Email Spam Detection with Machine Learning

1.1 Importing libraries in this enviroment.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

1.2 Importing skleran models for prediction.

In [2]:
```
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
```

2.1 Reading the "spam (1).csv" dataset using python's pandas libraries.

In [3]:
```
spam = pd.read_csv("spam (1).csv",encoding = 'ISO-8859-1')
```

In [4]:
```
spam.head()
```

Out[4]:

	v1	v2	Unnamed: 2	Unnamed: 3	Unnamed: 4
0	ham	Go until jurong point, crazy.. Available only ...	NaN	NaN	NaN
1	ham	Ok lar... Joking wif u oni...	NaN	NaN	NaN
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	NaN	NaN	NaN
3	ham	U dun say so early hor... U c already then say...	NaN	NaN	NaN
4	ham	Nah I don't think he goes to usf, he lives aro...	NaN	NaN	NaN

In [5]:
```
shape =spam.shape
shape
```

Out[5]:
```
(5572, 5)
```

The above dataframe shows that 3rd, 4th, and 5th column doesn't contain any data. So, dropping these columns.

In [6]:
```
spam.drop(['Unnamed: 2','Unnamed: 3','Unnamed: 4'],inplace =True,axis =1)
```

In [7]:
```
spam.head()
```

Out[7]:

	v1	v2
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

!!! Columns dropped successfully.

2.2 Change the columns name corresponding to the data it contains.

In [8]:
```
spam.columns = ['type','message']
```

In [9]:
```
spam.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5572 entries, 0 to 5571
Data columns (total 2 columns):
 #   Column   Non-Null Count  Dtype 
---  ------   --------------  ----- 
 0   type     5572 non-null   object
 1   message  5572 non-null   object
dtypes: object(2)
memory usage: 87.2+ KB
```

2.3 Removing duplicates from the dataset.

In [10]:
```
spam.drop_duplicates(inplace = True)
```

In [11]:
```
new = spam.shape
new
```

Out[11]:
```
(5169, 2)
```

In [12]:
```
duplicates = shape[0]-new[0]
print("Numbers of duplicates :",duplicates)
```

```
Numbers of duplicates : 403
```

2.4 Statistical measure of the dataset.

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

Out[13]:

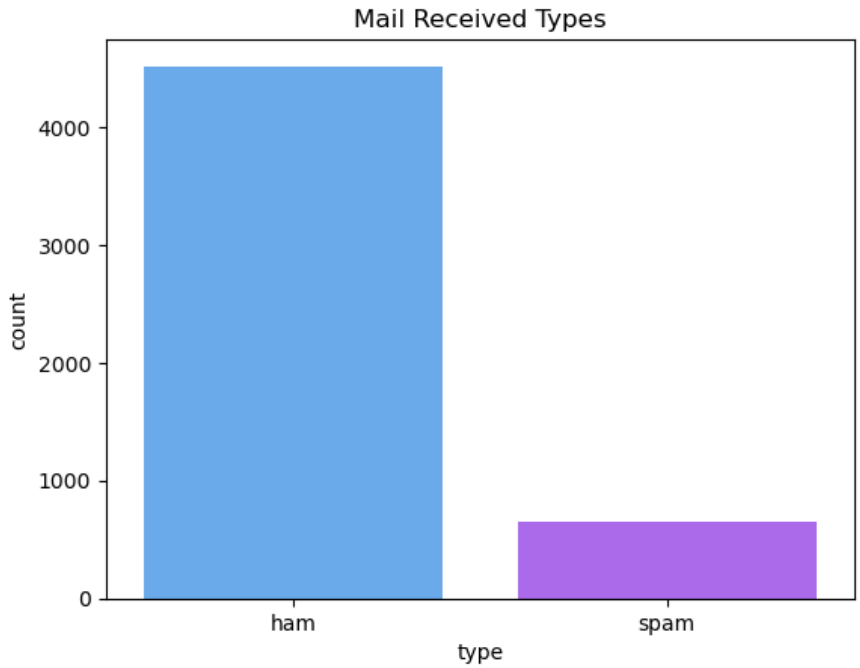
	type	message
count	5169	5169
unique	2	5169
top	ham	Go until jurong point, crazy.. Available only ...
freq	4516	1

