0.166777	0.332375	0.135299	0.098564	0.027
compactness_se	0.033961	0.206000	0.191975	0.250744	0.212583	0.318943	0.738722	0.670279	0.490
concavity_se	0.055239	0.194204	0.143293	0.228082	0.207660	0.248396	0.570517	0.691270	0.439
concave points_se	0.078768	0.376169	0.163851	0.407217	0.372320	0.380676	0.642262	0.683260	0.615
symmetry_se	-0.017306	-0.104321	0.009127	-0.081629	-0.072497	0.200774	0.229977	0.178009	0.095
fractal_dimension_se	0.025725	-0.042641	0.054458	-0.005523	-0.019887	0.283607	0.507318	0.449301	0.257
radius_worst	0.082405	0.969539	0.352573	0.969476	0.962746	0.213120	0.535315	0.688236	0.830
texture_worst	0.064720	0.297008	0.912045	0.303038	0.287489	0.036072	0.248133	0.299879	0.292
perimeter_worst	0.079986	0.965137	0.358040	0.970387	0.959120	0.238853	0.590210	0.729565	0.855

In [10]:
```
#check for the null value
df.isnull().sum()
```

Out[10]:
```
id                          0
diagnosis                   0
radius_mean                 0
texture_mean                0
perimeter_mean              0
area_mean                   0
smoothness_mean             0
compactness_mean            0
concavity_mean              0
concave points_mean         0
symmetry_mean               0
fractal_dimension_mean      0
radius_se                   0
texture_se                  0
perimeter_se                0
area_se                     0
smoothness_se               0
compactness_se              0
concavity_se                0
concave points_se           0
symmetry_se                 0
fractal_dimension_se        0
radius_worst                0
texture_worst               0
perimeter_worst             0
area_worst                  0
smoothness_worst            0
compactness_worst           0
concavity_worst             0
concave points_worst        0
symmetry_worst              0
fractal_dimension_worst     0
Unnamed: 32               569
dtype: int64
```

In [11]:
```
for i in df.columns:
    print(i)
    print(df[i].value_counts())
    print('----------------------*********-------------------------')
```

```
id
883263     1
906564     1
89122      1
9013579    1
868682     1
          ..
874158     1
914062     1
918192     1
872113     1
875878     1
Name: id, Length: 569, dtype: int64
----------------------*********--------------------------
diagnosis
B    357
M    212
Name: diagnosis, dtype: int64
----------------------*********--------------------------
radius_mean
```

In [12]:
```
df['diagnosis'].value_counts()
```

Out[12]:
```
B    357
M    212
Name: diagnosis, dtype: int64
```

In [13]:
```python
df= df.drop(["id"], axis = 1)
df
```

Out[13]:

	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_
0	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	0
1	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	0.07017	0
2	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	0.12790	0
3	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	0
4	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	0
...	...	...	...	...	...	...	...	...	...	
564	M	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0
565	M	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0
566	M	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0
567	M	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	0
568	B	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0

In [14]:
```python
df = df.drop(["Unnamed: 32"], axis = 1)
df
```

Out[14]:

	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_me
0	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	0.24
1	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	0.07017	0.18
2	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	0.12790	0.20
3	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	0.25
4	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	0.18
...	...	...	...	...	...	...	...	...	...	
564	M	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0.17
565	M	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0.17
566	M	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0.15
567	M	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	0.23
568	B	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0.15

569 rows × 31 columns

VISUALIZATION:

