SVM

September 3, 2025

1 Support Vector Machine – Cancer Data

1.1 Project Description:

This project applies Support Vector Machine (SVM) techniques to a breast cancer dataset from Kaggle in order to classify tumors as malignant or benign. The work involved both implementing SVMs from scratch (with L2 regularization, C-parameterization, epochs, and batch sizes) and using scikit-learn's SVC for comparison. Extensive data exploration, visualization, and evaluation of multiple performance metrics (accuracy, precision, recall, F1, ROC AUC) were performed to assess and refine model performance.

1.1.1 Objectives:

- Import, clean, and explore a publicly available cancer dataset from Kaggle.
- Visualize data distributions, relationships, and correlations between features.
- Implement SVM with hinge loss, L2 regularization, epochs, and mini-batch gradient descent from scratch.
- Compare different formulations: L2 regularization vs. C-parameterization.
- Evaluate performance across metrics including precision, recall, F1, and ROC AUC.
- Apply scikit-learn's SVC with pipelines, cross-validation, and GridSearchCV for hyperparameter tuning.
- Compare custom implementations against library implementations to validate correctness and generalization.

1.1.2 Public dataset source:

Kaggle Cancer Data Data Set This dataset contains the characteristics of patients diagnosed with cancer. The dataset contains a unique ID for each patient, the type of cancer (diagnosis), the visual characteristics of the cancer and the average values of these characteristics.

[62]:
```
# Import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
```

```
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split, cross_validate,␣
 ↪GridSearchCV, StratifiedKFold
from sklearn.metrics import confusion_matrix, classification_report,␣
 ↪make_scorer, accuracy_score, recall_score, roc_auc_score, f1_score,␣
 ↪ConfusionMatrixDisplay
```

1.2 Data Exploration

[2]:
```
# Establish file path and import data
path = 'cancer_data.csv'
df = pd.read_csv(path)
df.head()
```

[2]:
```
         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

   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_worst  \
0             0.6656           0.7119                0.2654          0.4601
1             0.1866           0.2416                0.1860          0.2750
2             0.4245           0.4504                0.2430          0.3613
3             0.8663           0.6869                0.2575          0.6638
4             0.2050           0.4000                0.1625          0.2364

   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]
```

[3]:
```python
df.describe()
```

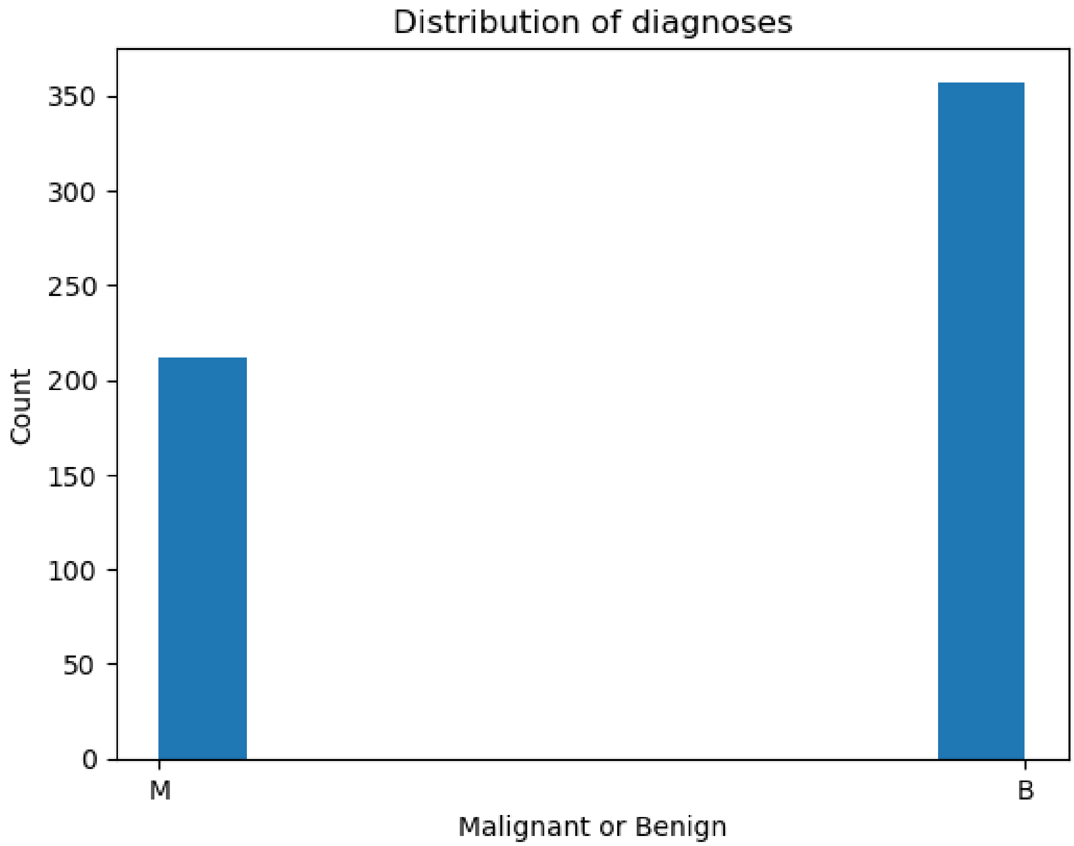
[3]:
```
                 id  radius_mean  texture_mean  perimeter_mean    area_mean  \
count  5.690000e+02   569.000000    569.000000      569.000000   569.000000
mean   3.037183e+07    14.127292     19.289649       91.969033   654.889104
std    1.250206e+08     3.524049      4.301036       24.298981   351.914129
min    8.670000e+03     6.981000      9.710000       43.790000   143.500000
25%    8.692180e+05    11.700000     16.170000       75.170000   420.300000
50%    9.060240e+05    13.370000     18.840000       86.240000   551.100000
75%    8.813129e+06    15.780000     21.800000      104.100000   782.700000
max    9.113205e+08    28.110000     39.280000      188.500000  2501.000000

       smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
count       569.000000        569.000000      569.000000           569.000000
mean          0.096360          0.104341        0.088799             0.048919
std           0.014064          0.052813        0.079720             0.038803
min           0.052630          0.019380        0.000000             0.000000
25%           0.086370          0.064920        0.029560             0.020310
50%           0.095870          0.092630        0.061540             0.033500
75%           0.105300          0.130400        0.130700             0.074000
max           0.163400          0.345400        0.426800             0.201200

       symmetry_mean  …  texture_worst  perimeter_worst   area_worst  \
count     569.000000  …     569.000000       569.000000   569.000000
mean        0.181162  …      25.677223       107.261213   880.583128
std         0.027414  …       6.146258        33.602542   569.356993
min         0.106000  …      12.020000        50.410000   185.200000
25%         0.161900  …      21.080000        84.110000   515.300000
50%         0.179200  …      25.410000        97.660000   686.500000
75%         0.195700  …      29.720000       125.400000  1084.000000
max         0.304000  …      49.540000       251.200000  4254.000000

       smoothness_worst  compactness_worst  concavity_worst  \
count        569.000000         569.000000       569.000000
mean           0.132369           0.254265         0.272188
std            0.022832           0.157336         0.208624
min            0.071170           0.027290         0.000000
25%            0.116600           0.147200         0.114500
50%            0.131300           0.211900         0.226700
75%            0.146000           0.339100         0.382900
max            0.222600           1.058000         1.252000

       concave points_worst  symmetry_worst  fractal_dimension_worst  \
```

```
count          569.000000   569.000000           569.000000
mean             0.114606     0.290076             0.083946
std              0.065732     0.061867             0.018061
min              0.000000     0.156500             0.055040
25%              0.064930     0.250400             0.071460
50%              0.099930     0.282200             0.080040
75%              0.161400     0.317900             0.092080
max              0.291000     0.663800             0.207500

       Unnamed: 32
count          0.0
mean           NaN
std            NaN
min            NaN
25%            NaN
50%            NaN
75%            NaN
max            NaN

[8 rows x 32 columns]
```

