

FAKE NEWS CLASSIFICATION USING LSTM

Dataset: [FakeNews](#)

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DOWNLOAD AND LOAD DATASET

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

- Mount Google Drive to access files, enabling interaction with files stored in your Google Drive directly from the Colab notebook environment.
- Set the Kaggle API token directory to a specific folder in your Google Drive, ensuring that the Kaggle API can access your Kaggle credentials securely.
- Download the dataset from Kaggle using the Kaggle API, allowing you to fetch datasets directly from Kaggle competitions or datasets.
- Unzip the downloaded files to extract the dataset contents for further processing and analysis.
- Read the train, test, and submission data into pandas DataFrames, enabling easy manipulation and analysis of the dataset using pandas, a powerful data manipulation library in Python.
- Return the train, test, and submission DataFrames, providing access to the dataset within the notebook for exploration, preprocessing, and modeling tasks.

In [4]:

```
from google.colab import drive
import os
import pandas as pd

def download_and_load_fake_news_dataset():
    # Mount Google Drive to access files
    drive.mount('/content/drive')

    # Set the Kaggle API token directory
    os.environ['KAGGLE_CONFIG_DIR'] = "/content/drive/MyDrive"

    # Download the dataset using the Kaggle API
    !kaggle competitions download -c fake-news

    # Unzip the downloaded files
    !unzip fake-news.zip

    # Read the train and test data into pandas DataFrames
    train = pd.read_csv("train.csv")
    test = pd.read_csv("test.csv")
    submit = pd.read_csv("submit.csv")

    return train, test , submit
```

- Load the fake news dataset using the `download_and_load_fake_news_dataset()` function, which downloads and loads the dataset from Kaggle.
- Assign the returned DataFrames to variables `train`, `test`, and `submit`.
- Check the shapes of the loaded DataFrames using the `shape` attribute, which returns the number of rows and columns in each DataFrame.
- Print the shapes of the train, test, and submit DataFrames to the console for inspection.

In [5]:

```
# Call the function to download and load the dataset
train ,test, submit = download_and_load_fake_news_dataset()

# Check the shapes of the loaded DataFrames
print("Shape of train dataset:", train.shape)
print("Shape of test dataset:", test.shape)
print("Shape of Submit dataset", submit.shape)
```

```
Mounted at /content/drive
Downloading fake-news.zip to /content
 95% 44.0M/46.5M [00:02<00:00, 25.7MB/s]
100% 46.5M/46.5M [00:02<00:00, 18.8MB/s]
Archive:  fake-news.zip
  inflating: submit.csv
```

```
inflating: test.csv
inflating: train.csv
Shape of train dataset: (20800, 5)
Shape of test dataset: (5200, 4)
Shape of Submit dataset (5200, 2)
```

In [6]:

```
train.head()
```

Out[6]:

id		title	author	text	label
0	0	House Dem Aide: We Didn't Even See Comey's Let...	Darrell Lucas	House Dem Aide: We Didn't Even See Comey's Let...	1
1	1	FLYNN: Hillary Clinton, Big Woman on Campus - ...	Daniel J. Flynn	Ever get the feeling your life circles the rou...	0
2	2	Why the Truth Might Get You Fired	Consortiumnews.com	Why the Truth Might Get You Fired October 29, ...	1
3	3	15 Civilians Killed In Single US Airstrike Hav...	Jessica Purkiss	Videos 15 Civilians Killed In Single US Aistr...	1
4	4	Iranian woman jailed for fictional unpublished...	Howard Portnoy	Print \nAn Iranian woman has been sentenced to...	1

In [195]:

```
submit.head()
```

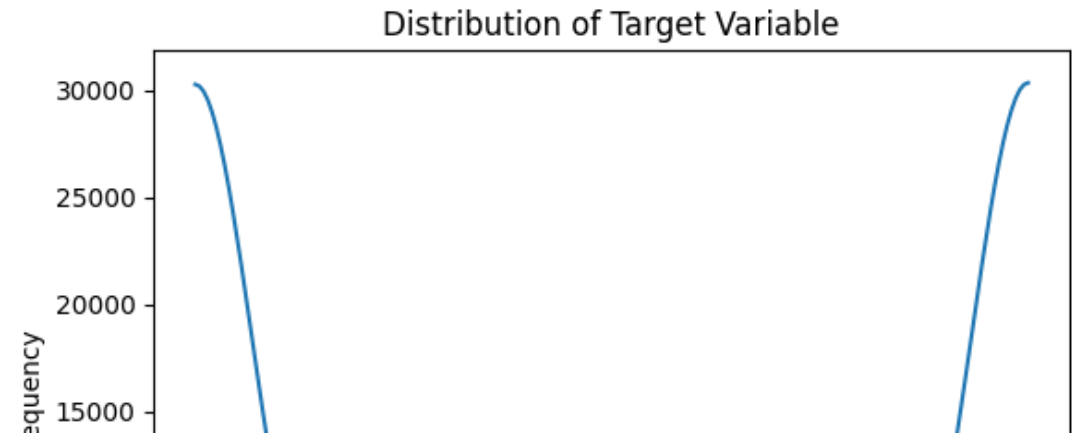
Out[195]:

