Project-2 : Spam Detection Using TensorFlow(Python)

0. Import the project dependencies

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import tensorflow as tf
import nltk
import string
from nltk.corpus import stopwords
import sklearn
from wordcloud import WordCloud
from sklearn.model_selection import train_test_split
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from keras.callbacks import EarlyStopping

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

Start coding or generate with AI.

1. Problem Statement

The Objective is to build a Machine Learning model to detect spam emails.

- Prepare the dataset for machine learning including data cleaning, removing missing values and splitting the data into training and test sets.
- Building a TensorFlow Model to detect spam emails.
- Evaluate the performance of the model on the test dataset
- Analyze the model coeffients to understand the importance of the different features.
- Build a report that descibes the steps you took to complete the task. the result of our analysis and conlcusions
- The code that i used to build also describe it.

2. Relevent Dataset

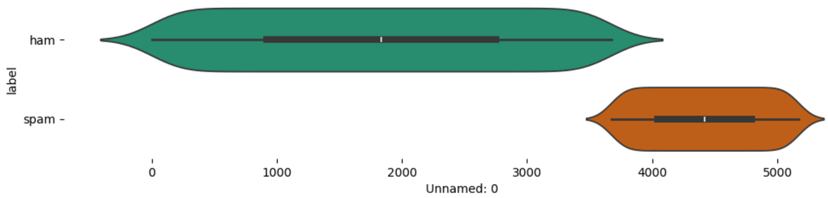
```
data = pd.read_csv("/content/spam_ham_dataset.csv")
data.head()
```

	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

Next steps: Generate code with data View recommended plots

label vs Unnamed: 0

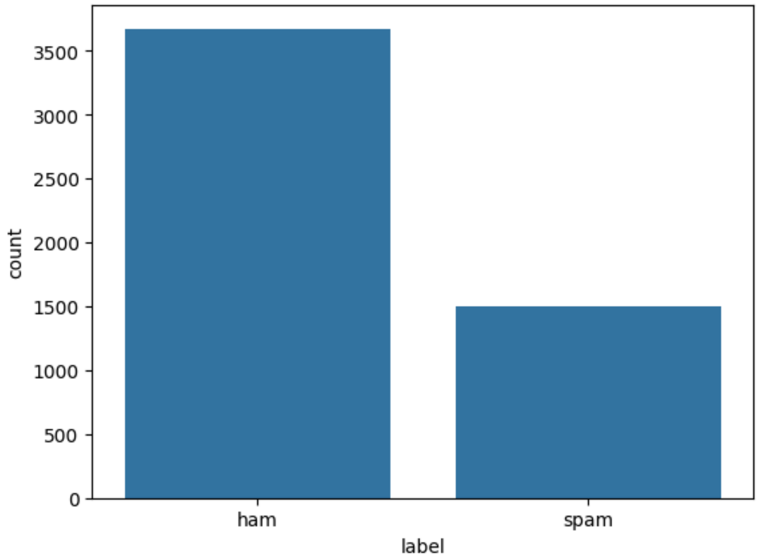
```
# @title label vs Unnamed: 0

from matplotlib import pyplot as plt
import seaborn as sns
figsize = (12, 1.2 * len(data['label'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(data, x='Unnamed: 0', y='label', inner='box', palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```



3. Data Exploration

Visualizing the data distribution

```
sns.countplot(x='label', data = data)
plt.show()
```

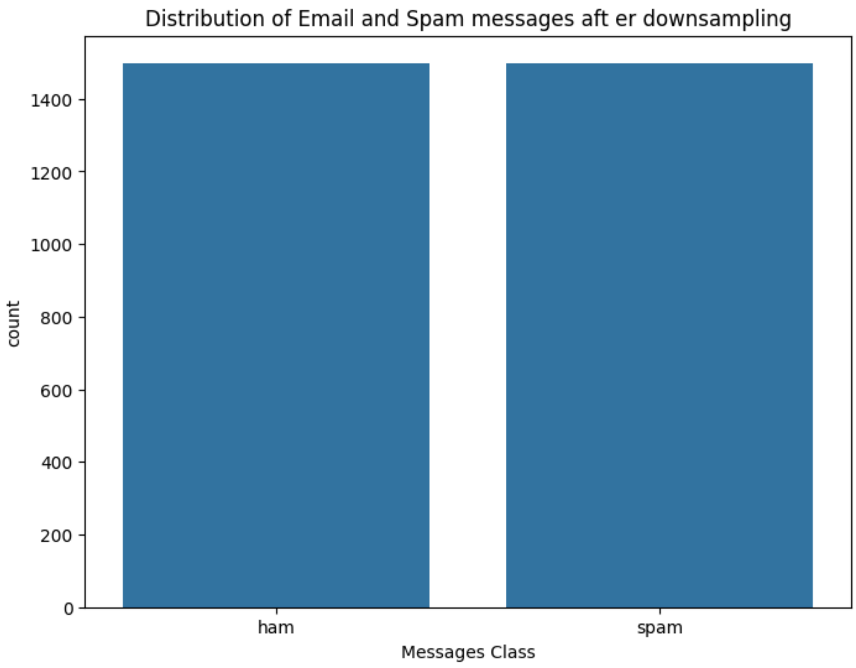


Dataset Balancing

