

Machine Learning Experiment 2

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AIM:

Study and implement the Decision tree using Python Sklearn on Breast Cancer dataset.

ALGORITHM:

1. Select the best attribute using Attribute Selection Measures (ASM) to split the records.
2. Make that attribute a decision node and breaks the dataset into smaller subsets.
3. Starts tree building by repeating this process recursively for each child until one of the conditions will match:
 - a. All the tuples belong to the same attribute value.
 - b. There are no more remaining attributes.
 - c. There are no more instances.

PROGRAM CODE SNIPPET:

LOADING DATA SET:

```
In [3]: import pandas as pd
df = pd.read_csv("C:/Users/WCOMeeting/Downloads/cancer.csv")
df
```

Out[3]:

	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 x 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	concave points_mean
id	1.000000	0.074626	0.099770	0.073159	0.098893	-0.012988	0.000096	0.050080	0.044158
radius_mean	0.074626	1.000000	0.323782	0.997855	0.987357	0.170581	0.506124	0.676764	0.822529
texture_mean	0.099770	0.323782	1.000000	0.329533	0.321086	-0.023389	0.236702	0.302418	0.293464
perimeter_mean	0.073159	0.997855	0.329533	1.000000	0.988507	0.207278	0.556936	0.716136	0.850977
area_mean	0.098893	0.987357	0.321086	0.988507	1.000000	0.177028	0.498502	0.685983	0.823269
smoothness_mean	-0.012988	0.170581	-0.023389	0.207278	0.177028	1.000000	0.659123	0.521984	0.553895
compactness_mean	0.000096	0.506124	0.236702	0.556936	0.498502	0.659123	1.000000	0.883121	0.831135
concavity_mean	0.050080	0.676764	0.302418	0.716136	0.685983	0.521984	0.883121	1.000000	0.921391
concave points_mean	0.044158	0.822529	0.293464	0.850977	0.823269	0.553895	0.831135	0.921391	1.000000
symmetry_mean	-0.022114	0.147741	0.071401	0.183027	0.151293	0.557775	0.602641	0.500667	0.462144
fractal_dimension_mean	-0.052511	-0.311631	-0.076437	-0.261477	-0.283110	0.584792	0.565369	0.336783	0.166190
radius_se	0.143048	0.679090	0.275889	0.691765	0.732562	0.301467	0.497473	0.631925	0.696190
texture_se	-0.007526	-0.097317	0.386358	-0.088761	-0.086280	0.068406	0.046205	0.076218	0.021391
perimeter_se	0.137331	0.674172	0.281673	0.693135	0.726628	0.296092	0.548905	0.660391	0.710391
area_se	0.177742	0.735864	0.256845	0.744983	0.800086	0.246552	0.456653	0.617427	0.696190
smoothness_se	0.098781	-0.222600	0.006614	-0.202694	-0.166777	0.332375	0.135299	0.098564	0.027144
compactness_se	0.033961	0.206000	0.191975	0.250744	0.212583	0.318943	0.738722	0.670279	0.496190
concavity_se	0.055239	0.194204	0.143293	0.228082	0.207660	0.248396	0.570517	0.691270	0.436190
concave points_se	0.078768	0.376169	0.163851	0.407217	0.372320	0.380676	0.642262	0.683260	0.616190
symmetry_se	-0.017306	-0.104321	0.009127	-0.081629	-0.072497	0.200774	0.229977	0.178009	0.096190
fractal_dimension_se	0.025725	-0.042641	0.054458	-0.005523	-0.019887	0.283607	0.507318	0.449301	0.257190
radius_worst	0.082405	0.969539	0.352573	0.969476	0.962746	0.213120	0.535315	0.688236	0.836190
texture_worst	0.064720	0.297008	0.912045	0.303038	0.287489	0.036072	0.248133	0.299879	0.296190
perimeter_worst	0.079986	0.965137	0.358040	0.970387	0.959120	0.238853	0.590210	0.729565	0.856190

```
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
dtvov: 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]: 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_mean
0	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	0.24030
1	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08890	0.07017	0.18139
2	M	19.69	21.25	130.00	1203.0	0.10980	0.15990	0.19740	0.12790	0.20601
3	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	0.25958
4	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	0.18139
...
564	M	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0.17127
565	M	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0.17127
566	M	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0.15155
567	M	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	0.23161
568	B	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0.15155

