Modeling_NN

July 1, 2022

In this notebook, we will train some neural network to filter out fake news.

1 Importing Libraries

We will import the following libraries

[21]:
```
import numpy as np
import pandas as pd
import string


import seaborn as sns
import matplotlib.pyplot as plt


from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report, plot_confusion_matrix
from sklearn.preprocessing import LabelEncoder


import tensorflow as tf
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.layers import Input, Dense, LSTM, Embedding, Flatten
from tensorflow.keras.layers import Dropout, Activation, Bidirectional,␣
 ↪GlobalMaxPool1D
from tensorflow.keras.models import Sequential
from tensorflow.keras import initializers, regularizers, constraints,␣
 ↪optimizers, layers
from tensorflow.keras.preprocessing import text, sequence
from tensorflow.keras.preprocessing.text import Tokenizer

from tensorflow.keras.callbacks import EarlyStopping


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

2 Functions We Use

In this section we put the functions that we are using in this notebook. With the first two functions, we perform some basic cleaning on the data and with the last function, we plot the results of the trained model on the test sets.

[4]:
```python
def text_from_token(data):

    cleaned_sentence = " ".join(data)

    return  cleaned_sentence
```

[5]:
```python
def new_cleaning(data):


    cleaned_data = data.replace("[", "").replace("]", "").replace("'", "")\
                                  .replace(" ", "").split(",")

    return cleaned_data
```

[73]:
```python
def print_results(model, X_train, y_train, X_test, y_test):


    train_loss = model.history.history["loss"]
    train_acc  = model.history.history["accuracy"]

    test_loss = model.history.history["val_loss"]
    test_acc  = model.history.history["val_accuracy"]


    sns.set(font_scale=1)

    cf_matrix_test  = confusion_matrix(y_test, np.rint(model.predict(X_test)))
    cf_matrix_train = confusion_matrix(y_train, np.rint(model.predict(X_train)))


    fig, axes = plt.subplots(nrows=2, ncols=2, figsize=(10,10))
    ax1 = axes[0][0]

    g = sns.heatmap(cf_matrix_test, annot=True, cmap='Blues', ax = ax1)

    g.xaxis.set_ticklabels(['Fake','True'])
    g.yaxis.set_ticklabels(['Fake','True'])


    ax1.set_title("Confusion Matrix for Test Set")

    ax2 = axes[0][1]
```

```
g = sns.heatmap(cf_matrix_train, annot=True, cmap='Blues', ax = ax2)
g.xaxis.set_ticklabels(['Fake','True'])
g.yaxis.set_ticklabels(['Fake','True'])


ax2.set_title("Confusion Matrix for Train Set")




ax3 = axes[1][0]

g = sns.lineplot(x = range(1,len(train_loss)+1),
                 y = train_loss,
                 label = "train_loss", ax = ax3);
g = sns.lineplot(x = range(1,len(test_loss)+1),
                 y = test_loss,
                 label = "test_loss", ax = ax3);



ax3.set_title("Loss vs. Epochs")



ax4 = axes[1][1]

g = sns.lineplot(x = range(1,len(train_acc)+1),
                 y = train_acc,
                 label = "train_accuracy", ax = ax4);
g = sns.lineplot(x = range(1,len(test_acc)+1),
                 y = test_acc,
                 label = "test_accuracy", ax = ax4);


ax4.set_title("Accuracy vs. Epochs")


