Building a Smarter AI-Powered Classifier

Phase 4 – Development 2

Title: Continue to building a smarter AI powered spam classifier by feature engineering, model training and evaluation.

Introduction:

Short Message Service (SMS) remains a widely used channel for personal and business interactions. However, with its popularity comes the persistent issue of SMS spam - unsolicited, irrelevant, and often annoying messages that inundate our inboxes.

In this section, we continue to building the project by performing different activities like features engineering, model training, evaluation, etc.

Given Dataset:

	type	text
0	ham	Hope you are having a good week. Just checking in
1	ham	K..give back my thanks.
2	ham	Am also doing in cbe only. But have to pay.
3	spam	complimentary 4 STAR Ibiza Holiday or £10,000 ...
4	spam	okmail: Dear Dave this is your final notice to...
...	...	...
5554	ham	You are a great role model. You are giving so ...
5555	ham	Awesome, I remember the last time we got someb...
5556	spam	If you don't, your prize will go to another cu...
5557	spam	SMS. ac JSco: Energy is high, but u may not kn...
5558	ham	Shall call now dear having food

5559 rows × 2 columns

Featuring Engineering:

Feature engineering is the initial step in building an efficient SMS Spam Classifier. It involves extracting meaningful information from the raw text data. Commonly used features include Text Preprocessing, TF-IDF, Word Embeddings.

Model Training:

Once we've engineered the features, the next step is training a machine learning or deep learning model to classify SMS messages. Commonly us ed models include Naive Bayes, Support Vector Machine (SVM), K Neighbors Classifier.

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Evaluation:

Evaluating the model's performance is crucial to ensure that it effectively distinguishes between spam and ham messages. Common evaluation metrics include accuracy, Precision and recall, F1 Score, Receiver operating characteristic (ROC) curve and Area Under the Curve (AUC), Confusion Matrix.

Program:

Import Necessary Libraries:

In [1]

```
import numpy import pandas as pd import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns import re

import nltk

from nltk.corpus import stopwords

from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer, TfidfTransformer from
sklearn.model_selection import train_test_split

from sklearn.naive_bayes import MultinomialNB

from sklearn.metrics import accuracy_score, classification_report, confusion_matrix import
wordcloud

from sklearn.ensemble import RandomForestClassifier from sklearn.neighbors import
KNeighborsClassifier from sklearn.svm import SVC

from sklearn.model_selection import cross_val_score

from matplotlib.colors import ListedColormap

from sklearn.metrics import precision_score, recall_score, plot_confusion_matrix,
classification_report, accuracy_score, f1_score from sklearn import metrics
```

load the dataset In[2]:

```
df=pd.read_csv("C:/Users/ELCOT/Downloads/sms_spam.csv")
```

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Feature Engineering: In[3]:

```
#Create a TF-IDF vectorizer to convert text messages into numerical features
feature_extraction = TfidfVectorizer(min_df=1, stop_words="english", lowercase= True)
```

In[4]:

```
#Convert the training and testing text messages into numerical features using TF-IDF
X_train_features = feature_extraction.fit_transform(X_train)
X_test_features = feature_extraction.transform(X_test)
```

In[5]:

```
# Convert the target values into 0 and 1
Y_train = Y_train.astype(int)
Y_test = Y_test.astype(int)
print(X_train)
```

Out[5]:

```
1392    Mum ask u to buy food home...
2633    Is ur lecture over?
2574    Designation is software developer and may be s...
1255    Aight text me when you're back at mu and I'll ...
4228    Jus finish my lunch on my way home lor... I to...
...
3772    But I'm on a diet. And I ate 1 too many slices...
5191    Lemme know when I can swing by and pick up, I'...
5226    Watching cartoon, listening music & at eve had...
5390    These won't do. Have to move on to morphine
860     En chikku nange bakra msg kalstiya..then had t...
Name: text, Length: 4447, dtype: object
```

