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Enroll- 00213202717

Class- CSE-1

EXPERIMENT-1

Problem Statement

To implement Decision Tree algorithm on a breast cancer dataset

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 Dataset

```
import pandas as pd

df = pd.read_csv("/content/drive/My Drive/project videos/cancer.csv")
df
```

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_mean	fractal_dimension_mean	r
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	0.2419	0.07871	
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	0.07017	0.1812	0.05667	
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	0.12790	0.2069	0.05999	
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	0.2597	0.09744	
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	0.1809	0.05883	
...	...	...	...	...	...	...	...	...	...	...	...	...	
564	926424	M	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0.1726	0.05623	
565	926682	M	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0.1752	0.05533	
566	926954	M	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0.1590	0.05648	
567	927241	M	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	0.2397	0.07016	
568	92751	B	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0.1587	0.05884	

569 rows × 32 columns

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_mean	fractal_dimension_mean	rad
0	842302	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	0.2419	0.07871	
1	842517	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	0.07017	0.1812	0.05667	
2	84300903	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	0.12790	0.2069	0.05999	
3	84348301	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	0.2597	0.09744	
4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	0.1809	0.05883	
5	843786	M	12.45	15.70	82.57	477.1	0.12780	0.17000	0.15780	0.08089	0.2087	0.07613	
6	844359	M	18.25	19.98	119.60	1040.0	0.09463	0.10900	0.11270	0.07400	0.1794	0.05742	
7	84458202	M	13.71	20.83	90.20	577.9	0.11890	0.16450	0.09366	0.05985	0.2196	0.07451	
8	844981	M	13.00	21.82	87.50	519.8	0.12730	0.19320	0.18590	0.09353	0.2350	0.07389	
9	84501001	M	12.46	24.04	83.97	475.9	0.11860	0.23960	0.22730	0.08543	0.2030	0.08243	

```
#to read the last end of data
df.tail()
```

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_mean	fractal_dimension_mean	rad
564	926424	M	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0.1726	0.05623	
565	926682	M	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0.1752	0.05533	
566	926954	M	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0.1590	0.05648	

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[4]

4	84358402	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	0.1809	0.05883	
5	843786	M	12.45	15.70	82.57	477.1	0.12780	0.17000	0.15780	0.08089	0.2087	0.07613	
6	844359	M	18.25	19.98	119.60	1040.0	0.09463	0.10900	0.11270	0.07400	0.1794	0.05742	
7	84458202	M	13.71	20.83	90.20	577.9	0.11890	0.16450	0.09366	0.05985	0.2196	0.07451	
8	844981	M	13.00	21.82	87.50	519.8	0.12730	0.19320	0.18590	0.09353	0.2350	0.07389	
9	84501001	M	12.46	24.04	83.97	475.9	0.11860	0.23960	0.22730	0.08543	0.2030	0.08243	

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564	926424	M	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0.1726	0.05623	
565	926682	M	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0.1752	0.05533	
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568	92751	B	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0.1587	0.05884	


```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 32 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
dtypes: float64(30), int64(1), object(1)
memory usage: 142.4+ KB
```

[7]

[8] `df.shape`

```
(569, 32)
```

```
#print all the columns of dataset
df.columns.values
```

```
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'], dtype=object)
```