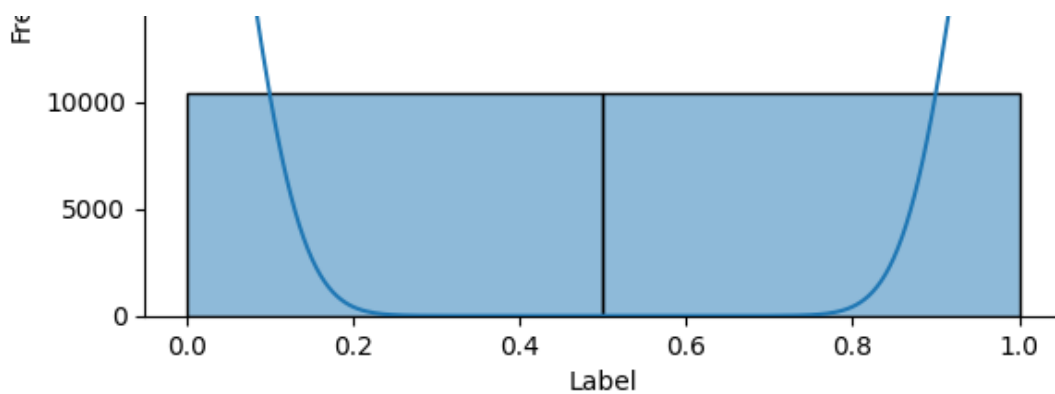
id	label
0	20800
1	20801
2	20802
3	20803
4	20804

DISTRIBUTION PLOT ON TARGET VARIABLE

In [7]:

```
# Create a distribution plot for the target variable train['label']
sns.histplot(data=train, x='label', bins=2, kde=True) # Assuming label is binary
plt.title('Distribution of Target Variable')
plt.xlabel('Label')
plt.ylabel('Frequency')
plt.show()
```





- A balanced dataset refers to a scenario where each class or category within the target variable is represented by a similar number of observations or instances.
- In a balanced dataset, the model is not biased towards any particular class, allowing it to learn effectively from all classes equally.
- Balanced datasets are highly desirable in machine learning tasks as they mitigate issues such as class imbalance, where one class dominates the dataset, potentially leading to biased predictions.

In [8]:

```
train.head(2)
```

Out[8]:

	id		title	author	text	label
0	0	House Dem Aide: We Didn't Even See Comey's Let...	Darrell Lucas	House Dem Aide: We Didn't Even See Comey's Let...		1
1	1	FLYNN: Hillary Clinton, Big Woman on Campus - ...	Daniel J. Flynn	Ever get the feeling your life circles the rou...		0

DATA PREPROCESSING

- Checked the shape of the DataFrame before preprocessing.
- Printed a separator line for better readability.
- Displayed the data information using `df.info()` , providing insights into the DataFrame's structure and data types.
- Checked and printed the count of null values in each column using `df.isnull().sum()` .
- Dropped rows with null values using `df.dropna()` and updated the DataFrame accordingly.
- Checked and printed the count of null values after dropping rows using `df.isnull().sum()` .
- Printed a separator line for better readability.
- Printed the count of duplicate values in the DataFrame using `df.duplicated().sum()` .
- Checked the shape of the DataFrame after preprocessing and returning the updated DataFrame.

In [9]:

```
def data_preprocessing(df):
    print(df.shape)
    print('\n', "+"*50 , '\n')
    print("Data Information")
    print(df.info())
    print('\n', "+"*50 , '\n')
    print("Data Null Values")
    print(df.isnull().sum())
    df = df.dropna()
    print("Data Null Values after Dropna")
    print(df.isnull().sum())
    print('\n', "+"*50 , '\n')
    print("Duplicate values count")
    print(df.duplicated().sum())
    print('\n', "+"*50 , '\n')
```

```
print(df.duplicated().sum())
print(df.shape)
return df
```

In [10]:

```
train1 = data_preprocessing(train)
```

```
(20800, 5)
```

```
+++++
```

Data Information

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 20800 entries, 0 to 20799
```

```
Data columns (total 5 columns):
```

#	Column	Non-Null Count	Dtype
0	id	20800 non-null	int64
1	title	20242 non-null	object
2	author	18843 non-null	object
3	text	20761 non-null	object
4	label	20800 non-null	int64

```
dtypes: int64(2), object(3)
```

```
memory usage: 812.6+ KB
```

```
None
```

```
+++++
```

Data Null Values

```
id          0
title       558
author     1957
text        39
label       0
```

```
dtype: int64
```

Data Null Values after Dropna

```
id          0
title       0
author      0
text        0
label       0
```

```
dtype: int64
```

```
+++++
```

Duplicate values count

```
+++++
```

```
0
(18285, 5)
```

TEXT CLEANING

- lowering the text
- removing the special symbols
- removing the tags [\n etc]
- Removing the Web tags [www. @ etc]
- removing numbers/figures

- Converted the text in the 'text' column to lowercase using `df['text'].str.lower()`.
- Removed HTML tags from the text in the 'text' column using regular expressions (`re.sub(r'<[^>]*>', '', x)`).
- Removed numbers from the text in the 'text' column using regular expressions (`re.sub(r'\d+', '', x)`).
- Removed taglines and newlines from the text in the 'text' column using regular expressions (`re.sub(r'[\n\+!'. ''].', x)`).

In [14]:

```
df2 = df1.copy()
```

- This function truncates the text in the 'text' column of a DataFrame to contain at most 100 words.
- It iterates over each row, splits the text into words, and counts the number of words. If the number of words exceeds 100, it truncates the text to the first 100 words.
- This helps to standardize the length of text entries in the DataFrame.

In [16]:

