Detecting Spam Emails Using Tensorflow in Python

Spam messages are unsolicited or unwanted emails/messages sent in bulk to users. Detecting spam emails automatically helps prevent unnecessary clutter in users' inboxes.

In this article, we will build a **spam email detection model that classifies emails as Spam or Ham (Not Spam)** using **TensorFlow,** one of the most popular deep learning libraries.

Step 1: Import Required Libraries

Before we begin let's import the necessary libraries: pandas, numpy, tensorflow, matplotlib, wordcloud, nltk for data processing, model building, and visualization.

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

```
import string
import nltk
from nltk.corpus import stopwords
from wordcloud import WordCloud
nltk.download('stopwords')
```

```
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from sklearn.model_selection import train_test_split
from keras.callbacks import EarlyStopping, ReduceLROnPlateau
```

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

Step 2: Load the Dataset

We'll use a dataset containing labeled emails (Spam or Ham). Let's load the dataset and inspect its structure. You can download the dataset from here:

```
data = pd.read_csv('/archive (4).zip')
data.head()
```

Output:

	Unnamed: 0	label	text	label_num
0	605	ham	Subject: enron methanol ; meter # : 988291\r\n...	0
1	2349	ham	Subject: hpl nom for january 9 , 2001\r\n(see...	0
2	3624	ham	Subject: neon retreat\r\nho ho ho , we ' re ar...	0
3	4685	spam	Subject: photoshop , windows , office . cheap ...	1
4	2030	ham	Subject: re : indian springs\r\nthis deal is t...	0

This will give us a glimpse into the first few rows of the dataset. You can also check the shape of the dataset:

- data.shape

Output:

(5171,4)

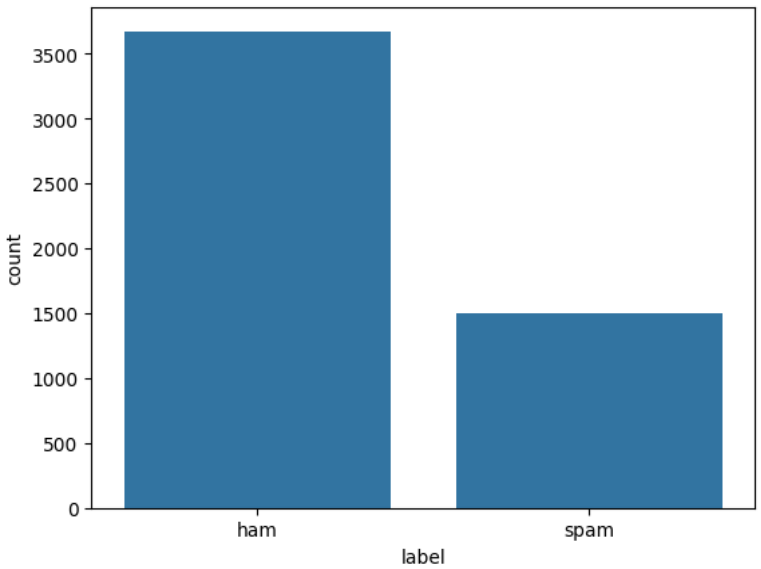
The data contains 5171 rows and four columns.

Now, let's visualize the label distribution to get understanding of the class distribution:

sns.countplot(x='label', data=data)

plt.show()

Output:



Step 3: Balance the Dataset

We can clearly see that number of samples of Ham is much more than that of Spam which implies that the dataset we are using is imbalanced. To address the imbalance we'll downsample the majority class (Ham) to match the minority class (Spam).

