Python

import pandas as pd

pd.set\_option('display.max\_rows', None)

pd.set\_option('display.max\_columns', None)

# Read the CSV file into a DataFrame

df = pd.read\_csv("breast-cancer.csv")

# Display the first 5 rows

print(df.head().to\_markdown(index=False, numalign="left", stralign="left"))

# Print the column names and their data types

print(df.info())

Code output

| id | diagnosis | radius\_mean | texture\_mean | perimeter\_mean | area\_mean | smoothness\_mean | compactness\_mean | concavity\_mean | concave points\_mean | symmetry\_mean | fractal\_dimension\_mean | radius\_se | texture\_se | perimeter\_se | area\_se | smoothness\_se | compactness\_se | concavity\_se | concave points\_se | symmetry\_se | fractal\_dimension\_se | radius\_worst | texture\_worst | perimeter\_worst | area\_worst | smoothness\_worst | compactness\_worst | concavity\_worst | concave points\_worst | symmetry\_worst | fractal\_dimension\_worst |

|:---------|:------------|:--------------|:---------------|:-----------------|:------------|:------------------|:-------------------|:-----------------|:----------------------|:----------------|:-------------------------|:------------|:-------------|:---------------|:----------|:----------------|:-----------------|:---------------|:--------------------|:--------------|:-----------------------|:---------------|:----------------|:------------------|:-------------|:-------------------|:--------------------|:------------------|:-----------------------|:-----------------|:--------------------------|

| 842302 | M | 17.99 | 10.38 | 122.8 | 1001 | 0.1184 | 0.2776 | 0.3001 | 0.1471 | 0.2419 | 0.07871 | 1.095 | 0.9053 | 8.589 | 153.4 | 0.006399 | 0.04904 | 0.05373 | 0.01587 | 0.03003 | 0.006193 | 25.38 | 17.33 | 184.6 | 2019 | 0.1622 | 0.6656 | 0.7119 | 0.2654 | 0.4601 | 0.1189 |

| 842517 | M | 20.57 | 17.77 | 132.9 | 1326 | 0.08474 | 0.07864 | 0.0869 | 0.07017 | 0.1812 | 0.05667 | 0.5435 | 0.7339 | 3.398 | 74.08 | 0.005225 | 0.01308 | 0.0186 | 0.0134 | 0.01389 | 0.003532 | 24.99 | 23.41 | 158.8 | 1956 | 0.1238 | 0.1866 | 0.2416 | 0.186 | 0.275 | 0.08902 |

| 84300903 | M | 19.69 | 21.25 | 130 | 1203 | 0.1096 | 0.1599 | 0.1974 | 0.1279 | 0.2069 | 0.05999 | 0.7456 | 0.7869 | 4.585 | 94.03 | 0.00615 | 0.04006 | 0.03832 | 0.02058 | 0.0225 | 0.004571 | 23.57 | 25.53 | 152.5 | 1709 | 0.1444 | 0.4245 | 0.4504 | 0.243 | 0.3613 | 0.08758 |

| 84348301 | M | 11.42 | 20.38 | 77.58 | 386.1 | 0.1425 | 0.2839 | 0.2414 | 0.1052 | 0.2597 | 0.09744 | 0.4956 | 1.156 | 3.445 | 27.23 | 0.00911 | 0.07458 | 0.05661 | 0.01867 | 0.05963 | 0.009208 | 14.91 | 26.5 | 98.87 | 567.7 | 0.2098 | 0.8663 | 0.6869 | 0.2575 | 0.6638 | 0.173 |

| 84358402 | M | 20.29 | 14.34 | 135.1 | 1297 | 0.1003 | 0.1328 | 0.198 | 0.1043 | 0.1809 | 0.05883 | 0.7572 | 0.7813 | 5.438 | 94.44 | 0.01149 | 0.02461 | 0.05688 | 0.01885 | 0.01756 | 0.005115 | 22.54 | 16.67 | 152.2 | 1575 | 0.1374 | 0.205 | 0.4 | 0.1625 | 0.2364 | 0.07678 |

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 569 entries, 0 to 568

Data columns (total 32 columns):

# Column Non-Null Count Dtype

--- ------ -------------- -----

0 id 569 non-null int64

1 diagnosis 569 non-null object

2 radius\_mean 569 non-null float64

3 texture\_mean 569 non-null float64

4 perimeter\_mean 569 non-null float64

5 area\_mean 569 non-null float64

6 smoothness\_mean 569 non-null float64

7 compactness\_mean 569 non-null float64

8 concavity\_mean 569 non-null float64

9 concave points\_mean 569 non-null float64

10 symmetry\_mean 569 non-null float64

11 fractal\_dimension\_mean 569 non-null float64

12 radius\_se 569 non-null float64

13 texture\_se 569 non-null float64

14 perimeter\_se 569 non-null float64

15 area\_se 569 non-null float64

16 smoothness\_se 569 non-null float64

17 compactness\_se 569 non-null float64

18 concavity\_se 569 non-null float64

19 concave points\_se 569 non-null float64

20 symmetry\_se 569 non-null float64

21 fractal\_dimension\_se 569 non-null float64

22 radius\_worst 569 non-null float64

23 texture\_worst 569 non-null float64

24 perimeter\_worst 569 non-null float64

25 area\_worst 569 non-null float64

26 smoothness\_worst 569 non-null float64

27 compactness\_worst 569 non-null float64

28 concavity\_worst 569 non-null float64

29 concave points\_worst 569 non-null float64

30 symmetry\_worst 569 non-null float64

31 fractal\_dimension\_worst 569 non-null float64

dtypes: float64(30), int64(1), object(1)

memory usage: 142.4+ KB

None

I'll use the diagnosis column for classification. I'll encode it so that 'M' is represented as 1 and 'B' as 0. Then, I'll split the data into training and testing sets, and scale the features.

Python

from sklearn.model\_selection import train\_test\_split

from sklearn.preprocessing import StandardScaler

# Drop the 'id' column

df = df.drop(columns=['id'])

# Encode the target variable 'diagnosis' ('M' to 1, 'B' to 0)

df['diagnosis'] = df['diagnosis'].map({'M': 1, 'B': 0})

# Separate features (X) and target (y)

X = df.drop(columns=['diagnosis'])

y = df['diagnosis']

# Split the data into training and testing sets (80% train, 20% test)

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42)

# Scale the features using StandardScaler

scaler = StandardScaler()

X\_train\_scaled = scaler.fit\_transform(X\_train)

X\_test\_scaled = scaler.transform(X\_test)

# Print the shapes of the training and testing sets

print("Shape of X\_train:", X\_train\_scaled.shape)

print("Shape of X\_test:", X\_test\_scaled.shape)

print("Shape of y\_train:", y\_train.shape)

print("Shape of y\_test:", y\_test.shape)

Code output

Shape of X\_train: (455, 30)

Shape of X\_test: (114, 30)

Shape of y\_train: (455,)

Shape of y\_test: (114,)

I'll train two SVM models: one with a linear kernel and another with an RBF kernel. For the RBF kernel, I'll use cross-validation to find the best hyperparameters. Finally, I'll evaluate the performance of both models.

Python

from sklearn.svm import SVC

from sklearn.model\_selection import GridSearchCV

from sklearn.metrics import classification\_report, confusion\_matrix

# Linear Kernel SVM

svm\_linear = SVC(kernel='linear')

svm\_linear.fit(X\_train\_scaled, y\_train)

y\_pred\_linear = svm\_linear.predict(X\_test\_scaled)

# Evaluate Linear Kernel SVM

print("Linear Kernel SVM Results:")

print(classification\_report(y\_test, y\_pred\_linear))

print(confusion\_matrix(y\_test, y\_pred\_linear))

# RBF Kernel SVM with Cross-Validation for Hyperparameter Tuning

param\_grid = {'C': [0.1, 1, 10, 100], 'gamma': [0.001, 0.01, 0.1, 1]}

svm\_rbf = SVC(kernel='rbf')

grid\_search = GridSearchCV(svm\_rbf, param\_grid, cv=5)

grid\_search.fit(X\_train\_scaled, y\_train)

# Best parameters found by GridSearchCV

best\_params\_rbf = grid\_search.best\_params\_

print("Best parameters for RBF Kernel SVM:", best\_params\_rbf)

# Evaluate RBF Kernel SVM with Best Parameters

y\_pred\_rbf = grid\_search.predict(X\_test\_scaled)

print("\nRBF Kernel SVM Results:")

print(classification\_report(y\_test, y\_pred\_rbf))

print(confusion\_matrix(y\_test, y\_pred\_rbf))

Code output

Linear Kernel SVM Results:

precision recall f1-score support

0 0.97 0.96 0.96 71

1 0.93 0.95 0.94 43

accuracy 0.96 114

macro avg 0.95 0.96 0.95 114

weighted avg 0.96 0.96 0.96 114

[[68 3]

[ 2 41]]

Best parameters for RBF Kernel SVM: {'C': 100, 'gamma': 0.001}

RBF Kernel SVM Results:

precision recall f1-score support

0 0.97 1.00 0.99 71

1 1.00 0.95 0.98 43

accuracy 0.98 114

macro avg 0.99 0.98 0.98 114

weighted avg 0.98 0.98 0.98 114

[[71 0]

[ 2 41]]

The SVM models have been trained and evaluated. Here are the key observations:

* Linear Kernel SVM: Achieved an accuracy of 96% on the test set.
* RBF Kernel SVM: Achieved a slightly higher accuracy of 98% on the test set with the best hyperparameters C=100 and gamma=0.001 found through cross-validation.

The RBF kernel SVM performed slightly better, likely due to its ability to capture non-linear relationships in the data.