In [14]:
```
spam['type'].value_counts()
```

Out[14]:
```
type
ham     4516
spam     653
Name: count, dtype: int64
```

In [15]:
```
sns.countplot(x='type',data =spam,palette = 'cool')
plt.title('Mail Received Types')
```

Out[15]:
```
Text(0.5, 1.0, 'Mail Received Types')
```



3.1 Data preparing for models.

In [16]:
```
lb = LabelEncoder()
```

In [17]:
```
spam['type'] =lb.fit_transform(spam['type'])
```

In [18]:
```
spam['type'].value_counts()
```

Out[18]:
```
type
0    4516
1     653
Name: count, dtype: int64
```

In [19]:
```
X = spam['message']
y =spam['type']
```

- Splitting the dataset into four parts X_train, X_test, y_train, y_test.

In [20]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,random_state=42)
```

In [21]:
```
feature_extraction = TfidfVectorizer(min_df=1, stop_words='english',lowercase=True)
X_train_new = feature_extraction.fit_transform(X_train)
X_test_new = feature_extraction.transform(X_test)
```

In [22]:
```
print(X_train.shape , X_test.shape)
print(y_train.shape, y_test.shape)
```

```
(4135,) (1034,)
(4135,) (1034,)
```

***3.2 Naive Bayes's model buliding , training and testing.**

In [23]:
```
nv =MultinomialNB()
nv.fit(X_train_new,y_train)
```

Out[23]:
```
MultinomialNB
MultinomialNB()
```

In [24]:
```
y_nv = nv.predict(X_test_new)
```

In [25]:
```
print('Accuracy of the Navie Bayes Model on the trian dataset: {:0.2f}%'.format((nv.score(X_train_new,y_trai
```

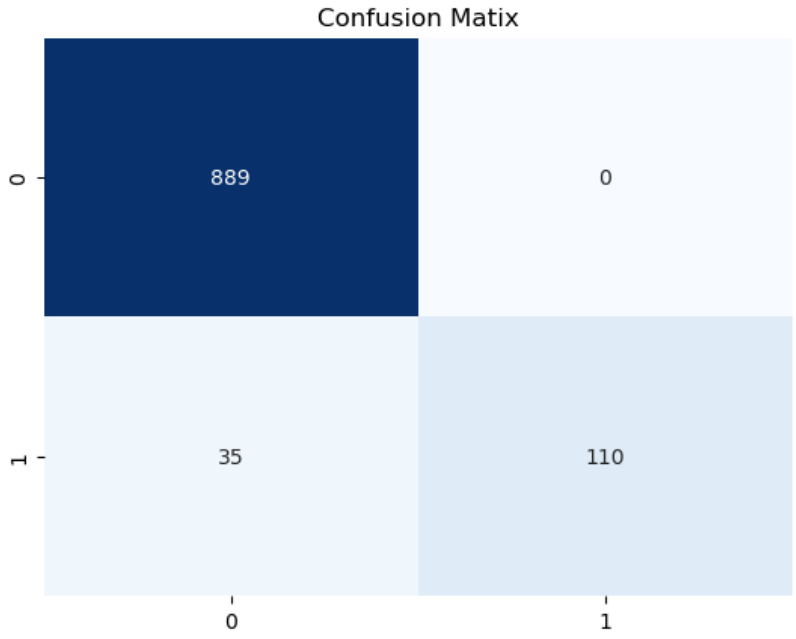
```
Accuracy of the Navie Bayes Model on the trian dataset: 97.87%
```

In [26]:
```
print('Accuracy of the Navie Bayes Model on the test dataset: {:0.2f}%'.format((nv.score(X_test_new,y_test)*
```

```
Accuracy of the Navie Bayes Model on the test dataset: 96.62%
```

In [27]:
```
cm_nv =confusion_matrix(y_test,y_nv)
sns.heatmap(cm_nv,annot =True,fmt ='d',cmap= 'Blues',cbar =False)
plt.title("Confusion Matix")
```

Out[27]:
```
Text(0.5, 1.0, 'Confusion Matix')
```



In [28]:
```
print("Classification Report of Navie Bayes Model :\n\n",classification_report(y_test,y_nv))
```

