# Data importation and vizualisation

In [ ]:

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
```

In [ ]:

```
data = load_breast_cancer()
X = pd.DataFrame(data.data, columns=data.feature_names)
y = pd.Series(data.target, name='target')
df = pd.concat([X, y], axis=1)
df.head()
```

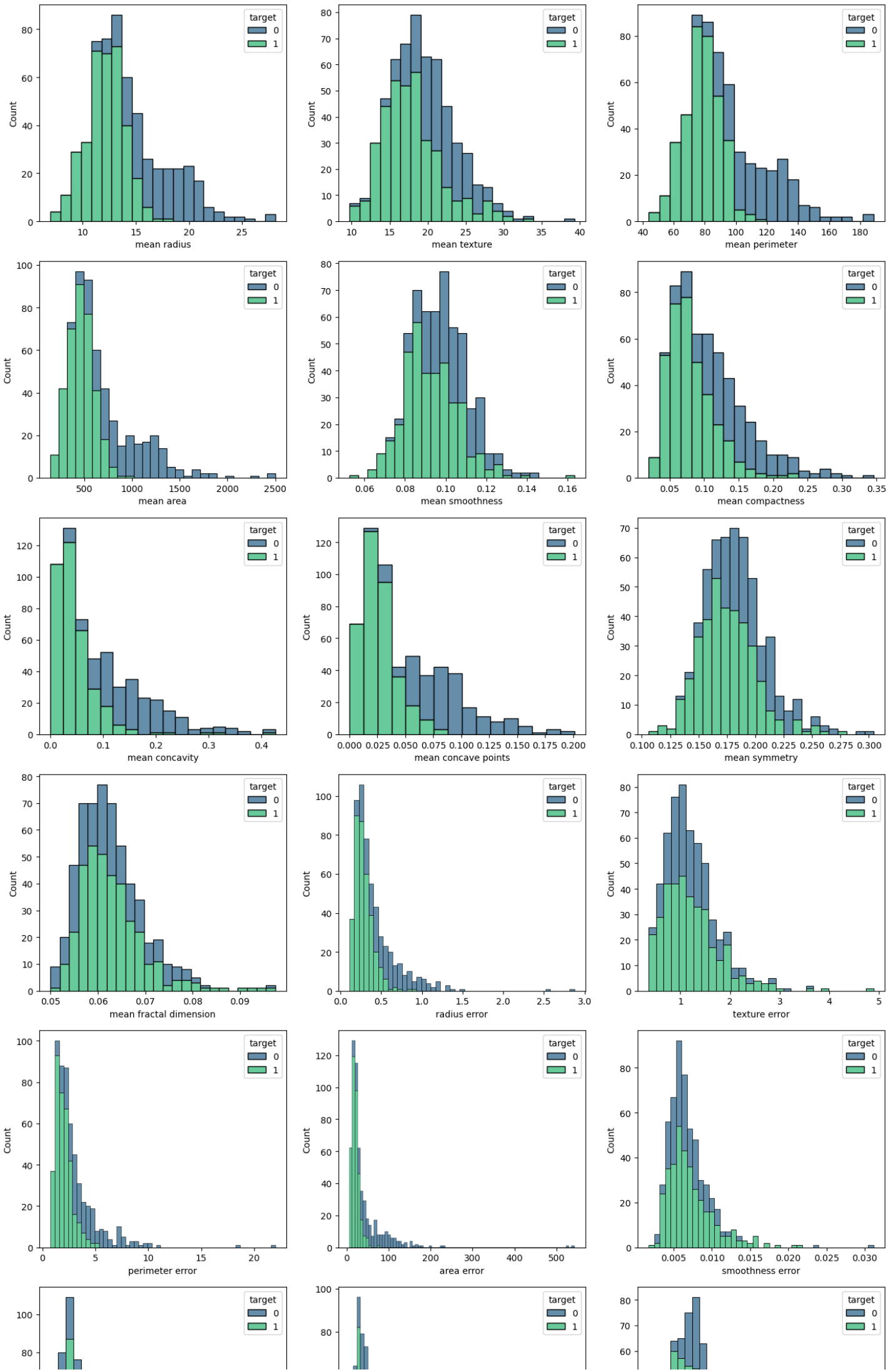
Out[ ]:

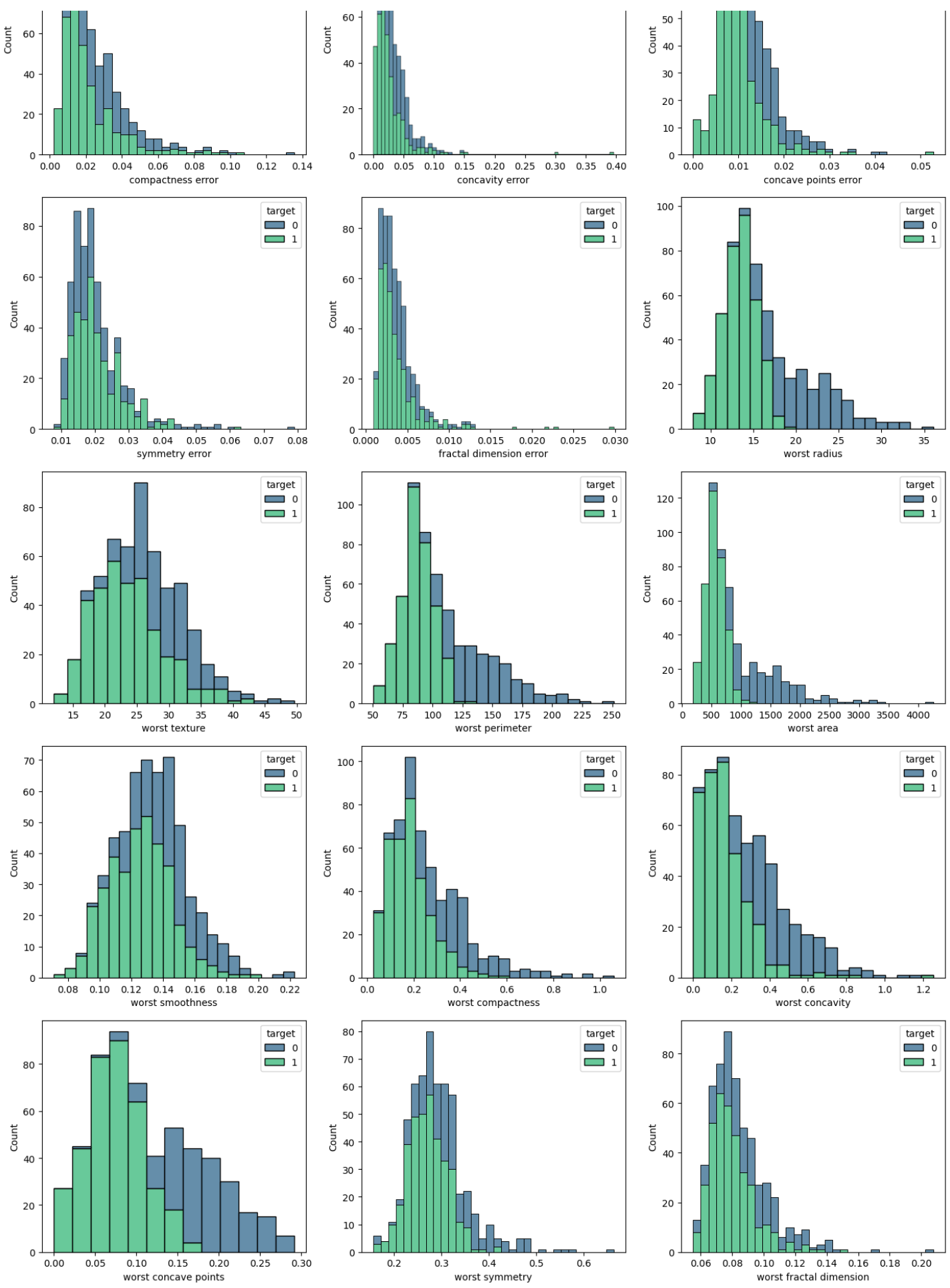
| | mean radius | mean texture | mean perimeter | mean area | mean