```
In [14]: 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_mean
0	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	0.24030
1	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08890	0.07017	0.18139
2	M	19.69	21.25	130.00	1203.0	0.10980	0.15990	0.19740	0.12790	0.20601
3	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	0.25958
4	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	0.18139
...
564	M	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0.17127
565	M	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0.17127
566	M	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0.15155
567	M	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	0.23161
568	B	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0.15155

569 rows x 31 columns

VISUALIZATION:

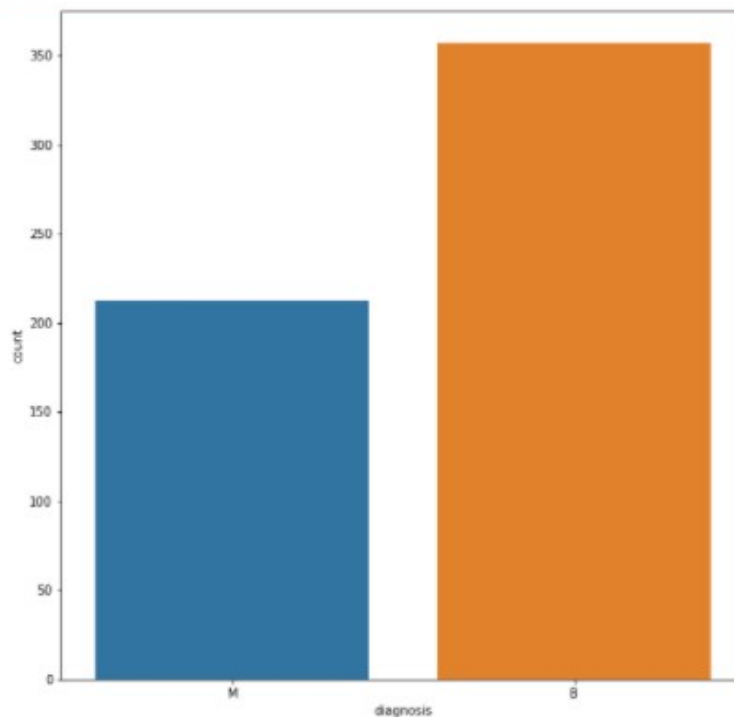
```
In [15]: import matplotlib.pyplot as plt  
import seaborn as sns
```

```
In [16]: 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 [17]: plt.figure(figsize=(10,10))  
sns.countplot(df['diagnosis'])  
plt.show()
```