Preprocessing/Cleaning of dataset

```
[10] df.corr()
```

	id	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_mean	fractal_dimension_
id	1.000000	0.074626	0.099770	0.073159	0.096893	-0.012968	0.000096	0.050080	0.044158	-0.022114	-0.0
radius_mean	0.074626	1.000000	0.323782	0.997855	0.987357	0.170581	0.506124	0.676764	0.822529	0.147741	-0.3
texture_mean	0.099770	0.323782	1.000000	0.329533	0.321086	-0.023389	0.236702	0.302418	0.293464	0.071401	-0.0
perimeter_mean	0.073159	0.997855	0.329533	1.000000	0.986507	0.207278	0.556936	0.716136	0.850977	0.183027	-0.2
area_mean	0.096893	0.987357	0.321086	0.986507	1.000000	0.177028	0.498502	0.685983	0.823269	0.151293	-0.2
smoothness_mean	-0.012968	0.170581	-0.023389	0.207278	0.177028	1.000000	0.659123	0.521984	0.553695	0.557775	0.5
compactness_mean	0.000096	0.506124	0.236702	0.556936	0.498502	0.659123	1.000000	0.883121	0.831135	0.602641	0.5
concavity_mean	0.050080	0.676764	0.302418	0.716136	0.685983	0.521984	0.883121	1.000000	0.921391	0.500667	0.3
concave points_mean	0.044158	0.822529	0.293464	0.850977	0.823269	0.553695	0.831135	0.921391	1.000000	0.462497	0.1
symmetry_mean	-0.022114	0.147741	0.071401	0.183027	0.151293	0.557775	0.602641	0.500667	0.462497	1.000000	0.4
fractal_dimension_mean	-0.052511	-0.311631	-0.076437	-0.261477	-0.283110	0.584792	0.565369	0.336783	0.166917	0.479921	1.0
radius_se	0.143048	0.679090	0.275869	0.691765	0.732562	0.301467	0.497473	0.631925	0.698050	0.303379	0.0
texture_se	-0.007526	-0.097317	0.386358	-0.086761	-0.066280	0.068406	0.046205	0.076218	0.021480	0.128053	0.1
perimeter_se	0.137331	0.674172	0.281673	0.693135	0.726628	0.296092	0.548905	0.660391	0.710650	0.313893	0.0
area_se	0.177742	0.735864	0.259845	0.744983	0.800086	0.246552	0.455653	0.617427	0.690299	0.223970	-0.0
smoothness_se	0.096781	-0.222600	0.006614	-0.202694	-0.166777	0.332375	0.135299	0.098564	0.027653	0.187321	0.4
compactness_se	0.033961	0.206000	0.191975	0.250744	0.212583	0.318943	0.738722	0.670279	0.490424	0.421659	0.5
concavity_se	0.055239	0.194204	0.143293	0.228082	0.207660	0.248396	0.570517	0.691270	0.439167	0.342627	0.4

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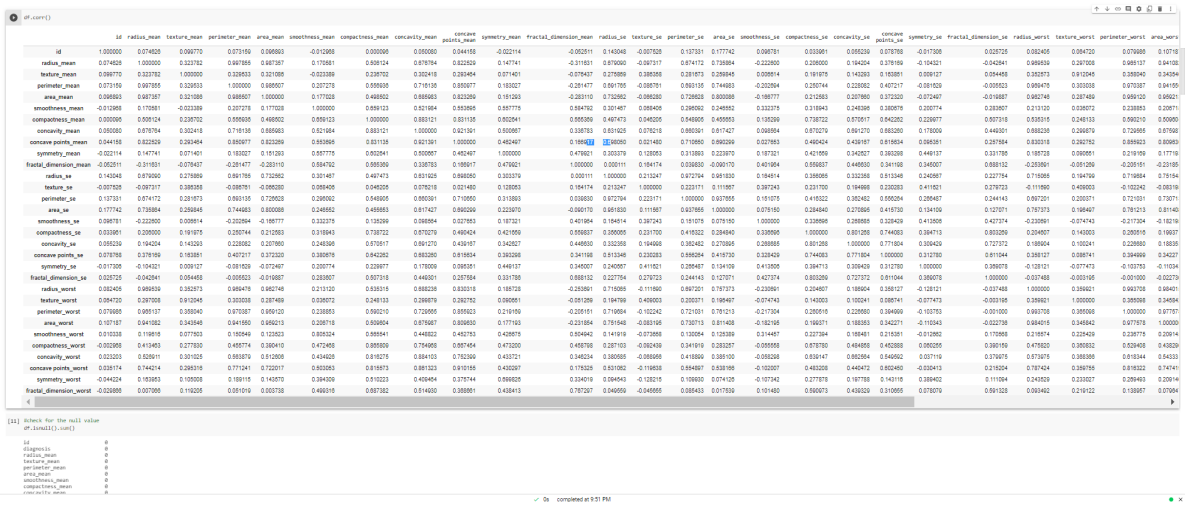
Finding Relationships:

A great aspect of the Pandas module is the corr() method.

