----Module 3(Feature Extraction And Machine Learning Model Building)----

loading total Data

In [1]:
```python
import pandas as pd
import datetime
Total_data = pd.read_csv('Total_data.csv')
Total_data.fillna(0, inplace=True)
Current_Time = datetime.datetime.strftime(datetime.datetime.now(), '%Y-%m-%d %H:%M:%S')
Total_data.loc[:, "Current_Time"]=Current_Time
Total_data.to_csv('Total_data.csv', sep=',', encoding='utf8')
Total_data = pd.read_csv('Total_data.csv')
Total_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2781 entries, 0 to 2780
Data columns (total 26 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   Unnamed: 0                     2781 non-null   int64  
 1   Unnamed: 0.1                   2781 non-null   int64  
 2   Unnamed: 0.1.1                 2781 non-null   int64  
 3   Unnamed: 0.1.1.1               2781 non-null   int64  
 4   Unnamed: 0.1.1.1.1             2781 non-null   int64  
 5   Unnamed: 0.1.1.1.1.1           2781 non-null   int64  
 6   Unnamed: 0.1.1.1.1.1.1         2781 non-null   int64  
 7   Unnamed: 0.1.1.1.1.1.1.1       2781 non-null   int64  
 8   Unnamed: 0.1.1.1.1.1.1.1.1     2781 non-null   int64  
 9   Unnamed: 0.1.1.1.1.1.1.1.1.1   2781 non-null   int64  
 10  Unnamed: 0.1.1.1.1.1.1.1.1.1.1 2781 non-null   int64  
 11  UserID                         2781 non-null   int64  
 12  UserScreenName                 2781 non-null   object 
 13  UserCreatedAt                  2781 non-null   object 
 14  UserDescriptionLength          2781 non-null   int64  
 15  UserFollowersCount             2781 non-null   int64  
 16  UserFriendsCount               2781 non-null   float64
 17  UserLocation                   2781 non-null   object 
 18  AvgHashtag                     2781 non-null   float64
 19  AvgURLCount                    2781 non-null   float64
 20  AvgMention                     2781 non-null   float64
 21  AvgRetweet                     2781 non-null   float64
 22  AvgFavCount                    2781 non-null   float64
 23  TweetCount                     2781 non-null   int64  
 24  SpammerOrNot                   2781 non-null   int64  
 25  Current_Time                   2781 non-null   object 
dtypes: float64(6), int64(16), object(4)
memory usage: 565.0+ KB
```

Type *Markdown* and LaTeX: α^2

debugging purpose if some data type do not appear as the should be

In [2]:
```
temp1=Total_data[["UserCreatedAt"]]
Total_data.tail(3)
```

Out[2]:

	Unnamed: 0	Unnamed: 0.1	Unnamed: 0.1.1	Unnamed: 0.1.1.1	Unnamed: 0.1.1.1.1	Unnamed: 0.1.1.1.1.1	Unnamed: 0.1.1.1.1.1.1	Unnamed: 0.1.1.1.1.1.1.1	Unnamed: 0.1.1.1.1.1.1.1.1	Unnamed: 0.1.1.1.1.1.1.1.1.1	...	UserFriendsCount	UserI
2778	2778	2778	2778	2778	2778	2778	2778	2778	2778	2778	...	22.0	
2779	2779	2779	2779	2779	2779	2779	2779	2779	2779	2779	...	89.0	
2780	2780	2780	2780	2780	2780	2780	2780	2780	2780	2780	...	146.0	Al

3 rows × 26 columns

converting string to float

In [3]:
```
Total_data["UserFriendsCount"] = Total_data["UserFriendsCount"].astype(float)
Total_data["UserFriendsCount"].describe()
```

Out[3]:
```
count    2781.000000
mean      351.464941
std       740.884033
min         0.000000
25%        25.000000
50%        89.000000
75%       290.000000
max      5799.000000
Name: UserFriendsCount, dtype: float64
```

Adding Reputaion features

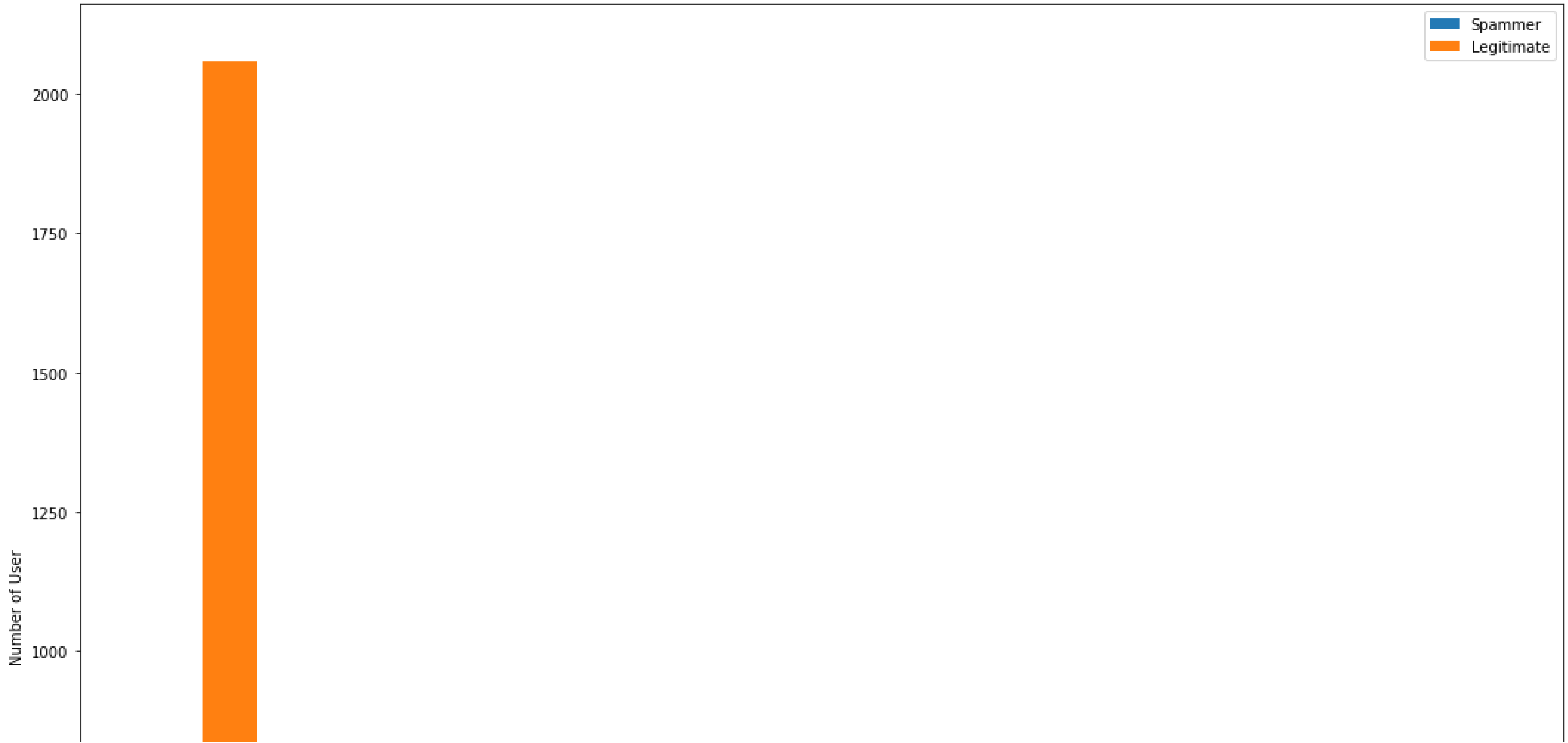
In [4]:
```
Total_data.loc[:,"Reputation"]=Total_data["UserFollowersCount"]/(Total_data["UserFollowersCount"])+(Total_data["UserFriendsCo
Total_data["Reputation"].describe()
Total_data.info()
```