```
def replace_text(df):  
    # Iterate over DataFrame rows  
    for index, row in df.iterrows():  
        # Split the text into words and count the number of words  
        text_words = row['text'].split()  
        num_words = len(text_words)  
  
        # Check if the number of words is less than 5  
        if num_words > 100:  
  
            df.at[index, 'text'] = ' '.join(text_words[:100])  
  
    return df
```

In [17]:

```
df5 = replace_text(df2)
```

In [18]:

```
df5
```

Out[18]:

	id	title	author	text	label
0	0	House Dem Aide: We Didn't Even See Comey's Let...	Darrell Lucas	house dem aide we didnt even see comeys letter...	1
1	1	FLYNN: Hillary Clinton, Big Woman on Campus - ...	Daniel J. Flynn	ever get the feeling your life circles the rou...	0
2	2	Why the Truth Might Get You Fired	Consortiumnews.com	why the truth might get you fired october the ...	1
3	3	15 Civilians Killed In Single US Airstrike Hav...	Jessica Purkiss	videos civilians killed in single us airstrike...	1
4	4	Iranian woman jailed for fictional unpublished...	Howard Portnoy	print an iranian woman has been sentenced to s...	1
...
20795	20795	Rapper T.I.: Trump a 'Poster Child For White S...	Jerome Hudson	rapper t i unloaded on black celebrities who m...	0
20796	20796	N.F.L. Playoffs: Schedule, Matchups and Odds -...	Benjamin Hoffman	when the green bay packers lost to the washing...	0
20797	20797	Macy's Is Said to Receive Takeover Approach by...	Michael J. de la Merced and Rachel Abrams	the macys of today grew from the union of seve...	0
20798	20798	NATO, Russia To Hold Parallel Exercises In Bal...	Alex Ansary	nato russia to hold parallel exercises in balk...	1
20799	20799	What Keeps the F-35 Alive	David Swanson	david swanson is an author activist journalist...	1

18285 rows x 5 columns

```
In [20]:
```

```
x= df5['text']
```

```
In [21]:
```

```
y= df5['label']
```

TOKENIZE AND REMOVE STOPWORDS

- Import the pandas library as pd for working with DataFrames.
- Import the nltk library for natural language processing tasks.
- Import the word_tokenize function from the nltk.tokenize module to tokenize words.
- Import the stopwords corpus from the nltk.corpus module to remove common stopwords from text data.
- Import the WordNetLemmatizer class from the nltk.stem module for lemmatization.
- Download the 'punkt' dataset if it's not already downloaded, which contains pre-trained tokenizers for various languages.
- Download the 'stopwords' dataset if it's not already downloaded, which contains a list of common stopwords in various languages.
- Download the 'wordnet' dataset if it's not already downloaded, which is a lexical database for the English language that provides information about word meanings and relationships between words.

```
In [63]:
```

```
import pandas as pd
import nltk
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
# Download stopwords if not already downloaded
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')
```

```
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

```
Out[63]:
```

```
True
```

This function tokenizes, removes stopwords, and lemmatizes text data.

- Initialize a WordNetLemmatizer object named lemmatizer for lemmatization.
- Create an empty list named tokenized_X to store the tokenized and processed text data.
- Create a set of stopwords for the English language using the stopwords.words('english') function.
- Iterate over each text in the input data X.
 - Tokenize the text using the word_tokenize function from the NLTK library.
 - Remove stopwords and lemmatize each word using list comprehension.
 - Join the filtered and lemmatized words into a single string.
 - Append the processed text to the tokenized_X list.
- Return the tokenized and processed text data stored in tokenized_X.

```
In [91]:
```

```
def tokenize_remove_stopwords_lemmatize(X):
    lemmatizer = WordNetLemmatizer()
    tokenized_X = []
    stop_words = set(stopwords.words('english'))

    for text in X:
```



```

    # Tokenize the text
    words = word_tokenize(text)
    # Remove stopwords and lemmatize
    filtered_words = [lemmatizer.lemmatize(word.lower()) for word in words if word.lower() not in stop_words]
    # Append the filtered and lemmatized words to the tokenized list
    filtered_words = ' '.join(filtered_words)
    tokenized_X.append(filtered_words)

    return tokenized_X

# Example usage:
# Assuming X is your input data
# tokenized_X = tokenize_remove_stopwords_lemmatize(X)

```

In [92]:

```
tokenized_X = tokenize_remove_stopwords_lemmatize(x)
```

ONE HOT ENCODING

This function performs one-hot encoding on a list of tokenized text data.

- Import the `one_hot` function from the `tensorflow.keras.preprocessing.text` module.
- Define a variable `vocab_size` to specify the size of the vocabulary.
- Define the `onehotencoding` function that takes two parameters: `tokenized_X` (the list of tokenized text data) and `vocab_size` (the size of the vocabulary).
- Iterate over each word in the tokenized text data using a list comprehension.
- Apply one-hot encoding to each word using the `one_hot` function with the specified vocabulary size.
- Store the one-hot encoded representations of words in a list named `onehot_rep`.
- Return the list of one-hot encoded representations of words.

In [94]:

```
from tensorflow.keras.preprocessing.text import one_hot
```

In [95]:

```
vocab_size = 20000
```

In [96]:

```
def onehotencoding(tokenized_X, vocab_size):
    onehot_rep = [one_hot(word, vocab_size) for word in tokenized_X]
    return onehot_rep
```

In [97]:

```
onehot_rep_x = onehotencoding(tokenized_X , vocab_size)
```

In [104]:

```
len(tokenized_X[0].split())
```

Out[104]:

60

In [105]:

```
len(onehot_rep_x[0])
```

Out[105]:

60

EMBEDDING REPRESENTATION

This function pads sequences of one-hot encoded text data to a specified length.