The corr() method calculates the relationship between each column in your data set.



```
[11] #check for the null value
     df.isnull().sum()
```

```
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
```

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

```
Name: radius_se, Length: 540, dtype: int64
----------------------*********---------------------------
texture_se
1.3500    3
1.2680    3
0.8561    3
1.1500    3
1.4280    2
         ..
0.8339    1
0.8652    1
1.2000    1
1.9250    1
1.3750    1
Name: texture_se, Length: 519, dtype: int64
----------------------*********---------------------------
perimeter_se
1.778    4
3.564    2
1.143    2
1.535    2
2.406    2
        ..
2.629    1
4.675    1
3.475    1
1.527    1
2.000    1
Name: perimeter_se, Length: 533, dtype: int64
----------------------*********---------------------------
area_se
17.67    3
```

```
[13] df['diagnosis'].value_counts()
```

```
B    357
M    212
Name: diagnosis, dtype: int64
```

```
df= df.drop(["id"], axis = 1)
df
```

	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
0	M	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.30010	0.14710	0.2419	0.07871	1.0950
1	M	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.08690	0.07017	0.1812	0.05667	0.5435
2	M	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.19740	0.12790	0.2069	0.05999	0.7456
3	M	11.42	20.38	77.58	386.1	0.14250	0.28390	0.24140	0.10520	0.2597	0.09744	0.4956
4	M	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.19800	0.10430	0.1809	0.05883	0.7572
...	...	...	...	...	...	...	...	...	...	...	...	...
564	M	21.56	22.39	142.00	1479.0	0.11100	0.11590	0.24390	0.13890	0.1726	0.05623	1.1760
565	M	20.13	28.25	131.20	1261.0	0.09780	0.10340	0.14400	0.09791	0.1752	0.05533	0.7655
566	M	16.60	28.08	108.30	858.1	0.08455	0.10230	0.09251	0.05302	0.1590	0.05648	0.4564
567	M	20.60	29.33	140.10	1265.0	0.11780	0.27700	0.35140	0.15200	0.2397	0.07016	0.7260
568	B	7.76	24.54	47.92	181.0	0.05263	0.04362	0.00000	0.00000	0.1587	0.05884	0.3857

569 rows × 31 columns

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Visualization

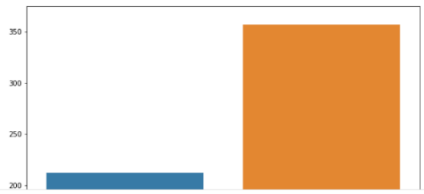
```
[16] import matplotlib.pyplot as plt
     import seaborn as sns
```

```
[17] 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
```

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

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and pa
  FutureWarning
```



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

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and pa
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```
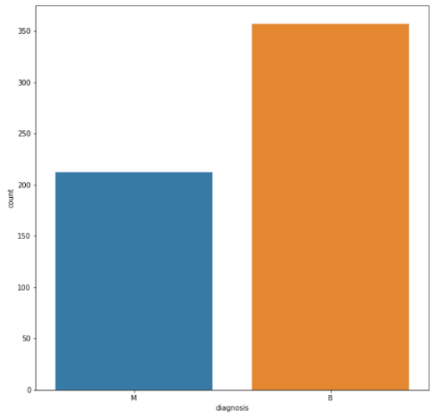
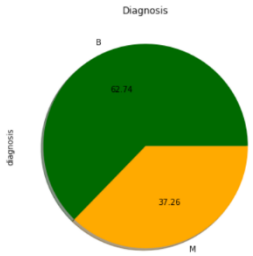




```
[19] print("% of Benign cell is ", benign*100/len(df))
     print("% of Malignant cell is ", malignant*100/len(df))
```

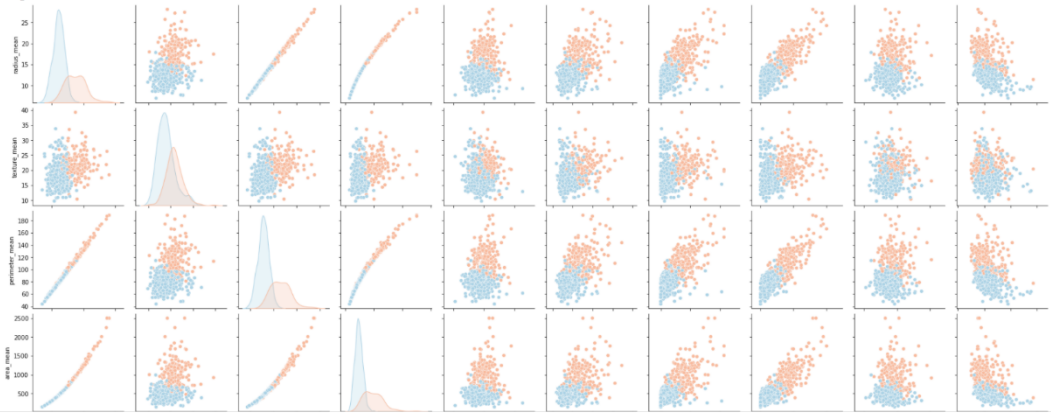
```
% of Benign cell is  62.74165202108963
% of Malignant cell is  37.25834797891037
```

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




