## Importing the Required Library.

Pandas, Numpy, Tensorflow, Sklearn, Keras, Tokenizer and etc.

```
import pandas as pd
import numpy as np
import tensorflow as tf

from sklearn.model_selection import train_test_split


import keras
from keras.preprocessing import text,sequence
from keras.models import Sequential
from keras.layers import Dense,Embedding,LSTM,Dropout
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense, Dropout, GlobalMaxPooling1D
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.callbacks import ModelCheckpoint, EarlyStopping
```

## Loading the dataset.

Dataset taken from Kaggle

```
data = pd.read_csv('/content/drive/MyDrive/clickbait_data.csv')
```

## Split dataset into training and testing sets using train and test split.

```
train_data, test_data = train_test_split(data, test_size=0.2, random_state=42)
```

## Tokenize the text data for computation.

To convert text in numerical sequence.

```
tokenizer = Tokenizer(num_words=5000)
tokenizer.fit_on_texts(train_data['headline'])
```

## Convert text data to sequences

```
train_sequences = tokenizer.texts_to_sequences(train_data['headline'])
test_sequences = tokenizer.texts_to_sequences(test_data['headline'])
```

## Pad the sequences to a fixed length

maximum length is 500

```
max_length = 500
train_padded_sequences = pad_sequences(train_sequences, maxlen=max_length, padding='post')
test_padded_sequences = pad_sequences(test_sequences, maxlen=max_length, padding='post')
```

## Load pre-trained word embeddings.

We use GloVe's 6 Billion tokens with 100 dimensions. It is faster and efficient for our problem statement.

```
embedding_dim = 100
embeddings_index = {}
with open('/content/drive/MyDrive/glove.6B.100d.txt', encoding='utf8') as f:
    for line in f:
        values = line.split()
        word = values[0]
```

```
        coefs = np.asarray(values[1:], dtype='float32')
        embeddings_index[word] = coefs
```

## Create embedding matrix using GloVe Word Embeddings.

```
num_words = min(5000, len(tokenizer.word_index) + 1)
embedding_matrix = np.zeros((num_words, embedding_dim))
for word, i in tokenizer.word_index.items():
    if i >= num_words:
        break
    embedding_vector = embeddings_index.get(word)
    if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector
```

Intialize the parameters for LSTM model.

```
vocab_size = 5000
maxlen = 500
embedding_size = 32
```

## Define the Model Structure

```
model = Sequential()
model.add(Embedding(input_dim=num_words, output_dim=embedding_dim, weights=[embedding_matrix], input_length=max_length, trainable=False))
model.add(LSTM(32, return_sequences=True))
model.add(GlobalMaxPooling1D())
model.add(Dropout(0.2))
model.add(Dense(1, activation='sigmoid'))
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 embedding_1 (Embedding)     (None, 500, 100)          500000    
                                                                 
 lstm_1 (LSTM)               (None, 500, 32)           17024     
                                                                 
 global_max_pooling1d_1 (Glo  (None, 32)               0         
 balMaxPooling1D)                                                
                                                                 
 dropout_1 (Dropout)         (None, 32)                0         
                                                                 
 dense_1 (Dense)             (None, 1)                 33        
                                                                 
=================================================================
Total params: 517,057
Trainable params: 17,057
Non-trainable params: 500,000
_________________________________________________________________
```

Callbacks use for prevent overfitting.

```
callbacks = [
    EarlyStopping(
        monitor='val_accuracy',
        min_delta=1e-4,
        patience=3,
        verbose=1
    ),
    ModelCheckpoint(
        filepath='weights.h5',
        monitor='val_accuracy',
        mode='max',
        save_best_only=True,
        save_weights_only=True,
        verbose=1
    )
]
```

## Compile the model

```
model.compile(loss='binary_crossentropy', optimizer=tf.keras.optimizers.Adam(learning_rate=0.001), metrics=['accuracy'])
```