smoothness | mean compactness | mean concavity | mean concave points | mean symmetry | mean fractal dimension | ... | worst texture | perim |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 17.99 | 10.38 | 122.80 | 1001.0 | 0.11840 | 0.27760 | 0.3001 | 0.14710 | 0.2419 | 0.07871 | ... | 17.33 | 18 |
| **1** | 20.57 | 17.77 | 132.90 | 1326.0 | 0.08474 | 0.07864 | 0.0869 | 0.07017 | 0.1812 | 0.05667 | ... | 23.41 | 15 |
| **2** | 19.69 | 21.25 | 130.00 | 1203.0 | 0.10960 | 0.15990 | 0.1974 | 0.12790 | 0.2069 | 0.05999 | ... | 25.53 | 15 |
| **3** | 11.42 | 20.38 | 77.58 | 386.1 | 0.14250 | 0.28390 | 0.2414 | 0.10520 | 0.2597 | 0.09744 | ... | 26.50 | 9 |
| **4** | 20.29 | 14.34 | 135.10 | 1297.0 | 0.10030 | 0.13280 | 0.1980 | 0.10430 | 0.1809 | 0.05883 | ... | 16.67 | 15 |

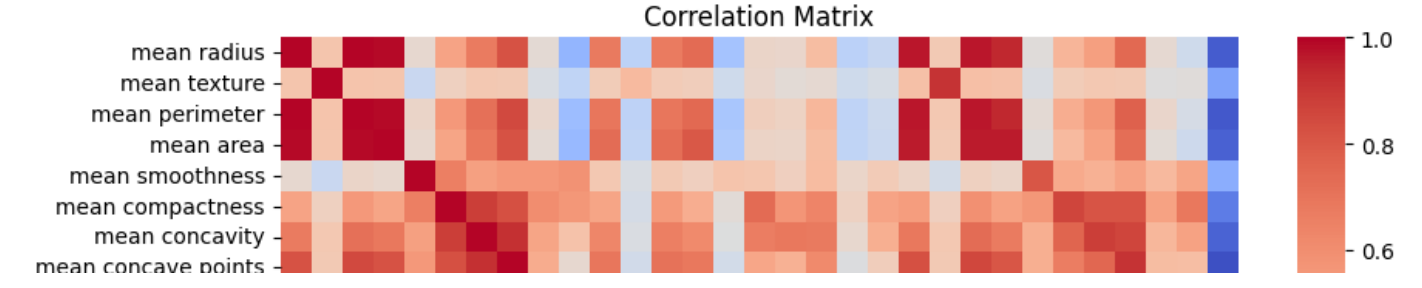
**5 rows × 31 columns**

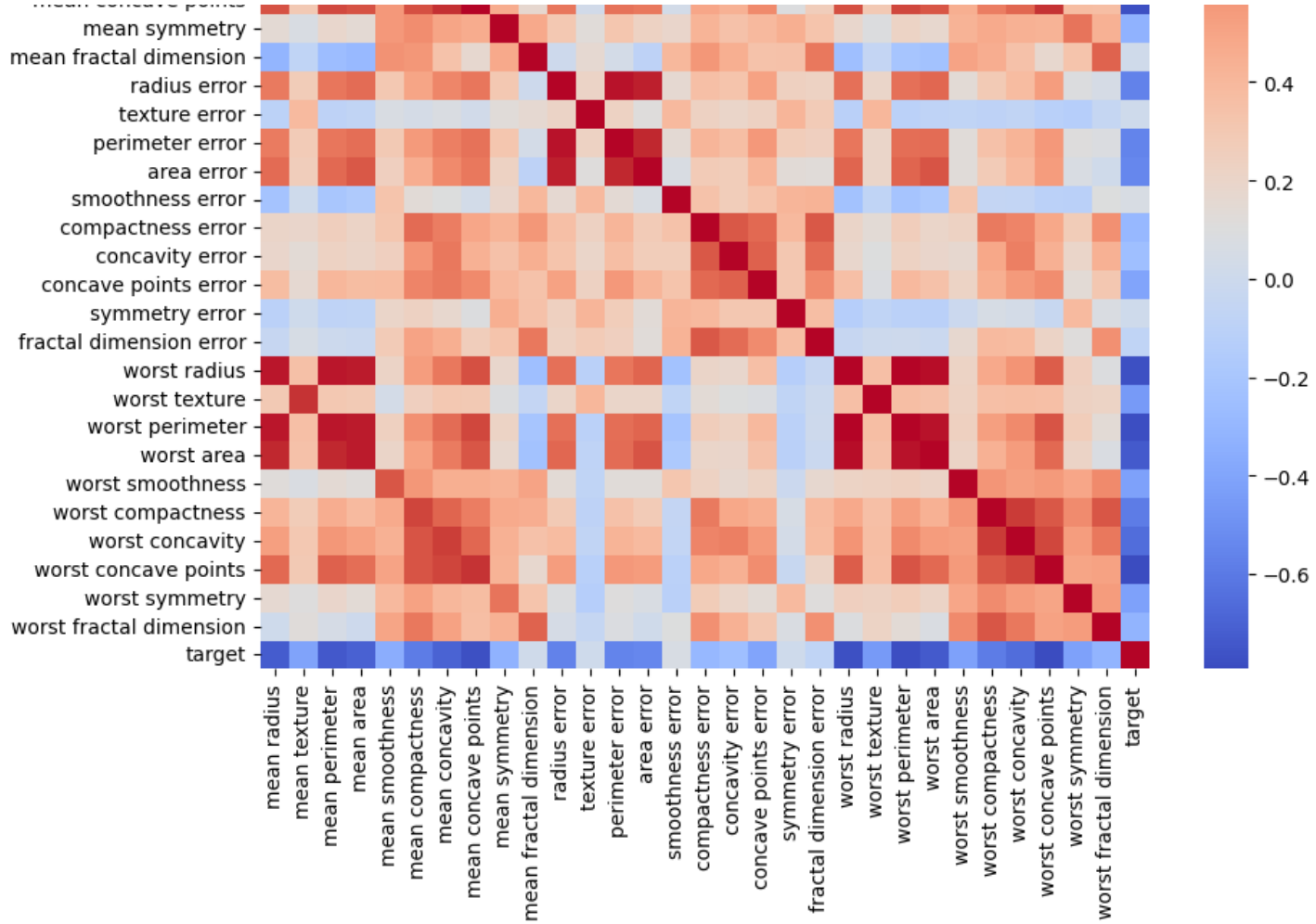
In [ ]:

```
# Load data
data = load_breast_cancer()
X = pd.DataFrame(data.data, columns=data.feature_names)
y = pd.Series(data.target, name='target')
df = pd.concat([X, y], axis=1)

# Visualization of distributions of each characteristic
def plot_feature_distributions(df, features):
    fig, axs = plt.subplots(nrows=len(features) // 3, ncols=3, figsize=(14, 4 * (len(fea
tures) // 3)))
    for i, feature in enumerate(features):
        row = i // 3
        col = i % 3
        sns.histplot(df, x=feature, hue="target", multiple="stack", ax=axs[row, col], pa
lette="viridis")
    plt.tight_layout()
    plt.show()

plot_feature_distributions(df, data.feature_names)

# Correlation matrix
corr_matrix = df.corr()
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=False, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```


target
0
1
Count
mean radius
mean texture
mean perimeter
mean area
mean smoothness
mean compactness
mean concavity
mean concave points
mean symmetry
mean fractal dimension
radius error
texture error
perimeter error
area error
smoothness error


Count
compactness error
concavity error
concave points error
target
0
1
symmetry error
fractal dimension error
worst radius
worst texture
worst perimeter
worst area
worst smoothness
worst compactness
worst concavity
worst concave points
worst symmetry
worst fractal dimension


Correlation Matrix
mean radius
mean texture
mean perimeter
mean area
mean smoothness
mean compactness
mean concavity
mean concave points
1.0
0.8
0.6




# Data preprocessing

In [ ]:

```
# Load data
data = load_breast_cancer()
X = data.data
y = data.target

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42
)

# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
# Transform labels: from 0,1 to -1,1
y = np.where(y == 0, -1, 1)
```

# Impelementation of Svm Classifier on the breast cancer dataset

# Using a linear kernel on this Svm

In [ ]:

```
class SMOSVM:
    def __init__(self, C=1.0, tol=0.01, max_passes=5, kernel='linear'):
        self.C = C
        self.tol = tol
        self.max_passes = max_passes
```

```
        self.kernel = kernel
        self.alphas = None
        self.b = 0
        self.X_train = None
        self.y_train = None

    def linear_kernel(self, x1, x2):
        return np.dot(x1, x2)

    def fit(self, X, y):
        self.X_train = X
        self.y_train = y
        n_samples, n_features = X.shape
        self.alphas = np.zeros(n_samples)
        passes = 0

        while passes < self.max_passes:
            num_changed_alphas = 0
            for i in range(n_samples):
                prediction = self.predict(self.X_train[i].reshape(1, -1))
                E_i = prediction - y[i]

                if (y[i] * E_i < -self.tol and self.alphas[i] < self.C) or (y[i] * E_i >
self.tol and self.alphas[i] > 0):
                    j = np.random.choice([n for n in range(n_samples) if n != i])
                    prediction_j = self.predict(self.X_train[j].reshape(1, -1))
                    E_j = prediction_j - y[j]

                    alpha_i_old, alpha_j_old = self.alphas[i], self.alphas[j]

                    if y[i] != y[j]:
                        L = max(0, self.alphas[j] - self.alphas[i])
                        H = min(self.C, self.C + self.alphas[j] - self.alphas[i])
                    else:
                        L = max(0, self.alphas[i] + self.alphas[j] - self.C)
                        H = min(self.C, self.alphas[i] + self.alphas[j])

                    if L == H:
                        continue

                    eta = 2 * self.linear_kernel(self.X_train[i], self.X_train[j]) - sel
f.linear_kernel(self.X_train[i], self.X_train[i]) - self.linear_kernel(self.X_train[j],
self.X_train[j])
                    if eta >= 0:
                        continue

                    self.alphas[j] -= (y[j] * (E_i - E_j)) / eta
                    self.alphas[j] = max(L, min(H, self.alphas[j]))

                    if abs(self.alphas[j] - alpha_j_old) < 0.00001:
                        continue

                    self.alphas[i] += y[i] * y[j] * (alpha_j_old - self.alphas[j])

                    b1 = self.b - E_i - y[i] * (self.alphas[i] - alpha_i_old) * self.lin
ear_kernel(self.X_train[i], self.X_train[i]) - y[j] * (self.alphas[j] - alpha_j_old) * s
elf.linear_kernel(self.X_train[i], self.X_train[j])
                    b2 = self.b - E_j - y[i] * (self.alphas[i] - alpha_i_old) * self.lin
ear_kernel(self.X_train[i], self.X_train[j]) - y[j] * (self.alphas[j] - alpha_j_old) * s
elf.linear_kernel(self.X_train[j], self.X_train[j])

                    if 0 < self.alphas[i] < self.C:
                        self.b = b1
                    elif 0 < self.alphas[j] < self.C:
                        self.b = b2
                    else:
                        self.b = (b1 + b2) / 2.0

                    num_changed_alphas += 1

            if num_changed_alphas == 0:
                passes += 1
```

```
            else:
                passes = 0

    def predict(self, X):
        f_x = np.zeros(X.shape[0])
        for i in range(X.shape[0]):
            sum_term = np.dot((self.alphas * self.y_train), self.X_train.dot(X[i].T))
            f_x[i] = sum_term + self.b
        return np.sign(f_x)
```