```
        'concave points_mean', 'symmetry_mean', 'fractal_dimension_mean']
plt.figure(figsize=(10,10))
sns.pairplot(data=df[cols],hue='diagnosis', palette='RdBu')
```

```
<seaborn.axisgrid.PairGrid at 0x7f71f43ec2d0>
<Figure size 720x720 with 0 Axes>
```



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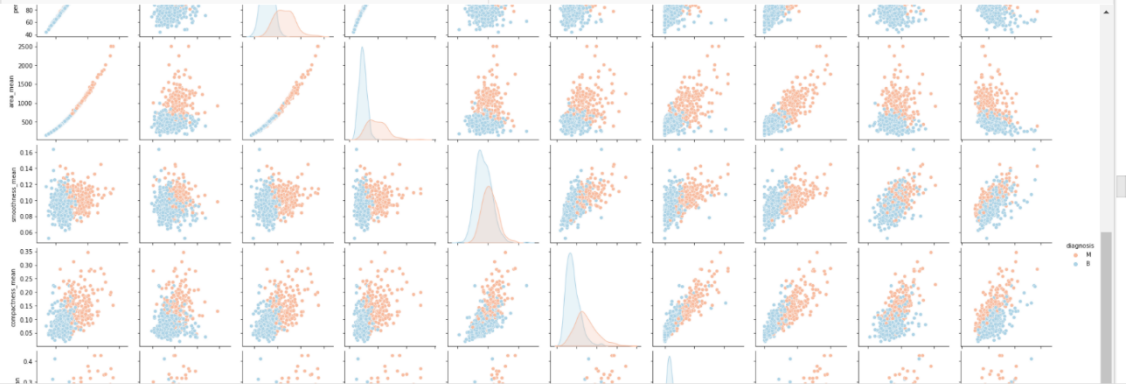
```
cols=['diagnosis','radius_mean', 'texture_mean', 'perimeter_mean',
       'area_mean','smoothness_mean', 'compactness_mean', 'concavity_mean',
       'concave points_mean', 'symmetry_mean', 'fractal_dimension_mean']
plt.figure(figsize=(10,10))
sns.pairplot(data=df[cols],hue='diagnosis', palette='RdBu')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



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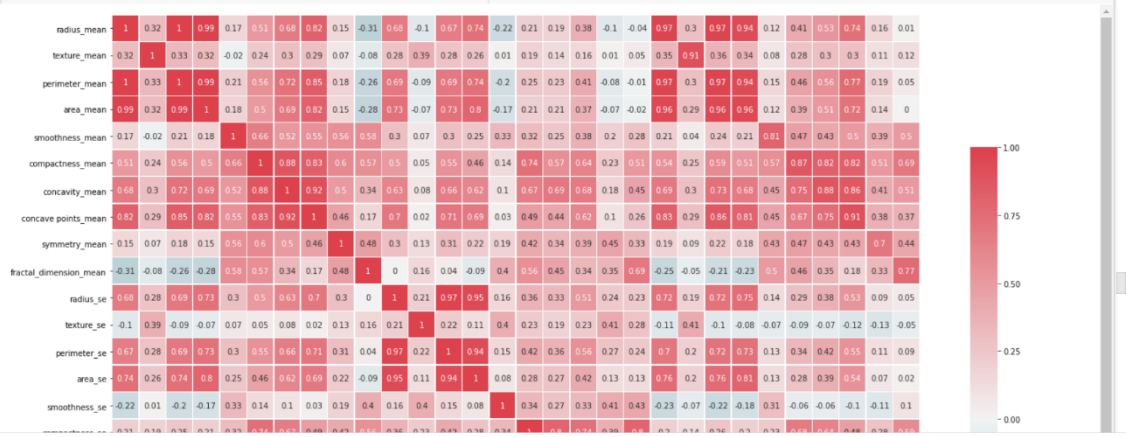
```
sns.heatmap(corr, mask=mask, cmap=cmap, vmin=-1, vmax=1, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5}, annot=True)

plt.tight_layout()
```