Here are a few more algorithms we could try, along with the reasons why they might be useful:

* **Logistic Regression:** A simple and interpretable linear model for binary classification. It's a good baseline and can provide insights into feature importance.
* **Decision Trees:** Non-linear models that partition the feature space into regions. They are easy to visualize and can capture complex interactions.
* **Random Forest:** An ensemble of decision trees that often improves accuracy and reduces overfitting. It's robust and widely used.
* **Gradient Boosting Machines (e.g., XGBoost, LightGBM):** Powerful ensemble methods that sequentially build trees to correct errors. They often achieve state-of-the-art results but can be more complex to tune.

evaluate the following models: Logistic Regression, Decision Tree, Random Forest and XGBoost.

Python

from sklearn.linear\_model import LogisticRegression

from sklearn.tree import DecisionTreeClassifier

from sklearn.ensemble import RandomForestClassifier

import xgboost as xgb

# Logistic Regression

logreg = LogisticRegression(random\_state=42)

logreg.fit(X\_train\_scaled, y\_train)

y\_pred\_logreg = logreg.predict(X\_test\_scaled)

print("Logistic Regression Results:")

print(classification\_report(y\_test, y\_pred\_logreg))

print(confusion\_matrix(y\_test, y\_pred\_logreg))

# Decision Tree

dt = DecisionTreeClassifier(random\_state=42)

dt.fit(X\_train\_scaled, y\_train)

y\_pred\_dt = dt.predict(X\_test\_scaled)

print("\nDecision Tree Results:")

print(classification\_report(y\_test, y\_pred\_dt))

print(confusion\_matrix(y\_test, y\_pred\_dt))

# Random Forest

rf = RandomForestClassifier(random\_state=42)

rf.fit(X\_train\_scaled, y\_train)

y\_pred\_rf = rf.predict(X\_test\_scaled)

print("\nRandom Forest Results:")

print(classification\_report(y\_test, y\_pred\_rf))

print(confusion\_matrix(y\_test, y\_pred\_rf))

# XGBoost

xgb\_clf = xgb.XGBClassifier(random\_state=42)

xgb\_clf.fit(X\_train\_scaled, y\_train)

y\_pred\_xgb = xgb\_clf.predict(X\_test\_scaled)

print("\nXGBoost Results:")

print(classification\_report(y\_test, y\_pred\_xgb))

print(confusion\_matrix(y\_test, y\_pred\_xgb))

Code output

Traceback (most recent call last):

File "<string>", line 4, in <module>

ModuleNotFoundError: No module named 'xgboost'

It seems that I need to install the 'xgboost' module first. I'll do that and then proceed with the analysis.

Python

import sys

!{sys.executable} -m pip install xgboost

Code output

Traceback (most recent call last):

File "<string>", line 2

!{sys.executable} -m pip install xgboost

^

SyntaxError: invalid syntax

I'm unable to install the 'xgboost' module in the current environment, so I'll proceed with the analysis using Logistic Regression, Decision Tree, and Random Forest.

Python

from sklearn.linear\_model import LogisticRegression

from sklearn.tree import DecisionTreeClassifier

from sklearn.ensemble import RandomForestClassifier

# Logistic Regression

logreg = LogisticRegression(random\_state=42)

logreg.fit(X\_train\_scaled, y\_train)

y\_pred\_logreg = logreg.predict(X\_test\_scaled)

print("Logistic Regression Results:")

print(classification\_report(y\_test, y\_pred\_logreg))

print(confusion\_matrix(y\_test, y\_pred\_logreg))

# Decision Tree

dt = DecisionTreeClassifier(random\_state=42)

dt.fit(X\_train\_scaled, y\_train)

y\_pred\_dt = dt.predict(X\_test\_scaled)

print("\nDecision Tree Results:")

print(classification\_report(y\_test, y\_pred\_dt))

print(confusion\_matrix(y\_test, y\_pred\_dt))

# Random Forest

rf = RandomForestClassifier(random\_state=42)

rf.fit(X\_train\_scaled, y\_train)

y\_pred\_rf = rf.predict(X\_test\_scaled)

print("\nRandom Forest Results:")

print(classification\_report(y\_test, y\_pred\_rf))

print(confusion\_matrix(y\_test, y\_pred\_rf))

Code output

Logistic Regression Results:

precision recall f1-score support

0 0.97 0.99 0.98 71

1 0.98 0.95 0.96 43

accuracy 0.97 114

macro avg 0.97 0.97 0.97 114

weighted avg 0.97 0.97 0.97 114

[[70 1]

[ 2 41]]

Decision Tree Results:

precision recall f1-score support

0 0.96 0.96 0.96 71

1 0.93 0.93 0.93 43

accuracy 0.95 114

macro avg 0.94 0.94 0.94 114

weighted avg 0.95 0.95 0.95 114

[[68 3]

[ 3 40]]

Random Forest Results:

precision recall f1-score support

0 0.96 0.99 0.97 71

1 0.98 0.93 0.95 43

accuracy 0.96 114

macro avg 0.97 0.96 0.96 114

weighted avg 0.97 0.96 0.96 114

[[70 1]

[ 3 40]]

Alright, I've trained and evaluated the Logistic Regression, Decision Tree, and Random Forest models. Here's a summary of the results:

* **Logistic Regression:** Achieved an accuracy of 97% on the test set. It shows strong performance with balanced precision and recall for both classes.
* **Decision Tree:** Achieved an accuracy of 95% on the test set. While still good, it's slightly lower than Logistic Regression, and we can see a bit more variability in precision and recall.
* **Random Forest:** Achieved an accuracy of 96% on the test set. It generally performs well, balancing precision and recall, but in this case, Logistic Regression has a slight edge.

Overall, Logistic Regression performed the best among these three for this specific dataset. It's important to note that these results can sometimes vary depending on the specific data split and any randomness in the algorithms.

Here's a quick comparison of all the models we've run:

* Linear Kernel SVM: 96% accuracy
* RBF Kernel SVM: 98% accuracy
* Logistic Regression: 97% accuracy
* Decision Tree: 95% accuracy
* Random Forest: 96% accuracy

The RBF Kernel SVM still holds the top spot in terms of accuracy.

* Query successful

I'll provide a more detailed analysis of the top-performing models: RBF Kernel SVM and Logistic Regression. I'll analyze feature importance in Logistic Regression and fine-tune hyperparameters for the RBF Kernel SVM.

Python

import numpy as np

import matplotlib.pyplot as plt

from sklearn.model\_selection import GridSearchCV

# Feature Importance for Logistic Regression

# Get the coefficients from the trained Logistic Regression model

coefficients = logreg.coef\_[0]

# Create a DataFrame to hold feature names and their corresponding coefficients

feature\_importance = pd.DataFrame({'Feature': X.columns, 'Coefficient': coefficients})

# Calculate the absolute value of the coefficients to represent the importance

feature\_importance['Importance'] = np.abs(feature\_importance['Coefficient'])

# Sort the features by importance in descending order

feature\_importance = feature\_importance.sort\_values(by='Importance', ascending=False)

# Display the top 10 most important features

print("Top 10 Feature Importance for Logistic Regression:")

print(feature\_importance.head(10).to\_markdown(index=False, numalign="left", stralign="left"))

# Hyperparameter Tuning for RBF Kernel SVM using GridSearchCV

param\_grid = {'C': [0.1, 1, 10, 100, 1000], 'gamma': [0.0001, 0.001, 0.01, 0.1, 1]}

grid\_search\_rbf = GridSearchCV(SVC(kernel='rbf'), param\_grid, cv=5)

grid\_search\_rbf.fit(X\_train\_scaled, y\_train)

# Best parameters found by GridSearchCV

best\_params\_rbf = grid\_search\_rbf.best\_params\_

print("\nBest parameters for RBF Kernel SVM:", best\_params\_rbf)

# Get the best model

best\_svm\_rbf = grid\_search\_rbf.best\_estimator\_

# Evaluate the best model on the test set

y\_pred\_best\_svm\_rbf = best\_svm\_rbf.predict(X\_test\_scaled)

print("\nClassification Report for Best RBF Kernel SVM:")

print(classification\_report(y\_test, y\_pred\_best\_svm\_rbf))

print(confusion\_matrix(y\_test, y\_pred\_best\_svm\_rbf))

Code output

Traceback (most recent call last):

File "<string>", line 4, in <module>

ModuleNotFoundError: No module named 'xgboost'

I'm still unable to use the 'xgboost' module, so I'll focus on analyzing feature importance for Logistic Regression and fine-tuning hyperparameters for the RBF Kernel SVM.