1.2.1 Data Visualization

[66]:
```python
plt.hist(df['diagnosis'])
plt.title("Distribution of diagnoses")
plt.ylabel('Count')
plt.xlabel('Malignant or Benign')
```

[66]:
```
Text(0.5, 0, 'Malignant or Benign')
```



[5]:
```
# View pairplots
px.scatter_matrix(df, dimensions=["radius_mean", "texture_mean",␣
↪"perimeter_mean","area_mean",'smoothness_mean','compactness_mean','concavity_mean','symmetr
```

[6]:
```
# View correlation matrix
df.corr(numeric_only = True)
```

[6]:

	id	radius_mean	texture_mean	perimeter_mean	\
id	1.000000	0.074626	0.099770	0.073159	
radius_mean	0.074626	1.000000	0.323782	0.997855	
texture_mean	0.099770	0.323782	1.000000	0.329533	
perimeter_mean	0.073159	0.997855	0.329533	1.000000	
area_mean	0.096893	0.987357	0.321086	0.986507	
smoothness_mean	-0.012968	0.170581	-0.023389	0.207278	
compactness_mean	0.000096	0.506124	0.236702	0.556936	
concavity_mean	0.050080	0.676764	0.302418	0.716136	
concave points_mean	0.044158	0.822529	0.293464	0.850977	
symmetry_mean	-0.022114	0.147741	0.071401	0.183027	
fractal_dimension_mean	-0.052511	-0.311631	-0.076437	-0.261477	
radius_se	0.143048	0.679090	0.275869	0.691765	

texture_se	-0.007526	-0.097317	0.386358	-0.086761
perimeter_se	0.137331	0.674172	0.281673	0.693135
area_se	0.177742	0.735864	0.259845	0.744983
smoothness_se	0.096781	-0.222600	0.006614	-0.202694
compactness_se	0.033961	0.206000	0.191975	0.250744
concavity_se	0.055239	0.194204	0.143293	0.228082
concave points_se	0.078768	0.376169	0.163851	0.407217
symmetry_se	-0.017306	-0.104321	0.009127	-0.081629
fractal_dimension_se	0.025725	-0.042641	0.054458	-0.005523
radius_worst	0.082405	0.969539	0.352573	0.969476
texture_worst	0.064720	0.297008	0.912045	0.303038
perimeter_worst	0.079986	0.965137	0.358040	0.970387
area_worst	0.107187	0.941082	0.343546	0.941550
smoothness_worst	0.010338	0.119616	0.077503	0.150549
compactness_worst	-0.002968	0.413463	0.277830	0.455774
concavity_worst	0.023203	0.526911	0.301025	0.563879
concave points_worst	0.035174	0.744214	0.295316	0.771241
symmetry_worst	-0.044224	0.163953	0.105008	0.189115
fractal_dimension_worst	-0.029866	0.007066	0.119205	0.051019
Unnamed: 32	NaN	NaN	NaN	NaN

	area_mean	smoothness_mean	compactness_mean	\
id	0.096893	-0.012968	0.000096	
radius_mean	0.987357	0.170581	0.506124	
texture_mean	0.321086	-0.023389	0.236702	
perimeter_mean	0.986507	0.207278	0.556936	
area_mean	1.000000	0.177028	0.498502	
smoothness_mean	0.177028	1.000000	0.659123	
compactness_mean	0.498502	0.659123	1.000000	
concavity_mean	0.685983	0.521984	0.883121	
concave points_mean	0.823269	0.553695	0.831135	
symmetry_mean	0.151293	0.557775	0.602641	
fractal_dimension_mean	-0.283110	0.584792	0.565369	
radius_se	0.732562	0.301467	0.497473	
texture_se	-0.066280	0.068406	0.046205	
perimeter_se	0.726628	0.296092	0.548905	
area_se	0.800086	0.246552	0.455653	
smoothness_se	-0.166777	0.332375	0.135299	
compactness_se	0.212583	0.318943	0.738722	
concavity_se	0.207660	0.248396	0.570517	
concave points_se	0.372320	0.380676	0.642262	
symmetry_se	-0.072497	0.200774	0.229977	
fractal_dimension_se	-0.019887	0.283607	0.507318	
radius_worst	0.962746	0.213120	0.535315	
texture_worst	0.287489	0.036072	0.248133	
perimeter_worst	0.959120	0.238853	0.590210	
area_worst	0.959213	0.206718	0.509604	

```
smoothness_worst          0.123523         0.805324          0.565541
compactness_worst         0.390410         0.472468          0.865809
concavity_worst           0.512606         0.434926          0.816275
concave points_worst      0.722017         0.503053          0.815573
symmetry_worst            0.143570         0.394309          0.510223
fractal_dimension_worst   0.003738         0.499316          0.687382
Unnamed: 32                    NaN              NaN               NaN

                         concavity_mean  concave points_mean  symmetry_mean  \
id                             0.050080             0.044158      -0.022114
radius_mean                    0.676764             0.822529       0.147741
texture_mean                   0.302418             0.293464       0.071401
perimeter_mean                 0.716136             0.850977       0.183027
area_mean                      0.685983             0.823269       0.151293
smoothness_mean                0.521984             0.553695       0.557775
compactness_mean               0.883121             0.831135       0.602641
concavity_mean                 1.000000             0.921391       0.500667
concave points_mean            0.921391             1.000000       0.462497
symmetry_mean                  0.500667             0.462497       1.000000
fractal_dimension_mean         0.336783             0.166917       0.479921
radius_se                      0.631925             0.698050       0.303379
texture_se                     0.076218             0.021480       0.128053
perimeter_se                   0.660391             0.710650       0.313893
area_se                        0.617427             0.690299       0.223970
smoothness_se                  0.098564             0.027653       0.187321
compactness_se                 0.670279             0.490424       0.421659
concavity_se                   0.691270             0.439167       0.342627
concave points_se              0.683260             0.615634       0.393298
symmetry_se                    0.178009             0.095351       0.449137
fractal_dimension_se           0.449301             0.257584       0.331786
radius_worst                   0.688236             0.830318       0.185728
texture_worst                  0.299879             0.292752       0.090651
perimeter_worst                0.729565             0.855923       0.219169
area_worst                     0.675987             0.809630       0.177193
smoothness_worst               0.448822             0.452753       0.426675
compactness_worst              0.754968             0.667454       0.473200
concavity_worst                0.884103             0.752399       0.433721
concave points_worst           0.861323             0.910155       0.430297
symmetry_worst                 0.409464             0.375744       0.699826
fractal_dimension_worst        0.514930             0.368661       0.438413
Unnamed: 32                         NaN                  NaN            NaN

                         …  texture_worst  perimeter_worst  area_worst  \
id                       …       0.064720         0.079986    0.107187
radius_mean              …       0.297008         0.965137    0.941082
texture_mean             …       0.912045         0.358040    0.343546
perimeter_mean           …       0.303038         0.970387    0.941550
```

