SMS SPAM DETECTION WITH TENSORFLOW.

IMPORTATION OF THE lIBRARIES

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow  as tf
from tensorflow import keras
from tensorflow.keras import layers
```

Loading dataset .read_csv()

```
# Using this to load the file from my External Hard drive AND Saving it to Uploaded
from google.colab import files
uploaded = files.upload()
```

Choose Files spam.csv

- **spam.csv**(text/csv) - 503663 bytes, last modified: 9/20/2019 - 100% done

```
Saving spam.csv to spam (2).csv
```

```
# when we load the data we use .dropna(axis=1) to drop the unamed columns with null values.
import io
# I will use this io.BytesIO(uploaded['spam (2).csv']) to read the csv file from the io that i uploaded the file.
df = pd.read_csv(io.BytesIO(uploaded['spam (2).csv']),encoding = 'latin-1').dropna(axis = 1)
df.head()
```

	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...

i will rename the columns v1 and v2 to label and Text respectively

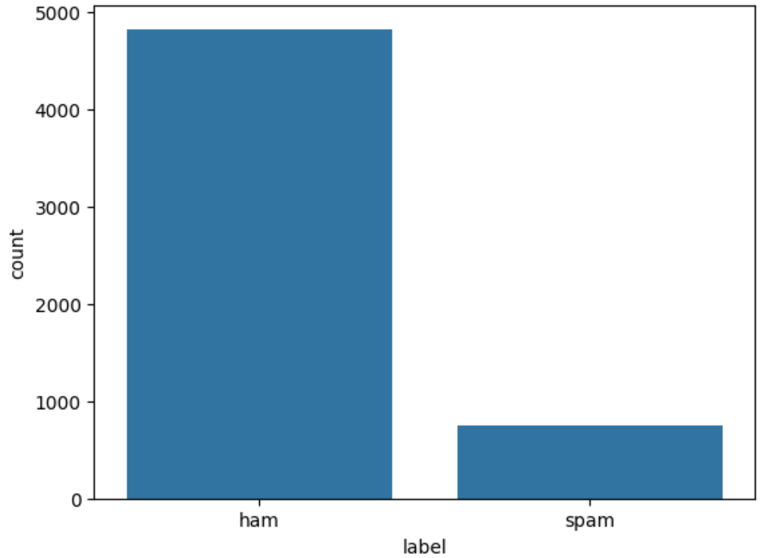
since the target variable is in string form I will encode it numerically using pandas function .map()

```
df =  df.rename(columns = {'v1': 'label',
                           'v2' : 'Text'})

df['label_enc'] = df['label'].map({'ham': 0,
                                   'spam':1})
df.head()
```

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

LETS VISUALIZE THE DISTRIBUTION OF HAM AND SPAM DATA

```
sns.countplot(x=df['label'])
plt.show()
```



NB

we can see that Ham data is comapratively higher than spam data, this is natural, since I will be using embeddings in our deep learning model, I do not have to balance the data. Now lets find the average number of words in all sentences in SMS data

```
# Average number of tokens in all sentences
avg_words_len = round(sum([len(i.split()) for i in df['Text']]) / len(df['Text']))

print (avg_words_len)
```

```
15
```

Now lets find the Total number of unique words in Corpus

```
s = set()
for sent in df['Text']:
    for word in sent.split():
        s.add(word)

total_words_length = len(s)
print(f"Total Words Length: {total_words_length}")
```

```
Total Words Length: 15585
```

SPLIT DATA INTO TRAINING AND TESTING PARTS

```
from sklearn.model_selection import train_test_split, cross_val_score

X, y = np.asanyarray(df['Text']),  np.asanyarray(df['label_enc'])
new_df = pd.DataFrame({'Text': X, 'label' : y})

X_train, X_test, y_train, y_test = train_test_split(new_df['Text'], new_df['label'],
                                                    test_size = 0.2, random_state = 42)

X_train.shape, y_train.shape, X_test.shape, y_test.shape

```

```
((4457,), (4457,), (1115,), (1115,))
```

Building The Model

first I will build a baseline model and then try to beat the performance of the baseline using deep learning models *(embeddings, LSTM and others)*

I will use **MultinomialNB()**, this performs very well for text Classififcation when featurs are dicrete like word counts of the words or **tf-idf vectors** (this is a measure that tells us how important or relevant a word is in the document)