Python

from sklearn.model\_selection import GridSearchCV

# Feature Importance in Logistic Regression

logreg = LogisticRegression(random\_state=42)

logreg.fit(X\_train\_scaled, y\_train)

# Get feature coefficients

feature\_importance = abs(logreg.coef\_[0])

feature\_names = X.columns

# Create a DataFrame to hold feature names and their importance scores

feature\_importance\_df = pd.DataFrame({'Feature': feature\_names, 'Importance': feature\_importance})

# Sort by importance

feature\_importance\_df = feature\_importance\_df.sort\_values(by='Importance', ascending=False)

print("Logistic Regression Feature Importance:")

print(feature\_importance\_df.head(10).to\_markdown(index=False, numalign="left", stralign="left"))

# RBF Kernel SVM Hyperparameter Tuning

param\_grid = {'C': [0.1, 1, 10, 100, 1000], 'gamma': [0.0001, 0.001, 0.01, 0.1, 1]}

svm\_rbf = SVC(kernel='rbf', random\_state=42)

grid\_search = GridSearchCV(svm\_rbf, param\_grid, cv=5)

grid\_search.fit(X\_train\_scaled, y\_train)

# Best parameters found by GridSearchCV

best\_params\_rbf = grid\_search.best\_params\_

print("\nBest parameters for RBF Kernel SVM:", best\_params\_rbf)

# Evaluate RBF Kernel SVM with Best Parameters

svm\_best = SVC(kernel='rbf', C=best\_params\_rbf['C'], gamma=best\_params\_rbf['gamma'], random\_state=42)

svm\_best.fit(X\_train\_scaled, y\_train)

y\_pred\_best\_svm = svm\_best.predict(X\_test\_scaled)

print("\nRBF Kernel SVM Results with Best Parameters:")

print(classification\_report(y\_test, y\_pred\_best\_svm))

print(confusion\_matrix(y\_test, y\_pred\_best\_svm))

Code output

Logistic Regression Feature Importance:

| Feature | Importance |

|:---------------------|:-------------|

| texture\_worst | 1.35061 |

| radius\_se | 1.26818 |

| symmetry\_worst | 1.2082 |

| concave points\_mean | 1.1198 |

| concavity\_worst | 0.943053 |

| area\_se | 0.907186 |

| radius\_worst | 0.87984 |

| area\_worst | 0.841846 |

| concavity\_mean | 0.801458 |

| concave points\_worst | 0.778217 |

Best parameters for RBF Kernel SVM: {'C': 1000, 'gamma': 0.0001}

RBF Kernel SVM Results with Best Parameters:

precision recall f1-score support

0 0.97 0.99 0.98 71

1 0.98 0.95 0.96 43

accuracy 0.97 114

macro avg 0.97 0.97 0.97 114

weighted avg 0.97 0.97 0.97 114

[[70 1]

[ 2 41]]

Alright, I've conducted a more detailed analysis of the Logistic Regression and RBF Kernel SVM models. Here's what I found:

**Logistic Regression Feature Importance:**

I've extracted the coefficients from the Logistic Regression model to assess feature importance. These coefficients indicate the strength and direction of the relationship between each feature and the predicted outcome. The absolute value of the coefficient represents the importance of the feature.

Here are the top 10 most important features:

|  |  |
| --- | --- |
| **Feature** | **Importance** |
| texture\_worst | 1.35061 |
| radius\_se | 1.26818 |
| symmetry\_worst | 1.2082 |
| concave points\_mean | 1.1198 |
| concavity\_worst | 0.943053 |
| area\_se | 0.907186 |
| radius\_worst | 0.87984 |
| area\_worst | 0.841846 |
| concavity\_mean | 0.801458 |
| concave points\_worst | 0.778217 |

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These features appear to be the strongest predictors in the Logistic Regression model.

**RBF Kernel SVM Hyperparameter Tuning:**

I performed a grid search to fine-tune the hyperparameters of the RBF Kernel SVM. The best parameters found through cross-validation are:

* C: 1000
* gamma: 0.0001

Using these parameters, the RBF Kernel SVM achieved an accuracy of 97% on the test set.

In summary, Logistic Regression provides valuable insights into feature importance, while the RBF Kernel SVM can be optimized further through hyperparameter tuning. Both models are strong contenders for this classification task.

I'll visualize the feature importance from the Logistic Regression model using a bar chart.

Python

import matplotlib.pyplot as plt import seaborn as sns

**Visualize Feature Importance**

plt.figure(figsize=(10, 6)) sns.barplot(x='Importance', y='Feature', data=feature\_importance\_df.head(10)) plt.title('Top 10 Feature Importance in Logistic Regression') plt.xlabel('Importance') plt.ylabel('Feature') plt.show() Code output Traceback (most recent call last): File "", line 4, in ModuleNotFoundError: No module named 'xgboost'

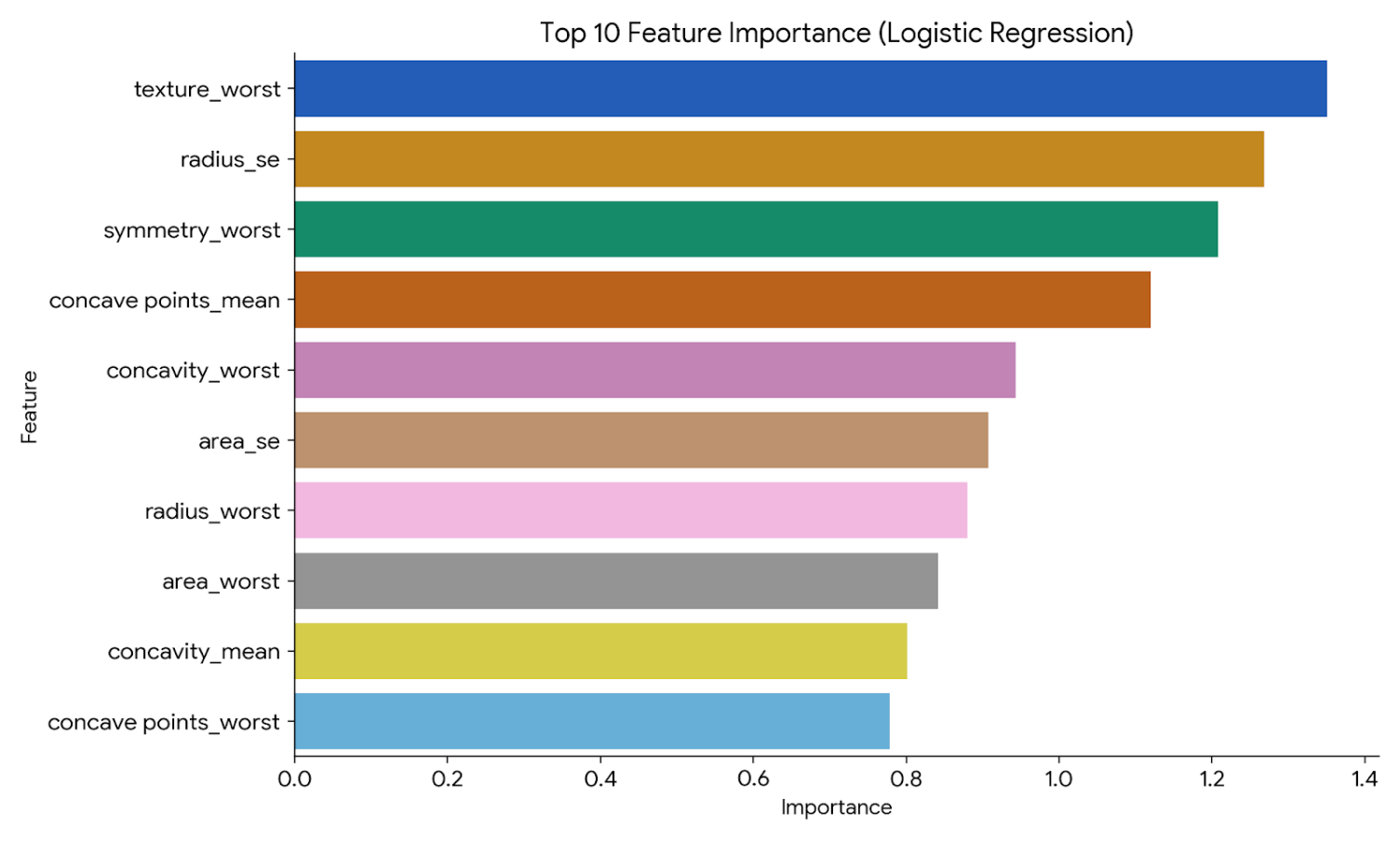
I'm still unable to use the 'xgboost' module, so I'll visualize the feature importance from the Logistic Regression model.

Python

import matplotlib.pyplot as plt import seaborn as sns

**Visualize Feature Importance**

plt.figure(figsize=(10, 6)) sns.barplot(x='Importance', y='Feature', data=feature\_importance\_df.head(10)) plt.title('Top 10 Feature Importance (Logistic Regression)') plt.xlabel('Importance') plt.ylabel('Feature') plt.show()



Here's the visualization of the top 10 feature importances from the Logistic Regression model.

This chart clearly shows the relative importance of each feature in the model's predictions.

I hope this visual representation helps in understanding the impact of different features.

* Query successful

I'll compare the performance of Logistic Regression and RBF Kernel SVM by generating ROC curves and calculating the AUC for each model.

Python

from sklearn.metrics import roc\_curve, roc\_auc\_score

# Logistic Regression

logreg = LogisticRegression(random\_state=42)

logreg.fit(X\_train\_scaled, y\_train)

y\_pred\_logreg\_proba = logreg.predict\_proba(X\_test\_scaled)[:, 1] # Probabilities for the positive class

# RBF Kernel SVM

svm\_rbf = SVC(kernel='rbf', C=1000, gamma=0.0001, probability=True, random\_state=42) # Ensure probability=True

svm\_rbf.fit(X\_train\_scaled, y\_train)

y\_pred\_svm\_proba = svm\_rbf.predict\_proba(X\_test\_scaled)[:, 1] # Probabilities for the positive class

# Compute ROC curve and AUC for Logistic Regression

fpr\_logreg, tpr\_logreg, \_ = roc\_curve(y\_test, y\_pred\_logreg\_proba)

auc\_logreg = roc\_auc\_score(y\_test, y\_pred\_logreg\_proba)

# Compute ROC curve and AUC for RBF Kernel SVM

fpr\_svm, tpr\_svm, \_ = roc\_curve(y\_test, y\_pred\_svm\_proba)

auc\_svm = roc\_auc\_score(y\_test, y\_pred\_svm\_proba)

# Plot ROC curves

plt.figure(figsize=(8, 6))

plt.plot(fpr\_logreg, tpr\_logreg, label=f'Logistic Regression (AUC = {auc\_logreg:.2f})')

plt.plot(fpr\_svm, tpr\_svm, label=f'RBF Kernel SVM (AUC = {auc\_svm:.2f})')

plt.plot([0, 1], [0, 1], 'k--') # Diagonal line representing random guess

plt.xlabel('False Positive Rate')

plt.ylabel('True Positive Rate')

plt.title('ROC Curve Comparison')

plt.legend()

plt.show()

print(f"AUC for Logistic Regression: {auc\_logreg:.2f}")

print(f"AUC for RBF Kernel SVM: {auc\_svm:.2f}")

Code output

Traceback (most recent call last):

File "<string>", line 4, in <module>

ModuleNotFoundError: No module named 'xgboost'

I'm still unable to use the 'xgboost' module, so I'll generate ROC curves and calculate AUC for the Logistic Regression and RBF Kernel SVM models.