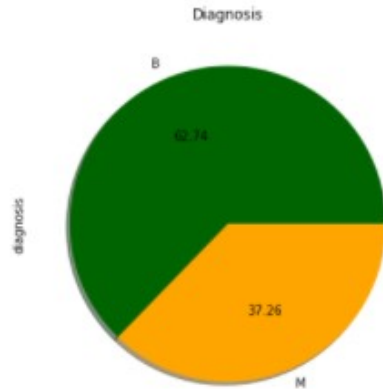
C:\Users\WCOMeeting\anaconda3\lib\site-packages\seaborn_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
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()
```

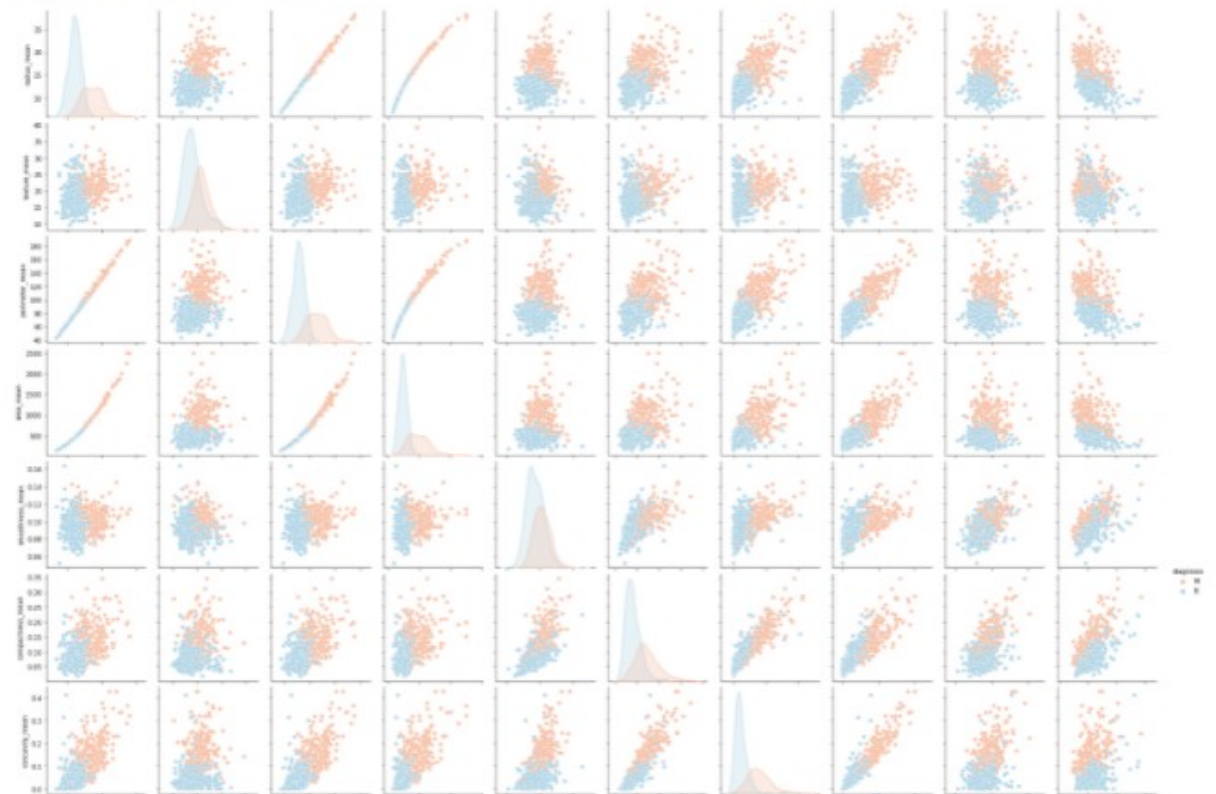


Pairplot helps to plot among the most useful feature