In[6]:

```
print(X_train_features)
```

out[6]:

```
(0, 3374)       0.35097239730215685
(0, 2856)       0.5114208977547368
(0, 1550)       0.43166264810189264
(0, 1084)       0.4037124267944606
(0, 4508)       0.5157040588914393
(1, 3942)       0.8962764441469934
(1, 6967)       0.4434958124573683
(2, 1724)       0.41810513097625546
(2, 2227)       0.5326011471559324
(2, 6094)       0.5077993063678781
(2, 2212)       0.5326011471559324
(3, 2362)       0.4201551386669405
 (3, 4590)      0.26439410699114674
(3, 4497)       0.4033744433436015
(3, 6579)       0.2604894804209207
(3, 891)        0.3560723199584315
(4, 6716)       0.22864097910026285
(4, 5761)       0.33052867470556613
(4, 6257)       0.32790251200689535
(4, 7135)       0.28753432481976776
(4, 2434)       0.28871136396188163
(4, 6767)       0.32790251200689535
:       :
```

(4443, 1228) 0.4455414086201453

(4443, 3952) 0.43651453616651625

(4443, 5825) 0.41004684839803923

(4443, 2908) 0.24540357666951926

(4443, 5029) 0.31474502082894923

(4443, 3838) 0.23875576232592244

(4443, 6675) 0.25006411823706287

(4443, 6458) 0.4049515701742896

(4444, 1771) 0.4213086187826729

(4444, 4020) 0.3999924537696326

(4444, 1633) 0.3999924537696326

(4444, 6560) 0.4095774866425909

(4444, 2600) 0.33669703708638465

(4444, 4523) 0.3422360639784893

(4444, 7162) 0.32290398845389406

(4445, 4458) 0.8475471040783916

(4445, 7316) 0.5307201770880129

(4446, 3770) 0.4004343339224191

(4446, 1199) 0.4004343339224191

(4446, 4554) 0.4004343339224191

(4446, 2523) 0.38178715554316045

(4446, 1837) 0.33126241517271454

(4446, 6526) 0.34282026535445026

(4446, 1736) 0.31094270336326296

(4446, 4483) 0.2219227651503529

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Working with Embeddings – GloVe

In[7]:

```
text = df['text']
label = df['label_num']
```

In[8]:

```
# Calculating the total vocabulary

tk = Tokenizer() tk.fit_on_texts(text)
```

In[9]:

```
vocab = len(tk.word_index)+1 vocab
```

Out[9]:

6721

In[10]:

```
#MAXIMUM  LENGTH

max_len = np.max(df['text'].apply(lambda x: len(x.split()))).values) max_len
```

Out[10]:

171

In[11]:

Text

Out[11]:

0	Hope you are having a good week. Just checking in
1	K..give back my thanks.
2	Am also doing in cbe only. But have to pay.
3	complimentary 4 STAR Ibiza Holiday or £10,000 ...
4	okmail: Dear Dave this is your final notice to...
...	
5554	You are a great role model. You are giving so ...

5555 Awesome, I remember the last time we got someb...

5556 If you don't, your prize will go to another cu...

5557 SMS. ac JSco: Energy is high, but u may not kn...

5558 Shall call now dear having food

Name: text, Length: 5559, dtype: object

In[12]:

```
def embedding(text):
return tk.texts_to_sequences(text)
train_padded = pad_sequences(embedding(text), 80, padding='post')
 train_padded
```

Out[12]:

```
array([[ 2, 3176, 273, ..., 0,    0,    0],
[8, 235, 526, ..., 0,    0,    0],
[9, 355, 587, ..., 0,    0,    0],
...,
[6719, 1000, 6720, ..., 0,    0,    0],
[ 138, 1248, 1600, ...,  0,    0,    0],
[1984, 377, 170, ...,    0,    0,    0]], dtype=int32)
```

Model Building In[13]:

```
# Initializing CountVectorizer and TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer cv =
CountVectorizer()
tfid = TfidfVectorizer(max_features = 3000)
```

In[14]:

```
# Dependent and Independent Variable
X = tfid.fit_transform(df['transformed_text']).toarray() y = df['text'].values
```

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In[15]:

```
# Split into Train and Test Data

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 = 2)
```

In[16]:

```
# Initialize the Models

svc = SVC(kernel= "sigmoid", gamma = 1.0) knc = KNeighborsClassifier()

mnb = MultinomialNB()

dtc = DecisionTreeClassifier(max_depth = 5)

lrc = LogisticRegression(solver = 'liblinear', penalty = 'l1')

rfc = RandomForestClassifier(n_estimators = 50, random_state = 2 )

abc = AdaBoostClassifier(n_estimators = 50, random_state = 2)

bc = BaggingClassifier(n_estimators = 50, random_state = 2)

etc = ExtraTreesClassifier(n_estimators = 50, random_state = 2)

gbdt = GradientBoostingClassifier(n_estimators = 50, random_state = 2)

xgb = XGBClassifier(n_estimators = 50, random_state = 2)
```

