

SPAM DETECTOR

My Jupyter Notebook:

https://github.com/alex80ds/Boulder-CU/blob/main/Spam_detector.ipynb

My PDF: https://github.com/alex80ds/Boulder-CU/blob/main/Spam_detector.pdf

```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
```

```
import warnings
warnings.filterwarnings("ignore")
```

```
C:\Users\LENOVO\anaconda3\lib\site-packages\scipy\__init__.py:155:
UserWarning: A NumPy version >=1.18.5 and <1.25.0 is required for this
version of SciPy (detected version 1.26.4
```

```
    warnings.warn(f"A NumPy version >={np_minversion} and
<{np_maxversion}")
```

```
df = pd.read_csv("https://raw.githubusercontent.com/alex80ds/Boulder-
CU/main/spam_detector.csv", encoding='latin1')
```

EDA

```
df.head()
```

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

	Unnamed: 3	Unnamed: 4
0	NaN	NaN
1	NaN	NaN
2	NaN	NaN
3	NaN	NaN
4	NaN	NaN

```

df.rename(columns = {"v1": "target", "v2": "text"}, inplace = True)

df.drop(["Unnamed: 2", "Unnamed: 3", "Unnamed: 4"], axis = 1, inplace = True)

df.head()

```

	target	text
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...

```

df.info()

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

df.describe()

