1. Data Understanding

In [105…
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [106…
```
file_path = '/Users/aadya/Downloads/New Folder With Items 2/New Folder Wi
data = pd.read_csv(file_path, header=0)
print(data.head())
print("\n----------\nColums: \n")
print(data.columns)
```

```
         id diagnosis  radius_mean  texture_mean  perimeter_mean  area_mea
n  \
0    842302         M        17.99         10.38          122.80     1001.
0
1    842517         M        20.57         17.77          132.90     1326.
0
2  84300903         M        19.69         21.25          130.00     1203.
0
3  84348301         M        11.42         20.38           77.58      386.
1
4  84358402         M        20.29         14.34          135.10     1297.
0

   smoothness_mean  compactness_mean  concavity_mean  concave points_mean
\
0          0.11840           0.27760          0.3001              0.14710
1          0.08474           0.07864          0.0869              0.07017
2          0.10960           0.15990          0.1974              0.12790
3          0.14250           0.28390          0.2414              0.10520
4          0.10030           0.13280          0.1980              0.10430

   ...  texture_worst  perimeter_worst  area_worst  smoothness_worst  \
0  ...          17.33           184.60      2019.0            0.1622
1  ...          23.41           158.80      1956.0            0.1238
2  ...          25.53           152.50      1709.0            0.1444
3  ...          26.50            98.87       567.7            0.2098
4  ...          16.67           152.20      1575.0            0.1374

   compactness_worst  concavity_worst  concave points_worst  symmetry_wors
t  \
0             0.6656           0.7119                0.2654          0.460
1
1             0.1866           0.2416                0.1860          0.275
0
2             0.4245           0.4504                0.2430          0.361
3
3             0.8663           0.6869                0.2575          0.663
8
4             0.2050           0.4000                0.1625          0.236
4
```

```
   fractal_dimension_worst  Unnamed: 32
0                  0.11890          NaN
1                  0.08902          NaN
2                  0.08758          NaN
3                  0.17300          NaN
4                  0.07678          NaN

[5 rows x 33 columns]

__________
Colums:

Index(['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_s
e',
       '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')
```

1.1 EDA

In [107…

```
#Check for duplicates, missing values
data_duplicates = data.duplicated().sum()
data_null = data.isnull().sum().sum()
print("Total duplicated values: ", data_duplicates)
print("Total missing values: ", data_null)
```

```
Total duplicated values:  0
Total missing values:  569
```

In [108…

```
data.describe().T
```

Out[108…

	count	mean	std	min	
id	569.0	3.037183e+07	1.250206e+08	8670.000000	86921
radius_mean	569.0	1.412729e+01	3.524049e+00	6.981000	1
texture_mean	569.0	1.928965e+01	4.301036e+00	9.710000	1
perimeter_mean	569.0	9.196903e+01	2.429898e+01	43.790000	7
area_mean	569.0	6.548891e+02	3.519141e+02	143.500000	42
smoothness_mean	569.0	9.636028e-02	1.406413e-02	0.052630	
compactness_mean	569.0	1.043410e-01	5.281276e-02	0.019380	
concavity_mean	569.0	8.879932e-02	7.971981e-02	0.000000	
concave points_mean	569.0	4.891915e-02	3.880284e-02	0.000000	
symmetry_mean	569.0	1.811619e-01	2.741428e-02	0.106000	
fractal_dimension_mean	569.0	6.279761e-02	7.060363e-03	0.049960	
radius_se	569.0	4.051721e-01	2.773127e-01	0.111500	
texture_se	569.0	1.216853e+00	5.516484e-01	0.360200	
perimeter_se	569.0	2.866059e+00	2.021855e+00	0.757000	
area_se	569.0	4.033708e+01	4.549101e+01	6.802000	1
smoothness_se	569.0	7.040979e-03	3.002518e-03	0.001713	
compactness_se	569.0	2.547814e-02	1.790818e-02	0.002252	
concavity_se	569.0	3.189372e-02	3.018606e-02	0.000000	
concave points_se	569.0	1.179614e-02	6.170285e-03	0.000000	
symmetry_se	569.0	2.054230e-02	8.266372e-03	0.007882	
fractal_dimension_se	569.0	3.794904e-03	2.646071e-03	0.000895	
radius_worst	569.0	1.626919e+01	4.833242e+00	7.930000	1
texture_worst	569.0	2.567722e+01	6.146258e+00	12.020000	2
perimeter_worst	569.0	1.072612e+02	3.360254e+01	50.410000	8
area_worst	569.0	8.805831e+02	5.693570e+02	185.200000	51
smoothness_worst	569.0	1.323686e-01	2.283243e-02	0.071170	
compactness_worst	569.0	2.542650e-01	1.573365e-01	0.027290	
concavity_worst	569.0	2.721885e-01	2.086243e-01	0.000000	
concave points_worst	569.0	1.146062e-01	6.573234e-02	0.000000	
symmetry_worst	569.0	2.900756e-01	6.186747e-02	0.156500	
fractal_dimension_worst	569.0	8.394582e-02	1.806127e-02	0.055040	
Unnamed: 32	0.0	NaN	NaN	NaN	

In [109…

```
#datatypes
data.dtypes
```

Out[109…

```
id                           int64
diagnosis                   object
radius_mean                float64
texture_mean               float64
perimeter_mean             float64
area_mean                  float64
smoothness_mean            float64
compactness_mean           float64
concavity_mean             float64
concave points_mean        float64
symmetry_mean              float64
fractal_dimension_mean     float64
radius_se                  float64
texture_se                 float64
perimeter_se               float64
area_se                    float64
smoothness_se              float64
compactness_se             float64
concavity_se               float64
concave points_se          float64
symmetry_se                float64
fractal_dimension_se       float64
radius_worst               float64
texture_worst              float64
perimeter_worst            float64
area_worst                 float64
smoothness_worst           float64
compactness_worst          float64
concavity_worst            float64
concave points_worst       float64
symmetry_worst             float64
fractal_dimension_worst    float64
Unnamed: 32                float64
dtype: object
```

In [110…

```
#removing unnecessary columns
removed = data.columns.get_loc('Unnamed: 32')
selected_data = data.iloc[:, :removed]



sdata_duplicates = selected_data.duplicated().sum()
sdata_null = selected_data.isnull().sum().sum()

print("Total duplicated values: ", sdata_duplicates)
print("Total missing values: ", sdata_null)
print(f"\n----------\nColums: {selected_data.columns}\n")
print("----------")
selected_data.head()
```

```
Total duplicated values:  0
Total missing values:  0

__________
Colums: Index(['id', 'diagnosis', 'radius_mean', 'texture_mean', 'perimete
r_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_s
e',
       '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')

__________
```

Out[110…

	id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean
0	842302	M	17.99	10.38	122.80	1001.0
1	842517	M	20.57	17.77	132.90	1326.0
2	84300903	M	19.69	21.25	130.00	1203.0
3	84348301	M	11.42	20.38	77.58	386.1
4	84358402	M	20.29	14.34	135.10	1297.0

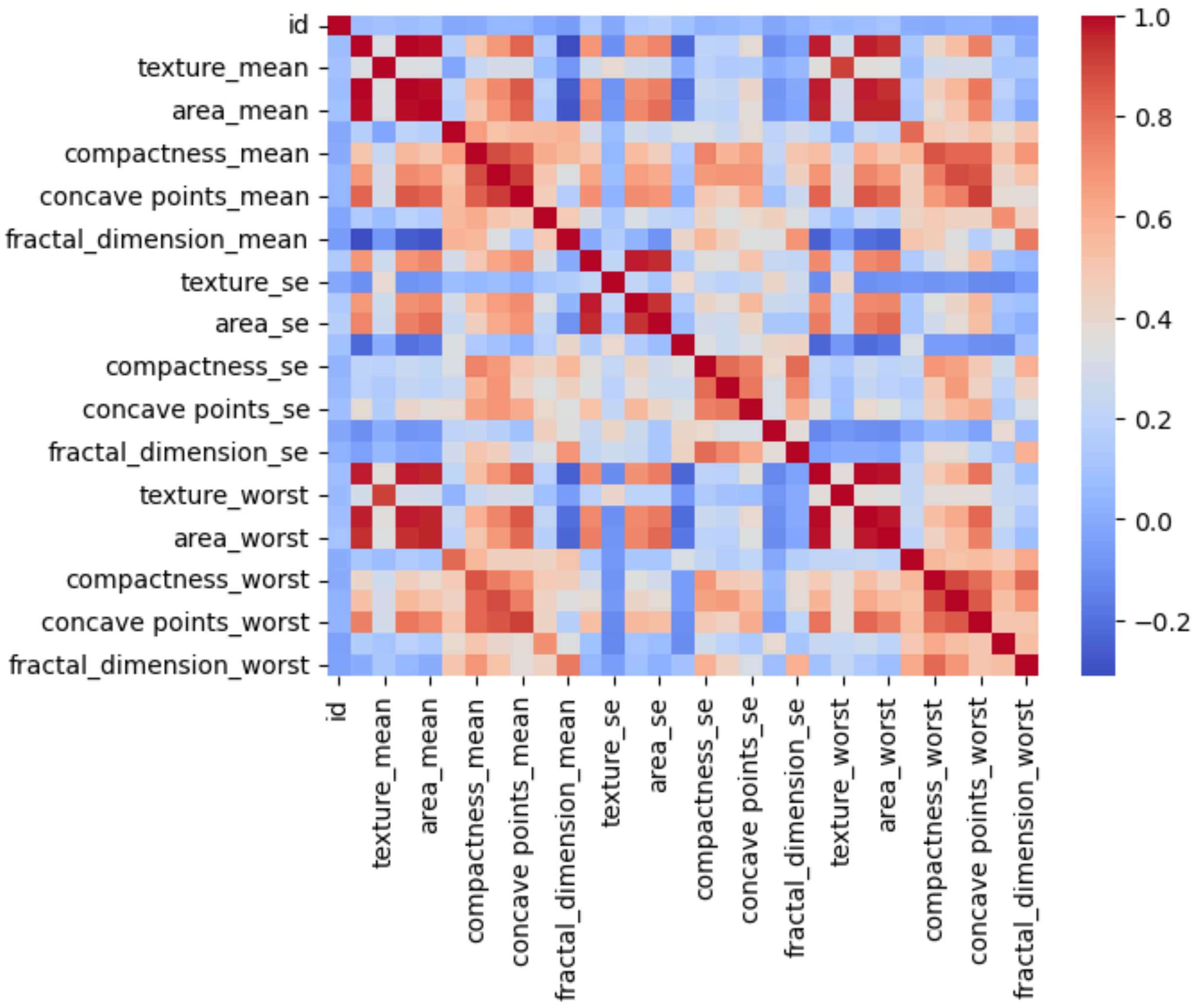
5 rows × 32 columns

In [111…

```
#understanding correlation of the numeric values
columns_corr = []
for i in range(len(selected_data.dtypes)):
    if selected_data.dtypes.iloc[i] != object:
        columns_corr.append(selected_data.columns[i])
numeric_data = selected_data.loc[:,columns_corr]
sns.heatmap(numeric_data.corr(), cmap = 'coolwarm')
```

Out[111…

```
<Axes: >
```



id column is entirely tending to 0 in the correlation above, so it can be safely assumed that it is not useful for other input variables

In [112…
```
diag = selected_data.loc[:,'diagnosis']
```

In [113…
```
inputs = numeric_data
inputs.head()
```

Out[113…

	id	radius_mean	texture_mean	perimeter_mean	area_mean	smoothne
0	842302	17.99	10.38	122.80	1001.0	
1	842517	20.57	17.77	132.90	1326.0	
2	84300903	19.69	21.25	130.00	1203.0	
3	84348301	11.42	20.38	77.58	386.1	
4	84358402	20.29	14.34	135.10	1297.0	

5 rows × 31 columns

In [114…
```
len(selected_data[selected_data.diagnosis=='M'])
```

Out[114…
```
212
```

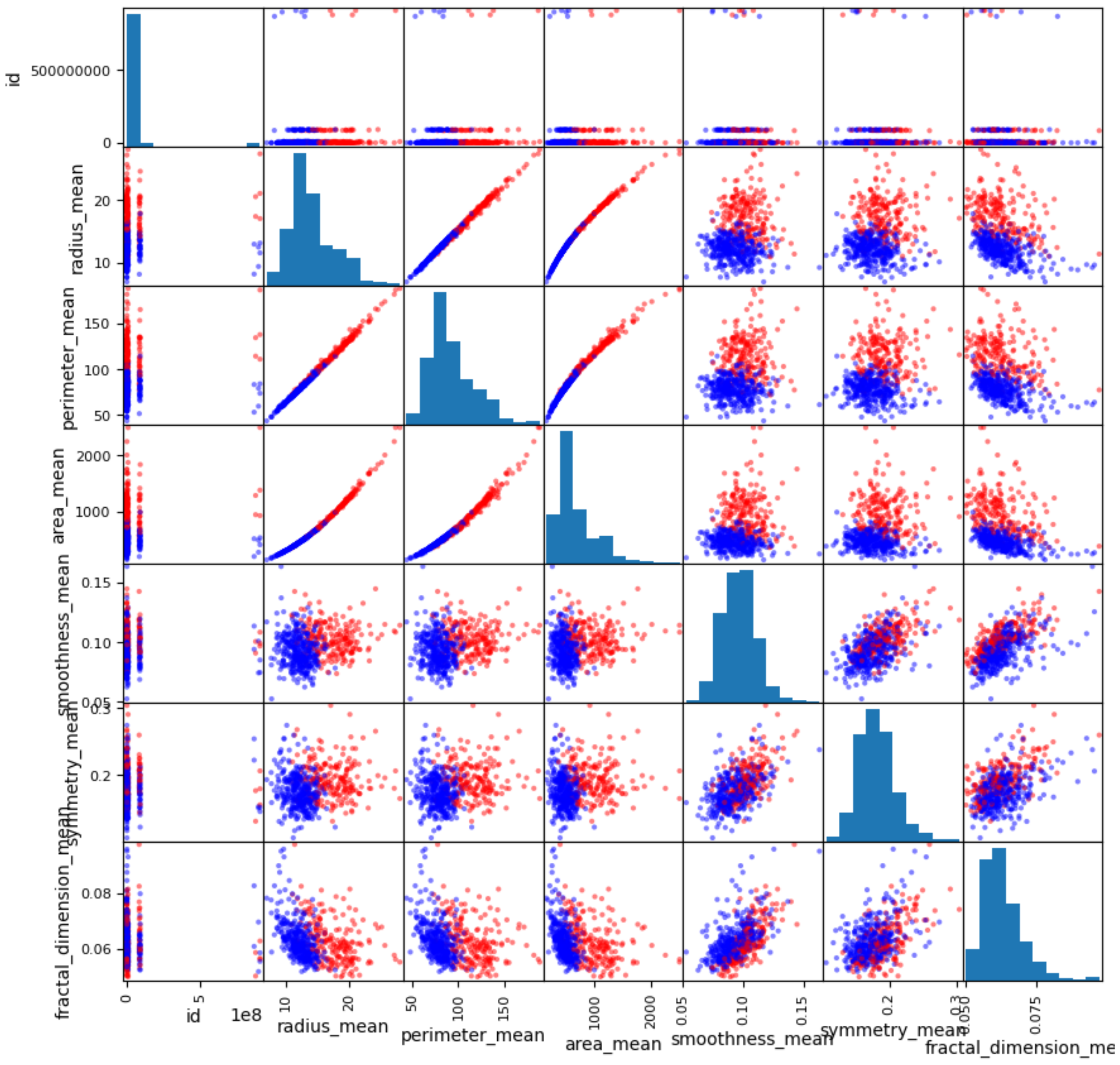
```
In [115…  len(selected_data[selected_data.diagnosis=='B'])
```

```
Out[115…  357
```

```
In [116…  diag_encode = diag.map(lambda val: 'red' if val=='M' else 'blue')
```

```
In [117…  #plotting inputs w.r.t output
          inputs_small = inputs.loc[:, ['id','radius_mean', 'perimeter_mean',
                'area_mean', 'smoothness_mean', 'symmetry_mean','fractal_dimension
          plt.figure()
          scatter = pd.plotting.scatter_matrix(inputs_small, c=diag_encode, figsize
          plt.show()
```

```
<Figure size 640x480 with 0 Axes>
```



From the scatter plot, id is again shown to be not useful.

```
In [118…  #ID is not important but is important enough to not be deleted, thus made
          clean_input = inputs.set_index('id')
          clean_input.head()
```

Out[118…

id	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_
842302	17.99	10.38	122.80	1001.0	0
842517	20.57	17.77	132.90	1326.0	0.
84300903	19.69	21.25	130.00	1203.0	0.
84348301	11.42	20.38	77.58	386.1	0.
84358402	20.29	14.34	135.10	1297.0	0.

5 rows × 30 columns

In [119…

```
count = 0
for i, feature in enumerate(clean_input.columns):
    count += 1
count
```

Out[119… 30

In [120…

```
selected_data_i = selected_data.set_index('id')
selected_data_i.head()
```

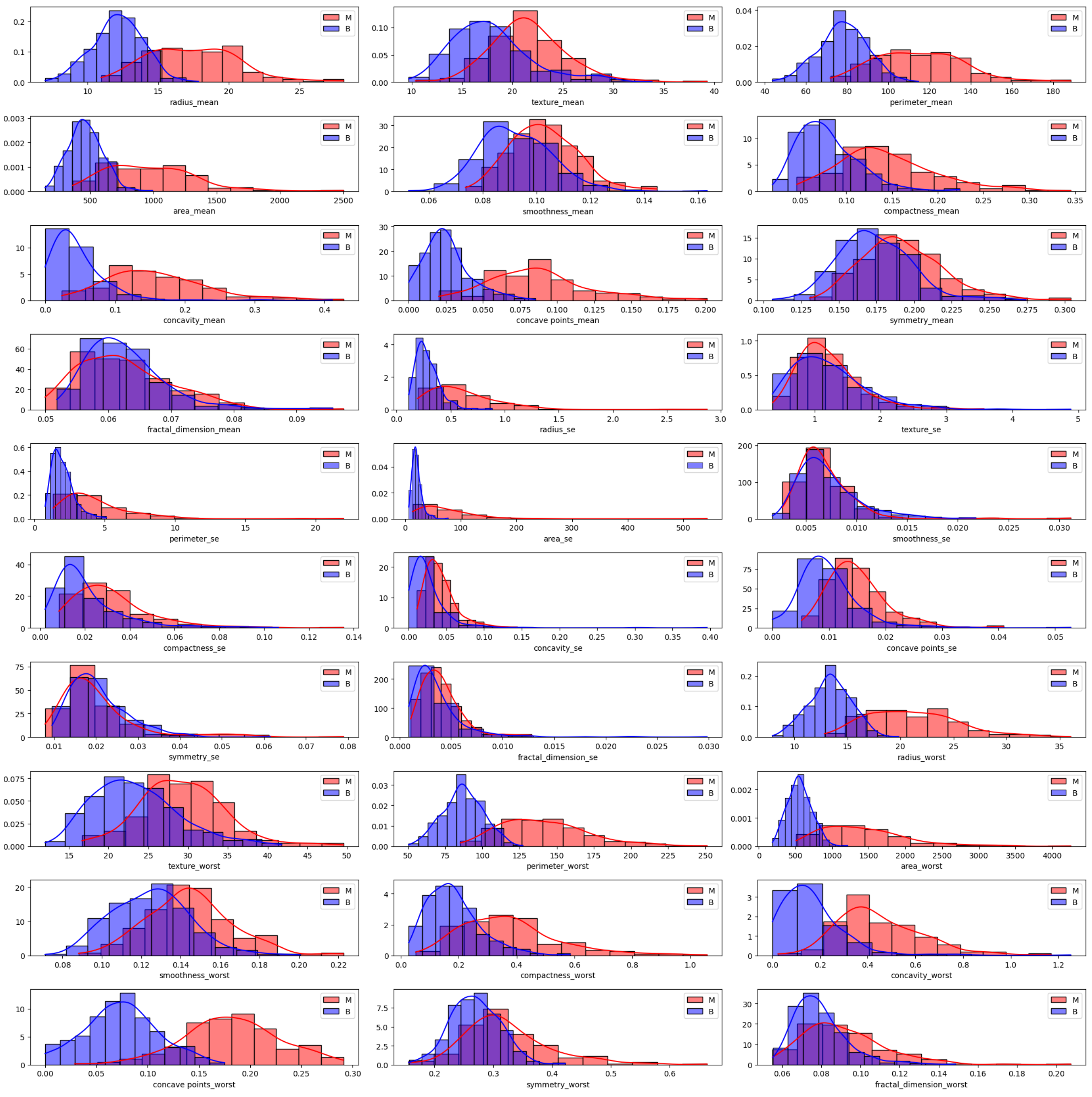
Out[120…

id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	s
842302	M	17.99	10.38	122.80	1001.0	
842517	M	20.57	17.77	132.90	1326.0	
84300903	M	19.69	21.25	130.00	1203.0	
84348301	M	11.42	20.38	77.58	386.1	
84358402	M	20.29	14.34	135.10	1297.0	

