models

December 7, 2023

```
[33]: import pickle
      from sklearn.preprocessing import StandardScaler
      from sklearn.model_selection import train_test_split
      from sklearn.linear model import LogisticRegression
      from sklearn.metrics import classification_report
      from nltk.tokenize import RegexpTokenizer
      from gensim.models import Word2Vec
      from nltk.tokenize import word_tokenize
      from tensorflow import keras
      import tensorflow as tf
      import numpy as np
      import matplotlib.pyplot as plt
      from sklearn.metrics import roc_curve, auc
      import matplotlib.pyplot as plt
      from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
      from tensorflow.keras.layers import Input, Dense
```

Generic Fucntions 1

```
[2]: labels=pickle.load( open('labels.pkl', 'rb'))
    features=pickle.load( open('features.pkl', 'rb'))
    features_tfidf= pickle.load( open('features_tfidf.pkl', 'rb'))
    word tfidf weights=pickle.load( open('word tfidf weights.pkl', 'rb'))
    non_text_features_np = features.drop(columns=['title', 'text', 'combined_text',__

¬'label']).to_numpy()
[3]: def get_metrics(clf,test_ft,test_labels):
       pred_labels=clf.predict(test_ft)
     [4]: def plot_ROC(test):
       pred_labels=clf.predict(test_ft)
       fpr, tpr, thresholds = roc_curve(test,pred_labels)
       roc_auc = auc(fpr, tpr)
```

```
# Plot ROC curve
plt.plot(fpr, tpr, label='ROC curve (AUC = {:.2f})'.format(roc_auc))
plt.plot([0, 1], [0, 1], 'k--') # Random guessing line
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate (FPR)')
plt.ylabel('True Positive Rate (TPR)')
plt.title('Receiver Operating Characteristic (ROC)')
plt.legend(loc='lower right')
plt.show()

class ANN_model(tf.keras.models.Model):
    def __init__(self):
        super(ANN_model,self).__init__()
        self.layer1= Dense(64, activation="relu")
        self_layer2= Dense(32, activation="relu")
```

```
[101]: class ANN_model(tf.keras.models.Model):
    def __init__(self):
        super(ANN_model,self).__init__()
        self.layer1= Dense(64, activation="relu")
        self.layer2= Dense(32,activation="relu")
        self.label= Dense(1,activation="sigmoid")

    def call(self,inputs):
        x=self.layer1(inputs)
        x=self.layer2(x)
        x=self.label(x)
```

```
[8]: def plot_loss_acc(history):
    plt.plot(history.history['loss'], label='Training Loss')
    plt.plot(history.history['val_loss'], label='Validation Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()
    plt.show()

plt.plot(history.history['accuracy'], label='Training Accuracy')
    plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()
    plt.show()
```

```
otrain_ft,test_ft,train_labels,test_labels=train_test_split(norm_features,labels,test_size=0
      42, train_size=0.8)
         print("-----\n")
         print(f" train data features shape {train_ft.shape} \n train data labels⊔
      ⇔shape {train_labels.shape}\n")
         print("-----Test data-----\n")
         print(f" test data features shape {test_ft.shape} \n test data labels shape_

√{test_labels.shape}")

         return train_ft,test_ft,train_labels,test_labels
[30]: def split_data_dl(features, labels):
      otrain_ft,test_ft,train_labels,test_labels=train_test_split(norm_features,labels,test_size=0
      \rightarrow2, train_size=0.8)
         X_train, X_val, y_train, y_val = train_test_split(train_ft, train_labels,_
      ⇔test_size=0.2, random_state=42)
         print("Training set shape:", X_train.shape)
         print("Validation set shape:", X_val.shape)
         print("Test set shape:", test_ft.shape)
         return X_train,y_train,X_val,y_val,test_ft,test_labels
        1. TF-IDF vectors + text characteristics
    2.1 Machine Learning models
[21]: features_tfidf_txt = np.hstack((features_tfidf, non_text_features_np))
[46]: pickle.dump(features_tfidf_txt, open('features_tfidf_txt.pkl', 'wb'))
     features_tfidf_txt = pickle.load( open('features_tfidf_txt.pkl', 'rb'))
    2.1.1 Logistic Regression
[22]: train_ft,test_ft,train_labels,test_labels=split_data_ml(features_tfidf_txt,labels)
     -----Train data-----
     train data features shape (57229, 115)
     train data labels shape (57229,)
     -----Test data-----
```

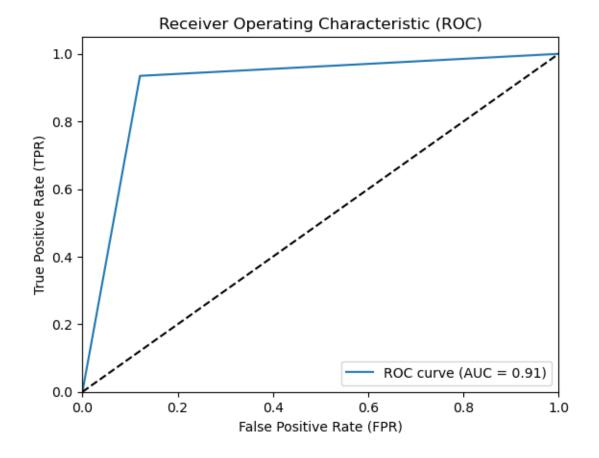
test data features shape (14308, 115) test data labels shape (14308,)