```
Classification Report of Navie Bayes Model :

              precision    recall  f1-score   support

           0       0.96      1.00      0.98       889
           1       1.00      0.76      0.86       145

    accuracy                           0.97      1034
   macro avg       0.98      0.88      0.92      1034
weighted avg       0.97      0.97      0.96      1034
```

3.3 Logistic Regression model building, training and testing.

In [29]:
```
lm = LogisticRegression()
```

In [30]:
```
lm.fit(X_train_new,y_train)
```

Out[30]:
```
LogisticRegression
LogisticRegression()
```

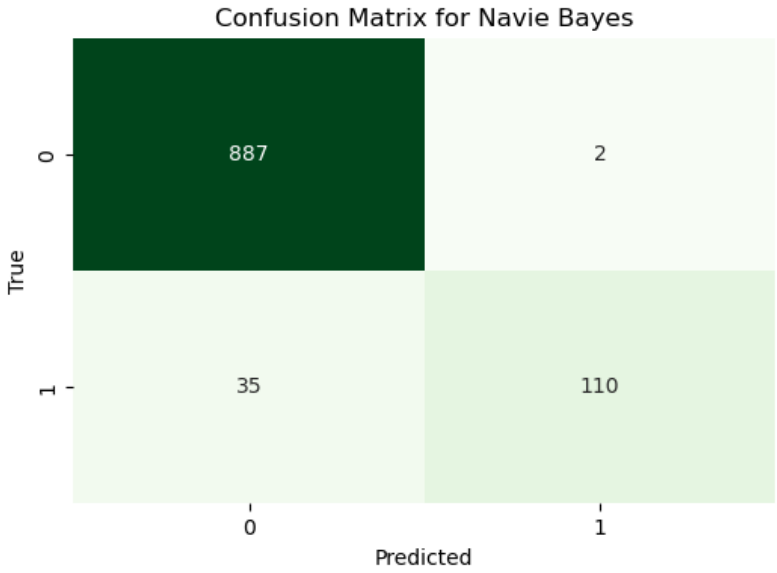
In [31]:
```
y_lm = lm.predict(X_test_new)
```

In [32]:
```
print('Accuracy of Logistic Regression on the trian data: {:0.2f}%'.format((lm.score(X_train_new,y_train)*10

print('Accuracy of Logistic Regression on the test data: {:0.2f}%'.format((lm.score(X_test_new,y_test)*100))
```

```
Accuracy of Logistic Regression on the trian data: 96.13%
Accuracy of Logistic Regression on the test data: 96.42%
```

In [33]:
```
cm_lm = confusion_matrix(y_test, y_lm)
plt.figure(figsize=(6, 4))
sns.heatmap(cm_lm, annot=True, fmt="d", cmap='Greens', cbar=False)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix for Navie Bayes')
plt.show()
```



In [34]:
```
print("Classification Report of Logistic Regerssion Model :\n\n",classification_report(y_test,y_lm))
```

```
Classification Report of Logistic Regerssion Model :

              precision    recall  f1-score   support

           0       0.96      1.00      0.98       889
           1       0.98      0.76      0.86       145

    accuracy                           0.96      1034
   macro avg       0.97      0.88      0.92      1034
weighted avg       0.96      0.96      0.96      1034
```

3.4 Random Forest Classifer model building, training and testing.

In [35]:
```
forest = RandomForestClassifier()
```

In [36]:
```
forest.fit(X_train_new,y_train)
```

Out[36]:
```
RandomForestClassifier
RandomForestClassifier()
```

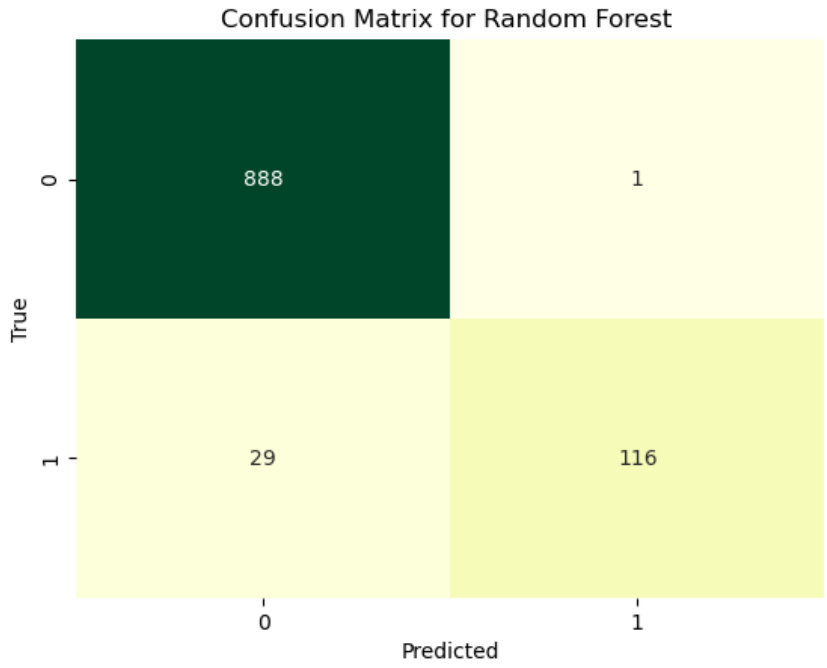
In [37]:
```
y_for =forest.predict(X_test_new)
```

In [38]:
```
print('Accuracy of Random Forest Classifier on the trian data: {:0.1f}%'.format((forest.score(X_train_new,y_
print('Accuracy of Random Forest Classifier on the test data: {:0.2f}%'.format((forest.score(X_test_new,y_te
```

