Assignment 4 - Mythili K

1. Importing libraries

In [1]:
```
# Importing libraries

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

# Tokenization libraries
import re
import nltk
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from tensorflow.keras.preprocessing.text import one_hot
from tensorflow.keras.preprocessing.sequence import pad_sequences
from sklearn.model_selection import train_test_split
from tensorflow.keras.layers import LSTM,Dense,Embedding,Dropout
from tensorflow.keras.models import Sequential
from tensorflow.keras.optimizers import Adam
from sklearn.metrics import accuracy_score,confusion_matrix
```

In [2]:
```
# Reading the dataset
df = pd.read_csv("spam.csv",delimiter = ',',encoding='latin-1')
df.head()
```

Out[2]:

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

In [3]:
```
df.columns
```

Out[3]:
```
Index(['v1', 'v2', 'Unnamed: 2', 'Unnamed: 3', 'Unnamed: 4'], dtype='object')
```

In [4]:
```
# Deleting unwanted columns and renaming the colunmns
df = df.drop(columns=['Unnamed: 2', 'Unnamed: 3', 'Unnamed: 4'])
df = df.rename(
{
    'v1':'Label',
    'v2':'Message'
},
    axis=1
)
```

In [5]:
```
df.info()
```

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

In [6]:
```
# Checking for null values
df.isnull().sum()
```

Out[6]:
```
Label      0
Message    0
dtype: int64
```

In [7]:
```
# Creating Message length as new column
df["Message Length"] = df["Message"].apply(len)
```