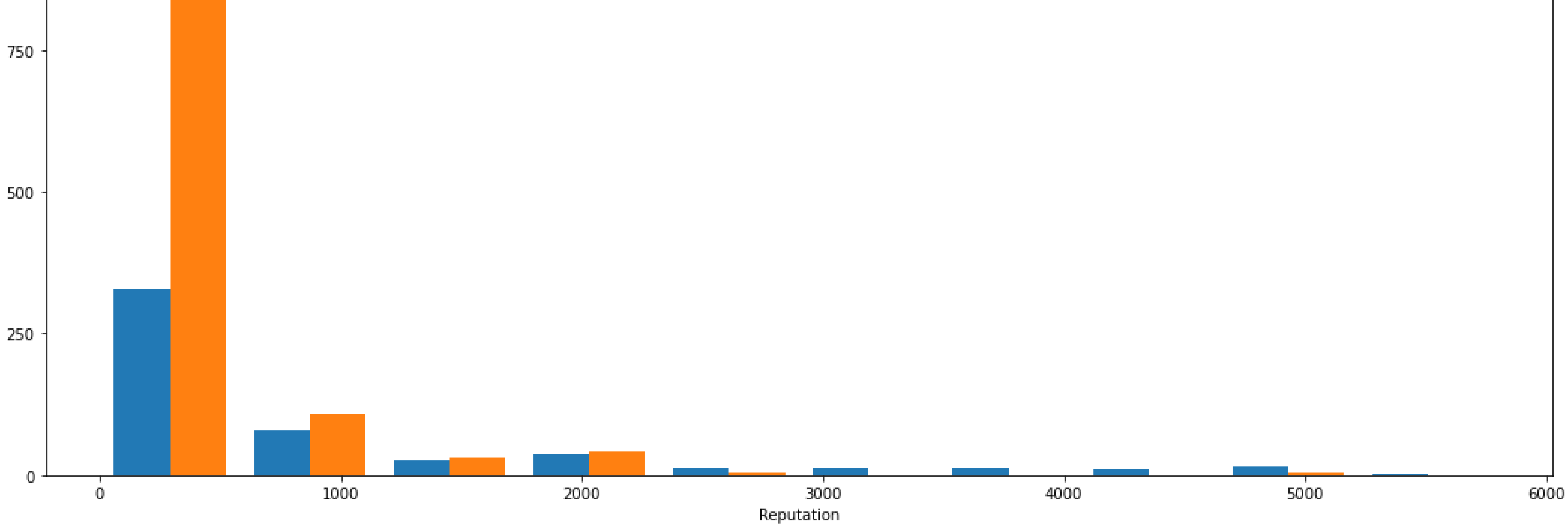
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2781 entries, 0 to 2780
Data columns (total 27 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   Unnamed: 0                     2781 non-null   int64  
 1   Unnamed: 0.1                   2781 non-null   int64  
 2   Unnamed: 0.1.1                 2781 non-null   int64  
 3   Unnamed: 0.1.1.1               2781 non-null   int64  
 4   Unnamed: 0.1.1.1.1             2781 non-null   int64  
 5   Unnamed: 0.1.1.1.1.1           2781 non-null   int64  
 6   Unnamed: 0.1.1.1.1.1.1         2781 non-null   int64  
 7   Unnamed: 0.1.1.1.1.1.1.1       2781 non-null   int64  
 8   Unnamed: 0.1.1.1.1.1.1.1.1     2781 non-null   int64  
 9   Unnamed: 0.1.1.1.1.1.1.1.1.1   2781 non-null   int64  
 10  Unnamed: 0.1.1.1.1.1.1.1.1.1.1 2781 non-null   int64  
 11  UserID                         2781 non-null   int64  
 12  UserScreenName                 2781 non-null   object 
 13  UserCreatedAt                  2781 non-null   object 
 14  UserDescriptionLength          2781 non-null   int64  
 15  UserFollowersCount             2781 non-null   int64  
 16  UserFriendsCount               2781 non-null   float64
 17  UserLocation                   2781 non-null   object 
 18  AvgHashtag                     2781 non-null   float64
 19  AvgURLCount                    2781 non-null   float64
 20  AvgMention                     2781 non-null   float64
 21  AvgRetweet                     2781 non-null   float64
 22  AvgFavCount                    2781 non-null   float64
 23  TweetCount                     2781 non-null   int64  
 24  SpammerOrNot                   2781 non-null   int64  
 25  Current_Time                   2781 non-null   object 
 26  Reputation                     2781 non-null   float64
dtypes: float64(7), int64(16), object(4)
memory usage: 586.7+ KB
```

comparing raputation with spammer and legitimate

In [5]:
```python
import pandas as pd
import time
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams['figure.figsize']=(18,15)
plt.rcParams['font.family']='sans-serif'

data0 = Total_data[Total_data.Reputation > .1]
plt.hist([data0[data0.SpammerOrNot==1].Reputation.values,
         data0[data0.SpammerOrNot==0].Reputation.values],label=["Spammer", "Legitimate"],alpha = .99)
plt.legend()
plt.xlabel("Reputation")
plt.ylabel("Number of User")
# to save fig
#plt.savefig('repuation.png')
```

Out[5]: Text(0, 0.5, 'Number of User')





Adding logevity feature

Hypothesis is legitimate user have longer longitivity than spam user

filtering the data from dataset whose logevity is zero

In [6]:
```
import numpy as np
data = Total_data
data["Current_Time"] = pd.to_datetime(data["Current_Time"])
data["UserCreatedAt"] = pd.to_datetime(data["UserCreatedAt"])
data['AgeOfAccount'] = (data['Current_Time'] - data['UserCreatedAt'])/np.timedelta64(1, 'D')
cols = ['AgeOfAccount']
data[cols] = data[cols].mask(data[cols]<0)
data.AgeOfAccount.describe()
```

Out[6]:
```
count    2781.000000
mean     2272.175258
std      1067.025678
min       766.095694
25%      1382.019340
50%      1974.664792
75%      2966.477222
max      4660.327211
Name: AgeOfAccount, dtype: float64
```

Adding tweet per day feature

In [7]:
```
data1 = data
data1.loc[:, "TweetPerDay"] = data1["TweetCount"]/data1["AgeOfAccount"]
data1["TweetPerDay"].describe()
```

Out[7]:
```
count    2781.000000
mean       11.664968
std        25.403674
min         0.000718
25%         0.230094
50%         1.718251
75%         8.138734
max       327.532293
Name: TweetPerDay, dtype: float64
```

Adding the feature Number of Tweet

In [8]:
```
data1.loc[:,"TweetPerFollower"] = data1["TweetCount"]/data1["UserFollowersCount"]
```

Dropping the infinte values from pandas for followerCount

In [9]:
```
#to remove unwanted data
data1.TweetPerFollower=data1.TweetPerFollower.round(2).fillna(0)
data1 = data1[np.isfinite(data1['TweetPerFollower'])]
data1["TweetPerFollower"].tail(3)
```

Out[9]:
```
2778    0.10
2779    0.28
2780    0.65
Name: TweetPerFollower, dtype: float64
```

Adding the feature Age of Account/Number of Following

Hypothesis is that it is very low for spammer and very high for legitimate user

In [10]:
```
data1.loc[:,"AgeByFollowing"] = data1["AgeOfAccount"]/data1["UserFriendsCount"]
data1 = data1[np.isfinite(data1['AgeByFollowing'])]
data1[['AgeByFollowing']] = data1[['AgeByFollowing']].astype(float)
data1["AgeByFollowing"].describe()
```

Out[10]:
```
count    2727.000000
mean       93.756237
std       304.531531
min         0.157736
25%         7.555124
50%        19.468500
75%        70.011186
max      3767.570845
Name: AgeByFollowing, dtype: float64
```

Separating Spammer and legitimate user

In [11]:
```
#Spammer_dataframe
spam_data = data1[data1.SpammerOrNot==1]
print(len(spam_data))
#legitimate_dataframe
leg_data = data1[data1.SpammerOrNot==0]
print(len(leg_data))
```