[23]: log_clf = LogisticRegression(random_state=0).fit(train_ft, train_labels)

[24]: get_metrics(log_clf,test_ft,test_labels)

	precision	recall	f1-score	support
	_			
fake	0.90	0.93	0.91	6762
real	0.93	0.91	0.92	7546
accuracy			0.92	14308
macro avg	0.92	0.92	0.92	14308
weighted avg	0.92	0.92	0.92	14308

[25]: plot_ROC(test_labels)



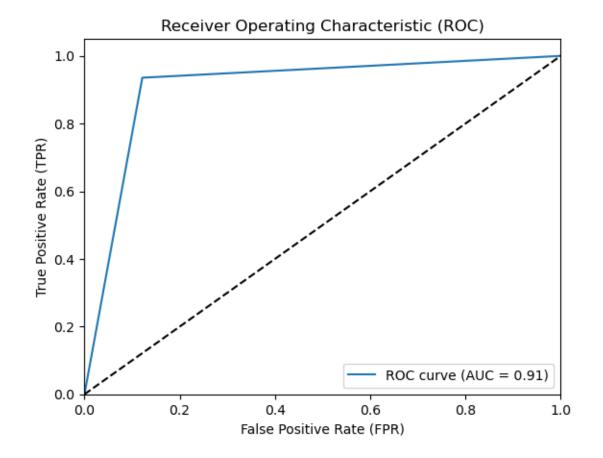
2.1.2 Linear Discriminant Analysis

[26]: clf = LinearDiscriminantAnalysis().fit(train_ft, train_labels)

[27]: get_metrics(clf,test_ft,test_labels)

	precision	recall	f1-score	support
fake	0.88	0.93	0.90	6580
real	0.94	0.89	0.91	7728
accuracy			0.91	14308
macro avg	0.91	0.91	0.91	14308
weighted avg	0.91	0.91	0.91	14308

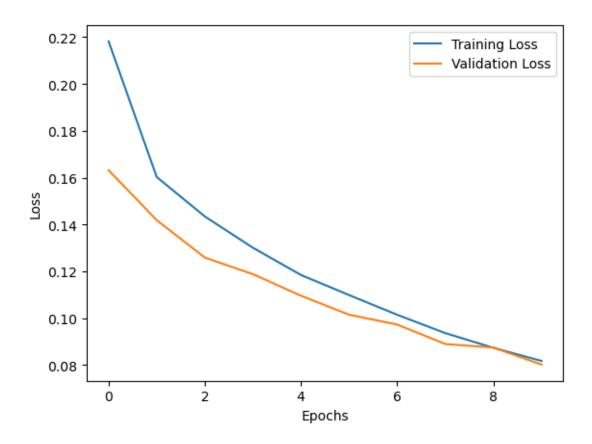
[28]: plot_ROC(test_labels)