### Presenting Classification Report as a DataFrame
train_class = classification_report(y_train, np.rint(model.
↪predict(X_train)),
                                    output_dict = True)
test_class  = classification_report(y_test, np.rint(model.predict(X_test)),
                                    output_dict = True)

train_df = pd.DataFrame(train_class)
test_df  = pd.DataFrame(test_class)
```

```
    train_df["data"] = "TRAIN"
    test_df["data"] = "TEST"


    report = pd.concat([test_df, train_df], axis = 0)
    report.rename(columns = {"1": f"{list(le.inverse_transform([1]))[0]}",
                             "0": f"{list(le.inverse_transform([0]))[0]}"},␣
↪inplace = True)
    report["index"] = list(report.index)

    report.set_index(["data", "index"], inplace = True)
    report.drop("accuracy", axis = 1, inplace = True)

    for item in list(report.columns):
        report[item] = report[item].apply(lambda x: np.round(x,2))

    return report
```

3 Importing Data

[8]:
```
train = pd.read_csv("../Modeling/train_test/train.csv")
test  = pd.read_csv("../Modeling/train_test/test.csv")

data = [train, test]

for df in data:

    df.drop("Unnamed: 0", axis = 1, inplace = True)
    df["cleaned"] =  df["cleaned"].apply(lambda x: new_cleaning(x))
    df["cleaned_text"] =  df["cleaned"].apply(lambda x: text_from_token(x))
    df["for_glove"] =  df["for_glove"].apply(lambda x: new_cleaning(x))
    df["cleaned_glove"] =  df["for_glove"].apply(lambda x: text_from_token(x))

print("DONE!")
```

```
DONE!
```

[10]:
```
data = train["cleaned"].values
total_vocabulary = set(word for headline in data for word in headline)
len(total_vocabulary)
```

[10]: 94187

4 Tokenizing

In this section, we will use TensorFlow to tokenize the data. Also, since each row of our data has different number of token, we need to use padding so that the input to the neural network has the same size.

[11]:
```
### Hyperparameters
vocab_size = 30000
max_length = 300
embedding_dim = 128
trunc_type='post'
oov_tok = "<OOV>"
```

[12]:
```
# Initialize the Tokenizer class
tokenizer = Tokenizer(num_words = vocab_size, oov_token = oov_tok)

# Generate the word index dictionary
tokenizer.fit_on_texts(train["cleaned_text"].values)

# Print the length of the word index
word_index = tokenizer.word_index
print(f'number of words in word_index: {len(word_index)}')

# Generate and pad the training sequences
training_sequences = tokenizer.texts_to_sequences(train["cleaned_text"].values)
training_padded = pad_sequences(training_sequences,
                             maxlen = max_length,
                             truncating=trunc_type)

print("Padding the Training Sequences: Done!")

# Generate and pad the test sequences
testing_sequences = tokenizer.texts_to_sequences(test["cleaned_text"].values)
testing_padded = pad_sequences(testing_sequences,maxlen=max_length)


print("Padding the Test Sequences: Done!")

le = LabelEncoder()
y_train = le.fit_transform(train["label"])
y_test = le.transform(test["label"])
```

```
number of words in word_index: 93783
Padding the Training Sequences: Done!
Padding the Test Sequences: Done!
```

5 Modeling

5.1 First Model

In the first model we use Embedding layer and LSTM. We do not use flattening and the LSTM is not bidirectional. By checking the final results, we see that this model is overfitted.

[79]:
```
# callbacks = EarlyStopping(monitor = 'val_loss', patience = 2, mode = "min")

model_1 = Sequential()
model_1.add(Embedding(vocab_size, embedding_dim, input_length=max_length))
model_1.add(LSTM(20, return_sequences=True))
model_1.add(GlobalMaxPool1D())
model_1.add(Dropout(0.5))
model_1.add(Dense(10, activation='relu'))
model_1.add(Dropout(0.5))
model_1.add(Dense(1, activation='sigmoid'))

model_1.compile(loss='binary_crossentropy', optimizer='adam',
                    metrics=['accuracy'])