```
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>



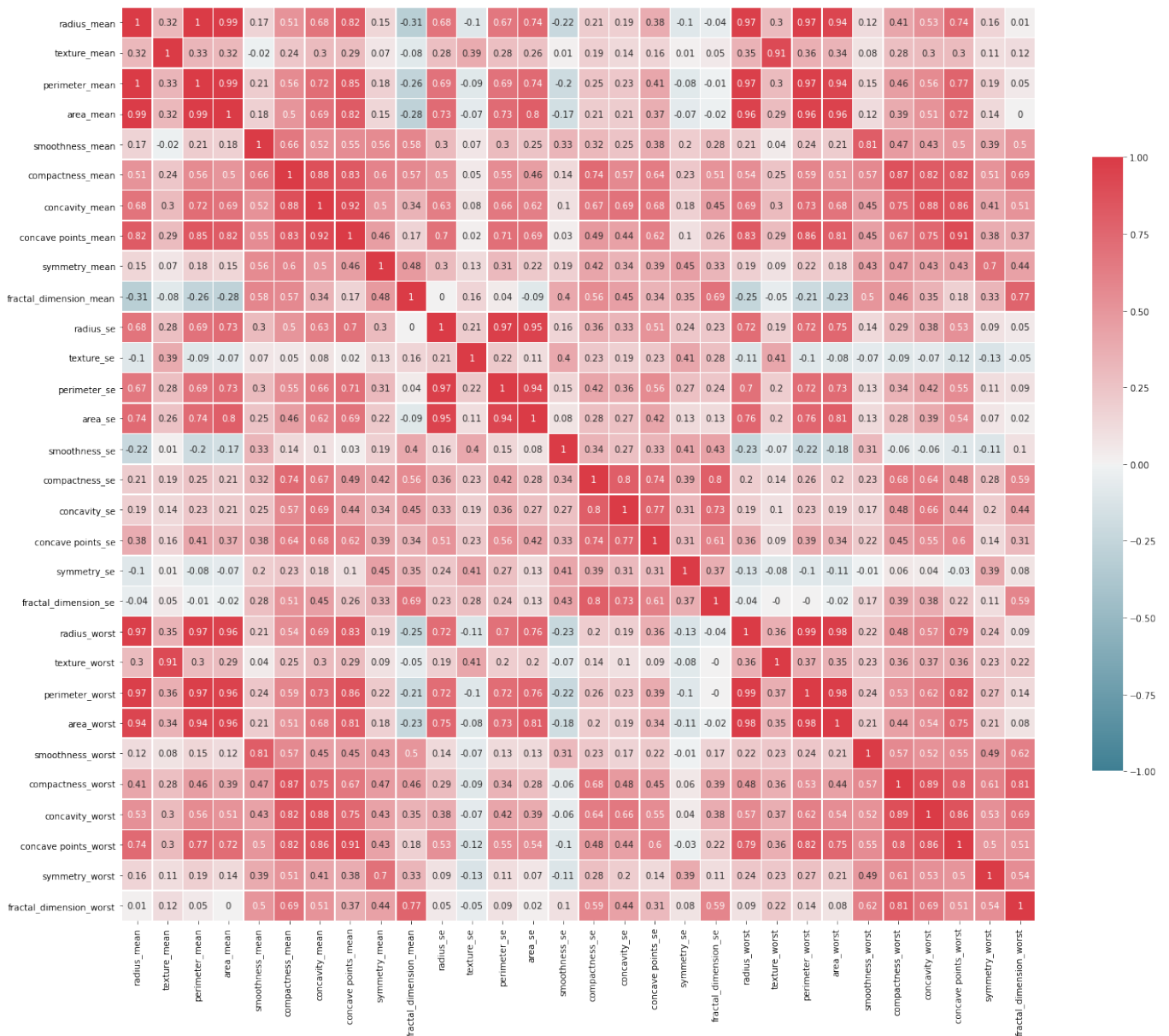
```
In [23]: import numpy as np
```

```
In [24]: #generate the 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)]
# 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)

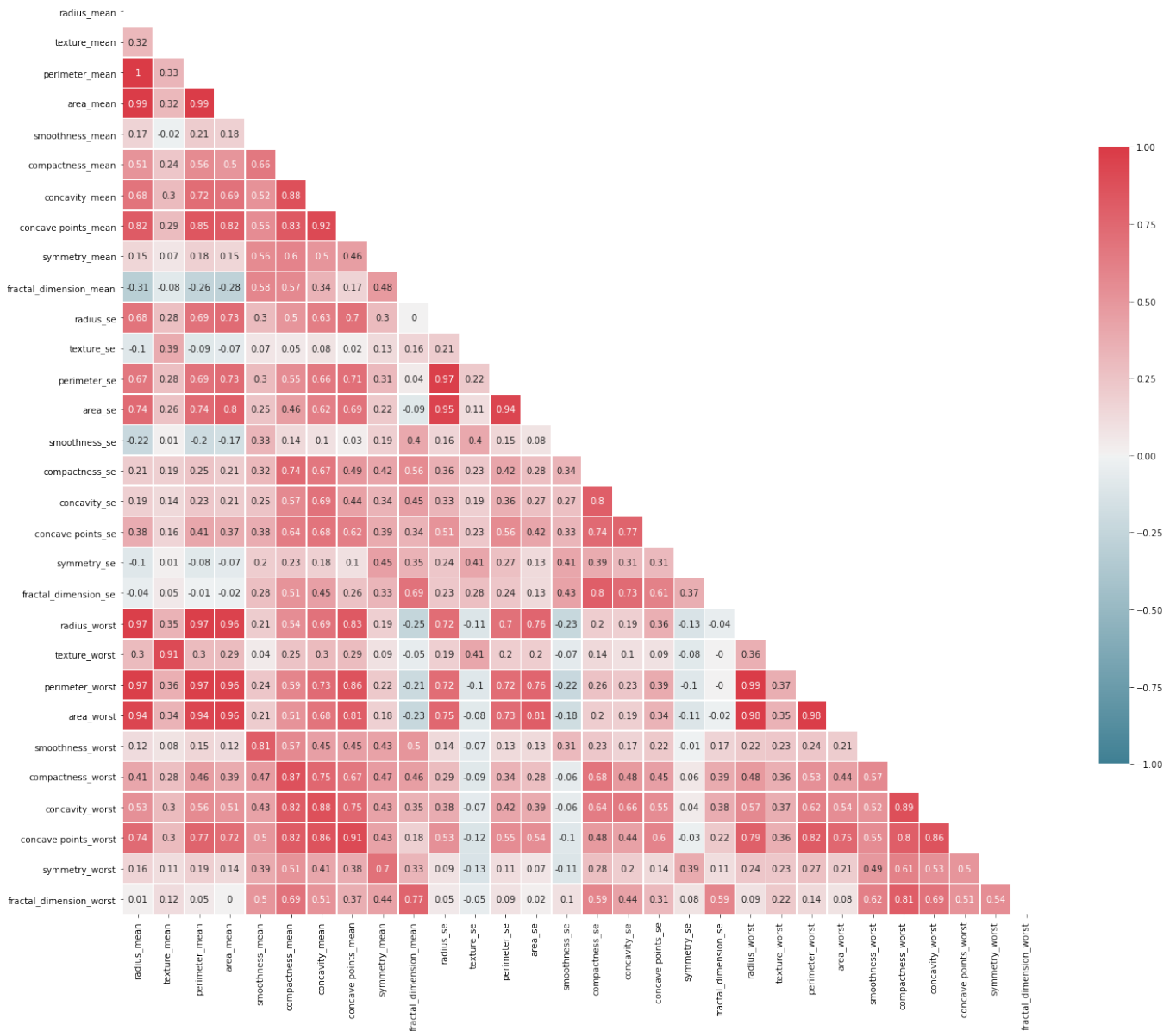
# Mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# 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()
```




```
In [26]: 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	0.2411
1	M	20.57	17.77	132.90	1326.0	0.08474	0.07884	0.0869	0.07017	0.1811
2	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2061