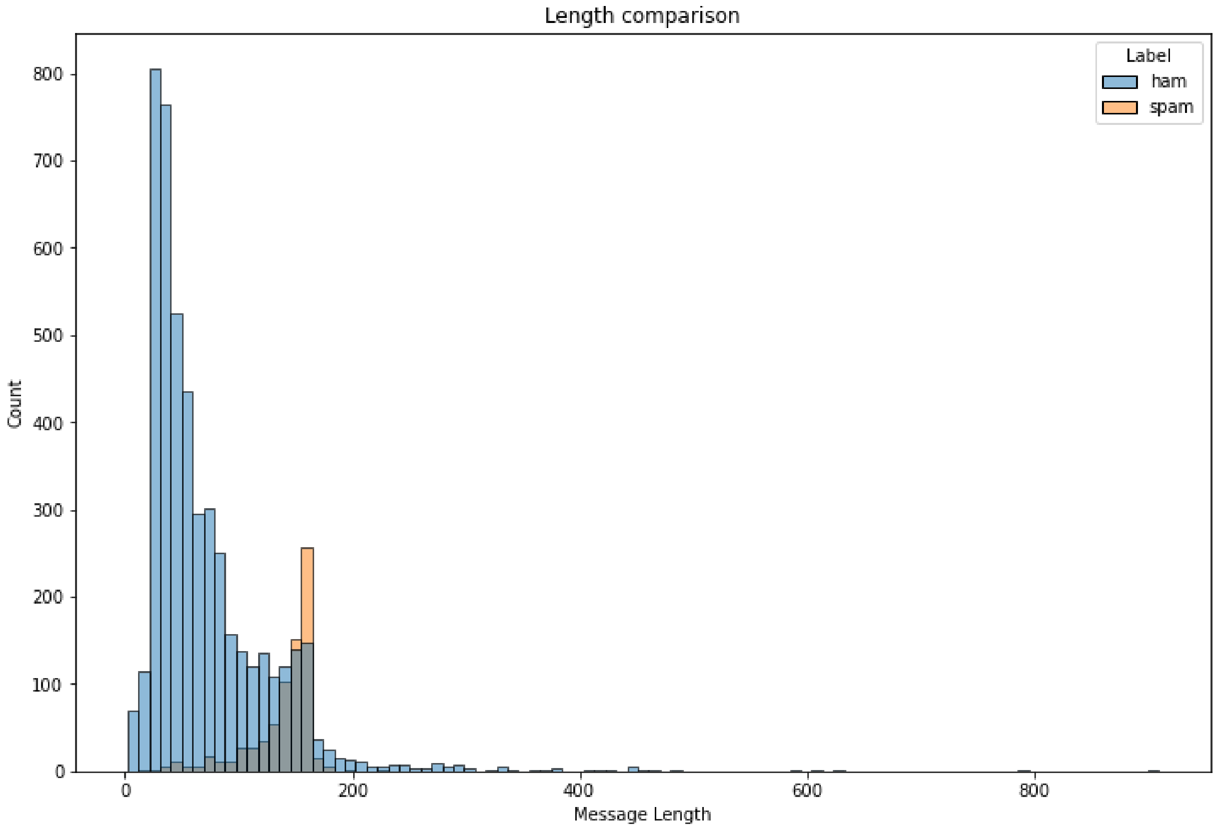
In [8]:
```
df.head()
```

Out[8]:

	Label	Message	Message Length
0	ham	Go until jurong point, crazy.. Available only ...	111
1	ham	Ok lar... Joking wif u oni...	29
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	155
3	ham	U dun say so early hor... U c already then say...	49
4	ham	Nah I don't think he goes to usf, he lives aro...	61

2.Message length visualization

In [9]:
```
fig=plt.figure(figsize=(12,8))
sns.histplot(
    x=df["Message Length"],
    hue=df["Label"]
)
plt.title("Length comparison")
plt.show()
```



3.Message Description

In [10]:
```
#Ham message description
ham_len = df[df['Label']=="ham"]["Message Length"].describe()
print("Description of ham messages:")
print(ham_len)
print()
#Spam message description
spam_len = df[df['Label']=="spam"]["Message Length"].describe()
print("Description of ham messages:")
print(spam_len)
```

```
Description of ham messages:
count    4825.000000
mean       71.023627
std        58.016023
min         2.000000
25%        33.000000
50%        52.000000
75%        92.000000
max       910.000000
Name: Message Length, dtype: float64

Description of ham messages:
count    747.000000
mean     138.866131
std       29.183082
min       13.000000
25%      132.500000
50%      149.000000
75%      157.000000
max      224.000000
Name: Message Length, dtype: float64
```

In [11]:
```
df.describe()
```

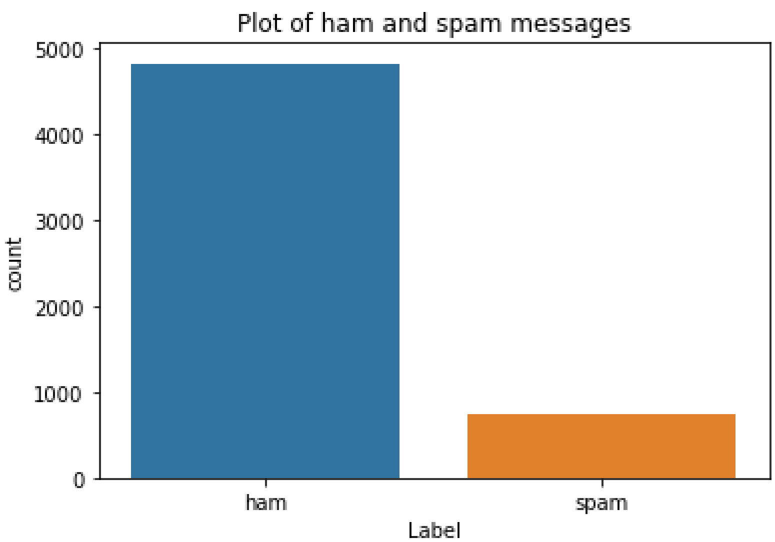
Out[11]:

	Message Length
count	5572.000000
mean	80.118808
std	59.690841
min	2.000000
25%	36.000000
50%	61.000000
75%	121.000000
max	910.000000