In [ ]:

```
X = data.data
y = data.target
# Transform labels from 0,1 to -1,1
y = np.where(y == 0, -1, 1)

# Split and scale data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42
)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Train and evaluate SVM
svm = SMOSVM(C=1.0, tol=0.01, max_passes=5)
svm.fit(X_train_scaled, y_train)
predictions = svm.predict(X_test_scaled)
linear_kernel_accuracy = accuracy_score(y_test, predictions)
print(f'Accuracy using SMO SVC with linear kernel: {linear_kernel_accuracy:.4f}')
```

```
<ipython-input-21-54433bd882f3>:49: DeprecationWarning: Conversion of an array with ndim
> 0 to a scalar is deprecated, and will error in future. Ensure you extract a single elem
ent from your array before performing this operation. (Deprecated NumPy 1.25.)
  self.alphas[j] -= (y[j] * (E_i - E_j)) / eta
<ipython-input-21-54433bd882f3>:78: DeprecationWarning: Conversion of an array with ndim
> 0 to a scalar is deprecated, and will error in future. Ensure you extract a single elem
ent from your array before performing this operation. (Deprecated NumPy 1.25.)
  f_x[i] = sum_term + self.b
```

```
Accuracy using SMO SVC with linear kernel: 0.9825
```

# Using a polynomial Kernel (degrees from 1 to 3)

In [ ]:

```
class SMOSVM_polynomial_kernel:
    def __init__(self, C=1.0, tol=0.01, max_passes=5, kernel='linear', degree=3, gamma=1
, r=0):
        self.C = C
        self.tol = tol
        self.max_passes = max_passes
        self.kernel = kernel
        self.degree = degree
        self.gamma = gamma
        self.r = r
        self.alphas = None
        self.b = 0
        self.X_train = None
        self.y_train = None

    def polynomial_kernel(self, x1, x2):
        return (self.gamma * np.dot(x1, x2) + self.r) ** self.degree

    def fit(self, X, y):
        self.X_train = X
        self.y_train = y
        n_samples, n_features = X.shape
        self.alphas = np.zeros(n_samples)
        passes = 0
```

```
        while passes < self.max_passes:
            num_changed_alphas = 0
            for i in range(n_samples):
                prediction = self.predict(X[i].reshape(1, -1))
                E_i = prediction - y[i]

                if (y[i] * E_i < -self.tol and self.alphas[i] < self.C) or (y[i] * E_i >
self.tol and self.alphas[i] > 0):
                    j = np.random.choice([n for n in range(n_samples) if n != i])
                    prediction_j = self.predict(X[j].reshape(1, -1))
                    E_j = prediction_j - y[j]

                    alpha_i_old, alpha_j_old = self.alphas[i], self.alphas[j]

                    if y[i] != y[j]:
                        L = max(0, self.alphas[j] - self.alphas[i])
                        H = min(self.C, self.C + self.alphas[j] - self.alphas[i])
                    else:
                        L = max(0, self.alphas[i] + self.alphas[j] - self.C)
                        H = min(self.C, self.alphas[i] + self.alphas[j])

                    if L == H:
                        continue

                    eta = 2 * self.polynomial_kernel(X[i], X[j]) - self.polynomial_kerne
l(X[i], X[i]) - self.polynomial_kernel(X[j], X[j])
                    if eta >= 0:
                        continue

                    self.alphas[j] -= (y[j] * (E_i - E_j)) / eta
                    self.alphas[j] = max(L, min(H, self.alphas[j]))

                    if abs(self.alphas[j] - alpha_j_old) < 0.00001:
                        continue

                    self.alphas[i] += y[i] * y[j] * (alpha_j_old - self.alphas[j])

                    b1 = self.b - E_i - y[i] * (self.alphas[i] - alpha_i_old) * self.pol
ynomial_kernel(X[i], X[i]) - y[j] * (self.alphas[j] - alpha_j_old) * self.polynomial_ker
nel(X[i], X[j])
                    b2 = self.b - E_j - y[i] * (self.alphas[i] - alpha_i_old) * self.pol
ynomial_kernel(X[i], X[j]) - y[j] * (self.alphas[j] - alpha_j_old) * self.polynomial_ker
nel(X[j], X[j])

                    if 0 < self.alphas[i] < self.C:
                        self.b = b1
                    elif 0 < self.alphas[j] < self.C:
                        self.b = b2
                    else:
                        self.b = (b1 + b2) / 2.0

                    num_changed_alphas += 1

            if num_changed_alphas == 0:
                passes += 1
            else:
                passes = 0

    def predict(self, X):
        f_x = np.zeros(X.shape[0])
        for i in range(X.shape[0]):
            sum_term = np.sum([self.alphas[j] * self.y_train[j] * self.polynomial_kernel
(X[i], self.X_train[j])
                               for j in range(self.X_train.shape[0])])
            f_x[i] = sum_term + self.b
        return np.sign(f_x)
```