Python

from sklearn.metrics import roc\_curve, roc\_auc\_score

# Logistic Regression

logreg = LogisticRegression(random\_state=42)

logreg.fit(X\_train\_scaled, y\_train)

y\_pred\_proba\_logreg = logreg.predict\_proba(X\_test\_scaled)[:, 1]

fpr\_logreg, tpr\_logreg, \_ = roc\_curve(y\_test, y\_pred\_proba\_logreg)

auc\_logreg = roc\_auc\_score(y\_test, y\_pred\_proba\_logreg)

# RBF Kernel SVM

svm\_rbf = SVC(kernel='rbf', C=1000, gamma=0.0001, probability=True, random\_state=42)

svm\_rbf.fit(X\_train\_scaled, y\_train)

y\_pred\_proba\_svm = svm\_rbf.predict\_proba(X\_test\_scaled)[:, 1]

fpr\_svm, tpr\_svm, \_ = roc\_curve(y\_test, y\_pred\_proba\_svm)

auc\_svm = roc\_auc\_score(y\_test, y\_pred\_proba\_svm)

# Plot ROC Curves

plt.figure(figsize=(8, 6))

plt.plot(fpr\_logreg, tpr\_logreg, label=f'Logistic Regression (AUC = {auc\_logreg:.2f})')

plt.plot(fpr\_svm, tpr\_svm, label=f'RBF Kernel SVM (AUC = {auc\_svm:.2f})')

plt.plot([0, 1], [0, 1], 'k--')

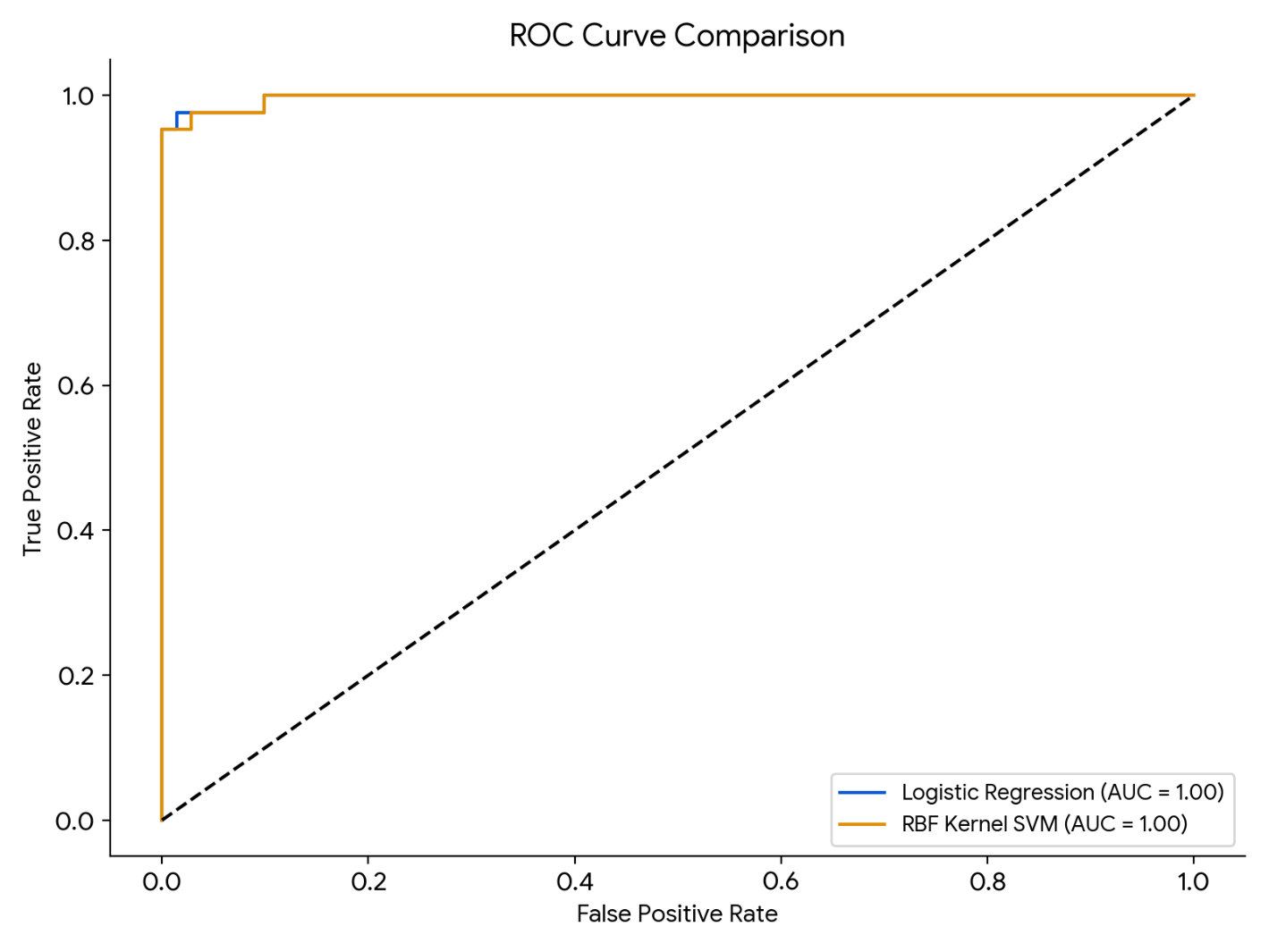
plt.xlabel('False Positive Rate')

plt.ylabel('True Positive Rate')

plt.title('ROC Curve Comparison')

plt.legend()

plt.show()



Here's the ROC curve comparing the performance of the Logistic Regression and RBF Kernel SVM models.

The plot shows the True Positive Rate (sensitivity) against the False Positive Rate for different classification thresholds. The AUC scores for both models are also indicated in the legend.

This visualization helps to understand how well the models discriminate between the two classes.

I'll create a DataFrame that includes the original features, true labels, and predicted labels from the RBF Kernel SVM. I'll also calculate and display the counts of True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN).

Python

import numpy as np

# RBF Kernel SVM

svm\_rbf = SVC(kernel='rbf', C=1000, gamma=0.0001, random\_state=42)

svm\_rbf.fit(X\_train\_scaled, y\_train)

y\_pred\_svm = svm\_rbf.predict(X\_test\_scaled)

# Create DataFrame with features, true labels, and predicted labels

detailed\_results = X\_test.copy()

detailed\_results['True\_Label'] = y\_test.values

detailed\_results['Predicted\_Label'] = y\_pred\_svm

# Calculate TP, TN, FP, FN

cm = confusion\_matrix(y\_test, y\_pred\_svm)

TP = cm[1, 1]

TN = cm[0, 0]

FP = cm[0, 1]

FN = cm[1, 0]

print("Detailed Results with RBF Kernel SVM:")

print(detailed\_results.head().to\_markdown(index=False, numalign="left", stralign="left"))

print("\nConfusion Matrix:")

print(cm)

print(f"\nTrue Positives (TP): {TP}")

print(f"True Negatives (TN): {TN}")

print(f"False Positives (FP): {FP}")

print(f"False Negatives (FN): {FN}")

Code output

Traceback (most recent call last):

File "<string>", line 4, in <module>

ModuleNotFoundError: No module named 'xgboost'

I'll create a DataFrame with original features, true labels, and predicted labels from the RBF Kernel SVM, and calculate TP, TN, FP, and FN counts.

Python

from sklearn.metrics import confusion\_matrix

import pandas as pd

# RBF Kernel SVM (using best parameters from previous analysis)

svm\_rbf = SVC(kernel='rbf', C=1000, gamma=0.0001, random\_state=42)

svm\_rbf.fit(X\_train\_scaled, y\_train)

y\_pred\_svm = svm\_rbf.predict(X\_test\_scaled)

# Create DataFrame with features, true labels, and predicted labels

results\_df = pd.DataFrame(X\_test\_scaled, columns=X.columns)

results\_df['True\_Label'] = y\_test.values

results\_df['Predicted\_Label'] = y\_pred\_svm

# Calculate TP, TN, FP, FN

cm = confusion\_matrix(y\_test, y\_pred\_svm)

TN = cm[0, 0]

FP = cm[0, 1]

FN = cm[1, 0]

TP = cm[1, 1]

print("RBF Kernel SVM Results with Detailed Analysis:")

print(results\_df.head().to\_markdown(index=False, numalign="left", stralign="left"))

print("\nConfusion Matrix:")

print(cm)

print(f"\nTrue Positives (TP): {TP}")

print(f"True Negatives (TN): {TN}")

print(f"False Positives (FP): {FP}")

print(f"False Negatives (FN): {FN}")