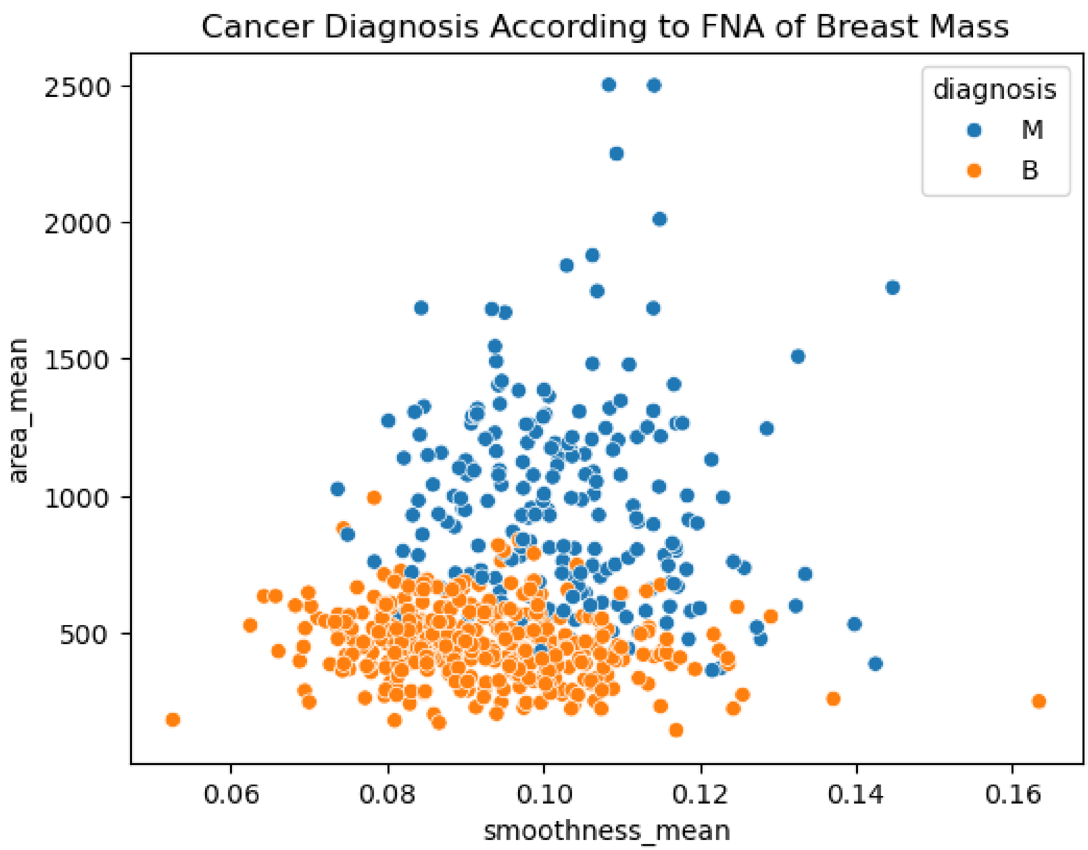
```
area_mean                ...      0.287489         0.959120    0.959213
smoothness_mean          ...      0.036072         0.238853    0.206718
compactness_mean         ...      0.248133         0.590210    0.509604
concavity_mean           ...      0.299879         0.729565    0.675987
concave points_mean      ...      0.292752         0.855923    0.809630
symmetry_mean            ...      0.090651         0.219169    0.177193
fractal_dimension_mean   ...     -0.051269        -0.205151   -0.231854
radius_se                ...      0.194799         0.719684    0.751548
texture_se               ...      0.409003        -0.102242   -0.083195
perimeter_se             ...      0.200371         0.721031    0.730713
area_se                  ...      0.196497         0.761213    0.811408
smoothness_se            ...     -0.074743        -0.217304   -0.182195
compactness_se           ...      0.143003         0.260516    0.199371
concavity_se             ...      0.100241         0.226680    0.188353
concave points_se        ...      0.086741         0.394999    0.342271
symmetry_se              ...     -0.077473        -0.103753   -0.110343
fractal_dimension_se     ...     -0.003195        -0.001000   -0.022736
radius_worst             ...      0.359921         0.993708    0.984015
texture_worst            ...      1.000000         0.365098    0.345842
perimeter_worst          ...      0.365098         1.000000    0.977578
area_worst               ...      0.345842         0.977578    1.000000
smoothness_worst         ...      0.225429         0.236775    0.209145
compactness_worst        ...      0.360832         0.529408    0.438296
concavity_worst          ...      0.368366         0.618344    0.543331
concave points_worst     ...      0.359755         0.816322    0.747419
symmetry_worst           ...      0.233027         0.269493    0.209146
fractal_dimension_worst  ...      0.219122         0.138957    0.079647
Unnamed: 32              ...           NaN              NaN         NaN

                         smoothness_worst  compactness_worst  concavity_worst  \
id                               0.010338          -0.002968         0.023203
radius_mean                      0.119616           0.413463         0.526911
texture_mean                     0.077503           0.277830         0.301025
perimeter_mean                   0.150549           0.455774         0.563879
area_mean                        0.123523           0.390410         0.512606
smoothness_mean                  0.805324           0.472468         0.434926
compactness_mean                 0.565541           0.865809         0.816275
concavity_mean                   0.448822           0.754968         0.884103
concave points_mean              0.452753           0.667454         0.752399
symmetry_mean                    0.426675           0.473200         0.433721
fractal_dimension_mean           0.504942           0.458798         0.346234
radius_se                        0.141919           0.287103         0.380585
texture_se                      -0.073658          -0.092439        -0.068956
perimeter_se                     0.130054           0.341919         0.418899
area_se                          0.125389           0.283257         0.385100
smoothness_se                    0.314457          -0.055558        -0.058298
compactness_se                   0.227394           0.678780         0.639147
```