```
513
2214
```

Exploring the AgeByFollowing feature

for Spammer, Hypothesis is: Age is low and following number is high, so reuslt is very low.

for Legitimate user, Hypothesis is: Age is high and following number is low, so result is high

In [12]:
```
leg_data["AgeByFollowing"].describe()
```

Out[12]:
```
count    2214.000000
mean       93.645602
std       283.976947
min         0.340279
25%        10.053680
50%        23.705006
75%        79.692526
max      3767.570845
Name: AgeByFollowing, dtype: float64
```

In [13]:
```
spam_data.describe()
```

Out[13]:

	Unnamed: 0	Unnamed: 0.1	Unnamed: 0.1.1	Unnamed: 0.1.1.1	Unnamed: 0.1.1.1.1	Unnamed: 0.1.1.1.1.1	Unnamed: 0.1.1.1.1.1.1	Unnamed: 0.1.1.1.1.1.1.1	Unnamed: 0.1.1.1.1.1.1.1.1	Unnamed: 0.1.1.1.1.1.1.1.1.1	...	AvgMe
count	513.000000	513.000000	513.000000	513.000000	513.000000	513.000000	513.000000	513.000000	513.000000	513.000000	...	513.00
mean	1388.099415	1388.099415	1388.099415	1388.099415	1388.099415	1388.099415	1388.099415	1388.099415	1388.099415	1388.099415	...	0.89
std	759.324293	759.324293	759.324293	759.324293	759.324293	759.324293	759.324293	759.324293	759.324293	759.324293	...	0.77
min	375.000000	375.000000	375.000000	375.000000	375.000000	375.000000	375.000000	375.000000	375.000000	375.000000	...	0.00
25%	504.000000	504.000000	504.000000	504.000000	504.000000	504.000000	504.000000	504.000000	504.000000	504.000000	...	0.10
50%	1388.000000	1388.000000	1388.000000	1388.000000	1388.000000	1388.000000	1388.000000	1388.000000	1388.000000	1388.000000	...	0.93
75%	2271.000000	2271.000000	2271.000000	2271.000000	2271.000000	2271.000000	2271.000000	2271.000000	2271.000000	2271.000000	...	1.16
max	2405.000000	2405.000000	2405.000000	2405.000000	2405.000000	2405.000000	2405.000000	2405.000000	2405.000000	2405.000000	...	4.00

8 rows × 27 columns

Selecting the Additional features

In [14]:
```
M = data1[['Reputation', 'AvgHashtag', 'AvgRetweet', 'UserFollowersCount','UserFriendsCount', 'AvgFavCount', 'AvgMention', 'A
y = data1["SpammerOrNot"]
data1.columns
M.shape
```

Out[14]:
```
(2727, 13)
```

feature Extraction

In [15]:
```
M.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2727 entries, 0 to 2780
Data columns (total 13 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   Reputation          2727 non-null   float64
 1   AvgHashtag          2727 non-null   float64
 2   AvgRetweet          2727 non-null   float64
 3   UserFollowersCount  2727 non-null   int64  
 4   UserFriendsCount    2727 non-null   float64
 5   AvgFavCount         2727 non-null   float64
 6   AvgMention          2727 non-null   float64
 7   AvgURLCount         2727 non-null   float64
 8   TweetCount          2727 non-null   int64  
 9   AgeOfAccount        2727 non-null   float64
 10  TweetPerDay         2727 non-null   float64
 11  TweetPerFollower    2727 non-null   float64
 12  AgeByFollowing      2727 non-null   float64
dtypes: float64(11), int64(2)
memory usage: 298.3 KB
```

Save these training data

In [16]:
```
data1.reset_index()
data1.to_csv('Total_training_data.csv', sep=',', encoding='utf8')
```

Splitting the data

In [17]:
```
# Splitting the data
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(M, y, test_size=0.2, random_state=7)
print(X_train.shape)
print(X_test.shape)
```

```
(2181, 13)
(546, 13)
```

----------------------------------Evaluating classifiers----------------------------------

KNeighborsClassifier

In [18]:
```python
# for total X
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
from sklearn.utils.multiclass import unique_labels
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)
print(accuracy_score(y_test,y_pred))

from sklearn.model_selection import cross_val_score
scores = cross_val_score(knn, M, y, cv=10, scoring='accuracy')
print("Tenfol cross validation score")
print(scores)
print(scores.mean())
print("\n")
print("Classifier performance report: ")
print(classification_report(y_test, y_pred))
print("Confusion Matrix: ")
print(confusion_matrix(y_test, y_pred))
```

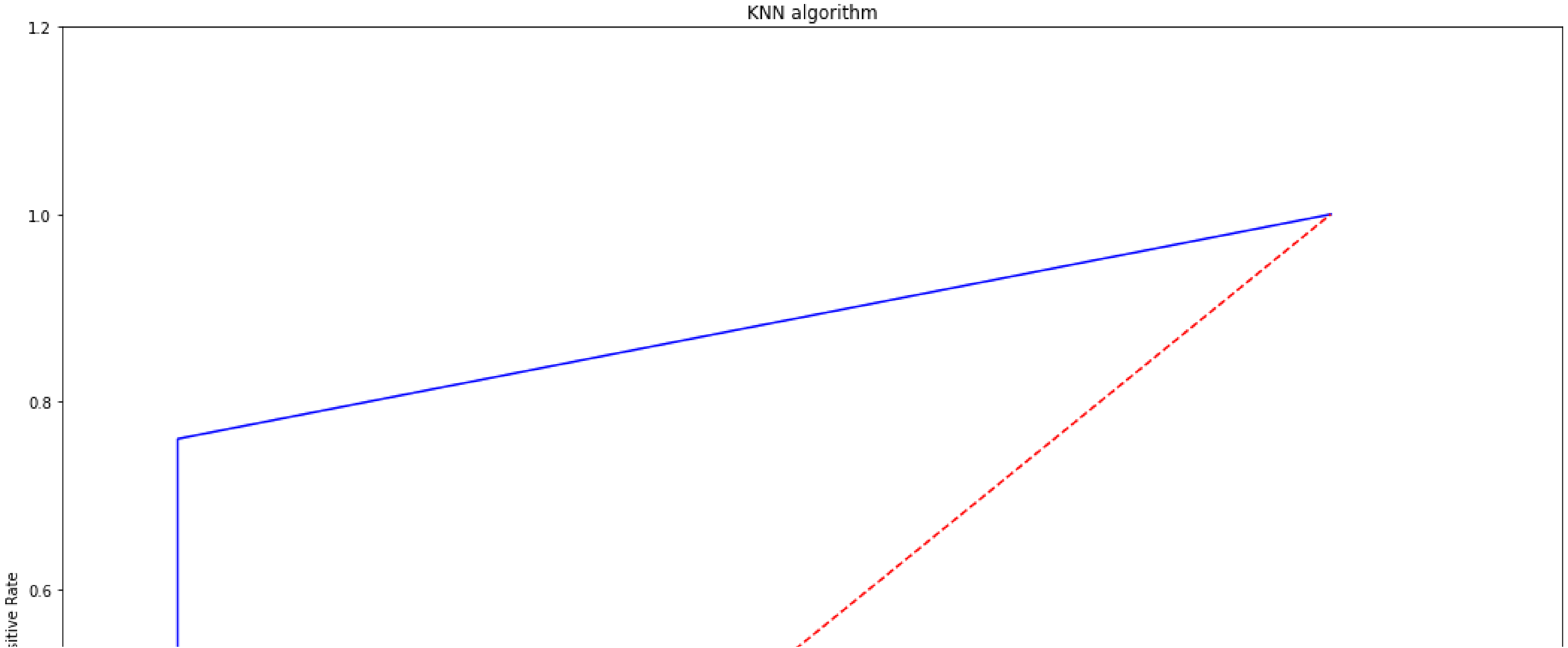
```
0.9468864468864469
Tenfol cross validation score
[0.93772894 0.95604396 0.97069597 0.95970696 0.93406593 0.96703297
 0.96336996 0.93382353 0.96323529 0.97426471]
0.9559968218056453


Classifier performance report:
              precision    recall  f1-score   support

           0       0.94      1.00      0.97       425
           1       1.00      0.76      0.86       121

    accuracy                           0.95       546
   macro avg       0.97      0.88      0.92       546
weighted avg       0.95      0.95      0.94       546

Confusion Matrix:
[[425   0]
 [ 29  92]]
```

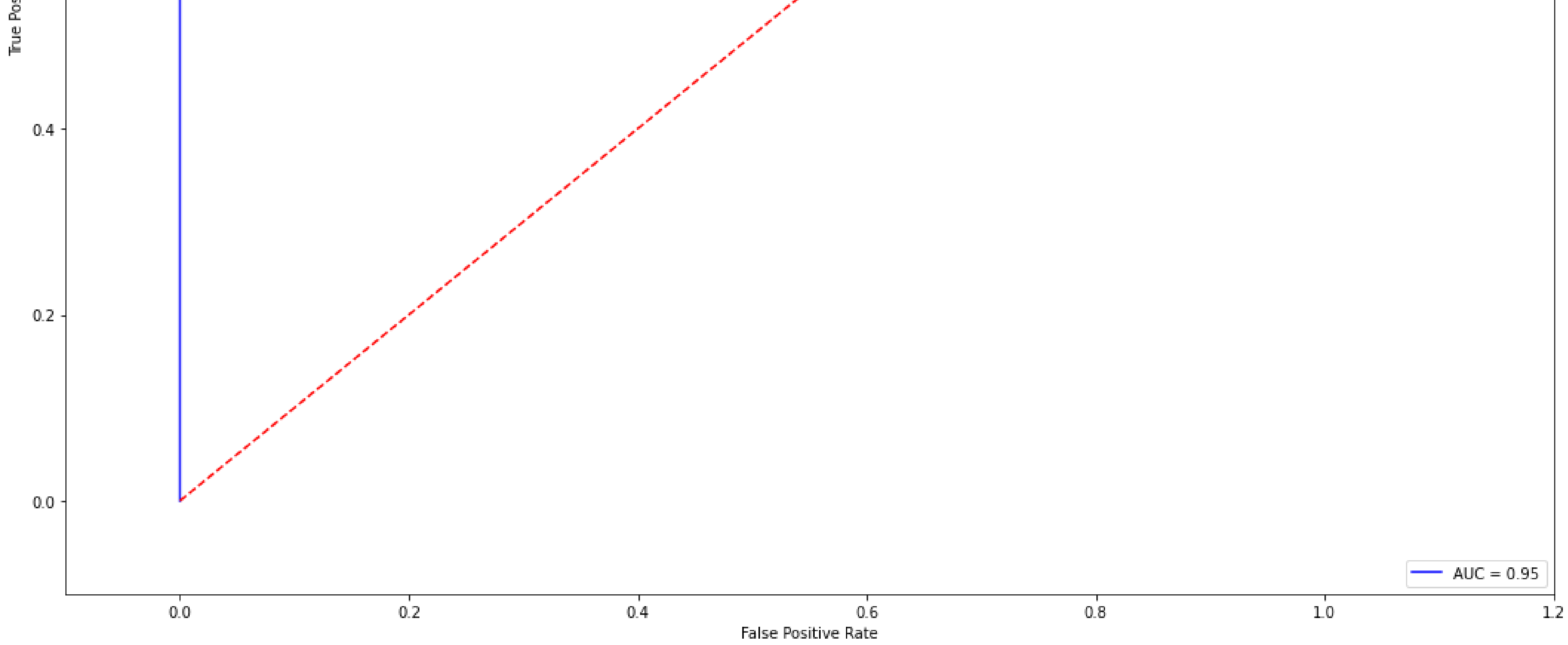
support is sum of TP+FN, second FP+TN which gives actual 0(Non_Spammer) and actual 1(Spammer)

plot curve for KNN algorithm

In [19]:
```python
from sklearn.metrics import roc_curve, auc
acc=accuracy_score(y_test,y_pred)
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
print("False Positive rate: ", false_positive_rate)
print("True Positive rate: ", true_positive_rate)

