`Spam Detection Using Fine-Tuned BERT`

`Dataset:` The SMS Spam Collection is a set of SMS tagged messages that have been collected for SMS Spam research. It contains one set of SMS messages in English of 5,574 messages, tagged acording being ham (legitimate) or spam.

`Objective:` Build an AI model that can classify messages as spam or legitimate using BERT model

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Loading Data

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In [1]:
```
# import modules
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import tensorflow as tf
import tensorflow_hub as hub
import tensorflow_text as text
import os
import joblib
import warnings #ignore warning
warnings.filterwarnings("ignore")
```

In [2]:
```
# Define file path
filepath ="D://Portfolio//Internship//AFAME//Project details//Spam SMS Detection
# Read the CSV file into a DataFrame with specified encoding
data = pd.read_csv(filepath, encoding='latin1')
# Display the first few rows of the DataFrame
data.head()
```

Out[2]:

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

In [3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5572 entries, 0 to 5571
Data columns (total 5 columns):
 #   Column      Non-Null Count  Dtype 
---  ------      --------------  ----- 
 0   v1          5572 non-null   object
 1   v2          5572 non-null   object
 2   Unnamed: 2  50 non-null     object
 3   Unnamed: 3  12 non-null     object
 4   Unnamed: 4  6 non-null      object
dtypes: object(5)
memory usage: 217.8+ KB
```

Data Preparation

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In [4]:
```
# removing excess unnecessary column
data = data.loc[:, ~data.columns.str.contains('^Unnamed')]
data.head()
```

Out[4]:

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

In [5]:
```
data.rename(columns={'v1': 'Class', 'v2': 'Text'}, inplace=True)
```

In [6]:
```
data['Class'] = data['Class'].map({'ham':0, 'spam':1})
data.head()
```

Out[6]:

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

In [7]:
```
# Checking null values
data.isnull().sum()
```

Out[7]:
```
Class    0
Text     0
dtype: int64
```

In [8]:
```
data.duplicated().sum()
```

Out[8]:
```
403
```

We are retaining the duplicate values as they are crucial for our task of identifying spam SMS messages.

In [9]:
```
# Viewing values in 'v1' column
data['Class'].value_counts()
```

Out[9]:
```
Class
0    4825
1     747
Name: count, dtype: int64
```

In [10]:
```
data.groupby('Class').describe()
```

Out[10]:

	Text			
	count	**unique**	**top**	**freq**
Class				
0	4825	4516	Sorry, I'll call later	30
1	747	653	Please call our customer service representativ...	4

In [11]:
```
# Viewing the imbalanced rate
747/4825
```

Out[11]:
```
0.15481865284974095
```

In [12]:
```
# Viewing unique values in 'v2'
data['Text'].nunique()
```

Out[12]:
```
5169
```

Exploratory Data Analysis (EDA)

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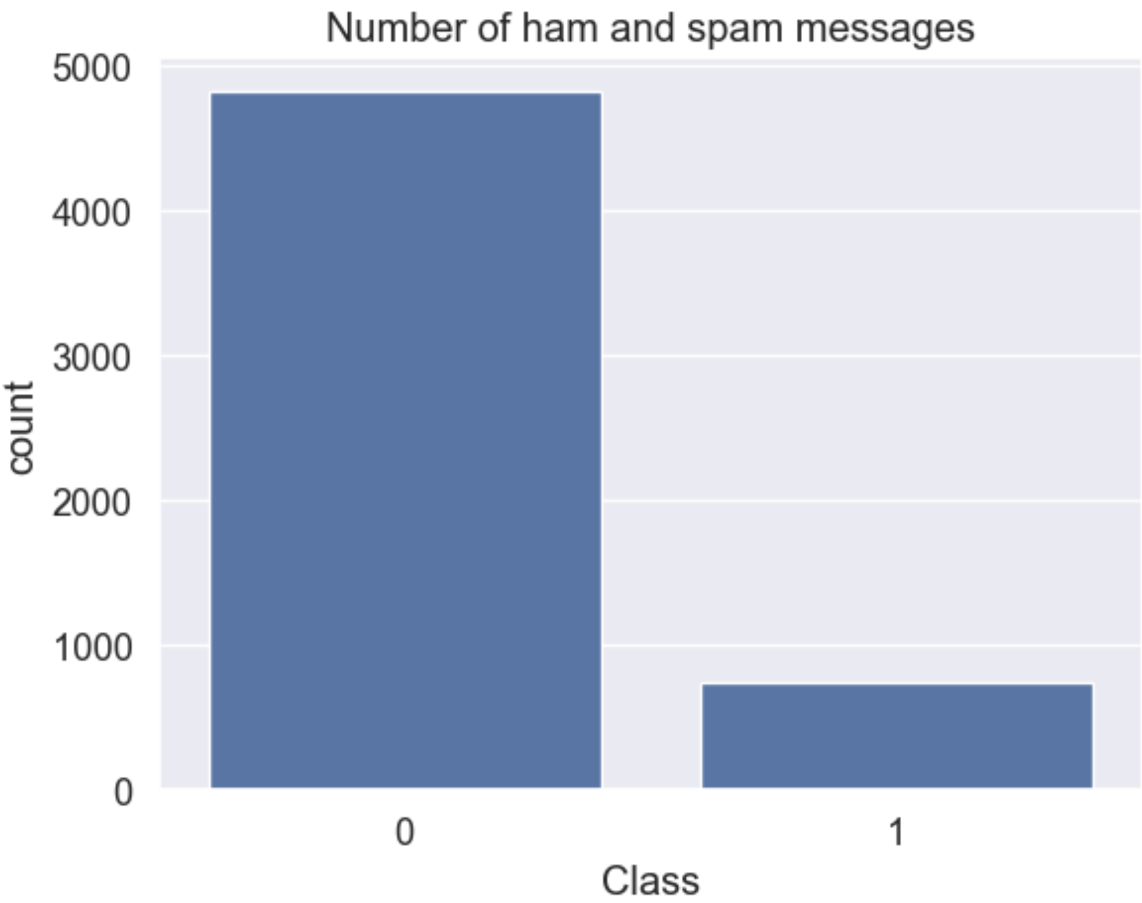
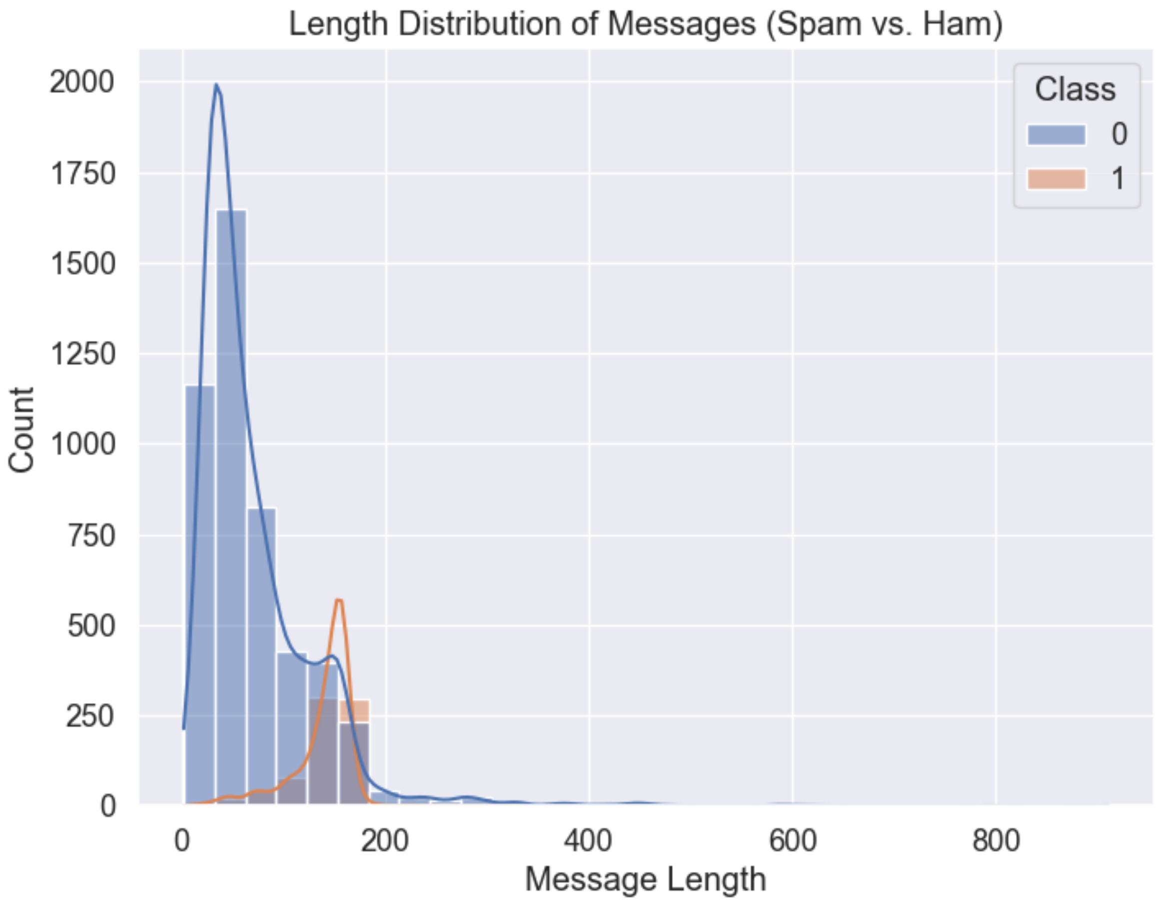
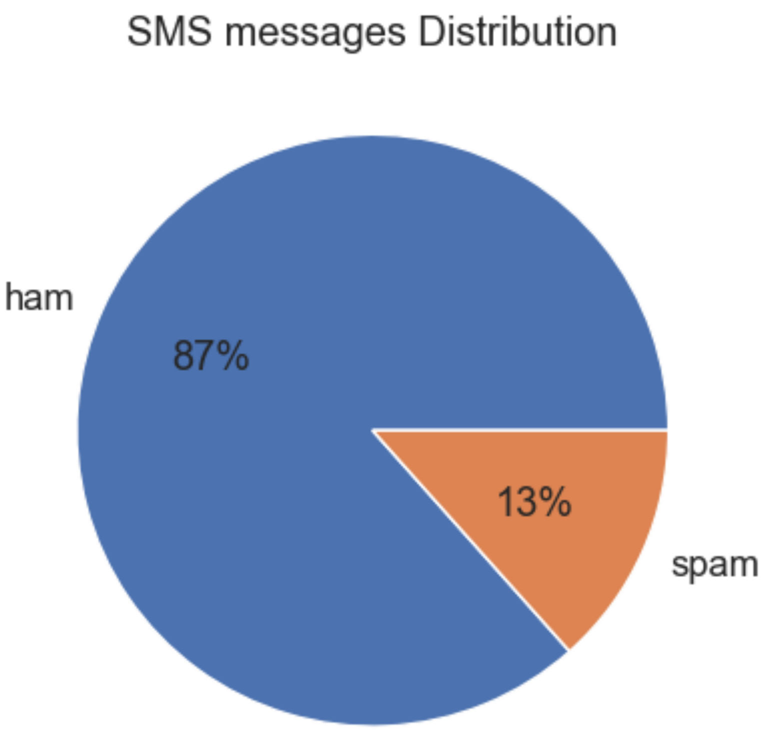
In [13]:
```
sns.set(style = "darkgrid" , font_scale = 1.2)
sns.countplot(data=data, x= 'Class').set_title("Number of ham and spam messages"
plt.show()
```



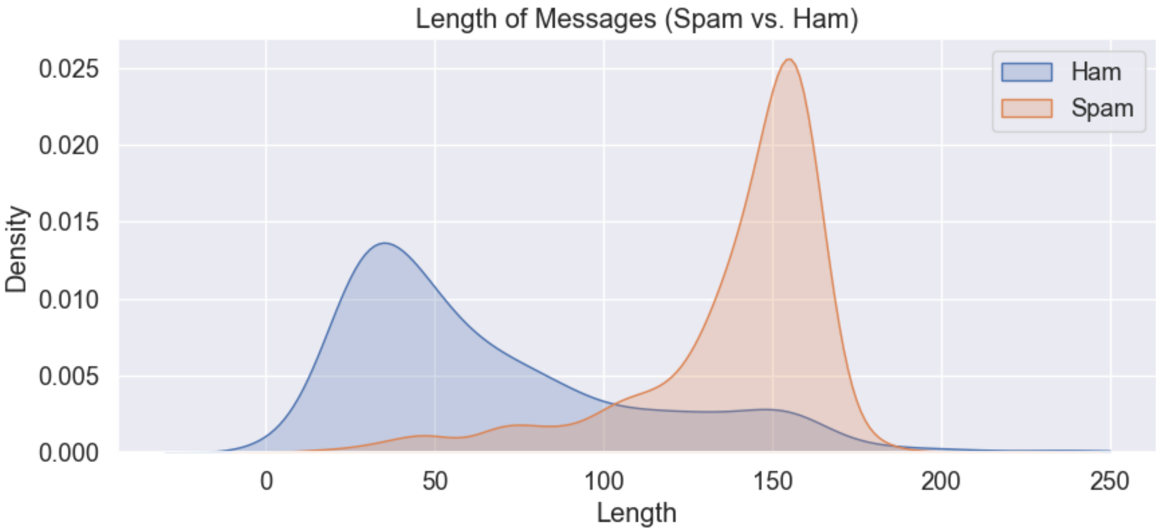
In [14]:
```
# Plot the distribution of message lengths
plt.figure(figsize=(8, 6))
sns.histplot(x=data['Text'].str.len(), bins=30, hue=data['Class'], kde=True)
plt.title('Length Distribution of Messages (Spam vs. Ham)')
plt.xlabel('Message Length')
plt.ylabel('Count')
plt.show()
```



In [15]:
```
sms = pd.value_counts(data["Class"], sort=True)
sms.plot(kind="pie", labels=["ham", "spam"], autopct="%1.0f%%")

plt.title("SMS messages Distribution")
plt.ylabel("")
plt.show()
```



In [16]:
```python
# Calculate lengths of messages directly in the plotting function
_, ax = plt.subplots(figsize=(10, 4))
sns.kdeplot(data.loc[data.Class == 0, 'Text'].str.len(), shade=True, label='Ham'
sns.kdeplot(data.loc[data.Class == 1, 'Text'].str.len(), shade=True, label='Spam