concavity_se	0.168481	0.484858	0.662564
concave points_se	0.215351	0.452888	0.549592
symmetry_se	-0.012662	0.060255	0.037119
fractal_dimension_se	0.170568	0.390159	0.379975
radius_worst	0.216574	0.475820	0.573975
texture_worst	0.225429	0.360832	0.368366
perimeter_worst	0.236775	0.529408	0.618344
area_worst	0.209145	0.438296	0.543331
smoothness_worst	1.000000	0.568187	0.518523
compactness_worst	0.568187	1.000000	0.892261
concavity_worst	0.518523	0.892261	1.000000
concave points_worst	0.547691	0.801080	0.855434
symmetry_worst	0.493838	0.614441	0.532520
fractal_dimension_worst	0.617624	0.810455	0.686511
Unnamed: 32	NaN	NaN	NaN

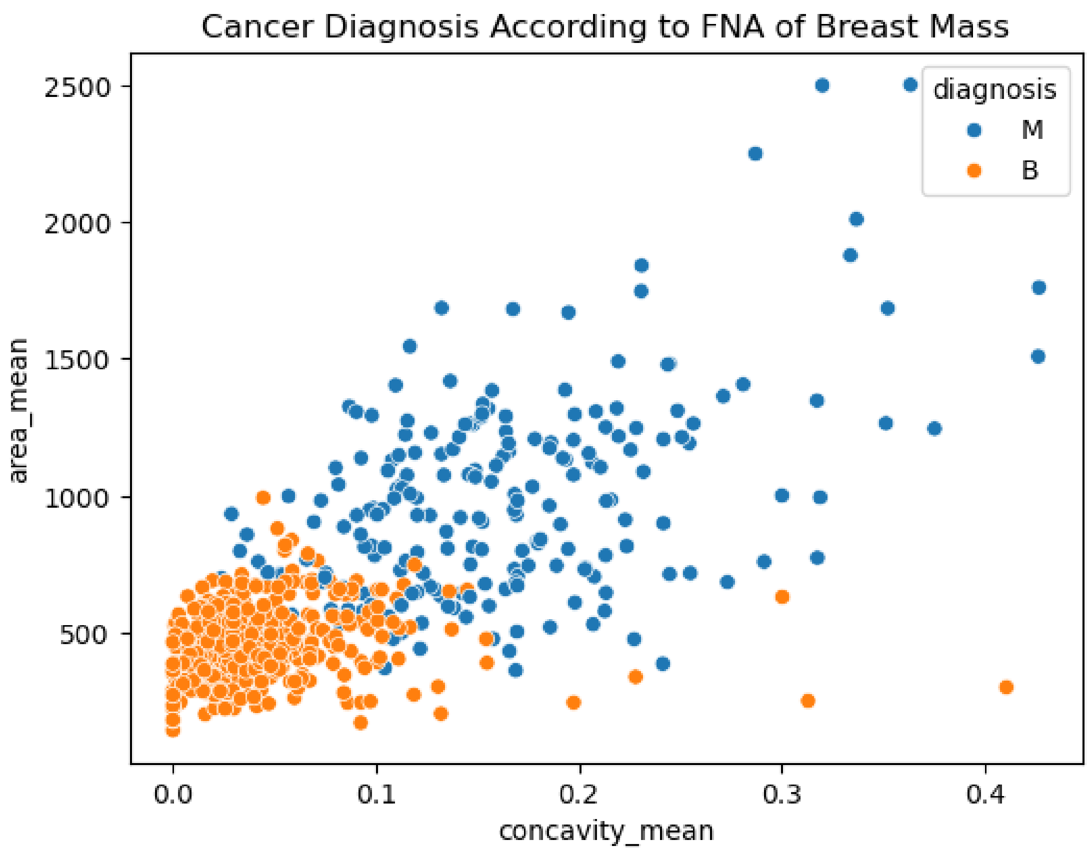
	concave points_worst	symmetry_worst	\
id	0.035174	-0.044224	
radius_mean	0.744214	0.163953	
texture_mean	0.295316	0.105008	
perimeter_mean	0.771241	0.189115	
area_mean	0.722017	0.143570	
smoothness_mean	0.503053	0.394309	
compactness_mean	0.815573	0.510223	
concavity_mean	0.861323	0.409464	
concave points_mean	0.910155	0.375744	
symmetry_mean	0.430297	0.699826	
fractal_dimension_mean	0.175325	0.334019	
radius_se	0.531062	0.094543	
texture_se	-0.119638	-0.128215	
perimeter_se	0.554897	0.109930	
area_se	0.538166	0.074126	
smoothness_se	-0.102007	-0.107342	
compactness_se	0.483208	0.277878	
concavity_se	0.440472	0.197788	
concave points_se	0.602450	0.143116	
symmetry_se	-0.030413	0.389402	
fractal_dimension_se	0.215204	0.111094	
radius_worst	0.787424	0.243529	
texture_worst	0.359755	0.233027	
perimeter_worst	0.816322	0.269493	
area_worst	0.747419	0.209146	
smoothness_worst	0.547691	0.493838	
compactness_worst	0.801080	0.614441	
concavity_worst	0.855434	0.532520	
concave points_worst	1.000000	0.502528	
symmetry_worst	0.502528	1.000000	

```
fractal_dimension_worst              0.511114        0.537848
Unnamed: 32                               NaN             NaN

                         fractal_dimension_worst  Unnamed: 32
id                                     -0.029866          NaN
radius_mean                             0.007066          NaN
texture_mean                            0.119205          NaN
perimeter_mean                          0.051019          NaN
area_mean                               0.003738          NaN
smoothness_mean                         0.499316          NaN
compactness_mean                        0.687382          NaN
concavity_mean                          0.514930          NaN
concave points_mean                     0.368661          NaN
symmetry_mean                           0.438413          NaN
fractal_dimension_mean                  0.767297          NaN
radius_se                               0.049559          NaN
texture_se                             -0.045655          NaN
perimeter_se                            0.085433          NaN
area_se                                 0.017539          NaN
smoothness_se                           0.101480          NaN
compactness_se                          0.590973          NaN
concavity_se                            0.439329          NaN
concave points_se                       0.310655          NaN
symmetry_se                             0.078079          NaN
fractal_dimension_se                    0.591328          NaN
radius_worst                            0.093492          NaN
texture_worst                           0.219122          NaN
perimeter_worst                         0.138957          NaN
area_worst                              0.079647          NaN
smoothness_worst                        0.617624          NaN
compactness_worst                       0.810455          NaN
concavity_worst                         0.686511          NaN
concave points_worst                    0.511114          NaN
symmetry_worst                          0.537848          NaN
fractal_dimension_worst                 1.000000          NaN
Unnamed: 32                                  NaN          NaN

[32 rows x 32 columns]
```