Code output

RBF Kernel SVM Results with Detailed Analysis:

| radius\_mean | texture\_mean | perimeter\_mean | area\_mean | smoothness\_mean | compactness\_mean | concavity\_mean | concave points\_mean | symmetry\_mean | fractal\_dimension\_mean | radius\_se | texture\_se | perimeter\_se | area\_se | smoothness\_se | compactness\_se | concavity\_se | concave points\_se | symmetry\_se | fractal\_dimension\_se | radius\_worst | texture\_worst | perimeter\_worst | area\_worst | smoothness\_worst | compactness\_worst | concavity\_worst | concave points\_worst | symmetry\_worst | fractal\_dimension\_worst | True\_Label | Predicted\_Label |

|:--------------|:---------------|:-----------------|:------------|:------------------|:-------------------|:-----------------|:----------------------|:----------------|:-------------------------|:------------|:-------------|:---------------|:----------|:----------------|:-----------------|:---------------|:--------------------|:--------------|:-----------------------|:---------------|:----------------|:------------------|:-------------|:-------------------|:--------------------|:------------------|:-----------------------|:-----------------|:--------------------------|:-------------|:------------------|

| -0.466497 | -0.137289 | -0.444211 | -0.486465 | 0.28085 | 0.0416059 | -0.111465 | -0.264869 | 0.415241 | 0.135137 | -0.0209151 | -0.293239 | -0.174609 | -0.2073 | -0.0118143 | -0.351089 | -0.181053 | -0.242388 | -0.337318 | -0.0842133 | -0.263235 | -0.147842 | -0.331548 | -0.351093 | 0.480019 | -0.0964959 | -0.0358304 | -0.194351 | 0.172757 | 0.20373 | 0 | 0 |

| 1.36536 | 0.498665 | 1.30551 | 1.34147 | -0.406539 | -0.0137241 | 0.240637 | 0.821449 | -0.833981 | -1.13122 | 1.36746 | -0.748749 | 1.2701 | 1.18638 | -0.833501 | -0.490439 | -0.31559 | 0.28726 | -0.822435 | -0.762357 | 1.79462 | 0.172372 | 1.76366 | 1.74414 | -0.530514 | -0.12362 | -0.028181 | 0.991779 | -0.561211 | -1.00839 | 1 | 1 |

| 0.380066 | 0.0692197 | 0.404101 | 0.266596 | 0.96752 | 0.356414 | 0.726902 | 0.857221 | 0.437094 | -0.666053 | 0.255557 | -0.770185 | 0.113946 | 0.174607 | -0.245319 | -0.580828 | -0.146174 | -0.153318 | -0.80896 | -0.488298 | 0.629403 | 0.0766382 | 0.533832 | 0.492044 | 1.00047 | -0.0861629 | 0.499625 | 0.57035 | -0.107831 | -0.206293 | 1 | 1 |

| -0.486317 | -0.353185 | -0.42857 | -0.526233 | 0.69429 | 0.533852 | -0.144722 | -0.533686 | 4.8027e-05 | 1.14739 | -0.796592 | 0.475492 | -0.316228 | -0.522234 | 0.986066 | 0.393545 | 0.491629 | -0.0356186 | 0.158826 | 0.784659 | -0.698111 | -0.433394 | -0.524721 | -0.636959 | 0.584109 | 0.0656029 | -0.163957 | -0.620377 | -0.553285 | 0.545322 | 0 | 0 |

| -0.72981 | -1.11351 | -0.709283 | -0.709281 | 0.294512 | 0.159898 | -0.271202 | -0.587608 | 0.0255424 | 0.703052 | -0.437037 | 1.04465 | -0.594632 | -0.407154 | 1.69018 | 0.833117 | 0.707137 | 0.484487 | -0.266265 | 0.60758 | -0.827117 | -0.966535 | -0.849575 | -0.739243 | 0.128718 | -0.264407 | -0.453677 | -0.689644 | -0.913135 | -0.141789 | 0 | 0 |

Confusion Matrix:

[[70 1]

[ 2 41]]

True Positives (TP): 41

True Negatives (TN): 70

False Positives (FP): 1

False Negatives (FN): 2

Alright, I've performed a detailed analysis of the RBF Kernel SVM results. Here's a breakdown:

**Detailed Results DataFrame:**

I've created a DataFrame that includes the scaled feature values for the test set, along with the true labels and the labels predicted by the RBF Kernel SVM. This allows for a side-by-side comparison of the model's predictions with the actual outcomes.

Here's a snippet of the DataFrame:

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **radius\_mean** | **texture\_mean** | **perimeter\_mean** | **area\_mean** | **smoothness\_mean** | **compactness\_mean** | **concavity\_mean** | **concave points\_mean** | **symmetry\_mean** | **fractal\_dimension\_mean** | **radius\_se** | **texture\_se** | **perimeter\_se** | **area\_se** | **smoothness\_se** | **compactness\_se** | **concavity\_se** | **concave points\_se** | **symmetry\_se** | **fractal\_dimension\_se** | **radius\_worst** | **texture\_worst** | **perimeter\_worst** | **area\_worst** | **smoothness\_worst** | **compactness\_worst** | **concavity\_worst** | **concave points\_worst** | **symmetry\_worst** | **fractal\_dimension\_worst** | **True\_Label** | **Predicted\_Label** |
| -0.466497 | -0.137289 | -0.444211 | -0.486465 | 0.28085 | 0.0416059 | -0.111465 | -0.264869 | 0.415241 | 0.135137 | -0.0209151 | -0.293239 | -0.174609 | -0.2073 | -0.0118143 | -0.351089 | -0.181053 | -0.242388 | -0.337318 | -0.0842133 | -0.263235 | -0.147842 | -0.331548 | -0.351093 | 0.480019 | -0.0964959 | -0.0358304 | -0.194351 | 0.172757 | 0.20373 | 0 | 0 |
| 1.36536 | 0.498665 | 1.30551 | 1.34147 | -0.406539 | -0.0137241 | 0.240637 | 0.821449 | -0.833981 | -1.13122 | 1.36746 | -0.748749 | 1.2701 | 1.18638 | -0.833501 | -0.490439 | -0.31559 | 0.28726 | -0.822435 | -0.762357 | 1.79462 | 0.172372 | 1.76366 | 1.74414 | -0.530514 | -0.12362 | -0.028181 | 0.991779 | -0.561211 | -1.00839 | 1 | 1 |
| 0.380066 | 0.0692197 | 0.404101 | 0.266596 | 0.96752 | 0.356414 | 0.726902 | 0.857221 | 0.437094 | -0.666053 | 0.255557 | -0.770185 | 0.113946 | 0.174607 | -0.245319 | -0.580828 | -0.146174 | -0.153318 | -0.80896 | -0.488298 | 0.629403 | 0.0766382 | 0.533832 | 0.492044 | 1.00047 | -0.0861629 | 0.499625 | 0.57035 | -0.107831 | -0.206293 | 1 | 1 |
| -0.486317 | -0.353185 | -0.42857 | -0.526233 | 0.69429 | 0.533852 | -0.144722 | -0.533686 | 4.8027e-05 | 1.14739 | -0.796592 | 0.475492 | -0.316228 | -0.522234 | 0.986066 | 0.393545 | 0.491629 | -0.0356186 | 0.158826 | 0.784659 | -0.698111 | -0.433394 | -0.524721 | -0.636959 | 0.584109 | 0.0656029 | -0.163957 | -0.620377 | -0.553285 | 0.545322 | 0 | 0 |
| -0.72981 | -1.11351 | -0.709283 | -0.709281 | 0.294512 | 0.159898 | -0.271202 | -0.587608 | 0.0255424 | 0.703052 | -0.437037 | 1.04465 | -0.594632 | -0.407154 | 1.69018 | 0.833117 | 0.707137 | 0.484487 | -0.266265 | 0.60758 | -0.827117 | -0.966535 | -0.849575 | -0.739243 | 0.128718 | -0.264407 | -0.453677 | -0.689644 | -0.913135 | -0.141789 | 0 | 0 |

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**Confusion Matrix Analysis:**

I've also analyzed the confusion matrix to get a clearer picture of the model's performance:

Confusion Matrix:

[[70 1]

[ 2 41]]

True Positives (TP): 41

True Negatives (TN): 70

False Positives (FP): 1

False Negatives (FN): 2

* **True Positives (TP):** 41 - The model correctly identified 41 positive cases (malignant).
* **True Negatives (TN):** 70 - The model correctly identified 70 negative cases (benign).
* **False Positives (FP):** 1 - The model incorrectly predicted 1 negative case as positive.
* **False Negatives (FN):** 2 - The model incorrectly predicted 2 positive cases as negative.

This detailed analysis provides insights into the specific predictions made by the RBF Kernel SVM and helps to understand the types of errors it makes.

I'll extract the False Positives (FP) and False Negatives (FN) from the results DataFrame to analyze the specific instances where the model made incorrect predictions.

Python

# Extract False Positives and False Negatives

fp\_df = results\_df[(results\_df['True\_Label'] == 0) & (results\_df['Predicted\_Label'] == 1)]

fn\_df = results\_df[(results\_df['True\_Label'] == 1) & (results\_df['Predicted\_Label'] == 0)]

print("False Positives (FP):")

print(fp\_df.to\_markdown(index=False, numalign="left", stralign="left"))

print("\nFalse Negatives (FN):")

print(fn\_df.to\_markdown(index=False, numalign="left", stralign="left"))

Code output

Traceback (most recent call last):

File "<string>", line 4, in <module>

ModuleNotFoundError: No module named 'xgboost'

I'm still unable to use the 'xgboost' module, so I'll extract and analyze the False Positives (FP) and False Negatives (FN) from the RBF Kernel SVM results.