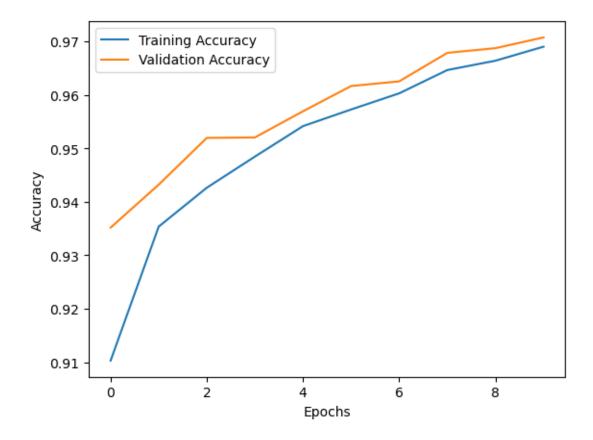


2.1.3 Artificial Neural network

```
[31]: x train, y train, X val, y val, test ft, test labels=split data dl(features tfidf txt, labels)
     Training set shape: (45783, 115)
     Validation set shape: (11446, 115)
     Test set shape: (14308, 115)
[34]: tfidf_txt_model= ANN_model()
     tfidf_txt_model.build((None,115))
     print(tfidf_txt_model.summary())
     Model: "ann_model_1"
     Layer (type)
                            Output Shape
                                                  Param #
     ______
      dense (Dense)
                             multiple
                                                   7424
      dense_1 (Dense)
                             multiple
                                                   2080
      dense 2 (Dense)
                             multiple
                                                   33
     Total params: 9,537
     Trainable params: 9,537
     Non-trainable params: 0
     None
[102]: tb_callback=tf.keras.callbacks.TensorBoard(log_dir="log/", histogram_freq=1)
     tfidf_txt_model.compile(optimizer='adam', loss='binary_crossentropy', __
      →metrics=['accuracy'])
     history=tfidf_txt_model.fit(train_ft, train_labels, epochs=10, batch_size=32,__
      →validation_data=(X_val, y_val),callbacks=[tb_callback])
     Epoch 1/10
     accuracy: 0.9642 - val_loss: 0.0852 - val_accuracy: 0.9678
     1789/1789 [============= ] - 3s 2ms/step - loss: 0.0854 -
     accuracy: 0.9678 - val_loss: 0.0751 - val_accuracy: 0.9727
     1789/1789 [============ ] - 3s 2ms/step - loss: 0.0783 -
     accuracy: 0.9713 - val_loss: 0.0723 - val_accuracy: 0.9754
     Epoch 4/10
     accuracy: 0.9736 - val_loss: 0.0692 - val_accuracy: 0.9746
     Epoch 5/10
```

```
1789/1789 [============ ] - 3s 2ms/step - loss: 0.0680 -
   accuracy: 0.9752 - val_loss: 0.0716 - val_accuracy: 0.9765
   Epoch 6/10
   1789/1789 [============ ] - 3s 2ms/step - loss: 0.0627 -
   accuracy: 0.9765 - val_loss: 0.0756 - val_accuracy: 0.9716
   Epoch 7/10
   accuracy: 0.9789 - val_loss: 0.0670 - val_accuracy: 0.9779
   Epoch 8/10
   1789/1789 [============= ] - 3s 2ms/step - loss: 0.0550 -
   accuracy: 0.9797 - val_loss: 0.0693 - val_accuracy: 0.9766
   accuracy: 0.9817 - val_loss: 0.0636 - val_accuracy: 0.9803
   Epoch 10/10
   accuracy: 0.9826 - val_loss: 0.0608 - val_accuracy: 0.9812
[38]: # Evaluate the model on the test set
    test_loss, test_accuracy = tfidf_txt_model.evaluate(test_ft, test_labels)
    print(f'Test Loss: {test_loss}, Test Accuracy: {test_accuracy}')
   accuracy: 0.9683
   Test Loss: 0.09243853390216827, Test Accuracy: 0.9683393836021423
[39]: plot_loss_acc(history)
```





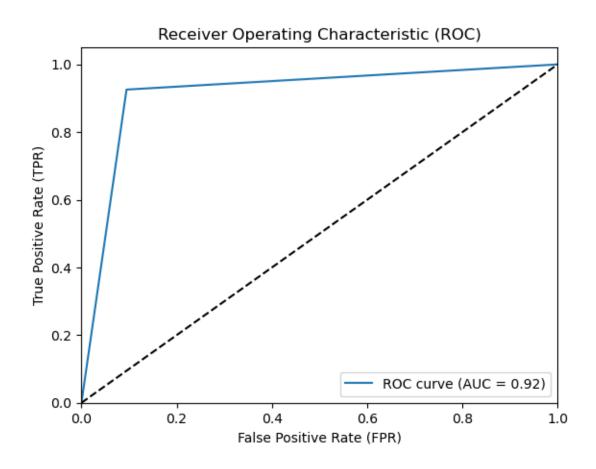
```
[100]: tfidf_txt_model.save_weights("tfidf_txt_model.h5")
```

3 2. Word2vec vectors + text characteristics

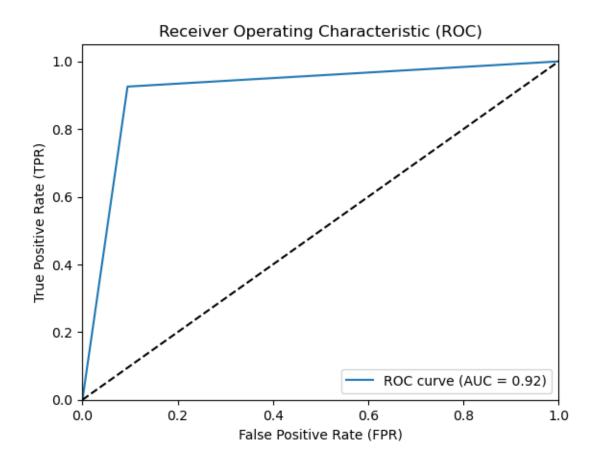
4 Machine Learning Models

```
[42]: model_doc=Word2Vec(doc_tokens_w2v,min_count=2,window=4)
[43]: sentence vectors = []
     for sentence in doc:
         tokens = word tokenize(sentence.lower())
         sentence_vector = np.zeros(model_doc.vector_size)
         if len(tokens)==0:
             sentence_vectors.append([0]*100)
         else:
             for token in tokens:
                 if token in model_doc.wv:
                     token_vector = model_doc.wv[token]
                     sentence_vector += token_vector
             sentence_vector /= len(tokens)
             sentence_vectors.append(sentence_vector)
      # Convert the list of sentence vectors to a NumPy array
     sentence_vectors = np.array(sentence_vectors)
[44]: | features_w2v_txt = np.hstack((sentence_vectors, non_text_features_np))
[47]: pickle.dump(features_w2v, open('features_w2v_txt.pkl', 'wb'))
[48]: features_w2v_txt = pickle.load( open('features_w2v_txt.pkl', 'rb'))
[49]: train_ft,test_ft,train_labels,test_labels=split_data_ml(features_w2v_txt,labels)
     -----Train data-----
      train data features shape (57229, 115)
      train data labels shape (57229,)
     -----Test data-----
      test data features shape (14308, 115)
      test data labels shape (14308,)
     4.0.1 Logistic Regression
[50]: clf = LogisticRegression(random_state=0).fit(train_ft, train_labels)
     get_metrics(clf,test_ft,test_labels)
     plot_ROC(test_labels)
                  precision
                             recall f1-score
                                                 support
            fake
                       0.91
                                 0.92
                                           0.91
                                                    6897
            real
                       0.93
                                 0.91
                                           0.92
                                                    7411
```