## Train the model

```
history = model.fit(train_padded_sequences, train_data['clickbait'], epochs=35, batch_size=512, validation_split=0.2, callbacks=callbacks
```

```
Epoch 7/35
39/40 [============================>.] - ETA: 0s - loss: 0.1020 - accuracy: 0.9670
Epoch 7: val_accuracy did not improve from 0.95820
40/40 [==============================] - 1s 32ms/step - loss: 0.1015 - accuracy: 0.9671 - val_loss: 0.1145 - val_accuracy: 0.957
Epoch 8/35
39/40 [============================>.] - ETA: 0s - loss: 0.0948 - accuracy: 0.9692
Epoch 8: val_accuracy improved from 0.95820 to 0.96348, saving model to weights.h5
40/40 [==============================] - 1s 33ms/step - loss: 0.0949 - accuracy: 0.9691 - val_loss: 0.1018 - val_accuracy: 0.963
Epoch 9/35
39/40 [============================>.] - ETA: 0s - loss: 0.0876 - accuracy: 0.9707
Epoch 9: val_accuracy improved from 0.96348 to 0.96387, saving model to weights.h5
40/40 [==============================] - 1s 33ms/step - loss: 0.0875 - accuracy: 0.9707 - val_loss: 0.1023 - val_accuracy: 0.963
Epoch 10/35
39/40 [============================>.] - ETA: 0s - loss: 0.0826 - accuracy: 0.9720
Epoch 10: val_accuracy improved from 0.96387 to 0.96816, saving model to weights.h5
40/40 [==============================] - 1s 33ms/step - loss: 0.0830 - accuracy: 0.9718 - val_loss: 0.0951 - val_accuracy: 0.968
Epoch 11/35
39/40 [============================>.] - ETA: 0s - loss: 0.0785 - accuracy: 0.9741
Epoch 11: val_accuracy did not improve from 0.96816
40/40 [==============================] - 1s 32ms/step - loss: 0.0783 - accuracy: 0.9740 - val_loss: 0.0947 - val_accuracy: 0.967
Epoch 12/35
39/40 [============================>.] - ETA: 0s - loss: 0.0739 - accuracy: 0.9749
Epoch 12: val_accuracy improved from 0.96816 to 0.97031, saving model to weights.h5
40/40 [==============================] - 1s 33ms/step - loss: 0.0738 - accuracy: 0.9750 - val_loss: 0.0915 - val_accuracy: 0.970
Epoch 13/35
39/40 [============================>.] - ETA: 0s - loss: 0.0696 - accuracy: 0.9768
Epoch 13: val_accuracy did not improve from 0.97031
40/40 [==============================] - 1s 32ms/step - loss: 0.0690 - accuracy: 0.9771 - val_loss: 0.0917 - val_accuracy: 0.969
Epoch 14/35
39/40 [============================>.] - ETA: 0s - loss: 0.0647 - accuracy: 0.9784
Epoch 14: val_accuracy improved from 0.97031 to 0.97109, saving model to weights.h5
40/40 [==============================] - 1s 32ms/step - loss: 0.0645 - accuracy: 0.9785 - val_loss: 0.0873 - val_accuracy: 0.971
Epoch 15/35
39/40 [============================>.] - ETA: 0s - loss: 0.0647 - accuracy: 0.9786
Epoch 15: val_accuracy did not improve from 0.97109
40/40 [==============================] - 1s 32ms/step - loss: 0.0648 - accuracy: 0.9786 - val_loss: 0.0926 - val_accuracy: 0.969
Epoch 16/35
39/40 [============================>.] - ETA: 0s - loss: 0.0636 - accuracy: 0.9810
Epoch 16: val_accuracy improved from 0.97109 to 0.97168, saving model to weights.h5
40/40 [==============================] - 1s 32ms/step - loss: 0.0638 - accuracy: 0.9809 - val_loss: 0.0942 - val_accuracy: 0.971
Epoch 17/35
39/40 [============================>.] - ETA: 0s - loss: 0.0621 - accuracy: 0.9796
Epoch 17: val_accuracy improved from 0.97168 to 0.97207, saving model to weights.h5
40/40 [==============================] - 1s 33ms/step - loss: 0.0623 - accuracy: 0.9797 - val_loss: 0.0912 - val_accuracy: 0.972
Epoch 18/35
39/40 [============================>.] - ETA: 0s - loss: 0.0527 - accuracy: 0.9831
Epoch 18: val_accuracy did not improve from 0.97207
40/40 [==============================] - 1s 32ms/step - loss: 0.0526 - accuracy: 0.9832 - val_loss: 0.0885 - val_accuracy: 0.970
Epoch 19/35
39/40 [============================>.] - ETA: 0s - loss: 0.0487 - accuracy: 0.9851
Epoch 19: val_accuracy did not improve from 0.97207
40/40 [==============================] - 1s 32ms/step - loss: 0.0486 - accuracy: 0.9851 - val_loss: 0.0969 - val_accuracy: 0.967
Epoch 20/35
39/40 [============================>.] - ETA: 0s - loss: 0.0489 - accuracy: 0.9848
Epoch 20: val_accuracy did not improve from 0.97207
40/40 [==============================] - 1s 32ms/step - loss: 0.0482 - accuracy: 0.9851 - val_loss: 0.0944 - val_accuracy: 0.969
Epoch 20: early stopping
```