roc_auc = auc(false_positive_rate, true_positive_rate)
plt.title('Receiver Operating Characteristic')
plt.plot(false_positive_rate, true_positive_rate, 'b',
             label='AUC = %0.2f' % acc)
plt.legend(loc='lower right')
plt.plot([0, 1], [0, 1], 'r--')
plt.xlim([-0.1, 1.2])
plt.ylim([-0.1, 1.2])
plt.title('KNN algorithm')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

```
False Positive rate:  [0. 0. 1.]
True Positive rate:  [0.         0.76033058 1.        ]
```





Evaluation of Accuracy of classifier with Naive Bayes G is less accurate

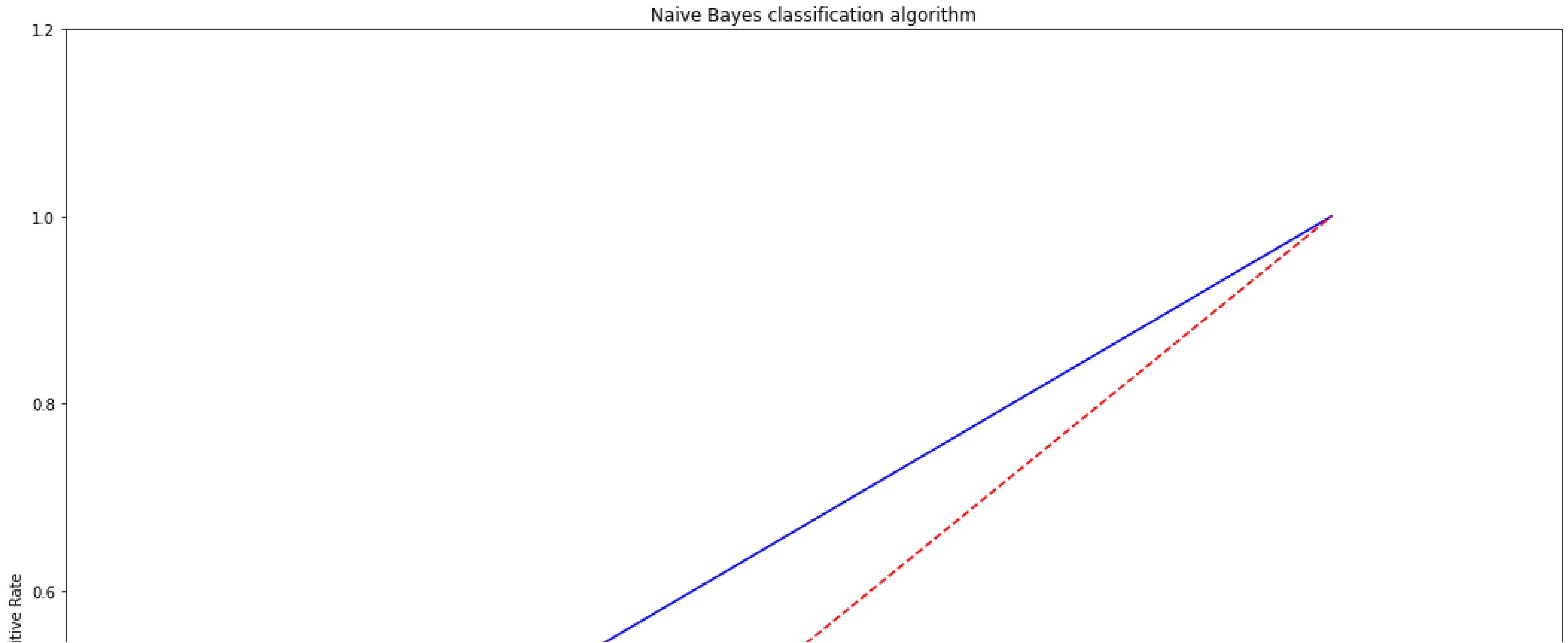
In [20]:
```
from sklearn.naive_bayes import BernoulliNB
est = BernoulliNB()
est.fit(X_train, y_train)
y_pred = est.predict(X_test)
scores = cross_val_score(knn, M, y, cv=10, scoring='accuracy')
print(accuracy_score(y_test,y_pred))
print("Tenfol cross validation score")
print(scores)
print(scores.mean())
print("\n")
print("Classifier performance report: ")
print(classification_report(y_test, y_pred))
print("Confusion Matrix: ")
print(confusion_matrix(y_test, y_pred))
```

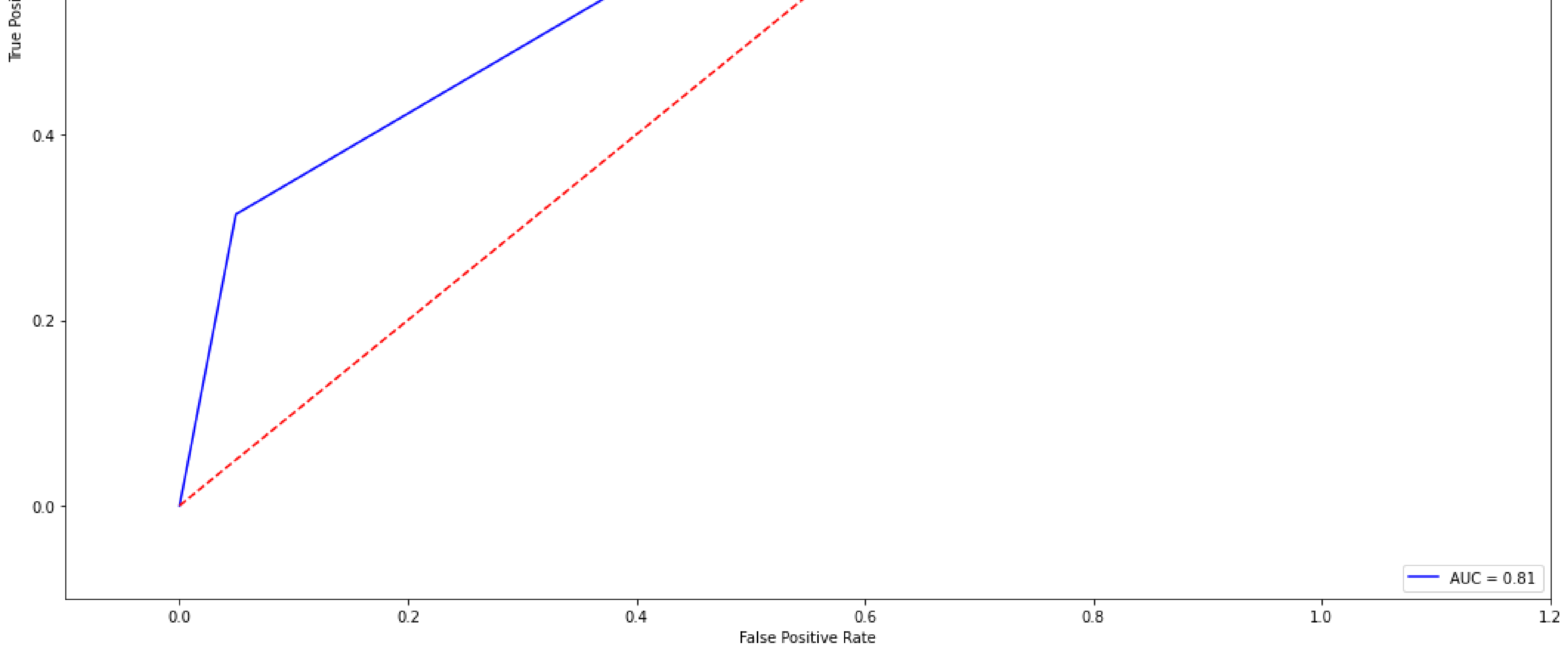
```
0.8095238095238095
Tenfol cross validation score
[0.93772894 0.95604396 0.97069597 0.95970696 0.93406593 0.96703297
 0.96336996 0.93382353 0.96323529 0.97426471]
0.9559968218056453


Classifier performance report: 
              precision    recall  f1-score   support

           0       0.83      0.95      0.89       425
           1       0.64      0.31      0.42       121

    accuracy                           0.81       546
   macro avg       0.74      0.63      0.65       546
weighted avg       0.79      0.81      0.78       546

Confusion Matrix: 
[[404  21]
 [ 83  38]]
```