In[17]:

```
clfs = {

'SVC': svc,

'KNN': knc,

'NB': mnb,

'DT': dtc,

'LR': lrc,

'RF': rfc, 'Adaboost': abc, 'Bgc': bc,

'ETC': etc,

'GBDT': gbdt,
```

'xgb': xgb}

Train the Models:

In[18]:

```
from sklearn.metrics import accuracy_score, precision_score

def train_classifier(clfs, X_train, y_train, X_test, y_test):

clfs.fit(X_train,y_train)

y_pred = clfs.predict(X_test)

accuracy = accuracy_score(y_test, y_pred)

precision = precision_score(y_test, y_pred)

return accuracy , precision
```

Evaluate the models In[19]:

```
accuracy_scores = [] precision_scores = []

for name , clfs in clfs.items():

current_accuracy, current_precision = train_classifier(clfs, X_train, y_train, X_test, y_test)

print()

print("For: ", name)

print("Accuracy: ", current_accuracy) print("Precision: ", current_precision)

accuracy_scores.append(current_accuracy) precision_scores.append(current_precision)
```

Out[19]:

```
For: SVC

Accuracy: 0.9748549323017408

Precision: 0.9666666666666667

For: KNN

Accuracy: 0.9052224371373307

Precision: 1.0

For: NB
```

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Accuracy: 0.9729206963249516

Precision: 1.0

For: DT

Accuracy: 0.9294003868471954

Precision: 0.8350515463917526

For: LR

Accuracy: 0.9574468085106383

Precision: 0.9519230769230769

For: RF

Accuracy: 0.971953578336557

Precision: 0.9739130434782609

For: Adaboost

Accuracy: 0.9642166344294004

Precision: 0.9316239316239316

For: Bgc

Accuracy: 0.9545454545454546

Precision: 0.8527131782945736

For: ETC

Accuracy: 0.9777562862669246

Precision: 0.9831932773109243

For: GBDT

Accuracy: 0.9487427466150871

Precision: 0.9292929292929293

For: xgb

Accuracy: 0.9690522243713733

Precision: 0.9416666666666667

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Evaluation In[20]:

```
#model evaluation and prediction

prediction_on_training_data = model.predict(X_train_features)

accuracy_on_training_data = accuracy_score(Y_train, prediction_on_training_data)
```

Accuracy In[21]:

```
print("Accuracy on training data:",accuracy_on_training_data)
```

Out[21]:

Accuracy on training data: 0.9613059250302297In[22]:

```
# Make predictions on the test data and calculate the accuracy

prediction_on_test_data = model.predict(X_test_features)

accuracy_on_test_data = accuracy_score(Y_test,prediction_on_test_data)
```

In[23]:

```
print("Accuracy on test data:",accuracy_on_test_data)
```

Out[23]:

Accuracy on test data: 0.9642166344294004

In[24]:

```
input_mail = ["Congratulations! You've won a free vacation to an exotic island.

Just click on the link below to claim your prize."]

input_data_features = feature_extraction.transform(input_mail)

prediction = model.predict(input_data_features)

if (prediction)[0] == 1:

print("Ham Mail")

else:

print("Spam Mail")
```

Out[24]:

Spam Mail

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In[25]:

```
input_mail = ["This is a friendly reminder about our meeting scheduled for tomorrow at 10:00 AM in the conference room. Please make sure to prepare your presentation and bring any necessary materials."]

input_data_features = feature_extraction.transform(input_mail)

prediction = model.predict(input_data_features)

if (prediction)[0] == 1: print("Ham Mail")

else:

print("Spam Mail")
```