## Evaluate the model on the test set

```
test_loss, test_accuracy = model.evaluate(test_padded_sequences, test_data['clickbait'])
print('Test accuracy:', test_accuracy)
```

```
200/200 [==============================] - 2s 9ms/step - loss: 0.0931 - accuracy: 0.9702
Test accuracy: 0.9701562523841858
```

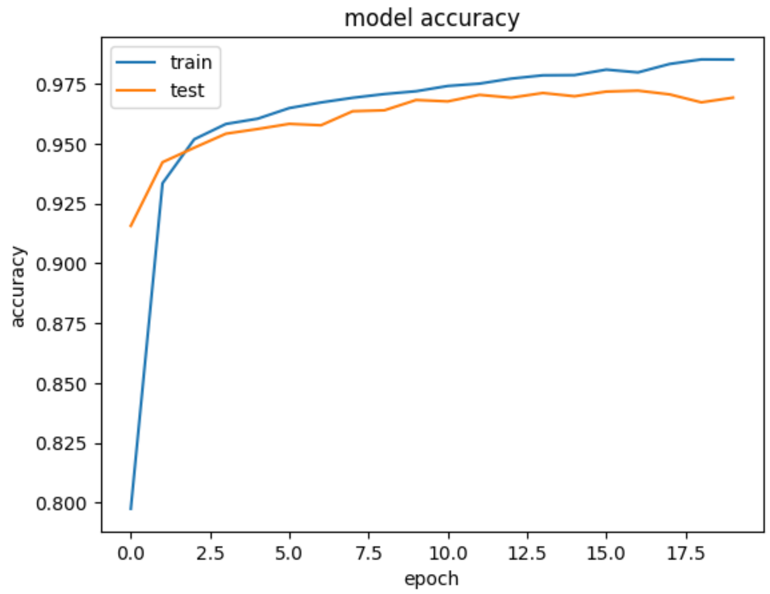
```
test = ["Man breaks into opera at eatery after seeing pizza","How A.I. and DNA Are Unlocking the Mysteries of Global Supply Chains,’ Prig
token_text = pad_sequences(tokenizer.texts_to_sequences(test), maxlen=max_length)
preds = [round(i[0]) for i in model.predict(token_text)]
```

