Informatics Institute of Technology
Department of Computing

Bsc(Hons) Artificial Intelligence and Data Science

Module: CM2604 Machine Learning

Module Coordinator: Mr. Prasan Yapa

Coursework Report

Vinuwara Ronath Jayasuriya
RGU ID – 2119942
IIT Student No. – 20210167

Spam dataset is done using the Decision Trees Classification and K Nearest Neighbors Classification (KNN)
Preprocessing techniques

Corpus Preparation

Data Cleaning: This was done by removing duplicates and null values from the dataset.

Removing duplicate in dataset.

Getting the duplicates in the dataset
Data_set.duplicated()
0 False 1 False 2 False 3 False 4 False ... 4596 False 4597 False 4598 False 4599 False 4600 False Length: 4601, dtype: bool
removing the duplicate values
Data_set.drop_duplicates(inplace=True)

Removing null values

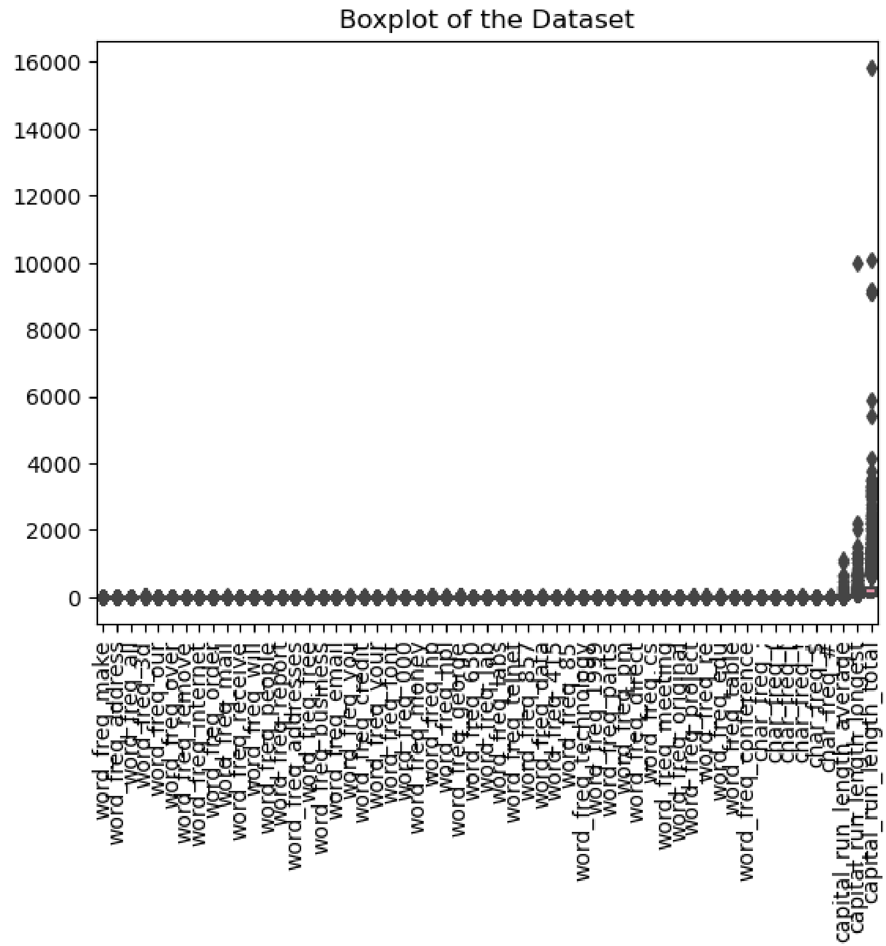
Data_set.isna().sum()
word_freq_make 0 word_freq_address 0 word_freq_all 0 word_freq_3d 0 word_freq_our 0 word_freq_over 0 word_freq_remove 0 word_freq_internet 0 word_freq_order 0 word_freq_mail 0 word_freq_receive 0 word_freq_will 0 word_freq_people 0 word_freq_report 0 word_freq_addresses 0 word_freq_free 0 word_freq_business 0 word_freq_email 0 word_freq_you 0

```
word_freq_credit             0
word_freq_your               0
word_freq_font               0
word_freq_000                0
word_freq_money              0
word_freq_hp                 0
word_freq_hpl                0
word_freq_george             0
word_freq_650                0
word_freq_lab                0
word_freq_labs               0
word_freq_telnet             0
word_freq_857                0
word_freq_data               0
word_freq_415                0
word_freq_85                 0
word_freq_technology         0
word_freq_1999               0
word_freq_parts              0
word_freq_pm                 0
word_freq_direct             0
word_freq_cs                 0
word_freq_meeting            0
word_freq_original           0
word_freq_project            0
word_freq_re                 0
word_freq_edu                0
word_freq_table              0
word_freq_conference         0
char_freq_;                  0
char_freq_(                  0
char_freq_[                  0
char_freq_!                  0
char_freq_$                  0
char_freq_#                  0
capital_run_length_average   0
capital_run_length_longest   0
capital_run_length_total     0
spam                         0
dtype: int64
```