```
email_msg = data[data.label_num == 0]
spam_msg = data[data.label_num == 1]
email_msg = email_msg.sample(n=len(spam_msg), random_state=42)
```

Let's Visualize the balanced dataset

```
balanced_data = pd.concat([email_msg, spam_msg], ignore_index=True)
plt.figure(figsize=(8 , 6))
sns.countplot(data = balanced_data, x = 'label')
plt.title('Distribution of Email and Spam messages aft er downsampling')
plt.xlabel('Messages Class')
plt.show()
```



4. Data Preprocessing

Let's Preprocess the text dataset

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

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
True
```

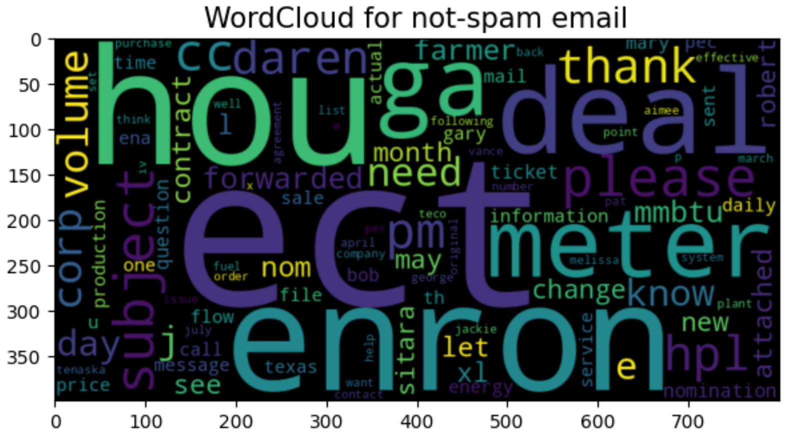
```
balanced_data['text'] = balanced_data['text'].str.replace('Subject', '')
punctuations_list = string.punctuation
def rem_punch(text):
    temp = str.maketrans('', '', punctuations_list)
    return text.translate(temp)

balanced_data['text'] =  balanced_data['text'].apply(lambda x: rem_punch(x))

def rem_stopwords(text):
    stop_words = stopwords.words('english')

    imp_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: rem_stopwords(text))
balanced_data.head()
```

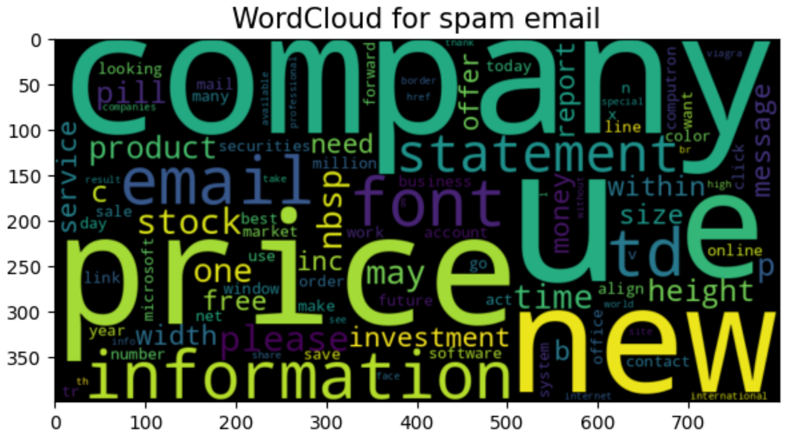
	Unnamed: 0	label	text	label_num
0	3444	ham	conoco big cowboy darren sure help know else a...	0
1	2982	ham	feb 01 prod sale teco gas processing sale deal...	0
2	2711	ham	california energy crisis california power cr...	0
3	3116	ham	nom actual volume april 23 rd agree eileen pon...	0
4	1314	ham	eastrans nomination changes effective 8 2 00 p...	0

Next steps: Generate code with balanced_data View recommended plots

Let's visualize the text dataset using wordcloud

```
def plot_words(data, typ):
    sms_corpus = " ".join(data['text'])

    plt.figure(figsize=(7, 7))

    wc = WordCloud(
        background_color='black',
        max_words = 100,
        width = 800,
        height = 400,
        collocations = False
        ).generate(sms_corpus)
    plt.imshow(wc, interpolation='bilinear')
    plt.title(f'WordCloud for {typ} email', fontsize=15)


plot_words(balanced_data[balanced_data['label_num'] == 0], typ='not-spam')
plot_words(balanced_data[balanced_data['label_num'] == 1], typ='spam')
```





Let's split the dataset into train and test sets

```
X_train, X_test, Y_train, Y_test = train_test_split(
    balanced_data['text'],
    balanced_data['label_num'],
    test_size=0.2,
    random_state=42
)
```