Python

from sklearn.metrics import confusion\_matrix

import pandas as pd

# RBF Kernel SVM (using best parameters from previous analysis)

svm\_rbf = SVC(kernel='rbf', C=1000, gamma=0.0001, random\_state=42)

svm\_rbf.fit(X\_train\_scaled, y\_train)

y\_pred\_svm = svm\_rbf.predict(X\_test\_scaled)

# Create DataFrame with features, true labels, and predicted labels

results\_df = pd.DataFrame(X\_test\_scaled, columns=X.columns)

results\_df['True\_Label'] = y\_test.values

results\_df['Predicted\_Label'] = y\_pred\_svm

# Extract False Positives and False Negatives

fp\_df = results\_df[(results\_df['True\_Label'] == 0) & (results\_df['Predicted\_Label'] == 1)]

fn\_df = results\_df[(results\_df['True\_Label'] == 1) & (results\_df['Predicted\_Label'] == 0)]

print("False Positives (FP) Analysis:")

if (len(fp\_df) > 0):

print(fp\_df.to\_markdown(index=False, numalign="left", stralign="left"))

else:

print("No False Positives")

print("\nFalse Negatives (FN) Analysis:")

if (len(fn\_df) > 0):

print(fn\_df.to\_markdown(index=False, numalign="left", stralign="left"))

else:

print("No False Negatives")

Code output

False Positives (FP) Analysis:

| radius\_mean | texture\_mean | perimeter\_mean | area\_mean | smoothness\_mean | compactness\_mean | concavity\_mean | concave points\_mean | symmetry\_mean | fractal\_dimension\_mean | radius\_se | texture\_se | perimeter\_se | area\_se | smoothness\_se | compactness\_se | concavity\_se | concave points\_se | symmetry\_se | fractal\_dimension\_se | radius\_worst | texture\_worst | perimeter\_worst | area\_worst | smoothness\_worst | compactness\_worst | concavity\_worst | concave points\_worst | symmetry\_worst | fractal\_dimension\_worst | True\_Label | Predicted\_Label |

|:--------------|:---------------|:-----------------|:------------|:------------------|:-------------------|:-----------------|:----------------------|:----------------|:-------------------------|:------------|:-------------|:---------------|:----------|:----------------|:-----------------|:---------------|:--------------------|:--------------|:-----------------------|:---------------|:----------------|:------------------|:-------------|:-------------------|:--------------------|:------------------|:-----------------------|:-----------------|:--------------------------|:-------------|:------------------|

| 0.0289827 | 2.0334 | 0.0274851 | -0.0859606 | -0.971694 | 0.00535521 | 0.269611 | -0.11047 | -1.70807 | -0.203667 | -0.235517 | 2.07209 | -0.364078 | -0.214293 | -0.223377 | 0.151432 | 0.176776 | -0.283742 | -1.06867 | -0.0831357 | -0.100937 | 2.4766 | -0.138074 | -0.199255 | -1.01626 | -0.065497 | 0.152057 | -0.49027 | -1.60906 | -0.331375 | 0 | 1 |

False Negatives (FN) Analysis:

| radius\_mean | texture\_mean | perimeter\_mean | area\_mean | smoothness\_mean | compactness\_mean | concavity\_mean | concave points\_mean | symmetry\_mean | fractal\_dimension\_mean | radius\_se | texture\_se | perimeter\_se | area\_se | smoothness\_se | compactness\_se | concavity\_se | concave points\_se | symmetry\_se | fractal\_dimension\_se | radius\_worst | texture\_worst | perimeter\_worst | area\_worst | smoothness\_worst | compactness\_worst | concavity\_worst | concave points\_worst | symmetry\_worst | fractal\_dimension\_worst | True\_Label | Predicted\_Label |

|:--------------|:---------------|:-----------------|:------------|:------------------|:-------------------|:-----------------|:----------------------|:----------------|:-------------------------|:------------|:-------------|:---------------|:-----------|:----------------|:-----------------|:---------------|:--------------------|:--------------|:-----------------------|:---------------|:----------------|:------------------|:-------------|:-------------------|:--------------------|:------------------|:-----------------------|:-----------------|:--------------------------|:-------------|:------------------|

| -0.0899325 | -0.79671 | -0.0597746 | -0.198215 | 0.356348 | 0.465167 | -0.138676 | 0.0633938 | -0.542617 | 0.403127 | -0.435977 | -1.07583 | -0.435613 | -0.354382 | -0.744095 | -0.268232 | -0.474418 | -0.427527 | -1.02579 | -0.248002 | 0.0696834 | -0.771765 | 0.095893 | -0.1139 | 0.414964 | 0.655229 | 0.0158028 | 0.369597 | -0.500972 | 1.07314 | 1 | 0 |

| -0.0446315 | -0.501027 | -0.0186144 | -0.1466 | 0.996281 | 0.463259 | 0.113275 | 0.10995 | 0.353327 | -0.202279 | 0.0812594 | -0.72602 | -0.142708 | -0.0917952 | -0.208967 | 0.0621184 | -0.050877 | 0.242725 | 0.00569498 | -0.404248 | 0.03223 | -0.572044 | 0.0299022 | -0.0899165 | 0.853006 | 0.474402 | 0.221379 | 0.355805 | 0.25836 | -0.241069 | 1 | 0 |

Alright, I've extracted the False Positives (FP) and False Negatives (FN) from the RBF Kernel SVM results. This will help us analyze the specific instances where the model made errors.

**False Positives (FP) Analysis:**

Here's the data for the single False Positive case:

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **radius\_mean** | **texture\_mean** | **perimeter\_mean** | **area\_mean** | **smoothness\_mean** | **compactness\_mean** | **concavity\_mean** | **concave points\_mean** | **symmetry\_mean** | **fractal\_dimension\_mean** | **radius\_se** | **texture\_se** | **perimeter\_se** | **area\_se** | **smoothness\_se** | **compactness\_se** | **concavity\_se** | **concave points\_se** | **symmetry\_se** | **fractal\_dimension\_se** | **radius\_worst** | **texture\_worst** | **perimeter\_worst** | **area\_worst** | **smoothness\_worst** | **compactness\_worst** | **concavity\_worst** | **concave points\_worst** | **symmetry\_worst** | **fractal\_dimension\_worst** | **True\_Label** | **Predicted\_Label** |
| 0.0289827 | 2.0334 | 0.0274851 | -0.0859606 | -0.971694 | 0.00535521 | 0.269611 | -0.11047 | -1.70807 | -0.203667 | -0.235517 | 2.07209 | -0.364078 | -0.214293 | -0.223377 | 0.151432 | 0.176776 | -0.283742 | -1.06867 | -0.0831357 | -0.100937 | 2.4766 | -0.138074 | -0.199255 | -1.01626 | -0.065497 | 0.152057 | -0.49027 | -1.60906 | -0.331375 | 0 | 1 |

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In this case, the actual diagnosis was benign (0), but the model predicted it as malignant (1).

**False Negatives (FN) Analysis:**

Here's the data for the two False Negative cases:

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **radius\_mean** | **texture\_mean** | **perimeter\_mean** | **area\_mean** | **smoothness\_mean** | **compactness\_mean** | **concavity\_mean** | **concave points\_mean** | **symmetry\_mean** | **fractal\_dimension\_mean** | **radius\_se** | **texture\_se** | **perimeter\_se** | **area\_se** | **smoothness\_se** | **compactness\_se** | **concavity\_se** | **concave points\_se** | **symmetry\_se** | **fractal\_dimension\_se** | **radius\_worst** | **texture\_worst** | **perimeter\_worst** | **area\_worst** | **smoothness\_worst** | **compactness\_worst** | **concavity\_worst** | **concave points\_worst** | **symmetry\_worst** | **fractal\_dimension\_worst** | **True\_Label** | **Predicted\_Label** |
| -0.0899325 | -0.79671 | -0.0597746 | -0.198215 | 0.356348 | 0.465167 | -0.138676 | 0.0633938 | -0.542617 | 0.403127 | -0.435977 | -1.07583 | -0.435613 | -0.354382 | -0.744095 | -0.268232 | -0.474418 | -0.427527 | -1.02579 | -0.248002 | 0.0696834 | -0.771765 | 0.095893 | -0.1139 | 0.414964 | 0.655229 | 0.0158028 | 0.369597 | -0.500972 | 1.07314 | 1 | 0 |
| -0.0446315 | -0.501027 | -0.0186144 | -0.1466 | 0.996281 | 0.463259 | 0.113275 | 0.10995 | 0.353327 | -0.202279 | 0.0812594 | -0.72602 | -0.142708 | -0.0917952 | -0.208967 | 0.0621184 | -0.050877 | 0.242725 | 0.00569498 | -0.404248 | 0.03223 | -0.572044 | 0.0299022 | -0.0899165 | 0.853006 | 0.474402 | 0.221379 | 0.355805 | 0.25836 | -0.241069 | 1 | 0 |

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In these two cases, the actual diagnosis was malignant (1), but the model predicted it as benign (0).

Analyzing these specific errors can sometimes reveal patterns or characteristics that the model is struggling with. This insight can be valuable for further model refinement or a deeper understanding of the data.

* Query successful

I'll compare the False Positives (FP) and False Negatives (FN) with a sample of correctly classified instances (True Positives (TP) and True Negatives (TN)) to identify patterns or characteristics that distinguish the misclassified cases.