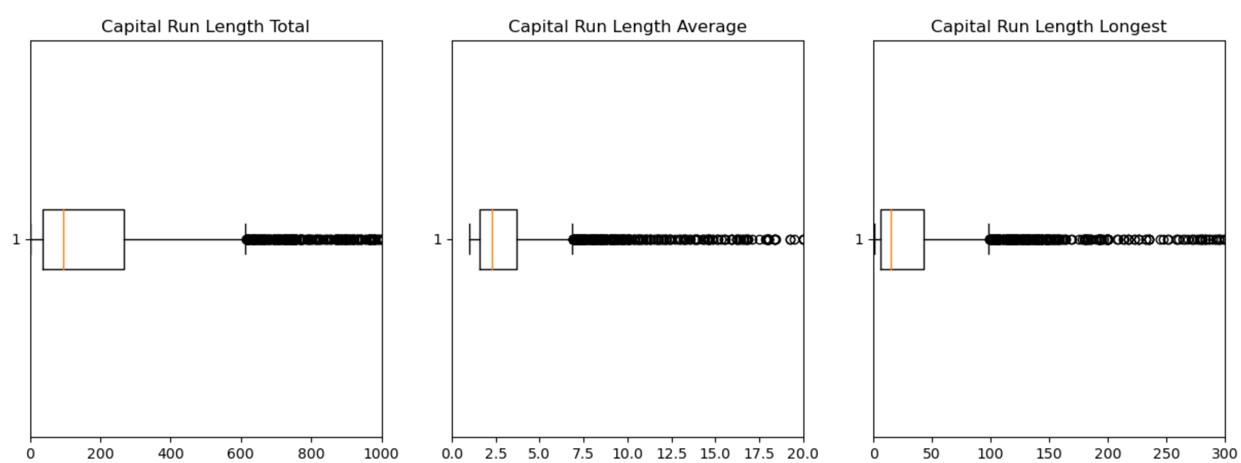
Removing the target column

```
data=Data_set.drop(labels=['spam'], axis=1)
data.head()
```

Data Transformation: outliers were removed using standard scaling.



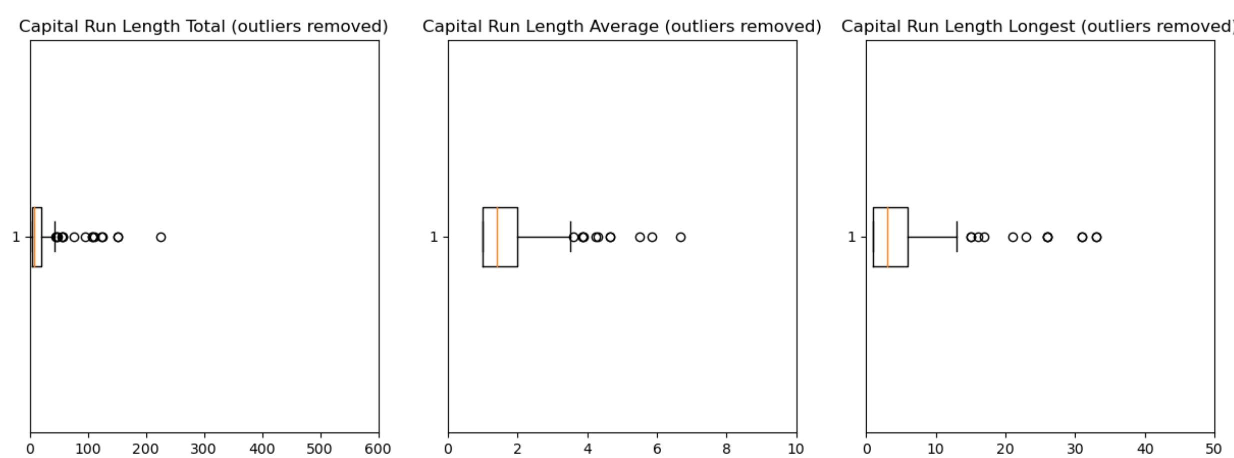
Since capital_run_lenghth_avarage,capital_run_length_longest and Capital_run_lenghth_total are outliers