```
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import classification_report, accuracy_score, confusion_matrix
```

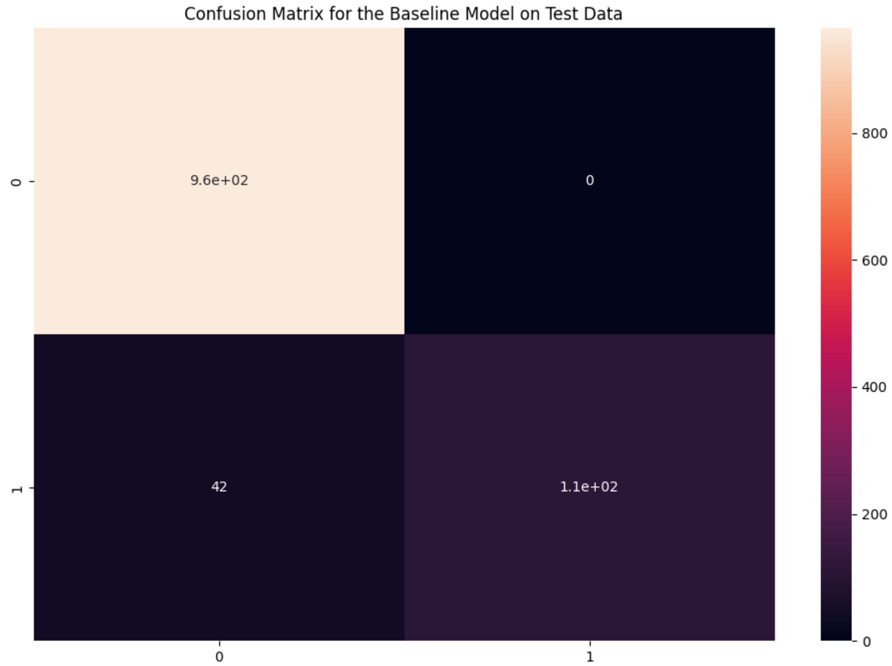
```
tfidf_vec = TfidfVectorizer().fit(X_train)

X_train_vec, X_test_vec = tfidf_vec.transform(X_train), tfidf_vec.transform(X_test)


baseline_model = MultinomialNB()
baseline_model.fit(X_train_vec, y_train)
```

```
▾ MultinomialNB
MultinomialNB()
```

Performance of baseline model

```
preds = baseline_model.predict(X_test_vec)

#using the K-fold for cross validation

def cv_scoring(estimator, X, y):
    return accuracy_score(y, estimator.predict(X))


print(f"Accuracy on Train Data: {accuracy_score(y_train, baseline_model.predict(X_train_vec))*100}")

print(f"Accuracy on Test Data : {accuracy_score(y_test, preds)*100}")

# The Confusion Matrix

cf_matrix = confusion_matrix(y_test, preds)
plt.figure(figsize = (12,8))
sns.heatmap(cf_matrix, annot = True)
plt.title("Confusion Matrix for the Baseline Model on Test Data")
plt.show()
```

```
Accuracy on Train Data: 97.28516939645502
Accuracy on Test Data : 96.23318385650225
```



Model 1: Creating custom Text Vectoriation and embeding layers:

```
- **Text vectorization** is turning text into numerical representation. example **Bag of words frequency, Binary Term frequency, etc**
- **Word Embedding** this is a learned representation of text in which words with related meanings have similar representations. each word assigne
```

Custom Text Vectorization layer (**TensorFlow**)

```
from tensorflow.keras.layers import TextVectorization
MAXTOKENS = total_words_length
OUTPUTLEN = avg_words_len

text_vec = TextVectorization(max_tokens = MAXTOKENS,
                             standardize = 'lower_and_strip_punctuation',
                             output_mode = 'int',
                             output_sequence_length = OUTPUTLEN )

text_vec.adapt(X_train)


```

Create an embedding layer

```
embedding_layer =layers.Embedding(input_dim = MAXTOKENS,
                                  output_dim = 128,
                                  embeddings_initializer = 'uniform',
                                  input_length = OUTPUTLEN )


```

input_dim is the size of vocabulary.

output_dim is the dimension of the embedding layer i.e, the size of the vector in which the words will be embedde.

input_length is the length of input sequenc.es

Now lets build and compile model 1 using tensorflow functional API

```
input_layer = layers.Input(shape= (1,), dtype = tf.string)
vec_layer = text_vec(input_layer)
embedding_layer_model = embedding_layer(vec_layer)
x = layers.GlobalAveragePooling1D()(embedding_layer_model)
x = layers.Flatten()(x)
x = layers.Dense(32, activation = 'relu')(x)
output_layer = layers.Dense(1, activation = 'sigmoid')(x)
model_1 = keras.Model(input_layer, output_layer)

model_1.compile(optimizer = 'adam', loss= keras.losses.BinaryCrossentropy(label_smoothing = 0.5),
                                                                          metrics = ['accuracy'])

```