```
Accuracy of Random Forest Classifier on the trian data: 100.0%
Accuracy of Random Forest Classifier on the test data: 97.10%
```

In [39]:
```
cm_for = confusion_matrix(y_test,y_for)
sns.heatmap(cm_for, annot =True,cmap ='YlGn',fmt='d', cbar =False)
plt.title("Confusion Matrix for Random Forest ")
plt.xlabel('Predicted')
plt.ylabel('True')
```

Out[39]:
```
Text(50.722222222222214, 0.5, 'True')
```



In [40]:
```
print("Classification Report of Random Forest Model :\n\n",classification_report(y_test,y_for))
```

```
Classification Report of Random Forest Model :

              precision    recall  f1-score   support

           0       0.97      1.00      0.98       889
           1       0.99      0.80      0.89       145

    accuracy                           0.97      1034
   macro avg       0.98      0.90      0.93      1034
weighted avg       0.97      0.97      0.97      1034
```

3.5 Decision Tree Classifier model building, training, and testing.

In [41]:
```
tree = DecisionTreeClassifier()
```

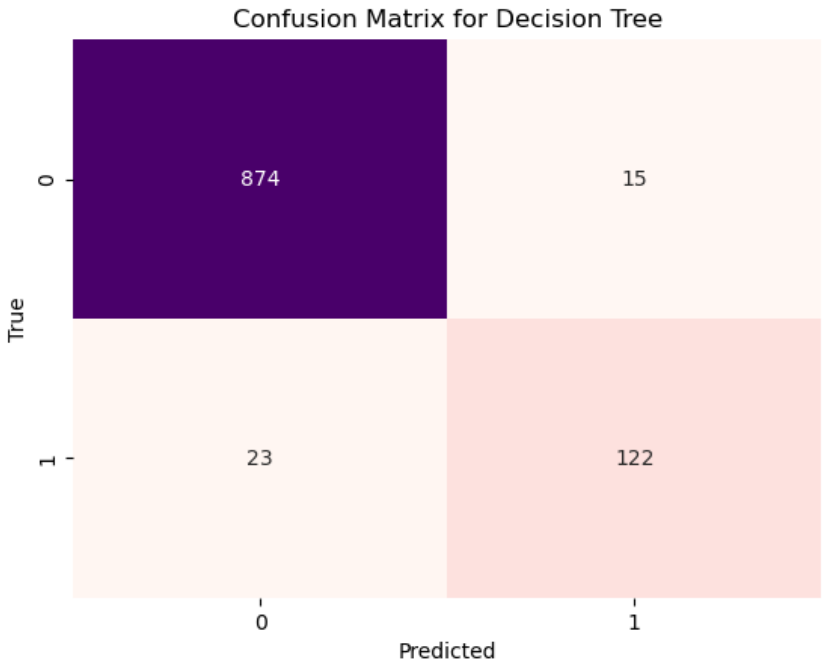
In [42]:
```
tree.fit(X_train_new,y_train)
y_tree =tree.predict(X_test_new)
```

In [43]:
```
print("Accuracy of the Decision Tree Classifier on train set: {:0.1f}%".format(tree.score(X_train_new,y_trai
print("Accuracy of the Decision Tree Classifier on test set: {:0.2f}%".format(tree.score(X_test_new,y_test)*
```