Remove the outliers using the IQR method

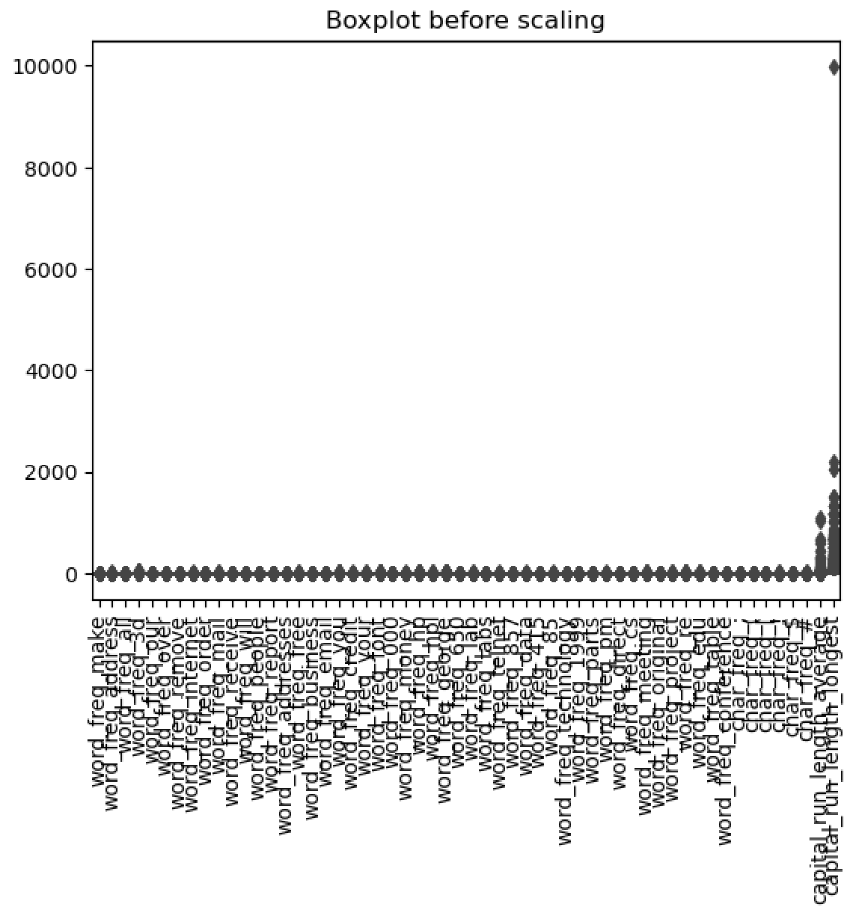
code

```
import numpy as np

# Calculate the interquartile range for each column
Q1 = Data_set.quantile(0.25)
Q3 = Data_set.quantile(0.75)
IQR = Q3 - Q1

# Remove the outliers using the IQR method
Data_set_outliers_removed = Data_set[~((Data_set < (Q1 - 1.5 * IQR)) | (Data_set > (Q3 + 1.5 *
IQR))).any(axis=1)]

# Create individual box plots for the columns with outliers removed
fig, axs = plt.subplots(1, 3, figsize=(15, 5))

axs[0].boxplot(Data_set_outliers_removed['capital_run_length_total'], vert=False)
axs[0].set_title('Capital Run Length Total (outliers removed)')
axs[0].set_xlabel('')
axs[0].set_xlim([0, 600])

axs[1].boxplot(Data_set_outliers_removed['capital_run_length_average'], vert=False)
axs[1].set_title('Capital Run Length Average (outliers removed)')
axs[1].set_xlabel('')
axs[1].set_xlim([0, 10])

axs[2].boxplot(Data_set_outliers_removed['capital_run_length_longest'], vert=False)
axs[2].set_title('Capital Run Length Longest (outliers removed)')
axs[2].set_xlabel('')
axs[2].set_xlim([0, 50])

plt.show()
```