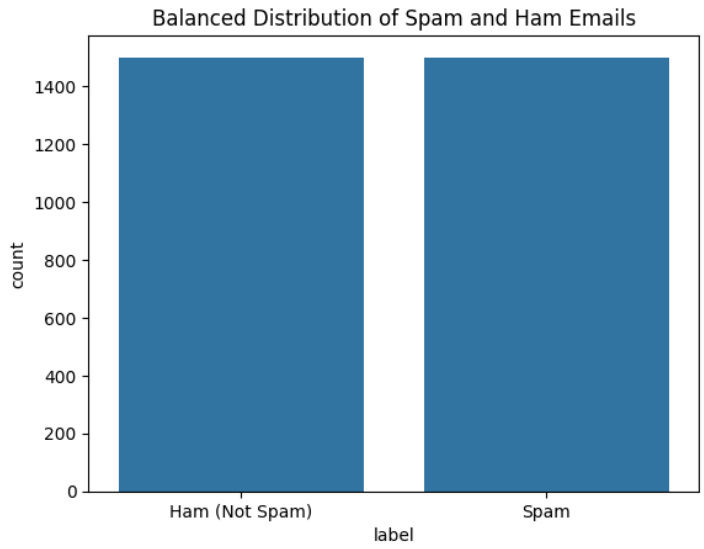
- ham_msg = data[data['label'] == 'ham']
- spam_msg = data[data['label'] == 'spam']

- *# Downsample Ham emails to match the number of Spam emails*
- ham_msg_balanced = ham_msg.sample(n=len(spam_msg), random_state=42)

- *# Combine balanced data*
- balanced_data = pd.concat([ham_msg_balanced, spam_msg]).reset_index(drop=**True**)

- *# Visualize the balanced dataset*
- sns.countplot(x='label', data=balanced_data)
- plt.title("Balanced Distribution of Spam and Ham Emails")
- plt.xticks(ticks=[0, 1], labels=['Ham (Not Spam)', 'Spam'])
- plt.show()

Output:



Step 4: Clean the Text

Textual data often requires preprocessing before feeding it into a machine learning model. Common steps include removing stopwords, punctuations, and performing stemming/lemmatization.

We'll perform the following steps:

- Stopwords Removal
- Punctuations Removal
- Stemming or Lemmatization

Although removing data means loss of information we need to do this to make the data perfect to feed into a machine learning model.

- balanced_data['text'] = balanced_data['text'].str.replace('Subject', '')
- balanced_data.head()

Output:

	Unnamed: 0	label	text	label_num
0	3444	ham	: conoco - big cowboy\r\ndarren :\r\ni ' m not...	0
1	2982	ham	: feb 01 prod : sale to teco gas processing\r\...	0
2	2711	ham	: california energy crisis\r\ncalifornia □ , s...	0
3	3116	ham	: re : nom / actual volume for april 23 rd\r\n...	0
4	1314	ham	: eastrans nomination changes effective 8 / 2 ...	0

- punctuations_list = string.punctuation
- **def** remove_punctuations(text):
- temp = str.maketrans('', '', punctuations_list)
- **return** text.translate(temp)

- balanced_data['text']= balanced_data['text'].apply(**lambda** x: remove_punctuations(x))
- balanced_data.head()

Output:

	Unnamed: 0	label	text	label_num
0	3444	ham	conoco big cowboy\r\ndarren \r\ni m not sur...	0
1	2982	ham	feb 01 prod sale to teco gas processing\r\ns...	0
2	2711	ham	california energy crisis\r\ncalifornia □ s p...	0
3	3116	ham	re nom actual volume for april 23 rd\r\nwe ...	0
4	1314	ham	eastrans nomination changes effective 8 2 0...	0

The below function is a helper function that will help us to remove the stop words.

- **def** remove_stopwords(text):
- stop_words = stopwords.words('english')

- imp_words = []
- *# Storing the important words*
- **for** word **in** str(text).split():
- word = word.lower()
- **if** word **not in** stop_words:
- imp_words.append(word)
- output = " ".join(imp_words)
- **return** output
- balanced_data['text'] = balanced_data['text'].apply(**lambda** text: remove_stopwords(text))
- balanced_data.head()

Output:

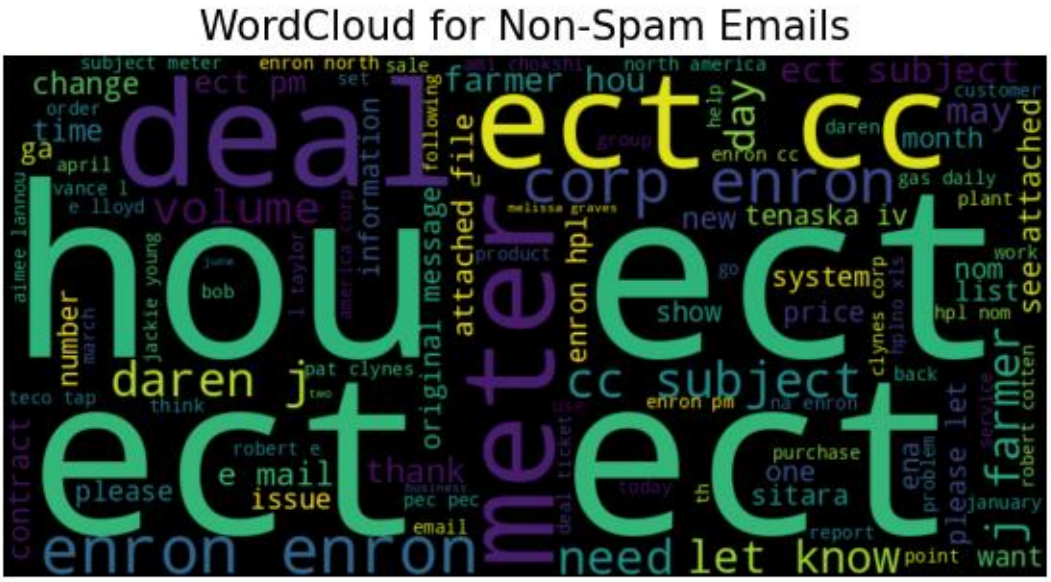
	Unnamed: 0	label	text	label_num
0	3444	ham	conoco big cowboy\r\ndarren \r\ni m not sur...	0
1	2982	ham	feb 01 prod sale to teco gas processing\r\ns...	0
2	2711	ham	california energy crisis\r\ncalifornia □ s p...	0
3	3116	ham	re nom actual volume for april 23 rd\r\nwe ...	0
4	1314	ham	eastrans nomination changes effective 8 2 0...	0

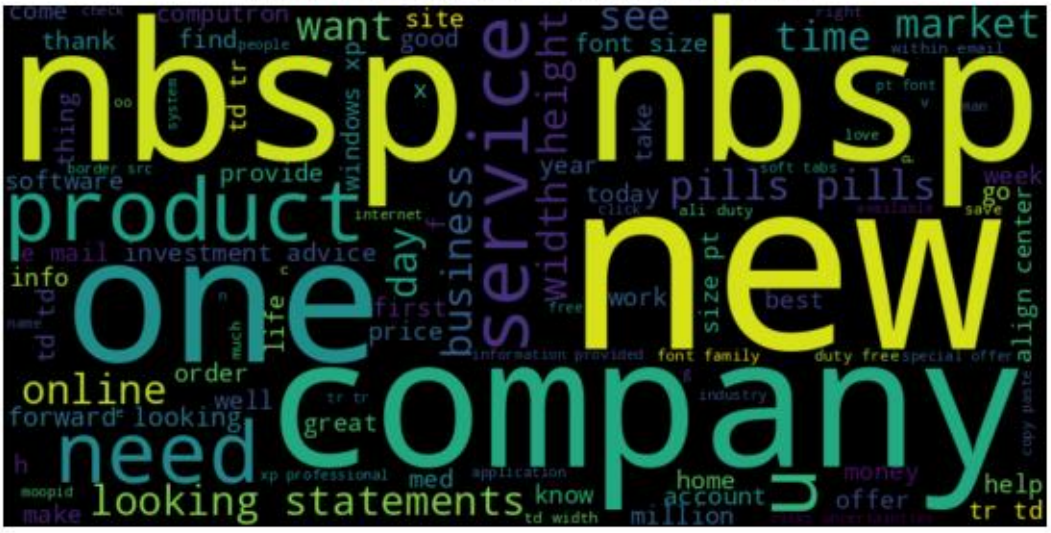
Visualization Word Cloud

A word cloud is a text visualization tool that help's us to get insights into the most frequent words present in the corpus of the data.

- **def** plot_word_cloud(data, typ):
- email_corpus = " ".join(data['text'])
- wc = WordCloud(background_color='black', max_words=100, width=800, height=400).generate(email_corpus)
- plt.figure(figsize=(7, 7))
- plt.imshow(wc, interpolation='bilinear')
- plt.title(f'WordCloud for {typ} Emails', fontsize=15)
- plt.axis('off')
- plt.show()
- plot_word_cloud(balanced_data[balanced_data['label'] == 'ham'], typ='Non-Spam')
- plot_word_cloud(balanced_data[balanced_data['label'] == 'spam'], typ='Spam')

Output:





Step 6: Tokenization and Padding

Machine learning models work with numbers, so we need to convert the text data into numerical vectors using **Tokenization** and **Padding**.