3	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2591
4	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1801

5 rows × 11 columns

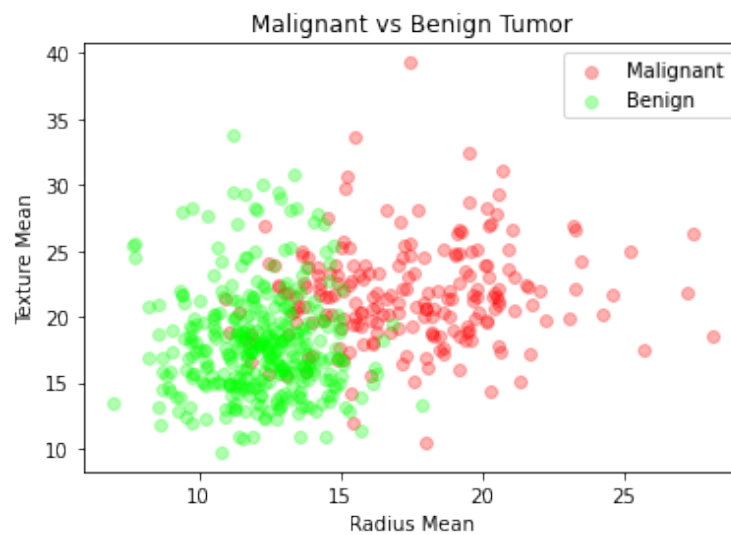
```
In [27]: B = df[df.diagnosis == "B"]
B.head()
```

Out[27]:

	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_mean
19	B	13.540	14.36	87.46	586.3	0.09779	0.08129	0.08664	0.047810	0.1811
20	B	13.080	15.71	85.63	520.0	0.10750	0.12700	0.04568	0.031100	0.1961
21	B	9.504	12.44	60.34	273.9	0.10240	0.06492	0.02956	0.020760	0.1811
37	B	13.030	18.42	82.61	523.8	0.08983	0.03766	0.02562	0.029230	0.1461
46	B	8.196	16.84	51.71	201.9	0.08600	0.05943	0.01588	0.005917	0.1761

5 rows × 11 columns

