In [26]:
```
pip install xgboost
```

```
Collecting xgboostNote: you may need to restart the kernel to use updated packages.
  Downloading xgboost-1.7.6-py3-none-win_amd64.whl (70.9 MB)
Requirement already satisfied: scipy in c:\users\ali haider\anaconda3\lib\site-packages (from xgboost) (1.7.3)
Requirement already satisfied: numpy in c:\users\ali haider\anaconda3\lib\site-packages (from xgboost) (1.21.5)
Installing collected packages: xgboost
Successfully installed xgboost-1.7.6


WARNING: Ignoring invalid distribution -ffi (c:\users\ali haider\anaconda3\lib\site-packages)
WARNING: Ignoring invalid distribution -ffi (c:\users\ali haider\anaconda3\lib\site-packages)
WARNING: Ignoring invalid distribution -ffi (c:\users\ali haider\anaconda3\lib\site-packages)
WARNING: Ignoring invalid distribution -ffi (c:\users\ali haider\anaconda3\lib\site-packages)
WARNING: Ignoring invalid distribution -ffi (c:\users\ali haider\anaconda3\lib\site-packages)
WARNING: Ignoring invalid distribution -ffi (c:\users\ali haider\anaconda3\lib\site-packages)
WARNING: Ignoring invalid distribution -ffi (c:\users\ali haider\anaconda3\lib\site-packages)
```