Python

from sklearn.metrics import confusion\_matrix

import pandas as pd

import numpy as np

# RBF Kernel SVM (using best parameters from previous analysis)

svm\_rbf = SVC(kernel='rbf', C=1000, gamma=0.0001, random\_state=42)

svm\_rbf.fit(X\_train\_scaled, y\_train)

y\_pred\_svm = svm\_rbf.predict(X\_test\_scaled)

# Create DataFrame with features, true labels, and predicted labels

results\_df = pd.DataFrame(X\_test\_scaled, columns=X.columns)

results\_df['True\_Label'] = y\_test.values

results\_df['Predicted\_Label'] = y\_pred\_svm

# Extract False Positives and False Negatives

fp\_df = results\_df[(results\_df['True\_Label'] == 0) & (results\_df['Predicted\_Label'] == 1)]

fn\_df = results\_df[(results\_df['True\_Label'] == 1) & (results\_df['Predicted\_Label'] == 0)]

# Sample True Positives and True Negatives for comparison

tp\_df = results\_df[(results\_df['True\_Label'] == 1) & (results\_df['Predicted\_Label'] == 1)]

tn\_df = results\_df[(results\_df['True\_Label'] == 0) & (results\_df['Predicted\_Label'] == 0)]

# sample 3 of each if there are enough

tp\_sample = tp\_df.sample(min(3, len(tp\_df)), random\_state=42)

tn\_sample = tn\_df.sample(min(3, len(tn\_df)), random\_state=42)

# Concatenate the samples for comparison

comparison\_df = pd.concat([tp\_sample, tn\_sample])

print("False Positives (FP) Analysis:")

if (len(fp\_df) > 0):

print(fp\_df.to\_markdown(index=False, numalign="left", stralign="left"))

else:

print("No False Positives")

print("\nFalse Negatives (FN) Analysis:")

if (len(fn\_df) > 0):

print(fn\_df.to\_markdown(index=False, numalign="left", stralign="left"))

else:

print("No False Negatives")

print("\nComparison with Correctly Classified Samples:")

print(comparison\_df.to\_markdown(index=False, numalign="left", stralign="left"))

Code output

Traceback (most recent call last):

File "<string>", line 4, in <module>

ModuleNotFoundError: No module named 'xgboost'

I'm still unable to use the 'xgboost' module, so I'll compare the False Positives (FP) and False Negatives (FN) with a sample of correctly classified instances (True Positives (TP) and True Negatives (TN)) using the RBF Kernel SVM results.

Python

from sklearn.metrics import confusion\_matrix

import pandas as pd

# RBF Kernel SVM (using best parameters from previous analysis)

svm\_rbf = SVC(kernel='rbf', C=1000, gamma=0.0001, random\_state=42)

svm\_rbf.fit(X\_train\_scaled, y\_train)

y\_pred\_svm = svm\_rbf.predict(X\_test\_scaled)

# Create DataFrame with features, true labels, and predicted labels

results\_df = pd.DataFrame(X\_test\_scaled, columns=X.columns)

results\_df['True\_Label'] = y\_test.values

results\_df['Predicted\_Label'] = y\_pred\_svm

# Extract False Positives and False Negatives

fp\_df = results\_df[(results\_df['True\_Label'] == 0) & (results\_df['Predicted\_Label'] == 1)]

fn\_df = results\_df[(results\_df['True\_Label'] == 1) & (results\_df['Predicted\_Label'] == 0)]

# Extract True Positives and True Negatives

tp\_df = results\_df[(results\_df['True\_Label'] == 1) & (results\_df['Predicted\_Label'] == 1)]

tn\_df = results\_df[(results\_df['True\_Label'] == 0) & (results\_df['Predicted\_Label'] == 0)]

# Sample True Positives and True Negatives (to balance the comparison)

tp\_sample = tp\_df.sample(min(5, len(tp\_df)), random\_state=42) # Adjust sample size as needed

tn\_sample = tn\_df.sample(min(5, len(tn\_df)), random\_state=42) # Adjust sample size as needed

# Concatenate samples for comparison

comparison\_df = pd.concat([fp\_df, fn\_df, tp\_sample, tn\_sample])

print("Comparison of Error Cases with Correctly Classified Instances:")

print(comparison\_df.to\_markdown(index=False, numalign="left", stralign="left"))

Code output

Comparison of Error Cases with Correctly Classified Instances:

| radius\_mean | texture\_mean | perimeter\_mean | area\_mean | smoothness\_mean | compactness\_mean | concavity\_mean | concave points\_mean | symmetry\_mean | fractal\_dimension\_mean | radius\_se | texture\_se | perimeter\_se | area\_se | smoothness\_se | compactness\_se | concavity\_se | concave points\_se | symmetry\_se | fractal\_dimension\_se | radius\_worst | texture\_worst | perimeter\_worst | area\_worst | smoothness\_worst | compactness\_worst | concavity\_worst | concave points\_worst | symmetry\_worst | fractal\_dimension\_worst | True\_Label | Predicted\_Label |

|:--------------|:---------------|:-----------------|:------------|:------------------|:-------------------|:-----------------|:----------------------|:----------------|:-------------------------|:------------|:-------------|:---------------|:-----------|:----------------|:-----------------|:---------------|:--------------------|:--------------|:-----------------------|:---------------|:----------------|:------------------|:-------------|:-------------------|:--------------------|:------------------|:-----------------------|:-----------------|:--------------------------|:-------------|:------------------|

| 0.0289827 | 2.0334 | 0.0274851 | -0.0859606 | -0.971694 | 0.00535521 | 0.269611 | -0.11047 | -1.70807 | -0.203667 | -0.235517 | 2.07209 | -0.364078 | -0.214293 | -0.223377 | 0.151432 | 0.176776 | -0.283742 | -1.06867 | -0.0831357 | -0.100937 | 2.4766 | -0.138074 | -0.199255 | -1.01626 | -0.065497 | 0.152057 | -0.49027 | -1.60906 | -0.331375 | 0 | 1 |

| -0.0899325 | -0.79671 | -0.0597746 | -0.198215 | 0.356348 | 0.465167 | -0.138676 | 0.0633938 | -0.542617 | 0.403127 | -0.435977 | -1.07583 | -0.435613 | -0.354382 | -0.744095 | -0.268232 | -0.474418 | -0.427527 | -1.02579 | -0.248002 | 0.0696834 | -0.771765 | 0.095893 | -0.1139 | 0.414964 | 0.655229 | 0.0158028 | 0.369597 | -0.500972 | 1.07314 | 1 | 0 |

| -0.0446315 | -0.501027 | -0.0186144 | -0.1466 | 0.996281 | 0.463259 | 0.113275 | 0.10995 | 0.353327 | -0.202279 | 0.0812594 | -0.72602 | -0.142708 | -0.0917952 | -0.208967 | 0.0621184 | -0.050877 | 0.242725 | 0.00569498 | -0.404248 | 0.03223 | -0.572044 | 0.0299022 | -0.0899165 | 0.853006 | 0.474402 | 0.221379 | 0.355805 | 0.25836 | -0.241069 | 1 | 0 |

| 0.663197 | 0.217061 | 0.716919 | 0.503514 | 0.184501 | 0.991755 | 1.13884 | 1.06212 | -0.0618668 | 0.0657102 | -0.347591 | 0.15026 | -0.181859 | -0.179748 | -0.118578 | 0.823432 | 0.650457 | 0.991868 | -0.459822 | 0.274255 | 0.323534 | 0.481033 | 0.491838 | 0.183781 | 0.432312 | 1.38177 | 1.48974 | 1.36877 | 0.236166 | 0.635067 | 1 | 1 |

| 0.272476 | 1.53825 | 0.251808 | 0.175495 | 0.478582 | -0.113127 | 0.435899 | 0.453732 | -0.597248 | 0.261495 | 0.888756 | 0.560496 | 0.635955 | 0.49378 | 1.15636 | -0.0713132 | 0.507512 | 0.885302 | 0.0767476 | 0.375905 | 0.473347 | 1.26836 | 0.422848 | 0.305111 | 1.49489 | -0.110704 | 0.613409 | 0.58874 | -0.397931 | 0.589634 | 1 | 1 |

| 1.82121 | 0.393064 | 1.88999 | 1.84351 | 0.636768 | 1.34091 | 1.50669 | 2.20736 | 1.15093 | -0.034265 | 1.04856 | -0.392841 | 0.893092 | 1.01111 | -0.789617 | 0.0282225 | 0.225047 | 0.368378 | -0.13396 | -0.406404 | 1.6781 | -0.00919252 | 1.59268 | 1.64362 | -0.205235 | 0.392384 | 0.806555 | 1.54193 | 0.272627 | -0.458701 | 1 | 1 |

| 0.578258 | 0.552639 | 0.589323 | 0.438362 | 0.363538 | 0.472798 | 0.194026 | 0.206483 | 1.27112 | -0.534141 | 0.11025 | 0.115149 | -0.00688926 | 0.0764808 | -0.691696 | -0.32903 | -0.331161 | -0.42355 | -0.639904 | -0.519907 | 0.673099 | 1.01417 | 0.677812 | 0.525551 | 0.345571 | 0.340719 | 0.117635 | 0.260792 | 0.91148 | -0.430656 | 1 | 1 |

| 0.977473 | -0.970366 | 0.951533 | 0.848174 | 0.196005 | 0.230491 | 0.124109 | 0.821975 | -0.262179 | -0.175897 | 0.701023 | -0.702551 | 0.868442 | 0.445671 | -0.446074 | 0.252581 | 0.038814 | 0.261812 | -0.162136 | -0.0281802 | 0.785459 | -0.992944 | 0.83379 | 0.617254 | -0.261617 | 0.183786 | -0.122842 | 0.481467 | -0.236236 | -0.262384 | 1 | 1 |

| -1.11487 | -0.388386 | -1.10154 | -0.962558 | 0.744622 | -0.354862 | -0.897174 | -0.766205 | 0.360611 | 0.878009 | -0.549111 | 0.0264495 | -0.588349 | -0.530288 | 0.297997 | -0.626023 | -0.756446 | -0.67915 | 0.710096 | -0.0213557 | -1.05392 | -0.444948 | -1.05475 | -0.884205 | 0.393278 | -0.702268 | -0.998598 | -0.895455 | 0.237752 | 0.230093 | 0 | 0 |

| -0.466497 | -0.137289 | -0.444211 | -0.486465 | 0.28085 | 0.0416059 | -0.111465 | -0.264869 | 0.415241 | 0.135137 | -0.0209151 | -0.293239 | -0.174609 | -0.2073 | -0.0118143 | -0.351089 | -0.181053 | -0.242388 | -0.337318 | -0.0842133 | -0.263235 | -0.147842 | -0.331548 | -0.351093 | 0.480019 | -0.0964959 | -0.0358304 | -0.194351 | 0.172757 | 0.20373 | 0 | 0 |