1. **Tokenization**: Converts each word into a unique integer.
2. **Padding**: Ensures that all text sequences have the same length, making them compatible with the model.

- train_X, test_X, train_Y, test_Y = train_test_split(
- balanced_data['text'], balanced_data['label'], test_size=0.2, random_state=42)

- tokenizer = Tokenizer()
- tokenizer.fit_on_texts(train_X)
- train_sequences = tokenizer.texts_to_sequences(train_X)
- test_sequences = tokenizer.texts_to_sequences(test_X)
- max_len = 100 *# Maximum sequence length*
- train_sequences = pad_sequences(train_sequences, maxlen=max_len, padding='post', truncating='post')
- test_sequences = pad_sequences(test_sequences, maxlen=max_len, padding='post', truncating='post')
- train_Y = (train_Y == 'spam').astype(int)
- test_Y = (test_Y == 'spam').astype(int)

Step 7: Define the Model

We will build a deep learning model using a **Sequential** architecture. This model will include:

- **Embedding Layer**: Learns vector representations of words.
- **LSTM Layer**: Captures patterns in sequences.
- **Fully Connected Layer**: Extracts relevant features.
- **Output Layer**: Predicts whether an email is spam or not.
- model = tf.keras.models.Sequential([tf.keras.layers.Embedding(input_dim=len(tokenizer.word_index) + 1, output_dim=32, input_length=max_len),
- tf.keras.layers.LSTM(16),
- tf.keras.layers.Dense(32, activation='relu'),
- tf.keras.layers.Dense(1, activation='sigmoid') *# Output layer*])
- model.compile(loss=tf.keras.losses.BinaryCrossentropy(from_logits=**True**),
- optimizer='adam',
- metrics=['accuracy'])

model.summary()

Output:

Model: "sequential"

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Layer (type) Output Shape Param #

==========

embedding (Embedding) (None, 100, 32) 1274912

lstm (LSTM) (None, 16) 3136

dense (Dense) (None, 32) 544

dense_1 (Dense) (None, 1) 33

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Total params: 1,278,625
Trainable params: 1,278,625

Non-trainable params: 0

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Step 8: Train the Model

We train the model using **EarlyStopping** and **ReduceLROnPlateau** callbacks. These callbacks help stop the training early if the model's performance doesn't improve and reduce the learning rate to fine-tune the model.

- es = EarlyStopping(patience=3, monitor='val_accuracy', restore_best_weights=**True**)
- lr = ReduceLROnPlateau(patience=2, monitor='val_loss', factor=0.5, verbose=0)
- history = model.fit(
- train_sequences, train_Y,
- validation_data=(test_sequences, test_Y),
- epochs=20,
- batch_size=32,
- callbacks=[lr, es])