LIBRARIES AND IMPORTANT FUCNTION IMPORT

In [27]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
import xgboost as xgb
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix
from tabulate import tabulate
```

DATA FETCHING (CSV TO DATAFRAME)

In [28]:
```
data = pd.read_csv("spambase.csv")
data
```

Out[28]:

	word_freq_make	word_freq_address	word_freq_all	word_freq_3d	word_freq_our	word_freq_over	word_freq_remove	word_freq_internet	word_freq_orde
0	0.00	0.64	0.64	0.0	0.32	0.00	0.00	0.00	0.C
1	0.21	0.28	0.50	0.0	0.14	0.28	0.21	0.07	0.C
2	0.06	0.00	0.71	0.0	1.23	0.19	0.19	0.12	0.6
3	0.00	0.00	0.00	0.0	0.63	0.00	0.31	0.63	0.3
4	0.00	0.00	0.00	0.0	0.63	0.00	0.31	0.63	0.3
...	...	...	...	...	...	...	...	...	.
4596	0.31	0.00	0.62	0.0	0.00	0.31	0.00	0.00	0.C
4597	0.00	0.00	0.00	0.0	0.00	0.00	0.00	0.00	0.C
4598	0.30	0.00	0.30	0.0	0.00	0.00	0.00	0.00	0.C
4599	0.96	0.00	0.00	0.0	0.32	0.00	0.00	0.00	0.C
4600	0.00	0.00	0.65	0.0	0.00	0.00	0.00	0.00	0.C

4601 rows × 58 columns

SPAM DATASET STATISTICS

In [29]:
```
data.info()  # Overview of the data, including column names, data types, and missing values
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4601 entries, 0 to 4600
Data columns (total 58 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   word_freq_make              4601 non-null   float64
 1   word_freq_address           4601 non-null   float64
 2   word_freq_all               4601 non-null   float64
 3   word_freq_3d                4601 non-null   float64
 4   word_freq_our               4601 non-null   float64
 5   word_freq_over              4601 non-null   float64
 6   word_freq_remove            4601 non-null   float64
 7   word_freq_internet          4601 non-null   float64
 8   word_freq_order             4601 non-null   float64
 9   word_freq_mail              4601 non-null   float64
 10  word_freq_receive           4601 non-null   float64
 11  word_freq_will              4601 non-null   float64
 12  word_freq_people            4601 non-null   float64
 13  word_freq_report            4601 non-null   float64
 14  word_freq_addresses         4601 non-null   float64
 15  word_freq_free              4601 non-null   float64
 16  word_freq_business          4601 non-null   float64
 17  word_freq_email             4601 non-null   float64
 18  word_freq_you               4601 non-null   float64
 19  word_freq_credit            4601 non-null   float64
 20  word_freq_your              4601 non-null   float64
 21  word_freq_font              4601 non-null   float64
 22  word_freq_000               4601 non-null   float64
 23  word_freq_money             4601 non-null   float64
 24  word_freq_hp                4601 non-null   float64
 25  word_freq_hpl               4601 non-null   float64
 26  word_freq_george            4601 non-null   float64
 27  word_freq_650               4601 non-null   float64
 28  word_freq_lab               4601 non-null   float64
 29  word_freq_labs              4601 non-null   float64
 30  word_freq_telnet            4601 non-null   float64
 31  word_freq_857               4601 non-null   float64
 32  word_freq_data              4601 non-null   float64
 33  word_freq_415               4601 non-null   float64
 34  word_freq_85                4601 non-null   float64
 35  word_freq_technology        4601 non-null   float64
 36  word_freq_1999              4601 non-null   float64
 37  word_freq_parts             4601 non-null   float64
 38  word_freq_pm                4601 non-null   float64