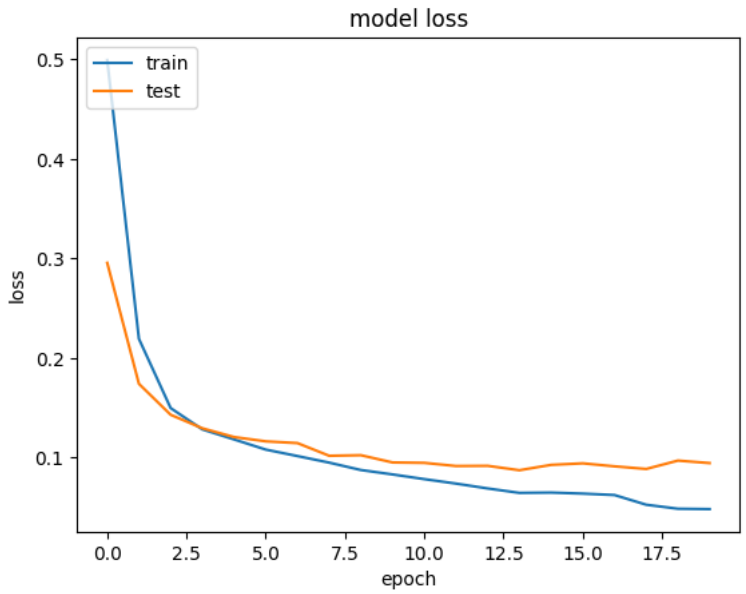
```
for (text, pred) in zip(test, preds):
    label = 'Clickbait' if pred == 1.0 else 'Not Clickbait'
    print("{} - {}".format(text, label))
```

```
1/1 [==============================] - 0s 362ms/step
Man breaks into opera at eatery after seeing pizza - Not Clickbait
How A.I. and DNA Are Unlocking the Mysteries of Global Supply Chains,’ Prigozhin says. - Clickbait
Shahid Kapoor and Kriti Sanon's new film poster leaves internet baffled - Not Clickbait
Anupam Kher reacts after Anurag Basu makes dosa for him on Metro In Dino sets - Not Clickbait
A Profit for Medco and a Loss for Tenet - Not Clickbait
```

## Plotting the Results for evaluting the model accuracy and efficiency.

```
import matplotlib.pyplot as plt
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
# summarize history for loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



```
model.load_weights('weights.h5')
from tensorflow.keras.models import save_model
save_model(model,'model8.h5')
```

```
from tensorflow.keras.models import load_model
mod = load_model('model8.h5',compile=False)
mod.load_weights('weights.h5')
```