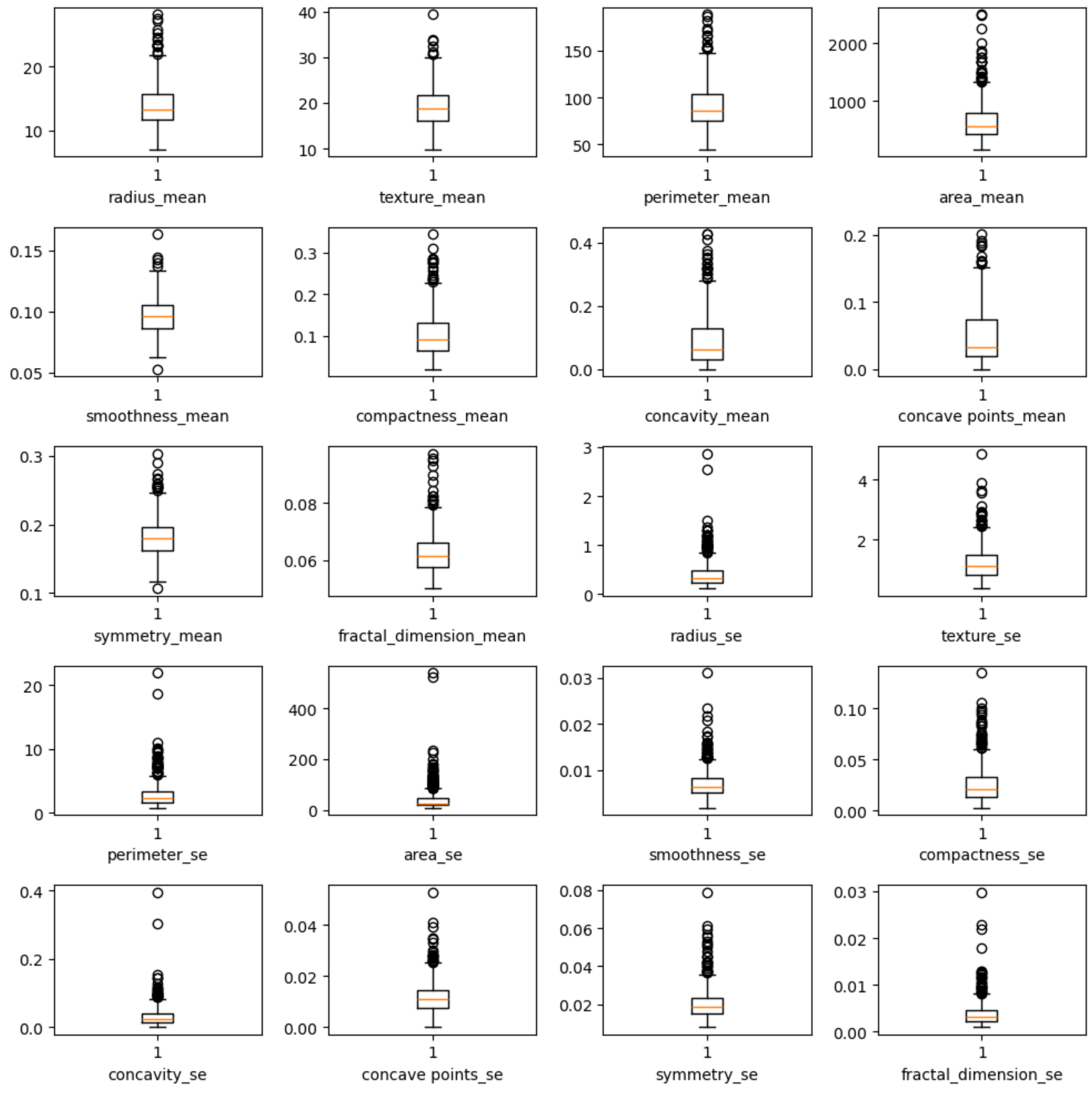
5 rows × 31 columns

In [121…

```
import warnings
warnings.filterwarnings('ignore')
bins = 12
plt.figure(figsize=(20,20))
for i, feature in enumerate(clean_input.columns):
  rows = 10
  cols = 3
  plt.subplot(rows,cols, i+1 )
  sns.histplot(selected_data_i[selected_data_i['diagnosis']=='M'][feature
  sns.histplot(selected_data_i[selected_data_i['diagnosis']=='B'][feature
  plt.legend(loc='upper right')
  plt.ylabel('')
  plt.tight_layout()
plt.show()
```



```
In [122…  fig, ax = plt.subplots(5,4,figsize=(10,10))
          # Plot boxplot side by side
          for i, feature in enumerate(clean_input.columns):
              rows = 5
              cols = 4
              if i+ 1 == 21:
                  break
              plt.subplot(rows,cols, i+1 )
              plt.boxplot(selected_data_i[feature])
              plt.xlabel(feature)
              plt.ylabel('')
              plt.tight_layout()

          plt.show()
```



1.2 Features

In [123…
```
#Now, M and B should also be numeric
#M --> 1 , B --> 0
encoding_logic = lambda value: 1 if value=='M' else 0
y = diag.map(encoding_logic)
x = clean_input
```

In [124…
```
from sklearn.model_selection import train_test_split
xtrain, xtest, ytrain, ytest = train_test_split(x,y, test_size=0.2, rando
print("x-train size: ", len(xtrain), ", y-train size: ", len(ytrain))
print("x-test size: ", len(xtest), ", y-test size: ", len(ytest))
```

```
x-train size:  455 , y-train size:  455
x-test size:  114 , y-test size:  114
```

In [125…
```
# Split the 20% subset above into two: one half for cross validation and
x_cv, x_test, y_cv, y_test = train_test_split(xtest, ytest, test_size=0.5
print("x-train size: ", len(xtrain), ", y-train size: ", len(ytrain))
print("x-cv size: ", len(x_cv), ", y-cv size: ", len(y_cv))
print("x-test size: ", len(x_test), ", y-test size: ", len(y_test))
```

```
x-train size:  455 , y-train size:  455
x-cv size:  57 , y-cv size:  57
x-test size:  57 , y-test size:  57
```

In [126…

```python
xtrain.head()
```

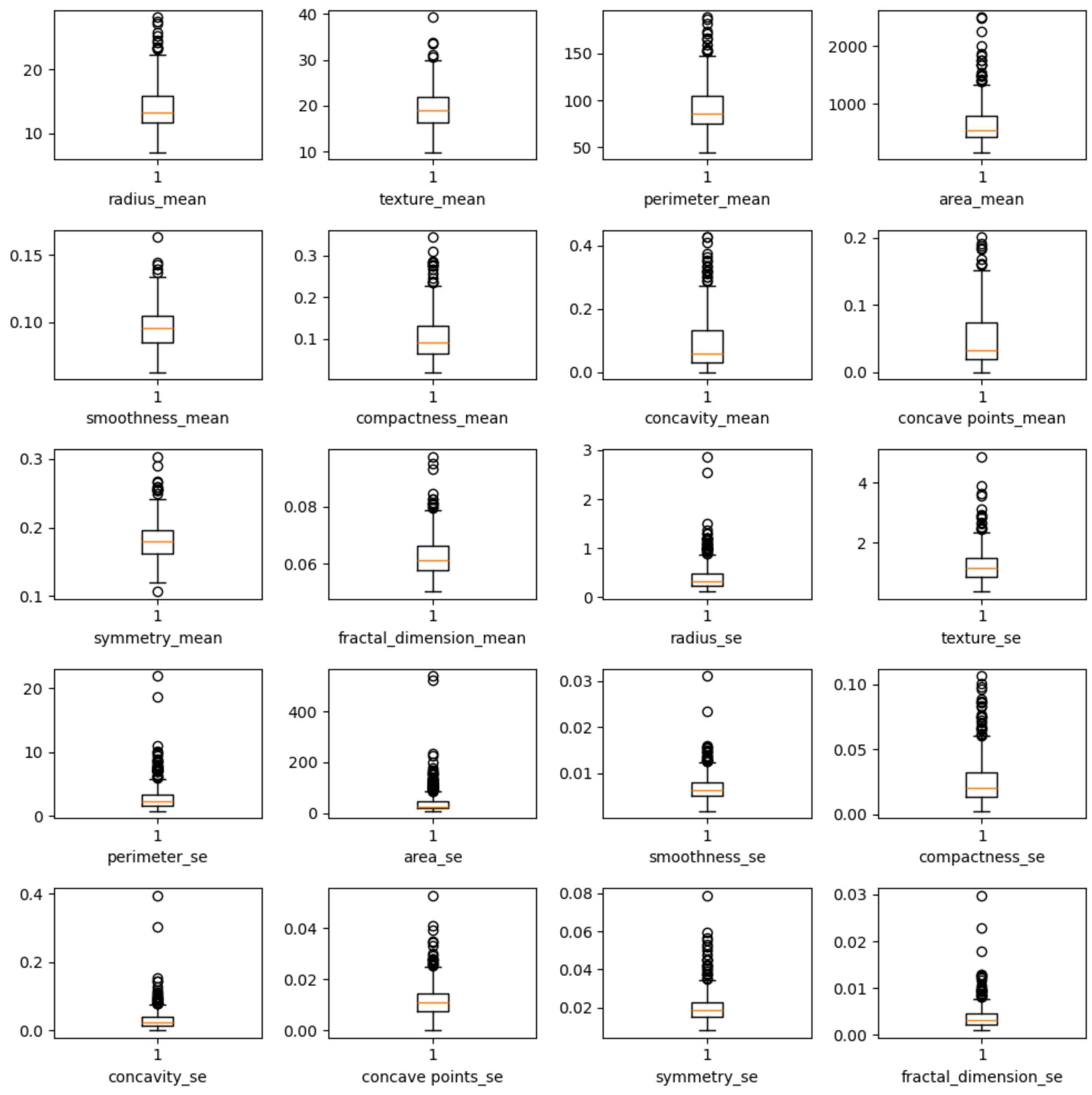
Out[126…

id	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_
845636	16.02	23.24	102.70	797.8	0.0
87139402	12.32	12.39	78.85	464.1	0.
905190	12.85	21.37	82.63	514.5	0.
907914	14.90	22.53	102.10	685.0	0.0
852781	18.61	20.25	122.10	1094.0	0.0

5 rows × 30 columns

In [127…

```python
plt.figure(figsize=(10,10))
# Plot boxplot side by side
for i, feature in enumerate(xtrain.columns):
    rows = 5
    cols = 4
    if i+ 1 == 21:
        break
    plt.subplot(rows,cols, i + 1)
    plt.boxplot(xtrain[feature])
    plt.xlabel(feature)
    plt.ylabel('')
    plt.tight_layout()


plt.show()
```



In [128…

```
# Feature Scaling
# Z-Score
#stat = xtrain.describe().T
#m = stat['mean']
#std = stat['std']
#scaled_input = (xtrain-m)/std
#scaled_input.head()
from sklearn.preprocessing import RobustScaler, StandardScaler
# Initialize the class
standard = StandardScaler()
robust = RobustScaler()
# Compute the mean and standard deviation of the training set then transf
x_train_scaled_stan = standard.fit_transform(xtrain)
x_cv_scaled_stan = standard.transform(x_cv)
x_test_scaled_stan = standard.transform(x_test)


x_train_scaled_r = robust.fit_transform(xtrain)
x_cv_scaled_r = robust.transform(x_cv)
x_test_scaled_r = robust.transform(x_test)
```

```
print(f"{x_train_scaled_stan[:4, :]}")
print("\n--------\n")
print(f"{x_train_scaled_r[:4, :]}")
```

```
[[ 0.518559  0.891826  0.424632  0.383925 -0.974744 -0.689772 -0.688586
  -0.398175 -1.039155 -0.825056 -0.109318 -0.055976 -0.210096 -0.015913
  -1.005184 -0.911942 -0.662816 -0.652561 -0.701889 -0.275394  0.579798
   1.313242  0.466908  0.445983 -0.596155 -0.634722 -0.610227 -0.235744
   0.054566  0.021837]
 [-0.516364 -1.63971  -0.541349 -0.542961  0.476219 -0.631834 -0.604281
  -0.303075  0.521543 -0.454523 -0.604378 -1.001046 -0.585429 -0.493454
   0.403212 -0.768173 -0.479187  0.114508 -0.142951 -0.577398 -0.582459
  -1.690291 -0.611934 -0.587014  0.273582 -0.814844 -0.712666 -0.323208
  -0.137576 -0.904402]
 [-0.368118  0.455515 -0.38825  -0.40297  -1.432979 -0.383927 -0.342175
  -0.765459 -0.850857 -0.226171  0.30398   1.051501 -0.169545 -0.000809
  -0.310104  1.10633   0.622585  0.273685  0.754483  1.508105 -0.398622
   0.181977 -0.475431 -0.420778 -1.622785 -0.391399 -0.431313 -0.890825
  -0.675893 -0.144016]
 [ 0.205285  0.726168  0.40033   0.070612  0.243253  2.203585  2.256094
   1.213233  0.818474  0.899791 -0.54573  -0.621677  0.261427 -0.353585
   0.02446   2.090728  1.490561  1.695127 -0.654909  0.767548 -0.000309
   0.274191  0.513776 -0.099482  0.418538  2.86597   2.958619  1.977064
  -0.075646  1.728848]]

--------


[[ 0.63432   0.789809  0.564497  0.670221 -0.666667 -0.384148 -0.257207
  -0.002022 -0.812594 -0.495707  0.207281  0.075746  0.088111  0.568004
  -0.753163 -0.572307 -0.582924 -0.477245 -0.513141 -0.039044  0.69262
   0.964409  0.610055  0.769523 -0.405616 -0.323614 -0.314999 -0.012752
   0.185185  0.213803]
 [-0.24142  -1.184713 -0.25047  -0.219408  0.382398 -0.337311 -0.190203
   0.067292  0.47976  -0.200343 -0.363636 -0.747041 -0.36148  -0.270202
   0.601991 -0.439306 -0.354465  0.215688  0.067584 -0.387366 -0.230333
  -1.129736 -0.249154 -0.221489  0.230889 -0.473339 -0.396471 -0.072328
   0.005926 -0.59749 ]
 [-0.115976  0.4495   -0.121305 -0.085044 -0.997977 -0.136906  0.018115
  -0.269719 -0.656672 -0.018317  0.683907  1.039924  0.136685  0.594516
  -0.08436   1.294798  1.01629   0.359479  1.        2.017986 -0.084347
   0.17566  -0.140441 -0.06201  -1.156942 -0.121355 -0.172705 -0.458965
  -0.496296  0.068533]
 [ 0.369231  0.660601  0.543995  0.369501  0.213961  1.954815  2.083171
   1.172458  0.725637  0.879222 -0.296002 -0.416759  0.652923 -0.024696
   0.237557  2.205465  2.096173  1.64354  -0.46433   1.163852  0.231955
   0.239954  0.647381  0.246227  0.336973  2.586288  2.523372  1.494517
   0.063704  1.708977]]
```

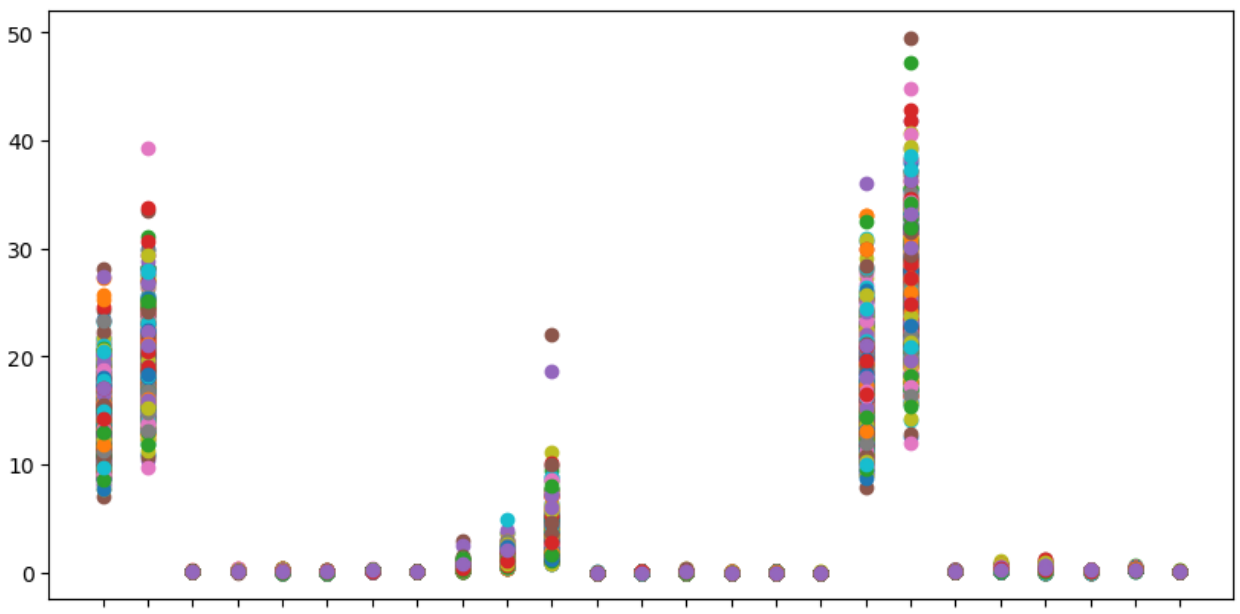
In [129…

```
def GFG(arr,prec):
    np.set_printoptions(suppress=True,precision=prec)
    return arr
x_train_range = xtrain.to_numpy()
ptpr = np.ptp(x_train_range,axis=0)
ptpn = np.ptp(x_train_scaled_stan,axis=0)
ptprb = np.ptp(x_train_scaled_r,axis=0)
print(f"Peak to Peak range by column in Raw X:{GFG(ptpr,6)}")
print("\n")
print(f"Peak to Peak range by column in Standardized X:{GFG(ptpn, 6)}")
print("\n")
print(f"Peak to Peak range by column in Standardized X:{GFG(ptprb, 6)}")
print("\n")
print(f"diff stand:{GFG(ptpn,6) - GFG(ptpr,6)}")
print(f"diff r:{GFG(ptprb,6) - GFG(ptpr,6)}")
```