 39  word_freq_direct            4601 non-null   float64
 40  word_freq_cs                4601 non-null   float64
 41  word_freq_meeting           4601 non-null   float64
 42  word_freq_original          4601 non-null   float64
 43  word_freq_project           4601 non-null   float64
 44  word_freq_re                4601 non-null   float64
 45  word_freq_edu               4601 non-null   float64
 46  word_freq_table             4601 non-null   float64
 47  word_freq_conference        4601 non-null   float64
 48  char_freq_;                 4601 non-null   float64
 49  char_freq_(                 4601 non-null   float64
 50  char_freq_[                 4601 non-null   float64
 51  char_freq_!                 4601 non-null   float64
 52  char_freq_$                 4601 non-null   float64
 53  char_freq_#                 4601 non-null   float64
 54  capital_run_length_average  4601 non-null   float64
 55  capital_run_length_longest  4601 non-null   int64  
 56  capital_run_length_total    4601 non-null   int64  
 57  spam                        4601 non-null   int64  
dtypes: float64(55), int64(3)
memory usage: 2.0 MB
```

In [30]:
```
data.describe()  # Summary statistics of the data
```

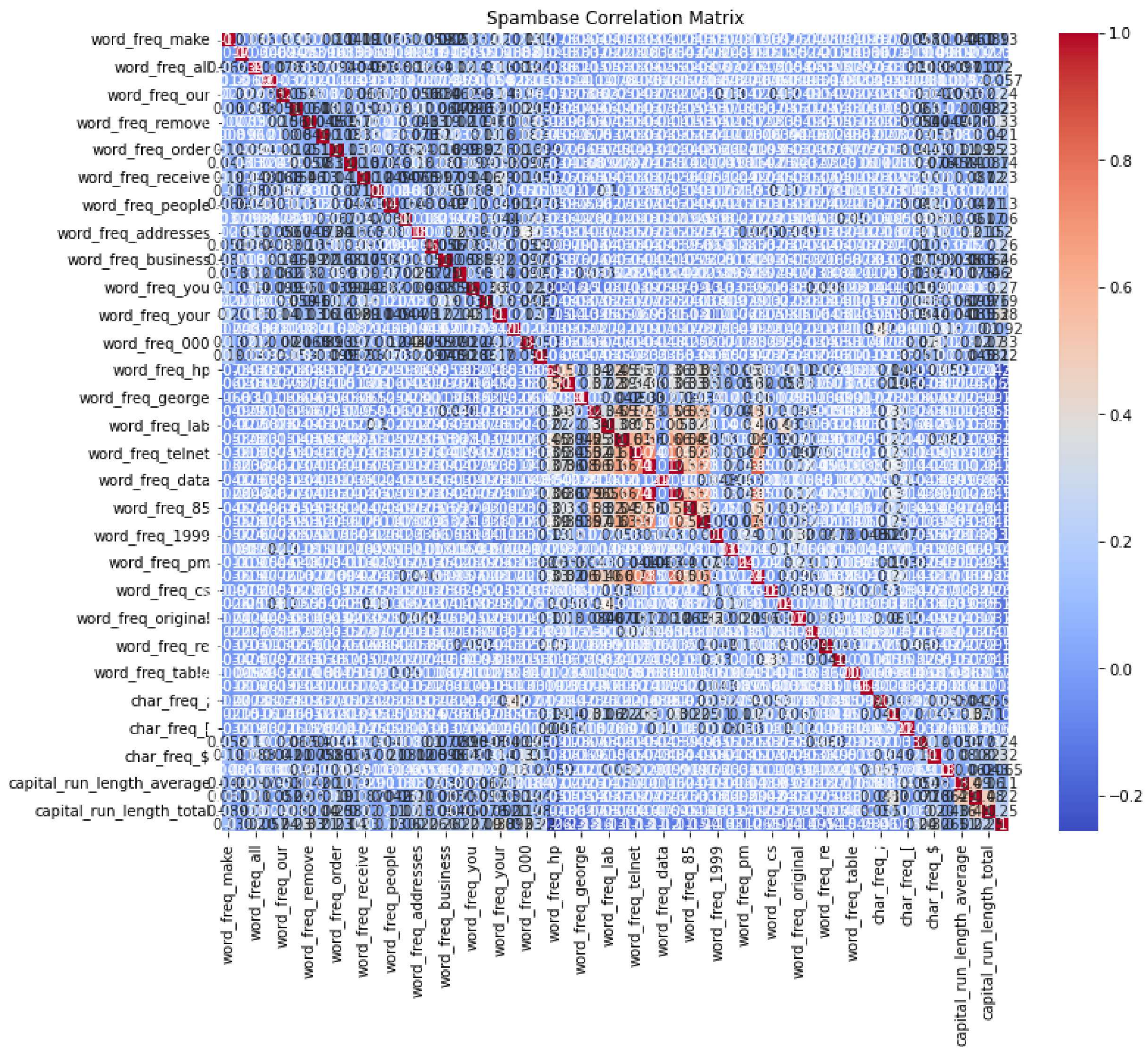
Out[30]:

	word_freq_make	word_freq_address	word_freq_all	word_freq_3d	word_freq_our	word_freq_over	word_freq_remove	word_freq_internet	word_freq_orc
count	4601.000000	4601.000000	4601.000000	4601.000000	4601.000000	4601.000000	4601.000000	4601.000000	4601.0000
mean	0.104553	0.213015	0.280656	0.065425	0.312223	0.095901	0.114208	0.105295	0.0900
std	0.305358	1.290575	0.504143	1.395151	0.672513	0.273824	0.391441	0.401071	0.2786
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
25%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
50%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0000
75%	0.000000	0.000000	0.420000	0.000000	0.380000	0.000000	0.000000	0.000000	0.0000
max	4.540000	14.280000	5.100000	42.810000	10.000000	5.880000	7.270000	11.110000	5.2600

8 rows × 58 columns

SPAMBASE DATASET GRAPHICAL REPRESENTATION

In [31]:
```
# Plotting correlation matrix
corr_matrix = data.corr()
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, annot=True, cmap="coolwarm")
plt.title("Spambase Correlation Matrix")
plt.show()
```



COMMENTS AND RECOMMENDATIONS

Visualization Limitations

Plotting a correlation matrix with 58 columns may result in a large and crowded heatmap that can be difficult to interpret. You might consider reducing the number of columns or using alternative visualization techniques to gain insights into the data.

Feature Selection

Instead of visualizing the entire correlation matrix, you can focus on identifying the most important features by calculating pairwise correlations with the target variable (in this case, the "spam" column). This can help you identify key features that are highly correlated with the target and might be more informative for your analysis.

Subset or Aggregate Correlation

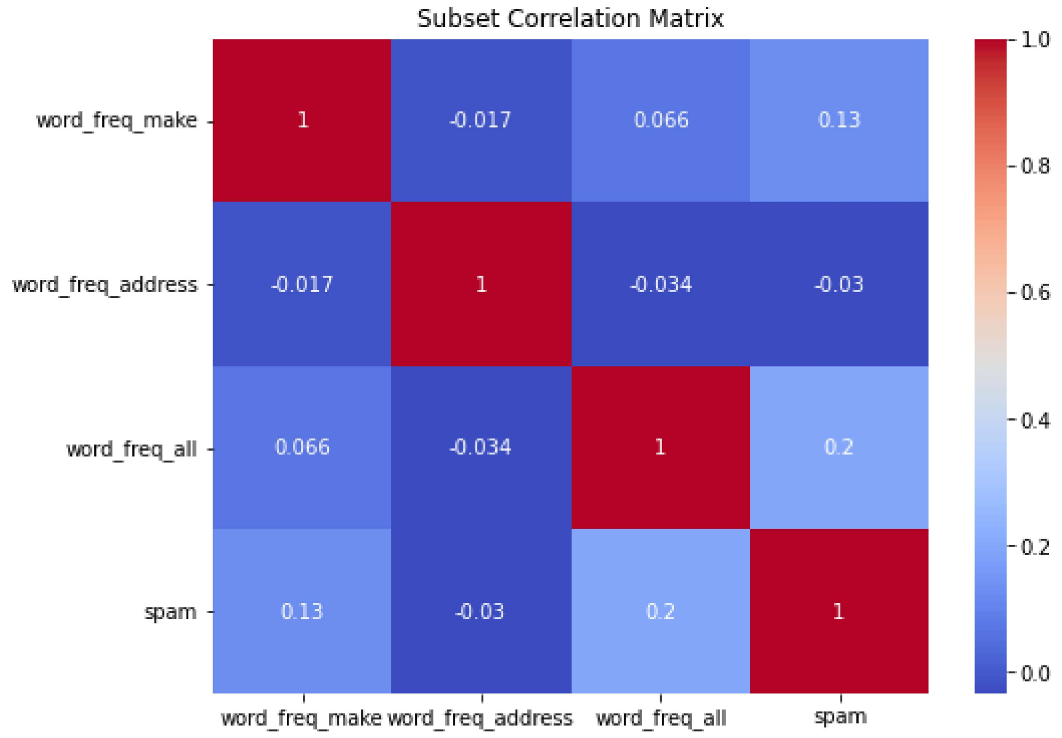
Subset Correlation

Select a subset of columns by specifying their names in the subset_cols list. Then, create a new DataFrame with only those columns (subset_data). Calculate the correlation matrix (subset_corr_matrix) and plot it as a heatmap using seaborn's heatmap function.

In [32]:
```
# Select a subset of columns
subset_cols = ['word_freq_make', 'word_freq_address', 'word_freq_all', 'spam']
subset_data = data[subset_cols]