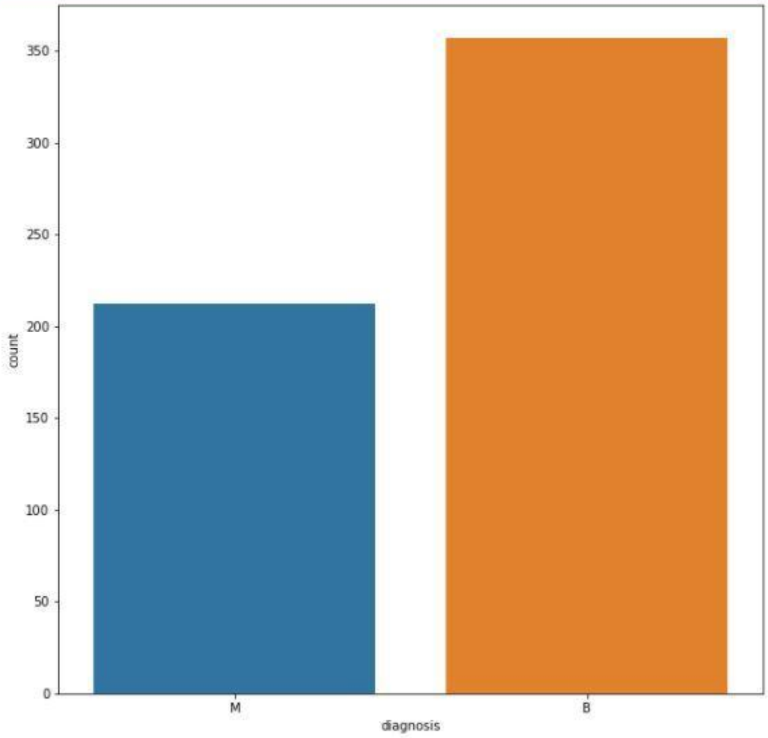
In [15]:
```python
import matplotlib.pyplot as plt
import seaborn as sns
```

In [16]:
```python
benign, malignant=df['diagnosis'].value_counts()
print("No of Benign cell", benign)
print("No of malignant cell", malignant)
```

```
No of Benign cell 357
No of malignant cell 212
```

```
In [19]: plt.figure(figsize=(10,10))
sns.countplot(df['diagnosis'])
plt.show()
```

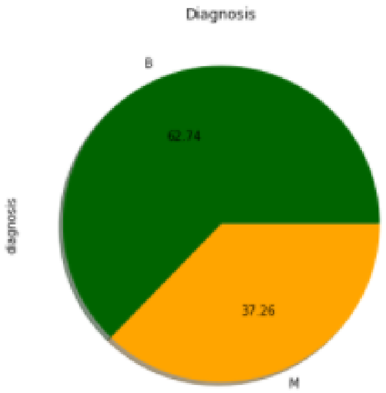
```
C:\Users\Is_dhillon\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyw
ord arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explic
it keyword will result in an error or misinterpretation.
  warnings.warn(
```




```
In [18]: print("% of Benign cell is ", benign*100/len(df))
print("% of Malignant cell is ", malignant*100/len(df))
```

```
% of Benign cell is  62.74165202108963
% of Malignant cell is  37.25834797891037
```

```
In [19]: df.diagnosis.value_counts().plot(kind='pie',shadow=True,colors=('darkgreen','orange'),autopct='%.2f',figsize=(8,6))
plt.title('Diagnosis')
plt.show()
```