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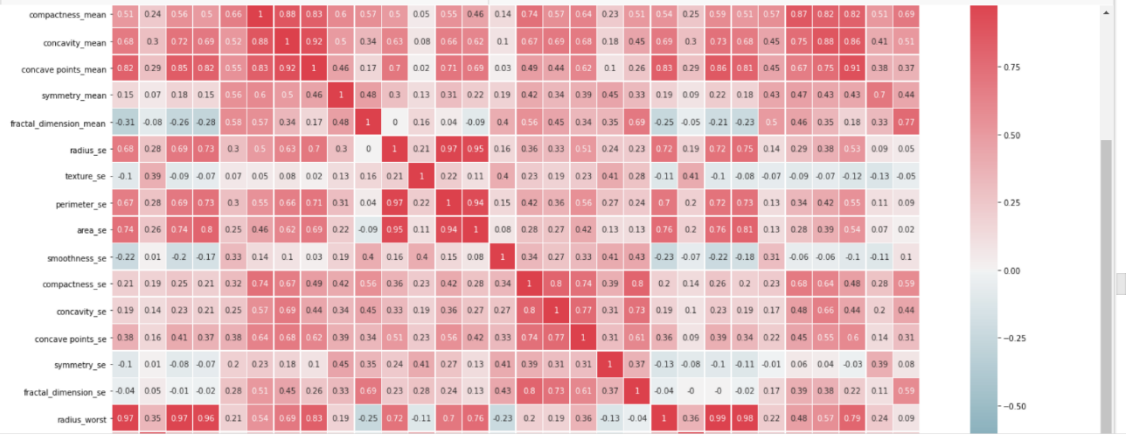
```
sns.heatmap(corr, mask=mask, cmap=cmap, vmin=-1, vmax=1, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5}, annot=True)

plt.tight_layout()
```