```
# The model summary
model_1.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 1)]               0

 text_vectorization (TextVe  (None, 15)                0
 ctorization)

 embedding (Embedding)       (None, 15, 128)           1994880

 global_average_pooling1d (  (None, 128)               0
 GlobalAveragePooling1D)

 flatten (Flatten)           (None, 128)               0

 dense (Dense)               (None, 32)                4128

 dense_1 (Dense)             (None, 1)                 33

=================================================================
Total params: 1999041 (7.63 MB)
Trainable params: 1999041 (7.63 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

CallBack

lets check and controll the models performance

```
from keras.callbacks import EarlyStopping, ReduceLROnPlateau

es = EarlyStopping(patience = 6,
                   monitor = 'val_accuracy',
                   restore_best_weights = True)

lr = ReduceLROnPlateau(patience = 2,
                       monitor = 'val_loss',
                       factor = 0.5,
                       verbose = 0)
```

Training the model_1

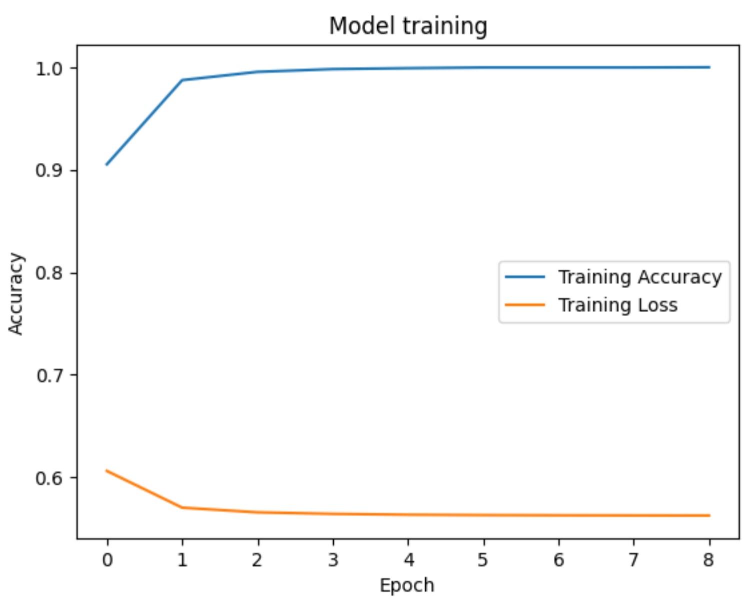
```
history = model_1.fit(X_train, y_train, validation_data=(X_test, y_test),
                      epochs = 20,
                      batch_size = 32,
                      callbacks = [lr,es])
```

```
Epoch 1/20
140/140 [==============================] - 5s 29ms/step - loss: 0.6060 - accuracy: 0.9053 - val_loss: 0.5775 - val_accuracy: 0.9740 - lr
Epoch 2/20
140/140 [==============================] - 5s 34ms/step - loss: 0.5702 - accuracy: 0.9874 - val_loss: 0.5735 - val_accuracy: 0.9803 - lr
Epoch 3/20
140/140 [==============================] - 4s 27ms/step - loss: 0.5656 - accuracy: 0.9955 - val_loss: 0.5726 - val_accuracy: 0.9830 - lr
Epoch 4/20
140/140 [==============================] - 4s 26ms/step - loss: 0.5641 - accuracy: 0.9982 - val_loss: 0.5724 - val_accuracy: 0.9830 - lr
Epoch 5/20
140/140 [==============================] - 5s 32ms/step - loss: 0.5633 - accuracy: 0.9991 - val_loss: 0.5726 - val_accuracy: 0.9803 - lr
Epoch 6/20
140/140 [==============================] - 4s 28ms/step - loss: 0.5630 - accuracy: 0.9998 - val_loss: 0.5726 - val_accuracy: 0.9803 - lr
Epoch 7/20
140/140 [==============================] - 4s 28ms/step - loss: 0.5628 - accuracy: 0.9998 - val_loss: 0.5725 - val_accuracy: 0.9803 - lr
Epoch 8/20
140/140 [==============================] - 5s 33ms/step - loss: 0.5626 - accuracy: 0.9998 - val_loss: 0.5726 - val_accuracy: 0.9803 - lr
Epoch 9/20
140/140 [==============================] - 4s 27ms/step - loss: 0.5625 - accuracy: 1.0000 - val_loss: 0.5727 - val_accuracy: 0.9803 - lr
```