plot curve for Naive Bayes

In [21]:
```python
from sklearn.metrics import roc_curve, auc
acc=accuracy_score(y_test,y_pred)
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
print("False Positive rate: ", false_positive_rate)
print("True Positive rate: ", true_positive_rate)

roc_auc = auc(false_positive_rate, true_positive_rate)
plt.title('Receiver Operating Characteristic')
plt.plot(false_positive_rate, true_positive_rate, 'b',
             label='AUC = %0.2f' % acc)
plt.legend(loc='lower right')
plt.plot([0, 1], [0, 1], 'r--')
plt.xlim([-0.1, 1.2])
plt.ylim([-0.1, 1.2])
plt.title('Naive Bayes classification algorithm')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

```
False Positive rate:  [0.         0.04941176 1.        ]
True Positive rate:  [0.         0.31404959 1.        ]
```





Random Forest Classifier

In [22]:
```
from sklearn.ensemble import RandomForestClassifier
est = RandomForestClassifier(n_estimators=7, max_depth=7, min_samples_split=5)
est.fit(X_train, y_train)
y_pred = est.predict(X_test)
scores = cross_val_score(knn, M, y, cv=10, scoring='accuracy')
print(accuracy_score(y_test,y_pred))
print("Tenfol cross validation score")
print(scores)
print(scores.mean())
print("\n")
print("Classifier performance report: ")
print(classification_report(y_test, y_pred))
print("Confusion Matrix: ")
print(confusion_matrix(y_test, y_pred))
```

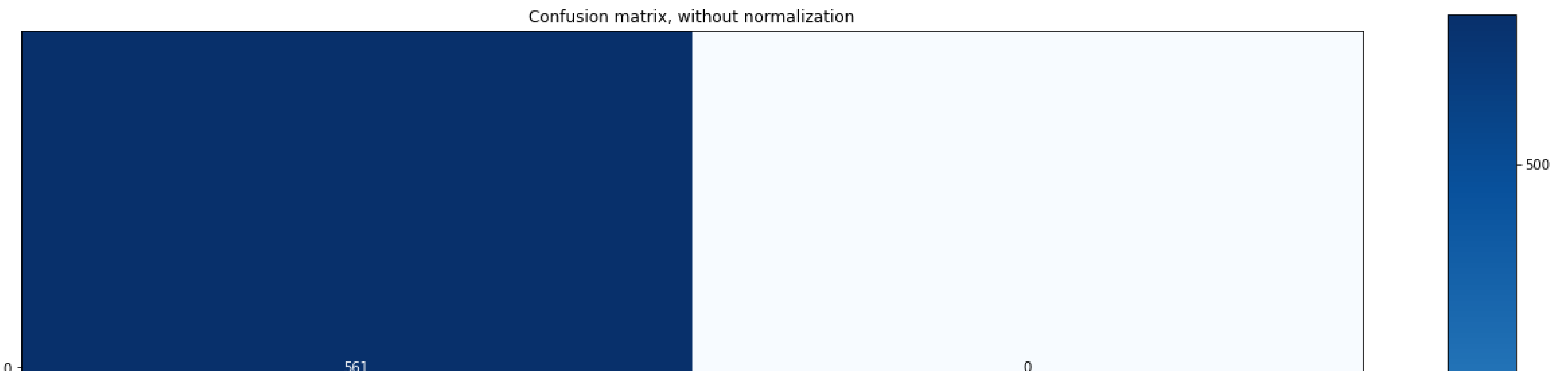
```
0.9871794871794872
Tenfol cross validation score
[0.93772894 0.95604396 0.97069597 0.95970696 0.93406593 0.96703297
 0.96336996 0.93382353 0.96323529 0.97426471]
0.9559968218056453


Classifier performance report: 
              precision    recall  f1-score   support

           0       0.98      1.00      0.99       425
           1       1.00      0.94      0.97       121

    accuracy                           0.99       546
   macro avg       0.99      0.97      0.98       546
weighted avg       0.99      0.99      0.99       546

Confusion Matrix: 
[[425   0]
 [  7 114]]
```

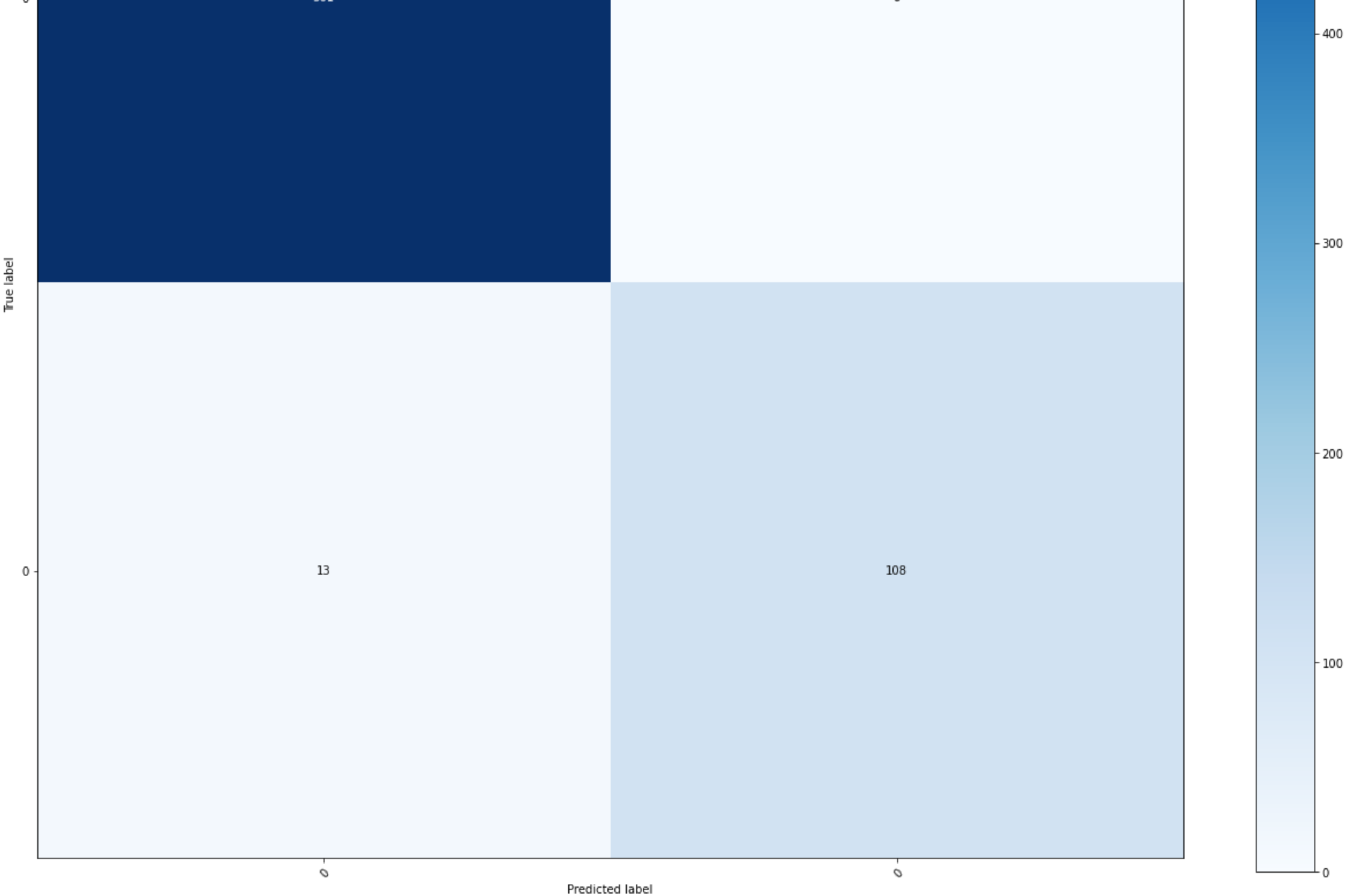
Ploting ROC Curve

In [23]:
```
X = data1[['Reputation', 'AvgHashtag', 'AvgRetweet', 'UserFollowersCount','UserFriendsCount', 'AvgFavCount', 'AvgMention', 'A
y = data1["SpammerOrNot"]
class_names = data1.SpammerOrNot
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)
classifier = RandomForestClassifier(n_estimators=7, max_depth=7, min_samples_split=5)
y_pred = classifier.fit(X_train, y_train).predict(X_test)