```
test = ["Why Pope Francis Is the Star of A.I.-Generated Photos","Thailand’s Unemployed Elephants Are Back Home, Huge and Hungry","How A.I
token_text = pad_sequences(tokenizer.texts_to_sequences(test), maxlen=max_length)
preds = [round(i[0]) for i in mod.predict(token_text)]
for (text, pred) in zip(test, preds):
    label = 'Clickbait' if pred > 0.5 else 'Not Clickbait'
    print("{} - {}".format(text, label))
```

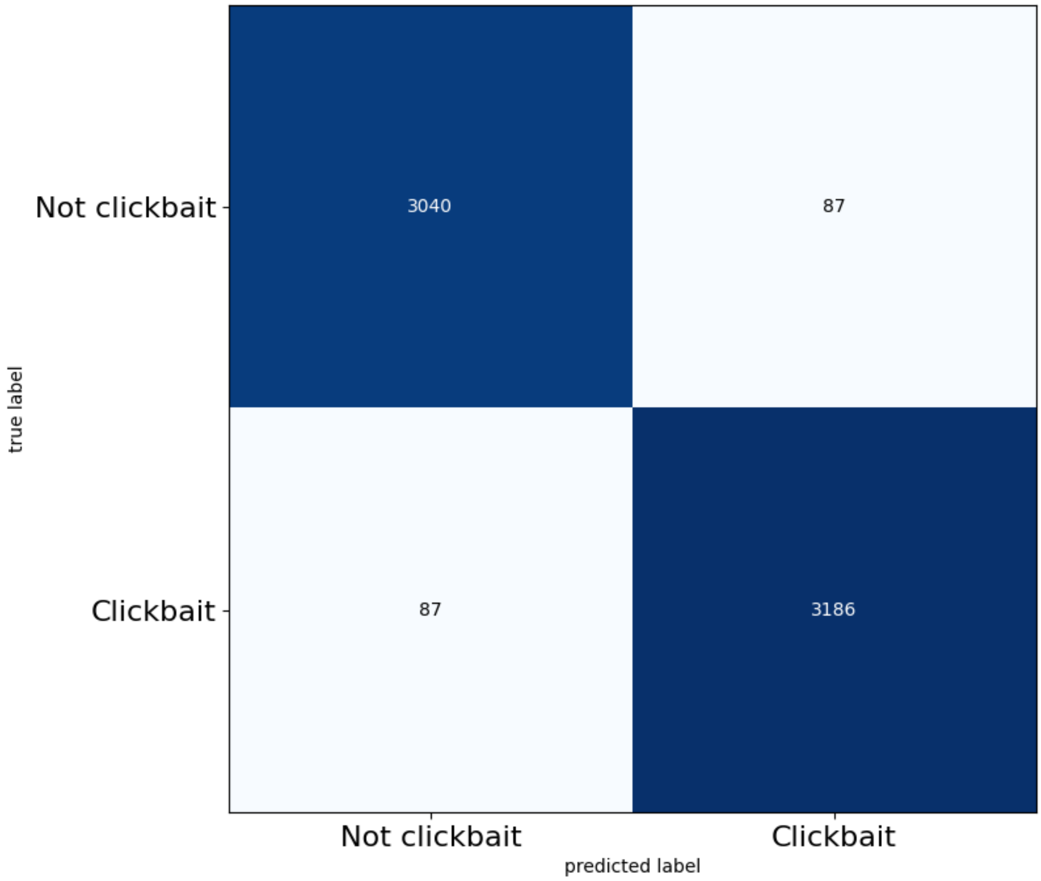
```
1/1 [==============================] - 1s 527ms/step
Why Pope Francis Is the Star of A.I.-Generated Photos - Not Clickbait
Thailand’s Unemployed Elephants Are Back Home, Huge and Hungry - Not Clickbait
How A.I. and DNA Are Unlocking the Mysteries of Global Supply Chains,’ Prigozhin says. - Not Clickbait
French Diplomacy Undercuts U.S. Efforts to Rein China In - Not Clickbait
Family from Gujarat drowns while attempting illegal crossing over St. Lawrence river on Canada-U.S. border - Not Clickbait
Why Pope Francis Is the Star of A.I.-Generated Photos - Not Clickbait
```

## Confusion Marix

```
from sklearn.metrics import confusion_matrix
from mlxtend.plotting import plot_confusion_matrix

preds = [round(i[0]) for i in mod.predict(test_padded_sequences)]
cm = confusion_matrix(test_data['clickbait'], preds)
plt.figure()
plot_confusion_matrix(cm, figsize=(12,8), hide_ticks=True, cmap=plt.cm.Blues)
plt.xticks(range(2), ['Not clickbait', 'Clickbait'], fontsize=16)
plt.yticks(range(2), ['Not clickbait', 'Clickbait'], fontsize=16)
plt.show()
```

```
200/200 [==============================] - 1s 7ms/step
<Figure size 640x480 with 0 Axes>
```



## Classification Report

```
from sklearn.metrics import classification_report

y_true = test_data['clickbait']  # True labels of the test set
y_pred_probs = mod.predict(test_padded_sequences)  # Predicted probabilities of the test set
y_pred = (y_pred_probs > 0.5).astype(int)

#classification report
print(classification_report(y_true, y_pred))
```

```
200/200 [==============================] - 1s 6ms/step
              precision    recall  f1-score   support

           0       0.97      0.97      0.97      3127
           1       0.97      0.97      0.97      3273

    accuracy                           0.97      6400
   macro avg       0.97      0.97      0.97      6400
weighted avg       0.97      0.97      0.97      6400
```

```
from google.colab import drive
drive.mount('/content/drive')
```

```
import pickle

# Create a tokenizer and fit it to your data

# Save the tokenizer as a pickle file
with open('tokenizer.pickle', 'wb') as handle:
    pickle.dump(tokenizer, handle, protocol=pickle.HIGHEST_PROTOCOL)
```