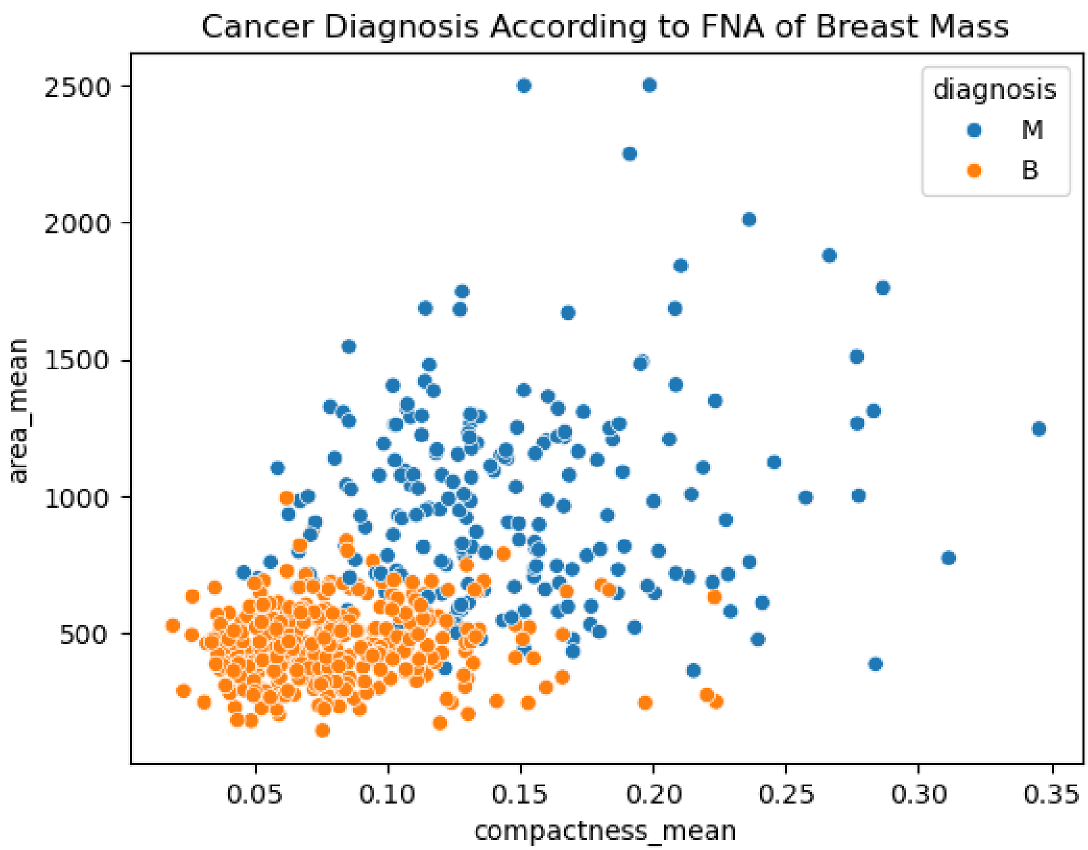
[21]:
```
sns.scatterplot(
    data=df,
    x='smoothness_mean',
    y='area_mean',
    hue='diagnosis'
)
plt.title('Cancer Diagnosis According to FNA of Breast Mass')
plt.show()
```



[26]:
```
sns.scatterplot(
    data=df,
    x='concavity_mean',
    y='area_mean',
    hue='diagnosis'
)
plt.title('Cancer Diagnosis According to FNA of Breast Mass')
plt.show()
```



[27]:
```
sns.scatterplot(
    data=df,
    x='compactness_mean',
    y='area_mean',
    hue='diagnosis'
)
plt.title('Cancer Diagnosis According to FNA of Breast Mass')
plt.show()
```



1.3 Model Development

[10]:
```
# Relationship looks quadratic, so a polynomial degree of 2
X = df[['concavity_mean','area_mean']] # Input
# Encode diagnosis variable to have outcomes of -1 or 1
df['diagnosis_encoded'] = df['diagnosis'].map({'B': -1, 'M': 1})
y = df['diagnosis_encoded'] # Target
```

[61]:
```
def svm_fit (X, y_true, lambda_param=0.01, n_iters=1000, learning_rate=0.01):
    # Initialize parameters
    n_samples, n_features = X.shape
    w = np.zeros(n_features)
    b = 0
    losses =[]

    # Fit dataset to SVM classifier
    for i in range(n_iters):
        yi = y_true[i]
        xi = X[i]
        margin = yi * (w @ xi + b)
```

```python
        # Gradient descent
        # L2 regularization
        if margin >= 1:
            grad_w = 2 * lambda_param * w
            grad_b = 0
        else:
            grad_w = 2 * lambda_param * w - yi * xi
            grad_b = yi

        # Update the parameters
        w -= learning_rate * grad_w
        b -= learning_rate * grad_b

        # Compute loss
        margins = y_true * (X @ w + b)
        hinge_losses = np.maximum(0, 1 - margins)
        # loss = 0.5 * np.dot(w, w) + C * np.sum(hinge_losses)
        loss = lambda_param * np.dot(w,w) + np.mean(hinge_losses)
        losses.append(loss)

        if i % 100 == 0:
            print(f"Iteration {i}: Loss = {losses[-1]:.4f}")

    return w, b, losses
```