accuracy			0.92	14308
macro avg	0.92	0.92	0.92	14308
weighted avg	0.92	0.92	0.92	14308



	precision	recall	f1-score	support
fake	0.91	0.92	0.91	6897
real	0.93	0.91	0.92	7411
accuracy			0.92	14308
macro avg	0.92	0.92	0.92	14308
veighted avg	0.92	0.92	0.92	14308



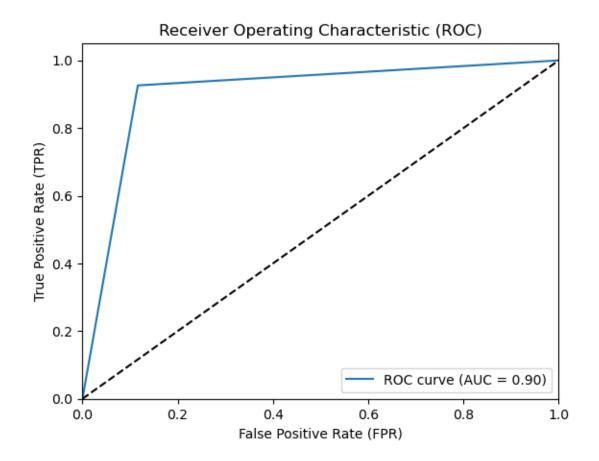
4.0.2 Linear Discriminant Analysis

[53]: clf = LinearDiscriminantAnalysis().fit(train_ft, train_labels)

[54]: get_metrics(clf,test_ft,test_labels)

	precision	recall	f1-score	support
fake	0.88	0.92	0.90	6741
real	0.93	0.89	0.91	7567
accuracy			0.91	14308
macro avg	0.90	0.91	0.91	14308
weighted avg	0.91	0.91	0.91	14308

[55]: plot_ROC(test_labels)



4.0.3 Artificial Neural Network

[56]: x_train,y_train,X_val,y_val,test_ft,test_labels=split_data_dl(features_w2v_txt,labels)

Training set shape: (45783, 115) Validation set shape: (11446, 115)

Test set shape: (14308, 115)

[57]: tfidf_w2v_model= ANN_model()
 tfidf_w2v_model.build((None,115))
 print(tfidf_w2v_model.summary())

Model: "ann_model_2"

Layer (type)	Output Shape	Param #
dense_3 (Dense)	multiple	7424
dense_4 (Dense)	multiple	2080

```
dense_5 (Dense)
                          multiple
    ______
    Total params: 9,537
    Trainable params: 9,537
    Non-trainable params: 0
    None
[58]: tfidf_w2v_model.compile(optimizer='adam', loss='binary_crossentropy', u
     →metrics=['accuracy'])
    history=tfidf_w2v_model.fit(train ft, train labels, epochs=10, batch_size=32,__
     →validation_data=(X_val, y_val))
    Epoch 1/10
    accuracy: 0.9081 - val_loss: 0.1626 - val_accuracy: 0.9355
    accuracy: 0.9368 - val_loss: 0.1464 - val_accuracy: 0.9393
    Epoch 3/10
    accuracy: 0.9429 - val_loss: 0.1313 - val_accuracy: 0.9472
    Epoch 4/10
    1789/1789 [============ - - 6s 3ms/step - loss: 0.1284 -
    accuracy: 0.9493 - val_loss: 0.1191 - val_accuracy: 0.9540
    Epoch 5/10
    1789/1789 [============== ] - 5s 3ms/step - loss: 0.1188 -
    accuracy: 0.9535 - val_loss: 0.1127 - val_accuracy: 0.9553
    Epoch 6/10
    1789/1789 [============ ] - 5s 3ms/step - loss: 0.1096 -
    accuracy: 0.9575 - val_loss: 0.1087 - val_accuracy: 0.9597
    Epoch 7/10
    1789/1789 [============= - - 5s 3ms/step - loss: 0.1011 -
    accuracy: 0.9612 - val_loss: 0.1018 - val_accuracy: 0.9640
    Epoch 8/10
    1789/1789 [============== ] - 5s 3ms/step - loss: 0.0949 -
    accuracy: 0.9636 - val_loss: 0.0984 - val_accuracy: 0.9651
    Epoch 9/10
    accuracy: 0.9661 - val_loss: 0.0922 - val_accuracy: 0.9676
    Epoch 10/10
    1789/1789 [=============== ] - 5s 3ms/step - loss: 0.0816 -
    accuracy: 0.9700 - val_loss: 0.0900 - val_accuracy: 0.9702
[60]: # Evaluate the model on the test set
    test_loss, test_accuracy = tfidf_w2v_model.evaluate(test_ft, test_labels)
```