```
In [28]: 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	19.99	21.25	130.00	1203.0	0.10980	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_di
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	0.289980	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	0.298055	0.571482	0.690358	0.338364	
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	0.287677	
567	0.644564	0.663510	0.665538	0.475716	0.588336	0.790197	0.823336	0.755467	0.675253	
568	0.036889	0.501522	0.028540	0.015907	0.000000	0.074351	0.000000	0.000000	0.288162	

569 rows x 10 columns

```
In [33]: from sklearn.model_selection import train_test_split

# for checking testing results
from sklearn.metrics import classification_report, confusion_matrix

# for visualizing tree
from sklearn.tree import plot_tree

# 80-20%
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size = 0.2, random_state = 0)

print("Training split input- ", x_train.shape)
print("Testing split input- ", x_test.shape)

Training split input- (455, 10)
Testing split input- (114, 10)
```

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

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

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

```
Out[36]: DecisionTreeClassifier()
```

```
In [37]: y_pred = dt.predict(x_test)
print("Classification report - \n", classification_report(y_test,y_pred))
```

```
Classification report -
              precision    recall  f1-score   support

     B         0.94         0.93         0.93         67
     M         0.90         0.91         0.91         47

 accuracy         0.92
 macro avg         0.92         0.92         0.92         114
 weighted avg         0.92         0.92         0.92         114
```

```
In [38]: cm=confusion_matrix(y_test,y_pred)
cm
```

```
Out[38]: array([[62,  5],
               [ 4, 43]], dtype=int64)
```

```
In [41]: plt.figure(figsize=(5,5))

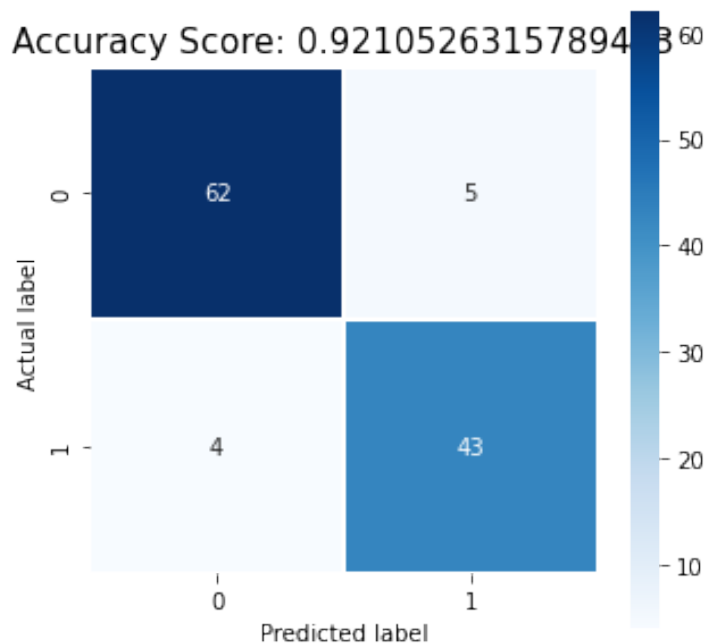
sns.heatmap(data=cm,linewidths=1.0, annot=True,square = True, cmap = 'Blues')

plt.ylabel('Actual label')
plt.xlabel('Predicted label')

all_sample_title = 'Accuracy Score: {0}'.format(dt.score(x_test, y_test))
plt.title(all_sample_title, size = 15)

#plt.savefig("D:/accu.png")
```