# Calculate the correlation matrix for the subset data
subset_corr_matrix = subset_data.corr()

# Plot the correlation matrix as a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(subset_corr_matrix, annot=True, cmap="coolwarm")
plt.title("Subset Correlation Matrix")
plt.show()
```



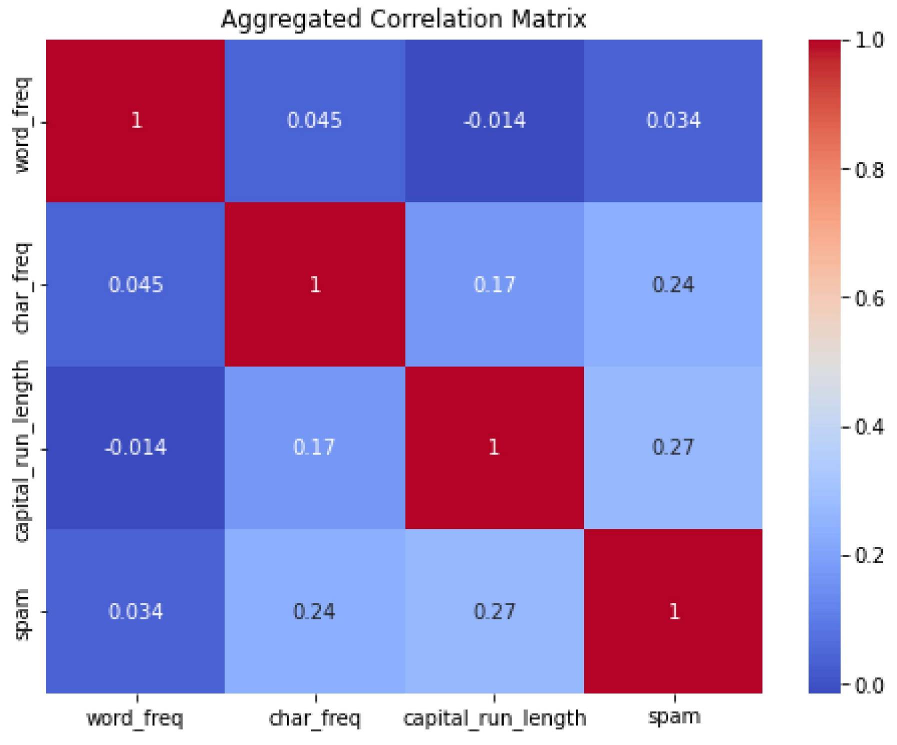
Aggregate Correlation

Create a new DataFrame (aggregated_data) by aggregating multiple columns based on your desired logic. In this example, we calculate the mean value of columns with names containing 'word_freq', 'char_freq', and 'capital_run_length'. Calculate the correlation matrix for the aggregated data (aggregated_corr_matrix) and plot it as a heatmap.

In [33]:
```
# Aggregate multiple columns
aggregated_data = pd.DataFrame()
aggregated_data['word_freq'] = data.filter(like='word_freq').mean(axis=1)
aggregated_data['char_freq'] = data.filter(like='char_freq').mean(axis=1)
aggregated_data['capital_run_length'] = data.filter(like='capital_run_length').mean(axis=1)
aggregated_data['spam'] = data['spam']