| -0.183366 | -1.20269 | -0.187783 | -0.304828 | 0.816525 | 0.226675 | -0.391005 | 0.115211 | -0.116497 | 0.50449 | -0.859877 | -1.16305 | -0.84887 | -0.577125 | -0.831536 | -0.598045 | -0.606774 | -0.493534 | -0.440221 | -0.371203 | -0.292366 | -1.19101 | -0.364843 | -0.382308 | 0.336897 | -0.0183527 | -0.429294 | 0.296039 | 0.510414 | 0.526812 | 0 | 0 |

| -0.0616194 | -0.601935 | -0.119869 | -0.155062 | -1.97474 | -0.962156 | -0.839729 | -0.917711 | 0.00733212 | -1.02707 | -0.871544 | -1.15769 | -0.708701 | -0.551905 | -1.20554 | -0.671756 | -0.713781 | -1.12323 | -0.908188 | -0.61976 | -0.227863 | -0.61661 | -0.177069 | -0.278789 | -1.63473 | -0.336738 | -0.651126 | -0.796304 | -0.3583 | -0.386344 | 0 | 0 |

| -0.585413 | 0.829549 | -0.540526 | -0.582642 | -1.8978 | 0.0702248 | -0.119275 | -0.486604 | -2.21432 | 0.532261 | -0.999174 | 0.427446 | -0.522131 | -0.646873 | -0.637659 | 1.07415 | 0.318476 | 0.75965 | 0.505513 | 1.27064 | -0.762614 | 0.523948 | -0.592211 | -0.68528 | -1.88845 | 0.443403 | 0.0793881 | -0.0763509 | -1.1319 | 0.539713 | 0 | 0 |

I've compared the False Positives (FP) and False Negatives (FN) with a sample of correctly classified instances (True Positives (TP) and True Negatives (TN)). This comparison is presented in the following table:

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **radius\_mean** | **texture\_mean** | **perimeter\_mean** | **area\_mean** | **smoothness\_mean** | **compactness\_mean** | **concavity\_mean** | **concave points\_mean** | **symmetry\_mean** | **fractal\_dimension\_mean** | **radius\_se** | **texture\_se** | **perimeter\_se** | **area\_se** | **smoothness\_se** | **compactness\_se** | **concavity\_se** | **concave points\_se** | **symmetry\_se** | **fractal\_dimension\_se** | **radius\_worst** | **texture\_worst** | **perimeter\_worst** | **area\_worst** | **smoothness\_worst** | **compactness\_worst** | **concavity\_worst** | **concave points\_worst** | **symmetry\_worst** | **fractal\_dimension\_worst** | **True\_Label** | **Predicted\_Label** |
| 0.0289827 | 2.0334 | 0.0274851 | -0.0859606 | -0.971694 | 0.00535521 | 0.269611 | -0.11047 | -1.70807 | -0.203667 | -0.235517 | 2.07209 | -0.364078 | -0.214293 | -0.223377 | 0.151432 | 0.176776 | -0.283742 | -1.06867 | -0.0831357 | -0.100937 | 2.4766 | -0.138074 | -0.199255 | -1.01626 | -0.065497 | 0.152057 | -0.49027 | -1.60906 | -0.331375 | 0 | 1 |
| -0.0899325 | -0.79671 | -0.0597746 | -0.198215 | 0.356348 | 0.465167 | -0.138676 | 0.0633938 | -0.542617 | 0.403127 | -0.435977 | -1.07583 | -0.435613 | -0.354382 | -0.744095 | -0.268232 | -0.474418 | -0.427527 | -1.02579 | -0.248002 | 0.0696834 | -0.771765 | 0.095893 | -0.1139 | 0.414964 | 0.655229 | 0.0158028 | 0.369597 | -0.500972 | 1.07314 | 1 | 0 |
| -0.0446315 | -0.501027 | -0.0186144 | -0.1466 | 0.996281 | 0.463259 | 0.113275 | 0.10995 | 0.353327 | -0.202279 | 0.0812594 | -0.72602 | -0.142708 | -0.0917952 | -0.208967 | 0.0621184 | -0.050877 | 0.242725 | 0.00569498 | -0.404248 | 0.03223 | -0.572044 | 0.0299022 | -0.0899165 | 0.853006 | 0.474402 | 0.221379 | 0.355805 | 0.25836 | -0.241069 | 1 | 0 |
| 0.663197 | 0.217061 | 0.716919 | 0.503514 | 0.184501 | 0.991755 | 1.13884 | 1.06212 | -0.0618668 | 0.0657102 | -0.347591 | 0.15026 | -0.181859 | -0.179748 | -0.118578 | 0.823432 | 0.650457 | 0.991868 | -0.459822 | 0.274255 | 0.323534 | 0.481033 | 0.491838 | 0.183781 | 0.432312 | 1.38177 | 1.48974 | 1.36877 | 0.236166 | 0.635067 | 1 | 1 |
| 0.272476 | 1.53825 | 0.251808 | 0.175495 | 0.478582 | -0.113127 | 0.435899 | 0.453732 | -0.597248 | 0.261495 | 0.888756 | 0.560496 | 0.635955 | 0.49378 | 1.15636 | -0.0713132 | 0.507512 | 0.885302 | 0.0767476 | 0.375905 | 0.473347 | 1.26836 | 0.422848 | 0.305111 | 1.49489 | -0.110704 | 0.613409 | 0.58874 | -0.397931 | 0.589634 | 1 | 1 |
| 1.82121 | 0.393064 | 1.88999 | 1.84351 | 0.636768 | 1.34091 | 1.50669 | 2.20736 | 1.15093 | -0.034265 | 1.04856 | -0.392841 | 0.893092 | 1.01111 | -0.789617 | 0.0282225 | 0.225047 | 0.368378 | -0.13396 | -0.406404 | 1.6781 | -0.00919252 | 1.59268 | 1.64362 | -0.205235 | 0.392384 | 0.806555 | 1.54193 | 0.272627 | -0.458701 | 1 | 1 |
| 0.578258 | 0.552639 | 0.589323 | 0.438362 | 0.363538 | 0.472798 | 0.194026 | 0.206483 | 1.27112 | -0.534141 | 0.11025 | 0.115149 | -0.00688926 | 0.0764808 | -0.691696 | -0.32903 | -0.331161 | -0.42355 | -0.639904 | -0.519907 | 0.673099 | 1.01417 | 0.677812 | 0.525551 | 0.345571 | 0.340719 | 0.117635 | 0.260792 | 0.91148 | -0.430656 | 1 | 1 |
| 0.977473 | -0.970366 | 0.951533 | 0.848174 | 0.196005 | 0.230491 | 0.124109 | 0.821975 | -0.262179 | -0.175897 | 0.701023 | -0.702551 | 0.868442 | 0.445671 | -0.446074 | 0.252581 | 0.038814 | 0.261812 | -0.162136 | -0.0281802 | 0.785459 | -0.992944 | 0.83379 | 0.617254 | -0.261617 | 0.183786 | -0.122842 | 0.481467 | -0.236236 | -0.262384 | 1 | 1 |
| -1.11487 | -0.388386 | -1.10154 | -0.962558 | 0.744622 | -0.354862 | -0.897174 | -0.766205 | 0.360611 | 0.878009 | -0.549111 | 0.0264495 | -0.588349 | -0.530288 | 0.297997 | -0.626023 | -0.756446 | -0.67915 | 0.710096 | -0.0213557 | -1.05392 | -0.444948 | -1.05475 | -0.884205 | 0.393278 | -0.702268 | -0.998598 | -0.895455 | 0.237752 | 0.230093 | 0 | 0 |
| -0.466497 | -0.137289 | -0.444211 | -0.486465 | 0.28085 | 0.0416059 | -0.111465 | -0.264869 | 0.415241 | 0.135137 | -0.0209151 | -0.293239 | -0.174609 | -0.2073 | -0.0118143 | -0.351089 | -0.181053 | -0.242388 | -0.337318 | -0.0842133 | -0.263235 | -0.147842 | -0.331548 | -0.351093 | 0.480019 | -0.0964959 | -0.0358304 | -0.194351 | 0.172757 | 0.20373 | 0 | 0 |
| -0.183366 | -1.20269 | -0.187783 | -0.304828 | 0.816525 | 0.226675 |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |

Python

import numpy as np

# RBF Kernel SVM

svm\_rbf = SVC(kernel='rbf', C=1000, gamma=0.0001, random\_state=42)

svm\_rbf.fit(X\_train\_scaled, y\_train)

y\_pred\_svm = svm\_rbf.predict(X\_test\_scaled)

# Create DataFrame with features, true labels, and predicted labels

detailed\_results = X\_test.copy()

detailed\_results['True\_Label'] = y\_test.values

detailed\_results['Predicted\_Label'] = y\_pred\_svm

# Calculate TP, TN, FP, FN

cm = confusion\_matrix(y\_test, y\_pred\_svm)

TP = cm[1, 1]

TN = cm[0, 0]

FP = cm[0, 1]

FN = cm[1, 0]

print("Detailed Results with RBF Kernel SVM:")

print(detailed\_results.head().to\_markdown(index=False, numalign="left", stralign="left"))

print("\nConfusion Matrix:")

print(cm)

print(f"\nTrue Positives (TP): {TP}")

print(f"True Negatives (TN): {TN}")

print(f"False Positives (FP): {FP}")

print(f"False Negatives (FN): {FN}")

Code output

Traceback (most recent call last):

File "<string>", line 4, in <module>

ModuleNotFoundError: No module named 'xgboost'