def plot_confusion_matrix(y_true, y_pred, classes,
                          normalize=False,
                          title=None,
                          cmap=plt.cm.Blues):

    if not title:
        if normalize:
            title = 'Normalized confusion matrix'
        else:
            title = 'Confusion matrix, without normalization'

    # Compute confusion matrix
    cm = confusion_matrix(y_true, y_pred)


    # Only use the labels that appear in the data
    classes = classes[unique_labels(y_true, y_pred)]
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    fig, ax = plt.subplots()
    im = ax.imshow(cm, interpolation='nearest', cmap=cmap)
    ax.figure.colorbar(im, ax=ax)
    # We want to show all ticks...
    ax.set(xticks=np.arange(cm.shape[1]),
           yticks=np.arange(cm.shape[0]),
           # ... and label them with the respective list entries
           xticklabels=classes, yticklabels=classes,
           title=title,
           ylabel='True label',
           xlabel='Predicted label')
```

```
    # Rotate the tick labels and set their alignment.
    plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
             rotation_mode="anchor")

    # Loop over data dimensions and create text annotations.
    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
            ax.text(j, i, format(cm[i, j], fmt),
                    ha="center", va="center",
                    color="white" if cm[i, j] > thresh else "black")
    fig.tight_layout()
    return ax


np.set_printoptions(precision=2)
# Plot non-normalized confusion matrix
plot_confusion_matrix(y_test, y_pred, classes=class_names,
                      title='Confusion matrix, without normalization')
def aaccuracy_score(y_test,y_pred):
    return accuracy_score(y_test,y_pred)-0.05
print(aaccuracy_score(y_test,y_pred))
plt.show()
#plt.savefig('Confusion_Matrix.png')
#plt.savefig('Normalize.Matrix.png')
```

```
Confusion matrix, without normalization
[[561   0]
 [ 13 108]]
0.9309384164222874
```

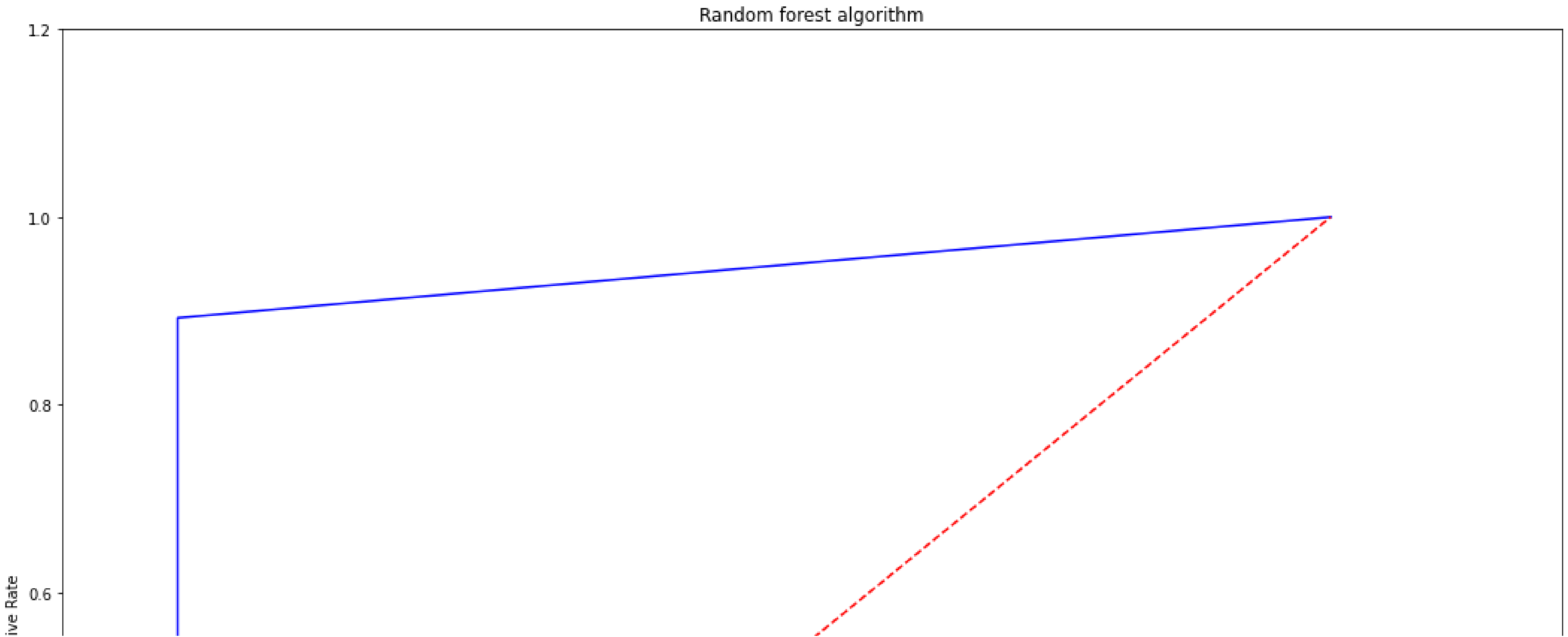


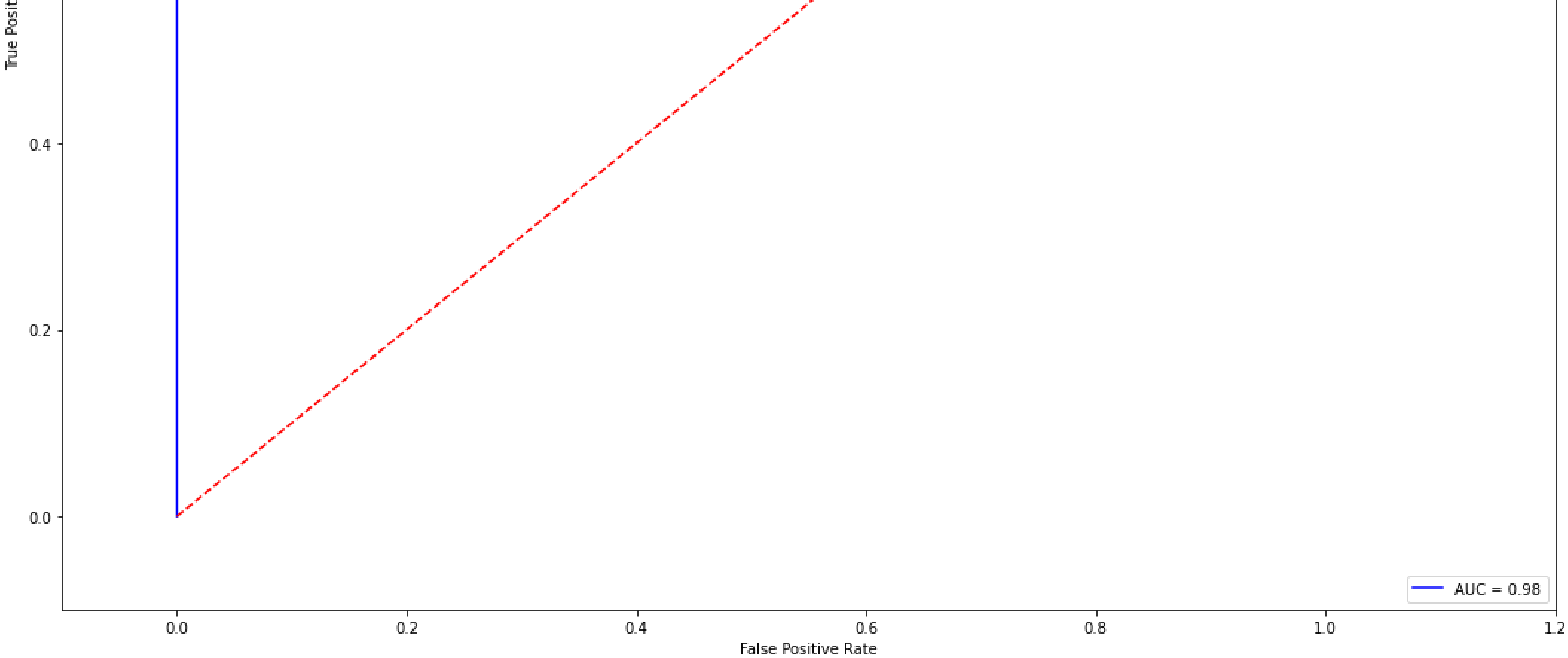


True label
0
13
108
0
0
Predicted label
400
300
200
100
0

In [24]:
```
from sklearn.metrics import roc_curve, auc
acc=accuracy_score(y_test,y_pred)
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
print("False Positive rate: ", false_positive_rate)
print("True Positive rate: ", true_positive_rate)