In [ ]:

```
# Define a list of degrees to test
```

```
degrees_to_test = [1, 2, 3]

# Initialize a dictionary to store accuracies for each degree
degree_accuracies = {}

# Loop over each degree
for degree in degrees_to_test:
    # Initialize SVM with the specified degree
    svm = SMOSVM_polynomial_kernel(C=1.0, tol=0.01, max_passes=5, kernel='polynomial', d
egree=degree)
    # Train the SVM
    svm.fit(X_train_scaled, y_train)
    # Make predictions
    predictions = svm.predict(X_test_scaled)
    # Calculate accuracy
    accuracy = np.mean(predictions == y_test)
    # Store the accuracy for this degree
    degree_accuracies[degree] = accuracy
    print(f"Degree: {degree}, Accuracy: {accuracy:.4f}")
```

```
<ipython-input-23-680b66bb45a7>:52: DeprecationWarning: Conversion of an array with ndim
> 0 to a scalar is deprecated, and will error in future. Ensure you extract a single elem
ent from your array before performing this operation. (Deprecated NumPy 1.25.)
  self.alphas[j] -= (y[j] * (E_i - E_j)) / eta
<ipython-input-23-680b66bb45a7>:82: DeprecationWarning: Conversion of an array with ndim
> 0 to a scalar is deprecated, and will error in future. Ensure you extract a single elem
ent from your array before performing this operation. (Deprecated NumPy 1.25.)
  f_x[i] = sum_term + self.b
```

```
Degree: 1, Accuracy: 0.9942
Degree: 2, Accuracy: 0.8480
Degree: 3, Accuracy: 0.9766
```

# Using Sigmoid Kernel

In [ ]:

```
class SMOSVM_sigmoid_kernel:
    def __init__(self, C=1.0, tol=0.01, max_passes=5, kernel='sigmoid', degree=3, gamma=
1, r=0):
        self.C = C
        self.tol = tol
        self.max_passes = max_passes
        self.kernel = kernel
        self.degree = degree
        self.gamma = gamma
        self.r = r
        self.alphas = None
        self.b = 0
        self.X_train = None
        self.y_train = None

    def sigmoid_kernel(self, x1, x2):
        return np.tanh(self.gamma * np.dot(x1, x2) + self.r)

    def fit(self, X, y):
        self.X_train = X
        self.y_train = y
        n_samples, n_features = X.shape
        self.alphas = np.zeros(n_samples)
        passes = 0

        while passes < self.max_passes:
            num_changed_alphas = 0
            for i in range(n_samples):
                E_i = self.predict(X[i].reshape(1, -1)) - y[i]

                if (y[i] * E_i < -self.tol and self.alphas[i] < self.C) or (y[i] * E_i >
self.tol and self.alphas[i] > 0):
                    j = np.random.choice([n for n in range(n_samples) if n != i])
```

```
                    E_j = self.predict(X[j].reshape(1, -1)) - y[j]

                    alpha_i_old, alpha_j_old = self.alphas[i], self.alphas[j]

                    if y[i] != y[j]:
                        L = max(0, self.alphas[j] - self.alphas[i])
                        H = min(self.C, self.C + self.alphas[j] - self.alphas[i])
                    else:
                        L = max(0, self.alphas[i] + self.alphas[j] - self.C)
                        H = min(self.C, self.alphas[i] + self.alphas[j])

                    if L == H:
                        continue

                    eta = 2 * self.sigmoid_kernel(X[i], X[j]) - self.sigmoid_kernel(X[i]
, X[i]) - self.sigmoid_kernel(X[j], X[j])
                    if eta >= 0:
                        continue

                    self.alphas[j] -= (y[j] * (E_i - E_j)) / eta
                    self.alphas[j] = max(L, min(H, self.alphas[j]))

                    if abs(self.alphas[j] - alpha_j_old) < 0.00001:
                        continue

                    self.alphas[i] += y[i] * y[j] * (alpha_j_old - self.alphas[j])

                    b1 = self.b - E_i - y[i] * (self.alphas[i] - alpha_i_old) * self.sig
moid_kernel(X[i], X[i]) - y[j] * (self.alphas[j] - alpha_j_old) * self.sigmoid_kernel(X[
i], X[j])
                    b2 = self.b - E_j - y[i] * (self.alphas[i] - alpha_i_old) * self.sig
moid_kernel(X[i], X[j]) - y[j] * (self.alphas[j] - alpha_j_old) * self.sigmoid_kernel(X[
j], X[j])

                    if 0 < self.alphas[i] < self.C:
                        self.b = b1
                    elif 0 < self.alphas[j] < self.C:
                        self.b = b2
                    else:
                        self.b = (b1 + b2) / 2.0

                    num_changed_alphas += 1

            if num_changed_alphas == 0:
                passes += 1
            else:
                passes = 0

    def predict(self, X):
        f_x = np.zeros(X.shape[0])
        for i in range(X.shape[0]):
            sum_term = np.dot((self.alphas * self.y_train), self.X_train.dot(X[i].T))
            f_x[i] = sum_term + self.b
        return np.sign(f_x)
```

In [ ]:

```
svm = SMOSVM_sigmoid_kernel(C=1.0, tol=0.01, max_passes=5, kernel='sigmoid')
svm.fit(X_train_scaled, y_train)
predictions = svm.predict(X_test_scaled)
sigmoid_kernel_accuracy = accuracy_score(y_test, predictions)
print(f'Accuracy with sigmoid kernel: {sigmoid_kernel_accuracy:.4f}')
```

```
<ipython-input-25-72054022dda8>:50: DeprecationWarning: Conversion of an array with ndim
> 0 to a scalar is deprecated, and will error in future. Ensure you extract a single elem
ent from your array before performing this operation. (Deprecated NumPy 1.25.)
  self.alphas[j] -= (y[j] * (E_i - E_j)) / eta
<ipython-input-25-72054022dda8>:79: DeprecationWarning: Conversion of an array with ndim
> 0 to a scalar is deprecated, and will error in future. Ensure you extract a single elem
ent from your array before performing this operation. (Deprecated NumPy 1.25.)
  f_x[i] = sum_term + self.b
```

```
Accuracy with sigmoid kernel: 0.9708
```