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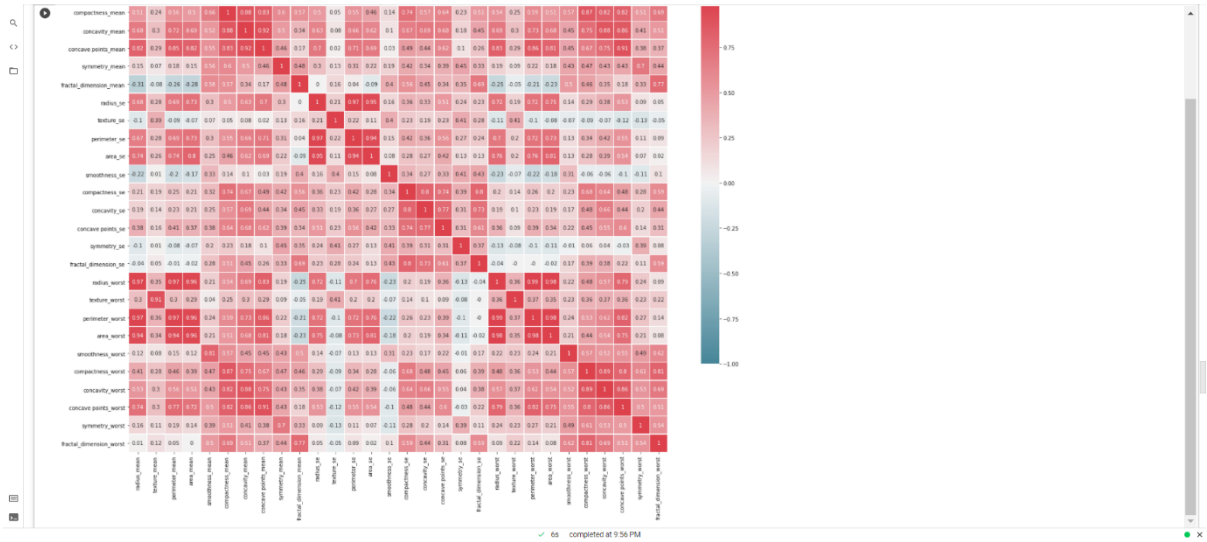
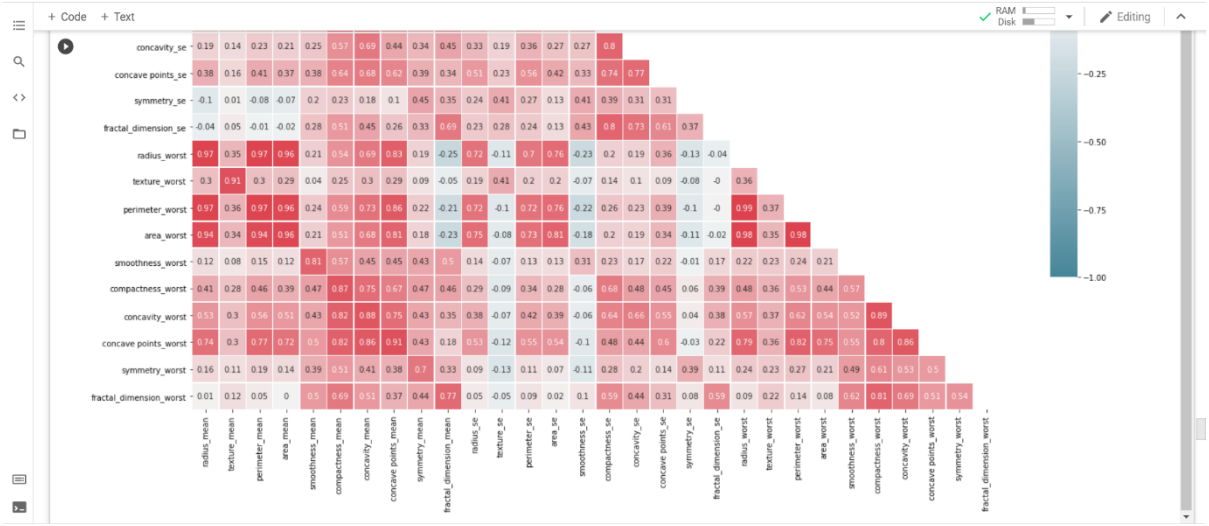
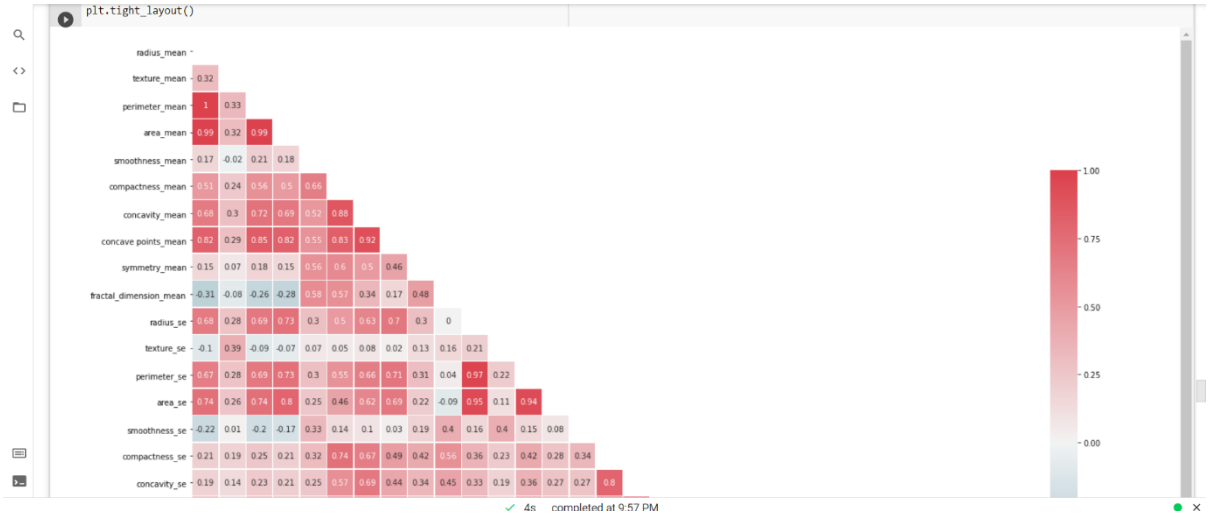

completed at 9:56 PM

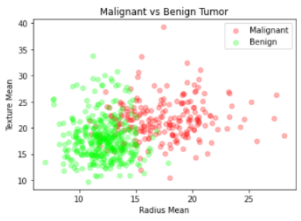

+ Code
+ Text
RAM
Disk
Editing

```
plt.tight_layout()
```



4s completed at 9:57 PM

```
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()
```



Algorithm Implementation

```
[28] feature_cols = ['radius_mean', 'texture_mean', 'perimeter_mean', 'area_mean','smoothness_mean', 'compactness_mean', 'concavity_mean','concave points_mean', 'symmetry_mean', 'fractal_c
```

```
[29] x = df[feature_cols]
     y = df.diagnosis.values
```

```
[30] x.head()
```

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_mean	fractal_dimension_mean
0	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	0.07871
1	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	0.05667
2	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	0.05999
3	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	0.2597	0.09744
4	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	0.1809	0.05883