In [12]:
```
# Two unique values
df['Label'].value_counts()
```

Out[12]:
```
ham     4825
spam     747
Name: Label, dtype: int64
```

In [13]:
```
# Visualization of labels
sns.countplot(data=df,x='Label')
plt.title('Plot of ham and spam messages')
plt.show()
```



The dataset is imbalanced with more than 85% of ham message and 15% of spam message

4.Undersampling

In [14]:
```
# Length computation
maj_len = len(df[df['Label']=='ham'])
min_len = len(df[df['Label']=='spam'])

#Storing of indices
maj_index = df[df['Label'] == 'ham'].index
min_index = df[df['Label'] == 'spam'].index

#new index
new_index = np.random.choice(maj_index,size=min_len,replace=False)
```

In [15]:
```
# Concatenate two indices
df1 = np.concatenate([min_index,new_index])
```

In [16]:
```
#new Dataframe
df1 = df.loc[df1]
```

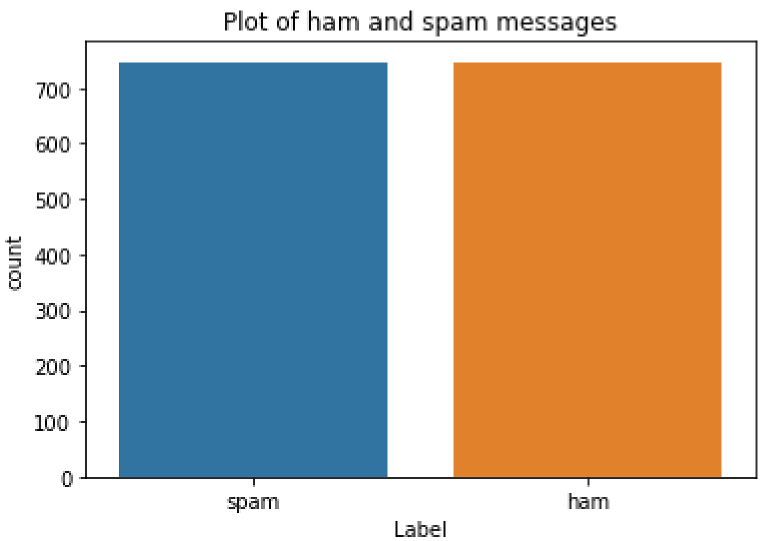
In [17]:
```
# Shuffling the sample
df1=df1.sample(frac=1)
df1=df1.reset_index()
df1 = df1.drop(
    columns=['index']
)
#shape
df1.shape
```

Out[17]:
```
(1494, 3)
```

In [18]:
```
df1['Label'].value_counts()
```

Out[18]:
```
spam    747
ham     747
Name: Label, dtype: int64
```

In [19]:
```
# Visualization of labels after undersampling
sns.countplot(data=df1,x='Label')
plt.title('Plot of ham and spam messages')
plt.show()
```



In [20]:
```
#Encoding ham and spam
df1['Value'] = df1['Label'].map(
{
    "ham" : 0,
    "spam" : 1
}
)
df1.head()
```

Out[20]:

	Label	Message	Message Length	Value
0	spam	You have won a guaranteed â£200 award or even ...	143	1
1	spam	You have been selected to stay in 1 of 250 top...	147	1
2	ham	\Keep ur problems in ur heart	29	0
3	spam	WIN a year supply of CDs 4 a store of ur choic...	147	1
4	spam	FreeMsg: Fancy a flirt? Reply DATE now & join ...	156	1