# Set axis labels and title
ax.set(
    xlabel='Length',
    ylabel='Density',
    title='Length of Messages (Spam vs. Ham)'
)
ax.legend(loc='upper right')

# Show plot
plt.show()
```



Original Data

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Train/Test Spliting

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In [17]:
```python
X = data['Text']
y = data['Class']
```

In [18]:
```python
X.shape
```

Out[18]: (5572,)

In [19]:
```python
y.shape
```

Out[19]: (5572,)

In [20]:
```
print(f'Length of X: {len(X)}')
print(f'Length of y: {len(y)}')
```

```
Length of X: 5572
Length of y: 5572
```

In [21]:
```
from sklearn.model_selection import train_test_split
random_seed = 42

# Split data into training and temporary sets (60% train, 40% temp)
X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.3, random_

# Split temporary set into validation and test sets (20% val, 20% test)
X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0.5, r

print(f'Training data: {len(X_train)}, {len(y_train)}')
print(f'Validation data: {len(X_val)}, {len(y_val)}')
print(f'Testing data: {len(X_test)}, {len(y_test)}')
```

```
Training data: 3900, 3900
Validation data: 836, 836
Testing data: 836, 836
```

Model Building

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In [22]:
```
%%time
bert_preprocessor = hub.KerasLayer('https://tfhub.dev/tensorflow/bert_en_uncased
bert_encoder = hub.KerasLayer('https://tfhub.dev/tensorflow/bert_en_uncased_L-12
```

```
CPU times: total: 9.64 s
Wall time: 13.9 s
```

In [23]:
```
%%time
from tensorflow.keras.layers import Input, Dropout, Dense, BatchNormalization
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam  # Import the optimizer

# Functional BERT layers
text_input = Input(shape=(), dtype=tf.string, name='Inputs')
encoder_inputs = bert_preprocessor(text_input)
embed = bert_encoder(encoder_inputs)

# Neural Network layers
dropout1 = Dropout(0.1, name='Dropout1')(embed['pooled_output'])
dense1 = Dense(128, activation='relu', name='Dense1')(dropout1)
batch_norm1 = BatchNormalization(name='BatchNorm1')(dense1)
dropout2 = Dropout(0.1, name='Dropout2')(batch_norm1)
dense2 = Dense(64, activation='relu', name='Dense2')(dropout2)
batch_norm2 = BatchNormalization(name='BatchNorm2')(dense2)
dropout3 = Dropout(0.1, name='Dropout3')(batch_norm2)
outputs = Dense(1, activation='sigmoid', name='Output')(dropout3)

# Creating final model
model = Model(inputs=[text_input], outputs=[outputs])
```

```
CPU times: total: 438 ms
Wall time: 616 ms
```

In [24]:

```
model.summary()
```

```
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to                     
==================================================================================================
 Inputs (InputLayer)            [(None,)]            0           []                               
                                                                                                  
 keras_layer (KerasLayer)       {'input_word_ids':   0           ['Inputs[0][0]']                 
                                (None, 128),                                                      
                                 'input_mask': (Non                                               
                                e, 128),                                                          
                                 'input_type_ids':                                                
                                (None, 128)}                                                      
                                                                                                  
 keras_layer_1 (KerasLayer)     {'sequence_output':  109482241   ['keras_layer[0][0]',            
                                 (None, 128, 768),                'keras_layer[0][1]',            
                                 'pooled_output': (               'keras_layer[0][2]']            
                                None, 768),                                                       
                                 'default': (None,                                                
                                768),                                                             
                                 'encoder_outputs':                                               
                                 [(None, 128, 768),                                               
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768),                                                
                                 (None, 128, 768)]}                                               
                                                                                                  
 Dropout1 (Dropout)             (None, 768)          0           ['keras_layer_1[0][13]']         
                                                                                                  
 Dense1 (Dense)                 (None, 128)          98432       ['Dropout1[0][0]']               
                                                                                                  
 BatchNorm1 (BatchNormalization  (None, 128)         512         ['Dense1[0][0]']                 
 )                                                                                                
                                                                                                  
 Dropout2 (Dropout)             (None, 128)          0           ['BatchNorm1[0][0]']             
                                                                                                  
 Dense2 (Dense)                 (None, 64)           8256        ['Dropout2[0][0]']               
                                                                                                  
 BatchNorm2 (BatchNormalization  (None, 64)          256         ['Dense2[0][0]']                 
 )                                                                                                
                                                                                                  
 Dropout3 (Dropout)             (None, 64)           0           ['BatchNorm2[0][0]']             
                                                                                                  
 Output (Dense)                 (None, 1)            65          ['Dropout3[0]
```

```
[0]']

=================================================================================
=================
Total params: 109,589,762
Trainable params: 107,137
Non-trainable params: 109,482,625
_________________________________________________________________________________
_________________
```

In [25]:
```
metrics = [
    tf.keras.metrics.BinaryAccuracy(name='accuracy'),
    tf.keras.metrics.Precision(name='precision'),
    tf.keras.metrics.Recall(name='recall')
]

model.compile(optimizer=Adam(learning_rate=0.001),
              loss='binary_crossentropy',
              metrics = metrics)
```

In [26]:
```
from tensorflow.keras.callbacks import EarlyStopping, ReduceLROnPlateau
# Define callbacks
early_stopping = EarlyStopping(monitor='val_loss',
                               patience=3,
                               restore_best_weights=True)

# Learning rate scheduler
lr_scheduler = ReduceLROnPlateau(monitor='val_loss',
                                 factor=0.2,
                                 patience=2,
                                 min_lr=1e-7)
```

In [27]:
```
%%time
# Fit the model
history = model.fit(X_train, y_train, epochs=20,
                    validation_data=(X_val, y_val),
                    callbacks=[early_stopping, lr_scheduler])
```

```
Epoch 1/20
122/122 [==============================] - 71s 499ms/step - loss: 0.4288 - accura
cy: 0.8308 - precision: 0.4365 - recall: 0.9006 - val_loss: 0.2376 - val_accuracy
: 0.9426 - val_precision: 0.9571 - val_recall: 0.5982 - lr: 0.0010
Epoch 2/20
122/122 [==============================] - 60s 490ms/step - loss: 0.1779 - accura
cy: 0.9518 - precision: 0.7787 - recall: 0.8948 - val_loss: 0.1249 - val_accuracy
: 0.9533 - val_precision: 1.0000 - val_recall: 0.6518 - lr: 0.0010
Epoch 3/20
122/122 [==============================] - 60s 490ms/step - loss: 0.1232 - accura
cy: 0.9618 - precision: 0.8555 - recall: 0.8604 - val_loss: 0.0707 - val_accuracy
: 0.9797 - val_precision: 0.9612 - val_recall: 0.8839 - lr: 0.0010
Epoch 4/20
122/122 [==============================] - 60s 490ms/step - loss: 0.1058 - accura
cy: 0.9672 - precision: 0.8926 - recall: 0.8585 - val_loss: 0.1003 - val_accuracy
: 0.9701 - val_precision: 0.8480 - val_recall: 0.9464 - lr: 0.0010
Epoch 5/20
122/122 [==============================] - 60s 491ms/step - loss: 0.1000 - accura
cy: 0.9687 - precision: 0.8970 - recall: 0.8662 - val_loss: 0.2649 - val_accuracy
: 0.9067 - val_precision: 0.5904 - val_recall: 0.9911 - lr: 0.0010
Epoch 6/20
122/122 [==============================] - 60s 492ms/step - loss: 0.0833 - accura
cy: 0.9726 - precision: 0.9127 - recall: 0.8795 - val_loss: 0.0596 - val_accuracy
: 0.9785 - val_precision: 0.9796 - val_recall: 0.8571 - lr: 2.0000e-04
Epoch 7/20
122/122 [==============================] - 60s 494ms/step - loss: 0.0800 - accura
cy: 0.9746 - precision: 0.9257 - recall: 0.8815 - val_loss: 0.0558 - val_accuracy
: 0.9844 - val_precision: 0.9714 - val_recall: 0.9107 - lr: 2.0000e-04
Epoch 8/20
122/122 [==============================] - 64s 522ms/step - loss: 0.0880 - accura
cy: 0.9697 - precision: 0.9042 - recall: 0.8662 - val_loss: 0.0513 - val_accuracy
: 0.9821 - val_precision: 0.9619 - val_recall: 0.9018 - lr: 2.0000e-04
Epoch 9/20
122/122 [==============================] - 64s 523ms/step - loss: 0.0773 - accura
cy: 0.9723 - precision: 0.9209 - recall: 0.8681 - val_loss: 0.0607 - val_accuracy
: 0.9797 - val_precision: 1.0000 - val_recall: 0.8482 - lr: 2.0000e-04
Epoch 10/20
122/122 [==============================] - 64s 527ms/step - loss: 0.0742 - accura
cy: 0.9759 - precision: 0.9281 - recall: 0.8891 - val_loss: 0.0458 - val_accuracy
: 0.9844 - val_precision: 0.9714 - val_recall: 0.9107 - lr: 2.0000e-04
Epoch 11/20
122/122 [==============================] - 64s 528ms/step - loss: 0.0797 - accura
cy: 0.9751 - precision: 0.9260 - recall: 0.8853 - val_loss: 0.0498 - val_accuracy
: 0.9809 - val_precision: 0.9800 - val_recall: 0.8750 - lr: 2.0000e-04
Epoch 12/20
122/122 [==============================] - 64s 521ms/step - loss: 0.0742 - accura
cy: 0.9759 - precision: 0.9231 - recall: 0.8948 - val_loss: 0.0488 - val_accuracy
: 0.9821 - val_precision: 0.9802 - val_recall: 0.8839 - lr: 2.0000e-04
Epoch 13/20
122/122 [==============================] - 63s 519ms/step - loss: 0.0721 - accura
cy: 0.9749 - precision: 0.9474 - recall: 0.8604 - val_loss: 0.0472 - val_accuracy
: 0.9833 - val_precision: 0.9804 - val_recall: 0.8929 - lr: 4.0000e-05
CPU times: total: 9min 33s
Wall time: 13min 32s
```

Model Evaluation

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In [28]:

```
# Evaluate the model
results = model.evaluate(X_test, y_test)
print(f"Test Loss: {results[0]}")
print(f"Test Accuracy: {results[1]}")
```

```
27/27 [==============================] - 11s 412ms/step - loss: 0.0418 - accuracy
: 0.9904 - precision: 0.9815 - recall: 0.9464
Test Loss: 0.04175851494073868
Test Accuracy: 0.9904305934906006
```

In [29]:

```
y_predict = model.predict(X_test)
y_predict = y_predict.flatten()
```

```
27/27 [==============================] - 12s 414ms/step
```

In [30]:

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

Out[30]:

```
array([0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1])
```

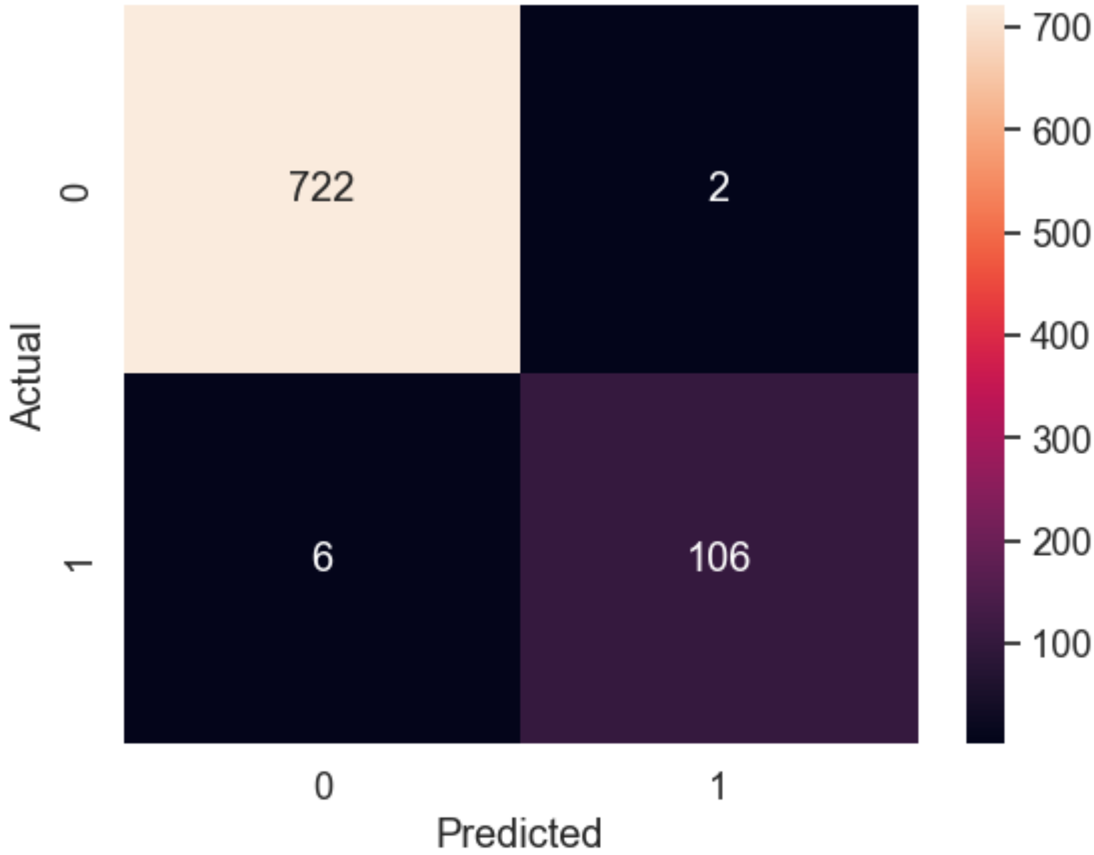
In [31]:
```python
from sklearn.metrics import confusion_matrix

cm = confusion_matrix(y_test, y_predict)
cm
```

Out[31]:
```
array([[722,   2],
       [  6, 106]], dtype=int64)
```

In [32]:
```python
sns.heatmap(cm, annot=True, fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

Out[32]:
```
Text(43.25, 0.5, 'Actual')
```



In [33]:
```python
from sklearn.metrics import classification_report

nml = classification_report(y_test, y_predict, target_names=['Ham', 'Spam'])
print(nml)
```

```
              precision    recall  f1-score   support

         Ham       0.99      1.00      0.99       724
        Spam       0.98      0.95      0.96       112

    accuracy                           0.99       836
   macro avg       0.99      0.97      0.98       836
weighted avg       0.99      0.99      0.99       836
```

Inference

In [34]:
```python
# Actual real examples
```

```
reviews = [
    'You will be hired at managerial roles in top companies',
    'Citrusbug Technolabs is hiring for AI/ML Engineer + 14 new Fresher Data Sci
    'Job opportunity from Wipro just for You!',
    'Dear Congratulations - Get Your Job Offer Letter @ Cognizant',
    'Practice Coding with A Very Big Sum'
]

# Detection of examples
nml_inf = model.predict(reviews)
nml_inf
```

```
1/1 [==============================] - 1s 897ms/step
```

Out[34]:
```
array([[0.02774307],
       [0.46297142],
       [0.15588982],
       [0.4203427 ],
       [0.00780586]], dtype=float32)
```

Hyperparameter Tuning with Keras Tuner (Original Data)

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In [35]:
```
%%time
import kerastuner as kt

# Function to compile your existing model with hyperparameters
def compile_model(hp):
    # Tune the learning rate
    learning_rate = hp.Choice('learning_rate', values=[1e-2, 1e-3, 1e-4])

    # Compile the model with the chosen learning rate
    model.compile(optimizer = Adam(learning_rate=learning_rate),
                  loss = 'binary_crossentropy',
                  metrics = metrics)
    return model

# Initialize Keras Tuner with the existing model
tuner = kt.Hyperband(
    compile_model,
    objective='val_accuracy',
    max_epochs=5,
    factor=3,
    directory=os.getcwd(),
    project_name='nml_model'
)

# Perform hyperparameter tuning
tuner.search(X_train, y_train, epochs=5, validation_data=(X_val, y_val))

# Get the best model
best_model_nml = tuner.get_best_models(num_models=1)[0]
```

```
Reloading Tuner from C:\Users\sathi\Career\Internship\AFAME\Spam SMS Detection\BE
RT\nml_model\tuner0.json
CPU times: total: 766 ms
Wall time: 1.75 s
```

In [36]:
```
# Evaluate the best model on the validation set
hp_results_val = best_model_nml.evaluate(X_val, y_val)
print(f"\nValidation Loss: {hp_results_val[0]}")
print(f"Validation Accuracy: {hp_results_val[1]}")
```

```
27/27 [==============================] - 12s 409ms/step - loss: 0.0464 - accuracy
: 0.9868 - precision: 0.9720 - recall: 0.9286

Validation Loss: 0.046408411115407944
Validation Accuracy: 0.9868420958518982
```

In [37]:
```
# Evaluate the best model on the test set
hp_results_test = best_model_nml.evaluate(X_test, y_test)
print(f"\Test Loss: {hp_results_test[0]}")
print(f"Test Accuracy: {hp_results_test[1]}")
```

```
27/27 [==============================] - 11s 413ms/step - loss: 0.0403 - accuracy
: 0.9916 - precision: 0.9817 - recall: 0.9554
\Test Loss: 0.040296293795108795
Test Accuracy: 0.9916267991065979
```

Model Building

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In [38]:
```
%%time
# Fitting best model on X_train, y_train, X_val, y_val, X_test, y_test
best_model_nml.fit(X_train, y_train, epochs=20,
                    validation_data=(X_val, y_val),
                    callbacks=[early_stopping, lr_scheduler])
```

```
Epoch 1/20
122/122 [==============================] - 69s 541ms/step - loss: 0.0681 - accura
cy: 0.9767 - precision: 0.9337 - recall: 0.8891 - val_loss: 0.0484 - val_accuracy
: 0.9844 - val_precision: 0.9304 - val_recall: 0.9554 - lr: 1.0000e-04
Epoch 2/20
122/122 [==============================] - 65s 532ms/step - loss: 0.0687 - accura
cy: 0.9756 - precision: 0.9280 - recall: 0.8872 - val_loss: 0.0435 - val_accuracy
: 0.9844 - val_precision: 0.9806 - val_recall: 0.9018 - lr: 1.0000e-04
Epoch 3/20
122/122 [==============================] - 65s 537ms/step - loss: 0.0689 - accura
cy: 0.9769 - precision: 0.9339 - recall: 0.8910 - val_loss: 0.0423 - val_accuracy
: 0.9844 - val_precision: 0.9806 - val_recall: 0.9018 - lr: 1.0000e-04
Epoch 4/20
122/122 [==============================] - 65s 533ms/step - loss: 0.0689 - accura
cy: 0.9754 - precision: 0.9261 - recall: 0.8872 - val_loss: 0.0417 - val_accuracy
: 0.9844 - val_precision: 0.9806 - val_recall: 0.9018 - lr: 1.0000e-04
Epoch 5/20
122/122 [==============================] - 66s 538ms/step - loss: 0.0640 - accura
cy: 0.9790 - precision: 0.9455 - recall: 0.8948 - val_loss: 0.0413 - val_accuracy
: 0.9844 - val_precision: 0.9806 - val_recall: 0.9018 - lr: 1.0000e-04
Epoch 6/20
122/122 [==============================] - 65s 533ms/step - loss: 0.0598 - accura
cy: 0.9818 - precision: 0.9397 - recall: 0.9235 - val_loss: 0.0416 - val_accuracy
: 0.9833 - val_precision: 0.9804 - val_recall: 0.8929 - lr: 1.0000e-04
Epoch 7/20
122/122 [==============================] - 64s 526ms/step - loss: 0.0693 - accura
cy: 0.9749 - precision: 0.9259 - recall: 0.8834 - val_loss: 0.0415 - val_accuracy
: 0.9844 - val_precision: 0.9714 - val_recall: 0.9107 - lr: 1.0000e-04
Epoch 8/20
122/122 [==============================] - 64s 524ms/step - loss: 0.0575 - accura
cy: 0.9823 - precision: 0.9614 - recall: 0.9044 - val_loss: 0.0416 - val_accuracy
: 0.9844 - val_precision: 0.9806 - val_recall: 0.9018 - lr: 2.0000e-05
CPU times: total: 5min 53s
Wall time: 8min 42s
```

Out[38]:
```
<keras.callbacks.History at 0x1bde4579b10>
```

Model Evaluation

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In [39]:
```python
y_predict_hp = best_model_nml.predict(X_test)
y_predict_hp = y_predict_hp.flatten()
```

```
27/27 [==============================] - 12s 421ms/step
```

In [40]:
```python
y_predict_hp = np.where(y_predict_hp > 0.5,1,0)
y_predict_hp
```

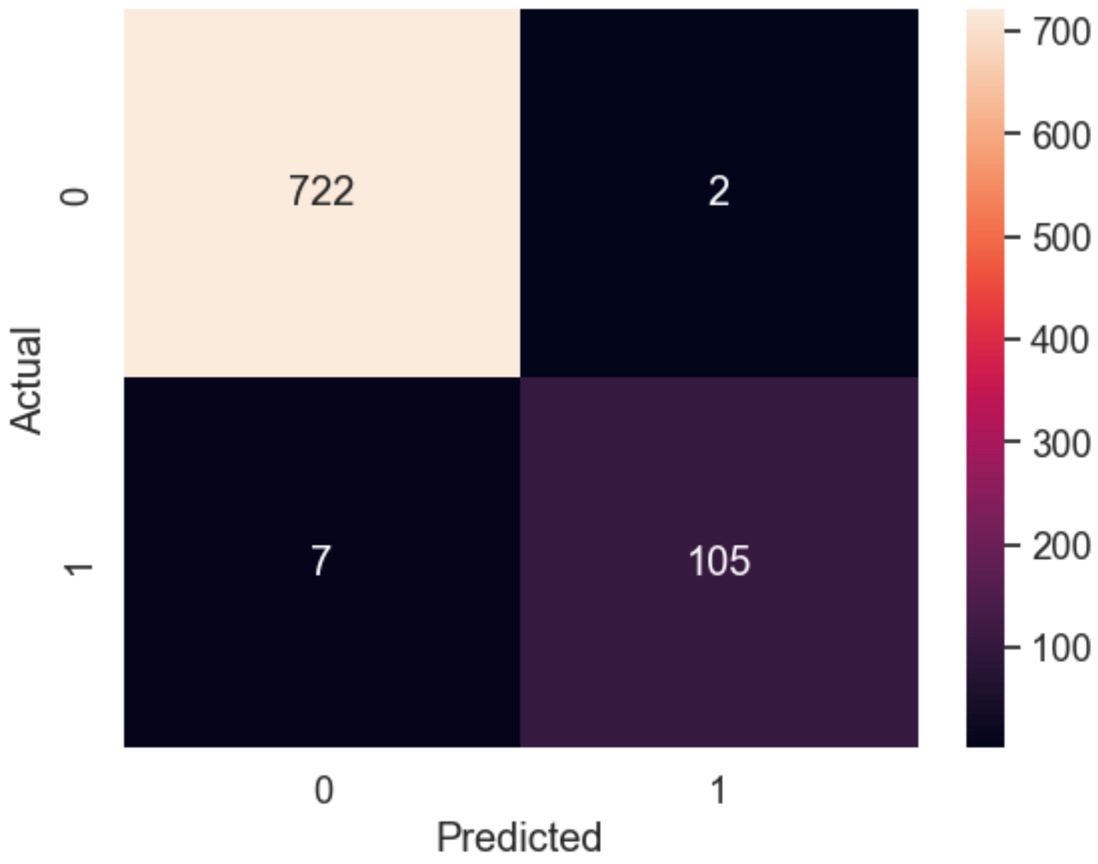
```
Out[40]: array([0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1])
```

```
In [41]: cm_hp = confusion_matrix(y_test, y_predict_hp)
cm_hp
```

```
Out[41]: array([[722,   2],
       [  7, 105]], dtype=int64)
```

```
In [42]: sns.heatmap(cm_hp, annot=True, fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

```
Out[42]: Text(43.25, 0.5, 'Actual')
```



In [43]:
```
nml_hp = classification_report(y_test, y_predict_hp, target_names=['Ham', 'Spam'
print(nml_hp)
```