```
Accuracy of the Decision Tree Classifier on train set: 100.0%
Accuracy of the Decision Tree Classifier on test set: 96.32%
```

In [44]:
```
cm_tree = confusion_matrix(y_test,y_tree)
sns.heatmap(cm_tree, annot =True, fmt ='d', cbar= False, cmap = 'RdPu')
plt.title("Confusion Matrix for Decision Tree")
plt.xlabel('Predicted')
plt.ylabel('True')
```

Out[44]:
```
Text(50.722222222222214, 0.5, 'True')
```



In [45]:
```
print("Classification Report of Decision Tree Model :\n\n",classification_report(y_test,y_tree))
```

```
Classification Report of Decision Tree Model :

              precision    recall  f1-score   support

           0       0.97      0.98      0.98       889
           1       0.89      0.84      0.87       145

    accuracy                           0.96      1034
   macro avg       0.93      0.91      0.92      1034
weighted avg       0.96      0.96      0.96      1034
```

3.6 Gradient Boosting Classifer model building, training and testing.

In [46]:
```
boost =GradientBoostingClassifier()
```

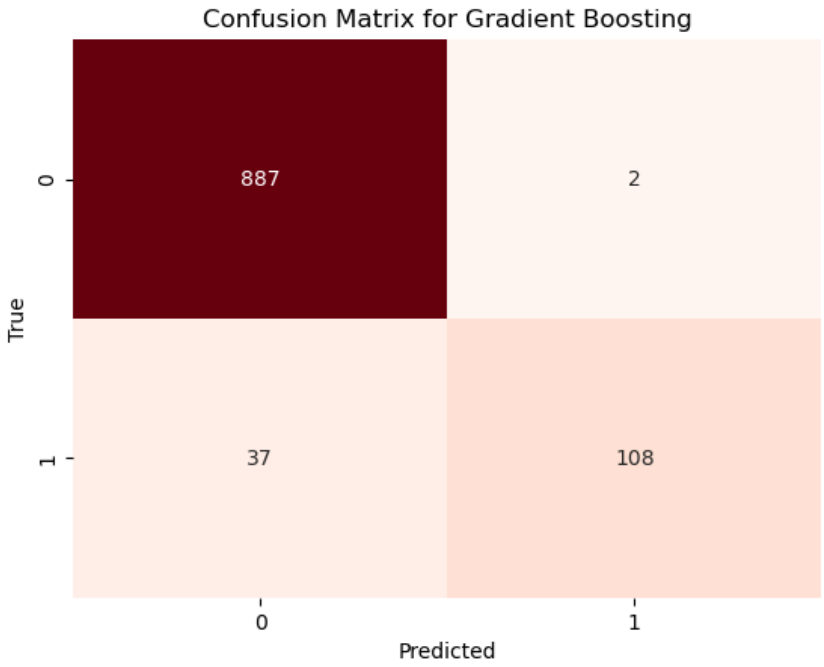
In [47]:
```
boost.fit(X_train_new,y_train)
y_boost = boost.predict(X_test_new)
```

In [48]:
```
print("Accuracy of the Gradient Boosting on train set: {:0.2f}%".format(boost.score(X_train_new,y_train)*100
print("Accuracy of the Gradient Boosting on test set: {:0.2f}%".format(boost.score(X_test_new,y_test)*100))
```

```
Accuracy of the Gradient Boosting on train set: 97.39%
Accuracy of the Gradient Boosting on test set: 96.23%
```

In [49]:
```
cm_boost = confusion_matrix(y_test,y_boost)
sns.heatmap(cm_boost,annot= True,cbar = False, fmt ='d',cmap = 'Reds')
plt.title("Confusion Matrix for Gradient Boosting")
plt.xlabel('Predicted')
plt.ylabel('True')
```

Out[49]:
```
Text(50.722222222222214, 0.5, 'True')
```



In [50]:
```
print("Classification Report of Gradient Boosting model :\n\n", classification_report(y_test,y_boost))
```

```
Classification Report of Gradient Boosting model :

              precision    recall  f1-score   support

           0       0.96      1.00      0.98       889
           1       0.98      0.74      0.85       145

    accuracy                           0.96      1034
   macro avg       0.97      0.87      0.91      1034
weighted avg       0.96      0.96      0.96      1034
```

4. Conclusion

From all the above models, Radom Forest Classifier model gives precise output.

!!! Thank You.

In [ ]:
```
```