[86]:
```python
def svm_pred(X,y,w,b,lambda_param):
    # Prediction
    scores = X @ w + b
    y_pred = np.sign(scores)

    # Hinge loss
    margins = y * scores
    hinge_losses = np.maximum(0, 1 - margins)

    # Objective
    test_loss = lambda_param * np.dot(w,w) + np.mean(hinge_losses)
    return test_loss, y_pred
```

[72]:
```python
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
 ↪random_state=42)
```

[12]:
```python
# Normalize X: Z-score
# Fit scaler on training data only
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
```

```
# Apply same transformation to test data
X_test_scaled = scaler.transform(X_test)

# Re-index y sets after splitting
y_train = y_train.to_numpy()
y_test = y_test.to_numpy()
```

[ ]:
```
X_train.shape
# Pretty small dataset, number of iterations will be less than 1000 in training
```

[ ]:
```
(455, 2)
```

[76]:
```
w, b, losses = svm_fit(X_train_scaled, y_train, lambda_param=0.01, n_iters=455,␣
 ↪learning_rate=0.001)
```

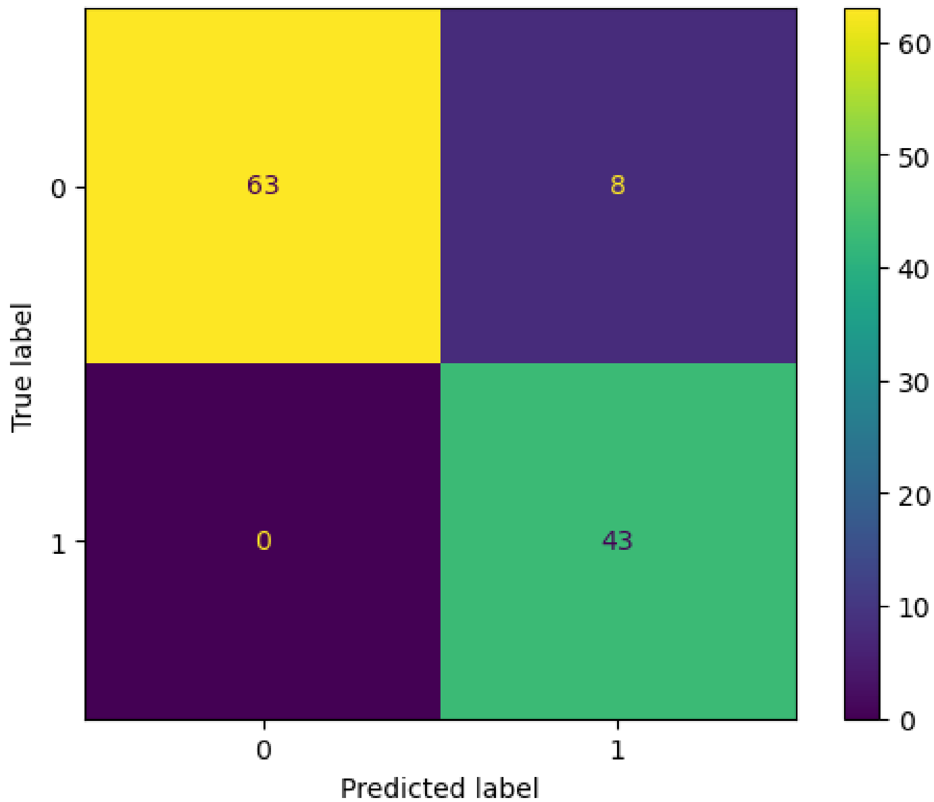
```
Iteration 0: Loss = 1.0014
Iteration 100: Loss = 0.9249
Iteration 200: Loss = 0.8567
Iteration 300: Loss = 0.7779
Iteration 400: Loss = 0.7081
```

[87]:
```
pred_test_loss, y_pred = svm_pred(X_test_scaled, y_test, w, b, lambda_param=0.
 ↪01)
print(f"Test loss: {pred_test_loss:.4f}")
```

```
Test loss: 0.6602
```

1.4 Model Evaluation

[96]:
```
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()
plt.show()
```



[ ]:
```python
tn, fp, fn, tp = cm.ravel()

print(f"True Negatives (TN): {tn}")
print(f"False Positives (FP): {fp}")
print(f"False Negatives (FN): {fn}")
print(f"True Positives (TP): {tp}")

precision = tp / (tp + fp)
recall = tp / (tp + fn)

print(f"Precision: {precision:.3f}")
print(f"Recall: {recall}")
```

```
True Negatives (TN): 63
False Positives (FP): 8
False Negatives (FN): 0
True Positives (TP): 43
Precision: 0.843
Recall: 1.0
```

[103]:
```python
f1 = f1_score(y_test,y_pred)
print(f"F1 Score: {f1:.3f}")
```

```
F1 Score: 0.915
```

The recall score indicates that all malignant cases were caught, whih is important for cancer detection. Of the cases that were predicted as malignant, about 16% were actually benign, which seems to be an acceptable trade-off for high recall. The F1 is quite high,however, this is a very small data set. Let's check for overfitting.

[68]:
```python
y_pred_train = np.sign(X_train_scaled @ w + b)
f1 = f1_score(y_train,y_pred_train)
print(f"F1 Score: {f1:.3f}")

# For ROC AUC, use the raw scores (distance from hyperplane)
y_scores_train = X_train_scaled @ w + b
roc_auc_train = roc_auc_score(y_train, y_scores_train)
print(f"ROC AUC Score: {roc_auc:.3f}")
```

```
F1 Score: 0.874
ROC AUC Score: 0.942
```

The training performance is not higher than the testing performance, which implies no overfitting.

1.5 C-parametrized model version vs L2 regularization

L2 Regularization encourages the model to learn smaller, more evenly distributed weights, reducing the impact of any single feature and preventing reliance on features that might just be noise in the training data. While C parametrization controls the trade-off between maximizing the margin (the distance between the separating hyperplane and the closest data points) and minimizing classification errors on the training data. This method does not perform feature selection directly and it is more common for SVM's.