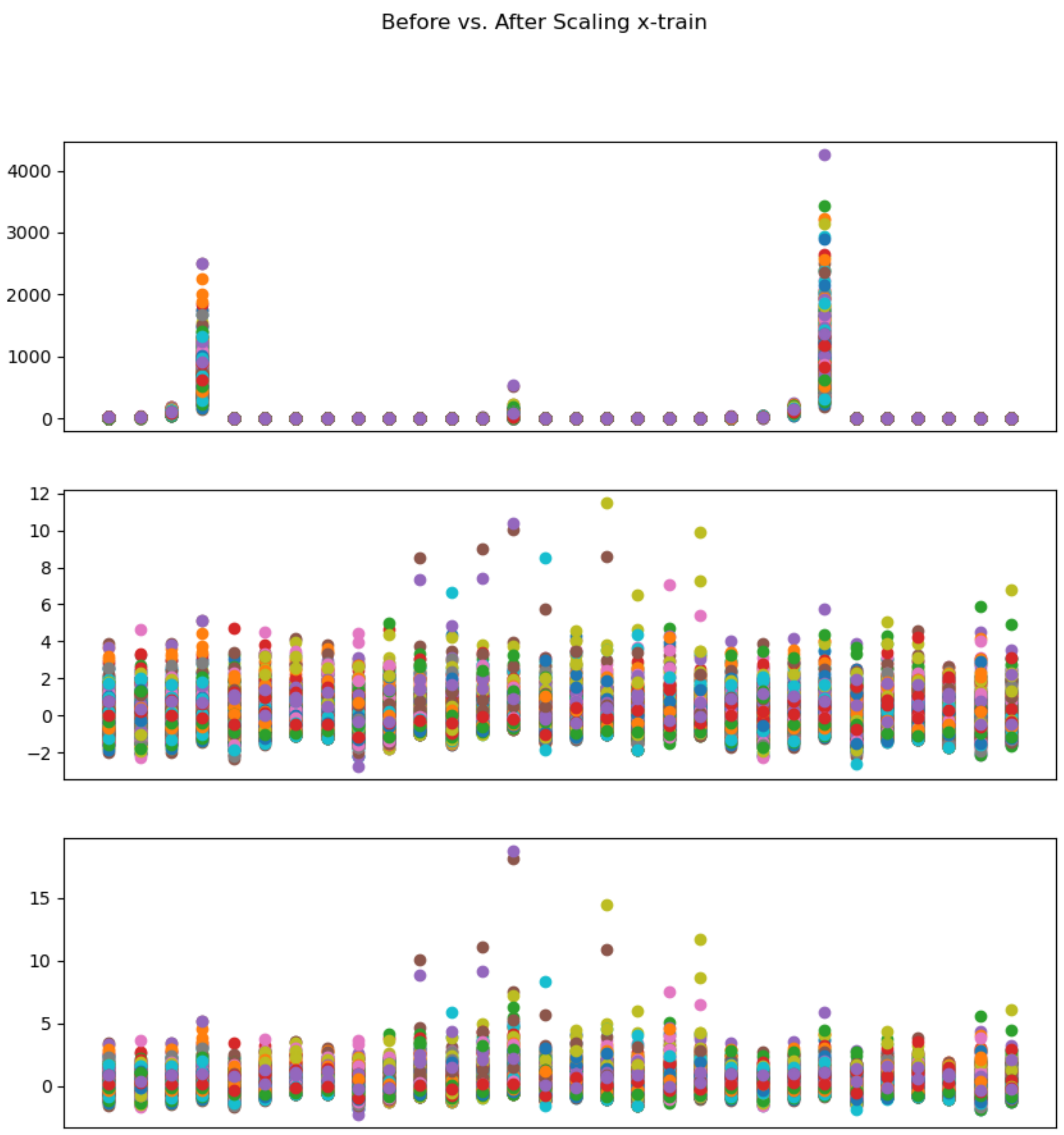
```
Peak to Peak range by column in Raw X:[  21.129      29.57      144.71
2357.5         0.10089     0.32602
    0.4268      0.2012      0.198       0.0472      2.7615      4.5248
   21.223     535.398       0.029417    0.104148    0.396       0.05279
    0.071068    0.028945   28.11       37.52      200.79     4068.8
    0.15143     1.03071     1.252       0.291       0.5073      0.15246 ]


Peak to Peak range by column in Standardized X:[ 5.909969  6.899311  5.861
091  6.548204  7.058227  6.054117  5.229868
  5.075382  7.169795  6.778751  9.52689   8.201486 10.007146 11.07774
 10.316431  5.915932 12.494321  8.402906  8.560912 11.009535  5.741834
  6.178321  5.881639  6.9946    6.45609   6.514169  5.910312  4.358221
  8.055696  8.400613]


Peak to Peak range by column in Standardized X:[ 5.000947  5.381256  4.944
815  6.284991  5.103187  4.894093  4.156603
  3.699209  5.937031  5.403549 10.986672  7.140287 11.987009 19.444271
  9.926438  5.472832 15.544652  7.590769  8.894618 12.698048  4.559611
  4.307692  4.684241  6.710316  4.724805  5.414815  4.700582  2.96863
  7.515556  7.358108]


diff stand:[  -15.219031   -22.670689  -138.848909 -2350.951796     6.9573
37
     5.728097     4.803068     4.874182     6.971795     6.731551
     6.76539      3.676686   -11.215854  -524.32026     10.287014
     5.811784    12.098321     8.350116     8.489844    10.98059
   -22.368166   -31.341679  -194.908361 -4061.8054       6.30466
     5.483459     4.658312     4.067221     7.548396     8.248153]
diff r:[  -16.128053   -24.188744  -139.765185 -2351.215009     5.002297
     4.568073     3.729803     3.498009     5.739031     5.356349
     8.225172     2.615487    -9.235991  -515.953729     9.897021
     5.368684    15.148652     7.537979     8.82355     12.669103
   -23.550389   -33.212308  -196.105759 -4062.089684     4.573375
     4.384105     3.448582     2.67763      7.008256     7.205648]
```

In [130…

```
for_plotting = xtrain.copy()
for_plotting = for_plotting.drop( for_plotting.columns[[2,3,13,22,23]], a


fig, ax = plt.subplots(1, 1, figsize = (10,5))
for i in range(len(for_plotting)):
    ax.scatter(for_plotting.columns, for_plotting.iloc[i,:])
ax.tick_params(axis='x', labelbottom=False)
plt.show()
```



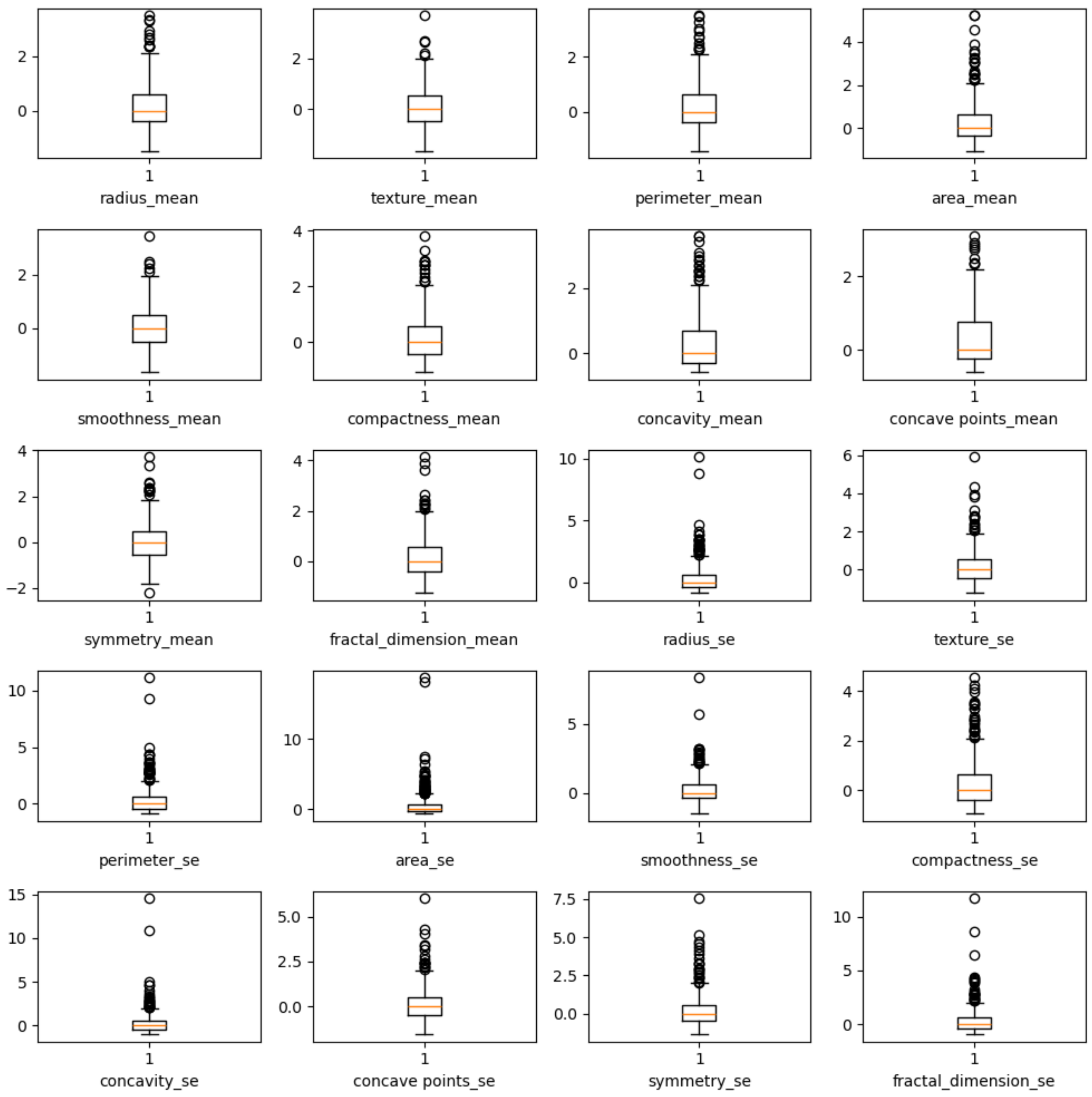
```
In [131…
fig, (ax1, ax2, ax3) = plt.subplots(nrows = 3, figsize = (10,10))
fig.suptitle('Before vs. After Scaling x-train')
for i in range(len(xtrain)):
    ax1.scatter(xtrain.columns,xtrain.iloc[i,:])
ax1.get_xaxis().set_visible(False)
for i in range(len(xtrain)):
    ax2.scatter(xtrain.columns, x_train_scaled_stan[i])#plt.xlabel('featu
ax2.get_xaxis().set_visible(False)
for i in range(len(xtrain)):
    ax3.scatter(xtrain.columns,x_train_scaled_r[i])
ax3.get_xaxis().set_visible(False)
plt.xlabel('Features')
plt.show()
```



I will use RobustScaler.

In [132…
```
x_train_scaled = x_train_scaled_r.copy()
x_cv_scaled = x_cv_scaled_r.copy()
x_test_scaled = x_test_scaled_r.copy()
del x_train_scaled_r, x_cv_scaled_r, x_test_scaled_r, x_train_scaled_stan
```

In [133…
```
plt.figure(figsize=(10,10))

for i, feature in enumerate(xtrain.columns):
    rows = 5
    cols = 4
    if i+ 1 == 21:
        break
    plt.subplot(rows,cols, i + 1)
    plt.boxplot(x_train_scaled[:,i])
    plt.xlabel(feature)
    plt.ylabel('')
    plt.tight_layout()
plt.show()
```



In [134…
```
#x_train_scaled.to_csv('/Users/aadya/Downloads/New Folder With Items 2/Ne
```

2. Model

In [135…
```
y.unique()
```

Out[135…
```
array([1, 0])
```

In [136…
```
y_test.to_numpy()
```

Out[136…
```
array([0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 0,
       0, 0, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 0,
       1, 0, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0])
```

In [137…
```
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier # TREE based
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC, LinearSVC # graph
import time
from sklearn.metrics import accuracy_score
# import warnings filter
from warnings import simplefilter
# ignore all future warnings
simplefilter(action='ignore', category=FutureWarning)
```

2.1 Tuning Parameters

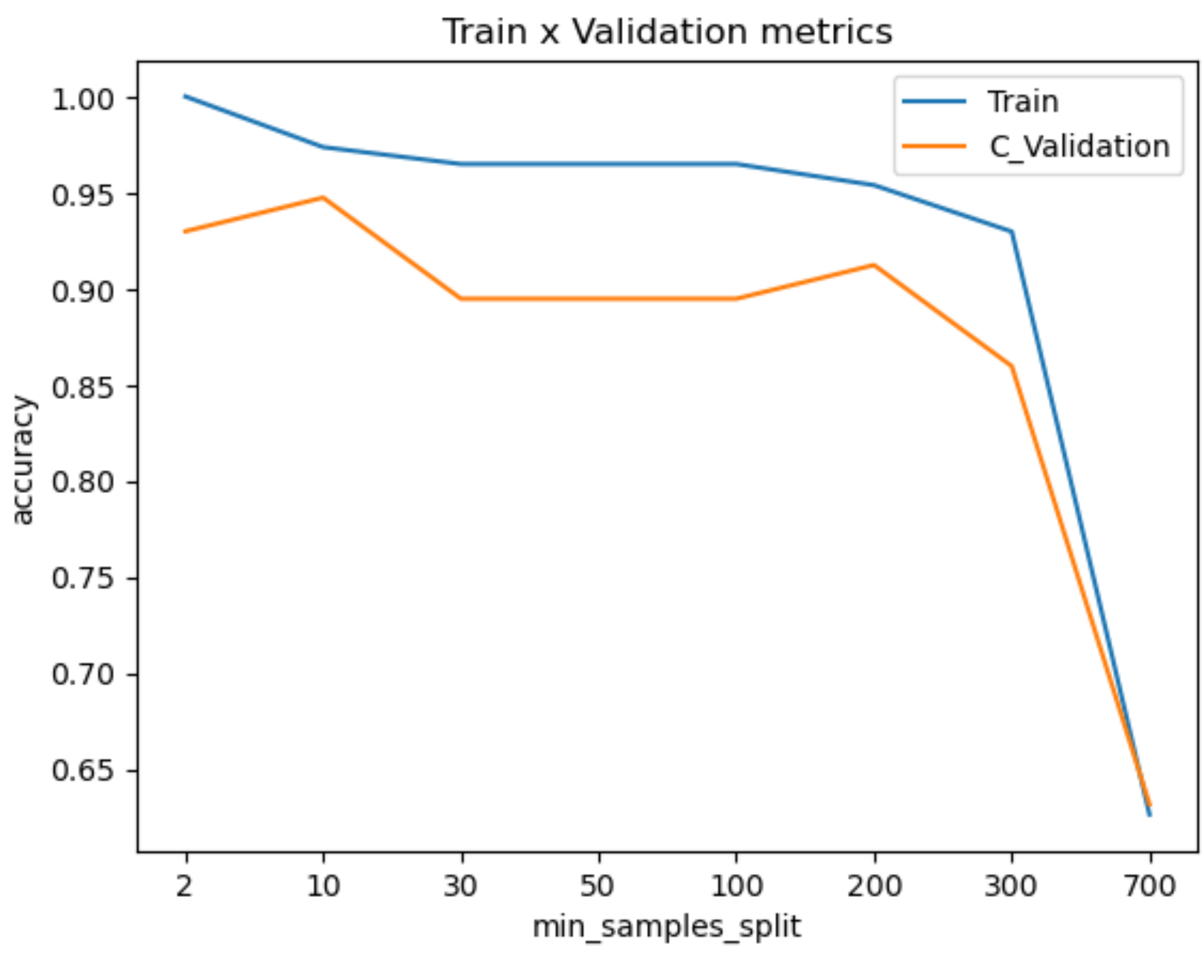
2.1.1 Determining parameters of Decision Tree

In [138…

```
min_samples_split_list = [2,10, 30, 50, 100, 200, 300, 700] ## If the num
max_depth_list = [1,2, 3, 4, 8, 16, 32, 64, None] # None means that there

accuracy_list_train = []
accuracy_list_cv = []
for min_samples_split in min_samples_split_list:

    model = DecisionTreeClassifier(min_samples_split = min_samples_split,
                                   random_state = 55).fit(x_train_scaled,
    predictions_train = model.predict(x_train_scaled) ## The predicted va
    predictions_cv = model.predict(x_cv_scaled) ## The predicted values f
    accuracy_train = accuracy_score(predictions_train,ytrain)
    accuracy_cv = accuracy_score(predictions_cv,y_cv)
    accuracy_list_train.append(accuracy_train)
    accuracy_list_cv.append(accuracy_cv)

plt.title('Train x Validation metrics')
plt.xlabel('min_samples_split')
plt.ylabel('accuracy')
plt.xticks(ticks = range(len(min_samples_split_list )),labels=min_samples
plt.plot(accuracy_list_train)
plt.plot(accuracy_list_cv)
plt.legend(['Train','C_Validation'])
```

Out[138…

```
<matplotlib.legend.Legend at 0x138fe1f90>
```



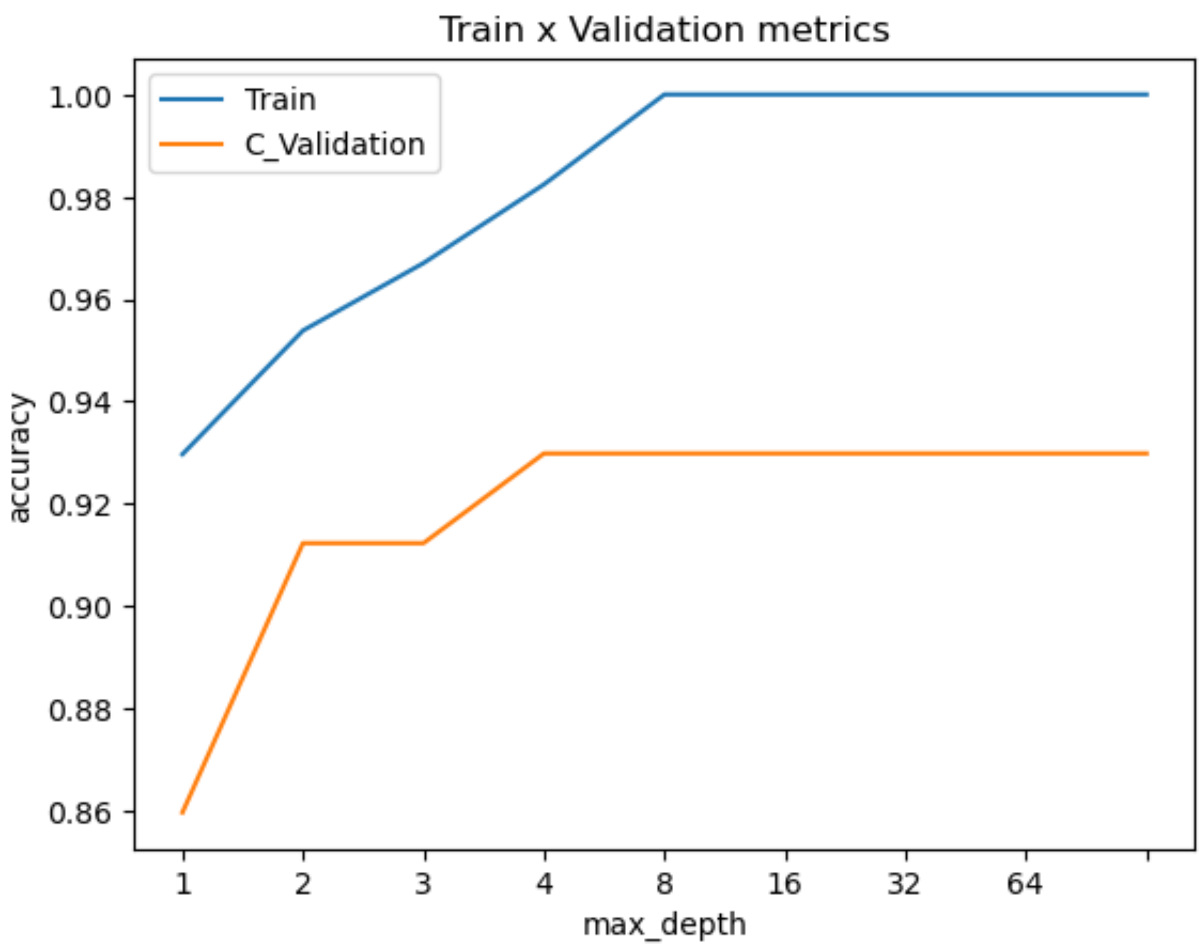
min_samples_split can be chosen to be 30. Here, the validation accuracy and train accuracy is high, and the train accuracy is closer to validation accuracy, which avoids overfitting.