Tokenization and Padding

```
tokenizer = Tokenizer()
tokenizer.fit_on_texts(X_train)
train_sequences = tokenizer.texts_to_sequences(X_train)
test_sequences = tokenizer.texts_to_sequences(X_test)
max_len = 100

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')
```

5. Machine Learning Model

```
model = tf.keras.models.Sequential()
model.add(tf.keras.layers.Embedding(input_dim = len(tokenizer.word_index) + 1, output_dim=32, input_length=100))
model.add(tf.keras.layers.LSTM(16))
model.add(tf.keras.layers.Dense(32, activation='relu'))
model.add(tf.keras.layers.Dense(1, activation='sigmoid'))
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 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        
                                                                 
=================================================================
Total params: 1278625 (4.88 MB)
Trainable params: 1278625 (4.88 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

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

```
history = model.fit(train_sequences, Y_train, epochs=20, batch_size=32, validation_data=(test_sequences, Y_test))
```

```
Epoch 1/20
75/75 [==============================] - 16s 169ms/step - loss: 0.6910 - accuracy: 0.5334 - val_loss: 0.6818 - val_accuracy: 0.5883
Epoch 2/20
75/75 [==============================] - 10s 133ms/step - loss: 0.3089 - accuracy: 0.9012 - val_loss: 0.1548 - val_accuracy: 0.9617
Epoch 3/20
75/75 [==============================] - 8s 114ms/step - loss: 0.1284 - accuracy: 0.9708 - val_loss: 0.1615 - val_accuracy: 0.9617
Epoch 4/20
75/75 [==============================] - 7s 96ms/step - loss: 0.1063 - accuracy: 0.9771 - val_loss: 0.1412 - val_accuracy: 0.9683
Epoch 5/20
75/75 [==============================] - 7s 93ms/step - loss: 0.0984 - accuracy: 0.9791 - val_loss: 0.1929 - val_accuracy: 0.9567
Epoch 6/20
75/75 [==============================] - 5s 66ms/step - loss: 0.1029 - accuracy: 0.9783 - val_loss: 0.1803 - val_accuracy: 0.9467
Epoch 7/20
75/75 [==============================] - 5s 66ms/step - loss: 0.1177 - accuracy: 0.9700 - val_loss: 0.0837 - val_accuracy: 0.9800
Epoch 8/20
75/75 [==============================] - 4s 51ms/step - loss: 0.0576 - accuracy: 0.9892 - val_loss: 0.0924 - val_accuracy: 0.9783
Epoch 9/20
75/75 [==============================] - 3s 42ms/step - loss: 0.0339 - accuracy: 0.9942 - val_loss: 0.1073 - val_accuracy: 0.9767
Epoch 10/20
75/75 [==============================] - 4s 49ms/step - loss: 0.0284 - accuracy: 0.9950 - val_loss: 0.1065 - val_accuracy: 0.9783
Epoch 11/20
75/75 [==============================] - 3s 39ms/step - loss: 0.0262 - accuracy: 0.9958 - val_loss: 0.1290 - val_accuracy: 0.9750
Epoch 12/20
75/75 [==============================] - 3s 41ms/step - loss: 0.0232 - accuracy: 0.9962 - val_loss: 0.1383 - val_accuracy: 0.9733
Epoch 13/20
75/75 [==============================] - 3s 39ms/step - loss: 0.0202 - accuracy: 0.9967 - val_loss: 0.1249 - val_accuracy: 0.9767
Epoch 14/20
75/75 [==============================] - 4s 51ms/step - loss: 0.0229 - accuracy: 0
Epoch 15/20
75/75 [==============================] - 4s 53ms/step - loss: 0.0210 - accuracy:
Epoch 16/20
75/75 [==============================] - 2s 26ms/step - loss: 0.0193 - accuracy: 0.
Epoch 17/20
```

```
75/75 [==============================] - 2s 25ms/step - loss: 0.0201 - accuracy: 0.9971 - val_loss: 0.1357 - val_accuracy: 0.9767
Epoch 18/20
75/75 [==============================] - 2s 28ms/step - loss: 0.0174 - accuracy: 0.9975 - val_loss: 0.1316 - val_accuracy: 0.9767
Epoch 19/20
75/75 [==============================] - 2s 21ms/step - loss: 0.0175 - accuracy: 0.9975 - val_loss: 0.1296 - val_accuracy: 0.9767
Epoch 20/20
75/75 [==============================] - 2s 27ms/step - loss: 0.0173 - accuracy: 0.9975 - val_loss: 0.1301 - val_accuracy: 0.9767
```

6. Model Evaluation

```
test_loss, test_accuracy = model.evaluate(test_sequences, Y_test)
print("Test Loss :", test_loss)
print("Test Accuracy :", test_accuracy)
```

```
19/19 [==============================] - 0s 4ms/step - loss: 0.1301 - accuracy: 0.9767
Test Loss : 0.13006488978862762
Test Accuracy : 0.9766666889190674
```

Visualizing the model's test accuracy

```
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()
```