# Using Gaussian Kernel

In [ ]:

```
class SMOSVM_gaussian_kernel:
    def __init__(self, C=1.0, tol=0.01, max_passes=5, kernel='rbf', gamma=0.5):
        self.C = C
        self.tol = tol
        self.max_passes = max_passes
        self.kernel = kernel
        self.gamma = gamma
        self.alphas = None
        self.b = 0
        self.X_train = None
        self.y_train = None

    def rbf_kernel(self, x1, x2):
        return np.exp((-0.5*(self.gamma)**-2) * np.linalg.norm(x1 - x2)**2)

    def fit(self, X, y):
        self.X_train = X
        self.y_train = y
        n_samples, n_features = X.shape
        self.alphas = np.zeros(n_samples)
        passes = 0

        while passes < self.max_passes:
            num_changed_alphas = 0
            for i in range(n_samples):
                E_i = self.predict(X[i].reshape(1, -1)) - y[i]

                if (y[i]*E_i < -self.tol and self.alphas[i] < self.C) or (y[i]*E_i > sel
f.tol and self.alphas[i] > 0):
                    j = np.random.choice([n for n in range(n_samples) if n != i])
                    E_j = self.predict(X[j].reshape(1, -1)) - y[j]

                    alpha_i_old, alpha_j_old = self.alphas[i], self.alphas[j]

                    if y[i] != y[j]:
                        L = max(0, self.alphas[j] - self.alphas[i])
                        H = min(self.C, self.C + self.alphas[j] - self.alphas[i])
                    else:
                        L = max(0, self.alphas[i] + self.alphas[j] - self.C)
                        H = min(self.C, self.alphas[i] + self.alphas[j])

                    if L == H:
                        continue

                    eta = 2 * self.rbf_kernel(X[i], X[j]) - self.rbf_kernel(X[i], X[i])
- self.rbf_kernel(X[j], X[j])
                    if eta >= 0:
                        continue

                    self.alphas[j] -= (y[j] * (E_i - E_j)) / eta
                    self.alphas[j] = max(L, min(H, self.alphas[j]))

                    if abs(self.alphas[j] - alpha_j_old) < 0.00001:
                        continue

                    self.alphas[i] += y[i] * y[j] * (alpha_j_old - self.alphas[j])

                    b1 = self.b - E_i - y[i] * (self.alphas[i] - alpha_i_old) * self.rbf
_kernel(X[i], X[i]) - y[j] * (self.alphas[j] - alpha_j_old) * self.rbf_kernel(X[i], X[j]
)
                    b2 = self.b - E_j - y[i] * (self.alphas[i] - alpha_i_old) * self.rbf
_kernel(X[i], X[j]) - y[j] * (self.alphas[j] - alpha_j_old) * self.rbf_kernel(X[j], X[j]
)
```

```
                    if 0 < self.alphas[i] < self.C:
                        self.b = b1
                    elif 0 < self.alphas[j] < self.C:
                        self.b = b2
                    else:
                        self.b = (b1 + b2) / 2.0

                    num_changed_alphas += 1

            if num_changed_alphas == 0:
                passes += 1
            else:
                passes = 0

    def predict(self, X):
        f_x = np.zeros(X.shape[0])
        for i in range(X.shape[0]):
            sum_term = sum(self.alphas[j] * self.y_train[j] * self.rbf_kernel(X[i], self
.X_train[j]) for j in range(self.X_train.shape[0]))
            f_x[i] = sum_term + self.b
        return np.sign(f_x)
```

In [ ]:

```
X = data.data
y = data.target
y = np.where(y == 0, -1, 1)  # Transform labels

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42
)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

svm = SMOSVM_gaussian_kernel(C=1.0, tol=0.01, max_passes=5, kernel='rbf', gamma=0.5)
svm.fit(X_train_scaled, y_train)
predictions = svm.predict(X_test_scaled)
Gaussian_kernel_accuracy = accuracy_score(y_test, predictions)
print(f'Accuracy: {accuracy:.4f}')
```

```
<ipython-input-27-629faf6cd499>:48: DeprecationWarning: Conversion of an array with ndim
> 0 to a scalar is deprecated, and will error in future. Ensure you extract a single elem
ent from your array before performing this operation. (Deprecated NumPy 1.25.)
  self.alphas[j] -= (y[j] * (E_i - E_j)) / eta
<ipython-input-27-629faf6cd499>:77: DeprecationWarning: Conversion of an array with ndim
> 0 to a scalar is deprecated, and will error in future. Ensure you extract a single elem
ent from your array before performing this operation. (Deprecated NumPy 1.25.)
  f_x[i] = sum_term + self.b
```