model_1.summary()
```

```
Model: "sequential_18"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_18 (Embedding)     (None, 300, 128)          3840000
_________________________________________________________________
lstm_6 (LSTM)                (None, 300, 20)           11920
_________________________________________________________________
global_max_pooling1d_6 (Glob (None, 20)                0
_________________________________________________________________
dropout_48 (Dropout)         (None, 20)                0
_________________________________________________________________
dense_48 (Dense)             (None, 10)                210
_________________________________________________________________
dropout_49 (Dropout)         (None, 10)                0
_________________________________________________________________
dense_49 (Dense)             (None, 1)                 11
=================================================================
Total params: 3,852,141
Trainable params: 3,852,141
Non-trainable params: 0
_________________________________________________________________
```

[80]:
```
model_1.fit(training_padded, y_train, epochs=10, batch_size=300,
         validation_data=(testing_padded, y_test))#, callbacks = [callbacks])
```

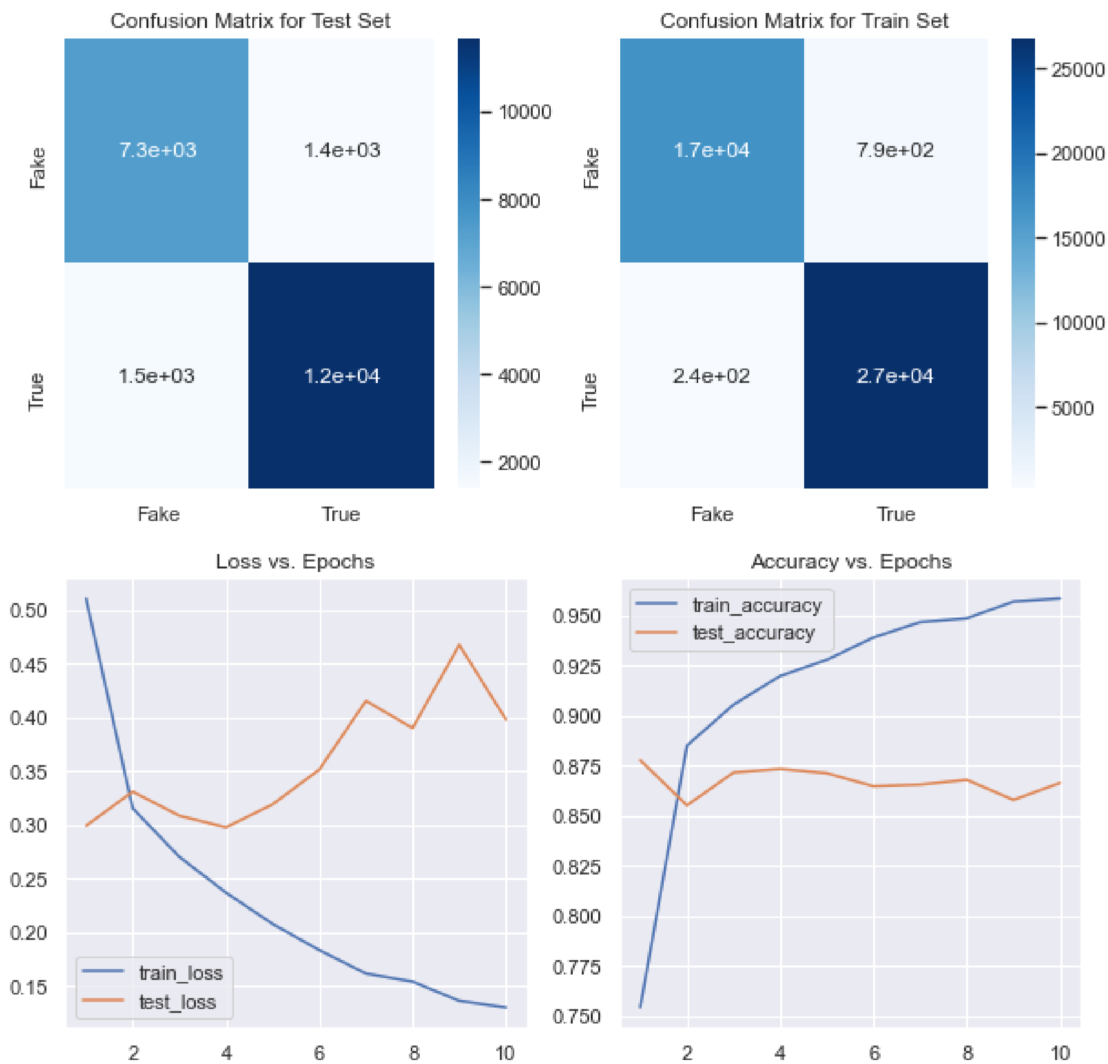
```
Epoch 1/10
149/149 [==============================] - 58s 390ms/step - loss: 0.5104 -
accuracy: 0.7545 - val_loss: 0.2989 - val_accuracy: 0.8778
Epoch 2/10
149/149 [==============================] - 56s 375ms/step - loss: 0.3152 -
accuracy: 0.8851 - val_loss: 0.3306 - val_accuracy: 0.8553
Epoch 3/10
149/149 [==============================] - 57s 380ms/step - loss: 0.2700 -
accuracy: 0.9055 - val_loss: 0.3083 - val_accuracy: 0.8717
Epoch 4/10
149/149 [==============================] - 60s 406ms/step - loss: 0.2366 -