roc_auc = auc(false_positive_rate, true_positive_rate)
plt.title('Receiver Operating Characteristic')
plt.plot(false_positive_rate, true_positive_rate, 'b',
             label='AUC = %0.2f' % acc)
plt.legend(loc='lower right')
plt.plot([0, 1], [0, 1], 'r--')
plt.xlim([-0.1, 1.2])
plt.ylim([-0.1, 1.2])
plt.title('Random forest algorithm')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

```
False Positive rate:  [0. 0. 1.]
True Positive rate:  [0.   0.89 1.  ]
```





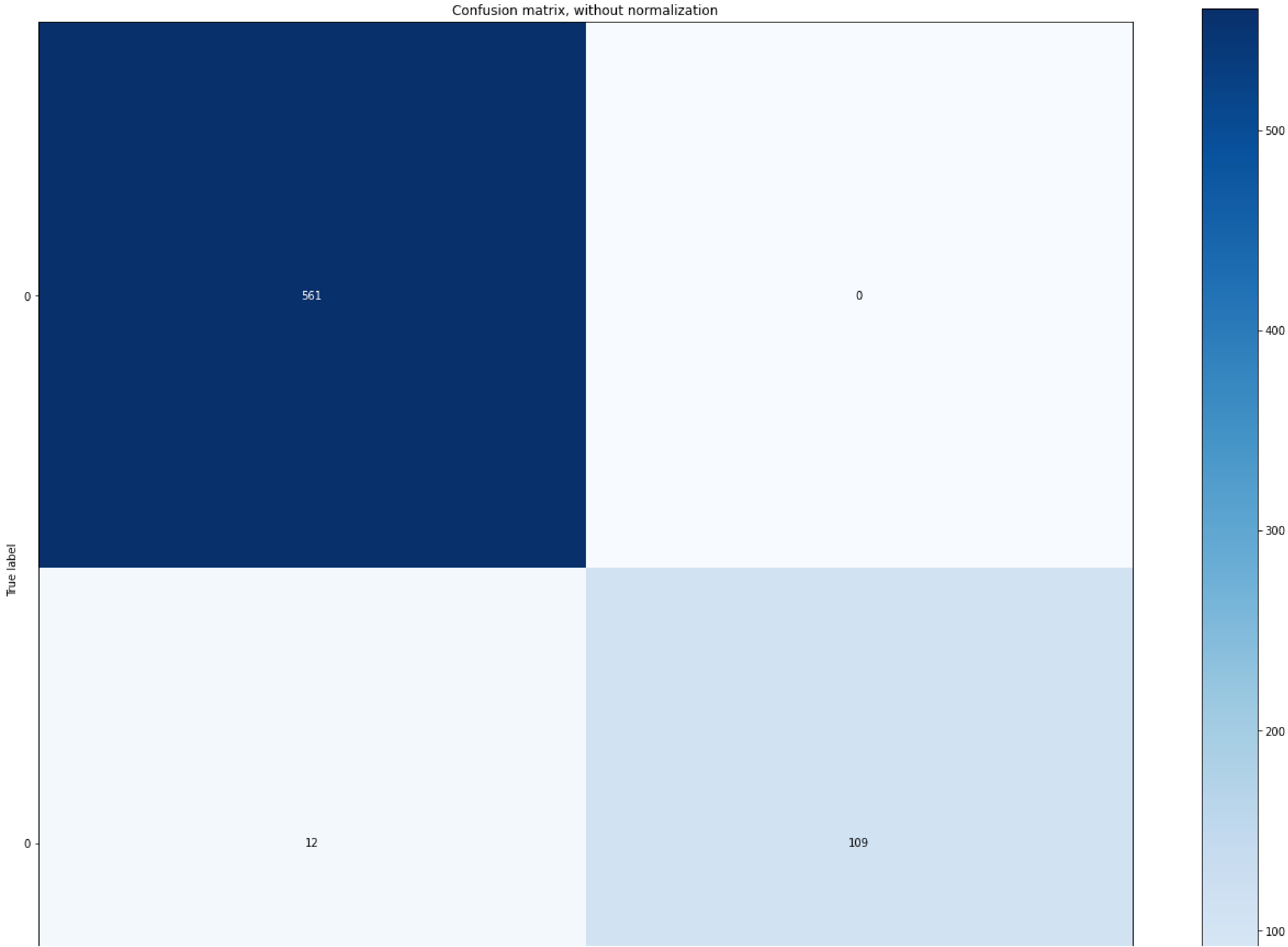
Support vector Classifier

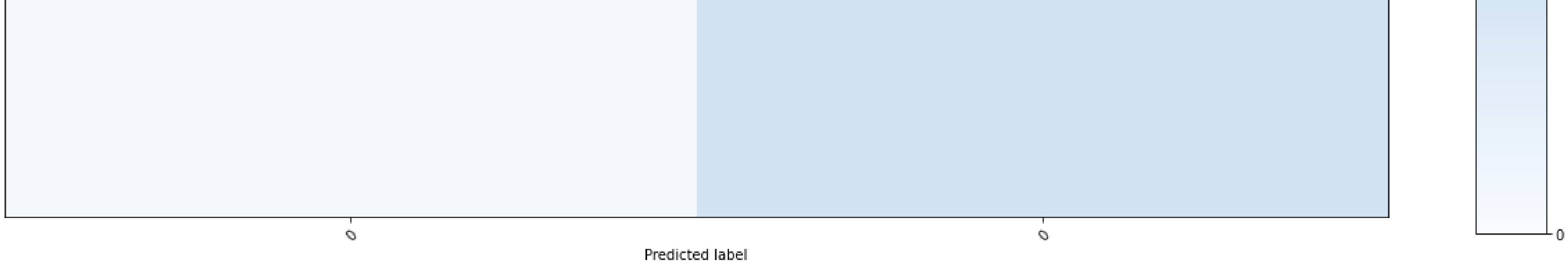
In [33]:
```
from sklearn.svm import SVC
import seaborn as sns
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import StratifiedKFold, train_test_split
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score
from sklearn.model_selection import learning_curve
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
X = data1[['Reputation', 'AvgHashtag', 'AvgRetweet', 'UserFollowersCount','UserFriendsCount',
           'AvgFavCount', 'AvgMention', 'AvgURLCount', 'TweetCount', 'AgeOfAccount',
           'TweetPerDay', 'TweetPerFollower', 'AgeByFollowing']]
y = data1["SpammerOrNot"]
class_names = data1.SpammerOrNot
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)
Cs = 10.0 ** np.arange(-2, 3, .5)
    # print(Cs)
gammas = 10.0 ** np.arange(-2, 3, .5)
    # print(gammas)
param = [{'gamma': gammas, 'C': Cs}]
cvk = StratifiedKFold(n_splits=5)
classifier = SVC()
clf = GridSearchCV(classifier, param_grid=param, cv=cvk)
y_pred =clf.fit(X_train, y_train).predict(X_test)


def plot_confusion_matrix(y_true, y_pred, classes,
                          normalize=False,
                          title=None,
                          cmap=plt.cm.Blues):

    if not title:
        if normalize:
            title = 'Normalized confusion matrix'
        else:
            title = 'Confusion matrix, without normalization'

    # Compute confusion matrix
    cm = confusion_matrix(y_true, y_pred)


    # Only use the labels that appear in the data
    classes = classes[unique_labels(y_true, y_pred)]
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
```

```
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    fig, ax = plt.subplots()
    im = ax.imshow(cm, interpolation='nearest', cmap=cmap)
    ax.figure.colorbar(im, ax=ax)
    # We want to show all ticks...
    ax.set(xticks=np.arange(cm.shape[1]),
           yticks=np.arange(cm.shape[0]),
           # ... and label them with the respective list entries
           xticklabels=classes, yticklabels=classes,
           title=title,
           ylabel='True label',
           xlabel='Predicted label')

    # Rotate the tick labels and set their alignment.
    plt.setp(ax.get_xticklabels(), rotation=45, ha="right",
             rotation_mode="anchor")

    # Loop over data dimensions and create text annotations.
    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i in range(cm.shape[0]):
        for j in range(cm.shape[1]):
            ax.text(j, i, format(cm[i, j], fmt),
                    ha="center", va="center",
                    color="white" if cm[i, j] > thresh else "black")
    fig.tight_layout()
    return ax


np.set_printoptions(precision=2)
# Plot non-normalized confusion matrix
plot_confusion_matrix(y_test, y_pred, classes=class_names,
                      title='Confusion matrix, without normalization')

print(accuracy_score(y_test,y_pred))
plt.show()
plt.savefig('Confusion_Matrix.png')
plt.savefig('Normalize.Matrix.png')
```

```
Confusion matrix, without normalization
```

```
[[561   0]
 [ 12 109]]
0.9824046920821115
```