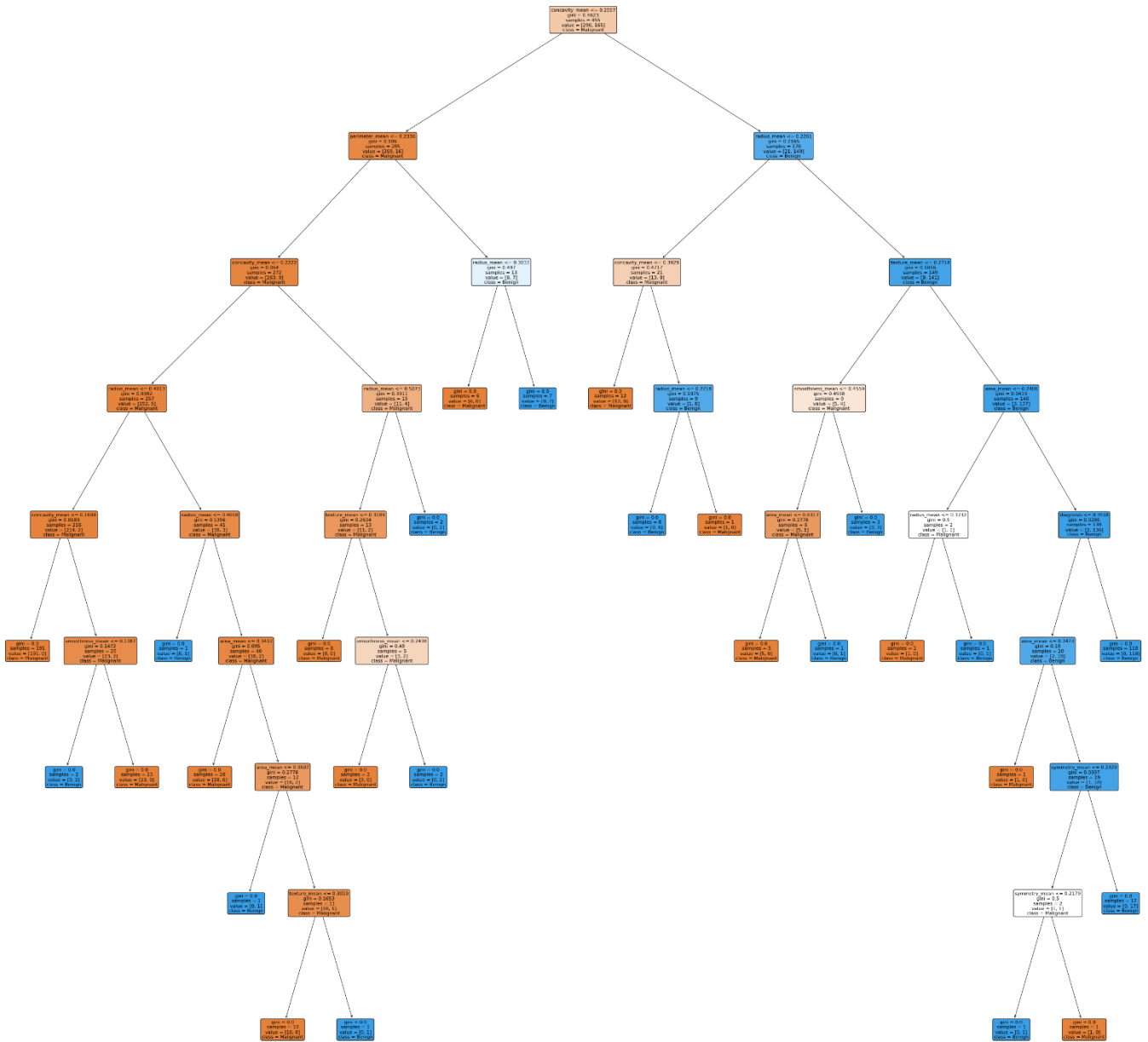
```
Out[41]: Text(0.5, 1.0, 'Accuracy Score: 0.9210526315789473')
```



FINAL GRAPHS:

In [42]: # Visualising the graph without the use of graphviz

```
plt.figure(figsize = (50,50))
dec_tree = plot_tree(decision_tree=dt, feature_names = df.columns, class_names=["Malignant", "Benign"], filled = True, precis
#plt.savefig("D:/dt.png")
```



GITHUB LINK:

[https://github.com/chanpreet1999/ML-](https://github.com/chanpreet1999/ML-Assignment/blob/master/Machine%20Learning%20Experiment%202.ipynb)

[Assignment/blob/master/Machine%20Learning%20Experiment%202.ipynb](https://github.com/chanpreet1999/ML-Assignment/blob/master/Machine%20Learning%20Experiment%202.ipynb)