```

	target	text
count	5572	5572
unique	2	5169
top	ham	Sorry, I'll call later
freq	4825	30

```

df.duplicated().sum()

403

df.drop_duplicates(inplace = True)

df.isnull().sum()

target    0
text      0
dtype: int64

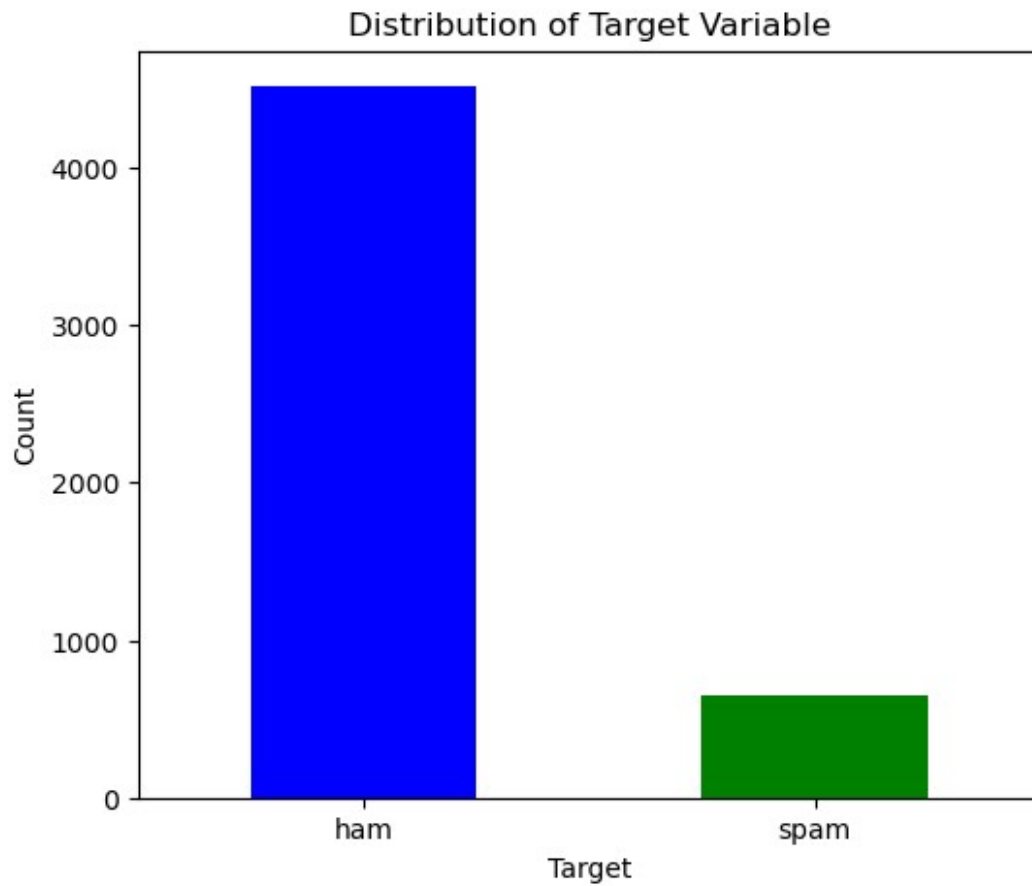
import matplotlib.pyplot as plt

target_counts = df['target'].value_counts()

plt.figure(figsize=(6, 5))
target_counts.plot(kind='bar', color=['blue', 'green'])

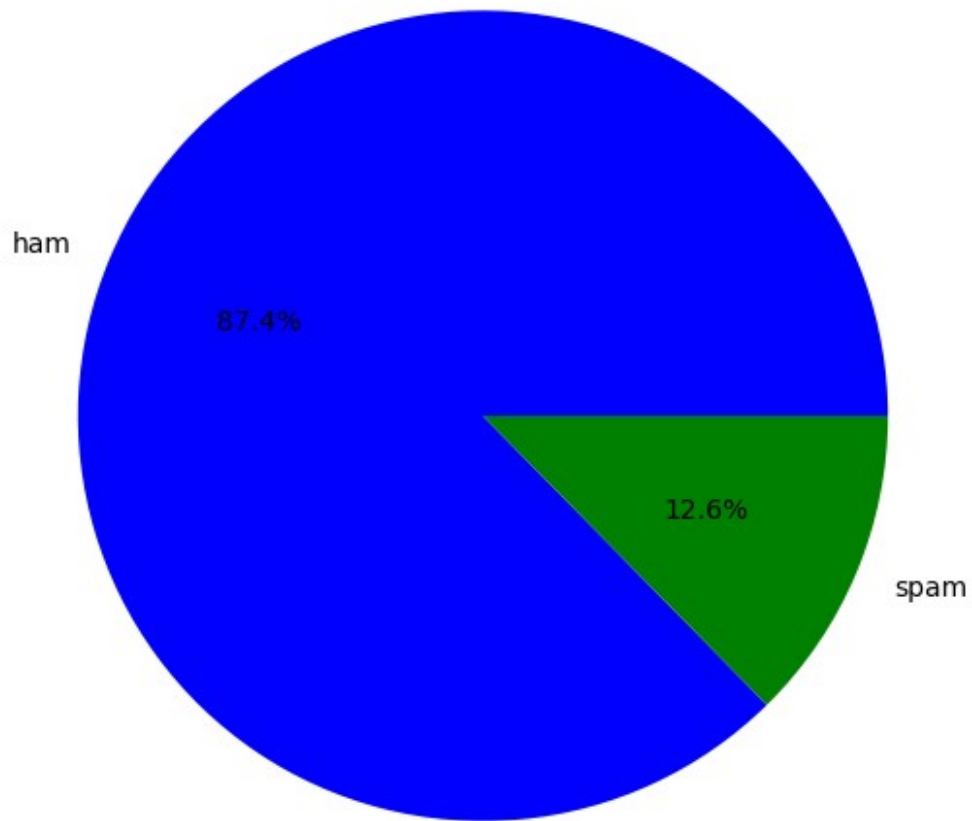
```

```
plt.title('Distribution of Target Variable')
plt.xlabel('Target')
plt.ylabel('Count')
plt.xticks(rotation=0)
plt.show()
```