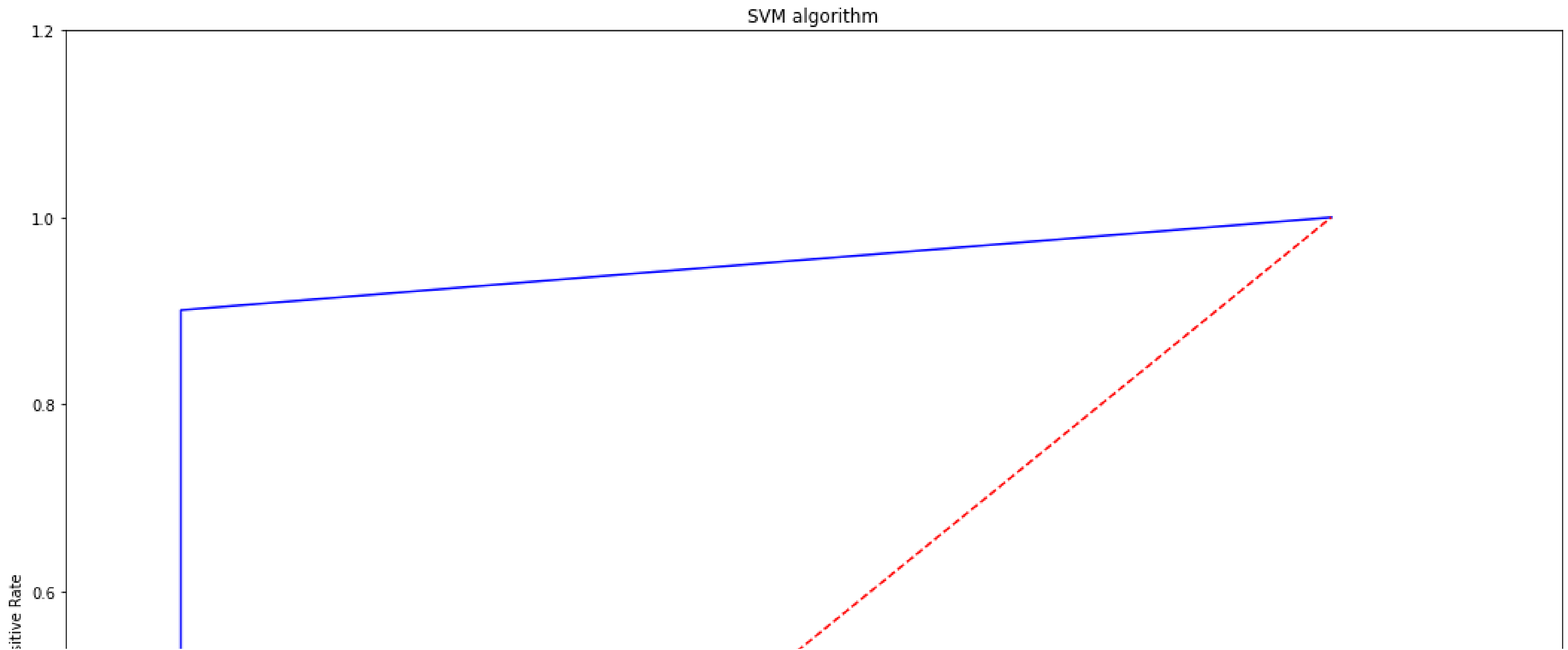


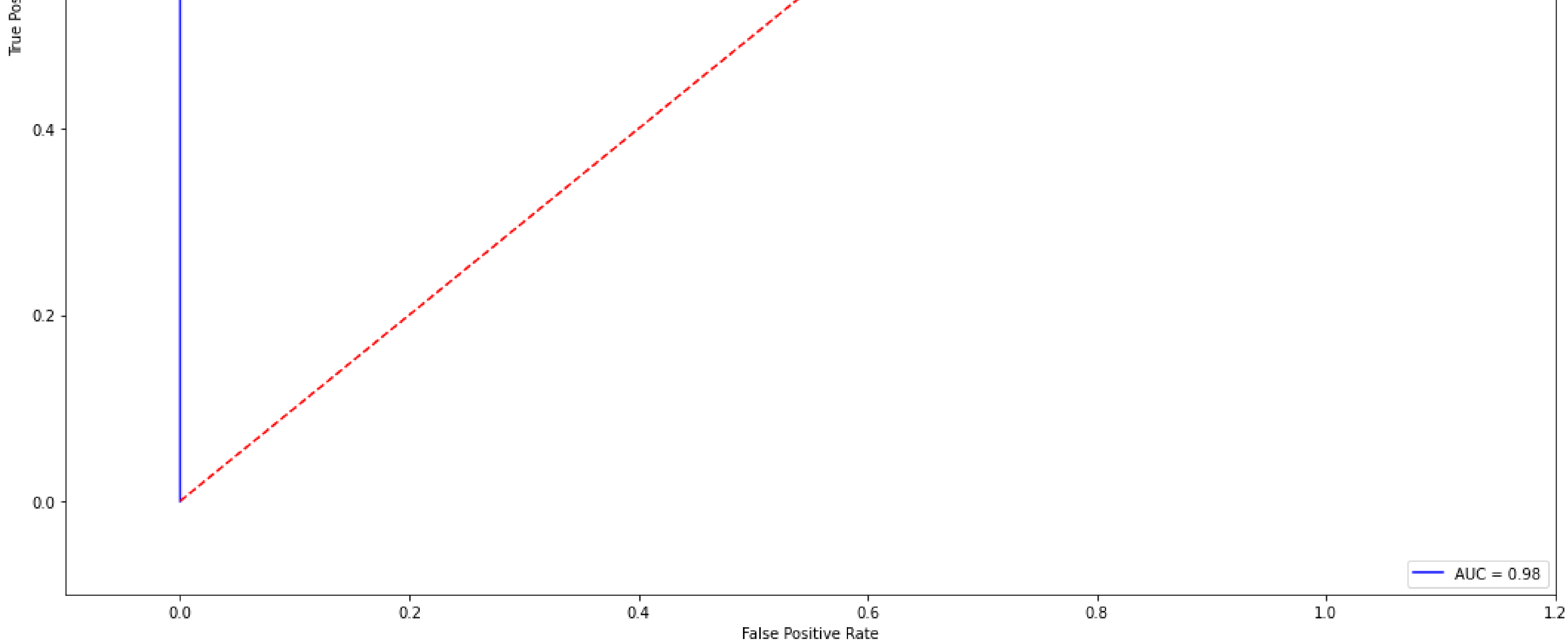


<Figure size 1296x1080 with 0 Axes>

In [34]:
```python
from sklearn.metrics import roc_curve, auc
acc=accuracy_score(y_test,y_pred)
false_positive_rate, true_positive_rate, thresholds = roc_curve(y_test, y_pred)
print("False Positive rate: ", false_positive_rate)
print("True Positive rate: ", true_positive_rate)

roc_auc = auc(false_positive_rate, true_positive_rate)
plt.title('Receiver Operating Characteristic')
plt.plot(false_positive_rate, true_positive_rate, 'b',
              label='AUC = %0.2f' % acc)
plt.legend(loc='lower right')
plt.plot([0, 1], [0, 1], 'r--')
plt.xlim([-0.1, 1.2])
plt.ylim([-0.1, 1.2])
plt.title('SVM algorithm')
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

```
False Positive rate:  [0. 0. 1.]
True Positive rate:  [0.  0.9 1. ]
```





True Pos
0.4
0.2
0.0
AUC = 0.98
0.0
0.2
0.4
0.6
0.8
1.0
1.2
False Positive Rate


```
In [ ]:
```