[123]:
```python
def svm_C2fit (X, y_true, C = 1.0, n_iters=1000, learning_rate=0.001):
    # Initialize parameters
    n_samples, n_features = X.shape
    w = np.zeros(n_features)
    b = 0
    losses =[]

    # Fit dataset to SVM classifier
    for i in range(n_iters):
        yi = y_true[i]
        xi = X[i]
        margin = yi * (w @ xi + b)
        # Gradient descent
        if margin >= 1:
            grad_w = w
            grad_b = 0
```

```
        else:
            grad_w = w - C * yi * xi
            grad_b = -C * yi

        # Update the parameters
        w -= learning_rate * grad_w
        b -= learning_rate * grad_b

        # Compute loss
        margins = y_true * (X @ w + b)
        hinge_losses = np.maximum(0, 1 - margins)
        loss = 0.5 * np.dot(w, w) + C * np.sum(hinge_losses)
        mean_hinge = hinge_losses.mean()
        losses.append(loss)

        if i % 100 == 0:
            print(f"Iteration {i}: hinge loss sum = {losses[-1]:.4f} | hinge␣
↪loss mean = {mean_hinge:.4f}")

    return w, b, losses
```

[129]:
```
w, b, losses = svm_C2fit(X_train_scaled, y_train, C=1, n_iters=455,␣
↪learning_rate=0.001)
```

```
Iteration 0: hinge loss sum = 455.3830 | hinge loss mean = 1.0008
Iteration 100: hinge loss sum = 414.5040 | hinge loss mean = 0.9110
Iteration 200: hinge loss sum = 380.8816 | hinge loss mean = 0.8371
Iteration 300: hinge loss sum = 342.5799 | hinge loss mean = 0.7529
Iteration 400: hinge loss sum = 316.8039 | hinge loss mean = 0.6962
```

The mean loss is decreasing steadily, but has not converged. Especially given that this is a small dataset, having multiple passes (i.e., epochs) and shuffling the examples before calculating loss can help to fully converge. However, the performance with this model (C-parametrization) is pretty comparable to that of L2 regularization when comparing the mean hinge loss alone.

1.6 Epochs and Batch Sizes

[14]:
```
def svm_fit (X, y_true, lambda_param=0.01, epochs=10, batch_size=32,␣
↪learning_rate=0.01):
    """
    Fead in X and y_true (normalized) data for training of the model
    lamba_param: regularization strength
    epochs: how many passes through the dataset
    batch_size: number of samples per gradient descent update
    learning_rate: step size for gradient descent
    """
    # Initialize parameters
    n_samples, n_features = X.shape
```

```
    w = np.zeros(n_features)
    b = 0
    losses =[]

    for epoch in range(epochs): # Each epoch is one pass through the dataset
        # Shuffle dataset at the start of each epoch
        indices = np.arange(n_samples) # Make array of row indices
        np.random.shuffle(indices) # Randomly shuffle the indices
        X = X[indices] # Reassign the shuffled indices to the data
        y_true = y_true[indices]

        # Mini batch loop
        for start in range(0, n_samples, batch_size): # Slice dataset into␣
↪chinks of size batch size. aka how many updates per epoch
            end = start + batch_size # Find the start and end points for each␣
↪epoch update
            X_batch = X[start:end]
            y_batch = y_true[start:end]

            # Compute svm margins
            margins = y_batch * (X_batch @ w + b) # If the margin >=1 then␣
↪point is correct, so the loss is 0
            condition = margins < 1 # If margin <1 then sample contributes to␣
↪gradient, will want to only keep TRUE conditions

            # Gradient descent
            # L2 regularization and hinge loss, which only depends on samples␣
↪where margin<1
            grad_w = 2 * lambda_param * w - np.mean((condition * y_batch)[:,␣
↪None] * X_batch, axis=0)
                # Subtracting contributions from misclassified or low-margin␣
↪points
            grad_b = -np.mean(condition * y_batch)

            # Update parameters
            w -= learning_rate * grad_w
            b -= learning_rate * grad_b

        # Compute loss
        margins = y_true * (X @ w + b)
        hinge_losses = np.maximum(0, 1 - margins)
        loss = lambda_param * np.dot(w,w) + np.mean(hinge_losses)
        losses.append(loss)

        print(f"Epoch {epoch+1}/{epochs}: Loss = {loss:.4f}")
```

```
    return w, b, losses
```

[23]:
```
def svm_predict(X, y_test, w, b, lambda_param=0.1):
    """ Labels for classes as {-1, +1}
    L2 regularized hinge loss
    """
    scores = X @ w + b
    y_pred = np.where(scores >= 0, 1, -1) # Avoids 0 edge case

    margins = y_test * scores
    hinge = np.maximum(0, 1 - margins)
    loss = lambda_param * np.dot(w,w) + hinge.mean()
    return y_pred, scores, loss
```

[26]:
```
# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# Normalize data
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
# Re-index y sets after splitting
y_train = y_train.to_numpy()
y_test = y_test.to_numpy()

# Fit the data
w, b, losses = svm_fit(X_train_scaled, y_train, lambda_param=0.01,␣
 ↪batch_size=32, epochs=10, learning_rate=0.1)

# Make predictions
y_pred, scores, loss = svm_predict(X_test_scaled, y_test, w, b, lambda_param=0.
 ↪01)
print(f"Test loss: {loss:.4f}")
```

```
Epoch 1/10: Loss = 0.3036
Epoch 2/10: Loss = 0.2718
Epoch 3/10: Loss = 0.2655
Epoch 4/10: Loss = 0.2611
Epoch 5/10: Loss = 0.2591
Epoch 6/10: Loss = 0.2580
Epoch 7/10: Loss = 0.2573
Epoch 8/10: Loss = 0.2568
Epoch 9/10: Loss = 0.2564
Epoch 10/10: Loss = 0.2561
Test loss: 0.1938
```

By incorporating mini-batches for gradient descent and epochs for iterating over the entire dataset, this significantly improved the hinge loss of the model. The training loss drops quickly and then plateaus (stable convergence) and the test loss is less than the training loss (no overfitting). Let's re-evaluate the model with some more metrics.

[69]:
```
cm = confusion_matrix(y_test, y_pred)
tn, fp, fn, tp = cm.ravel()

print(f"True Negatives (TN): {tn}")
print(f"False Positives (FP): {fp}")
print(f"False Negatives (FN): {fn}")
print(f"True Positives (TP): {tp}")

precision = tp / (tp + fp)
recall = tp / (tp + fn)

print(f"Precision: {precision:.3f}")
print(f"Recall: {recall}")

f1 = f1_score(y_test,y_pred)
print(f"F1 Score: {f1:.3f}")
```

```
True Negatives (TN): 71
False Positives (FP): 0
False Negatives (FN): 5
True Positives (TP): 38
Precision: 1.000
Recall: 0.8837209302325582
F1 Score: 0.938
```

Improved performance with precision and F1 score compared to model with batch gradient descent and no epochs. Similar performance for ROC AUC score and slightly worse recall.