accuracy: 0.9198 - val_loss: 0.2974 - val_accuracy: 0.8735
Epoch 5/10
149/149 [==============================] - 64s 428ms/step - loss: 0.2075 -
accuracy: 0.9279 - val_loss: 0.3188 - val_accuracy: 0.8713
Epoch 6/10
149/149 [==============================] - 58s 391ms/step - loss: 0.1831 -
accuracy: 0.9390 - val_loss: 0.3511 - val_accuracy: 0.8648
Epoch 7/10
149/149 [==============================] - 57s 382ms/step - loss: 0.1613 -
accuracy: 0.9467 - val_loss: 0.4151 - val_accuracy: 0.8657
Epoch 8/10
149/149 [==============================] - 55s 372ms/step - loss: 0.1538 -
accuracy: 0.9486 - val_loss: 0.3898 - val_accuracy: 0.8680
Epoch 9/10
149/149 [==============================] - 57s 383ms/step - loss: 0.1359 -
accuracy: 0.9570 - val_loss: 0.4672 - val_accuracy: 0.8580
Epoch 10/10
149/149 [==============================] - 57s 385ms/step - loss: 0.1298 -
accuracy: 0.9585 - val_loss: 0.3978 - val_accuracy: 0.8665
```

[80]:
```
<tensorflow.python.keras.callbacks.History at 0x7f9fb2466070>
```

[81]:
```
print_results(model_1, training_padded, y_train, testing_padded, y_test)
```

[81]:

data	index	Fake	True	macro avg	weighted avg
TEST	precision	0.83	0.89	0.86	0.87
	recall	0.84	0.88	0.86	0.87
	f1-score	0.83	0.89	0.86	0.87
	support	8719.00	13194.00	21913.00	21913.00
TRAIN	precision	0.99	0.97	0.98	0.98
	recall	0.95	0.99	0.97	0.98
	f1-score	0.97	0.98	0.98	0.98
	support	17502.00	26987.00	44489.00	44489.00



5.2 Second Model

For the second model, we will not use LSTM layer but we will Flatten the output of the Embedding layer. In this model we will monitor validation loss for early stopping. By checking the final result, we see that this model is overfitted even though we used early stopping.

[82]:
```
callbacks = EarlyStopping(monitor = 'val_loss', patience = 2, mode = "min")