Ploting the models history

```
print('Train Accuracy: ', np.max(history.history['accuracy'] )*100, '%')
print('Train Loss: ', np.min(history.history['loss'])*100,'%')

plt.plot(history.history['accuracy'],label = 'Training Accuracy')
plt.plot(history.history['loss'],label = 'Training Loss')
plt.title('Model training')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.show()
```

```
Train Accuracy:  100.0 %
Train Loss:  56.25426173210144 %
```



Helper function for compiling fitting and evaluating the model

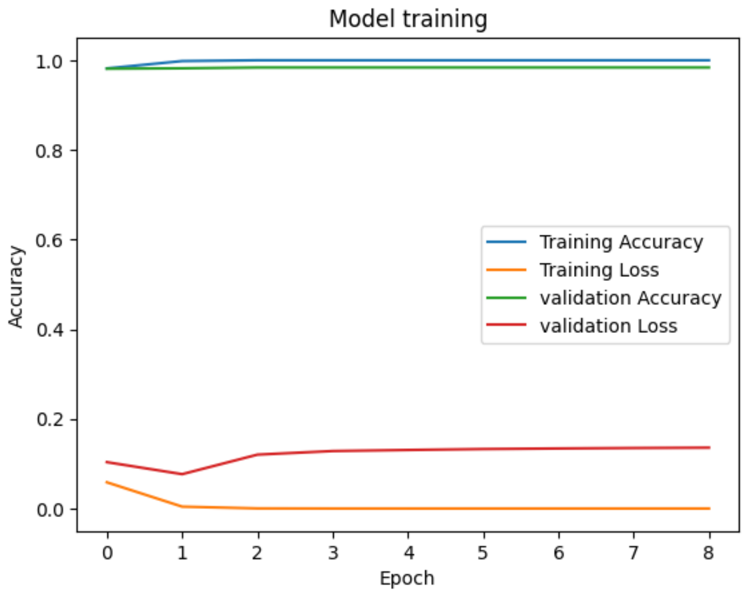
```
from sklearn.metrics import precision_score, recall_score, f1_score

def compile_model(model):
    # Simply compile the model with adam optimizer
    model.compile(optimizer = keras.optimizers.Adam(),
                  loss = keras.losses.BinaryCrossentropy(),
                  metrics = ['accuracy'])

def fit_model(model, epochs, X_train = X_train, y_train = y_train,  X_test = X_test, y_test = y_test):
    # fi the model with the given epochs, training and test data
    history = model.fit(X_train,
                        y_train,
                        epochs = epochs,
                        validation_data=(X_test, y_test),
                        validation_steps=int(0.2*len(X_test)),
                       callbacks = [lr,es])
    print('Train Accuracy: ', np.max(history.history['accuracy'] )*100, '%')
    print('Train Loss: ', np.min(history.history['loss'])*100,'%')

    plt.plot(history.history['accuracy'],label = 'Training Accuracy')
    plt.plot(history.history['loss'],label = 'Training Loss')
    plt.plot(history.history['val_accuracy'], label = 'validation Accuracy')
    plt.plot(history.history['val_loss'],label = 'validation Loss')
    plt.title('Model training')
    plt.ylabel('Accuracy')
    plt.xlabel('Epoch')
    plt.legend()
    plt.show()
    return history

def evaluate_model(model, X,y):
    # evaluate the model and return accuracy, precision, recall and f1-score

    y_preds = np.round(model.predict(X))
    accuracy = accuracy_score(y, y_preds)
    accuracy = accuracy_score(y, y_preds)
    precision = precision_score(y, y_preds)
    recall = recall_score(y, y_preds)
    f1 = f1_score(y, y_preds)
    print("Model Performance in percentage (%)")
    model_results_dict = {'accuracy': accuracy * 100,
                          'precision': precision * 100,
                          'recall': recall * 100,
                          'f1-score': f1 * 100}


    return model_results_dict
```