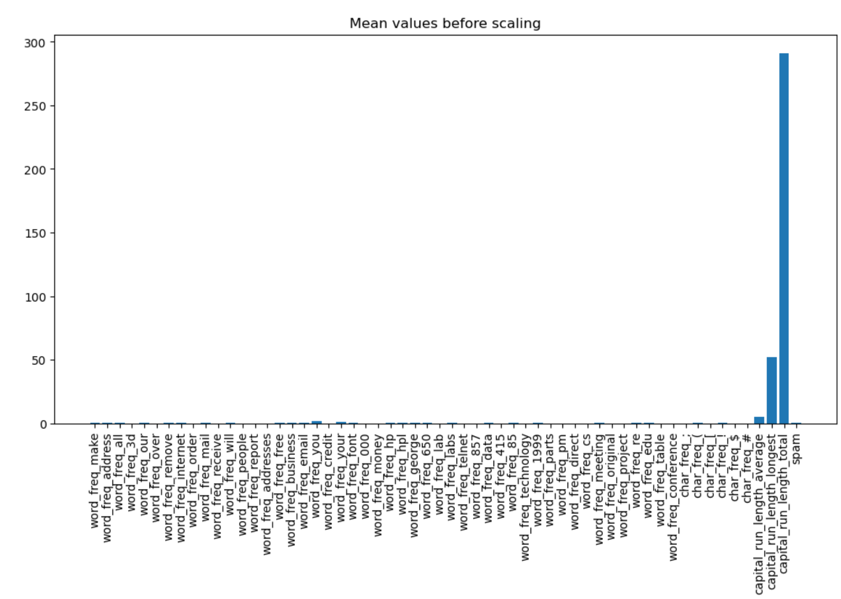


Used Standard Scaler on the dataset

Before standard scaler



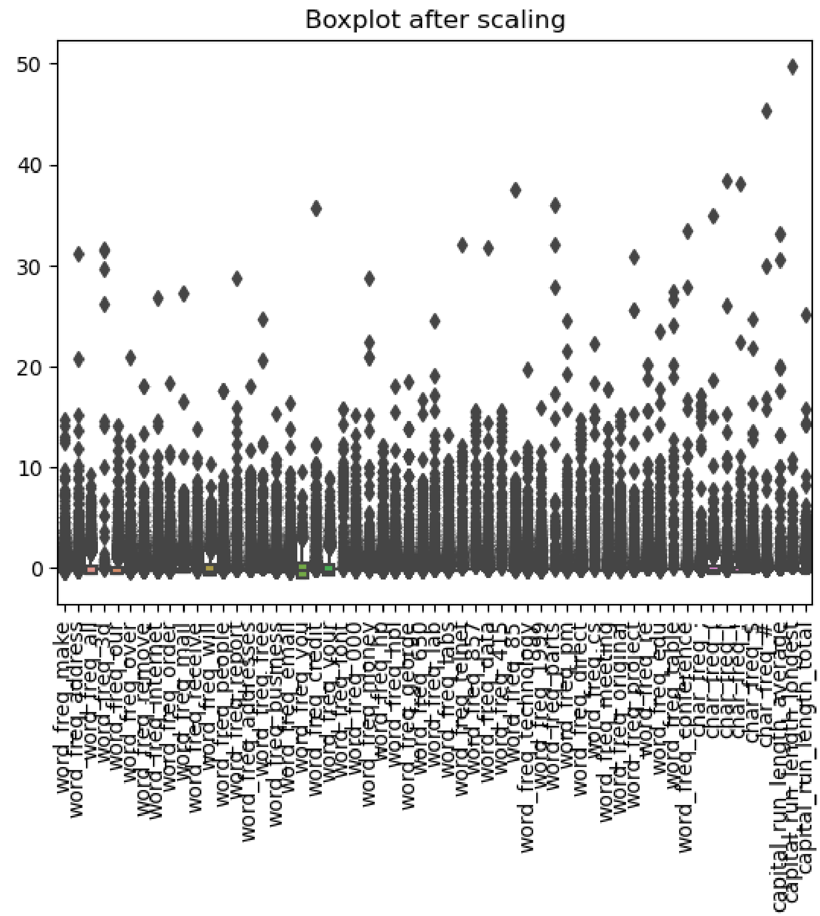
Mean



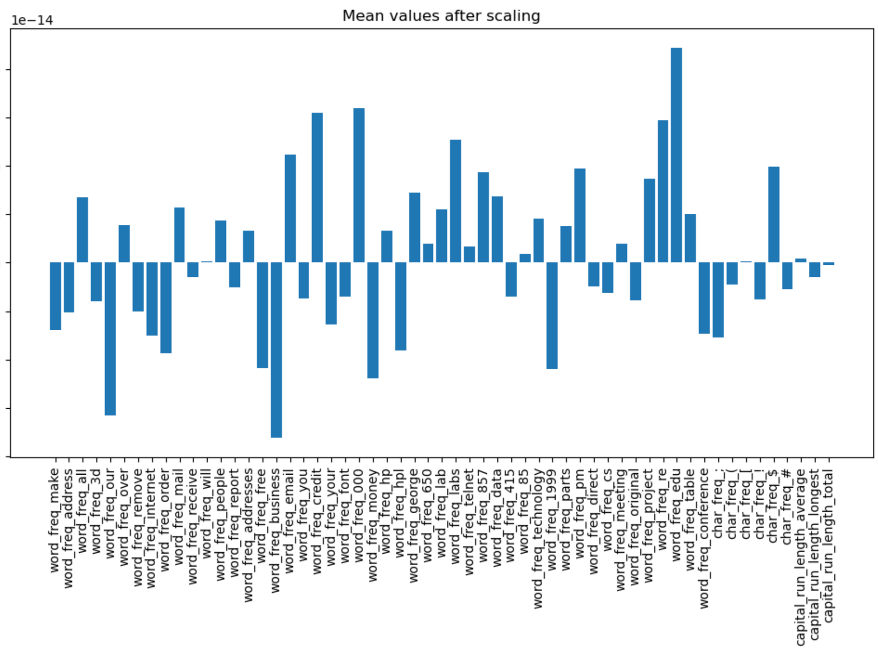
Code – performing standard scaler on the dataset

```