- Import the Embedding layer from the tensorflow.keras.layers module.
- Import the pad_sequences function from the tensorflow.keras.preprocessing.sequence module.
- Define a variable sent_length to specify the maximum length of the sequences.
- Define the ebedded function that takes two parameters: text (the list of one-hot encoded text data) and sent_length (the maximum length of the sequences).
- Use the pad_sequences function to pad the sequences in text with zeros before (pre-padding) to ensure they have a uniform length of sent_length.
- Return the padded sequences stored in ebedded_doc.
- Example usage: embedded_X = ebedded(onehot_rep_x, sent_length)

In [106]:

```
sent_length = 120
```

In [108]:

```
from tensorflow.keras.layers import Embedding
from tensorflow.keras.preprocessing.sequence import pad_sequences
```

In [111]:

```
def ebedded(text , sent_length):
    ebedded_doc= pad_sequences(text, padding='pre', maxlen = sent_length)
    return ebedded_doc
```

In [112]:

```
embedded_X = ebedded(onehot_rep_x, sent_length)
```

In [113]:

```
embedded_X
```

Out[113]:

```
array([[ 0,  0,  0, ..., 3647, 16487,  8930],
       [ 0,  0,  0, ..., 10215, 3577, 18462],
       [ 0,  0,  0, ..., 14267, 13024, 17140],
       ...,
       [ 0,  0,  0, ..., 6534, 19005,  1747],
       [ 0,  0,  0, ..., 3694,  5277, 16277],
       [ 0,  0,  0, ..., 10240,  6033, 12018]], dtype=int32)
```

Feature Creation for Each vector

This function defines a sequential model architecture for text classification using an embedding layer and LSTM layer.

- Import the Sequential class from the tensorflow.keras.models module.
- Import the LSTM and Dense layers from the tensorflow.keras.layers module.
- Define the model function that takes three parameters: vocab_size (the size of the vocabulary), features (the dimensionality of the embedding space), and sent_length (the maximum length of sequences).
- Create a Sequential model object named model.
- Add an Embedding layer to the model with vocab_size as the input dimension, features as the output dimension, and input_length as sent_length.
- Add an LSTM layer to the model with 100 units.
 - In Keras, when you add an LSTM layer using model.add(LSTM(100)), the number 100 represents the number of units or neurons in the LSTM layer.
- Add a Dense layer to the model with one unit and a sigmoid activation function for binary classification.
- Compile the model with binary_crossentropy as the loss function, adam as the optimizer, and accuracy as

- Compile the model with `binary_crossentropy` as the loss function, `adam` as the optimizer, and `accuracy` as the evaluation metric.
- Print a summary of the model architecture using `model.summary()`.
- Return the compiled model.

In [114]:

```
features = 40
```

In [116]:

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM
from tensorflow.keras.layers import Dense
```

In [132]:

```
def model(vocab_size, features, sent_length):
    model = Sequential()
    model.add(Embedding(vocab_size, features , input_length = sent_length))
    model.add(LSTM(100))
    '''
    In Keras, when you add an LSTM layer using model.add(LSTM(100)),
    the number 100 represents the number of units or neurons in the LSTM layer.
    '''
    model.add(Dense(1, activation = 'sigmoid'))
    model.compile(loss = 'binary_crossentropy', optimizer = 'adam' , metrics=['accuracy'])
    print(model.summary())
    return model
```

In [133]:

```
model = model(vocab_size, features, sent_length)
```

Model: "sequential_2"

Layer (type)	Output Shape	Param #
embedding_2 (Embedding)	(None, 120, 40)	800000
lstm_2 (LSTM)	(None, 100)	56400
dense_2 (Dense)	(None, 1)	101

```
=====
Total params: 856501 (3.27 MB)
Trainable params: 856501 (3.27 MB)
Non-trainable params: 0 (0.00 Byte)
```

None

DATA SPLITTING AND MAKE IT READY FOR X , Y

- Print the shape of the target variable `y` using the `y.shape` attribute.
- Assign the embedded sequences to the variable `X`.
- Print the shape of the input data `X` using the `X.shape` attribute.
- Print the shape of the target variable `y` again to ensure consistency.

In [122]:

```
y.shape
```

Out[122]:

```
(18285,)
```

In [125]:

```
X = embedded_X
```

In [126]:

```
print("X shape",X.shape)
print("y Shape",y.shape)
```

```
X shape (18285, 120)
y Shape (18285,)
```

TRAIN TEST SPLIT

Split the dataset into training and testing sets using the `train_test_split` function from the `sklearn.model_selection` module.

- Assign the input data **X** and the target variable **y** to **X_train**, **X_test**, **y_train**, and **y_test** respectively.
- Set the `test_size` parameter to 0.25 to split the data into 75% training and 25% testing sets.
- Use a random state of 123 for reproducibility.

In [129]:

```
from sklearn.model_selection import train_test_split
```

```
X_train , X_test, y_train, y_test = train_test_split(X, y, test_size=.25, random_state=123)
```

In [130]:

```
print("X_train shape",X_train.shape)
print("X_test shape",X_test.shape)
print("y_train shape",y_train.shape)
print("y_test shape",y_test.shape)
```