Pairplot helps to plot among the most useful feature

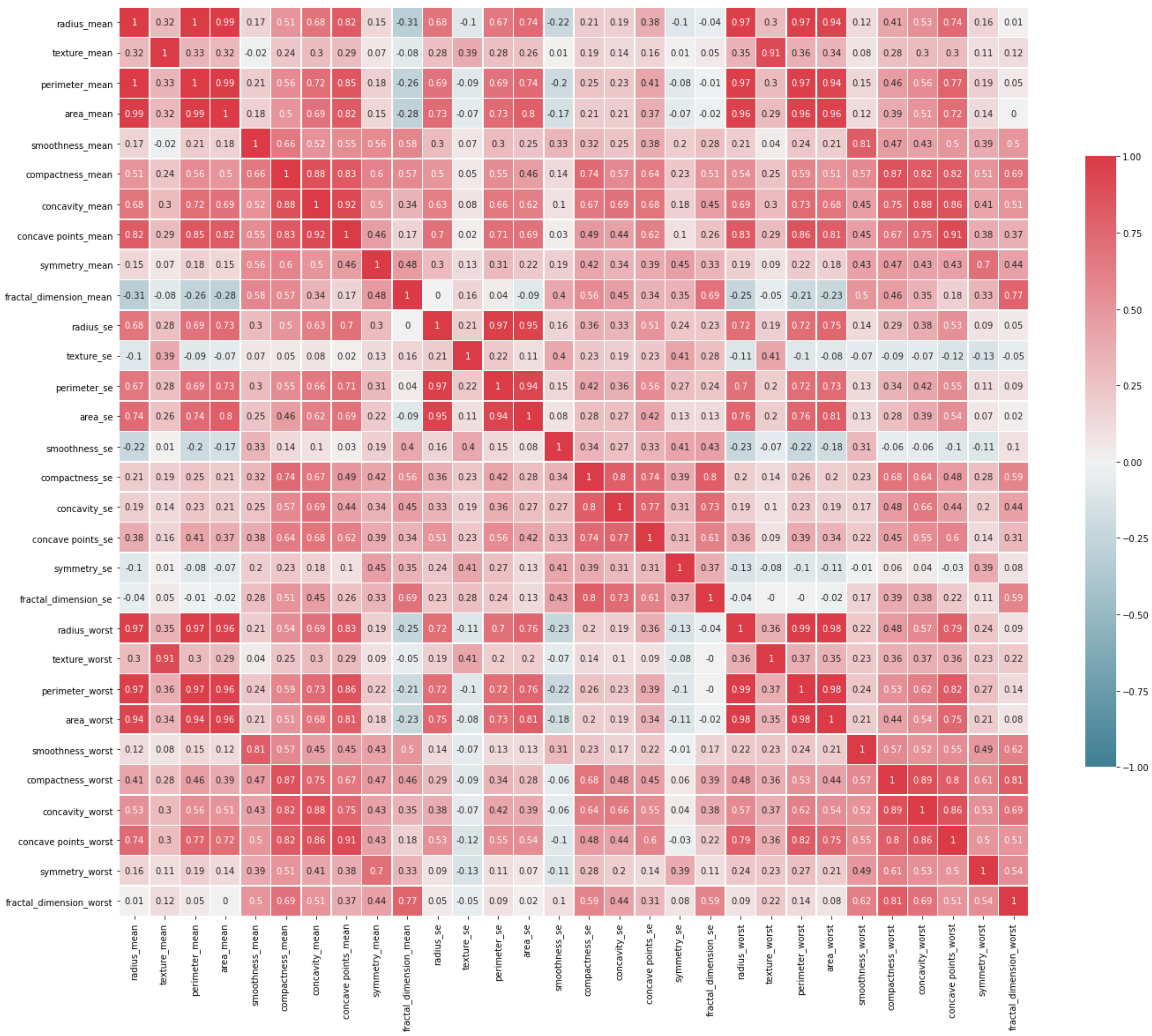
In [20]:
```
cols=['diagnosis','radius_mean', 'texture_mean', 'perimeter_mean',
        'area_mean','smoothness_mean', 'compactness_mean', 'concavity_mean',
        'concave points_mean', 'symmetry_mean', 'fractal_dimension_mean']
plt.figure(figsize=(10,10))
sns.pairplot(data=df[cols],hue='diagnosis', palette='RdBu')
```