```
              precision    recall  f1-score   support

         Ham       0.99      1.00      0.99       724
        Spam       0.98      0.94      0.96       112

    accuracy                           0.99       836
   macro avg       0.99      0.97      0.98       836
weighted avg       0.99      0.99      0.99       836
```

Additional Metrics (ROC-AUC) for BERT

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In [44]:
```
from sklearn.metrics import roc_auc_score

roc_auc_test = roc_auc_score(y_test, y_predict_hp)
print(f'ROC-AUC Score on Test Set: {roc_auc_test:.4f}')
```

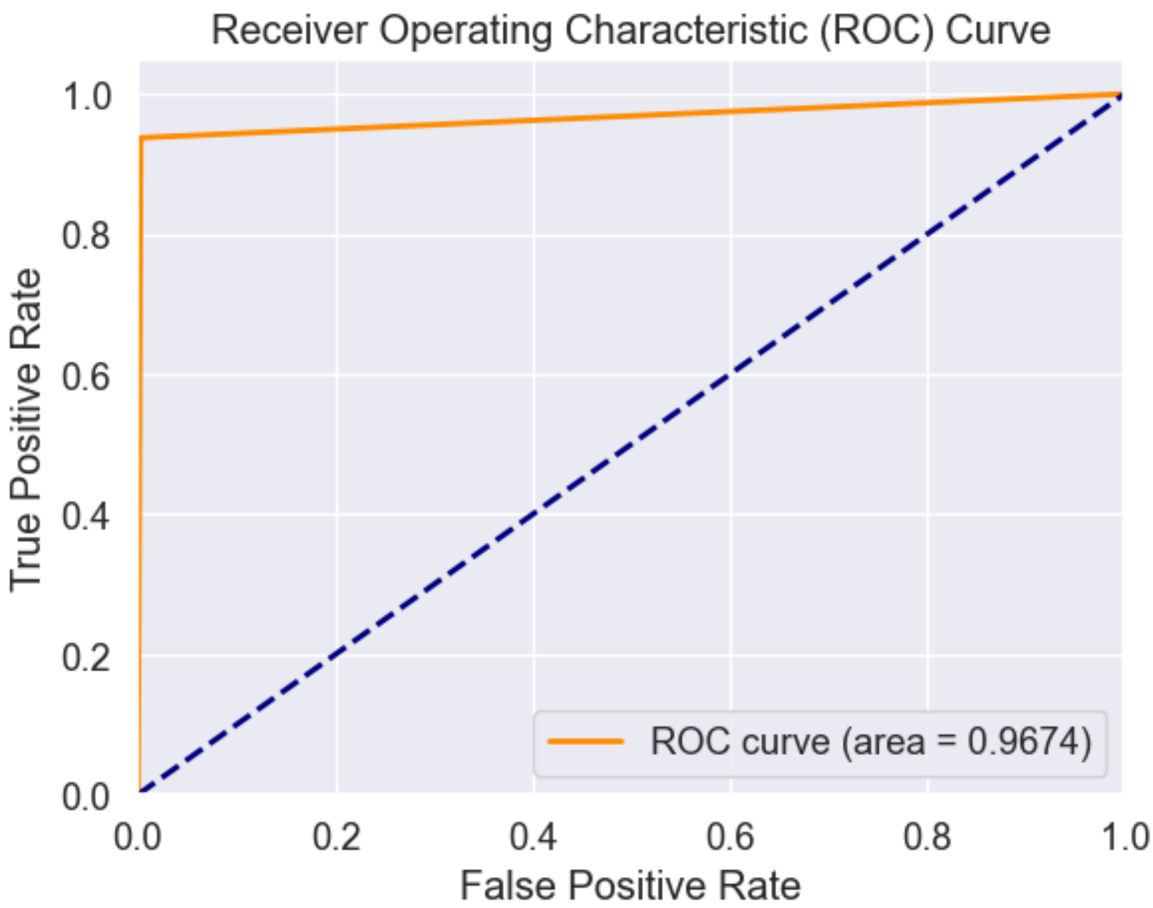
```
ROC-AUC Score on Test Set: 0.9674
```

In [45]:
```
from sklearn.metrics import roc_curve, auc

# Assuming y_test and y_predict_hp are already defined
fpr, tpr, _ = roc_curve(y_test, y_predict_hp)
roc_auc = auc(fpr, tpr)

# Plotting the ROC curve
plt.figure()
```

```
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {roc_auc:
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```



In [46]:
```
# Detection of examples
nml_inf_hp = best_model_nml.predict(reviews)
nml_inf_hp
```

```
1/1 [==============================] - 1s 921ms/step
```

Out[46]:
```
array([[0.02172732],
       [0.39693063],
       [0.2005491 ],
       [0.35874367],
       [0.00429705]], dtype=float32)
```

Downsampling Data

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In [47]:
```
data_dwn = data.copy(deep=True)
```

In [48]:
```
data_dwn.head()
```

Out[48]:

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

In [49]:
```
data_spam = data_dwn[data_dwn['Class']==1]
data_spam.shape
```

Out[49]: (747, 2)

In [50]:
```
data_ham = data_dwn[data_dwn['Class']==0]
data_ham.shape
```

Out[50]: (4825, 2)

In [51]:
```
data_ham_downsampled = data_ham.sample(data_spam.shape[0])
data_ham_downsampled.shape
```

Out[51]: (747, 2)

In [52]:
```
data_balanced_dwn = pd.concat([data_spam,data_ham_downsampled])
data_balanced_dwn.shape
```

Out[52]: (1494, 2)

In [53]:
```
data_balanced_dwn['Class'].value_counts()
```

Out[53]:
```
Class
1    747
0    747
Name: count, dtype: int64
```

Train/Test Splitting

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In [54]:
```
X_dwn = data_balanced_dwn['Text']
y_dwn = data_balanced_dwn['Class']
```

In [55]:
```
# Split data into training and temporary sets (60% train, 40% temp)
X_train_dwn, X_temp_dwn, y_train_dwn, y_temp_dwn = train_test_split(X_dwn, y_dwn

# Split temporary set into validation and test sets (20% val, 20% test)
X_val_dwn, X_test_dwn, y_val_dwn, y_test_dwn = train_test_split(X_temp_dwn, y_te

print(f'Training data: {len(X_train_dwn)}, {len(y_train_dwn)}')
print(f'Validation data: {len(X_val_dwn)}, {len(y_val_dwn)}')
print(f'Testing data: {len(X_test_dwn)}, {len(y_test_dwn)}')
```

```
Training data: 1045, 1045
Validation data: 224, 224
Testing data: 225, 225
```

Model Building

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In [56]:
```
%%time
# Fit the model
history_dwn = model.fit(X_train_dwn, y_train_dwn, epochs=20,
                        validation_data=(X_val_dwn, y_val_dwn),
                        callbacks=[early_stopping, lr_scheduler])
```

```
Epoch 1/20
33/33 [==============================] - 18s 534ms/step - loss: 0.7489 - accuracy
: 0.7522 - precision: 1.0000 - recall: 0.5048 - val_loss: 0.1234 - val_accuracy:
0.9554 - val_precision: 1.0000 - val_recall: 0.9107 - lr: 2.0000e-05
Epoch 2/20
33/33 [==============================] - 17s 517ms/step - loss: 0.7105 - accuracy
: 0.7732 - precision: 1.0000 - recall: 0.5468 - val_loss: 0.1597 - val_accuracy:
0.9330 - val_precision: 1.0000 - val_recall: 0.8661 - lr: 2.0000e-05
Epoch 3/20
33/33 [==============================] - 17s 519ms/step - loss: 0.6482 - accuracy
: 0.7876 - precision: 1.0000 - recall: 0.5755 - val_loss: 0.1856 - val_accuracy:
0.9241 - val_precision: 1.0000 - val_recall: 0.8482 - lr: 2.0000e-05
Epoch 4/20
33/33 [==============================] - 17s 524ms/step - loss: 0.6164 - accuracy
: 0.8038 - precision: 0.9969 - recall: 0.6099 - val_loss: 0.2278 - val_accuracy:
0.9196 - val_precision: 1.0000 - val_recall: 0.8393 - lr: 4.0000e-06
CPU times: total: 49.2 s
Wall time: 1min 8s
```

Model Evaluation

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In [57]:
```
# Evaluate the model
results_dwn = model.evaluate(X_test_dwn, y_test_dwn)
print(f"Test Loss: {results_dwn[0]}")
print(f"Test Accuracy: {results_dwn[1]}")
```

```
8/8 [==============================] - 3s 376ms/step - loss: 0.1270 - accuracy: 0
.9600 - precision: 1.0000 - recall: 0.9196
Test Loss: 0.12701144814491272
Test Accuracy: 0.9599999785423279
```

In [58]:
```
y_predict_dwn = model.predict(X_test_dwn)
y_predict_dwn = y_predict_dwn.flatten()
```

```
8/8 [==============================] - 3s 418ms/step
```

In [59]:
```
y_predict_dwn = np.where(y_predict_dwn > 0.5,1,0)
y_predict_dwn
```

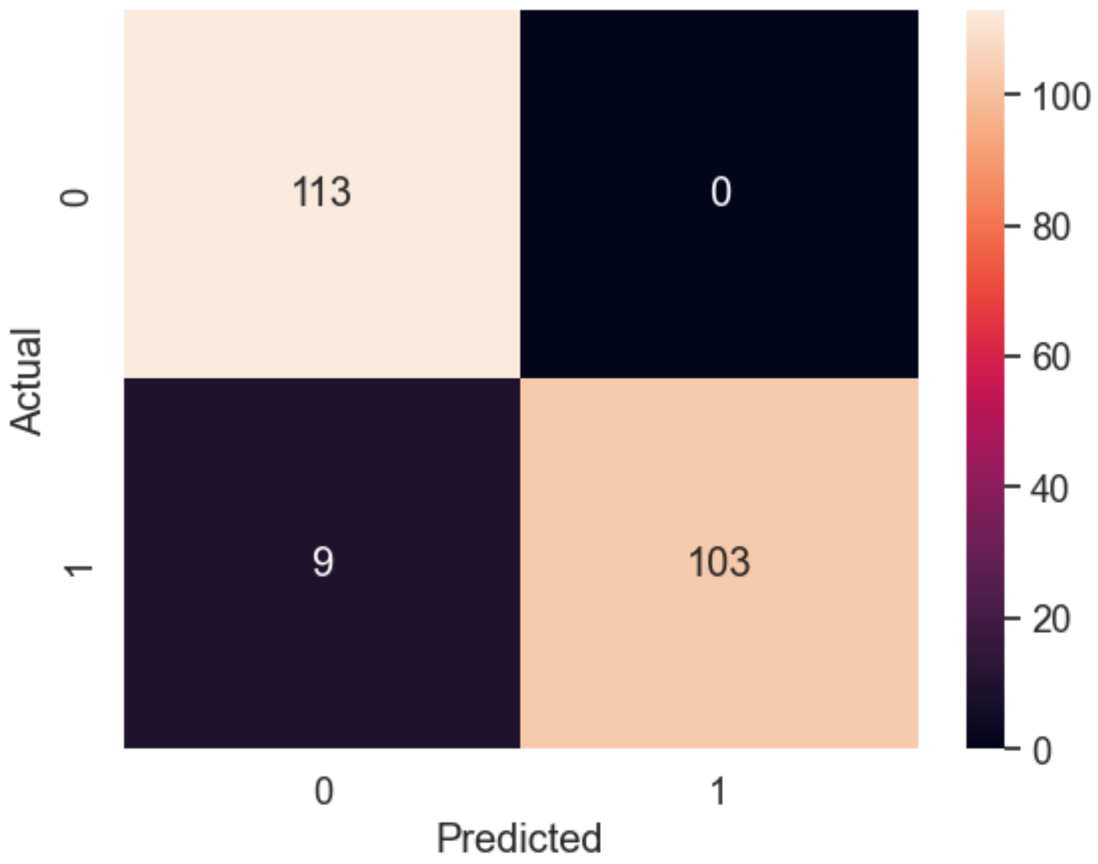
```
Out[59]: array([1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 1,
                1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0,
                0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0,
                1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1,
                1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1,
                1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1,
                1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0,
                0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0,
                1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1,
                0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 0, 1,
                1, 0, 1, 0, 1])
```

```
In [60]: cm_dwn = confusion_matrix(y_test_dwn, y_predict_dwn)
         cm_dwn
```

```
Out[60]: array([[113,   0],
                [  9, 103]], dtype=int64)
```

```
In [61]: sns.heatmap(cm_dwn, annot=True, fmt = 'd')
         plt.xlabel('Predicted')
         plt.ylabel('Actual')
```

```
Out[61]: Text(43.25, 0.5, 'Actual')
```




```
In [62]: dwn = classification_report(y_test_dwn, y_predict_dwn, target_names=['Ham', 'Spa
         print(dwn)
```

```
              precision    recall  f1-score   support

         Ham       0.93      1.00      0.96       113
        Spam       1.00      0.92      0.96       112

    accuracy                           0.96       225
   macro avg       0.96      0.96      0.96       225
weighted avg       0.96      0.96      0.96       225
```

In [63]:
```
# Detection of examples
dwn_inf = model.predict(reviews)
dwn_inf
```

```
1/1 [==============================] - 0s 47ms/step
```

Out[63]:
```
array([[0.00748722],
       [0.21018825],
       [0.08766864],
       [0.2078424 ],
       [0.00202337]], dtype=float32)
```

Hyperparameter Tuning with Keras Tuner (Downsampled Data)

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In [64]:
```
%%time
# Initialize Keras Tuner with the existing model
tuner = kt.Hyperband(
    compile_model,
    objective='val_accuracy',
    max_epochs=5,
    factor=3,
    directory=os.getcwd(),
    project_name='dwn_model'
)

# Perform hyperparameter tuning
tuner.search(X_train_dwn, y_train_dwn, epochs=5, validation_data=(X_val_dwn, y_v

# Get the best model
best_model_dwn = tuner.get_best_models(num_models=1)[0]
```

```
Reloading Tuner from C:\Users\sathi\Career\Internship\AFAME\Spam SMS Detection\BE
RT\dwn_model\tuner0.json
CPU times: total: 828 ms
Wall time: 1.65 s
```