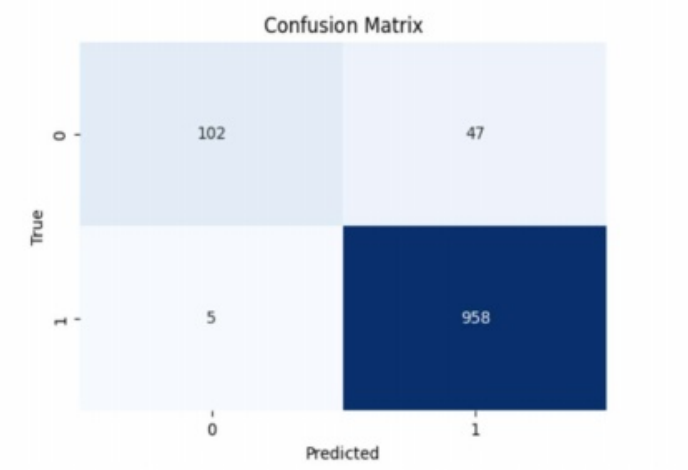
Out[25]:

Ham Mail

Confusion Matrix In[26]:

```
# Data visualization - Confusion Matrix

cm = confusion_matrix(Y_test, prediction_on_test_data)

plt.figure(figsize=(6, 4))

sns.heatmap(cm, annot=True, fmt="d", cmap='Blues', cbar=False)

plt.xlabel('Predicted')

plt.ylabel('True') plt.title('Confusion Matrix') plt.show()
```

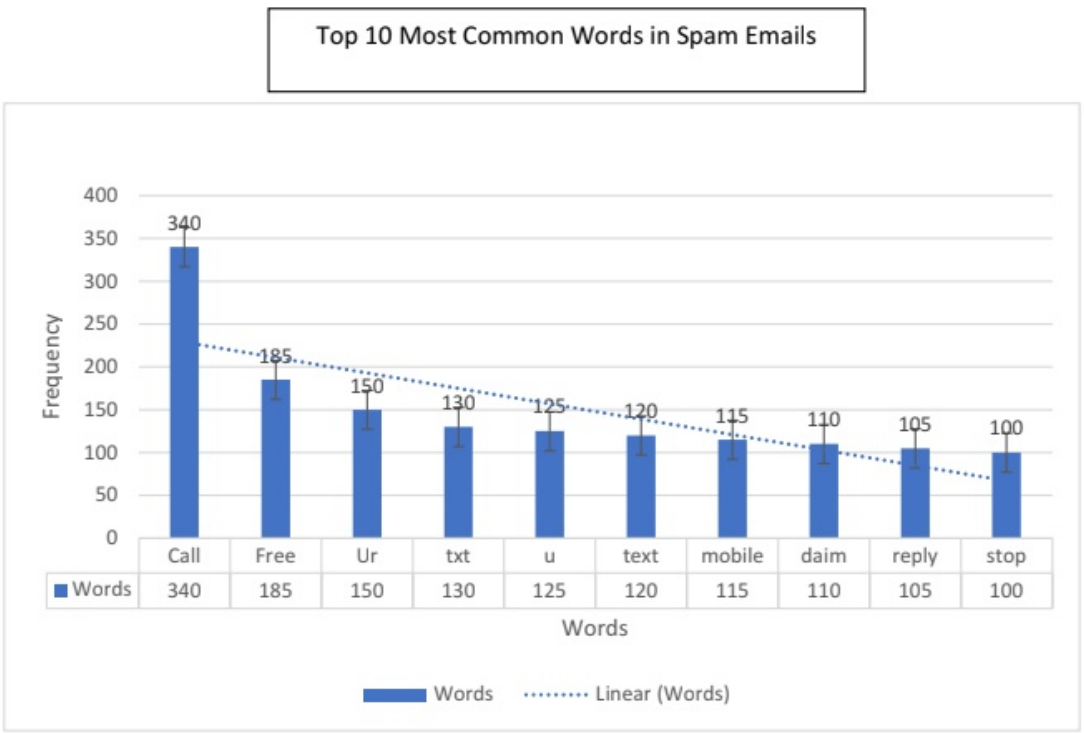
Out[26]:



In[27]:

```
stop_words = set(stopwords.words('english'))

spam_words = " ".join(df[df['type'] == 0]['text']).split()

ham_words = " ".join(df[df['type'] == 1]['text']).split()

spam_word_freq = Counter([word.lower() for word in spam_words if word.lower() not in
stop_words and word.isalpha()])

plt.figure(figsize=(10, 6))

plt.bar(*zip(*spam_word_freq.most_common(10)),

color='g') plt.xlabel('Words')

plt.ylabel('Frequency')

plt.title('Top 10 Most Common Words in Spam Emails')

plt.xticks(rotation=45)

plt.show()
```