Out[20]: <seaborn.axisgrid.PairGrid at 0x276b14608b0>

<Figure size 720x720 with 0 Axes>

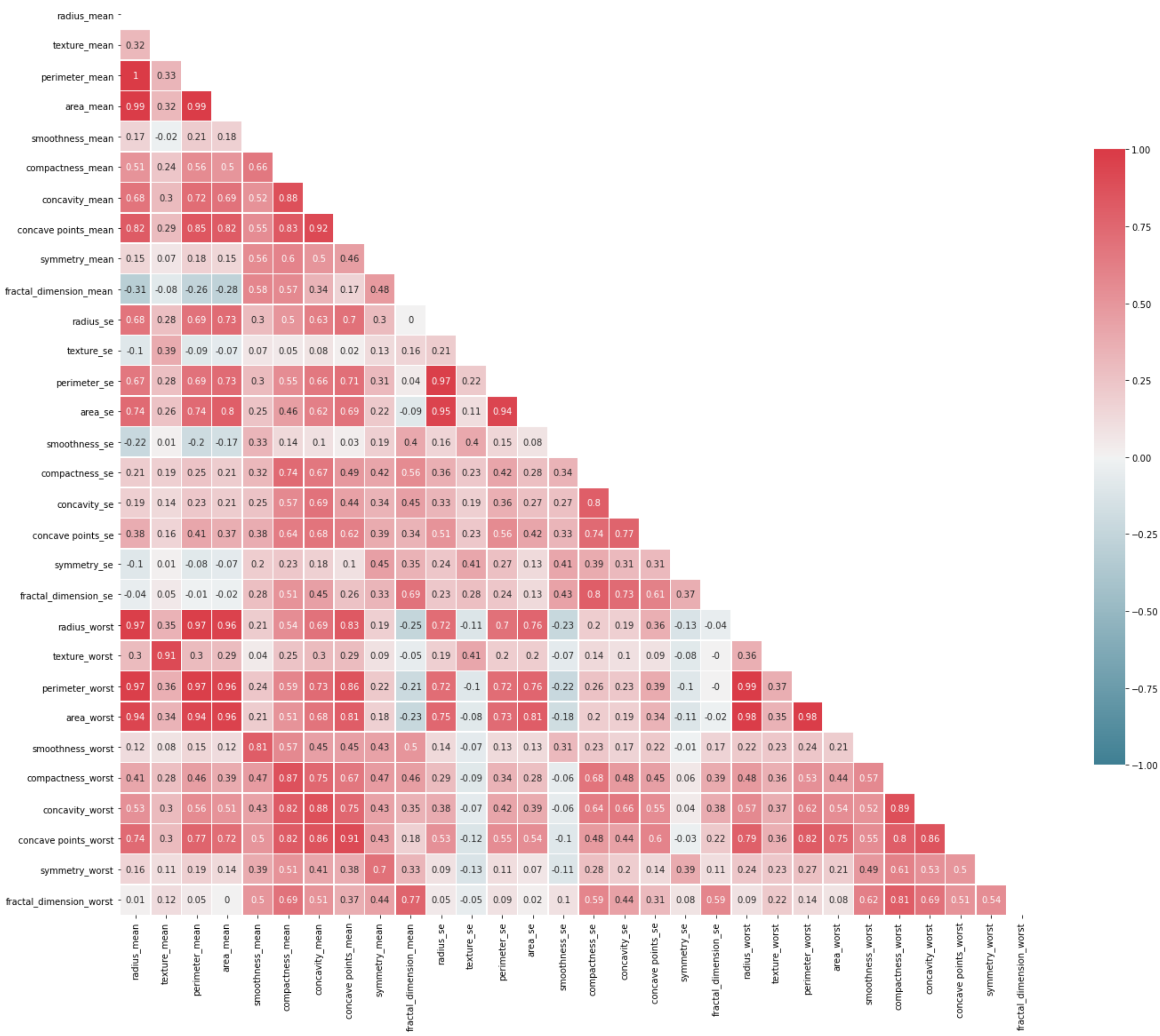
In [23]:
```
import numpy as np
```

In [24]:
```
#generate the corelation matrix
corr=df.corr().round(2)
#mask for the upper triangle
mask=np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)]
# Set figure size
f, ax = plt.subplots(figsize=(20, 20))

#define custom colormap
cmap=sns.diverging_palette(220,10, as_cmap=True)

#draw the heatmap
sns.heatmap(corr, mask=mask, cmap=cmap, vmin=-1, vmax=1, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5}, annot=True)

plt.tight_layout()
```



In [25]:

```
# Generate and visualize the correlation matrix
corr = df.corr().round(2)

# Mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set figure size
f, ax = plt.subplots(figsize=(20, 20))

# Define custom colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap
sns.heatmap(corr, mask=mask, cmap=cmap, vmin=-1, vmax=1, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5}, annot=True)

plt.tight_layout()
```