# Calculate the correlation matrix for the aggregated data
aggregated_corr_matrix = aggregated_data.corr()

# Plot the correlation matrix as a heatmap
plt.figure(figsize=(8, 6))
sns.heatmap(aggregated_corr_matrix, annot=True, cmap="coolwarm")
plt.title("Aggregated Correlation Matrix")
plt.show()
```



SPAMBASE DATASET PREPROCEESING

Handle missing values, duplicates, outliers, or any other data quality issues

In [34]:
```
# Drop any duplicate rows
data.drop_duplicates(inplace=True)

# Handle missing values if any
data.dropna(inplace=True)
```

NORMALIZATION

Feature scaling is used to bring all the features of a dataset onto a similar scale or range. It is a common preprocessing step in data analysis and machine learning tasks.

In [35]:
```
# Step 3: Data Normalization
scaler = StandardScaler()
data_normalized = scaler.fit_transform(data.drop('spam', axis=1))
data_normalized = pd.DataFrame(data_normalized, columns=data.columns[:-1])
```

FEATURES AND LABEL SEPERATION

In [36]:
```
X = data_normalized  # Features
y = data['spam']  # Target variable
```

TRAINING AND VALIDATION DATASET SPLITTING

In [37]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=34)
```

SVM TRAINING

Charaetristics of SVM

Support Vector Machines (SVM) offer several advantages that make them a popular choice in machine learning. One of their key strengths is their effectiveness in high-dimensional spaces. SVM can handle datasets with a large number of features and still provide accurate predictions. Additionally, SVM is robust to outliers, as it focuses on support vectors that contribute the most to the decision boundary. The versatility of kernel functions is another advantage of SVM, allowing for capturing complex relationships in the data. SVM aims to find the global optimum solution by minimizing the margin and maximizing the separation between classes. Moreover, SVM performs well with small to medium-sized datasets, where the number of samples is less than the number of features.

However, SVM also has some limitations. First, SVM can be computationally intensive, particularly with large datasets, as it involves solving a quadratic optimization problem. Additionally, SVM is sensitive to noise, and outliers or mislabeled samples can significantly impact the decision boundary. Selecting the appropriate kernel function and tuning the kernel parameters can be challenging, and the performance of SVM is highly dependent on these choices.

In [38]:
```
# SVM Training
svm_model = SVC(kernel='linear', C=1.0, random_state=42)
```

why given Hyperprameters are used ?