In [65]:
```
# Evaluate the best model on the validation set
hp_results_val_dwn = best_model_dwn.evaluate(X_val_dwn, y_val_dwn)
print(f"\nValidation Loss: {hp_results_val[0]}")
print(f"Validation Accuracy: {hp_results_val[1]}")
```

```
7/7 [==============================] - 4s 423ms/step - loss: 0.0493 - accuracy: 0
.9733 - precision: 0.9953 - recall: 0.9509

Validation Loss: 0.046408411115407944
Validation Accuracy: 0.9868420958518982
```

In [66]:
```python
# Evaluate the best model on the Test set
hp_results_test_dwn = best_model_dwn.evaluate(X_test_dwn, y_test_dwn)
print(f"\Test Loss: {hp_results_test_dwn[0]}")
print(f"Test Accuracy: {hp_results_test_dwn[1]}")
```

```
8/8 [==============================] - 4s 372ms/step - loss: 0.1388 - accuracy: 0
.9511 - precision: 0.9391 - recall: 0.9643
\Test Loss: 0.13879336416721344
Test Accuracy: 0.9511111378669739
```

Model Building

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In [67]:
```python
%%time
# Fitting best model on X_train, y_train, X_val, y_val, X_test, y_test
best_model_dwn.fit(X_train_dwn, y_train_dwn, epochs=20,
                    validation_data=(X_val_dwn, y_val_dwn),
                    callbacks=[early_stopping, lr_scheduler])
```

```
Epoch 1/20
33/33 [==============================] - 21s 547ms/step - loss: 0.2156 - accuracy
: 0.9359 - precision: 0.9831 - recall: 0.8872 - val_loss: 0.7917 - val_accuracy:
0.7411 - val_precision: 0.6588 - val_recall: 1.0000 - lr: 0.0010
Epoch 2/20
33/33 [==============================] - 17s 525ms/step - loss: 0.1898 - accuracy
: 0.9349 - precision: 0.9577 - recall: 0.9101 - val_loss: 0.1175 - val_accuracy:
0.9598 - val_precision: 0.9328 - val_recall: 0.9911 - lr: 0.0010
Epoch 3/20
33/33 [==============================] - 17s 528ms/step - loss: 0.1424 - accuracy
: 0.9608 - precision: 0.9671 - recall: 0.9541 - val_loss: 0.0829 - val_accuracy:
0.9777 - val_precision: 0.9908 - val_recall: 0.9643 - lr: 0.0010
Epoch 4/20
33/33 [==============================] - 17s 527ms/step - loss: 0.1279 - accuracy
: 0.9627 - precision: 0.9672 - recall: 0.9579 - val_loss: 0.0738 - val_accuracy:
0.9777 - val_precision: 0.9820 - val_recall: 0.9732 - lr: 0.0010
Epoch 5/20
33/33 [==============================] - 17s 513ms/step - loss: 0.1582 - accuracy
: 0.9541 - precision: 0.9612 - recall: 0.9465 - val_loss: 0.1764 - val_accuracy:
0.9196 - val_precision: 0.8672 - val_recall: 0.9911 - lr: 0.0010
Epoch 6/20
33/33 [==============================] - 17s 514ms/step - loss: 0.1145 - accuracy
: 0.9656 - precision: 0.9692 - recall: 0.9618 - val_loss: 0.1427 - val_accuracy:
0.9420 - val_precision: 0.9024 - val_recall: 0.9911 - lr: 0.0010
Epoch 7/20
33/33 [==============================] - 17s 527ms/step - loss: 0.1315 - accuracy
: 0.9512 - precision: 0.9591 - recall: 0.9426 - val_loss: 0.1130 - val_accuracy:
0.9554 - val_precision: 0.9250 - val_recall: 0.9911 - lr: 2.0000e-04
CPU times: total: 1min 29s
Wall time: 2min 3s
```

Out[67]:
```
<keras.callbacks.History at 0x1bd01c623e0>
```

Model Evaluation

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In [68]:
```
y_predict_hp_dwn = best_model_dwn.predict(X_test_dwn)
y_predict_hp_dwn = y_predict_hp_dwn.flatten()
```

```
8/8 [==============================] - 4s 416ms/step
```

In [69]:
```
y_predict_hp_dwn = np.where(y_predict_hp_dwn > 0.5,1,0)
y_predict_hp_dwn
```

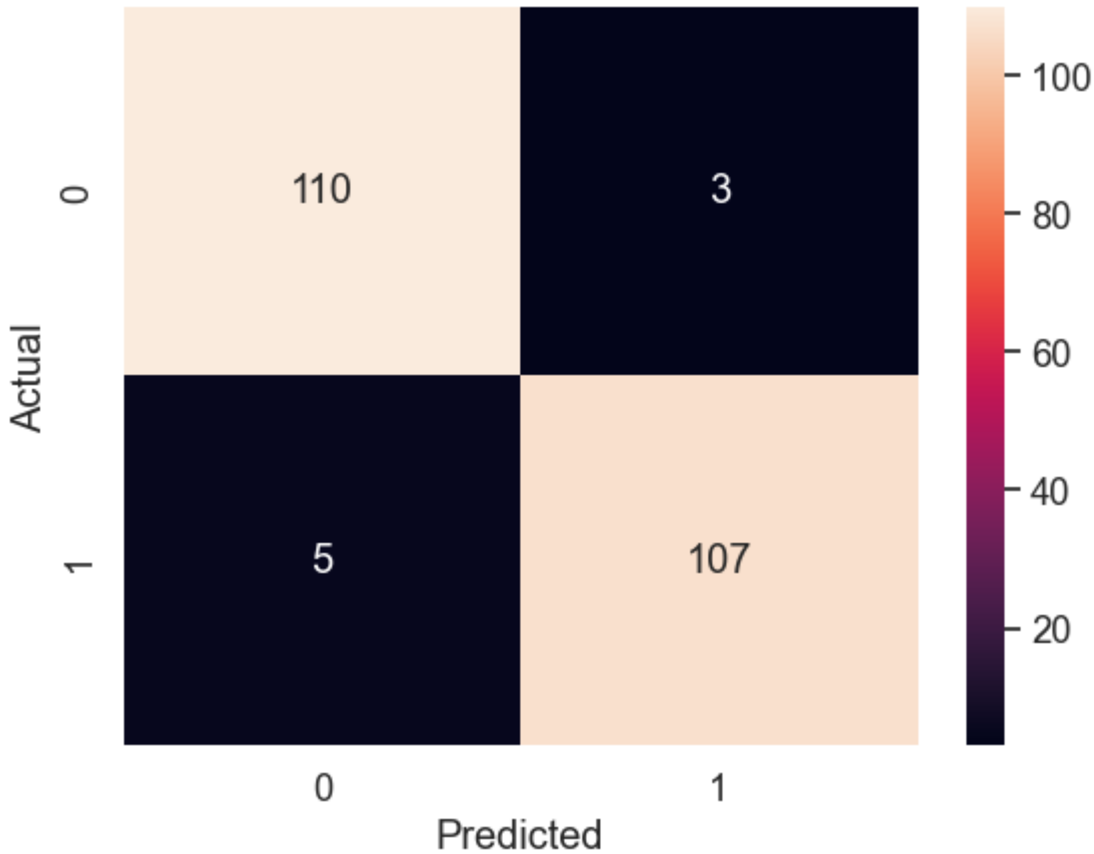
Out[69]:
```
array([1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1,
       1, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0,
       1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1,
       1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 0, 1,
       1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 0, 1, 1, 1,
       1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0,
       1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1,
       1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1, 0, 1,
       1, 0, 1, 0, 1])
```

In [70]:
```
cm_hp_dwn = confusion_matrix(y_test_dwn, y_predict_hp_dwn)
cm_hp_dwn
```

Out[70]:
```
array([[110,   3],
       [  5, 107]], dtype=int64)
```

In [71]:
```
sns.heatmap(cm_hp_dwn, annot=True, fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

Out[71]:
```
Text(43.25, 0.5, 'Actual')
```



In [72]:
```
dwn_hp = classification_report(y_test_dwn, y_predict_hp_dwn, target_names=['Ham'
print(dwn_hp)
```

```
              precision    recall  f1-score   support

         Ham       0.96      0.97      0.96       113
        Spam       0.97      0.96      0.96       112

    accuracy                           0.96       225
   macro avg       0.96      0.96      0.96       225
weighted avg       0.96      0.96      0.96       225
```

Additional Metrics (ROC-AUC) for BERT

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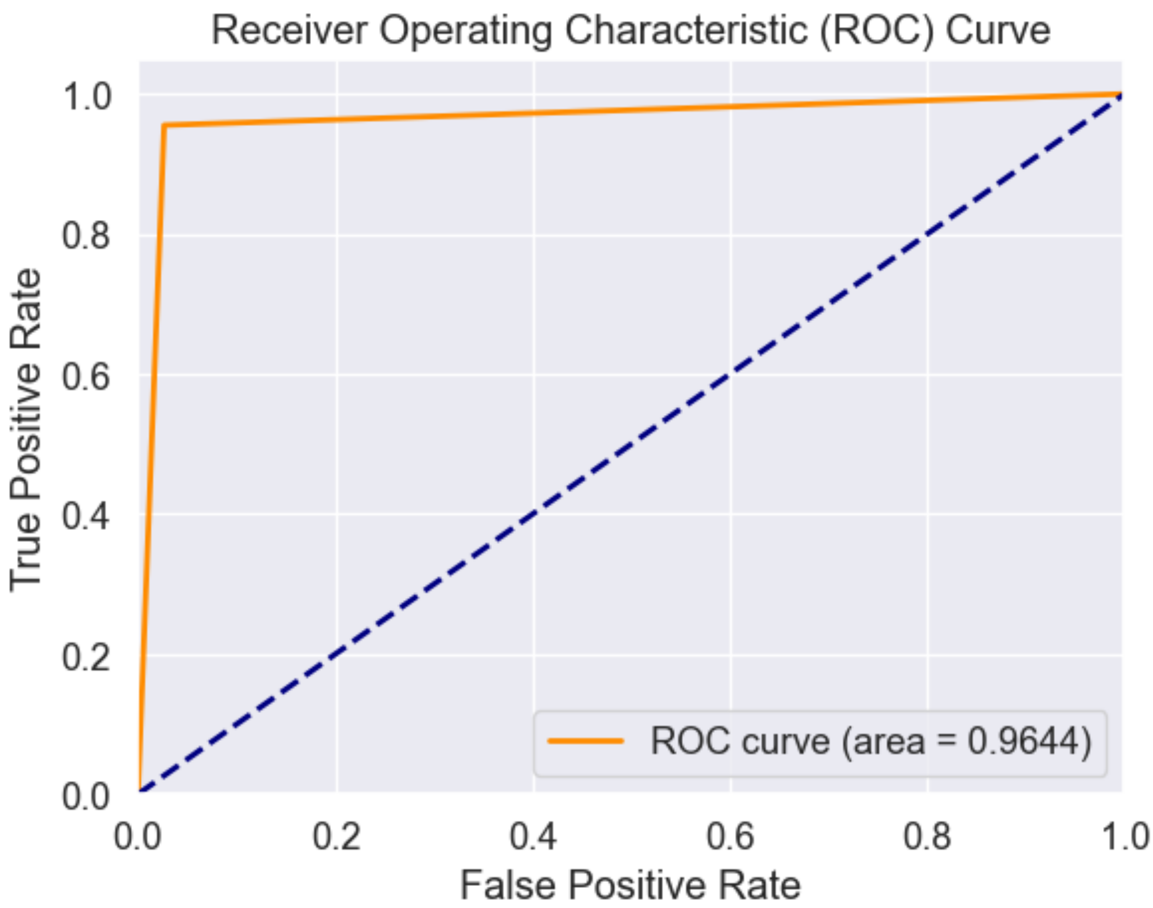
In [73]:
```
roc_auc_test = roc_auc_score(y_test_dwn, y_predict_hp_dwn)
print(f'ROC-AUC Score on Test Set: {roc_auc_test:.4f}')
```

```
ROC-AUC Score on Test Set: 0.9644
```

In [74]:
```
# y_test and y_predict_hp are already defined
fpr, tpr, _ = roc_curve(y_test_dwn, y_predict_hp_dwn)
roc_auc = auc(fpr, tpr)

# Plotting the ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {roc_auc:
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```



In [75]:
```
# Detection of examples
dwn_inf_hp = best_model_dwn.predict(reviews)
dwn_inf_hp
```

```
1/1 [==============================] - 1s 839ms/step
```

Out[75]:
```
array([[0.04702015],
       [0.44492415],
       [0.8023651 ],
       [0.7688524 ],
       [0.00090111]], dtype=float32)
```

Upsampling Data

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In [76]:
```
data_up = data.copy(deep=True)
data_up
```

Out[76]:

	Class	Text
0	0	Go until jurong point, crazy.. Available only ...
1	0	Ok lar... Joking wif u oni...
2	1	Free entry in 2 a wkly comp to win FA Cup fina...
3	0	U dun say so early hor... U c already then say...
4	0	Nah I don't think he goes to usf, he lives aro...
...	...	...
5567	1	This is the 2nd time we have tried 2 contact u...
5568	0	Will Ì_ b going to esplanade fr home?
5569	0	Pity, * was in mood for that. So...any other s...
5570	0	The guy did some bitching but I acted like i'd...
5571	0	Rofl. Its true to its name

5572 rows × 2 columns

In [77]:
```
data_spam_up = data_up[data_up['Class']==1]
data_spam_up.shape
```

Out[77]: (747, 2)