radius_mean
texture_mean 0.32
perimeter_mean 1 0.33
area_mean 0.99 0.32 0.99
smoothness_mean 0.17 -0.02 0.21 0.18
compactness_mean 0.51 0.24 0.56 0.5 0.66
concavity_mean 0.68 0.3 0.72 0.69 0.52 0.88
concave points_mean 0.82 0.29 0.85 0.82 0.55 0.83 0.92
symmetry_mean 0.15 0.07 0.18 0.15 0.56 0.6 0.5 0.46
fractal_dimension_mean -0.31 -0.08 -0.26 -0.28 0.58 0.57 0.34 0.17 0.48
radius_se 0.68 0.28 0.69 0.73 0.3 0.5 0.63 0.7 0.3 0
texture_se -0.1 0.39 -0.09 -0.07 0.07 0.05 0.08 0.02 0.13 0.16 0.21
perimeter_se 0.67 0.28 0.69 0.73 0.3 0.55 0.66 0.71 0.31 0.04 0.97 0.22
area_se 0.74 0.26 0.74 0.8 0.25 0.46 0.62 0.69 0.22 -0.09 0.95 0.11 0.94
smoothness_se -0.22 0.01 -0.2 -0.17 0.33 0.14 0.1 0.03 0.19 0.4 0.16 0.4 0.15 0.08
compactness_se 0.21 0.19 0.25 0.21 0.32 0.74 0.67 0.49 0.42 0.56 0.36 0.23 0.42 0.28 0.34
concavity_se 0.19 0.14 0.23 0.21 0.25 0.57 0.69 0.44 0.34 0.45 0.33 0.19 0.36 0.27 0.27 0.8
concave points_se 0.38 0.16 0.41 0.37 0.38 0.64 0.68 0.62 0.39 0.34 0.51 0.23 0.56 0.42 0.33 0.74 0.77
symmetry_se -0.1 0.01 -0.08 -0.07 0.2 0.23 0.18 0.1 0.45 0.35 0.24 0.41 0.27 0.13 0.41 0.39 0.31 0.31
fractal_dimension_se -0.04 0.05 -0.01 -0.02 0.28 0.51 0.45 0.26 0.33 0.69 0.23 0.28 0.24 0.13 0.43 0.8 0.73 0.61 0.37
radius_worst 0.97 0.35 0.97 0.96 0.21 0.54 0.69 0.83 0.19 -0.25 0.72 -0.11 0.7 0.76 -0.23 0.2 0.19 0.36 -0.13 -0.04
texture_worst 0.3 0.91 0.3 0.29 0.04 0.25 0.3 0.29 0.09 -0.05 0.19 0.41 0.2 0.2 -0.07 0.14 0.1 0.09 -0.08 -0 0.36
perimeter_worst 0.97 0.36 0.97 0.96 0.24 0.59 0.73 0.86 0.22 -0.21 0.72 -0.1 0.72 0.76 -0.22 0.26 0.23 0.39 -0.1 -0 0.99 0.37
area_worst 0.94 0.34 0.94 0.96 0.21 0.51 0.68 0.81 0.18 -0.23 0.75 -0.08 0.73 0.81 -0.18 0.2 0.19 0.34 -0.11 -0.02 0.98 0.35 0.98
smoothness_worst 0.12 0.08 0.15 0.12 0.81 0.57 0.45 0.45 0.43 0.5 0.14 -0.07 0.13 0.13 0.31 0.23 0.17 0.22 -0.01 0.17 0.22 0.23 0.24 0.21
compactness_worst 0.41 0.28 0.46 0.39 0.47 0.87 0.75 0.67 0.47 0.46 0.29 -0.09 0.34 0.28 -0.06 0.68 0.48 0.45 0.06 0.39 0.48 0.36 0.53 0.44 0.57
concavity_worst 0.53 0.3 0.56 0.51 0.43 0.82 0.88 0.75 0.43 0.35 0.38 -0.07 0.42 0.39 -0.06 0.64 0.66 0.55 0.04 0.38 0.57 0.37 0.62 0.54 0.52 0.89
concave points_worst 0.74 0.3 0.77 0.72 0.5 0.82 0.86 0.91 0.43 0.18 0.53 -0.12 0.55 0.54 -0.1 0.48 0.44 0.6 -0.03 0.22 0.79 0.36 0.82 0.75 0.55 0.8 0.86
symmetry_worst 0.16 0.11 0.19 0.14 0.39 0.51 0.41 0.38 0.7 0.33 0.09 -0.13 0.11 0.07 -0.11 0.28 0.2 0.14 0.39 0.11 0.24 0.23 0.27 0.21 0.49 0.61 0.53 0.5
fractal_dimension_worst 0.01 0.12 0.05 0 0.5 0.69 0.51 0.37 0.44 0.77 0.05 -0.05 0.09 0.02 0.1 0.59 0.44 0.31 0.08 0.59 0.09 0.22 0.14 0.08 0.62 0.81 0.69 0.51 0.54
radius_mean
texture_mean
perimeter_mean
area_mean
smoothness_mean
compactness_mean
concavity_mean
concave points_mean
symmetry_mean
fractal_dimension_mean
radius_se
texture_se
perimeter_se
area_se
smoothness_se
compactness_se
concavity_se
concave points_se
symmetry_se
fractal_dimension_se
radius_worst
texture_worst
perimeter_worst
area_worst
smoothness_worst
compactness_worst
concavity_worst
concave points_worst
symmetry_worst
fractal_dimension_worst
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