In [139…

```
accuracy_list_train = []
accuracy_list_cv = []
for max_depth in max_depth_list:

    model = DecisionTreeClassifier(max_depth = max_depth,
                                   random_state = 55).fit(x_train_scaled,
    predictions_train = model.predict(x_train_scaled) ## The predicted va
    predictions_cv = model.predict(x_cv_scaled) ## The predicted values f
    accuracy_train = accuracy_score(predictions_train,ytrain)
    accuracy_cv = accuracy_score(predictions_cv,y_cv)
    accuracy_list_train.append(accuracy_train)
    accuracy_list_cv.append(accuracy_cv)

plt.title('Train x Validation metrics')
plt.xlabel('max_depth')
plt.ylabel('accuracy')
plt.xticks(ticks = range(len(max_depth_list )),labels=max_depth_list)
plt.plot(accuracy_list_train)
plt.plot(accuracy_list_cv)
plt.legend(['Train','C_Validation'])
```

Out[139…

```
<matplotlib.legend.Legend at 0x13963b7d0>
```



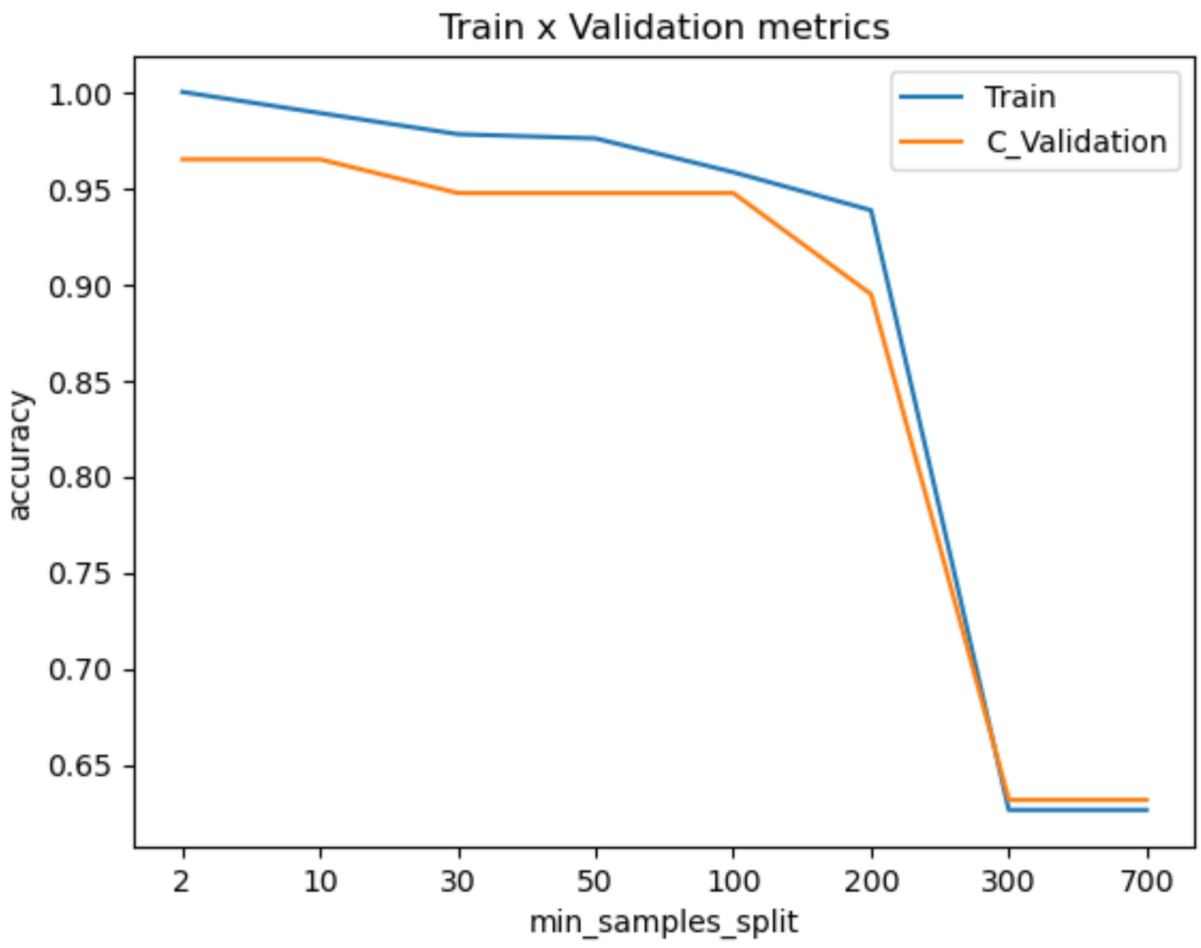
max_depth should be 3

```
In [140…  decision_tree_model = DecisionTreeClassifier(min_samples_split = 30,
                                                      max_depth = 3,
                                                      random_state = 55)
```

2.1.2 Determining parameters of Random Forest

```
In [141…  min_samples_split_list = [2,10, 30, 50, 100, 200, 300, 700]  ## If the nu
                                                      ## If it is a float, then it
          max_depth_list = [2, 4, 8, 16, 32, 64, None]
          n_estimators_list = [10,50,100,500]

          accuracy_list_train = []
          accuracy_list_cv = []
          for min_samples_split in min_samples_split_list:
              model = RandomForestClassifier(min_samples_split = min_samples_split,
                                             random_state = 55).fit(x_train_scaled,
              predictions_train = model.predict(x_train_scaled) ## The predicted va
              predictions_cv = model.predict(x_cv_scaled) ## The predicted values f
              accuracy_train = accuracy_score(predictions_train,ytrain)
              accuracy_cv = accuracy_score(predictions_cv,y_cv)
              accuracy_list_train.append(accuracy_train)
              accuracy_list_cv.append(accuracy_cv)

          plt.title('Train x Validation metrics')
          plt.xlabel('min_samples_split')
          plt.ylabel('accuracy')
          plt.xticks(ticks = range(len(min_samples_split_list )),labels=min_samples
          plt.plot(accuracy_list_train)
          plt.plot(accuracy_list_cv)
          plt.legend(['Train','C_Validation'])
```

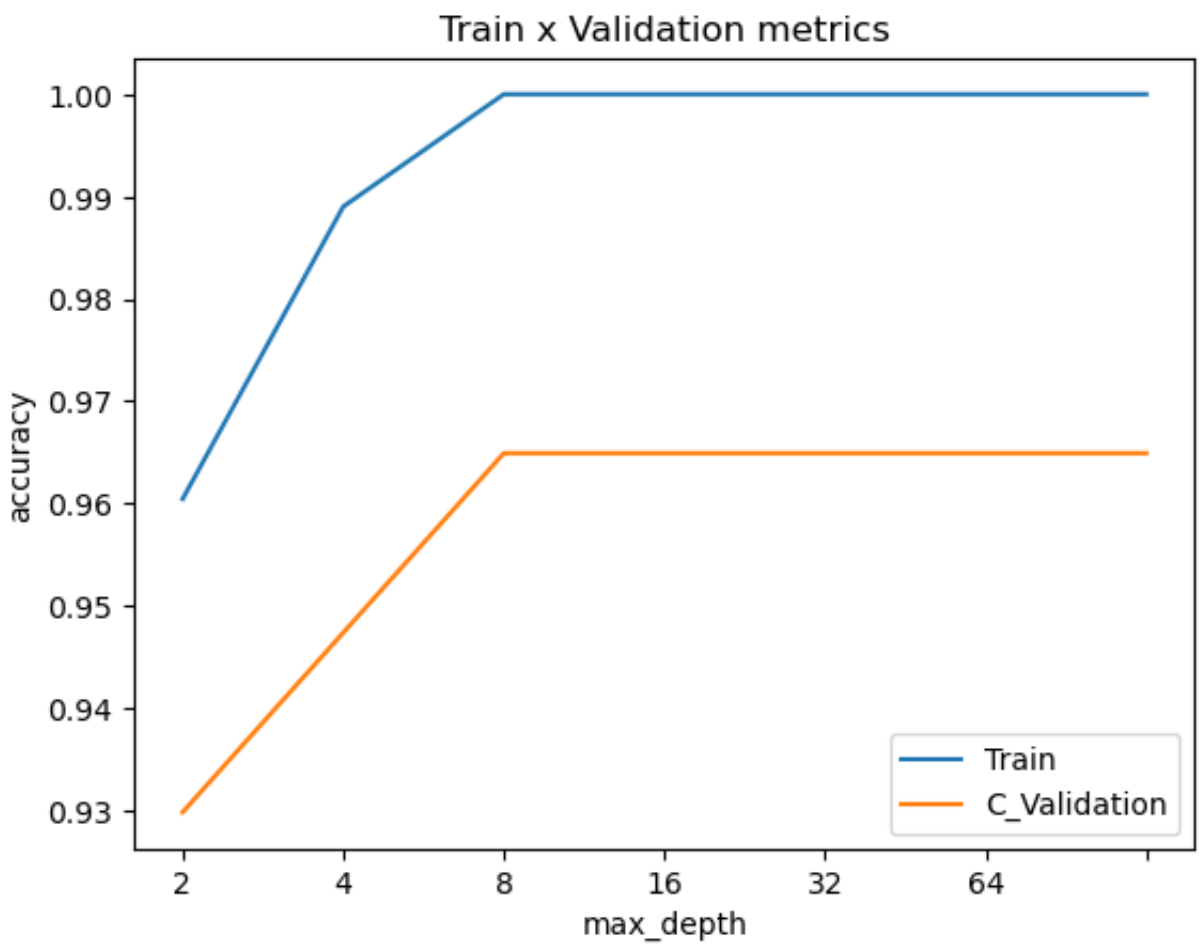
Out[141… <matplotlib.legend.Legend at 0x1370eb7d0>



In [142…

```
accuracy_list_train = []
accuracy_list_cv = []
for max_depth in max_depth_list:

    model = RandomForestClassifier(max_depth = max_depth,
                                   random_state = 55).fit(x_train_scaled,
    predictions_train = model.predict(x_train_scaled) ## The predicted va
    predictions_cv = model.predict(x_cv_scaled) ## The predicted values f
    accuracy_train = accuracy_score(predictions_train,ytrain)
    accuracy_cv = accuracy_score(predictions_cv,y_cv)
    accuracy_list_train.append(accuracy_train)
    accuracy_list_cv.append(accuracy_cv)

plt.title('Train x Validation metrics')
plt.xlabel('max_depth')
plt.ylabel('accuracy')
plt.xticks(ticks = range(len(max_depth_list )),labels=max_depth_list)
plt.plot(accuracy_list_train)
plt.plot(accuracy_list_cv)
plt.legend(['Train','C_Validation'])
```

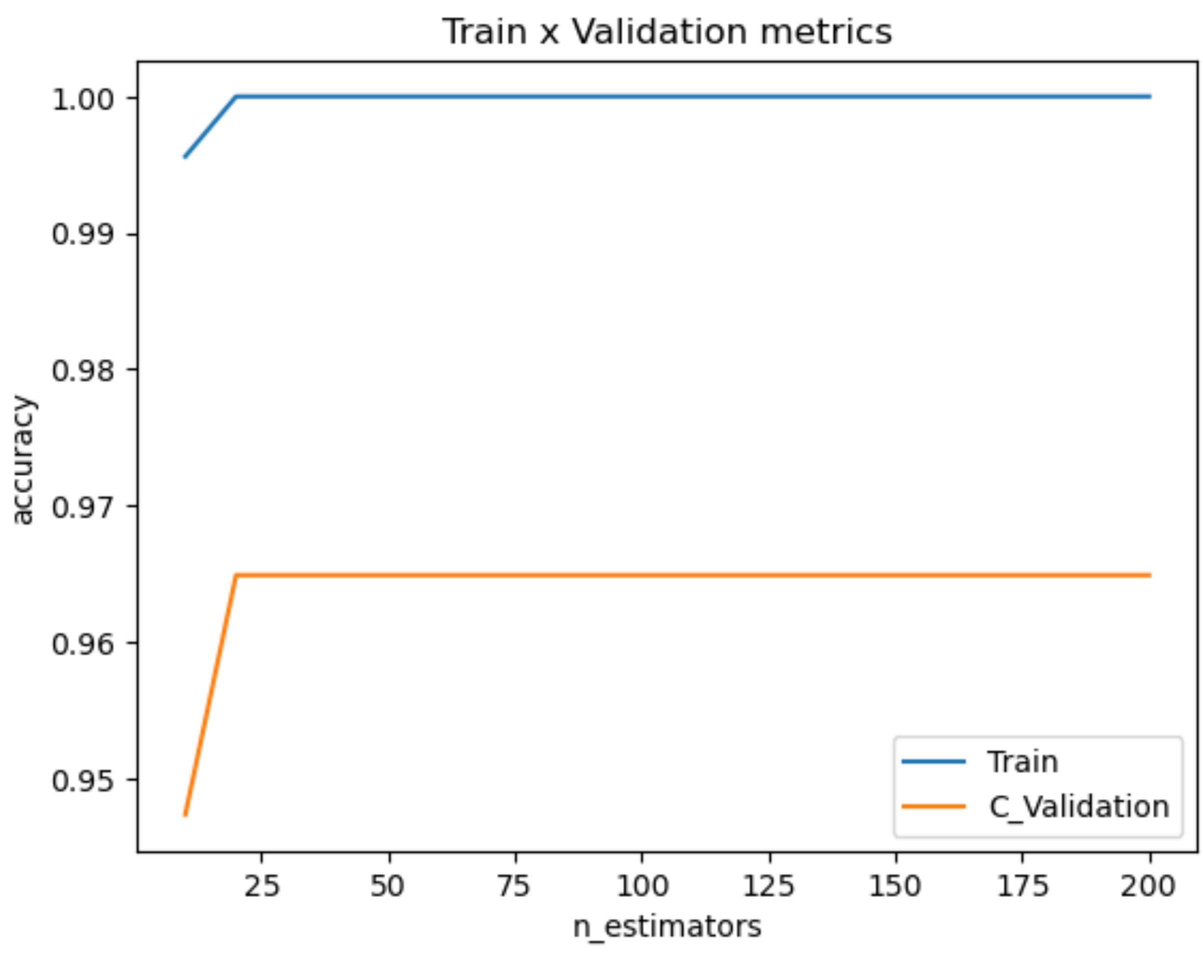
Out[142… <matplotlib.legend.Legend at 0x1370eb2d0>



min_samples_split = 30, max_depth = 4

```
In [143…  accuracy_list_train = []
          accuracy_list_cv = []
          estimations = [n for n in range(1, 201) if n % 10 == 0]
          for est in estimations:
              model = RandomForestClassifier(n_estimators= est,
                                             random_state = 55).fit(x_train_scaled,
              predictions_train = model.predict(x_train_scaled) ## The predicted va
              predictions_cv = model.predict(x_cv_scaled) ## The predicted values f
              accuracy_train = accuracy_score(predictions_train,ytrain)
              accuracy_cv = accuracy_score(predictions_cv,y_cv)
              accuracy_list_train.append(accuracy_train)
              accuracy_list_cv.append(accuracy_cv)
          #print(accuracy_list_train[:5])


          plt.plot(estimations, accuracy_list_train)
          plt.plot(estimations,accuracy_list_cv)
          plt.title('Train x Validation metrics')
          plt.xlabel('n_estimators')
          plt.ylabel('accuracy')
          plt.legend(['Train','C_Validation'])
```

```
Out[143…  <matplotlib.legend.Legend at 0x138e2a450>
```

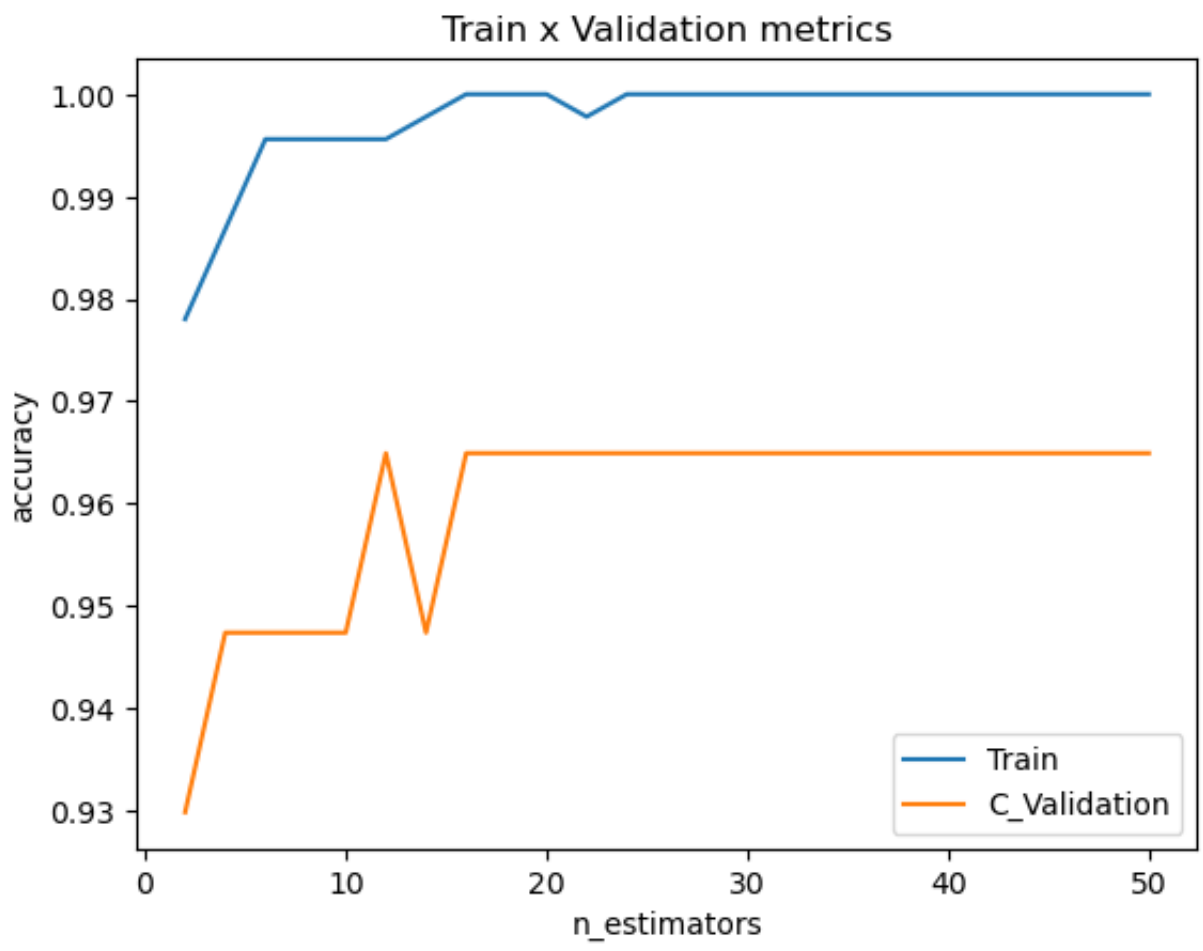


In [144…

```
accuracy_list_train = []
accuracy_list_cv = []
estimations = [n for n in range(1, 51) if n % 2 == 0]
for est in estimations:
    model = RandomForestClassifier(n_estimators= est,
                                   random_state = 55).fit(x_train_scaled,
    predictions_train = model.predict(x_train_scaled) ## The predicted va
    predictions_cv = model.predict(x_cv_scaled) ## The predicted values f
    accuracy_train = accuracy_score(predictions_train,ytrain)
    accuracy_cv = accuracy_score(predictions_cv,y_cv)
    accuracy_list_train.append(accuracy_train)
    accuracy_list_cv.append(accuracy_cv)
#print(accuracy_list_train[:5])


plt.plot(estimations, accuracy_list_train)
plt.plot(estimations,accuracy_list_cv)
plt.title('Train x Validation metrics')
plt.xlabel('n_estimators')
plt.ylabel('accuracy')
plt.legend(['Train','C_Validation'])
```

Out[144…

```
<matplotlib.legend.Legend at 0x13a199f90>
```



```
In [145…  random_forest_model = RandomForestClassifier(n_estimators = 37,
                                                       max_depth = 4,
                                                       min_samples_split = 30, rand
```

2.1.3 Determining parameters of XGBoost

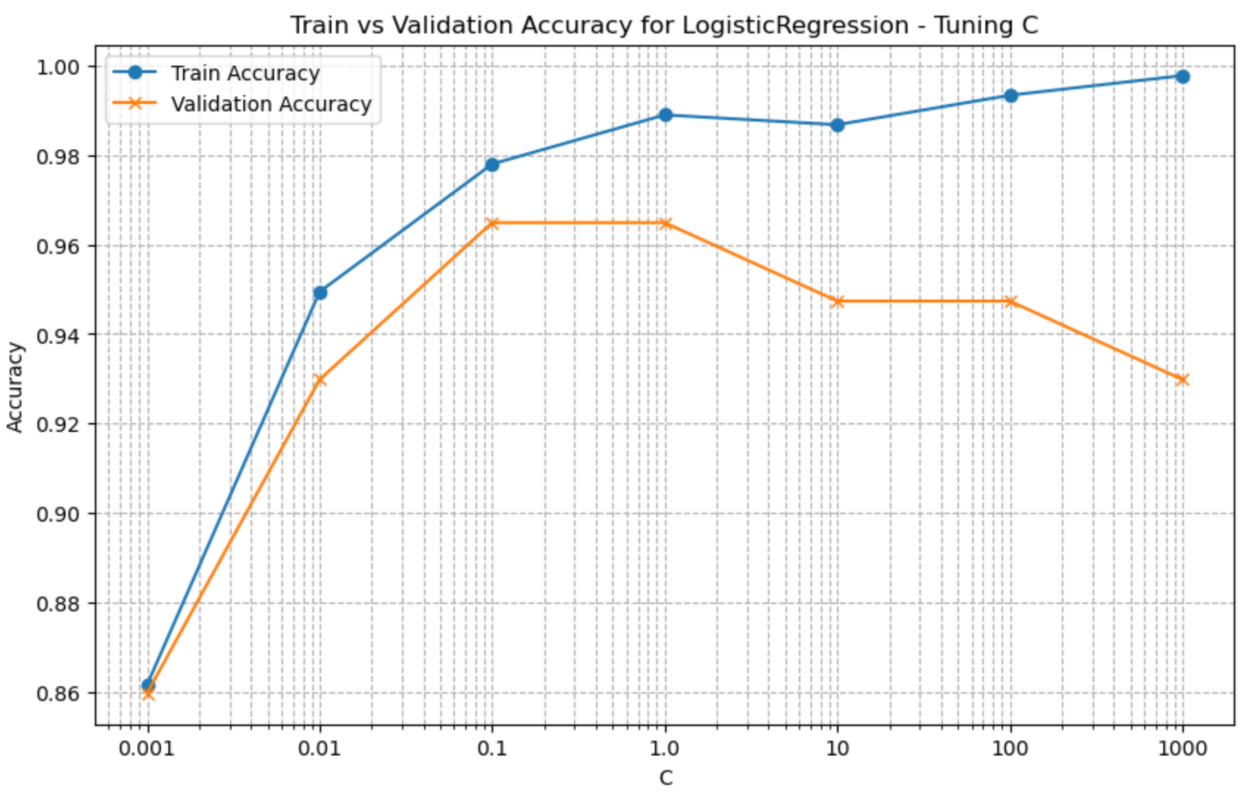
```
In [146…  from sklearn.model_selection import RandomizedSearchCV
          import scipy.stats as stats

          # Define the hyperparameter distributions
          param_dist = {
              'max_depth': stats.randint(3, 10),
              'learning_rate': stats.uniform(0.01, 0.1),
              'subsample': stats.uniform(0.5, 0.5),
              'n_estimators':stats.randint(10, 200)
          }

          # Create the XGBoost model object
          xgb_model = XGBClassifier()

          # Create the RandomizedSearchCV object
          random_search = RandomizedSearchCV(xgb_model, param_distributions=param_d
          random_search.fit(x_train_scaled, ytrain)
          cv_score = random_search.score(x_cv_scaled, y_cv)
          print("Best: %f using %s, with cv score %f" % (random_search.best_score_,
```

```
Best: 0.969130 using {'learning_rate': 0.10770186195240529, 'max_depth': 9
, 'n_estimators': 157, 'subsample': 0.8554571406530628}, with cv score 0.9
82456
```