In [78]:
```
data_ham_up = data_up[data_up['Class']==0]
data_ham_up.shape
```

Out[78]: (4825, 2)

In [79]:
```
data_spam_upsampled = data_spam_up.sample(data_ham_up.shape[0], replace=True)
data_spam_upsampled.shape
```

Out[79]: (4825, 2)

In [80]:
```
data_balanced_up = pd.concat([data_ham_up,data_spam_upsampled])
data_balanced_up.shape
```

Out[80]: (9650, 2)

In [81]:
```
data_balanced_up['Class'].value_counts()
```

Out[81]:
```
Class
0    4825
1    4825
Name: count, dtype: int64
```

Train/Test Splitting

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In [82]:
```
X_up = data_balanced_up['Text']
```

```python
y_up = data_balanced_up['Class']
```

In [83]:
```python
# Split data into training and temporary sets (60% train, 40% temp)
X_train_up, X_temp_up, y_train_up, y_temp_up = train_test_split(X_up, y_up, test_

# Split temporary set into validation and test sets (20% val, 20% test)
X_val_up, X_test_up, y_val_up, y_test_up = train_test_split(X_temp_up, y_temp_up

print(f'Training data: {len(X_train_up)}, {len(y_train_up)}')
print(f'Validation data: {len(X_val_up)}, {len(y_val_up)}')
print(f'Testing data: {len(X_test_up)}, {len(y_test_up)}')
```

```
Training data: 6755, 6755
Validation data: 1447, 1447
Testing data: 1448, 1448
```

Model Building

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In [84]:
```python
%%time
# Fit the model
history_up = model.fit(X_train_up, y_train_up, epochs=20,
                    validation_data=(X_val_up, y_val_up),
                    callbacks=[early_stopping, lr_scheduler])
```

```
Epoch 1/20
212/212 [==============================] - 111s 522ms/step - loss: 0.1430 - accur
acy: 0.9560 - precision: 0.9622 - recall: 0.9494 - val_loss: 0.0633 - val_accurac
y: 0.9786 - val_precision: 0.9613 - val_recall: 0.9972 - lr: 2.0000e-04
Epoch 2/20
212/212 [==============================] - 109s 516ms/step - loss: 0.1374 - accur
acy: 0.9560 - precision: 0.9573 - recall: 0.9547 - val_loss: 0.0504 - val_accurac
y: 0.9834 - val_precision: 0.9768 - val_recall: 0.9903 - lr: 2.0000e-04
Epoch 3/20
212/212 [==============================] - 110s 521ms/step - loss: 0.1221 - accur
acy: 0.9587 - precision: 0.9605 - recall: 0.9568 - val_loss: 0.0529 - val_accurac
y: 0.9786 - val_precision: 0.9873 - val_recall: 0.9696 - lr: 2.0000e-04
Epoch 4/20
212/212 [==============================] - 111s 525ms/step - loss: 0.1245 - accur
acy: 0.9585 - precision: 0.9586 - recall: 0.9586 - val_loss: 0.0444 - val_accurac
y: 0.9869 - val_precision: 0.9848 - val_recall: 0.9889 - lr: 2.0000e-04
Epoch 5/20
212/212 [==============================] - 111s 522ms/step - loss: 0.1109 - accur
acy: 0.9634 - precision: 0.9636 - recall: 0.9633 - val_loss: 0.0470 - val_accurac
y: 0.9834 - val_precision: 0.9794 - val_recall: 0.9876 - lr: 2.0000e-04
Epoch 6/20
212/212 [==============================] - 110s 521ms/step - loss: 0.1191 - accur
acy: 0.9617 - precision: 0.9637 - recall: 0.9594 - val_loss: 0.0523 - val_accurac
y: 0.9779 - val_precision: 0.9832 - val_recall: 0.9723 - lr: 2.0000e-04
Epoch 7/20
212/212 [==============================] - 111s 522ms/step - loss: 0.1056 - accur
acy: 0.9639 - precision: 0.9628 - recall: 0.9651 - val_loss: 0.0428 - val_accurac
y: 0.9862 - val_precision: 0.9835 - val_recall: 0.9889 - lr: 4.0000e-05
Epoch 8/20
212/212 [==============================] - 111s 525ms/step - loss: 0.1062 - accur
acy: 0.9630 - precision: 0.9633 - recall: 0.9627 - val_loss: 0.0425 - val_accurac
y: 0.9889 - val_precision: 0.9862 - val_recall: 0.9917 - lr: 4.0000e-05
Epoch 9/20
212/212 [==============================] - 112s 527ms/step - loss: 0.0998 - accur
acy: 0.9633 - precision: 0.9606 - recall: 0.9663 - val_loss: 0.0425 - val_accurac
y: 0.9883 - val_precision: 0.9849 - val_recall: 0.9917 - lr: 4.0000e-05
Epoch 10/20
212/212 [==============================] - 114s 539ms/step - loss: 0.1071 - accur
acy: 0.9630 - precision: 0.9630 - recall: 0.9630 - val_loss: 0.0431 - val_accurac
y: 0.9883 - val_precision: 0.9862 - val_recall: 0.9903 - lr: 4.0000e-05
Epoch 11/20
212/212 [==============================] - 113s 533ms/step - loss: 0.1030 - accur
acy: 0.9662 - precision: 0.9668 - recall: 0.9657 - val_loss: 0.0424 - val_accurac
y: 0.9883 - val_precision: 0.9849 - val_recall: 0.9917 - lr: 8.0000e-06
Epoch 12/20
212/212 [==============================] - 112s 528ms/step - loss: 0.1062 - accur
acy: 0.9654 - precision: 0.9621 - recall: 0.9689 - val_loss: 0.0427 - val_accurac
y: 0.9855 - val_precision: 0.9769 - val_recall: 0.9945 - lr: 8.0000e-06
Epoch 13/20
212/212 [==============================] - 112s 527ms/step - loss: 0.1018 - accur
acy: 0.9624 - precision: 0.9613 - recall: 0.9636 - val_loss: 0.0414 - val_accurac
y: 0.9889 - val_precision: 0.9862 - val_recall: 0.9917 - lr: 1.6000e-06
Epoch 14/20
212/212 [==============================] - 112s 528ms/step - loss: 0.1032 - accur
acy: 0.9643 - precision: 0.9636 - recall: 0.9651 - val_loss: 0.0417 - val_accurac
y: 0.9883 - val_precision: 0.9849 - val_recall: 0.9917 - lr: 1.6000e-06
Epoch 15/20
212/212 [==============================] - 112s 527ms/step - loss: 0.1029 - accur
acy: 0.9657 - precision: 0.9637 - recall: 0.9677 - val_loss: 0.0416 - val_accurac
y: 0.9889 - val_precision: 0.9862 - val_recall: 0.9917 - lr: 1.6000e-06
```

```
Epoch 16/20
212/212 [==============================] - 112s 528ms/step - loss: 0.1084 - accur
acy: 0.9631 - precision: 0.9636 - recall: 0.9627 - val_loss: 0.0417 - val_accurac
y: 0.9889 - val_precision: 0.9862 - val_recall: 0.9917 - lr: 3.2000e-07
CPU times: total: 20min 25s
Wall time: 29min 42s
```

Model Evaluation

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In [85]:
```
# Evaluate the model
results_up = model.evaluate(X_test_up, y_test_up)
print(f"Test Loss: {results_up[0]}")
print(f"Test Accuracy: {results_up[1]}")
```

```
46/46 [==============================] - 20s 425ms/step - loss: 0.0483 - accuracy
: 0.9827 - precision: 0.9781 - recall: 0.9876
Test Loss: 0.04834875836968422
Test Accuracy: 0.9827347993850708
```

In [86]:
```
y_predict_up = model.predict(X_test_up)
y_predict_up = y_predict_up.flatten()
```

```
46/46 [==============================] - 19s 423ms/step
```

In [87]:
```
y_predict_up = np.where(y_predict_up > 0.5,1,0)
y_predict_up
```

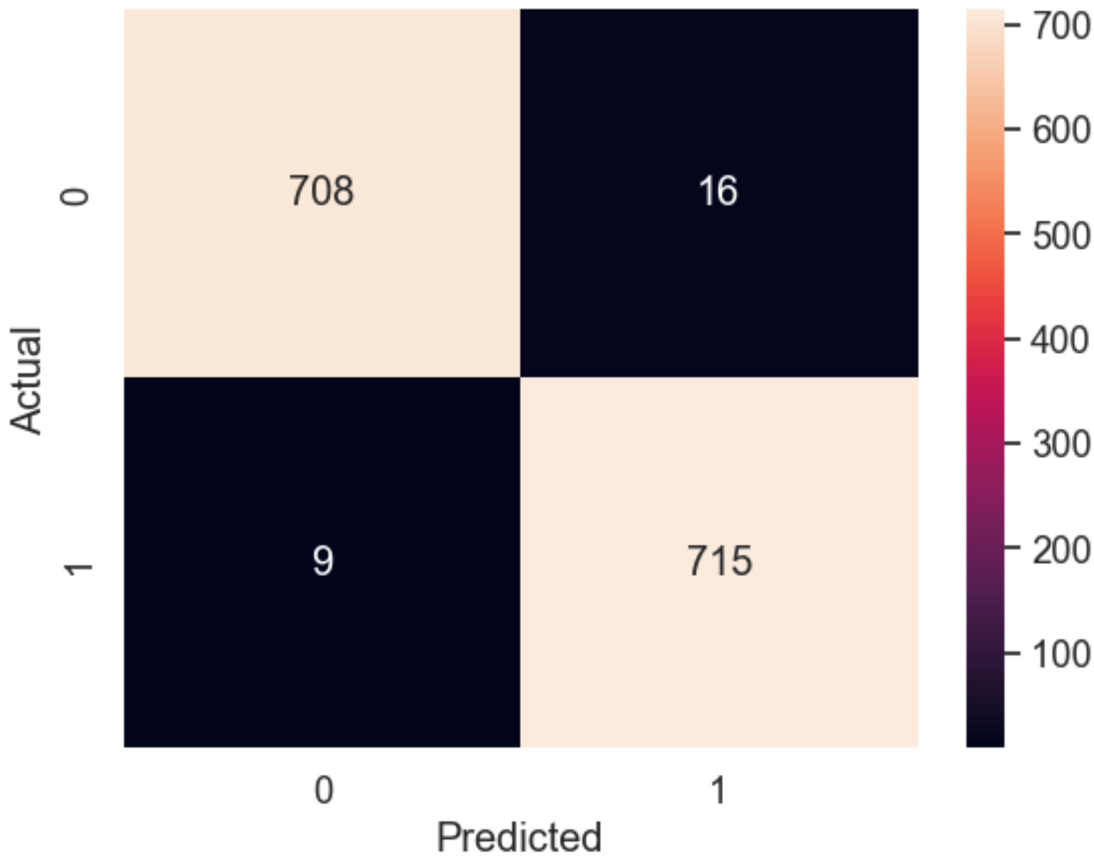
Out[87]:
```
array([1, 1, 1, ..., 1, 0, 1])
```

In [88]:
```
cm_up = confusion_matrix(y_test_up, y_predict_up)
cm_up
```

Out[88]:
```
array([[708,  16],
       [  9, 715]], dtype=int64)
```

In [89]:
```
sns.heatmap(cm_up, annot=True, fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

Out[89]:
```
Text(43.25, 0.5, 'Actual')
```



In [90]:
```
up = classification_report(y_test_up, y_predict_up, target_names=['Ham', 'Spam']
print(up)
```

```
              precision    recall  f1-score   support

         Ham       0.99      0.98      0.98       724
        Spam       0.98      0.99      0.98       724

    accuracy                           0.98      1448
   macro avg       0.98      0.98      0.98      1448
weighted avg       0.98      0.98      0.98      1448
```

In [91]:
```
# Detection of examples
up_inf = model.predict(reviews)
up_inf
```

```
1/1 [==============================] - 0s 48ms/step
```

Out[91]:
```
array([[0.21406454],
       [0.7806962 ],
       [0.7113453 ],
       [0.7660223 ],
       [0.00785503]], dtype=float32)
```

Hyperparameter Tuning with Keras Tuner (Upsampled Data)

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In [92]:
```
%%time
# Initialize Keras Tuner with the existing model
```

```
tuner = kt.Hyperband(
    compile_model,
    objective='val_accuracy',
    max_epochs=5,
    factor=3,
    directory=os.getcwd(),
    project_name='up_model'
)

# Perform hyperparameter tuning
tuner.search(X_train_up, y_train_up, epochs=5, validation_data=(X_val_up, y_val_

# Get the best model
best_model_up = tuner.get_best_models(num_models=1)[0]
```

```
Reloading Tuner from C:\Users\sathi\Career\Internship\AFAME\Spam SMS Detection\BE
RT\up_model\tuner0.json
CPU times: total: 812 ms
Wall time: 2.2 s
```

In [93]:

```
# Evaluate the best model on the validation set
hp_results_val_up = best_model_up.evaluate(X_val_up, y_val_up)
print(f"\nValidation Loss: {hp_results_val_up[0]}")
print(f"Validation Accuracy: {hp_results_val_up[1]}")
```

```
46/46 [==============================] - 21s 424ms/step - loss: 0.2839 - accuracy
: 0.9592 - precision: 0.9819 - recall: 0.9357