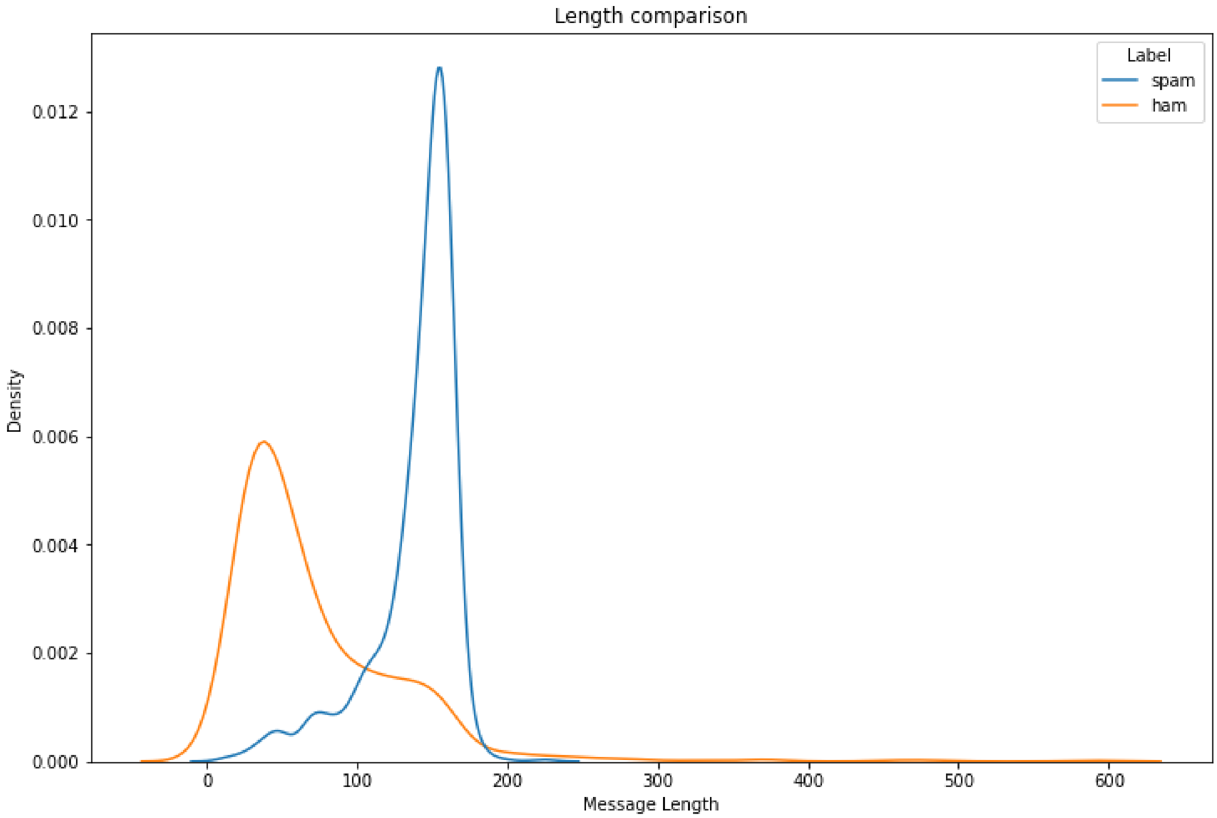
In [21]:
```
stemmer = PorterStemmer()
corpus = []
for msg in df1["Message"]:
    msg = re.sub('[^a-zA-Z]'," ",msg)
    msg = msg.lower()
    msg = msg.split()
    msg = [stemmer.stem(words)
           for words in msg
           if words not in set(stopwords.words("english"))
          ]
    msg = " ".join(msg)
    corpus.append(msg)
```

In [22]:
```
vocab = 10000
onehot_doc = [one_hot(words,n=vocab)
              for words in corpus]
```

In [23]:
```
df1["Message Length"].describe()
```

Out[23]:
```
count    1494.000000
mean      105.265730
std        56.849913
min         3.000000
25%        50.250000
50%       120.000000
75%       153.000000
max       588.000000
Name: Message Length, dtype: float64
```

In [24]:
```
fig=plt.figure(figsize=(12,8))
sns.kdeplot(
    x = df1['Message Length'],
    hue = df1['Label']
)
plt.title("Length comparison")
plt.show()
```