# Perform Standard Scaling on the data
scaler = StandardScaler()
scaled_data = scaler.fit_transform(Data_set.iloc[:, :-1])
Data_scaled = pd.DataFrame(data=scaled_data, columns=Data_set.columns[:-1])
```

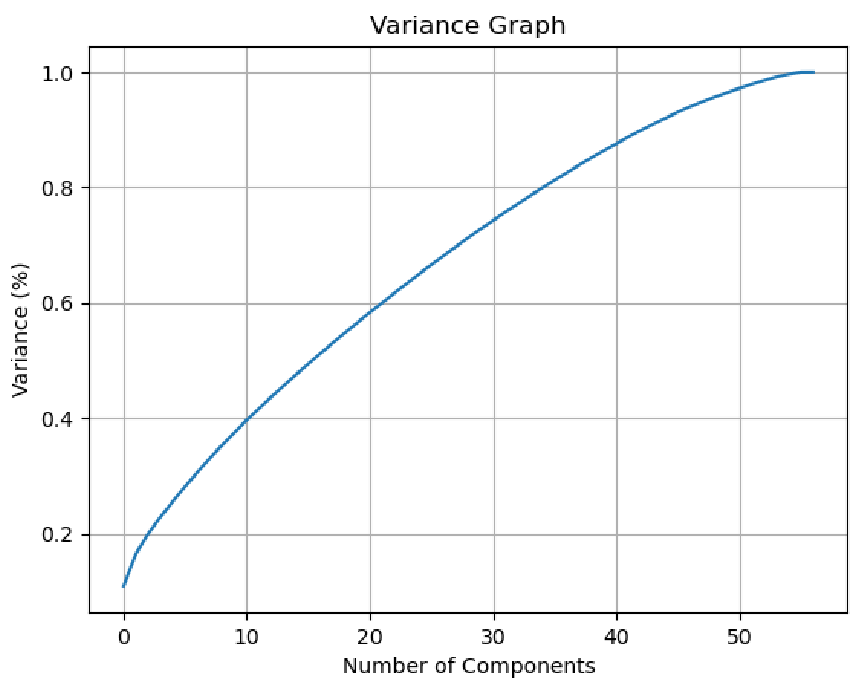
Boxplot after performing the standard scaler on the dataset