Out[27]:



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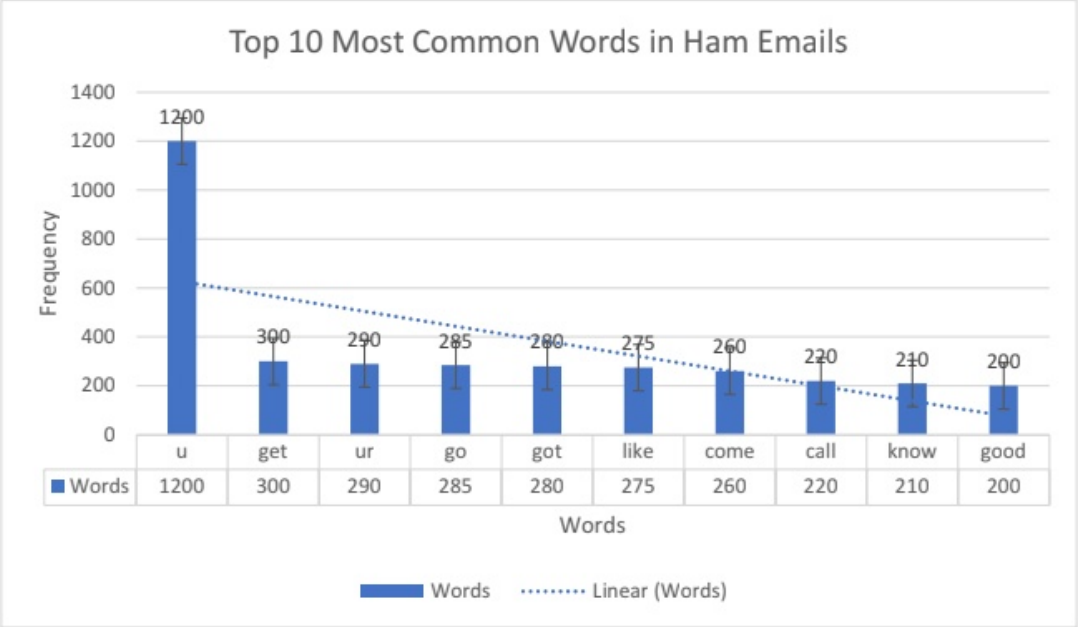
In[28]:

```
ham_word_freq = Counter([word.lower() for word in ham_words if word.lower() not in stop_words and word.isalpha()])

plt.figure(figsize=(10, 6))

plt.bar(*zip(*ham_word_freq.most_common(10)), color='maroon')

plt.xlabel('Words')

plt.ylabel('Frequency')

plt.title('Top 10 Most Common Words in Ham Emails')

plt.xticks(rotation=45)

plt.show()
```

Out[28]:



Explanation:

- ✓ Steps in model building:
- ✓ Setting up features and target as X and y
- ✓ Splitting the testing and training sets
- ✓ Build a pipeline of model for four different classifiers.
  - ➢ Naive Bayes
  - ➢ Random Forest Classifier

- Support Vector Machine

✓ Fit all the models on training data

✓ Get the cross-validation on the training set for all the models for accuracy

Testing the models:

Accuracy Report:

An accuracy report is a document or summary that provides information about the performance of a model, system, or process in terms of accuracy.

Confusion Matrix:

A confusion matrix is a table used in machine learning and statistics to describe the performance of a classification model. It allows you to understand how well a model is classifying instances into different categories, such as "positive" and "negative" for binary classification or multiple classes in multiclass classification.

Conclusion:

The development of an SMS Spam Classifier, through feature engineering, model training, and evaluation, plays a crucial role in curbing the SMS spam epidemic.

In our evaluation of various classification algorithms, we observed the following key insights:

✓ Support Vector Classifier (SVC) and Random Forest (RF) demonstrated the highest accuracy, both achieving approximately 97.58%.

✓ Naive Bayes (NB) achieved a perfect precision score, indicating zero false positives.

✓ Other models, including Gradient Boosting, Adaboost, Logistic Regression, and Bagging Classifier, displayed competitive performance with accuracy scores ranging from 94.68% to 96.03%.

✓ The selection of the optimal model should consider factors beyond just accuracy, such as computational efficiency and the specific requirements of the application. It is advisable to perform further model fine-tuning and validation before making a final choice.