Validation Loss: 0.28387752175331116
Validation Accuracy: 0.9592400789260864
```

In [94]:

```
# Evaluate the best model on the Test set
hp_results_test_up = best_model_up.evaluate(X_test_up, y_test_up)
print(f"\Test Loss: {hp_results_test_up[0]}")
print(f"Test Accuracy: {hp_results_test_up[1]}")
```

```
46/46 [==============================] - 20s 425ms/step - loss: 0.3052 - accuracy
: 0.9289 - precision: 0.9829 - recall: 0.8729
\Test Loss: 0.30517911911101074
Test Accuracy: 0.9288673996925354
```

Model Building

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In [95]:

```
%%time
# Fitting best model on X_train, y_train, X_val, y_val, X_test, y_test
best_model_up.fit(X_train_up, y_train_up, epochs=20,
                    validation_data=(X_val_up, y_val_up),
                    callbacks=[early_stopping, lr_scheduler])
```

```
Epoch 1/20
212/212 [==============================] - 115s 528ms/step - loss: 0.1590 - accur
acy: 0.9442 - precision: 0.9446 - recall: 0.9438 - val_loss: 0.1823 - val_accurac
y: 0.9302 - val_precision: 0.8793 - val_recall: 0.9972 - lr: 0.0100
Epoch 2/20
212/212 [==============================] - 113s 532ms/step - loss: 0.1397 - accur
acy: 0.9482 - precision: 0.9487 - recall: 0.9476 - val_loss: 0.0907 - val_accurac
y: 0.9682 - val_precision: 0.9971 - val_recall: 0.9391 - lr: 0.0100
Epoch 3/20
212/212 [==============================] - 112s 529ms/step - loss: 0.1398 - accur
acy: 0.9510 - precision: 0.9533 - recall: 0.9485 - val_loss: 0.5105 - val_accurac
y: 0.7630 - val_precision: 0.6782 - val_recall: 1.0000 - lr: 0.0100
Epoch 4/20
212/212 [==============================] - 110s 520ms/step - loss: 0.1400 - accur
acy: 0.9491 - precision: 0.9496 - recall: 0.9485 - val_loss: 0.0769 - val_accurac
y: 0.9730 - val_precision: 0.9817 - val_recall: 0.9640 - lr: 0.0100
Epoch 5/20
212/212 [==============================] - 110s 518ms/step - loss: 0.1226 - accur
acy: 0.9565 - precision: 0.9589 - recall: 0.9538 - val_loss: 0.0684 - val_accurac
y: 0.9744 - val_precision: 0.9738 - val_recall: 0.9751 - lr: 0.0100
Epoch 6/20
212/212 [==============================] - 112s 530ms/step - loss: 0.1300 - accur
acy: 0.9510 - precision: 0.9538 - recall: 0.9479 - val_loss: 0.0652 - val_accurac
y: 0.9737 - val_precision: 0.9561 - val_recall: 0.9931 - lr: 0.0100
Epoch 7/20
212/212 [==============================] - 112s 530ms/step - loss: 0.1250 - accur
acy: 0.9560 - precision: 0.9586 - recall: 0.9532 - val_loss: 0.0522 - val_accurac
y: 0.9793 - val_precision: 0.9846 - val_recall: 0.9737 - lr: 0.0100
Epoch 8/20
212/212 [==============================] - 111s 524ms/step - loss: 0.1160 - accur
acy: 0.9596 - precision: 0.9622 - recall: 0.9568 - val_loss: 0.0911 - val_accurac
y: 0.9634 - val_precision: 0.9589 - val_recall: 0.9682 - lr: 0.0100
Epoch 9/20
212/212 [==============================] - 110s 520ms/step - loss: 0.1182 - accur
acy: 0.9587 - precision: 0.9610 - recall: 0.9562 - val_loss: 0.0638 - val_accurac
y: 0.9772 - val_precision: 0.9650 - val_recall: 0.9903 - lr: 0.0100
Epoch 10/20
212/212 [==============================] - 111s 525ms/step - loss: 0.1066 - accur
acy: 0.9618 - precision: 0.9594 - recall: 0.9645 - val_loss: 0.0484 - val_accurac
y: 0.9827 - val_precision: 0.9929 - val_recall: 0.9723 - lr: 0.0020
Epoch 11/20
212/212 [==============================] - 113s 534ms/step - loss: 0.1021 - accur
acy: 0.9633 - precision: 0.9677 - recall: 0.9586 - val_loss: 0.0475 - val_accurac
y: 0.9862 - val_precision: 0.9930 - val_recall: 0.9793 - lr: 0.0020
Epoch 12/20
212/212 [==============================] - 112s 528ms/step - loss: 0.0997 - accur
acy: 0.9645 - precision: 0.9656 - recall: 0.9633 - val_loss: 0.0418 - val_accurac
y: 0.9896 - val_precision: 0.9876 - val_recall: 0.9917 - lr: 0.0020
Epoch 13/20
212/212 [==============================] - 111s 525ms/step - loss: 0.1025 - accur
acy: 0.9643 - precision: 0.9656 - recall: 0.9630 - val_loss: 0.0560 - val_accurac
y: 0.9800 - val_precision: 0.9957 - val_recall: 0.9640 - lr: 0.0020
Epoch 14/20
212/212 [==============================] - 112s 529ms/step - loss: 0.1062 - accur
acy: 0.9627 - precision: 0.9649 - recall: 0.9603 - val_loss: 0.0441 - val_accurac
y: 0.9876 - val_precision: 0.9930 - val_recall: 0.9820 - lr: 0.0020
Epoch 15/20
212/212 [==============================] - 111s 525ms/step - loss: 0.0974 - accur
acy: 0.9661 - precision: 0.9679 - recall: 0.9642 - val_loss: 0.0427 - val_accurac
y: 0.9896 - val_precision: 0.9917 - val_recall: 0.9876 - lr: 4.0000e-04
```

```
CPU times: total: 19min 5s
Wall time: 27min 56s
```

Out[95]:
```
<keras.callbacks.History at 0x1be44de0640>
```

Model Evaluation

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In [96]:
```
y_predict_hp_up = best_model_up.predict(X_test_up)
y_predict_hp_up = y_predict_hp_up.flatten()
```

```
46/46 [==============================] - 20s 421ms/step
```

In [97]:
```
y_predict_hp_up = np.where(y_predict_hp_up > 0.5,1,0)
y_predict_hp_up
```

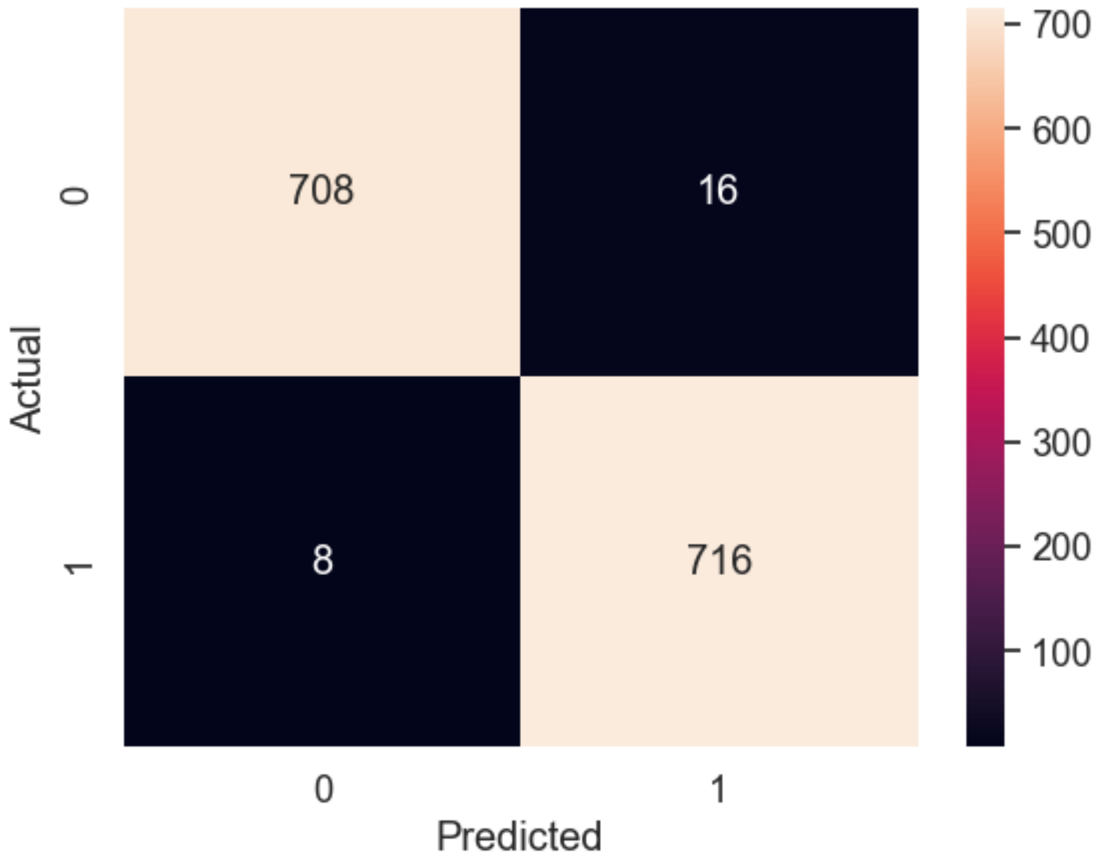
Out[97]:
```
array([1, 1, 1, ..., 1, 0, 1])
```

In [98]:
```
cm_hp_up = confusion_matrix(y_test_up, y_predict_hp_up)
cm_hp_up
```

Out[98]:
```
array([[708,  16],
       [  8, 716]], dtype=int64)
```

In [99]:
```
sns.heatmap(cm_hp_up, annot=True, fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

Out[99]:
```
Text(43.25, 0.5, 'Actual')
```



In [100…
```
up_hp = classification_report(y_test_up, y_predict_hp_up, target_names=['Ham', '
```

```
print(up_hp)
```

```
              precision    recall  f1-score   support

         Ham       0.99      0.98      0.98       724
        Spam       0.98      0.99      0.98       724

    accuracy                           0.98      1448
   macro avg       0.98      0.98      0.98      1448
weighted avg       0.98      0.98      0.98      1448
```

Additional Metrics (ROC-AUC) for BERT

Table of Contents

In [101…

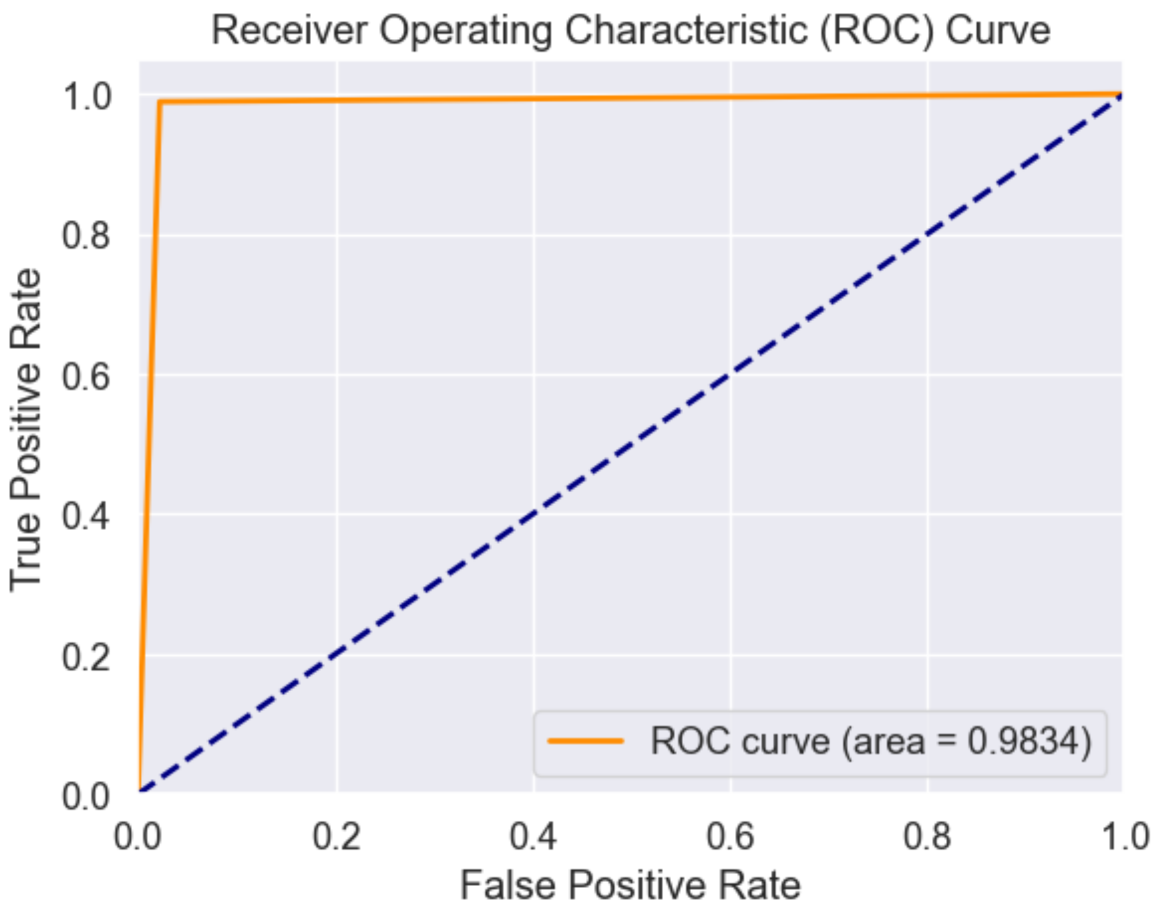
```
roc_auc_test = roc_auc_score(y_test_up, y_predict_hp_up)
print(f'ROC-AUC Score on Test Set: {roc_auc_test:.4f}')
```

```
ROC-AUC Score on Test Set: 0.9834
```