33

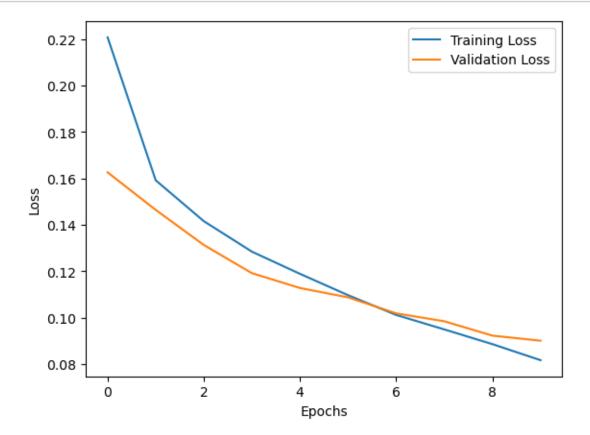
```
print(f'Test Loss: {test_loss}, Test Accuracy: {test_accuracy}')
```

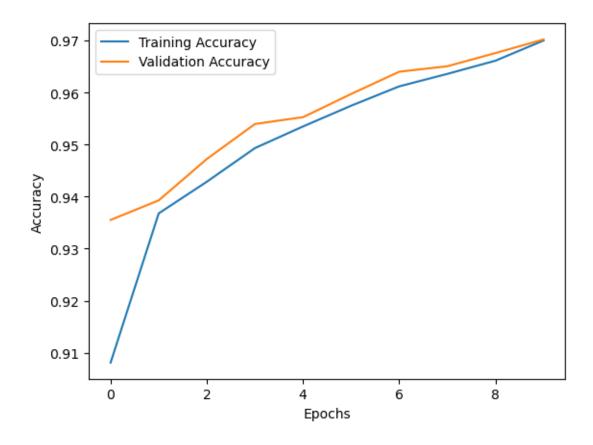
448/448 [============] - 1s 2ms/step - loss: 0.0943 -

accuracy: 0.9678

Test Loss: 0.09433166682720184, Test Accuracy: 0.9677802920341492

[61]: plot_loss_acc(history)



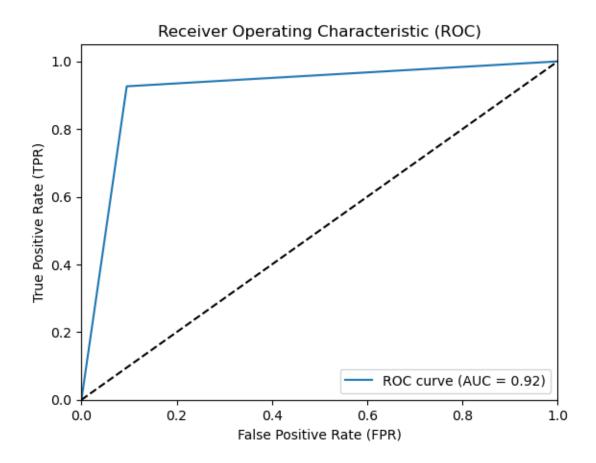


```
[63]: tfidf_w2v_model.save_weights("tfidf_w2v_model.h5")
```

5 3. TF-IDF weighted Word2vec vectors

5.1 Machine learning models

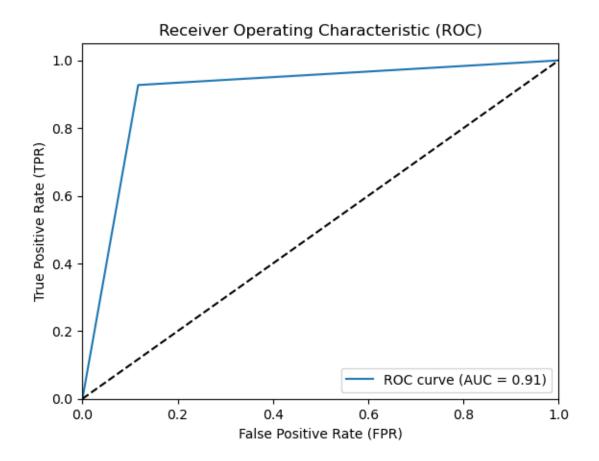
```
sentence_vector /= len(tokens)
             sentence_vector *= word_tfidf_weights[i]
             sentence_vectors_tf.append(sentence_vector)
     # Convert the list of sentence vectors to a NumPy array
     sentence_vectors_tf = np.array(sentence_vectors)
     sentence_vectors_tf = np.nan_to_num(sentence_vectors_tf, nan=0.0)
[73]: sentence_vectors_tf.shape
[73]: (71537, 100)
    pickle.dump(sentence_vectors_tf, open('features_w2v_tf_wts.pkl', 'wb'))
[78]: features_w2v_tf_wts=pickle.load( open('features_w2v_tf_wts.pkl', 'rb'))
[80]: train ft, test ft, train labels, test labels=split data ml(features w2v tf wts, labels)
     -----Train data-----
     train data features shape (57229, 115)
     train data labels shape (57229,)
     -----Test data-----
     test data features shape (14308, 115)
     test data labels shape (14308,)
     5.1.1 Logistic Regression
[81]: clf = LogisticRegression(random_state=0, max_iter=300).fit(train_ft,__
      get_metrics(clf,test_ft,test_labels)
     plot_ROC(test_labels)
                  precision
                              recall f1-score
                                                support
            fake
                       0.90
                                0.92
                                          0.91
                                                   6816
            real
                       0.93
                                0.91
                                          0.92
                                                   7492
                                          0.92
                                                  14308
        accuracy
       macro avg
                       0.92
                                0.92
                                          0.92
                                                  14308
     weighted avg
                                          0.92
                       0.92
                                0.92
                                                  14308
```