model_2 = Sequential()
model_2.add(Embedding(vocab_size, embedding_dim, input_length=max_length))
model_2.add(Flatten())
model_2.add(Dense(50, activation='relu'))
model_2.add(Dropout(0.5))
model_2.add(Dense(1, activation='sigmoid'))
```

```
model_2.compile(loss='binary_crossentropy', optimizer='adam',␣
 ↪metrics=['accuracy'])

model_2.summary()
```

```
Model: "sequential_19"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_19 (Embedding)     (None, 300, 128)          3840000
_________________________________________________________________
flatten_12 (Flatten)         (None, 38400)             0
_________________________________________________________________
dense_50 (Dense)             (None, 50)                1920050
_________________________________________________________________
dropout_50 (Dropout)         (None, 50)                0
_________________________________________________________________
dense_51 (Dense)             (None, 1)                 51
=================================================================
Total params: 5,760,101
Trainable params: 5,760,101
Non-trainable params: 0
_________________________________________________________________
```

[83]:
```
model_2.fit(training_padded, y_train, epochs=10, batch_size=500,
          validation_data=(testing_padded, y_test), callbacks = [callbacks])
```

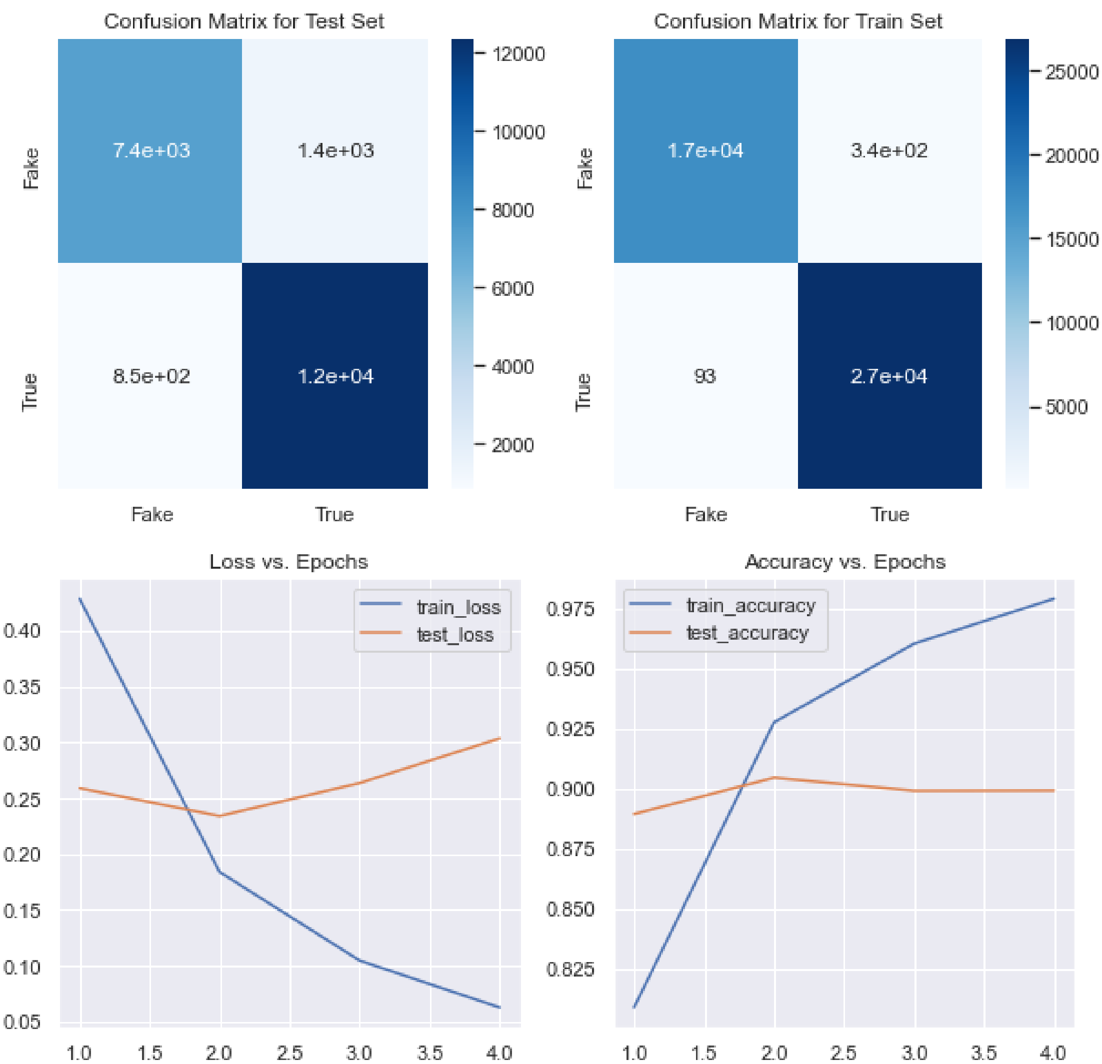
```
Epoch 1/10
89/89 [==============================] - 10s 115ms/step - loss: 0.4286 -
accuracy: 0.8090 - val_loss: 0.2589 - val_accuracy: 0.8894
Epoch 2/10
89/89 [==============================] - 11s 125ms/step - loss: 0.1838 -
accuracy: 0.9276 - val_loss: 0.2339 - val_accuracy: 0.9045
Epoch 3/10
89/89 [==============================] - 11s 119ms/step - loss: 0.1044 -
accuracy: 0.9603 - val_loss: 0.2634 - val_accuracy: 0.8991
Epoch 4/10
89/89 [==============================] - 12s 133ms/step - loss: 0.0624 -
accuracy: 0.9790 - val_loss: 0.3035 - val_accuracy: 0.8992
```

[83]:
```
<tensorflow.python.keras.callbacks.History at 0x7f9fd23f69a0>
```

[84]:
```
print_results(model_2, training_padded, y_train, testing_padded, y_test)
```

[84]:
```
                                Fake      True  macro avg  weighted avg
data   index
```

TEST	precision	0.90	0.90	0.90	0.90
	recall	0.84	0.94	0.89	0.90
	f1-score	0.87	0.92	0.89	0.90
	support	8719.00	13194.00	21913.00	21913.00
TRAIN	precision	0.99	0.99	0.99	0.99
	recall	0.98	1.00	0.99	0.99
	f1-score	0.99	0.99	0.99	0.99
	support	17502.00	26987.00	44489.00	44489.00



5.3 3rd Model

In the third neural network, we will use five dense layers after we flatten the out put of the LSTM layer. According to the diagrams we can see that this model is overfitted.

[93]:
```
model_3 = Sequential()