Mean



Variance graph



Performing PCA to the Dataset

Code

```
pca = PCA(n_components=44)
new_data = pca.fit_transform(Data_set)

# The new data fed to the algorithm.
principal_Df = pd.DataFrame(data = new_data, columns = [
    'PC1', 'PC2','PC3','PC4','PC5','PC6','PC7','PC8','PC9','PC10',
    'PC11','PC12','PC13','PC14','PC15','PC16','PC17','PC18','PC19','PC20',
    'PC21', 'PC22','PC23','PC24','PC25','PC26','PC27','PC28','PC29','PC30',
    'PC31','PC32','PC33','PC34','PC35','PC36','PC37','PC38','PC39','PC40',
    'PC41','PC42','PC43','PC44'
])
```

Splitting the dataset into the Training set and Test set

- 20 percent of the dataset was used to test the dataset.
- 80 percent of the dataset was used to train the dataset

Code

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.20, random_state = 0)
```

Decision Tree Classification

Accuracy of testing dataset : 0.9560570071258907

Summary of the dataset

code

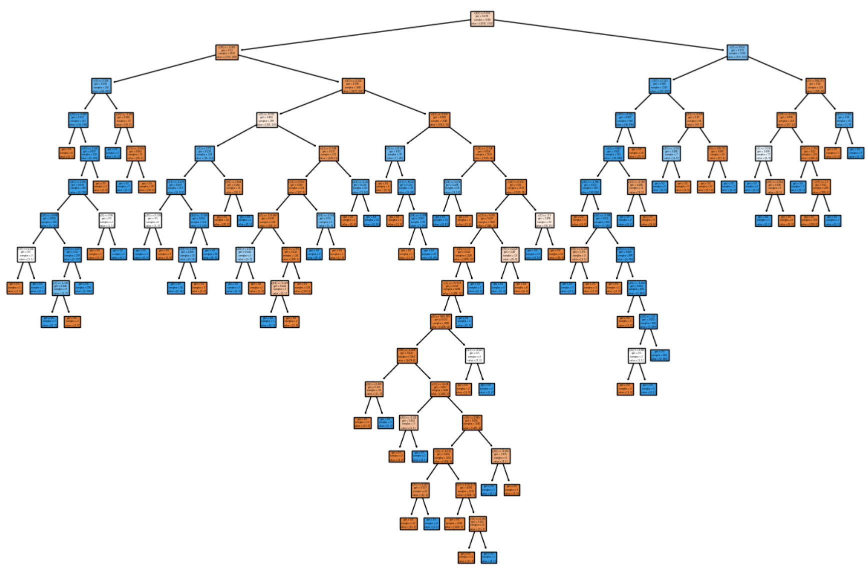
```
from sklearn.metrics import classification_report
predicted_labels = clf.predict(X_test)
classification_report = classification_report(y_test, predicted_labels)