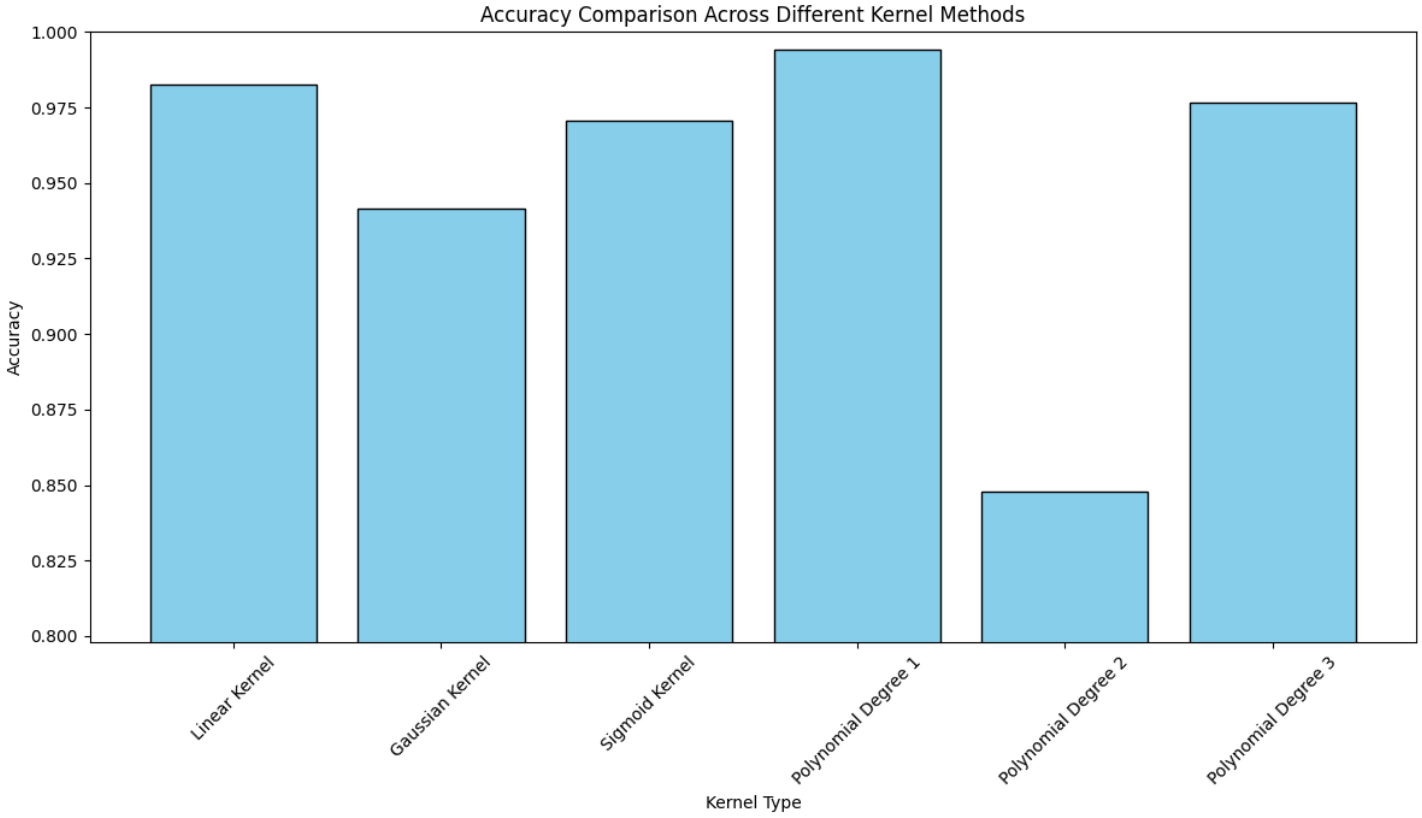
```
Accuracy: 0.9766
```

# A Comparative Visualization between each Kernel used in this project

In [ ]:

```
kernel_names = ['Linear Kernel', 'Gaussian Kernel', 'Sigmoid Kernel'] + [f'Polynomial Deg
ree {d}' for d in sorted(degree_accuracies.keys())]
accuracies = [linear_kernel_accuracy, Gaussian_kernel_accuracy, sigmoid_kernel_accuracy]
+ [degree_accuracies[d] for d in sorted(degree_accuracies.keys())]
plt.figure(figsize=(12, 7))
positions = np.arange(len(kernel_names))
plt.bar(positions, accuracies, color='skyblue', edgecolor='black')
plt.xlabel('Kernel Type')
plt.ylabel('Accuracy')
plt.title('Accuracy Comparison Across Different Kernel Methods')
plt.xticks(positions, kernel_names, rotation=45)
plt.ylim(min(accuracies) - 0.05, 1)
plt.tight_layout()
```

```
plt.show()
```


Accuracy Comparison Across Different Kernel Methods
1.000
0.975
0.950
0.925
0.900
0.875
0.850
0.825
0.800
Accuracy
Linear Kernel
Gaussian Kernel
Sigmoid Kernel
Polynomial Degree 1
Polynomial Degree 2
Polynomial Degree 3
Kernel Type