model_3.add(Embedding(vocab_size, embedding_dim, input_length=max_length))
model_3.add(LSTM(20, return_sequences=True))
model_3.add(GlobalMaxPool1D())
model_3.add(Dense(10, activation='relu'))
model_2.add(Dropout(0.5))
model_3.add(Dense(15, activation='relu'))
model_2.add(Dropout(0.5))
model_3.add(Dense(5, activation='relu'))
model_2.add(Dropout(0.5))
model_3.add(Dense(2, activation='relu'))
model_3.add(Dense(1, activation='sigmoid'))

model_3.compile(loss='binary_crossentropy', optimizer='adam',␣
↪metrics=['accuracy'])

model_3.summary()
```

```
Model: "sequential_26"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_26 (Embedding)     (None, 300, 128)          3840000
_________________________________________________________________
lstm_9 (LSTM)                (None, 300, 20)           11920
_________________________________________________________________
global_max_pooling1d_11 (Glo (None, 20)                0
_________________________________________________________________
dense_52 (Dense)             (None, 10)                210
_________________________________________________________________
dense_53 (Dense)             (None, 15)                165
_________________________________________________________________
dense_54 (Dense)             (None, 5)                 80
_________________________________________________________________
dense_55 (Dense)             (None, 2)                 12
_________________________________________________________________
dense_56 (Dense)             (None, 1)                 3
=================================================================
Total params: 3,852,390
Trainable params: 3,852,390
Non-trainable params: 0
_________________________________________________________________
```

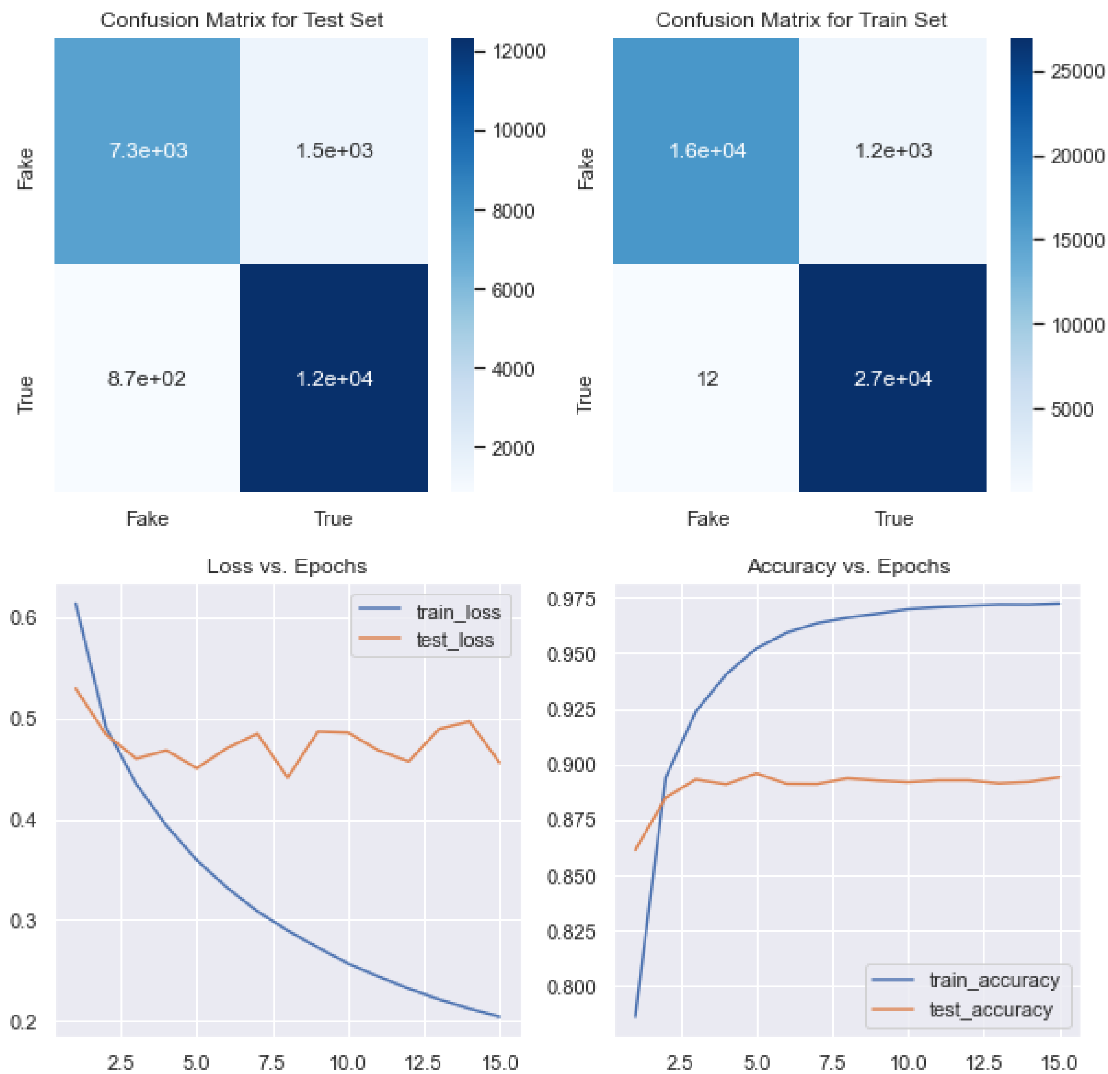
[94]:
```
model_3.fit(training_padded, y_train, epochs=15, batch_size=500,
         validation_data=(testing_padded, y_test))
```