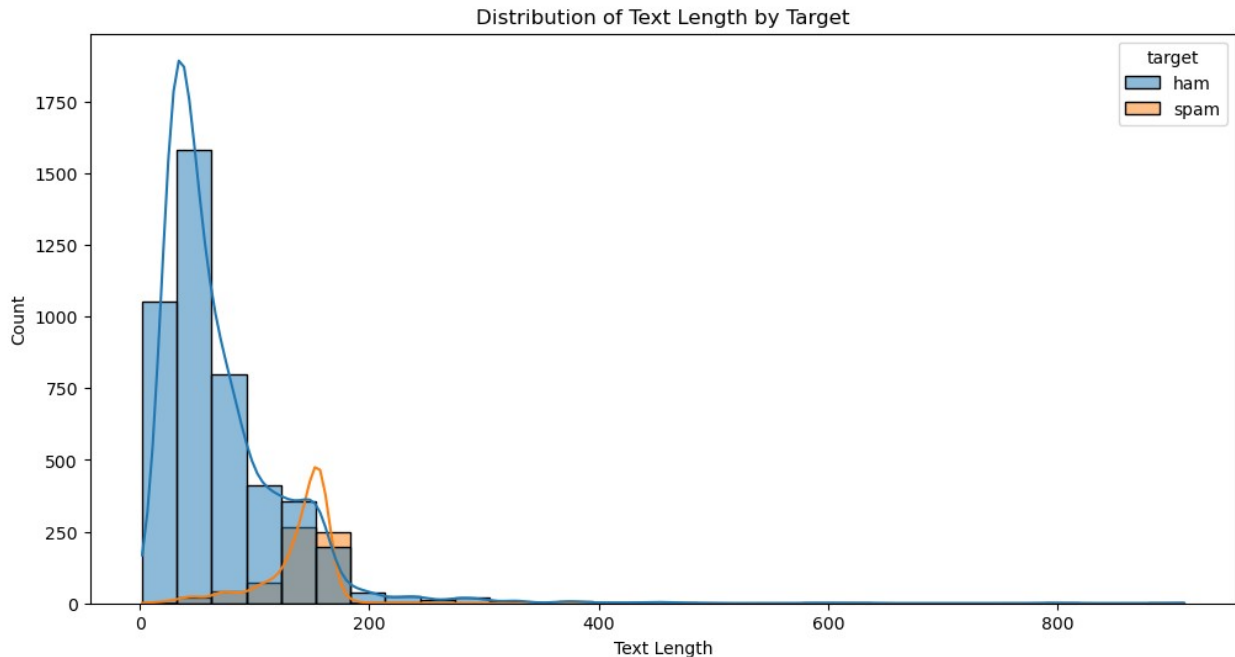
```
plt.figure(figsize=(8, 6))
plt.pie(target_counts, labels=target_counts.index, autopct='%1.1f%%',
        colors=['blue', 'green'])
plt.title('Distribution of Target Variable')
plt.axis('equal')
plt.show()
```

Distribution of Target Variable



```
df['text_length'] = df['text'].apply(len)

plt.figure(figsize=(12, 6))
sns.histplot(data=df, x='text_length', hue='target', bins=30,
kde=True)
plt.title('Distribution of Text Length by Target')
plt.xlabel('Text Length')
plt.ylabel('Count')
plt.show()
```



DATA PREPROCESSING

```
import re
import nltk
import pandas as pd
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
```

```
nltk.download('punkt')
nltk.download('stopwords')
```

```
[nltk_data] Downloading package punkt to
[nltk_data]   C:\Users\LENOVO\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]   C:\Users\LENOVO\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
```

True

```
def preprocess_text(text):
    text = text.lower()
    text = re.sub('[\.\?]', '', text)
    text = re.sub('\W', ' ', text)
    text = re.sub('https?://\S+|www\.\S+', '', text)
    text = re.sub('<.*?>+', '', text)
    text = re.sub('\n', '', text)
    text = re.sub('\w*\d\w*', '', text)
```

```

text = re.sub(r'^\w\s\d]', '', text)

tokens = word_tokenize(text)

clean_tokens = [re.sub(r'^a-zA-Z0-9]', '', token) for token in
tokens if re.sub(r'^a-zA-Z0-9]', '', token)]

stop_words = set(stopwords.words('english'))
filtered_tokens = [token for token in clean_tokens if token not in
stop_words]

stemmer = PorterStemmer()
stemmed_tokens = [stemmer.stem(token) for token in
filtered_tokens]

preprocessed_text = ' '.join(stemmed_tokens)

return preprocessed_text

df['text'] = df['text'].apply(preprocess_text)

```

```
df
```

	target	text
0	ham	go jurong point crazi avail bugi n great world...
1	ham	ok lar joke wif u oni
2	spam	free entri wkli comp win fa cup final tkt may ...
3	ham	u dun say earli hor u c already say
4	ham	nah think goe usf live around though
...
5567	spam	time tri contact u u pound prize claim easi ca...
5568	ham	b go esplanad fr home
5569	ham	piti mood suggest
5570	ham	guy bitch act like interest buy someth els nex...
5571	ham	rofl true name

```
[5169 rows x 3 columns]
```