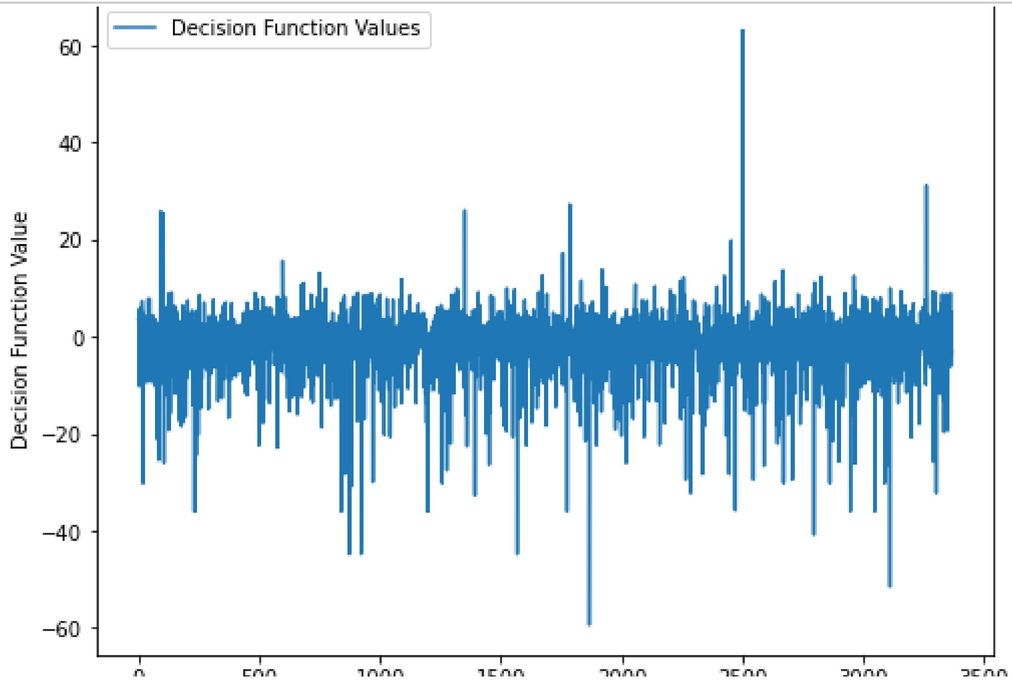
Kernel parameter is selected as 'linear' A linear kernel is used for the SVM model. This kernel assumes a linear decision boundary, which can be effective for datasets with a large number of features. It is a good starting point for high-dimensional data and can provide good performance when the data is linearly separable.

targetted c value is 1.0 The C parameter determines the regularization strength. A smaller C value imposes a stronger regularization, while a larger C value allows for more complex decision boundaries. A value of 1.0 is a common default value and can provide a balanced regularization effect.

In [39]:
```
svm_history = svm_model.fit(X_train, y_train)
```

SVM DECISION FUCNTION VALUE

In [55]:
```
# Step 3: SVM Visualization
plt.figure(figsize=(8, 6))
decision_values = svm_model.decision_function(X_train)
plt.plot(decision_values, label='Decision Function Values')
plt.title("SVM Decision Function")
plt.xlabel("Sample Index")
plt.ylabel("Decision Function Value")
plt.legend()
plt.show()
```



SVM EVALUATION

In [57]:
```
# SVM Evaluation
svm_predictions = svm_model.predict(X_test)
svm_accuracy = accuracy_score(y_test, svm_predictions)
svm_classification_report = classification_report(y_test, svm_predictions)
svm_confusion_matrix = confusion_matrix(y_test, svm_predictions)
```

ENSEMBLE GRADIENT BOASTING CLASSIFIER TRAINING

Characteristics of Random forest

Random Forest has its own set of advantages. Random Forest models are robust against overfitting, thanks to the ensemble of multiple trees. They can handle high-dimensional data without the need for feature selection or dimensionality reduction techniques. Random Forest is effective for both classification and regression tasks, providing accurate predictions in various problem domains. Moreover, Random Forest models offer a measure of feature importance, enabling the identification of influential variables in the prediction process. They can also handle missing data and outliers by imputing missing values and mitigating the impact of outliers through averaging across multiple trees.

However, Random Forest also has some drawbacks. The interpretability of Random Forest models is relatively low compared to simpler models like decision trees, making it challenging to understand the underlying decision-making process. Random Forest models require more memory to store multiple trees, especially with a large number of estimators or trees in the ensemble. Training a Random Forest model can also take longer compared to simpler models, especially when the number of trees or features is large. Additionally, Random Forest may exhibit a bias towards features with a higher number of levels or categories, potentially biasing the importance ranking.