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

	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_mean	fractal_dimension_mean
0	0.521037	0.022658	0.545989	0.363733	0.593753	0.792037	0.703140	0.731113	0.686364	0.605518
1	0.643144	0.272574	0.615783	0.501591	0.289880	0.181768	0.203608	0.348757	0.379798	0.141323
2	0.601496	0.390260	0.595743	0.449417	0.514309	0.431017	0.462512	0.635686	0.509596	0.211247
3	0.210090	0.360839	0.233501	0.102906	0.811321	0.811361	0.565604	0.522863	0.776263	1.000000
4	0.629893	0.156578	0.630986	0.489290	0.430351	0.347893	0.463918	0.518390	0.378283	0.186816
...	...	...	...	...	...	...	...	...	...	...
564	0.690000	0.428813	0.678668	0.566490	0.526948	0.296055	0.571462	0.690358	0.336364	0.132056
565	0.622320	0.626987	0.604036	0.474019	0.407782	0.257714	0.337395	0.486630	0.349495	0.113100
566	0.455251	0.621238	0.445788	0.303118	0.288165	0.254340	0.216753	0.263519	0.267677	0.137321
567	0.644564	0.663510	0.665538	0.475716	0.588336	0.790197	0.823336	0.755467	0.675253	0.425442
568	0.036869	0.501522	0.028540	0.015907	0.000000	0.074351	0.000000	0.000000	0.266162	0.187026

569 rows × 10 columns

```
from sklearn.model_selection import train_test_split

#for checking testing results
```

[31]

4	0.629893	0.156578	0.630986	0.489290	0.430351	0.347893	0.463918	0.518390	0.378283	0.186816
...	...	...	...	...	...	...	...	...	...	...
564	0.690000	0.428813	0.678668	0.566490	0.526948	0.296055	0.571462	0.690358	0.336364	0.132056
565	0.622320	0.626987	0.604036	0.474019	0.407782	0.257714	0.337395	0.486630	0.349495	0.113100
566	0.455251	0.621238	0.445788	0.303118	0.288165	0.254340	0.216753	0.263519	0.267677	0.137321
567	0.644564	0.663510	0.665538	0.475716	0.588336	0.790197	0.823336	0.755467	0.675253	0.425442
568	0.036869	0.501522	0.028540	0.015907	0.000000	0.074351	0.000000	0.000000	0.266162	0.187026

569 rows × 10 columns

```
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

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)
```

```
[33] from sklearn.tree import DecisionTreeClassifier
```

```
[32] #for checking testing results
     from sklearn.metrics import classification_report, confusion_matrix

     #for visualizing tree
     from sklearn.tree import plot_tree

     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)
```

```
[33] from sklearn.tree import DecisionTreeClassifier
```

```
[34] dt = DecisionTreeClassifier()
```

```
dt.fit(x_train, y_train)
```

```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=None, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

Final Graph/ROC/Confusion Matrix

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

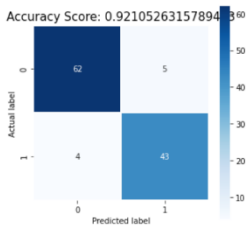
```
Classification report -
              precision    recall  f1-score   support

           B       0.94      0.93      0.93        67
           M       0.90      0.91      0.91        47

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

```
[37] cm=confusion_matrix(y_test,y_pred)
     cm
```

```
array([[62,  5],
       [ 4, 43]])
```

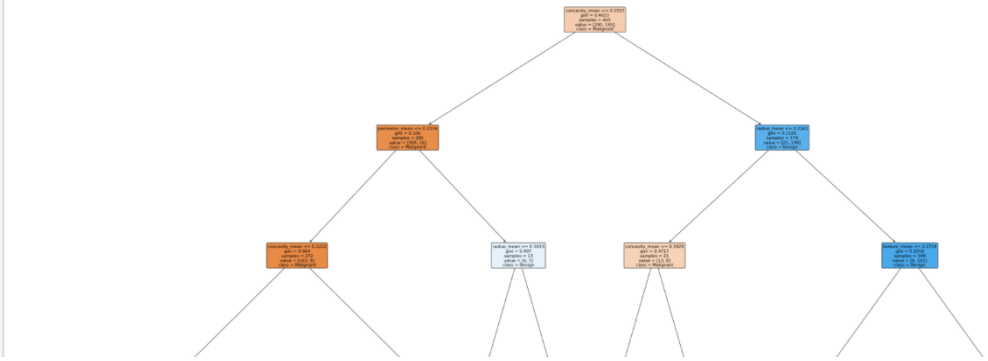
```
plt.figure(figsize=(5,5))

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)
```