In [25]:
```
# word embedding
sen_len = 200
embed = pad_sequences(onehot_doc,maxlen=sen_len,padding="pre")
```

In [26]:
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1494 entries, 0 to 1493
Data columns (total 4 columns):
 #   Column          Non-Null Count  Dtype 
---  ------          --------------  ----- 
 0   Label           1494 non-null   object
 1   Message         1494 non-null   object
 2   Message Length  1494 non-null   int64 
 3   Value           1494 non-null   int64 
dtypes: int64(2), object(2)
memory usage: 46.8+ KB
```

In [27]:
```
# Creating dataframe
new_dataframe = pd.DataFrame(data = embed)
target=df1["Value"]
```

In [28]:
```
# Dataframe concatenation
df_final = pd.concat([new_dataframe,target],axis=1)
```

In [29]:
```
df_final.head()
```

Out[29]:

	0	1	2	3	4	5	6	7	8	9	...	191	192	193	194	195	196	197	198	199	Value
0	0	0	0	0	0	0	0	0	0	0	...	9399	5142	5213	2808	4862	8633	8127	4708	2307	1
1	0	0	0	0	0	0	0	0	0	0	...	3451	910	5654	890	5213	8663	6573	8858	4832	1
2	0	0	0	0	0	0	0	0	0	0	...	0	0	0	0	2824	9399	5131	9399	2003	0
3	0	0	0	0	0	0	0	0	0	0	...	188	4911	7336	3396	606	5367	2381	6178	5347	1
4	0	0	0	0	0	0	0	0	0	0	...	4925	746	693	9347	2454	237	4862	9698	9794	1

5 rows × 201 columns

In [30]:
```
# Splitting dataframe
x = df_final.drop("Value",axis=1)
y = df_final["Value"]
```

In [31]:
```
# Train test split
xtrainval,xtest,ytrainval,ytest=train_test_split(x,y,random_state=42,test_size=0.
```

In [32]:
```
xtrain,xval,ytrain,yval=train_test_split(xtrainval,ytrainval,random_state=42,test
```

5.Model building

In [33]:
```
model = Sequential()
```

In [34]:
```
feature_num = 100
model.add(Embedding(input_dim=vocab,output_dim=feature_num,input_length=sen_len))
model.add(LSTM(units=128,activation = 'relu',return_sequences=True))
model.add(Dropout(0.2))
#Layer2
model.add(LSTM(units=60, activation = 'relu'))
model.add(Dropout(0.3))
#output layer
model.add(Dense(units=1,activation="sigmoid"))
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 200, 100)          1000000

 lstm (LSTM)                 (None, 200, 128)          117248

 dropout (Dropout)           (None, 200, 128)          0

 lstm_1 (LSTM)               (None, 60)                45360

 dropout_1 (Dropout)         (None, 60)                0

 dense (Dense)               (None, 1)                 61

=================================================================
Total params: 1,162,669
Trainable params: 1,162,669
Non-trainable params: 0
_________________________________________________________________
```

In [35]:
```
# Compilation of model
model.compile(optimizer=Adam(learning_rate=0.001),loss='binary_crossentropy',metr
```

6.Model Training

In [36]:
```
# Model fit
model.fit(xtrain,ytrain,validation_data=(xval,yval),epochs=50)
```

```
Epoch 1/50
34/34 [==============================] - 20s 483ms/step - loss: nan - accuracy:
0.5473 - val_loss: nan - val_accuracy: 0.4503
Epoch 2/50
34/34 [==============================] - 15s 427ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 3/50
34/34 [==============================] - 15s 425ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 4/50
34/34 [==============================] - 19s 552ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 5/50
34/34 [==============================] - 22s 635ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 6/50
34/34 [==============================] - 19s 554ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 7/50
34/34 [==============================] - 15s 447ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 8/50
34/34 [==============================] - 15s 443ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 9/50
34/34 [==============================] - 14s 418ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 10/50
34/34 [==============================] - 15s 450ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 11/50
34/34 [==============================] - 15s 434ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 12/50
34/34 [==============================] - 16s 464ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 13/50
34/34 [==============================] - 15s 430ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 14/50
34/34 [==============================] - 16s 468ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 15/50
34/34 [==============================] - 24s 700ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 16/50
34/34 [==============================] - 25s 707ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 17/50
34/34 [==============================] - 25s 745ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 18/50
34/34 [==============================] - 23s 661ms/step - loss: nan - accuracy:
```