BUILDING MODEL

```
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split

from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, Flatten, Dense

label_encoder = LabelEncoder()
df['target_encoded'] = label_encoder.fit_transform(df['target'])

tokenizer = Tokenizer()
tokenizer.fit_on_texts(df['text'])
sequences = tokenizer.texts_to_sequences(df['text'])

max_sequence_length = max([len(seq) for seq in sequences])
sequences_padded = pad_sequences(sequences,
maxlen=max_sequence_length)

X_train, X_test, y_train, y_test = train_test_split(sequences_padded,
df['target_encoded'], test_size=0.2, random_state=42)

embedding_dim = 50
model = Sequential()
model.add(Embedding(input_dim=len(tokenizer.word_index)+1,
output_dim=embedding_dim))
model.add(Flatten())
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['accuracy'])

history = model.fit(X_train, y_train, epochs=10, batch_size=64,
validation_split=0.2)

test_loss, test_accuracy = model.evaluate(X_test, y_test)
print(f"Test Loss: {test_loss}, Test Accuracy: {test_accuracy}")

Epoch 1/10
52/52 _____ 3s 14ms/step - accuracy: 0.8668 - loss:
0.3818 - val_accuracy: 0.8924 - val_loss: 0.1624
Epoch 2/10
```

```
52/52 _____ 0s 8ms/step - accuracy: 0.9193 - loss:
0.1591 - val_accuracy: 0.9710 - val_loss: 0.1223
Epoch 3/10
52/52 _____ 0s 8ms/step - accuracy: 0.9805 - loss:
0.1172 - val_accuracy: 0.9782 - val_loss: 0.1144
Epoch 4/10
52/52 _____ 0s 8ms/step - accuracy: 0.9917 - loss:
0.1008 - val_accuracy: 0.9758 - val_loss: 0.1066
Epoch 5/10
52/52 _____ 0s 8ms/step - accuracy: 0.9963 - loss:
0.0543 - val_accuracy: 0.9831 - val_loss: 0.0607
Epoch 6/10
52/52 _____ 0s 8ms/step - accuracy: 0.9987 - loss:
0.0120 - val_accuracy: 0.9867 - val_loss: 0.0550
Epoch 7/10
52/52 _____ 0s 8ms/step - accuracy: 0.9983 - loss:
0.0117 - val_accuracy: 0.9855 - val_loss: 0.0490
Epoch 8/10
52/52 _____ 0s 8ms/step - accuracy: 0.9995 - loss:
0.0058 - val_accuracy: 0.9794 - val_loss: 0.0608
Epoch 9/10
52/52 _____ 0s 8ms/step - accuracy: 0.9993 - loss:
0.0036 - val_accuracy: 0.9867 - val_loss: 0.0489
Epoch 10/10
52/52 _____ 0s 7ms/step - accuracy: 0.9996 - loss:
0.0051 - val_accuracy: 0.9855 - val_loss: 0.0485
33/33 _____ 0s 3ms/step - accuracy: 0.9804 - loss:
0.0552
Test Loss: 0.056219857186079025, Test Accuracy: 0.9816247820854187
```

CONCLUSION

Based on the test results of the text classification model:

High Accuracy: The model achieved a test accuracy of approximately 98.16%, indicating that it can effectively classify text messages into their respective categories (e.g., spam or ham).

Effective Generalization: The high accuracy on the test set suggests that the model has generalized well to unseen data, which is essential for real-world applications.

Potential for Real-World Use: With its high accuracy, the model shows promise for real-world use cases such as spam detection in emails or text messages. It could potentially help in filtering out unwanted messages and improving user experience.

Further Analysis: While accuracy is an important metric, it's essential to perform further analysis to gain deeper insights into the model's performance. This may include examining the confusion matrix, precision, recall, F1-score, ROC curve, and AUC. These analyses can provide a more comprehensive understanding of the model's behavior and any potential areas for improvement.

Model Deployment: If the model meets the requirements and performs well in various evaluation metrics, it could be considered for deployment in production environments. However, it's crucial to continuously monitor its performance and update it as necessary to maintain effectiveness over time.

In conclusion, the text classification model demonstrates strong performance in accurately categorizing text messages, making it a valuable tool for tasks such as spam detection. However, further analysis and evaluation are necessary to ensure its robustness and suitability for real-world applications.