In [26]:
```python
M = df[df.diagnosis == "M"]
M.head()
```

Out[26]:

	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_mean
0	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.241
1	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.181
2	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.206
3	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.259
4	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.180

5 rows × 31 columns

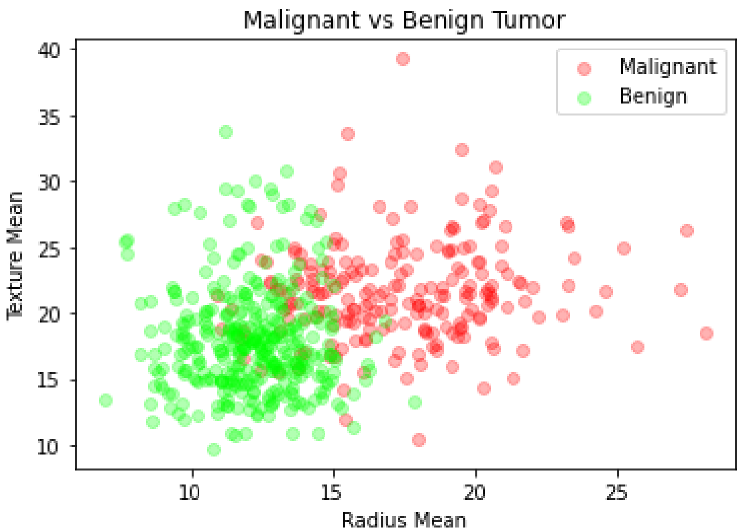
In [27]:
```python
B = df[df.diagnosis == "B"]
B.head()
```

Out[27]:

	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_mea
19	B	13.540	14.36	87.46	566.3	0.09779	0.08129	0.06664	0.047810	0.18
20	B	13.080	15.71	85.63	520.0	0.10750	0.12700	0.04568	0.031100	0.19
21	B	9.504	12.44	60.34	273.9	0.10240	0.06492	0.02956	0.020760	0.18
37	B	13.030	18.42	82.61	523.8	0.08983	0.03766	0.02562	0.029230	0.14
46	B	8.196	16.84	51.71	201.9	0.08600	0.05943	0.01588	0.005917	0.17

5 rows × 31 columns

In [28]:
```python
plt.title("Malignant vs Benign Tumor")
plt.xlabel("Radius Mean")
plt.ylabel("Texture Mean")
plt.scatter(M.radius_mean, M.texture_mean, color = "red", label = "Malignant", alpha = 0.3)
plt.scatter(B.radius_mean, B.texture_mean, color = "lime", label = "Benign", alpha = 0.3)
plt.legend()
plt.show()
```



ML ALGORITHM IMPLEMENTATION:

In [29]:
```
feature_cols = ['radius_mean', 'texture_mean', 'perimeter_mean', 'area_mean','smoothness_mean', 'compactness_mean', 'concavity_m
```

In [30]:
```
x = df[feature_cols]
y = df.diagnosis.values
```

In [31]:
```
x.head()
```

Out[31]:

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_mean	fractal_di
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597	
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809	