Model_2 Bidirectional LSTM

this will effectively improve the networkd accesible information, boosting the context for the algorithm.

```
input_layer = layers.Input(shape = (1,), dtype = tf.string)
vec_layer = text_vec(input_layer)

embedding_layer_model = embedding_layer(vec_layer)

bi_lstm = layers.Bidirectional(layers.LSTM(64,
                                           activation ='tanh',
                                           return_sequences =True))(embedding_layer_model)

lstm = layers.Bidirectional(layers.LSTM(64))(bi_lstm)
flatten = layers.Flatten()(lstm)
dropout = layers.Dropout(.1)(flatten)

x = layers.Dense(32, activation = 'relu')(dropout)
output_layer = layers.Dense(1, activation ='sigmoid')(x)

model_2 = keras.Model(input_layer, output_layer)

compile_model(model_2) # Compile the model
history_2 = fit_model(model_2, epochs = 20) # fit the model
```

```
Epoch 1/20
140/140 [==============================] - 20s 88ms/step - loss: 0.0584 - accuracy: 0.98
Epoch 2/20
140/140 [==============================] - 11s 76ms/step - loss: 0.0042 - accuracy: 0.99
Epoch 3/20
140/140 [==============================] - 11s 78ms/step - loss: 2.3725e-04 - accuracy:
Epoch 4/20
140/140 [==============================] - 13s 90ms/step - loss: 2.9430e-05 - accuracy:
Epoch 5/20
140/140 [==============================] - 11s 75ms/step - loss: 1.6673e-05 - accuracy:
Epoch 6/20
140/140 [==============================] - 11s 77ms/step - loss: 1.4300e-05 - accuracy:
Epoch 7/20
140/140 [==============================] - 11s 79ms/step - loss: 1.2129e-05 - accuracy:
Epoch 8/20
140/140 [==============================] - 10s 71ms/step - loss: 9.7068e-06 - accuracy:
Epoch 9/20
140/140 [==============================] - 11s 75ms/step - loss: 1.0131e-05 - accuracy:
Train Accuracy:  100.0 %
Train Loss:  0.0009706817763799336 %
```



MODEL_2 EVALUATION

```
1 evaluate_model(model_2,X_test,y_test)
```

```
35/35 [==============================] - 2s 19ms/step
Model Performance in percentage (%)
{'accuracy': 98.38565022421525,
 'precision': 97.82608695652173,
 'recall': 90.0,
 'f1-score': 93.75}
```

Model- 3 Transfer Learning with USE Encoder

Transfer learning is an approch where one model generated for one job is utilized as the foundation for model on a different task.

USE Layer (universal Sentence Encoder) this converts text into high dimensional vectors that may be used for text categorization, semantic similarity and other language applications

The USE is from Tensorflow_hub and can be used as a layer **.kerasLayer()**

```
1 import tensorflow_hub as hub
```

Model_3 with Sequential api

```
1 model_3 = keras.Sequential()
```

Universal-sentence-encoderlayer

```
# directly from tfhub
use_layer = hub.KerasLayer("https://tfhub.dev/google/universal-sentence-encoder/4",
                           trainable = False,
                           input_shape =[],
                           dtype = tf.string,
                           name ='USE')

model_3.add(use_layer)
model_3.add(layers.Dropout(0.2))
model_3.add(layers.Dense(64, activation = keras.activations.relu))
model_3.add(layers.Dense(1, activation = keras.activations.sigmoid))

compile_model(model_3)

history_3 = fit_model(model_3, epochs =5)
```

```
Epoch 1/5
140/140 [==============================] - 10s 48ms/step - loss: 0.2772 - accuracy: 0.92
Epoch 2/5
140/140 [==============================] - 4s 29ms/step - loss: 0.0779 - accuracy: 0.977
Epoch 3/5
140/140 [==============================] - 6s 46ms/step - loss: 0.0556 - accuracy: 0.983
Epoch 4/5
140/140 [==============================] - 4s 30ms/step - loss: 0.0465 - accuracy: 0.986
Epoch 5/5
140/140 [==============================] - 4s 30ms/step - loss: 0.0403 - accuracy: 0.988
Train Accuracy:  98.8332986831665 %
Train Loss:  4.025813192129135 %
```

Now evaluatig all the models

```
baseline_model_results = evaluate_model(baseline_model, X_test_vec, y_test)
model_1_results = evaluate_model(model_1,X_test,y_test)
model_2_results = evaluate_model(model_2,X_test,y_test)
model_3_results = evaluate_model(model_3,X_test,y_test)

total_results = pd.DataFrame({'MultinomialNB Model' : baseline_model_results,
                              'Custom-Vec-Embedding Model': model_1_results,
                              'Bidirectional-LSTM Model':model_2_results,
                              'USE-Transfer Learning Model':model_3_results}).transpose()

total_results

```

```
Model Performance in percentage (%)
35/35 [==============================] - 0s 2ms/step
Model Performance in percentage (%)
35/35 [==============================] - 0s 11ms/step
```