5.1.2 Linear Discriminant Analysis

[82]: clf = LinearDiscriminantAnalysis().fit(train_ft, train_labels)
get_metrics(clf,test_ft,test_labels)
plot_ROC(test_labels)

support	f1-score	recall	precision	
6658	0.90	0.92	0.88	fake
7650	0.91	0.89	0.93	real
14308	0.91			accuracy
14308	0.91	0.91	0.91	macro avg
14308	0.91	0.91	0.91	weighted avg



5.1.3 Artificial Neural Networks

[83]: x_train,y_train,X_val,y_val,test_ft,test_labels=split_data_dl(features_w2v_tf_wts,labels)

Training set shape: (45783, 115)
Validation set shape: (11446, 115)

Test set shape: (14308, 115)

[84]: tfidf_w2v_wts_model= ANN_model()
 tfidf_w2v_wts_model.build((None,115))
 print(tfidf_w2v_model.summary())

Model: "ann_model_3"

Layer (type)	Output Shape	Param #
dense_6 (Dense)	multiple	7424
dense_7 (Dense)	multiple	2080

```
dense_8 (Dense)
                       multiple
                                           33
   ______
   Total params: 9,537
   Trainable params: 9,537
   Non-trainable params: 0
   ______
   None
[85]: opt = keras.optimizers.SGD(learning_rate=0.1)
    tfidf_w2v_wts_model.compile(optimizer=opt, loss='binary_crossentropy',_
     →metrics=['accuracy'])
    history=tfidf_w2v_wts_model.fit(train_ft, train_labels, epochs=10,_
     ⇒batch_size=32, validation_data=(X_val, y_val))
   Epoch 1/10
   accuracy: 0.9123 - val_loss: 0.1794 - val_accuracy: 0.9275
   Epoch 2/10
   1789/1789 [============= ] - 5s 3ms/step - loss: 0.1643 -
   accuracy: 0.9348 - val_loss: 0.1585 - val_accuracy: 0.9368
   Epoch 3/10
   accuracy: 0.9409 - val_loss: 0.1460 - val_accuracy: 0.9416
   Epoch 4/10
   accuracy: 0.9464 - val_loss: 0.1368 - val_accuracy: 0.9464
   Epoch 5/10
   accuracy: 0.9498 - val_loss: 0.1314 - val_accuracy: 0.9469
   Epoch 6/10
   accuracy: 0.9533 - val_loss: 0.1231 - val_accuracy: 0.9519
   Epoch 7/10
   1789/1789 [============= ] - 5s 3ms/step - loss: 0.1123 -
   accuracy: 0.9565 - val_loss: 0.1176 - val_accuracy: 0.9552
   Epoch 8/10
   1789/1789 [============= - - 5s 3ms/step - loss: 0.1050 -
   accuracy: 0.9592 - val_loss: 0.1167 - val_accuracy: 0.9553
   1789/1789 [============= - - 5s 3ms/step - loss: 0.1015 -
   accuracy: 0.9607 - val_loss: 0.1078 - val_accuracy: 0.9594
   Epoch 10/10
   1789/1789 [============= - - 5s 3ms/step - loss: 0.0955 -
   accuracy: 0.9633 - val_loss: 0.1046 - val_accuracy: 0.9615
```

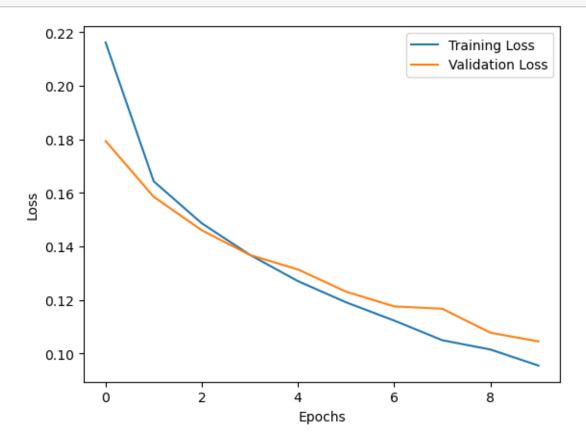
```
[86]: # Evaluate the model on the test set
test_loss, test_accuracy = tfidf_w2v_wts_model.evaluate(test_ft, test_labels)
print(f'Test Loss: {test_loss}, Test Accuracy: {test_accuracy}')
```