Output:

```
Epoch 1/20
75/75 ━━━━━━━━━━━━━━━━━━━━ 8s 62ms/step - accuracy: 0.5564 - loss: 0.6823 - val_accuracy: 0.9483 - val_loss: 0.2895 - learning_rate: 0.0010
Epoch 2/20
75/75 ━━━━━━━━━━━━━━━━━━━━ 3s 44ms/step - accuracy: 0.9517 - loss: 0.2152 - val_accuracy: 0.9617 - val_loss: 0.1588 - learning_rate: 0.0010
Epoch 3/20
75/75 ━━━━━━━━━━━━━━━━━━━━ 6s 62ms/step - accuracy: 0.9705 - loss: 0.1300 - val_accuracy: 0.9617 - val_loss: 0.1608 - learning_rate: 0.0010
Epoch 4/20
75/75 ━━━━━━━━━━━━━━━━━━━━ 4s 45ms/step - accuracy: 0.9738 - loss: 0.1157 - val_accuracy: 0.9633 - val_loss: 0.1583 - learning_rate: 0.0010
Epoch 5/20
75/75 ━━━━━━━━━━━━━━━━━━━━ 5s 43ms/step - accuracy: 0.9810 - loss: 0.0908 - val_accuracy: 0.9617 - val_loss: 0.1651 - learning_rate: 0.0010
Epoch 6/20
75/75 ━━━━━━━━━━━━━━━━━━━━ 5s 61ms/step - accuracy: 0.9674 - loss: 0.1330 - val_accuracy: 0.9283 - val_loss: 0.2129 - learning_rate: 0.0010
Epoch 7/20
75/75 ━━━━━━━━━━━━━━━━━━━━ 4s 43ms/step - accuracy: 0.9347 - loss: 0.1965 - val_accuracy: 0.9700 - val_loss: 0.1202 - learning_rate: 5.0000e-04
Epoch 8/20
75/75 ━━━━━━━━━━━━━━━━━━━━ 5s 45ms/step - accuracy: 0.9745 - loss: 0.1062 - val_accuracy: 0.9700 - val_loss: 0.1374 - learning_rate: 5.0000e-04
Epoch 9/20
75/75 ━━━━━━━━━━━━━━━━━━━━ 5s 45ms/step - accuracy: 0.9879 - loss: 0.0602 - val_accuracy: 0.9683 - val_loss: 0.1481 - learning_rate: 5.0000e-04
Epoch 10/20
75/75 ━━━━━━━━━━━━━━━━━━━━ 3s 46ms/step - accuracy: 0.9883 - loss: 0.0587 - val_accuracy: 0.9683 - val_loss: 0.1495 - learning_rate: 2.5000e-04
```

After training, we evaluate the model on the test data to measure its performance.

- test_loss, test_accuracy = model.evaluate(test_sequences, test_Y)
- print('Test Loss :',test_loss)
- print('Test Accuracy :',test_accuracy)

Output:

Test Loss: 0.1202
Test Accuracy: 0.9700

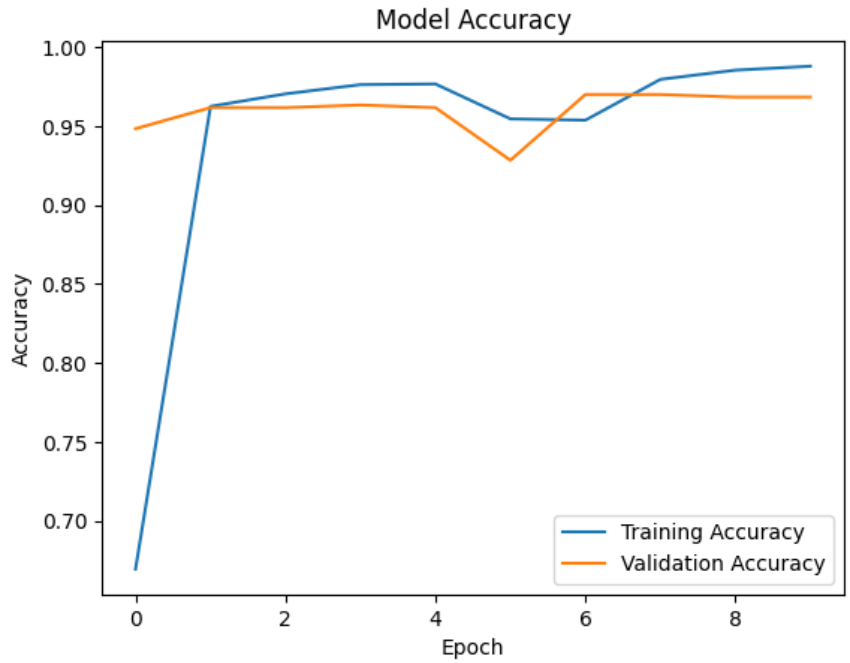
Thus, the training accuracy turns out to be 97% which is quite satisfactory.

Having trained our model, we can plot a graph depicting the variance of training and validation accuracies with the no. of epochs.

- plt.plot(history.history['accuracy'], label='Training Accuracy')
- plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
- plt.title('Model Accuracy')
- plt.ylabel('Accuracy')
- plt.xlabel('Epoch')
- plt.legend()

- plt.show()

Output:



By following these steps, we have successfully built a machine learning model that can classify emails as spam or ham. With further optimization, this model can be fine-tuned to improve its performance even more.