Is the dataset imbalanced? How many diagnoses are malignant? How many are benign?

[5]:
```
df.groupby('diagnosis').diagnosis.value_counts()
```

[5]:
```
diagnosis
B    357
M    212
Name: count, dtype: int64
```

The split is 62.7% benign and 37.3% malignant, which presents an imablanced dataset, but not severely so. Extreme cases would be a 90/10 or 95/5 split. As we can see from the precision, recall, and F1 scores, the model is not defaulting to predicting the majority class.

1.7 Scikit-learn Implementation

[29]:
```
# Split data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

```
# Normalize data
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
# Re-index y sets after splitting
y_train = y_train.to_numpy()
y_test = y_test.to_numpy()
```

[ ]:
```
# Implement support vector classification through scikit learn
# solving a quadratic programming optimization problem
model = SVC()
model.fit(X_train_scaled,y_train)
model.score(X_test_scaled,y_test) # Mean accuracy score
```

[ ]: 0.9473684210526315

[42]:
```
# With L2 regularization
model_reg = SVC(C=0.1)
model_reg.fit(X_train_scaled,y_train)
model_reg.score(X_test_scaled,y_test)
```

[42]: 0.956140350877193

[ ]:
```
y_pred = model_reg.predict(X_test_scaled)
print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
[[71  0]
 [ 5 38]]
              precision    recall  f1-score   support

          -1       0.93      1.00      0.97        71
           1       1.00      0.88      0.94        43

    accuracy                           0.96       114
   macro avg       0.97      0.94      0.95       114
weighted avg       0.96      0.96      0.96       114
```

My model performed pretty comparably to the scikit learn SVC model.

[71]:
```
# Try with cross validation instead of a single train/test split
# For more reliable estimate of generalization
scoring = {
    "accuracy": "accuracy",
    "precision": "precision",
    "recall": "recall",
    "f1": "f1"
```

```
}

model = SVC(C=0.1)

cv_results = cross_validate(
    model,
    X_train_scaled,
    y_train,
    cv=5,
    scoring=scoring,
    return_train_score=True
)

print("Mean CV scores:")
for metric in scoring.keys():
    mean_score = cv_results[f'test_{metric}'].mean()
    print(f"{metric}: {mean_score:.2f}")
```

```
Mean CV scores:
accuracy: 0.91
precision: 0.92
recall: 0.83
f1: 0.87
```

[ ]:
```
# Try with cross validation instead of a single train/test split
# For more reliable estimate of generalization
# Implement a Pipeline, a chain of preprocessing steps plus the model to ensure␣
↪no data leakage

# 5-fold for cross validation, shuffle data before splitting, reproducibility
cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42) # Folding with␣
↪class balance

# Metrics for evaluation
scoring = {
    "accuracy": "accuracy",
    "precision": "precision",
    "recall": "recall",
    "f1": "f1"
}

# First apply the z-score normalization
# Then apply the Support Vector Classifier model
pipe = Pipeline([
    ("scaler", StandardScaler()),
    ("svc", SVC(C=0.1, kernel="linear"))  # prob=True for AUC
])
```

```
# Run the cross validation
cv_results = cross_validate(
    pipe,
    X_train, y_train,
    cv=cv, # Use stratified K fold
    scoring=scoring, # Calculate all metrics
    return_train_score=False
)

# After CV, train a final model on the full training set
pipe.fit(X_train, y_train)

# Use the trained model to predict labels on test set
y_pred = pipe.predict(X_test)

print("\nConfusion matrix (test):")
print(confusion_matrix(y_test, y_pred))
print("\nClassification report (test):")
print(classification_report(y_test, y_pred))
```

```
Confusion matrix (test):
[[71  0]
 [ 5 38]]

Classification report (test):
              precision    recall  f1-score   support

          -1       0.93      1.00      0.97        71
           1       1.00      0.88      0.94        43

    accuracy                           0.96       114
   macro avg       0.97      0.94      0.95       114
weighted avg       0.96      0.96      0.96       114
```

This method actually seemed to perform slightly worse than without cross-validation. Averaging across folds usually gives a harsher but more reliable estimate of generalization, because of greater variance across different splits. Moreover, the nature of the small dataset could cause fluctuations.

[77]:
```
# Add hyperparameter tuning as well through GridSearchCV

# Dictionary of parameters
param_grid = {
    "svc__C": [0.01, 0.1, 1, 10], # Generate a combination of parameters
    "svc__kernel": ["linear"] # Establish kernel type
}
```

```python
# Define scoring metrics
multi_scoring = {
    "accuracy": "accuracy",
    "precision": "precision",
    "recall": "recall",
    "f1": "f1"
}

# Create a pipeline to chain the normalization and model training
pipe = Pipeline([
    ("scaler", StandardScaler()),
    ("svc", SVC())
])

grid = GridSearchCV(
    estimator=pipe, # The pipeline is the model to optimize
    param_grid=param_grid, # Hyperparameters to try
    scoring=multi_scoring, # Compute multiple metrics
    refit="f1", # Choose which metric selects best model
    cv=cv, # Splitting the data into folds
    n_jobs=-1 # CPU cores
)

# For each parameters, run CV, compute metrics, average across folds
grid.fit(X_train, y_train)

print("Best parameters:", grid.best_params_)
print("Best mean F1:", f"{grid.best_score_:.2f}")

# Evaluate on test set
best_model = grid.best_estimator_
y_pred = best_model.predict(X_test)

print("\nConfusion matrix (test):")
print(confusion_matrix(y_test, y_pred))
print("\nClassification report (test):")
print(classification_report(y_test, y_pred))
```

```
Best parameters: {'svc__C': 0.1, 'svc__kernel': 'linear'}
Best mean F1: 0.86

Confusion matrix (test):
[[71  0]
 [ 5 38]]

Classification report (test):
              precision    recall  f1-score   support
```

```
          -1       0.93      1.00      0.97        71
           1       1.00      0.88      0.94        43

    accuracy                           0.96       114
   macro avg       0.97      0.94      0.95       114
weighted avg       0.96      0.96      0.96       114
```