2.1.3 Determining parameters of Logistic Regression

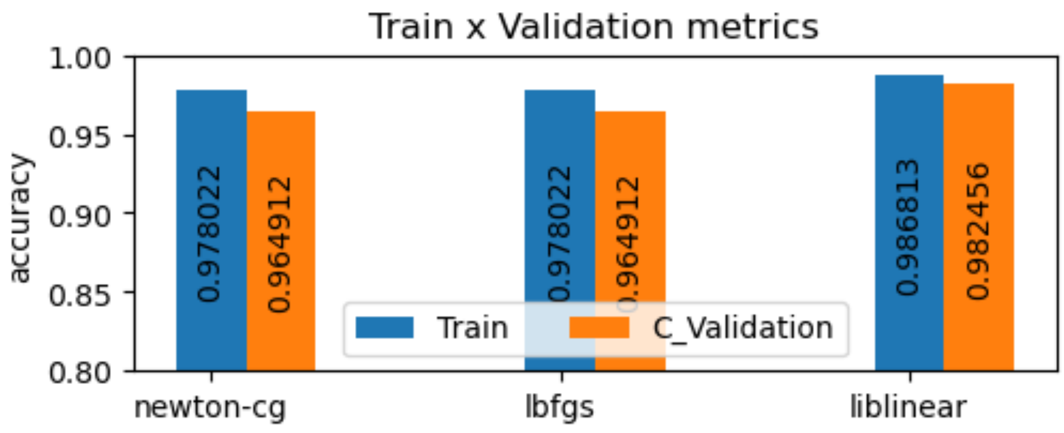
In [147…
```
def plot_parameter(model_class, p_name, p_list):
    """
    Plots training and validation accuracy for a given model and hyperpar

    Args:
        model_class: The scikit-learn model class (e.g., LogisticRegressi
        p_name (str): The name of the hyperparameter to tune (e.g., 'C',
        p_list (list): A list of values to test for the hyperparameter.
    """
    accuracy_list_train = []
    accuracy_list_val = []

    for p_value in p_list:
        # Create a dictionary for the parameter to pass to the model cons
        model_params = {p_name: p_value}

        # Instantiate the model with the current parameter value
        model = model_class(**model_params)

        # Fit the model
        model.fit(x_train_scaled, ytrain)

        # Make predictions
        predictions_train = model.predict(x_train_scaled)
        predictions_val = model.predict(x_cv_scaled)

        # Calculate accuracy
        accuracy_train = accuracy_score(predictions_train, ytrain)
        accuracy_val = accuracy_score(predictions_val, y_cv)

        accuracy_list_train.append(accuracy_train)
        accuracy_list_val.append(accuracy_val)

    plt.figure(figsize=(10, 6))
    plt.title(f'Train vs Validation Accuracy for {model_class.__name__} -
    plt.xlabel(p_name)
    plt.ylabel('Accuracy')
    plt.plot(p_list, accuracy_list_train, label='Train Accuracy', marker=
    plt.plot(p_list, accuracy_list_val, label='Validation Accuracy', mark
    plt.xscale('log') # Useful for parameters like C that span wide range
    plt.xticks(ticks=p_list, labels=[str(p) for p in p_list]) # Ensure la
    plt.legend()
    plt.grid(True, which="both", ls="--", c='0.7')
    plt.show()
```

In [148…
```
plot_parameter(LogisticRegression, 'C', [1000, 100, 10, 1.0, 0.1, 0.01, 0
```



In [149…
```
solvers = ['newton-cg', 'lbfgs', 'liblinear']
```

In [150…
```
accuracy_list_train = []
accuracy_list_cv = []
for s in solvers:

    model = LogisticRegression(C = 0.15, solver = s, penalty= 'l2').fit(x
    predictions_train = model.predict(x_train_scaled) ## The predicted va
    predictions_cv = model.predict(x_cv_scaled) ## The predicted values f
    accuracy_train = accuracy_score(predictions_train,ytrain)
    accuracy_cv = accuracy_score(predictions_cv,y_cv)
    accuracy_list_train.append(accuracy_train)
    accuracy_list_cv.append(accuracy_cv)


dict_ = {
    'Train': accuracy_list_train,
    'C_Validation': accuracy_list_cv,
}

x = np.arange(len(solvers))  # the label locations
width = 0.2  # the width of the bars
multiplier = 0

fig, ax = plt.subplots(layout='constrained', figsize = (5,2))

for attribute, measurement in dict_.items():
    offset = width * multiplier
    rects = ax.bar(x + offset, measurement, width, label=attribute)
    ax.bar_label(rects, label_type = 'center', rotation=90)
    multiplier += 1

# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('accuracy')
ax.set_title('Train x Validation metrics')
ax.set_xticks(range(len(solvers)),solvers)
ax.legend(['Train','C_Validation'], ncols=2)
ax.set_ylim(0.8, 1.0)

plt.show()
```



C=0.1, solver = 'liblinear'

In [183…

```
LogisticR = LogisticRegression(C = 0.06, solver = 'liblinear', penalty =
```

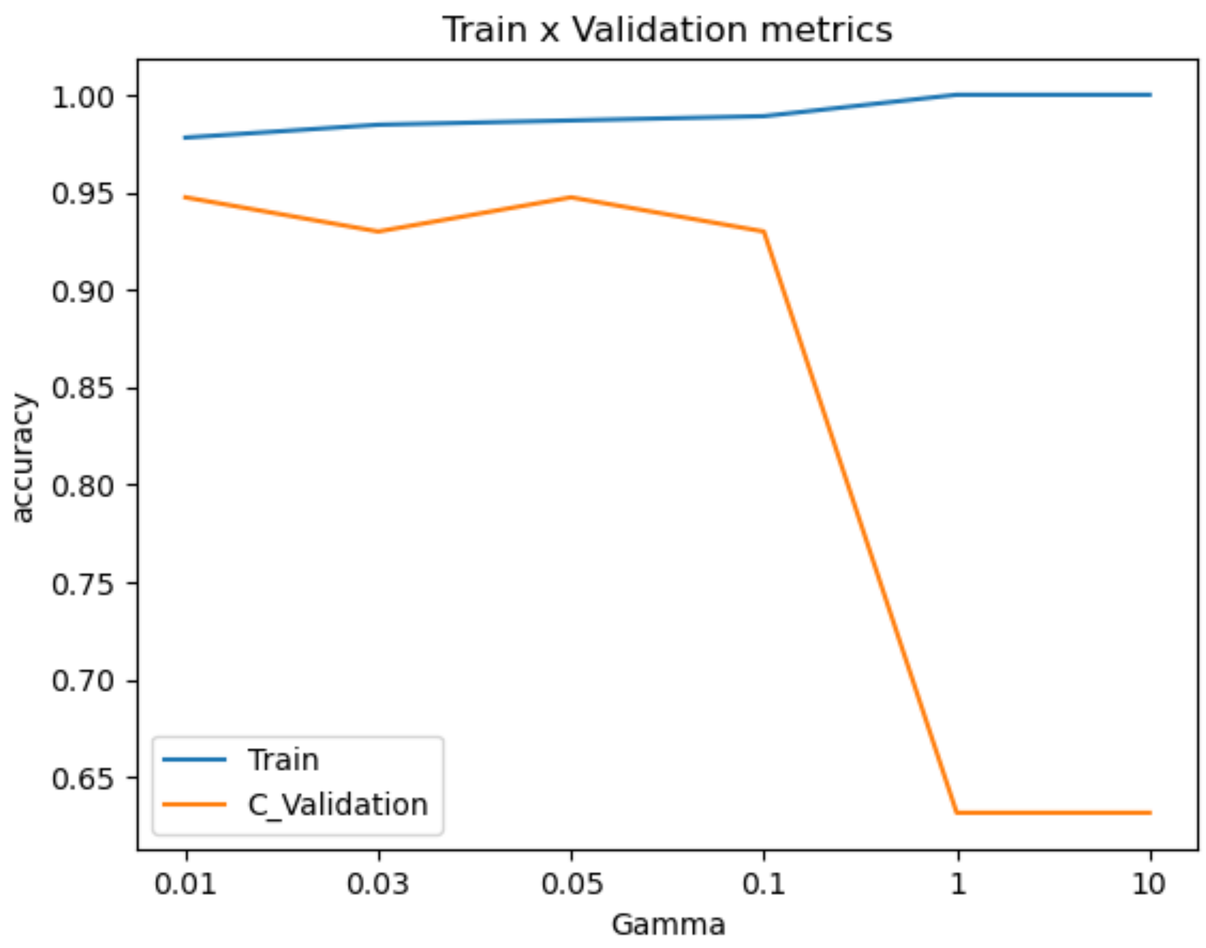
2.1.3 Determining parameters of SVC

In [152…

```
kernels = ['linear', 'rbf', 'poly']
gammas = [0.01,0.03, 0.05,0.1, 1, 10]
accuracy_list_train = []
accuracy_list_cv = []
for s in gammas:

    model = SVC(gamma = s).fit(x_train_scaled,ytrain)
    predictions_train = model.predict(x_train_scaled) ## The predicted va
    predictions_cv = model.predict(x_cv_scaled) ## The predicted values f
    accuracy_train = accuracy_score(predictions_train,ytrain)
    accuracy_cv = accuracy_score(predictions_cv,y_cv)
    accuracy_list_train.append(accuracy_train)
    accuracy_list_cv.append(accuracy_cv)

plt.title('Train x Validation metrics')
plt.xlabel('Gamma')
plt.ylabel('accuracy')
plt.xticks(ticks = range(len(gammas)),labels=gammas)
plt.plot(accuracy_list_train)
plt.plot(accuracy_list_cv)
plt.legend(['Train','C_Validation'])
```

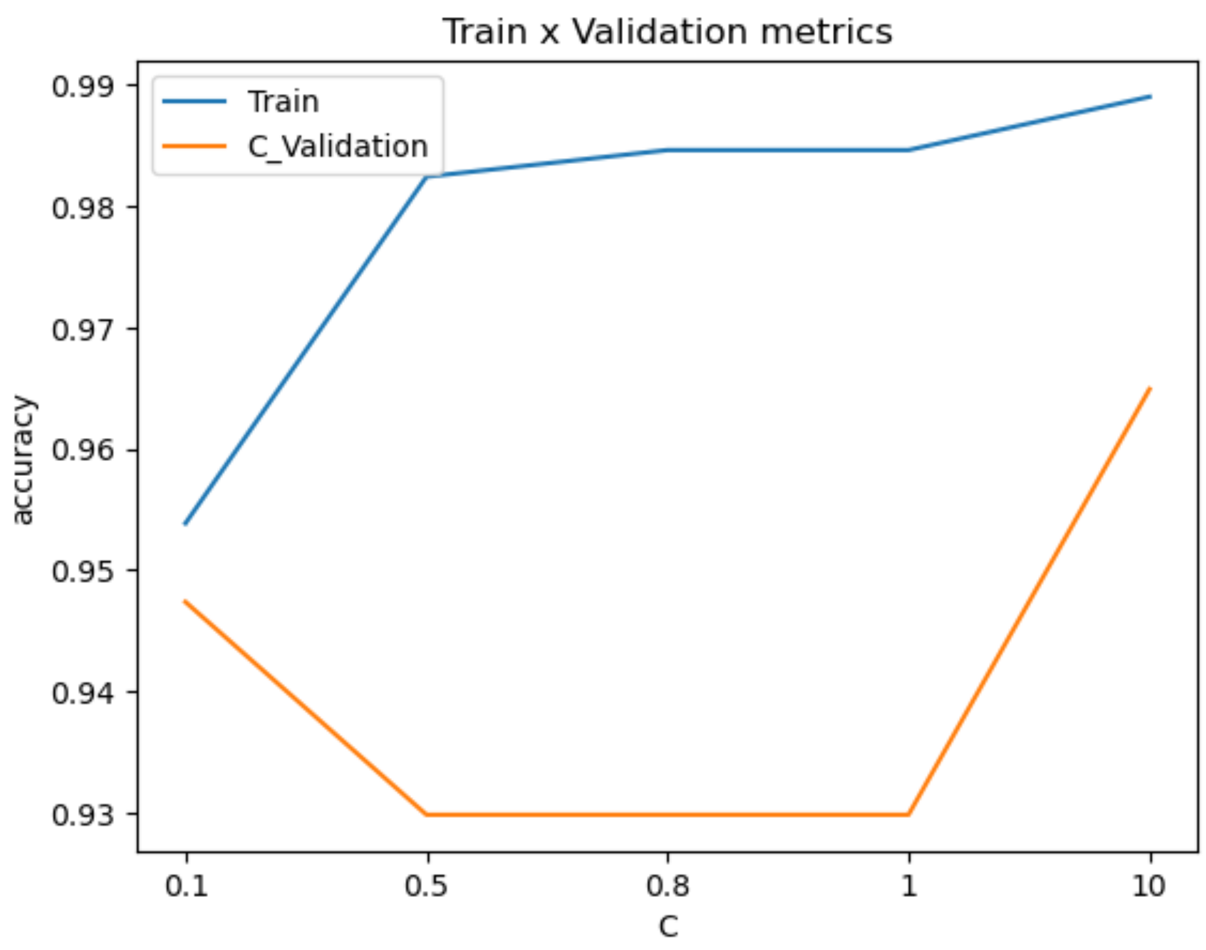
Out[152…

```
<matplotlib.legend.Legend at 0x137d85050>
```



```
In [153…  cs = [0.1, 0.5, 0.8, 1, 10]
          accuracy_list_train = []
          accuracy_list_cv = []
          for s in cs:

              model = SVC(C = s).fit(x_train_scaled,ytrain)
              predictions_train = model.predict(x_train_scaled) ## The predicted va
              predictions_cv = model.predict(x_cv_scaled) ## The predicted values f
              accuracy_train = accuracy_score(predictions_train,ytrain)
              accuracy_cv = accuracy_score(predictions_cv,y_cv)
              accuracy_list_train.append(accuracy_train)
              accuracy_list_cv.append(accuracy_cv)

          plt.title('Train x Validation metrics')
          plt.xlabel('C')
          plt.ylabel('accuracy')
          plt.xticks(ticks = range(len(cs)),labels=cs)
          plt.plot(accuracy_list_train)
          plt.plot(accuracy_list_cv)
          plt.legend(['Train','C_Validation'])
```

```
Out[153…  <matplotlib.legend.Legend at 0x13a994390>
```

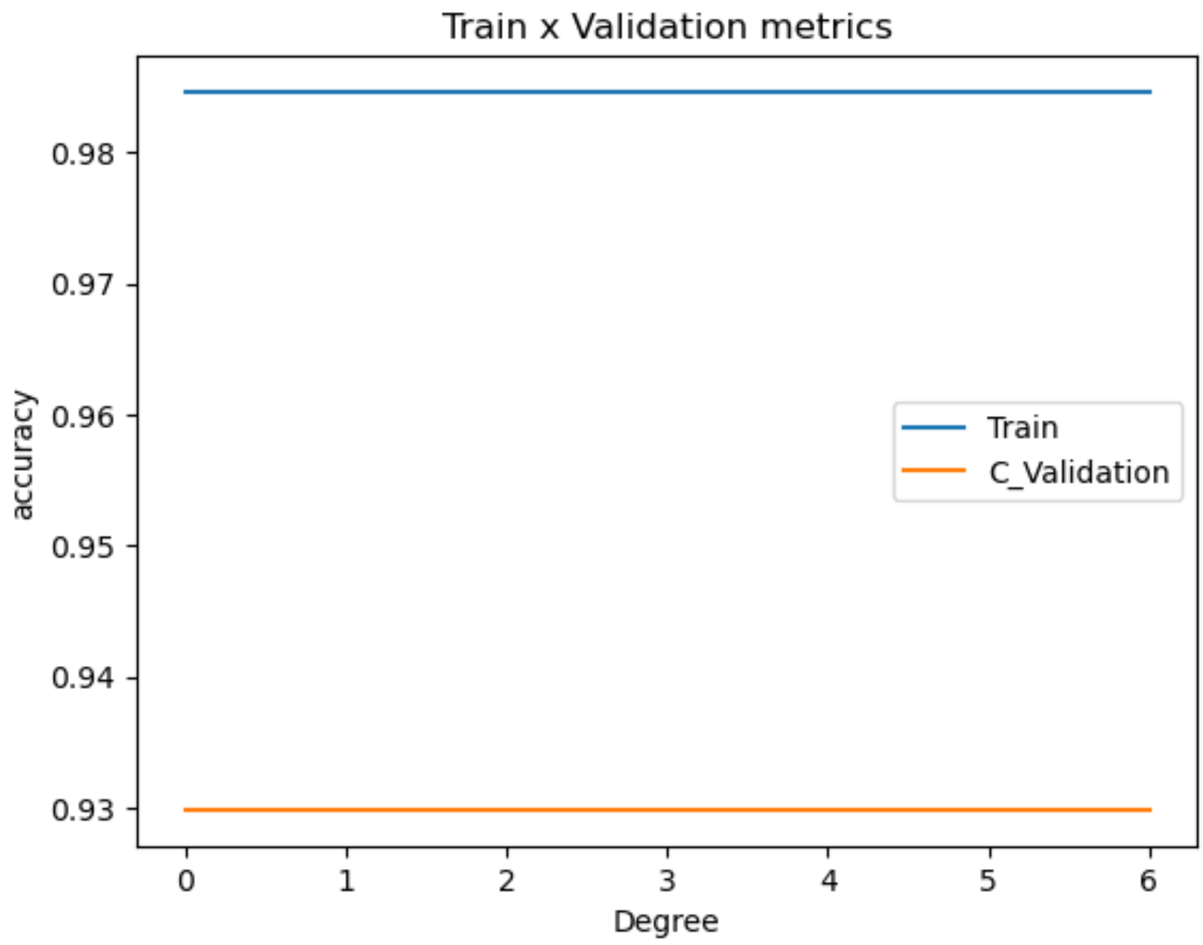


In [154…

```
accuracy_list_train = []
accuracy_list_cv = []
degrees = [0,1,2,3,4,5,6]
for s in degrees:

    model = SVC(degree = s).fit(x_train_scaled,ytrain)
    predictions_train = model.predict(x_train_scaled) ## The predicted va
    predictions_cv = model.predict(x_cv_scaled) ## The predicted values f
    accuracy_train = accuracy_score(predictions_train,ytrain)
    accuracy_cv = accuracy_score(predictions_cv,y_cv)
    accuracy_list_train.append(accuracy_train)
    accuracy_list_cv.append(accuracy_cv)

plt.title('Train x Validation metrics')
plt.xlabel('Degree')
plt.ylabel('accuracy')
plt.xticks(ticks = range(len(degrees)),labels=degrees)
plt.plot(accuracy_list_train)
plt.plot(accuracy_list_cv)
plt.legend(['Train','C_Validation'])
```