```
Epoch 1/15
89/89 [==============================] - 58s 647ms/step - loss: 0.6133 -
accuracy: 0.7862 - val_loss: 0.5291 - val_accuracy: 0.8613
Epoch 2/15
89/89 [==============================] - 58s 652ms/step - loss: 0.4907 -
accuracy: 0.8939 - val_loss: 0.4837 - val_accuracy: 0.8849
Epoch 3/15
89/89 [==============================] - 54s 607ms/step - loss: 0.4346 -
accuracy: 0.9237 - val_loss: 0.4598 - val_accuracy: 0.8931
Epoch 4/15
89/89 [==============================] - 55s 622ms/step - loss: 0.3934 -
accuracy: 0.9404 - val_loss: 0.4678 - val_accuracy: 0.8909
Epoch 5/15
89/89 [==============================] - 54s 607ms/step - loss: 0.3592 -
accuracy: 0.9522 - val_loss: 0.4503 - val_accuracy: 0.8958
Epoch 6/15
89/89 [==============================] - 55s 623ms/step - loss: 0.3320 -
accuracy: 0.9592 - val_loss: 0.4702 - val_accuracy: 0.8911
Epoch 7/15
89/89 [==============================] - 54s 609ms/step - loss: 0.3085 -
accuracy: 0.9634 - val_loss: 0.4843 - val_accuracy: 0.8910
Epoch 8/15
89/89 [==============================] - 55s 620ms/step - loss: 0.2895 -
accuracy: 0.9659 - val_loss: 0.4410 - val_accuracy: 0.8936
Epoch 9/15
89/89 [==============================] - 55s 613ms/step - loss: 0.2728 -
accuracy: 0.9677 - val_loss: 0.4866 - val_accuracy: 0.8926
Epoch 10/15
89/89 [==============================] - 55s 618ms/step - loss: 0.2568 -
accuracy: 0.9698 - val_loss: 0.4854 - val_accuracy: 0.8919
Epoch 11/15
89/89 [==============================] - 58s 648ms/step - loss: 0.2439 -
accuracy: 0.9707 - val_loss: 0.4677 - val_accuracy: 0.8928
Epoch 12/15
89/89 [==============================] - 55s 614ms/step - loss: 0.2319 -
accuracy: 0.9713 - val_loss: 0.4570 - val_accuracy: 0.8928
Epoch 13/15
89/89 [==============================] - 55s 621ms/step - loss: 0.2214 -
accuracy: 0.9718 - val_loss: 0.4890 - val_accuracy: 0.8913
Epoch 14/15
89/89 [==============================] - 54s 604ms/step - loss: 0.2122 -
accuracy: 0.9718 - val_loss: 0.4966 - val_accuracy: 0.8920
Epoch 15/15
89/89 [==============================] - 58s 648ms/step - loss: 0.2042 -
accuracy: 0.9723 - val_loss: 0.4557 - val_accuracy: 0.8942
```

```
[94]: <tensorflow.python.keras.callbacks.History at 0x7f9fd221b730>
```

[95]:
```
print_results(model_3, training_padded, y_train, testing_padded, y_test)
```

[95]:
```
                         Fake      True  macro avg  weighted avg
data  index
TEST  precision          0.89      0.89       0.89          0.89
      recall             0.83      0.93       0.88          0.89
      f1-score           0.86      0.91       0.89          0.89
      support         8719.00  13194.00   21913.00      21913.00
TRAIN precision          1.00      0.96       0.98          0.97
      recall             0.93      1.00       0.97          0.97
      f1-score           0.96      0.98       0.97          0.97
      support        17502.00  26987.00   44489.00      44489.00
```



6 Summary of Models

We can see that eventhough the accuracy scores of these models are better than some of the models introduced in other notebooks, but their recall scores are not as good as the logistic model or lightgbm. On the other hand, these models show significant overfitting. Therefore, these models are not reliable. One way to improve these models might be using optuna to optimize the hyperparameters of these models, or using embedded layers from other models. We will use that in the next notebook.

[ ]:

```

```