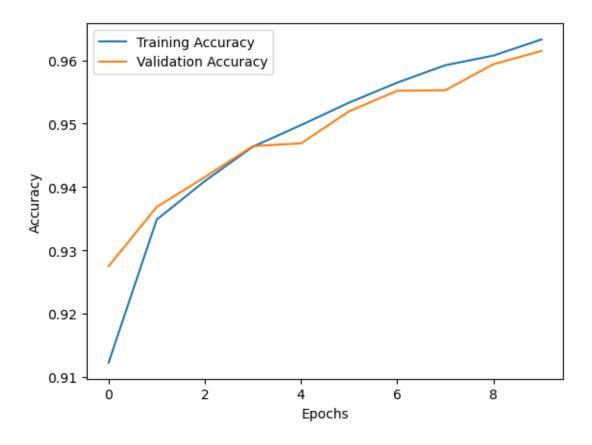
448/448 [============] - 1s 2ms/step - loss: 0.0964 -

accuracy: 0.9639

Test Loss: 0.09637467563152313, Test Accuracy: 0.9638663530349731

[87]: plot_loss_acc(history)





```
[88]: tfidf_w2v_wts_model.save_weights("tfidf_w2v_wts_model.h5")
```

6 4 TF-IDF weighted Word2vec with non numeric features

6.1 Machine Learning Models

```
[89]: features_w2v_tfidf_txt = np.hstack((sentence_vectors_tf, non_text_features_np))
```

6.1.1 Logistic Regression

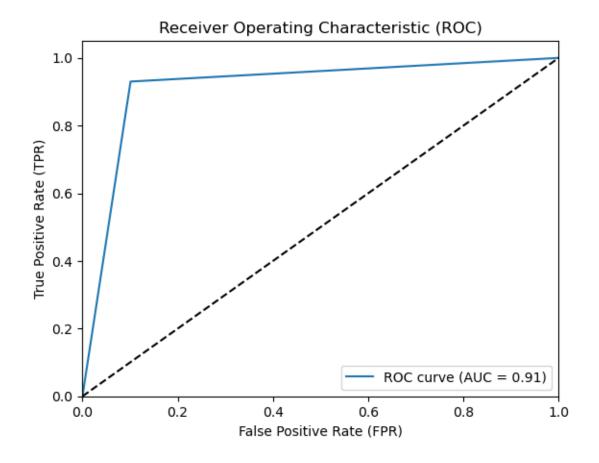
```
[90]: train_ft,test_ft,train_labels,test_labels=split_data_ml(features_w2v_tfidf_txt,labels)
------Train data------

train data features shape (57229, 115)
train data labels shape (57229,)
------Test data------

test data features shape (14308, 115)
```

test data labels shape (14308,)

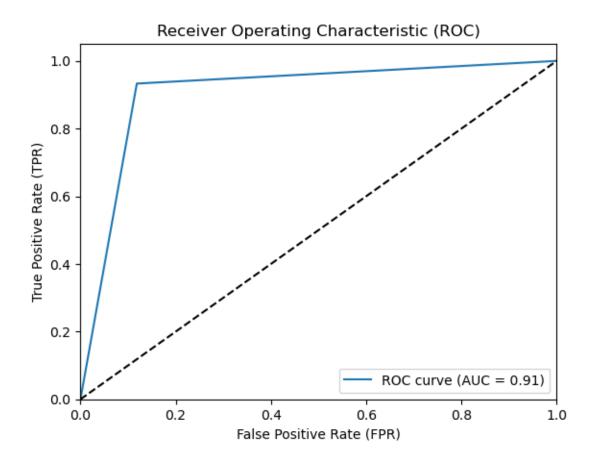
	precision	recall	f1-score	support
fake	0.90	0.92	0.91	6809
real	0.93	0.91	0.92	7499
accuracy			0.91	14308
macro avg	0.91	0.92	0.91	14308
weighted avg	0.92	0.91	0.91	14308



6.1.2 Linear Discriminant Analysis

[92]: clf = LinearDiscriminantAnalysis().fit(train_ft, train_labels)
 get_metrics(clf,test_ft,test_labels)
 plot_ROC(test_labels)

	precision	recall	f1-score	support
fake	0.88	0.93	0.90	6666
real	0.93	0.89	0.91	7642
accuracy			0.91	14308
macro avg	0.91	0.91	0.91	14308
weighted avg	0.91	0.91	0.91	14308