print(classification_report)
```

Classification report

	precision	recall	f1-score	support
0	0.96	0.96	0.96	495
1	0.94	0.94	0.94	347
accuracy			0.95	842
macro avg	0.95	0.95	0.95	842
weighted avg	0.95	0.95	0.95	842

Accuracy of the training dataset of the decision tree: 1.0

Decision tree



Confusion Matrix before pruning

Equations

True positive rate: measures the proportion of positive instances correctly identified as positive.

- FN = False Negative : Number of positive instances that are incorrectly classified as positive.

$$TPR = TP / (TP + FN)$$

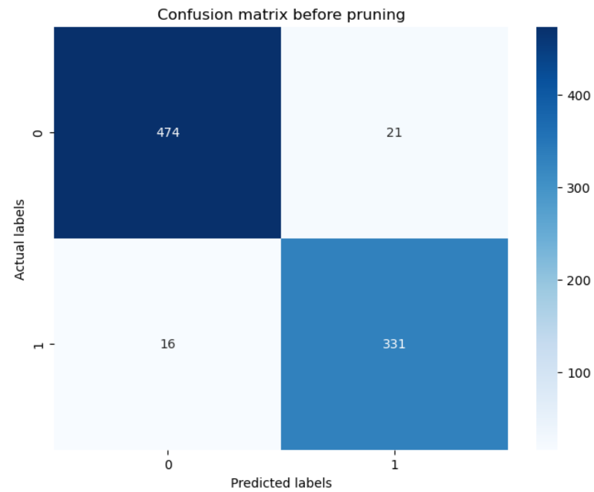
False positive rate : measures the proportion of negative instances incorrectly identified as positive.

- TN = true negative : The number of negative instances that are correctly classified as negative

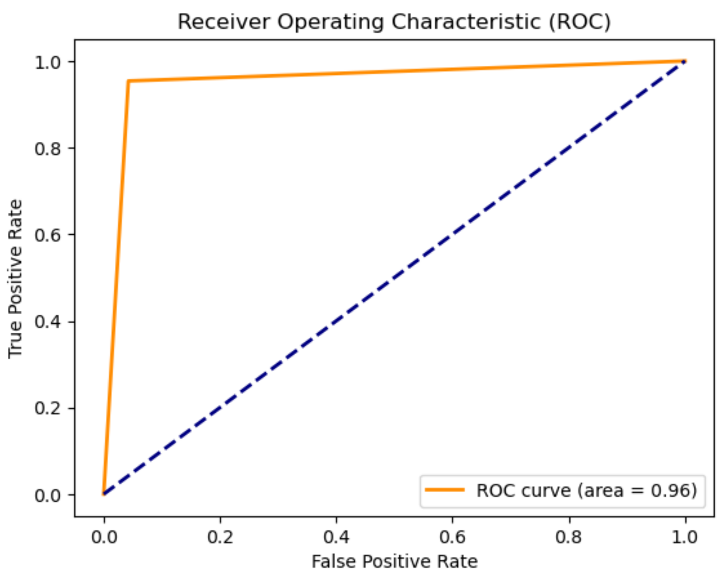
$$FPR = FP / (FP + TN$$

Experiments

- TP :474 mails are correctly identified as not spam.
- FP : 21 mails are incorrectly identified as spam as not spam.
- TN :331 mails are correctly identified as spam.
- FN : 16 mails are incorrectly identified as not spam as spam.



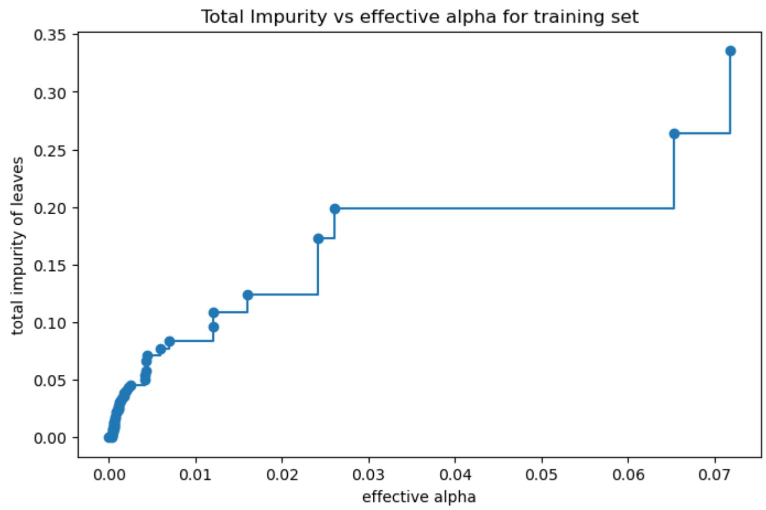
Receiver Operating Characteristics (ROC) : A plot to test sensitivity as the y coordinate versus its 1-specificity or false positive rate (FPR) as the x coordinate, is an effective method of evaluating the performance of diagnostic tests.

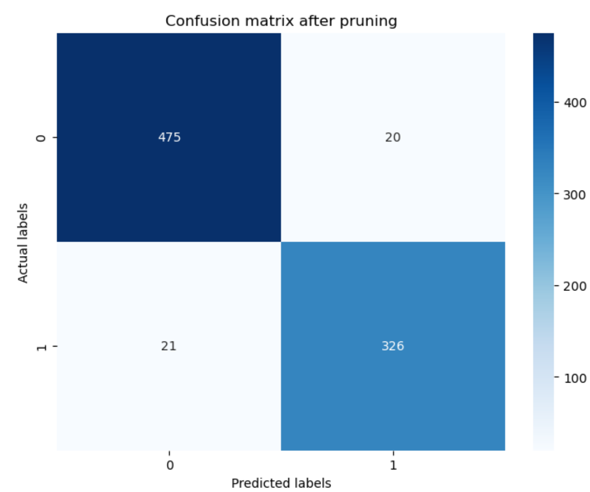


AUC score for the code: 0.96

Pruning the Decision tree : Pruning is a technique that removes the parts of the Decision Tree which prevent i t from growing to its full depth. The parts that it removes from the tree are the parts that do not provide the po wer to classify instances.