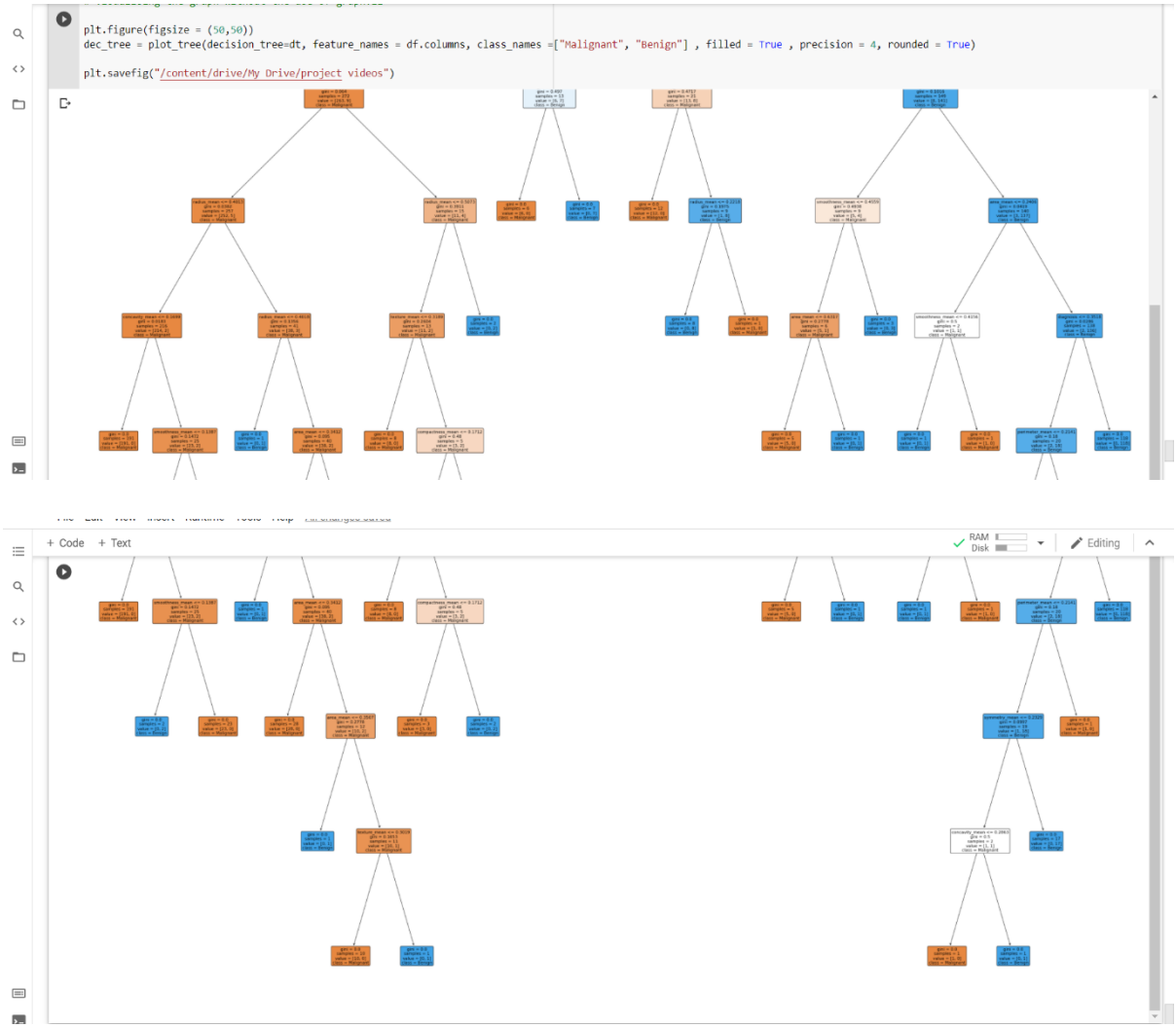
```
plt.figure(figsize=(5,5))

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("/content/drive/My Drive/project videos")
```




```
[40] ! pip install graphviz
```

```
plt.figure(figsize = (50,50))
dec_tree = plot_tree(decision_tree=dt, feature_names = df.columns, class_names =["Malignant", "Benign"] , filled = True , precision = 4, rounded = True)

plt.savefig("/content/drive/My Drive/project videos")
```





Github Link

https://github.com/AkSingh03/MACHINE_LEARNING/blob/main/Experinmnet_1.ipynb