Out[154…

```
<matplotlib.legend.Legend at 0x13a9d37d0>
```

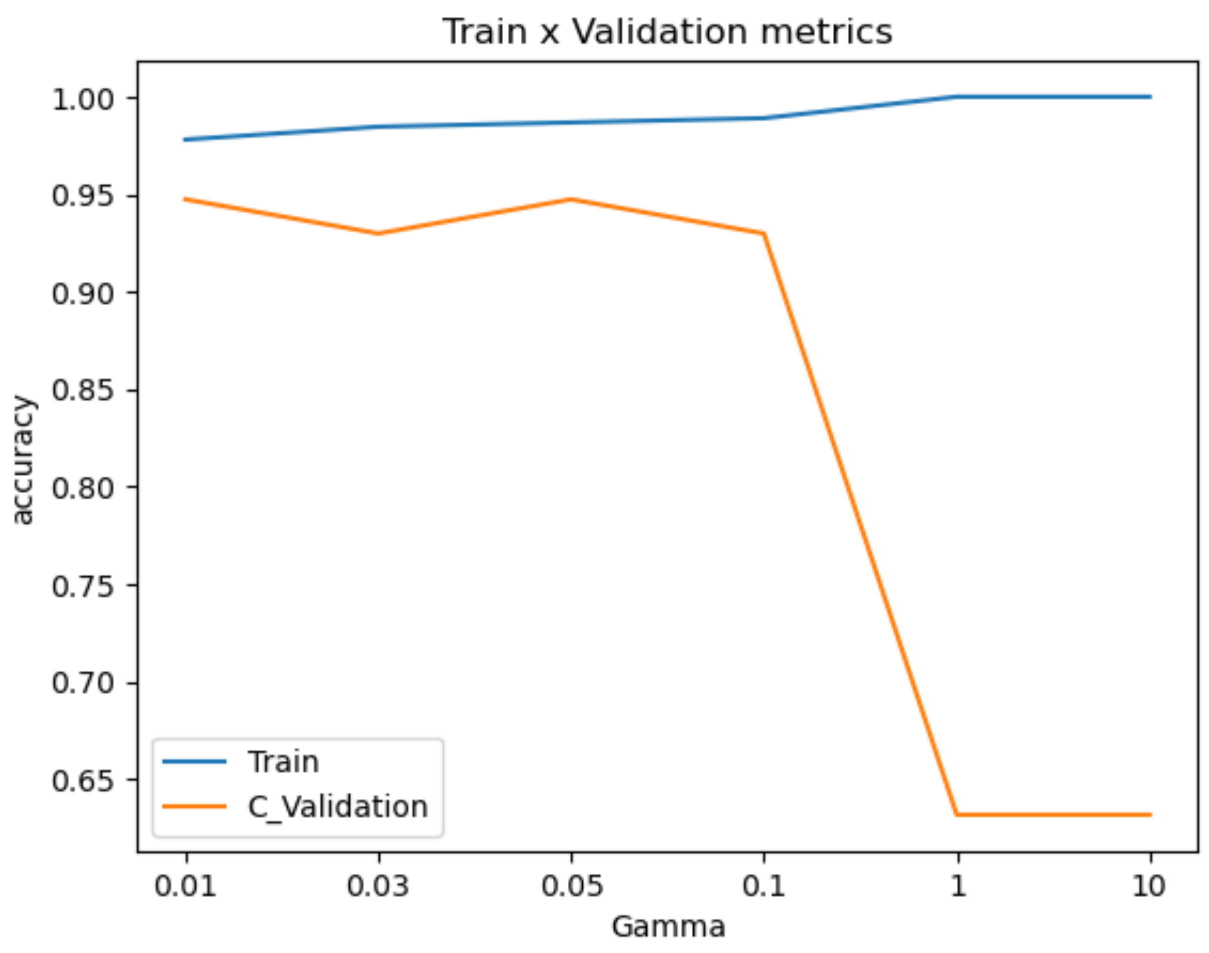


In [155…

```
accuracy_list_train = []
accuracy_list_cv = []
for s in gammas:

    model = SVC(gamma = s).fit(x_train_scaled,ytrain)
    predictions_train = model.predict(x_train_scaled) ## The predicted va
    predictions_cv = model.predict(x_cv_scaled) ## The predicted values f
    accuracy_train = accuracy_score(predictions_train,ytrain)
    accuracy_cv = accuracy_score(predictions_cv,y_cv)
    accuracy_list_train.append(accuracy_train)
    accuracy_list_cv.append(accuracy_cv)

plt.title('Train x Validation metrics')
plt.xlabel('Gamma')
plt.ylabel('accuracy')
plt.xticks(ticks = range(len(gammas)),labels=gammas)
plt.plot(accuracy_list_train)
plt.plot(accuracy_list_cv)
plt.legend(['Train','C_Validation'])
```

Out[155…

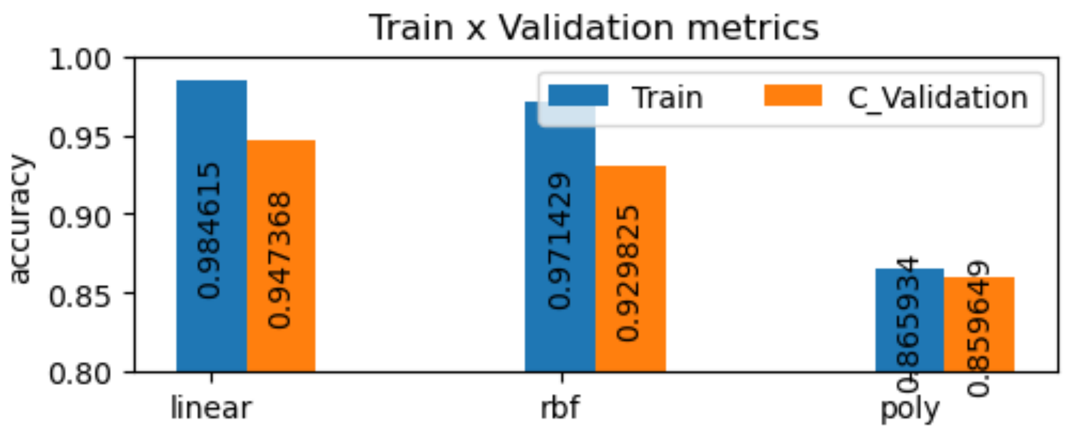
```
<matplotlib.legend.Legend at 0x13b71b7d0>
```



In [156…

```
accuracy_list_train = []
accuracy_list_cv = []
for s in kernels:

    model = SVC(kernel = s, gamma = 0.04, C = 0.3, degree = 5).fit(x_trai
    predictions_train = model.predict(x_train_scaled) ## The predicted va
    predictions_cv = model.predict(x_cv_scaled) ## The predicted values f
    accuracy_train = accuracy_score(predictions_train,ytrain)
    accuracy_cv = accuracy_score(predictions_cv,y_cv)
    accuracy_list_train.append(accuracy_train)
    accuracy_list_cv.append(accuracy_cv)

dict_ = {
    'Train': accuracy_list_train,
    'C_Validation': accuracy_list_cv,
}

x = np.arange(len(kernels))  # the label locations
width = 0.2  # the width of the bars
multiplier = 0

fig, ax = plt.subplots(layout='constrained', figsize = (5,2))

for attribute, measurement in dict_.items():
    offset = width * multiplier
    rects = ax.bar(x + offset, measurement, width, label=attribute)
    ax.bar_label(rects, label_type = 'center', rotation=90)
    multiplier += 1
```

```
# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('accuracy')
ax.set_title('Train x Validation metrics')
ax.set_xticks(range(len(kernels)),kernels)
ax.legend(['Train','C_Validation'], ncols=2)
ax.set_ylim(0.8, 1.0)

plt.show()
```



In [178…

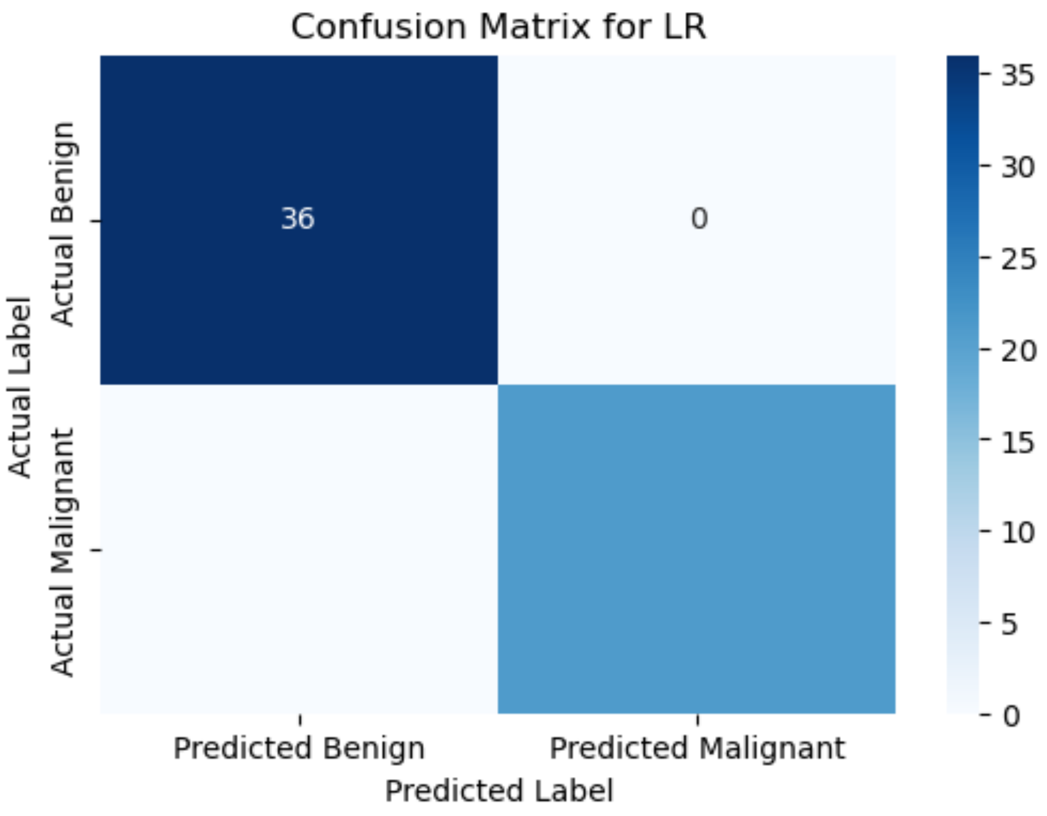
```
CustomSVC = SVC(kernel = 'linear', gamma = 0.04, C = 0.3, degree = 5, pro
```

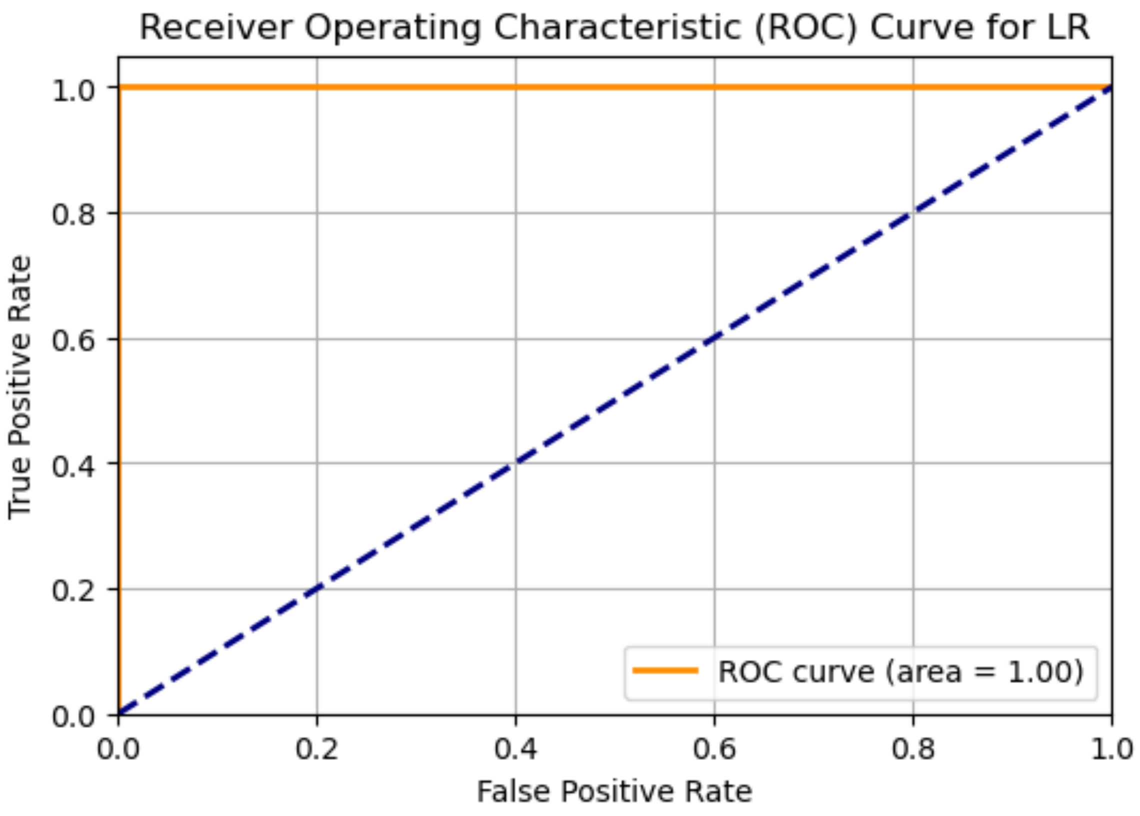
2.2 Comparing Models

In [186…

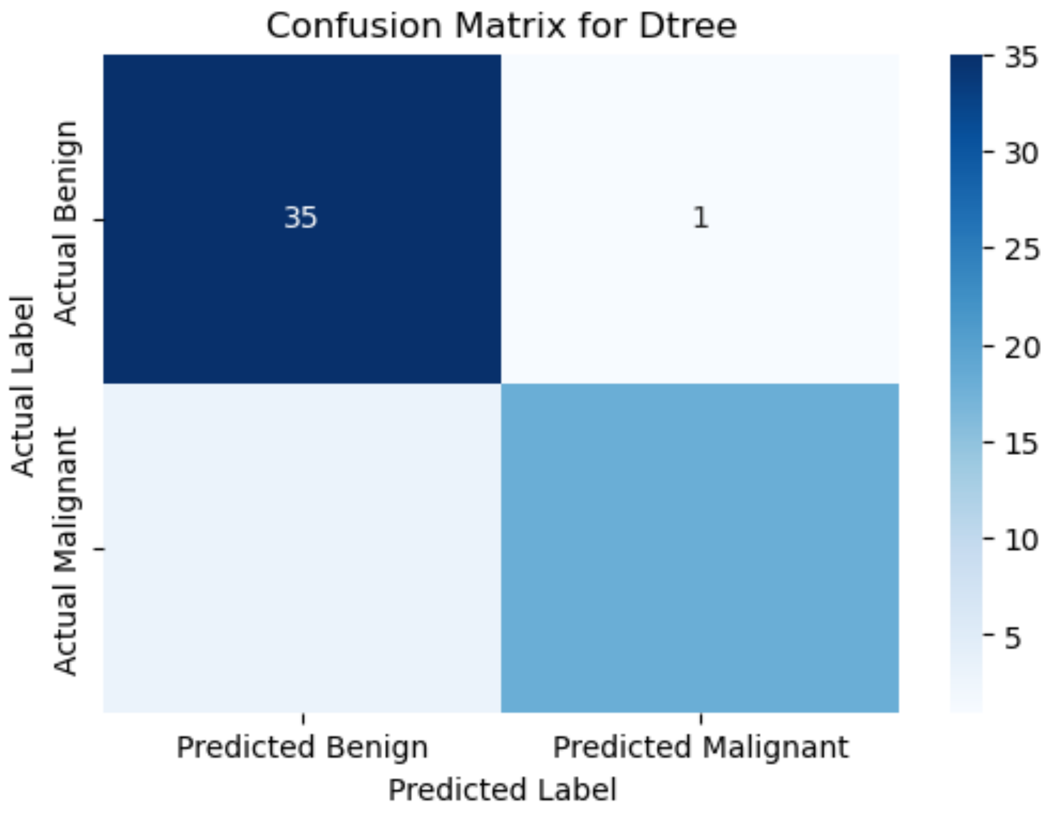
```
from sklearn.metrics import confusion_matrix, classification_report, roc_
import matplotlib.pyplot as plt
models = {
          'LR': LogisticR,
          'Dtree':decision_tree_model,
          'RFPlain': RandomForestClassifier(),
          'RF200':RandomForestClassifier(n_estimators=200, max_depth = 4,
                                          min_samples_split = 30),
          'CustomRF': random_forest_model,
          'XGBoost': XGBClassifier(tree_method = 'approx', learning_rate=
          'SVC':SVC(probability=True),
          'CustomSVC':CustomSVC,
         }

results = {}

for name, model in models.items():
    print(f"\n--- Evaluating {name} ---")
    model.fit(x_train_scaled, ytrain)
    # Predict on the test set
    y_pred = model.predict(x_test_scaled)
    y_pred_proba = model.predict_proba(x_test_scaled)[:, 1] # Probability

    # Calculate metrics
    accuracy = accuracy_score(y_test, y_pred)
    conf_matrix = confusion_matrix(y_test, y_pred)
    class_report = classification_report(y_test, y_pred)
    roc_auc = roc_auc_score(y_test, y_pred_proba)

    results[name] = {
        'Accuracy': accuracy,
        'Confusion Matrix': conf_matrix,
        'Classification Report': class_report,
        'ROC AUC': roc_auc
    }

    print(f"Accuracy: {accuracy:.4f}")
    print("Confusion Matrix:\n", conf_matrix)
    print("Classification Report:\n", class_report)
    print(f"ROC AUC: {roc_auc:.4f}")

    # Plot Confusion Matrix
    plt.figure(figsize=(6, 4))
    sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues',
                xticklabels=['Predicted Benign', 'Predicted Malignant'],
                yticklabels=['Actual Benign', 'Actual Malignant'])
    plt.title(f'Confusion Matrix for {name}')
    plt.ylabel('Actual Label')
    plt.xlabel('Predicted Label')
    plt.show()

    # Plot ROC Curve
    fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
    plt.figure(figsize=(6, 4))
    plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area
    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(f'Receiver Operating Characteristic (ROC) Curve for {name}'
    plt.legend(loc="lower right")
    plt.grid(True)
    plt.show()
```

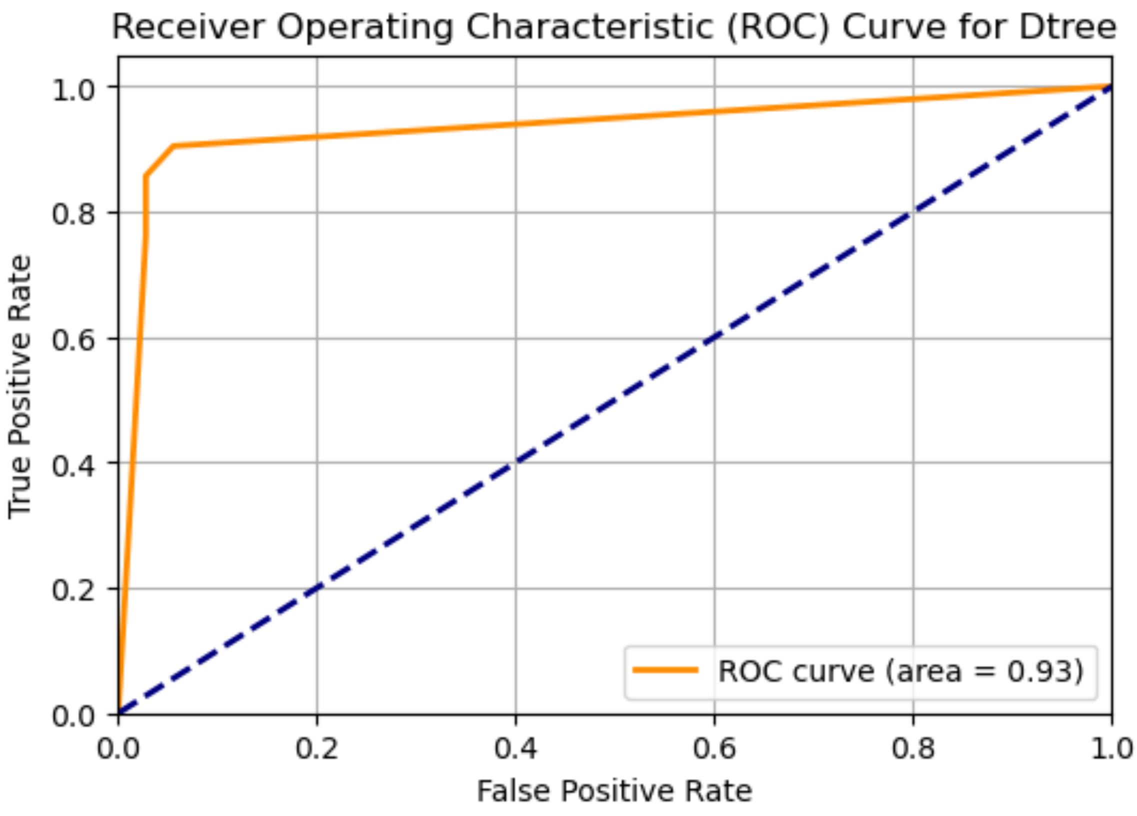
```
--- Evaluating LR ---
Accuracy: 1.0000
Confusion Matrix:
 [[36  0]
 [ 0 21]]
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00        36
           1       1.00      1.00      1.00        21

    accuracy                           1.00        57
   macro avg       1.00      1.00      1.00        57
weighted avg       1.00      1.00      1.00        57

ROC AUC: 1.0000
```


Confusion Matrix for LR
Actual Label
Actual Benign
Actual Malignant
36
0
Predicted Benign
Predicted Malignant
Predicted Label
35
30
25
20
15
10
5
0