```
X_train shape (13713, 120)
X_test shape (4572, 120)
y_train shape (13713,)
y_test shape (4572,)
```

MODEL TRAINING

- Train the model using the `fit()` function, providing the training data **X_train** and **y_train**.
- Set the `validation_data` parameter to (**X_test**, **y_test**) to use the testing data for validation during training.
- Set the number of epochs to 10 using the `epochs` parameter.
- Set the batch size to 64 using the `batch_size` parameter.

In [131]:

```
model.fit(X_train, y_train, validation_data =(X_test, y_test), epochs =10 , batch_size=64)
#model with LSTM(200) neurons
```

Epoch 1/10

215/215 [=====] - 87s 393ms/step - loss: 0.4221 - accuracy: 0.7850 - val_loss: 0.2300 - val_accuracy: 0.9156

Epoch 2/10

215/215 [=====] - 85s 393ms/step - loss: 0.1296 - accuracy: 0.9595 - val_loss: 0.2254 - val_accuracy: 0.9237

Epoch 3/10

215/215 [=====] - 88s 411ms/step - loss: 0.0497 - accuracy: 0.9870 - val_loss: 0.2878 - val_accuracy: 0.9204

Epoch 4/10

215/215 [=====] - 83s 386ms/step - loss: 0.0252 - accuracy: 0.9944 - val loss: 0.4062 - val accuracv: 0.9154

```
Epoch 5/10
215/215 [=====] - 84s 390ms/step - loss: 0.0282 - accuracy: 0.99
21 - val_loss: 0.2956 - val_accuracy: 0.9105
Epoch 6/10
215/215 [=====] - 86s 402ms/step - loss: 0.0230 - accuracy: 0.99
39 - val_loss: 0.3547 - val_accuracy: 0.9066
Epoch 7/10
215/215 [=====] - 87s 404ms/step - loss: 0.0217 - accuracy: 0.99
40 - val_loss: 0.4032 - val_accuracy: 0.9031
Epoch 8/10
215/215 [=====] - 86s 399ms/step - loss: 0.0125 - accuracy: 0.99
75 - val_loss: 0.5356 - val_accuracy: 0.9110
Epoch 9/10
215/215 [=====] - 85s 397ms/step - loss: 0.0039 - accuracy: 0.99
93 - val_loss: 0.5351 - val_accuracy: 0.9086
Epoch 10/10
215/215 [=====] - 87s 403ms/step - loss: 0.0080 - accuracy: 0.99
77 - val_loss: 0.4962 - val_accuracy: 0.9097
```

Out[131]:

```
<keras.src.callbacks.History at 0x7e8db9c72b90>
```

OBSERVATION

Observations from the training and validation metrics for the last epoch (Epoch 10/10):

- The loss on the training dataset is very low (0.0080), indicating that the model has achieved a good fit to the training data.
- The accuracy on the training dataset is high (99.77%), indicating that the model is able to correctly classify the majority of the samples in the training set.
- The validation loss is relatively higher (0.4962) compared to the training loss, indicating that the model may be slightly overfitting to the training data.
- The validation accuracy is also high (90.97%), indicating that the model is performing well on the unseen validation data.

Overall, the model appears to perform well on both the training and validation datasets, with high accuracy and relatively low loss. However, there may be some degree of overfitting, as evidenced by the higher validation loss compared to the training loss. Regularization techniques or model adjustments may be necessary to address this issue and improve generalization performance.

Reduce Model Complexity: If your model is too complex, it may overfit the training data. Try reducing the number of layers, the number of units in each layer, or using regularization techniques such as dropout or L2 regularization.

- accuracy: 0.9977
- val_accuracy: 0.9097

In [192]:

```
history = model.fit(X_train, y_train, validation_data=(X_test, y_test), epochs=10, batch_size=64)
#modelLSTM with 100 neuron
```

```
Epoch 1/10
215/215 [=====] - 47s 217ms/step - loss: 0.0080 - accuracy: 0.99
73 - val_loss: 0.5868 - val_accuracy: 0.9088
Epoch 2/10
215/215 [=====] - 41s 192ms/step - loss: 0.0124 - accuracy: 0.99
61 - val_loss: 0.4709 - val_accuracy: 0.8933
Epoch 3/10
215/215 [=====] - 44s 206ms/step - loss: 0.0082 - accuracy: 0.99
78 - val_loss: 0.5723 - val_accuracy: 0.9049
Epoch 4/10
215/215 [=====] - 47s 218ms/step - loss: 0.0164 - accuracy: 0.99
50 - val_loss: 0.5020 - val_accuracy: 0.8898
Epoch 5/10
```

```

215/215 [=====] - 51s 239ms/step - loss: 0.0114 - accuracy: 0.99
68 - val_loss: 0.4757 - val_accuracy: 0.9062
Epoch 6/10
215/215 [=====] - 44s 204ms/step - loss: 0.0071 - accuracy: 0.99
82 - val_loss: 0.5246 - val_accuracy: 0.9075
Epoch 7/10
215/215 [=====] - 44s 205ms/step - loss: 0.0019 - accuracy: 0.99
96 - val_loss: 0.6142 - val_accuracy: 0.9079
Epoch 8/10
215/215 [=====] - 44s 205ms/step - loss: 9.0654e-04 - accuracy:
0.9999 - val_loss: 0.6804 - val_accuracy: 0.9086
Epoch 9/10
215/215 [=====] - 57s 266ms/step - loss: 6.5587e-04 - accuracy:
0.9999 - val_loss: 0.6880 - val_accuracy: 0.9094
Epoch 10/10
215/215 [=====] - 53s 247ms/step - loss: 5.8915e-04 - accuracy:
0.9999 - val_loss: 0.7333 - val_accuracy: 0.9088

```

MODEL PREDICT

- Compute the accuracy score between the true labels (`y_test`) and the predicted labels (`y_pred`) using the `accuracy_score` function from `sklearn.metrics`.
- Compute the confusion matrix between the true labels (`y_test`) and the predicted labels (`y_pred`) using the `confusion_matrix` function from `sklearn.metrics`.
- Compute the classification report, including precision, recall, F1-score, and support, between the true labels (`y_test`) and the predicted labels (`y_pred`) using the `classification_report` function from `sklearn.metrics`.
- Print the computed accuracy score.
- Print a separator line for better readability.
- Print the computed confusion matrix.
- Print a separator line for better readability.
- Print the computed classification report.

In [135]:

```
y_pred = model.predict(X_test)
```

```
143/143 [=====] - 8s 49ms/step
```

In [137]:

```
y_pred = np.where(y_pred > 0.5, 1, 0)
```

In [142]:

```
from sklearn.metrics import accuracy_score , confusion_matrix, classification_report
```

In [158]:

```

def metrics_result(y_test, y_pred):
    accuracy = accuracy_score(y_test, y_pred)
    accuracy
    confusion = confusion_matrix(y_test, y_pred)
    classification = classification_report(y_test, y_pred)
    print(accuracy)
    print('\n', "+"*50 , '\n')
    print(confusion)
    print('\n', "+"*50 , '\n')
    print(classification)

```

Metrix Observations:

- The computed accuracy score is approximately 0.907, indicating that the model achieved an accuracy of around 90.7% on the test data.
- The confusion matrix shows that the model correctly predicted 2319 true negatives (TN), 1826 true positives

(TP), 253 false positives (FP), and 174 false negatives (FN).

- The classification report provides a detailed breakdown of precision, recall, F1-score, and support for both classes (0 and 1). Overall, the model performs well, with high precision, recall, and F1-score for both classes, indicating good performance in classifying both true and fake news articles.

In [159]:

```
metrics_result(y_test, y_pred)
```

```
0.9066054243219598
```

```
+++++
```

```
[[2319  253]
 [ 174 1826]]
```

```
+++++
```

	precision	recall	f1-score	support
0	0.93	0.90	0.92	2572
1	0.88	0.91	0.90	2000
accuracy			0.91	4572
macro avg	0.90	0.91	0.91	4572
weighted avg	0.91	0.91	0.91	4572

MODEL EVALUTION

Graph Observations:

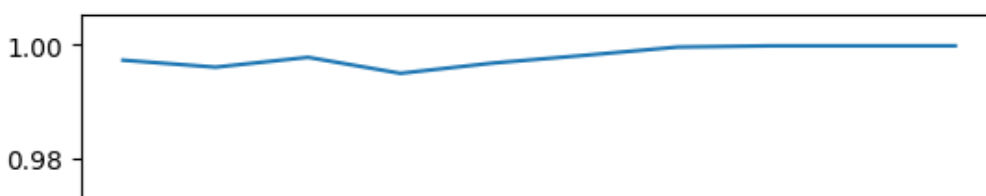
- The accuracy plot shows that the model achieves near-perfect accuracy (99%) on the training dataset, indicating that it has learned the training data well. However, the accuracy on the testing dataset is around 90%, suggesting a slight drop in performance on unseen data, which could indicate overfitting.
- The loss plot shows a decreasing trend in both training and testing loss over epochs, which indicates that the model is learning and improving its performance. However, there may be some overfitting as the training loss continues to decrease while the testing loss stabilizes or increases slightly.

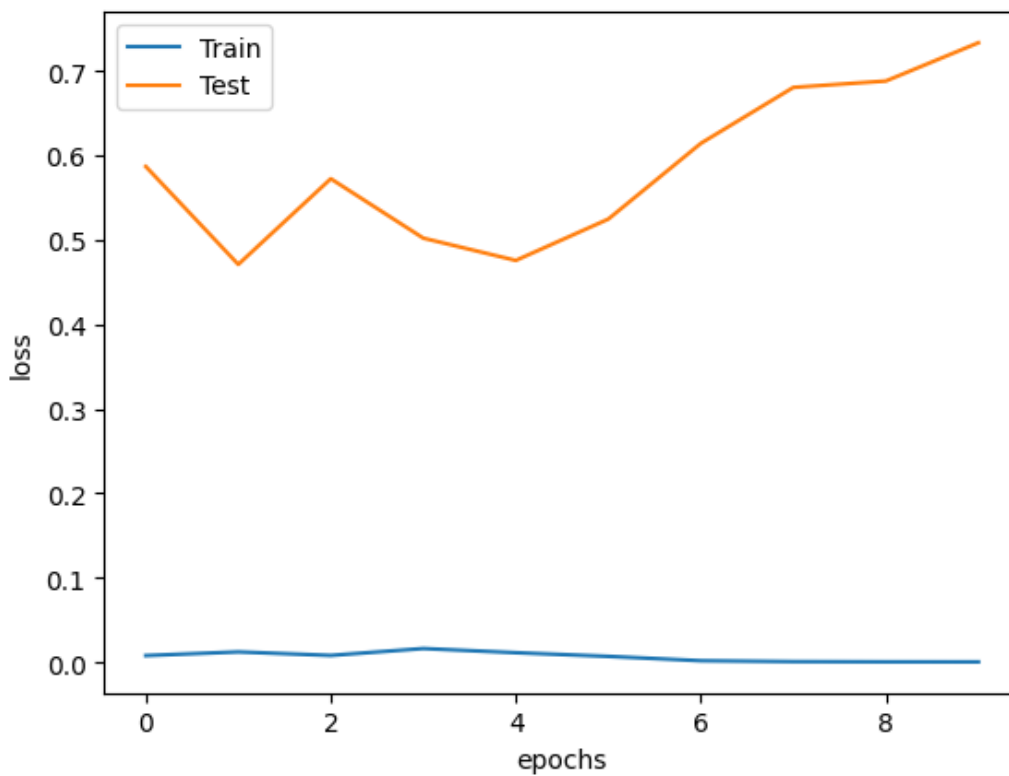
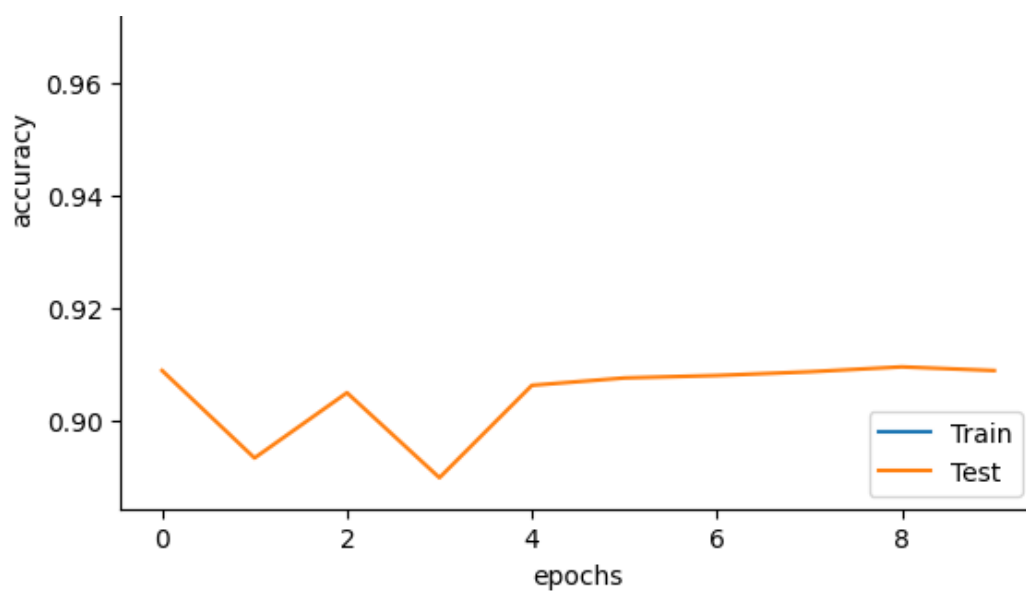
In [193]:

```
# Assuming you have trained your model and stored the history object as 'history'

# Plot accuracy
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.xlabel('epochs')
plt.ylabel('accuracy')
plt.legend(['Train', 'Test'])
plt.show()

# Plot loss
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.xlabel('epochs')
plt.ylabel('loss')
plt.legend(['Train', 'Test'])
plt.show()
```





TEST DATA

In [145]:

```
test.head()
```

Out[145]:

	id	title	author	text
0	20800	Specter of Trump Loosens Tongues, if Not Purse...	David Streitfeld	PALO ALTO, Calif. — After years of scorning...
1	20801	Russian warships ready to strike terrorists ne...	NaN	Russian warships ready to strike terrorists ne...
2	20802	#NoDAPL: Native American Leaders Vow to Stay A...	Common Dreams	Videos #NoDAPL: Native American Leaders Vow to...
3	20803	Tim Tebow Will Attempt Another Comeback, This ...	Daniel Victor	If at first you don't succeed, try a different...
4	20804	Keiser Report: Meme Wars (E995)	Truth Broadcast Network	42 mins ago 1 Views 0 Comments 0 Likes 'For th...

Define the `test_data_process` function that takes a `DataFrame` `df` as input.

- Preprocess the `DataFrame` by performing data preprocessing using the `data_preprocessing` function.
- Clean the text data in the `DataFrame` using the `text_cleaning` function to lowercase the text, remove HTML tags, numbers, special characters, stopwords, and perform lemmatization.
- Replace text in the `DataFrame` with a maximum of 100 words using the `replace_text` function.

Return the processed `DataFrame`.

In [146]:

```
def test_data_process(df):  
    df = data_preprocessing(df)  
    df = text_cleaning(df)  
    df = replace_text(df)  
  
    return df
```

In [147]:

```
test_df = test_data_process(test)
```

(5200, 4)

+++++

Data Information

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 5200 entries, 0 to 5199

Data columns (total 4 columns):

#	Column	Non-Null Count	Dtype
0	id	5200 non-null	int64
1	title	5078 non-null	object
2	author	4697 non-null	object
3	text	5193 non-null	object

dtypes: int64(1), object(3)

memory usage: 162.6+ KB

None

+++++

Data Null Values

id	0
title	122
author	503
text	7

dtype: int64

Data Null Values after Dropna

id	0
title	0
author	0
text	0

dtype: int64

+++++

Duplicate values count

+++++

0
(4575, 4)
Data Lower case successfull
data html tags removed successfull
data Numbers removed successfull
data TagLines/Newlines removed successfull
data Double quote, single quote hypen removed successfull
data websitetags removed successfull
data punctuation removed successfull

+++++

Data Cleaning is completed Successfully

In [152]:

```
test_df
```

Out[152]:

	id	title	author	text
0	20800	Specter of Trump Loosens Tongues, if Not Purse...	David Streitfeld	palo alto calif — after years of scorning the ...
2	20802	#NoDAPL: Native American Leaders Vow to Stay A...	Common Dreams	videos nodapl native american leaders vow to s...
3	20803	Tim Tebow Will Attempt Another Comeback, This ...	Daniel Victor	if at first you dont succeed try a different s...
4	20804	Keiser Report: Meme Wars (E995)	Truth Broadcast Network	mins ago views comments likes for the firs...
6	20806	Pelosi Calls for FBI Investigation to Find Out...	Pam Key	sunday on nbcs meet the press house minority l...
...
5194	25994	Trump on If 'Tapes' Exist of Comey Conversatio...	Pam Key	pres trump on if tapes exist of his conversati...
5195	25995	The Bangladeshi Traffic Jam That Never Ends - ...	Jody Rosen	of all the dysfunctions that plague the worlds...
5196	25996	John Kasich Signs One Abortion Bill in Ohio bu...	Sheryl Gay Stolberg	washington — gov john kasich of ohio on tuesda...
5197	25997	California Today: What, Exactly, Is in Your Su...	Mike McPhate	good morning want to get california today by e...
5199	25999	Awkward Sex, Onscreen and Off - The New York T...	Teddy Wayne	perhaps youve seen the new tv series whose pil...

4575 rows x 4 columns

In [153]:

```
test = test_df['text']
```

Define the `nlp_preprocess` function that takes three parameters: `test` (the input text data), `vocab_size` (the size of the vocabulary), and `sent_length` (the maximum length of sequences).

- Tokenize, remove stopwords, and lemmatize the input text data using the `tokenize_remove_stopwords_lemmatize` function.
- Perform one-hot encoding on the tokenized text data using the `onehotencoding` function with the specified vocabulary size.
- Pad the one-hot encoded sequences to the specified length using the `ebedded` function.

Return the padded sequences representing the preprocessed text data.

In [154]:

```
def nlp_preprocess(test, vocab_size , sent_length):  
  
    tokenized_X = tokenize_remove_stopwords_lemmatize(test)  
    onehot_rep_x = onehotencoding(tokenized_X , vocab_size)  
    embedded_test = ebedded(onehot_rep_x, sent_length)  
  
    return embedded_test
```

In [155]:

```
embedded_test = nlp_preprocess(test, vocab_size , sent_length)
```

```
In [157]:
```

```
test_pred = model.predict(embedded_test)
```

```
143/143 [=====] - 5s 32ms/step
```

```
In [162]:
```

```
test_pred = np.where(test_pred > 0.5 , 1,0)
```

```
In [165]:
```

```
len(test_pred)
```

```
Out[165]:
```

```
4575
```

```
In [166]:
```

```
len(submit['label'])
```

```
Out[166]:
```

```
5200
```

SUBMISSION

- Create a DataFrame `test_id` containing the 'id' column from the test DataFrame using `pd.DataFrame`.
- Generate predictions for the test data using the trained model and the preprocessed test data (`embedded_test`), thresholding the predictions at 0.5 to convert them to binary labels (0 or 1) using the `model.predict` method.
- Compute performance metrics such as accuracy, confusion matrix, and classification report using the `metrics_result` function with the true labels from the 'label' column of the submit DataFrame and the predicted labels.
- Reset the index of the `test_id` DataFrame to ensure consistency.
- Convert the NumPy array of predictions to a DataFrame with column name "label" using `pd.DataFrame`.
- Concatenate the `test_id` and `predictions_test_df` DataFrames along the columns axis using `pd.concat`.
- Rename the columns of the concatenated DataFrame to "id" and "label" using the `.columns` attribute.
- Save the concatenated DataFrame to a CSV file named "Submission.csv" using `to_csv`, excluding the index.

```
In [170]:
```

```
test_id = pd.DataFrame(test_df["id"])  
prediction_test = (model.predict(embedded_test) > 0.5).astype("int32")
```

```
143/143 [=====] - 6s 43ms/step
```

```
In [187]:
```

```
metrics_result(submit['label'][:4575] , prediction_test)
```

```
0.49901639344262294
```

```
+++++
```

```
[[1140  918]  
 [1374 1143]]
```

```
+++++
```

	precision	recall	f1-score	support
--	-----------	--------	----------	---------

0	0.45	0.55	0.50	2058
1	0.55	0.45	0.50	2517

accuracy			0.50	4575
macro avg	0.50	0.50	0.50	4575
weighted avg	0.51	0.50	0.50	4575

In [182]:

```
# Reset the index of test_id DataFrame
test_id.reset_index(drop=True, inplace=True)
# Convert the NumPy array to a DataFrame
predictions_test_df = pd.DataFrame(prediction_test, columns=["label"])
# Concatenate DataFrames
submission = pd.concat([test_id, predictions_test_df], axis=1)
submission.columns = ["id", "label"]
submission.to_csv("Submission.csv", index=False)
```

In [186]:

```
submission.head(20)
```

Out[186]:

	id	label
0	20800	0
1	20802	1
2	20803	0
3	20804	1
4	20806	0
5	20807	1
6	20810	1
7	20811	1
8	20812	1
9	20813	1
10	20814	1
11	20815	0
12	20816	0
13	20817	0
14	20818	1
15	20819	0
16	20820	0
17	20821	1
18	20823	1
19	20824	1