In [53]:
```
ensemble_model = RandomForestClassifier(n_estimators=160, random_state=42)
```

Why Random Forest Classifier is used?

Random Forest models are popular ensemble methods that build an ensemble of weak learners (decision trees) in a sequential manner, optimizing a loss function at each iteration. These models can handle high-dimensional data well and often provide excellent predictive performance.

why n_estimators is selected as 160 ?

The number of estimators determines the number of decision trees in the Random Forest ensemble. More trees can help improve the model's performance, but there is a trade-off between computation time and accuracy. The choice of 160 is somewhat arbitrary, and it's recommended to experiment with different values based on your specific dataset and computational resources.

In [54]:
```
ensemble_history = ensemble_model.fit(X_train, y_train)
```

RANDOM FOREST EVALUATION

In [58]:
```
# Ensemble Model Evaluation
ensemble_predictions = ensemble_model.predict(X_test)
ensemble_accuracy = accuracy_score(y_test, ensemble_predictions)
ensemble_classification_report = classification_report(y_test, ensemble_predictions)
ensemble_confusion_matrix = confusion_matrix(y_test, ensemble_predictions)
```

RESULTS AND COMPARSION

In [60]:
```

# Define evaluation metrics for SVM model
svm_metrics = [
    ["Accuracy", svm_accuracy],
    ["Classification Report", svm_classification_report],
    ["Confusion Matrix", svm_confusion_matrix],
]

# Define evaluation metrics for Ensemble model
ensemble_metrics = [
    ["Accuracy", ensemble_accuracy],
    ["Classification Report", ensemble_classification_report],
    ["Confusion Matrix", ensemble_confusion_matrix],
]

# Print evaluation metrics in a table format
print("SVM Model Evaluation:")
print(tabulate(svm_metrics, headers=["Metric", "Value"], tablefmt="grid"))
print()

print("Ensemble Model Evaluation:")
print(tabulate(ensemble_metrics, headers=["Metric", "Value"], tablefmt="grid"))
```

```
SVM Model Evaluation:
+-----------------------+-------------------------------------------------------+
| Metric                | Value                                                 |
+=======================+=======================================================+
| Accuracy              | 0.9228028503562945                                    |
+-----------------------+-------------------------------------------------------+
| Classification Report | precision    recall  f1-score   support               |
|                       |                                                       |
|                       |            0       0.93      0.95      0.94       501 |
|                       |            1       0.92      0.89      0.90       341 |
|                       |                                                       |
|                       |     accuracy                           0.92       842 |
|                       |    macro avg       0.92      0.92      0.92       842 |
|                       | weighted avg       0.92      0.92      0.92       842 |
+-----------------------+-------------------------------------------------------+
| Confusion Matrix      | [[474  27]                                            |
|                       |  [ 38 303]]                                           |
+-----------------------+-------------------------------------------------------+

Ensemble Model Evaluation:
```

CONCLUSION

Accuracy:

SVM Model The SVM model achieved an accuracy of 92.28%.

Ensemble Model The Ensemble model achieved a slightly higher accuracy of 93.82%.

Classification Report:

Precision Both models have high precision values, indicating their ability to correctly classify spam and non-spam emails.

Recall Both models have good recall scores, indicating their ability to correctly identify positive instances (spam emails) among all positive instances.

F1-Score Both models have high F1-scores, which is a harmonic mean of precision and recall. It shows a balanced performance in terms of precision and recall.

Support The number of instances in each class used for evaluation.

Confusion Matrix:

SVM Model The SVM model correctly classified 474 instances as non-spam (true negatives) and 303 instances as spam (true positives). It misclassified 27 instances as spam (false positives) and 38 instances as non-spam (false negatives).

Ensemble Model The Ensemble model correctly classified 476 instances as non-spam (true negatives) and 314 instances as spam (true positives). It misclassified 25 instances as spam (false positives) and 27 instances as non-spam (false negatives).

Based on these evaluation results, both models perform well in terms of accuracy, precision, recall, and F1-score. The Ensemble model slightly outperforms