A graph is plotted between 'Total impurity of leaves' as Y axis and 'Effective alpha' as the X axis. Using the graph, we can find the optimal 'ccp alpha' value required for pruning.The regularization parameter ccp alpha balances the accuracy and model complexity in decision trees.

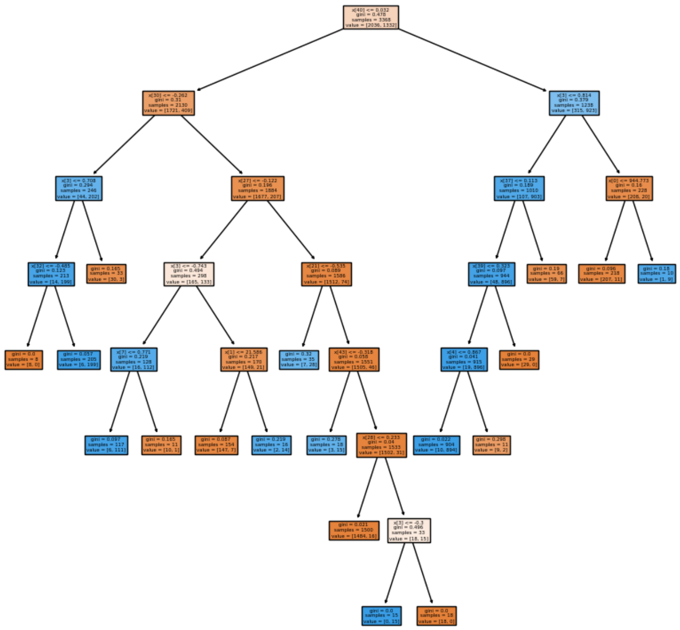




- TP :475 mails are correctly identified as not spam.
- FP : 20 mails are incorrectly identified as spam as not spam.
- TN :326 mails are correctly identified as spam.
- FN : 21 mails are incorrectly identified as not spam as spam.

	precision	recall	f1-score	support
0	0.96	0.96	0.96	495
1	0.94	0.94	0.94	347
accuracy			0.95	842
macro avg	0.95	0.95	0.95	842
weighted avg	0.95	0.95	0.95	842

Decision Tree obtaining after pruning.

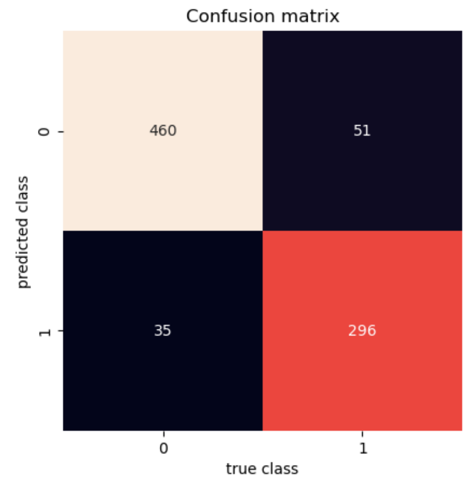


K Nearest Neighbors (KNN) Classification

Classification Report of KNN

	precision	recall	f1-score	support
0	0.90	0.93	0.91	495
1	0.89	0.85	0.87	347
accuracy			0.90	842
macro avg	0.90	0.89	0.89	842
weighted avg	0.90	0.90	0.90	842

Confusion matrix of KNN



- TP: 480 mails are correctly identified as not spam.
- FP: 51 mails are incorrectly identified as spam as not spam.
- TN: 296 mails are correctly identified as spam.
- FN: 35 mails are incorrectly identified as spam as spam.

```
KNN Accuracy:  0.8729216152019003
```

Limitations & Enhancements

Limitations

- Due to the dataset being small the accuracy of the model would be effected.
- Feature engineering step may not have included all the relevant information, making the model performance suboptimal.

Future Enhancements

- Training the model with a larger dataset would increase the accuracy of it
- Utilizing other machine learning algorithms
  - Support vector machines - SVM
  - Random Forest
- Experiment with different feature engineering techniques