```
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 19/50
34/34 [==============================] - 21s 633ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 20/50
34/34 [==============================] - 25s 746ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 21/50
34/34 [==============================] - 19s 549ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 22/50
34/34 [==============================] - 22s 653ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 23/50
34/34 [==============================] - 22s 640ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 24/50
34/34 [==============================] - 17s 514ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 25/50
34/34 [==============================] - 28s 836ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 26/50
34/34 [==============================] - 24s 712ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 27/50
34/34 [==============================] - 25s 744ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 28/50
34/34 [==============================] - 21s 630ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 29/50
34/34 [==============================] - 19s 565ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 30/50
34/34 [==============================] - 20s 581ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 31/50
34/34 [==============================] - 20s 604ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 32/50
34/34 [==============================] - 26s 773ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 33/50
34/34 [==============================] - 22s 646ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 34/50
34/34 [==============================] - 17s 500ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 35/50
34/34 [==============================] - 16s 459ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 36/50
34/34 [==============================] - 18s 519ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 37/50
34/34 [==============================] - 18s 517ms/step - loss: nan - accuracy:
```

```
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 38/50
34/34 [==============================] - 19s 553ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 39/50
34/34 [==============================] - 31s 936ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 40/50
34/34 [==============================] - 19s 566ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 41/50
34/34 [==============================] - 25s 736ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 42/50
34/34 [==============================] - 24s 700ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 43/50
34/34 [==============================] - 18s 544ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 44/50
34/34 [==============================] - 19s 556ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 45/50
34/34 [==============================] - 27s 819ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 46/50
34/34 [==============================] - 18s 545ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 47/50
34/34 [==============================] - 16s 483ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 48/50
34/34 [==============================] - 17s 498ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 49/50
34/34 [==============================] - 16s 462ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
Epoch 50/50
34/34 [==============================] - 14s 399ms/step - loss: nan - accuracy:
0.5009 - val_loss: nan - val_accuracy: 0.4503
```

```
Out[36]: <keras.callbacks.History at 0x21b188da4f0>
```

In [37]:

```
# prediction
y_pred = model.predict(xtest)
y_pred = (y_pred>0.5)
```

In [38]:

```
# Model accuracy score
score=accuracy_score(ytest,y_pred)
print("Test Score:{:.2f}%".format(score*100))
```

```
Test Score:53.78%
```

7.Model Evaluation

In [39]:
```
model.evaluate(xtest,ytest)
```

```
8/8 [==============================] - 1s 130ms/step - loss: nan - accuracy: 0.
5378
```

Out[39]:
```
[nan, 0.5377777814865112]
```

In [40]:
```
def cls_message(model,msg):
    msg = re.sub('[^a-zA-Z]'," ",msg)
    msg = msg.lower()
    msg = msg.split()
    msg = [stemmer.stem(words)
           for words in msg
           if words not in set(stopwords.words("english"))
          ]
    msg = " ".join(msg)
    oneHot=[one_hot(msg,n=vocab)]
    text=pad_sequences(oneHot,maxlen=sen_len,padding="pre")
    predict=model.predict(text)
    if predict>0.5:
        print("It is a spam")
    else:
        print("It is not a spam")
```

8.Testing

In [41]:
```
#message
msg1 = "Your gonna have to pick up a $1 burger for yourself on your way home. I c
msg2 = "Hurray!! You won a cash prize of 3000rs."
```

In [42]:
```
cls_message(model,msg1)
```

```
It is not a spam
```

In [43]:
```
cls_message(model,msg2)
```

```
It is not a spam
```