In [32]:
```
# Normalization:
x = (x - np.min(x)) / (np.max(x) - np.min(x))
x
```

Out[32]:

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_mean	fractal_
0	0.521037	0.022658	0.545989	0.363733	0.593753	0.792037	0.703140	0.731113	0.686364	
1	0.643144	0.272574	0.615783	0.501591	0.289880	0.181768	0.203608	0.348757	0.379798	
2	0.601496	0.390260	0.595743	0.449417	0.514309	0.431017	0.462512	0.635686	0.509596	
3	0.210090	0.360839	0.233501	0.102906	0.811321	0.811361	0.565604	0.522863	0.776263	
4	0.629893	0.156578	0.630986	0.489290	0.430351	0.347893	0.463918	0.518390	0.378283	
...	...	...	...	...	...	...	...	...	...	
564	0.690000	0.428813	0.678668	0.566490	0.526948	0.296055	0.571462	0.690358	0.336364	
565	0.622320	0.626987	0.604036	0.474019	0.407782	0.257714	0.337395	0.486630	0.349495	
566	0.455251	0.621238	0.445788	0.303118	0.288165	0.254340	0.216753	0.263519	0.267677	
567	0.644564	0.663510	0.665538	0.475716	0.588336	0.790197	0.823336	0.755467	0.675253	
568	0.036869	0.501522	0.028540	0.015907	0.000000	0.074351	0.000000	0.000000	0.266162	

569 rows × 10 columns

In [30]:
```
## Splitting the Dataset
from sklearn.model_selection import train_test_split
```

In [31]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.3)
```

In [32]:
```
x_train.shape, x_test.shape, y_train.shape, y_test.shape
```

Out[32]: ((398, 30), (171, 30), (398,), (171,))

In [34]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import cross_val_score
```

In [35]:
```
model1 = DecisionTreeClassifier()
```

In [36]:
```
model1.fit(x_train,y_train)
```

Out[36]: DecisionTreeClassifier()

```
In [37]: model1.predict(x_test)

Out[37]: array(['B', 'M', 'B', 'M', 'M', 'B', 'B', 'B', 'B', 'B', 'B', 'B', 'M',
                'M', 'M', 'B', 'M', 'B', 'B', 'M', 'M', 'B', 'M', 'B', 'M', 'B',
                'B', 'B', 'B', 'B', 'B', 'B', 'M', 'M', 'B', 'M', 'M', 'B', 'B',
                'B', 'B', 'B', 'B', 'M', 'M', 'B', 'B', 'B', 'B', 'B', 'B', 'B',
                'B', 'B', 'M', 'M', 'B', 'B', 'B', 'M', 'B', 'B', 'M', 'B', 'B',
                'M', 'M', 'M', 'B', 'B', 'M', 'M', 'M', 'M', 'M', 'B', 'M', 'M',
                'B', 'M', 'M', 'B', 'M', 'B', 'B', 'B', 'B', 'B', 'B', 'B', 'B',
                'B', 'B', 'B', 'M', 'B', 'B', 'B', 'B', 'M', 'M', 'M', 'B', 'B',
                'B', 'B', 'B', 'M', 'B', 'B', 'B', 'B', 'M', 'M', 'M', 'B', 'M',
                'B', 'M', 'M', 'B', 'B', 'M', 'B', 'B', 'B', 'M', 'B', 'B', 'M',
                'M', 'B', 'M', 'M', 'B', 'M', 'B', 'B', 'B', 'B', 'B', 'M', 'B',
                'B', 'B', 'M', 'M', 'B', 'M', 'M', 'B', 'M', 'B', 'M', 'M', 'M',
                'B', 'B', 'B', 'M', 'B', 'M', 'M', 'B', 'B', 'M', 'B', 'B', 'M',
                'B', 'B'], dtype=object)
```

FINAL RESULT:

```
In [39]: cross_val_score(model1, x, y, cv=5)

Out[39]: array([0.9122807 , 0.9122807 , 0.92105263, 0.94736842, 0.90265487])

In [ ]:
```

Github Link

https://github.com/avnish9898/Ml-Experiment/blob/main/exp3.ipynb