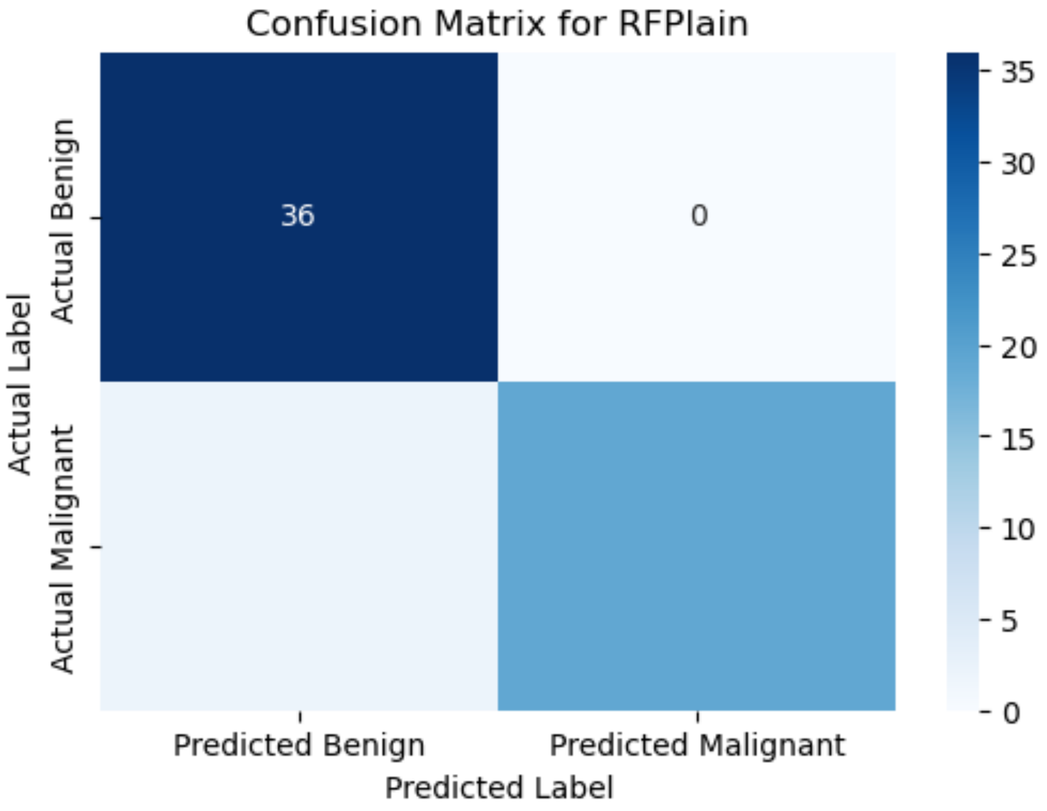

Receiver Operating Characteristic (ROC) Curve for LR
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve (area = 1.00)

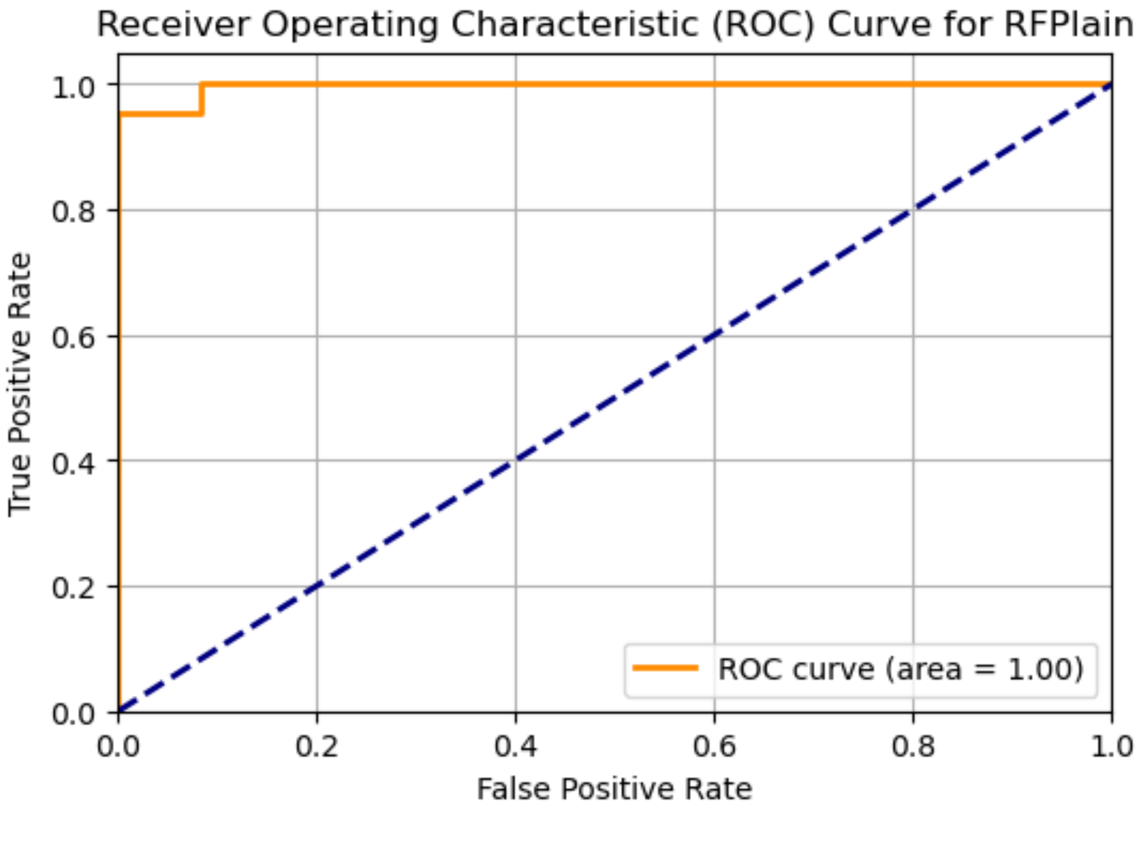
```
--- Evaluating Dtree ---
Accuracy: 0.9298
Confusion Matrix:
 [[35  1]
 [ 3 18]]
Classification Report:
               precision    recall  f1-score   support

           0       0.92      0.97      0.95        36
           1       0.95      0.86      0.90        21

    accuracy                           0.93        57
   macro avg       0.93      0.91      0.92        57
weighted avg       0.93      0.93      0.93        57

ROC AUC: 0.9345
```



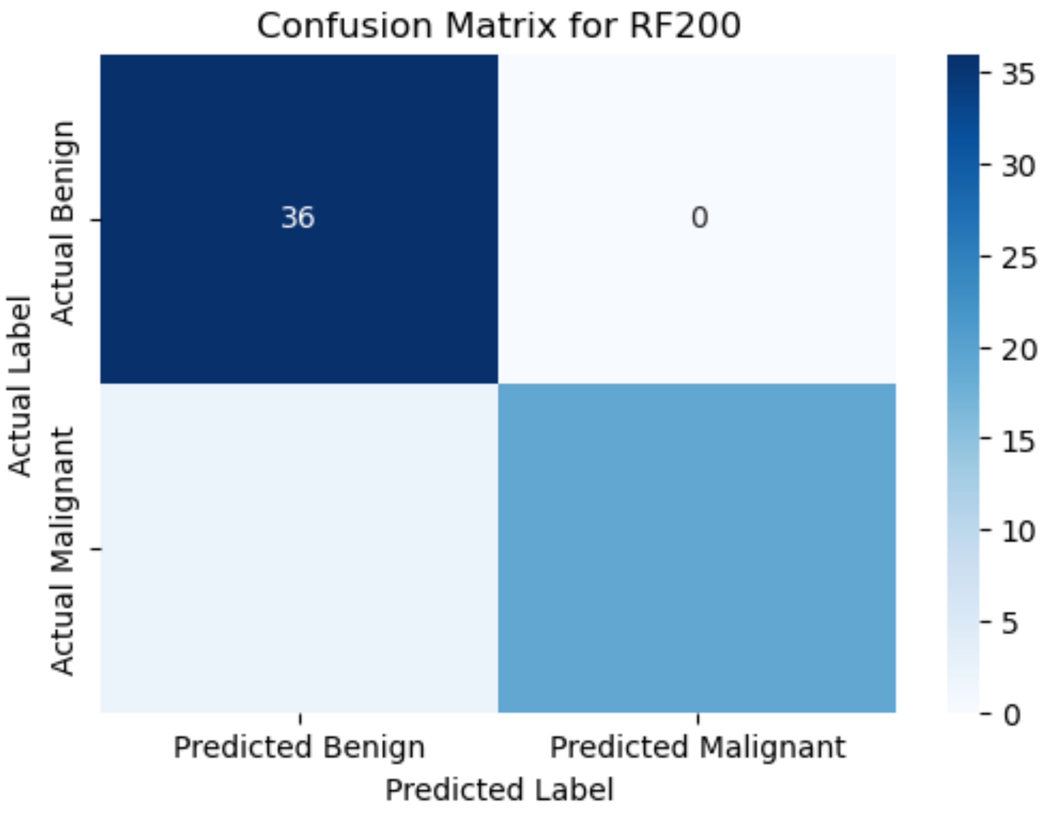


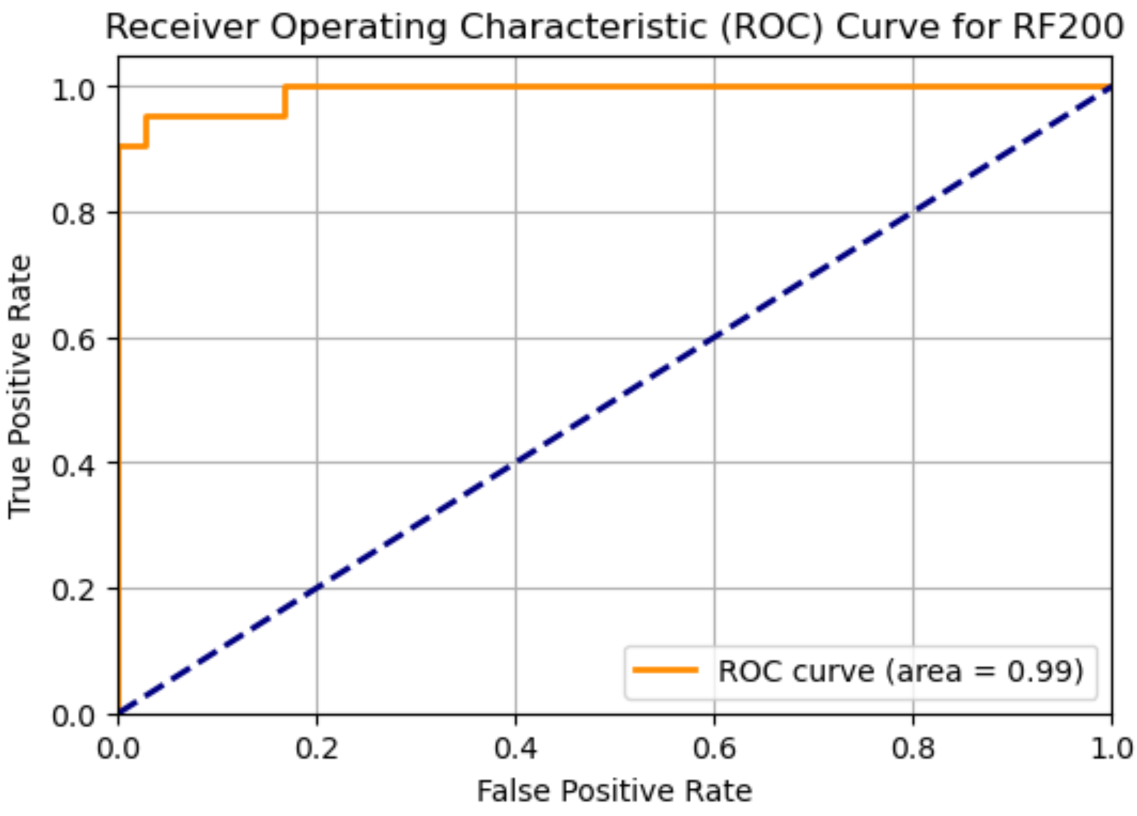
```
--- Evaluating RFPlain ---
Accuracy: 0.9649
Confusion Matrix:
 [[36  0]
 [ 2 19]]
Classification Report:
              precision    recall  f1-score   support

           0       0.95      1.00      0.97        36
           1       1.00      0.90      0.95        21

    accuracy                           0.96        57
   macro avg       0.97      0.95      0.96        57
weighted avg       0.97      0.96      0.96        57

ROC AUC: 0.9960
```


Confusion Matrix for RFPlain
Actual Benign
Actual Malignant
Actual Label
36
0
Predicted Benign
Predicted Malignant
Predicted Label
35
30
25
20
15
10
5
0

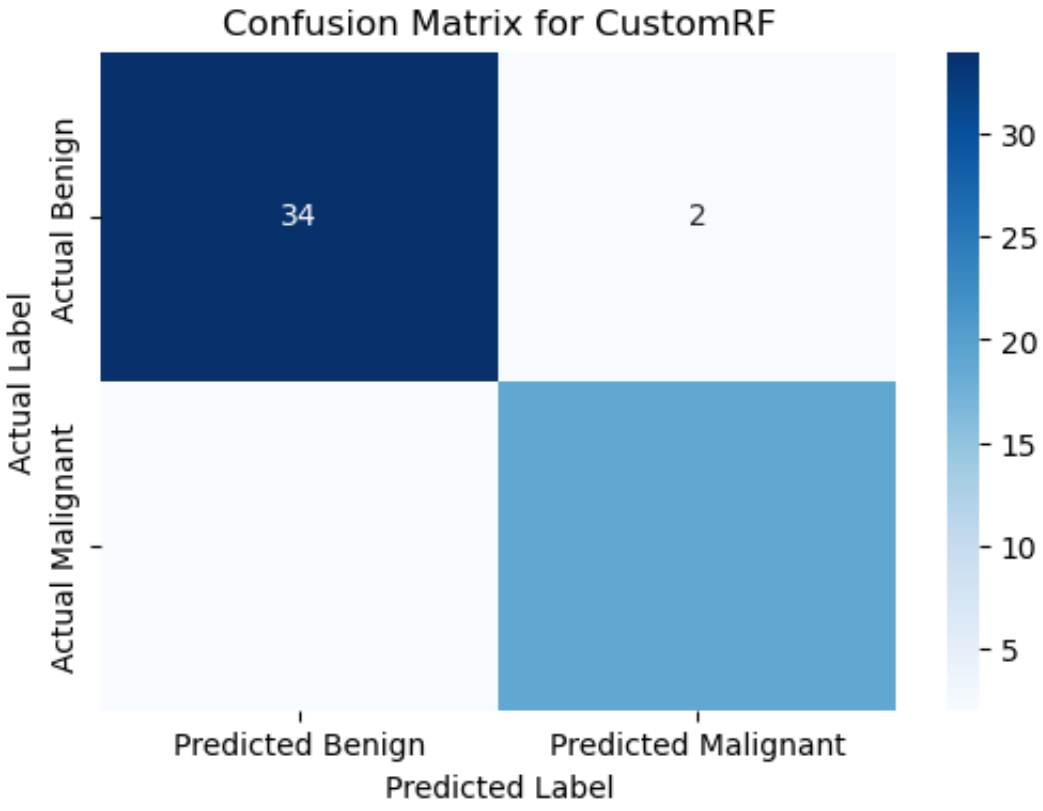

Receiver Operating Characteristic (ROC) Curve for RFPlain
True Positive Rate
False Positive Rate
ROC curve (area = 1.00)
0.0
0.2
0.4
0.6
0.8
1.0

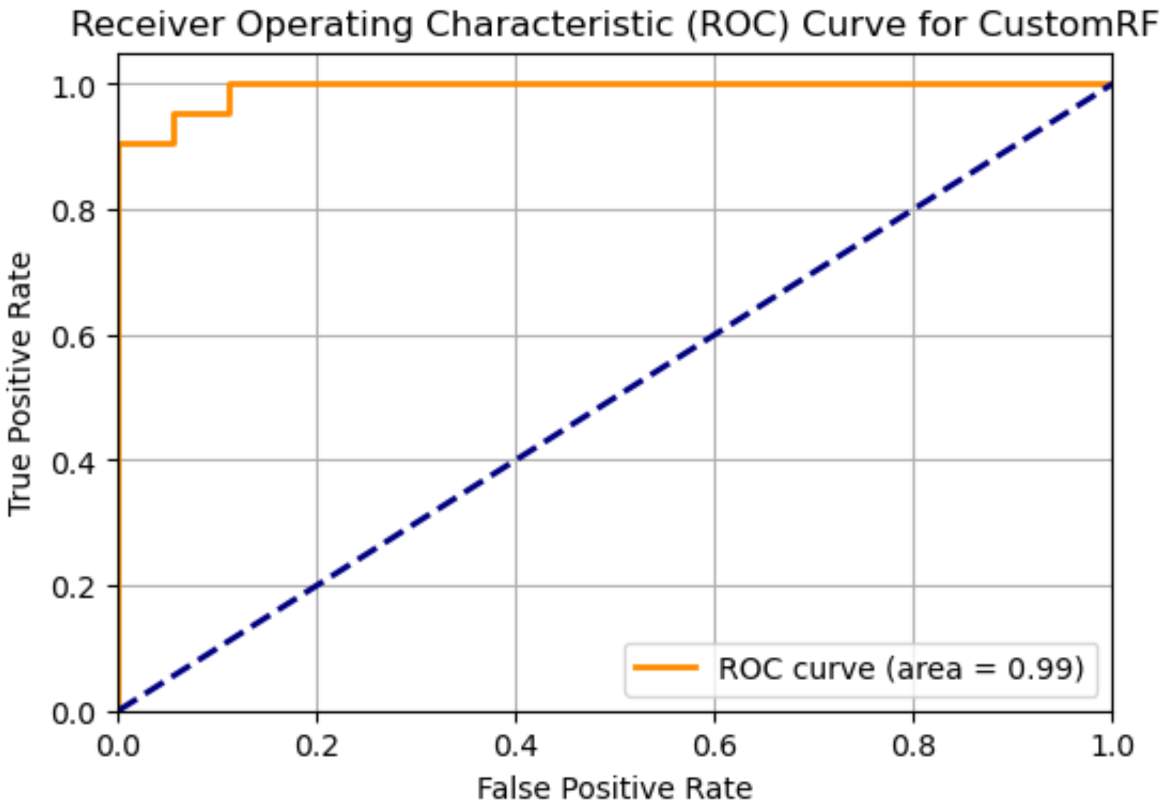
```
--- Evaluating RF200 ---
Accuracy: 0.9649
Confusion Matrix:
 [[36  0]
 [ 2 19]]
Classification Report:
               precision    recall  f1-score   support

           0       0.95      1.00      0.97        36
           1       1.00      0.90      0.95        21

    accuracy                           0.96        57
   macro avg       0.97      0.95      0.96        57
weighted avg       0.97      0.96      0.96        57

ROC AUC: 0.9907
```