6.1.3 Artificial Neural Networks

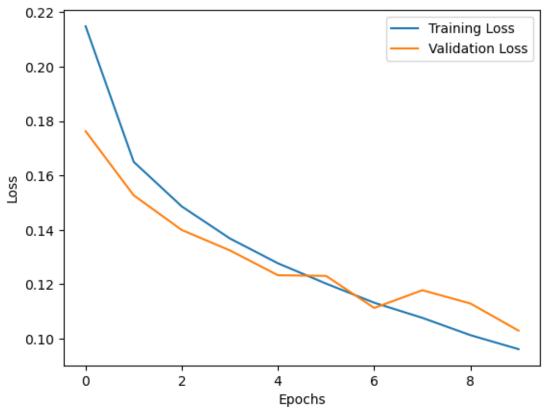
[93]: x_train,y_train,X_val,y_val,test_ft,test_labels=split_data_dl(features_w2v_tfidf_txt,labels)

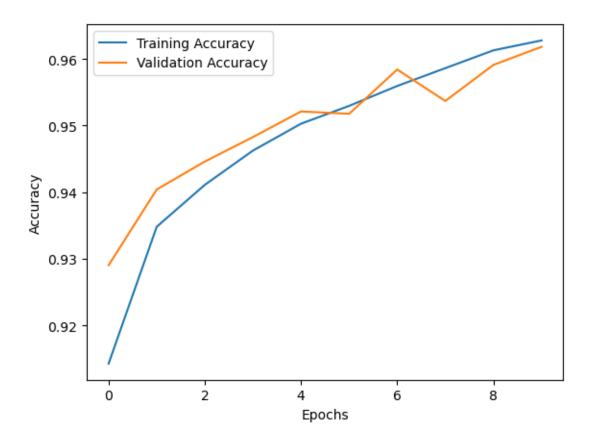
Training set shape: (45783, 115)

```
Test set shape: (14308, 115)
[95]: tfidf w2v txt model= ANN model()
    tfidf_w2v_txt_model.build((None, 115))
    print(tfidf_w2v_txt_model.summary())
    Model: "ann model 6"
    Layer (type) Output Shape
                                             Param #
    ______
    dense_15 (Dense)
                          multiple
                                              7424
    dense_16 (Dense)
                          multiple
                                              2080
    dense_17 (Dense)
                          multiple
                                              33
    ______
    Total params: 9,537
    Trainable params: 9,537
    Non-trainable params: 0
    -----
    None
[96]: opt = keras.optimizers.SGD(learning rate=0.1)
    tfidf_w2v_txt_model.compile(optimizer=opt, loss='binary_crossentropy', u
     →metrics=['accuracy'])
    history=tfidf_w2v_txt_model.fit(train_ft, train_labels, epochs=10,u
     ⇒batch_size=32, validation_data=(X_val, y_val))
    Epoch 1/10
    1789/1789 [============ ] - 6s 3ms/step - loss: 0.2148 -
    accuracy: 0.9143 - val_loss: 0.1763 - val_accuracy: 0.9291
    accuracy: 0.9348 - val_loss: 0.1527 - val_accuracy: 0.9404
    Epoch 3/10
    1789/1789 [============= ] - 5s 3ms/step - loss: 0.1486 -
    accuracy: 0.9411 - val_loss: 0.1400 - val_accuracy: 0.9446
    accuracy: 0.9463 - val_loss: 0.1325 - val_accuracy: 0.9483
    Epoch 5/10
    1789/1789 [============== ] - 5s 3ms/step - loss: 0.1277 -
    accuracy: 0.9503 - val_loss: 0.1233 - val_accuracy: 0.9521
    Epoch 6/10
    1789/1789 [============ - - 5s 3ms/step - loss: 0.1203 -
    accuracy: 0.9530 - val_loss: 0.1231 - val_accuracy: 0.9518
```

Validation set shape: (11446, 115)

```
Epoch 7/10
    1789/1789 [============ ] - 5s 3ms/step - loss: 0.1132 -
    accuracy: 0.9559 - val_loss: 0.1113 - val_accuracy: 0.9584
    Epoch 8/10
    1789/1789 [============= - - 5s 3ms/step - loss: 0.1077 -
    accuracy: 0.9586 - val_loss: 0.1178 - val_accuracy: 0.9537
    1789/1789 [============= ] - 5s 3ms/step - loss: 0.1013 -
    accuracy: 0.9613 - val_loss: 0.1130 - val_accuracy: 0.9591
    Epoch 10/10
    1789/1789 [============ - - 5s 3ms/step - loss: 0.0962 -
    accuracy: 0.9628 - val_loss: 0.1030 - val_accuracy: 0.9618
[97]: # Evaluate the model on the test set
     test_loss, test_accuracy = tfidf_w2v_txt_model.evaluate(test_ft, test_labels)
     print(f'Test Loss: {test_loss}, Test Accuracy: {test_accuracy}')
    accuracy: 0.9605
    Test Loss: 0.10413851588964462, Test Accuracy: 0.9605116248130798
[98]: plot_loss_acc(history)
           0.22
```





```
[99]: tfidf_w2v_txt_model.save_weights("tfidf_w2v_txt_model.h5")

[118]: %load_ext tensorboard
    %tensorboard --logdir=log/train

The tensorboard extension is already loaded. To reload it, use:
        %reload_ext tensorboard
        <IPython.core.display.HTML object>

[]:
```