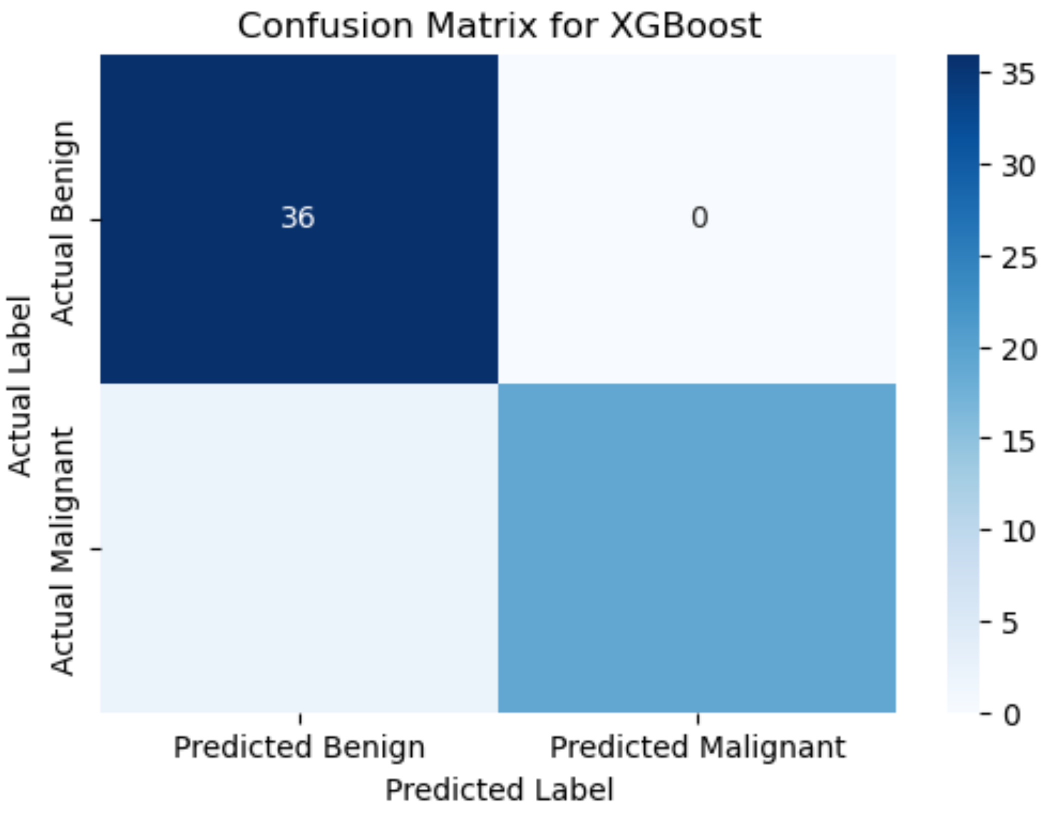


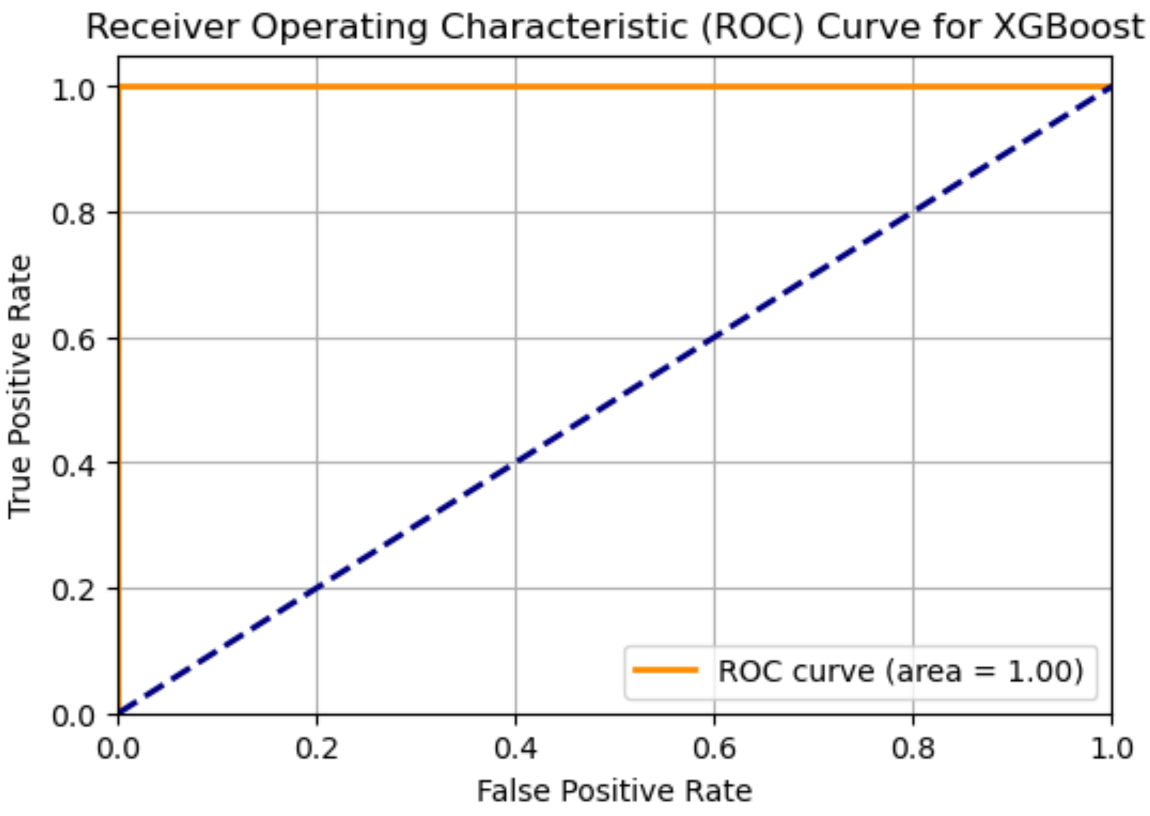
```
--- Evaluating CustomRF ---
Accuracy: 0.9298
Confusion Matrix:
 [[34  2]
 [ 2 19]]
Classification Report:
               precision    recall  f1-score   support

           0       0.94      0.94      0.94        36
           1       0.90      0.90      0.90        21

    accuracy                           0.93        57
   macro avg       0.92      0.92      0.92        57
weighted avg       0.93      0.93      0.93        57

ROC AUC: 0.9921
```


Confusion Matrix for CustomRF
Actual Label
Actual Benign
Actual Malignant
34
2
Predicted Benign
Predicted Malignant
Predicted Label
30
25
20
15
10
5

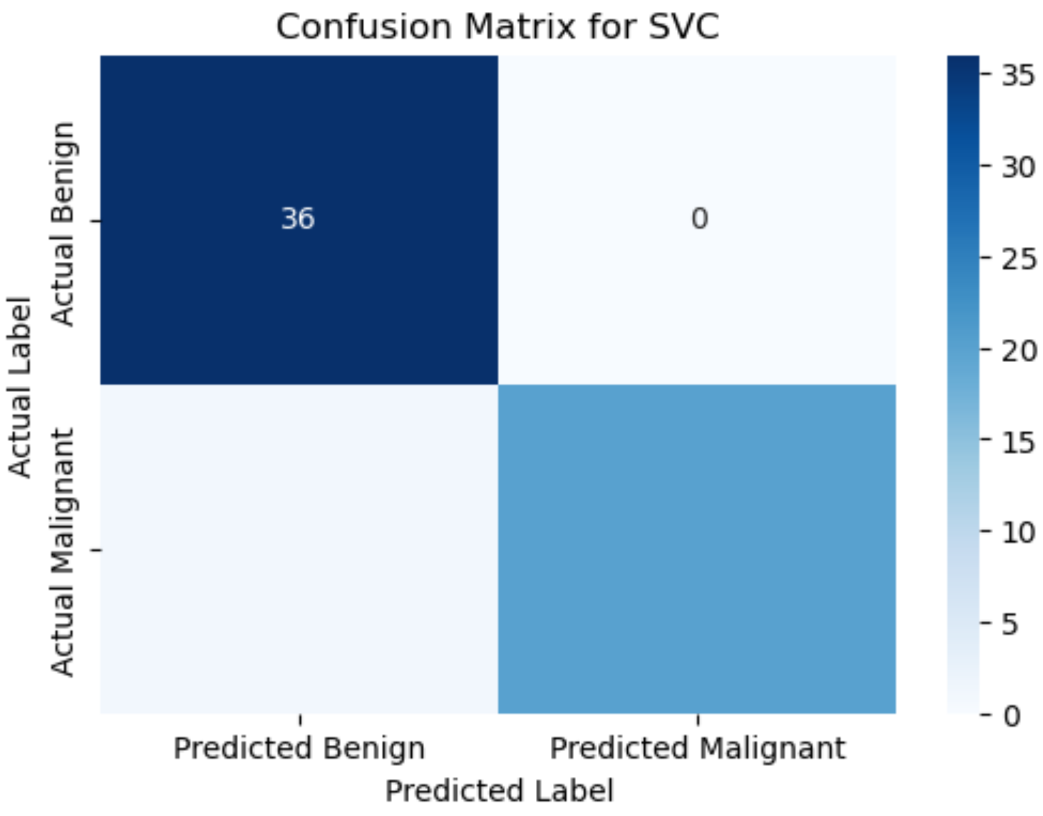

Receiver Operating Characteristic (ROC) Curve for CustomRF
True Positive Rate
False Positive Rate
ROC curve (area = 0.99)
0.0
0.2
0.4
0.6
0.8
1.0

```
--- Evaluating XGBoost ---
Accuracy: 0.9649
Confusion Matrix:
 [[36  0]
 [ 2 19]]
Classification Report:
               precision    recall  f1-score   support

           0       0.95      1.00      0.97        36
           1       1.00      0.90      0.95        21

    accuracy                           0.96        57
   macro avg       0.97      0.95      0.96        57
weighted avg       0.97      0.96      0.96        57

ROC AUC: 1.0000
```

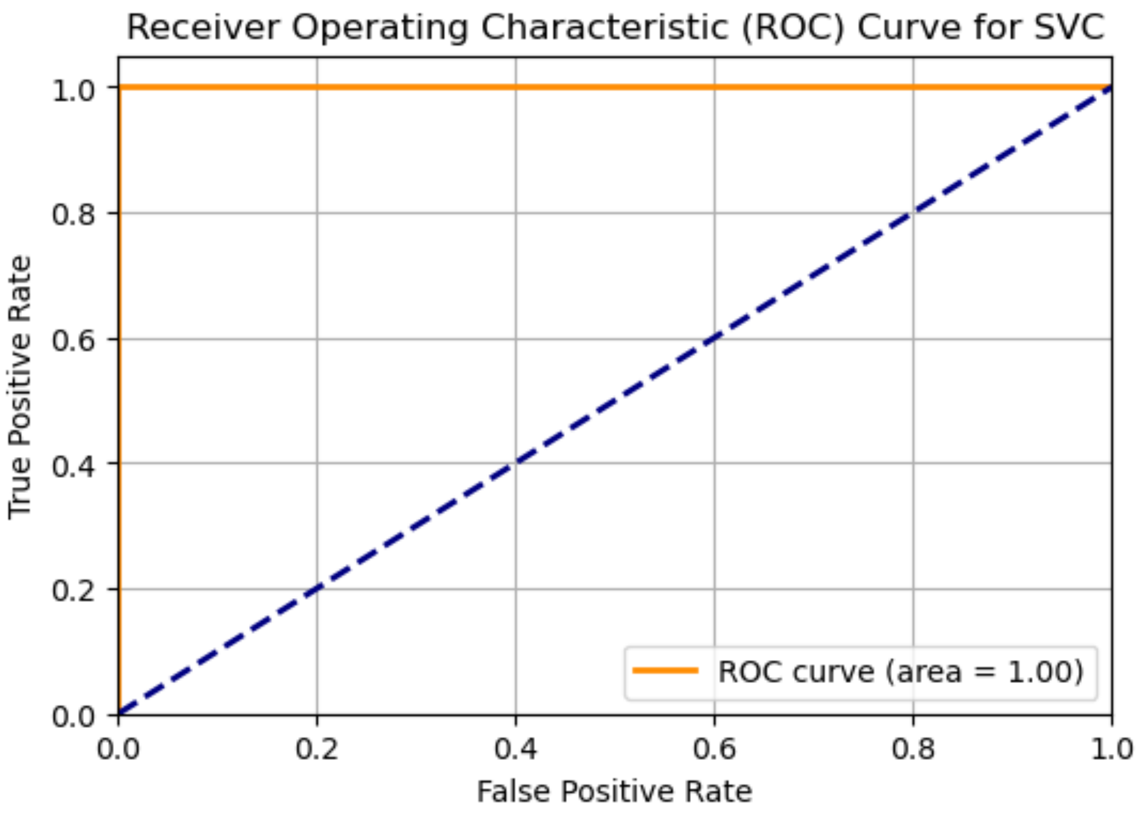




```
--- Evaluating SVC ---
Accuracy: 0.9825
Confusion Matrix:
 [[36  0]
 [ 1 20]]
Classification Report:
               precision    recall  f1-score   support

           0       0.97      1.00      0.99        36
           1       1.00      0.95      0.98        21

    accuracy                           0.98        57
   macro avg       0.99      0.98      0.98        57
weighted avg       0.98      0.98      0.98        57

ROC AUC: 1.0000
```

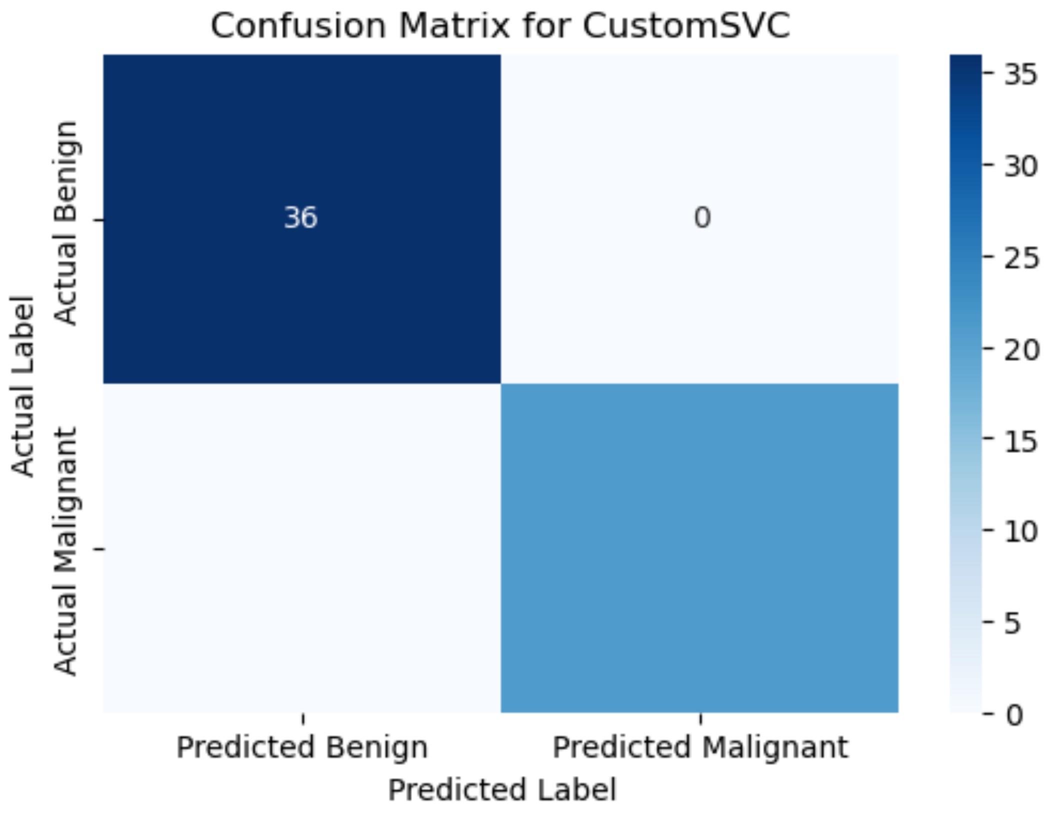


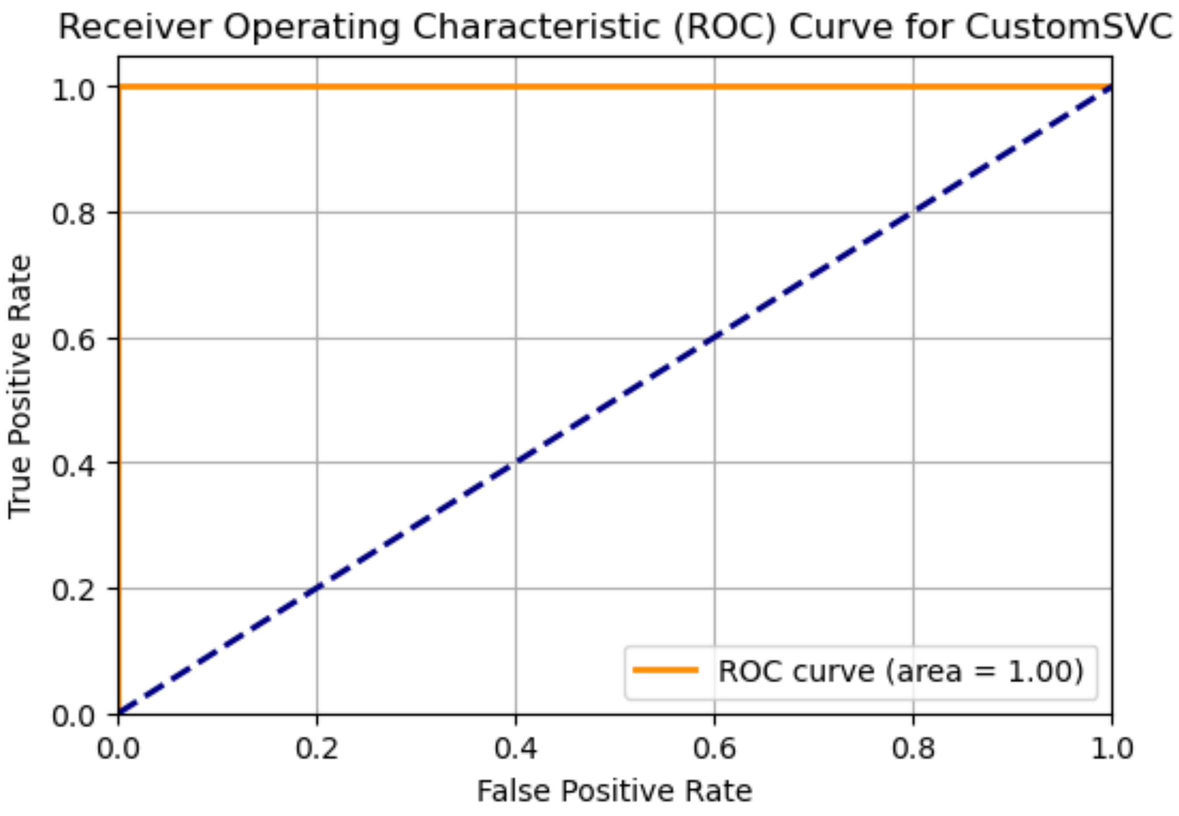
Confusion Matrix for SVC
Actual Label
Actual Benign
Actual Malignant
36
0
Predicted Benign
Predicted Malignant
Predicted Label
35
30
25
20
15
10
5
0



Receiver Operating Characteristic (ROC) Curve for SVC
True Positive Rate
False Positive Rate
ROC curve (area = 1.00)
0.0
0.2
0.4
0.6
0.8
1.0

```
--- Evaluating CustomSVC ---
Accuracy: 1.0000
Confusion Matrix:
 [[36  0]
 [ 0 21]]
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00        36
           1       1.00      1.00      1.00        21

    accuracy                           1.00        57
   macro avg       1.00      1.00      1.00        57
weighted avg       1.00      1.00      1.00        57

ROC AUC: 1.0000
```





In [187…

```
import pandas as pd
import numpy as np # For array handling if needed, though direct parsing

metrics_data = results

# Prepare data for the summary table
summary_rows = []
for model_name, data in metrics_data.items():
    accuracy = data['Accuracy']
    roc_auc = data['ROC AUC']
    conf_matrix = data['Confusion Matrix']

    # Extract metrics for Class 1 (Malignant) from the classification rep
    # A more robust way would be to parse the string, but given the fixed
    # we can directly extract from the string or recalculate from confusi
    # For simplicity, let's extract or compute them

    # Confusion Matrix: [[TN, FP], [FN, TP]]
    TN = conf_matrix[0, 0]
    FP = conf_matrix[0, 1]
    FN = conf_matrix[1, 0]
    TP = conf_matrix[1, 1]

    # Calculate metrics for Class 1 (Malignant)
    # Handle division by zero for precision/recall if applicable
    precision_1 = TP / (TP + FP) if (TP + FP) > 0 else 0
    recall_1 = TP / (TP + FN) if (TP + FN) > 0 else 0
    f1_score_1 = (2 * precision_1 * recall_1) / (precision_1 + recall_1)

    summary_rows.append({
        "Model": model_name,
        "Accuracy": f"{accuracy:.4f}",
        "Precision (Malignant)": f"{precision_1:.4f}",
        "Recall (Malignant)": f"{recall_1:.4f}",
        "F1-Score (Malignant)": f"{f1_score_1:.4f}",
        "ROC AUC": f"{roc_auc:.4f}",
        "False Negatives (FN)": FN,
        "False Positives (FP)": FP
    })

summary_table = pd.DataFrame(summary_rows)
summary_table = summary_table.set_index("Model")

print("--- Model Performance Summary Table (on Test Set) ---")
print(summary_table)
```

```
--- Model Performance Summary Table (on Test Set) ---
          Accuracy Precision (Malignant) Recall (Malignant)  \
Model
LR          1.0000                1.0000             1.0000
Dtree       0.9298                0.9474             0.8571
RFPlain     0.9649                1.0000             0.9048
RF200       0.9649                1.0000             0.9048
CustomRF    0.9298                0.9048             0.9048
XGBoost     0.9649                1.0000             0.9048
SVC         0.9825                1.0000             0.9524
CustomSVC   1.0000                1.0000             1.0000

          F1-Score (Malignant) ROC AUC  False Negatives (FN)  \
Model
LR                      1.0000  1.0000                     0
Dtree                   0.9000  0.9345                     3
RFPlain                 0.9500  0.9960                     2
RF200                   0.9500  0.9907                     2
CustomRF                0.9048  0.9921                     2
XGBoost                 0.9500  1.0000                     2
SVC                     0.9756  1.0000                     1
CustomSVC               1.0000  1.0000                     0

           False Positives (FP)
Model
LR                            0
Dtree                         1
RFPlain                       0
RF200                         0
CustomRF                      2
XGBoost                       0
SVC                           0
CustomSVC                     0
```

Logistic Regression, Custom SVC, and SVC are potentially the best models. Setting the baseline level of performance - Existing breast classification can achieve an accuracy of 98%. Therefore, Logistic Regression and SVC can be the way to go.