In [102…

```
# y_test and y_predict_hp are already defined
fpr, tpr, _ = roc_curve(y_test_up, y_predict_hp_up)
roc_auc = auc(fpr, tpr)

# Plotting the ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {roc_auc:
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```



In [103…
```
# Detection of examples
up_inf_hp = best_model_up.predict(reviews)
up_inf_hp
```

```
1/1 [==============================] - 1s 746ms/step
```

Out[103…
```
array([[0.36807302],
       [0.89284533],
       [0.7597308 ],
       [0.90501106],
       [0.00621142]], dtype=float32)
```

Class Weights

Table of Contents

In [104…
```
# Calculate class weights
class_weights = {
    0: len(y_train) / (2 * (len(y_train) - np.sum(y_train))),  # Weight for ham
    1: len(y_train) / (2 * np.sum(y_train))  # Weight for spam
}
```

In [105…
```
%%time
clw_model = tf.keras.models.clone_model(model)
```

```
CPU times: total: 10.2 s
Wall time: 11.5 s
```

In [106…
```
# Compile the model with class weights
clw_model.compile(optimizer=Adam(learning_rate=0.001),
                  loss='binary_crossentropy',
```

```
                  metrics = metrics)
```

Model Building

Table of Contents

In [107…

```
%%time
# Fit the model
history_clw = model.fit(X_train, y_train, epochs=20,
                    validation_data=(X_val, y_val),
                    class_weight=class_weights,
                    callbacks=[early_stopping, lr_scheduler])
```

```
Epoch 1/20
122/122 [==============================] - 68s 543ms/step - loss: 0.3629 - accura
cy: 0.7838 - precision: 0.3827 - recall: 0.9981 - val_loss: 0.1253 - val_accuracy
: 0.9605 - val_precision: 0.7762 - val_recall: 0.9911 - lr: 4.0000e-04
Epoch 2/20
122/122 [==============================] - 65s 534ms/step - loss: 0.1899 - accura
cy: 0.8808 - precision: 0.5297 - recall: 0.9885 - val_loss: 0.1105 - val_accuracy
: 0.9797 - val_precision: 0.8740 - val_recall: 0.9911 - lr: 4.0000e-04
Epoch 3/20
122/122 [==============================] - 72s 592ms/step - loss: 0.1398 - accura
cy: 0.9382 - precision: 0.6911 - recall: 0.9751 - val_loss: 0.0931 - val_accuracy
: 0.9833 - val_precision: 0.8952 - val_recall: 0.9911 - lr: 4.0000e-04
Epoch 4/20
122/122 [==============================] - 64s 527ms/step - loss: 0.1366 - accura
cy: 0.9523 - precision: 0.7519 - recall: 0.9618 - val_loss: 0.0849 - val_accuracy
: 0.9844 - val_precision: 0.9024 - val_recall: 0.9911 - lr: 4.0000e-04
Epoch 5/20
122/122 [==============================] - 64s 525ms/step - loss: 0.1178 - accura
cy: 0.9528 - precision: 0.7482 - recall: 0.9771 - val_loss: 0.0739 - val_accuracy
: 0.9844 - val_precision: 0.9091 - val_recall: 0.9821 - lr: 4.0000e-04
Epoch 6/20
122/122 [==============================] - 64s 524ms/step - loss: 0.1203 - accura
cy: 0.9592 - precision: 0.7835 - recall: 0.9618 - val_loss: 0.0897 - val_accuracy
: 0.9797 - val_precision: 0.8740 - val_recall: 0.9911 - lr: 4.0000e-04
Epoch 7/20
122/122 [==============================] - 64s 523ms/step - loss: 0.1115 - accura
cy: 0.9610 - precision: 0.7930 - recall: 0.9598 - val_loss: 0.0878 - val_accuracy
: 0.9797 - val_precision: 0.8740 - val_recall: 0.9911 - lr: 4.0000e-04
Epoch 8/20
122/122 [==============================] - 65s 530ms/step - loss: 0.1182 - accura
cy: 0.9628 - precision: 0.8000 - recall: 0.9637 - val_loss: 0.0734 - val_accuracy
: 0.9844 - val_precision: 0.9024 - val_recall: 0.9911 - lr: 8.0000e-05
Epoch 9/20
122/122 [==============================] - 64s 524ms/step - loss: 0.1145 - accura
cy: 0.9641 - precision: 0.8084 - recall: 0.9598 - val_loss: 0.0698 - val_accuracy
: 0.9833 - val_precision: 0.9016 - val_recall: 0.9821 - lr: 8.0000e-05
Epoch 10/20
122/122 [==============================] - 63s 518ms/step - loss: 0.1178 - accura
cy: 0.9636 - precision: 0.8058 - recall: 0.9598 - val_loss: 0.0723 - val_accuracy
: 0.9809 - val_precision: 0.8810 - val_recall: 0.9911 - lr: 8.0000e-05
Epoch 11/20
122/122 [==============================] - 63s 520ms/step - loss: 0.1172 - accura
cy: 0.9646 - precision: 0.8130 - recall: 0.9560 - val_loss: 0.0689 - val_accuracy
: 0.9833 - val_precision: 0.9016 - val_recall: 0.9821 - lr: 8.0000e-05
Epoch 12/20
122/122 [==============================] - 63s 520ms/step - loss: 0.1182 - accura
cy: 0.9577 - precision: 0.7762 - recall: 0.9618 - val_loss: 0.0663 - val_accuracy
: 0.9833 - val_precision: 0.9016 - val_recall: 0.9821 - lr: 8.0000e-05
Epoch 13/20
122/122 [==============================] - 64s 523ms/step - loss: 0.1240 - accura
cy: 0.9587 - precision: 0.7828 - recall: 0.9579 - val_loss: 0.0666 - val_accuracy
: 0.9833 - val_precision: 0.9016 - val_recall: 0.9821 - lr: 8.0000e-05
Epoch 14/20
122/122 [==============================] - 68s 562ms/step - loss: 0.1126 - accura
cy: 0.9636 - precision: 0.8098 - recall: 0.9522 - val_loss: 0.0643 - val_accuracy
: 0.9833 - val_precision: 0.9016 - val_recall: 0.9821 - lr: 8.0000e-05
Epoch 15/20
122/122 [==============================] - 66s 540ms/step - loss: 0.1024 - accura
cy: 0.9641 - precision: 0.8025 - recall: 0.9713 - val_loss: 0.0653 - val_accuracy
: 0.9833 - val_precision: 0.9016 - val_recall: 0.9821 - lr: 8.0000e-05
```

```
Epoch 16/20
122/122 [==============================] - 66s 541ms/step - loss: 0.0973 - accura
cy: 0.9674 - precision: 0.8183 - recall: 0.9732 - val_loss: 0.0613 - val_accuracy
: 0.9844 - val_precision: 0.9091 - val_recall: 0.9821 - lr: 8.0000e-05
Epoch 17/20
122/122 [==============================] - 65s 534ms/step - loss: 0.1156 - accura
cy: 0.9654 - precision: 0.8160 - recall: 0.9579 - val_loss: 0.0642 - val_accuracy
: 0.9844 - val_precision: 0.9091 - val_recall: 0.9821 - lr: 8.0000e-05
Epoch 18/20
122/122 [==============================] - 63s 520ms/step - loss: 0.1117 - accura
cy: 0.9646 - precision: 0.8090 - recall: 0.9637 - val_loss: 0.0648 - val_accuracy
: 0.9833 - val_precision: 0.9016 - val_recall: 0.9821 - lr: 8.0000e-05
Epoch 19/20
122/122 [==============================] - 64s 522ms/step - loss: 0.1127 - accura
cy: 0.9631 - precision: 0.8022 - recall: 0.9618 - val_loss: 0.0644 - val_accuracy
: 0.9833 - val_precision: 0.9016 - val_recall: 0.9821 - lr: 1.6000e-05
CPU times: total: 14min 7s
Wall time: 20min 35s
```

Model Evaluation

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In [108…

```
# Evaluate the model
results_clw = model.evaluate(X_test, y_test)
print(f"Test Loss: {results[0]}")
print(f"Test Accuracy: {results[1]}")
```

```
27/27 [==============================] - 11s 413ms/step - loss: 0.0506 - accuracy
: 0.9904 - precision: 0.9483 - recall: 0.9821
Test Loss: 0.041758514940738 68
Test Accuracy: 0.9904305934906006
```

In [109…

```
y_predict_clw = clw_model.predict(X_test)
y_predict_clw = y_predict_clw.flatten()
```

```
27/27 [==============================] - 12s 414ms/step
```

In [110…

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

Out[110…

```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
```

In [111…

```python
clw_cm = confusion_matrix(y_test, y_predict)
clw_cm
```

Out[111…

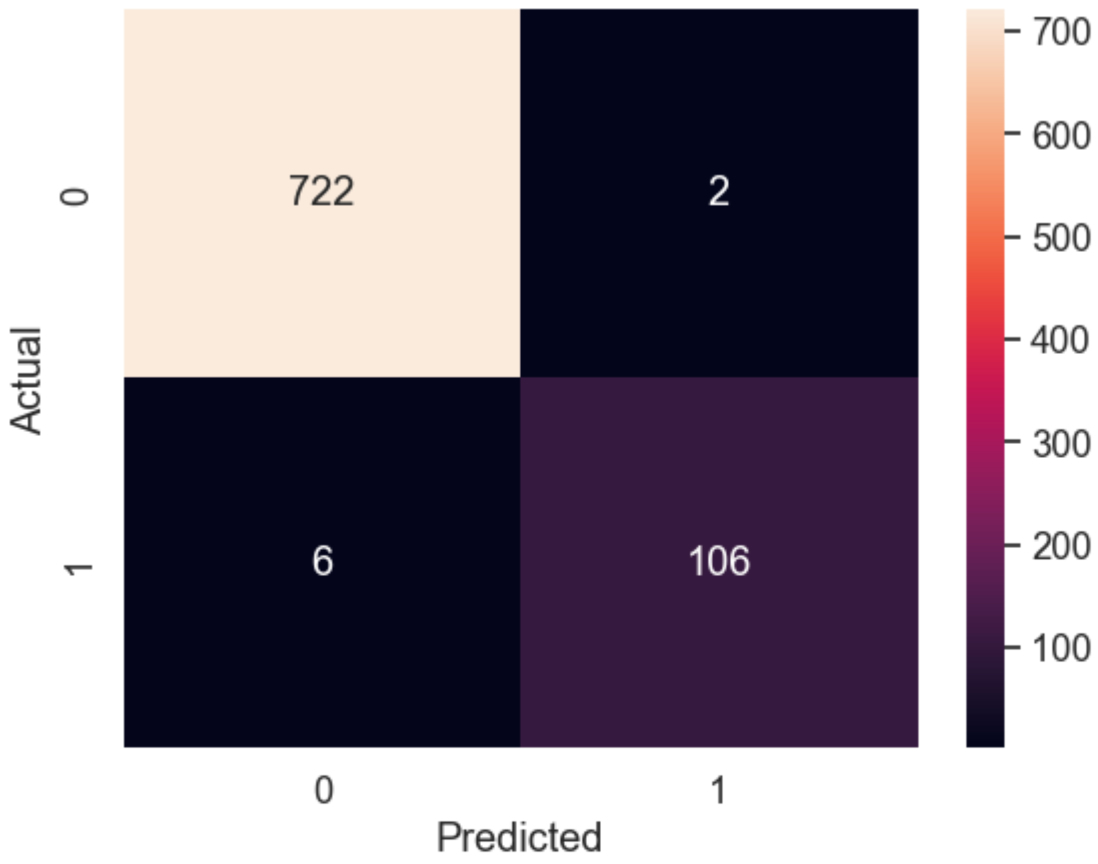
```
array([[722,   2],
       [  6, 106]], dtype=int64)
```

In [112…

```python
sns.heatmap(clw_cm, annot=True, fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

Out[112…

```
Text(43.25, 0.5, 'Actual')
```



In [113…
```
clw = classification_report(y_test, y_predict_clw, target_names=['Ham', 'Spam'])
print(clw)
```

```
              precision    recall  f1-score   support

         Ham       1.00      0.02      0.04       724
        Spam       0.14      1.00      0.24       112

    accuracy                           0.15       836
   macro avg       0.57      0.51      0.14       836
weighted avg       0.88      0.15      0.07       836
```

In [114…
```
# Detection of examples
clw_inf = clw_model.predict(reviews)
clw_inf
```

```
1/1 [==============================] - 1s 753ms/step
```

Out[114…
```
array([[0.627704  ],
       [0.6396768 ],
       [0.52495974],
       [0.59353304],
       [0.5944877 ]], dtype=float32)
```

Hyperparameter Tuning with Keras Tuner (Class Weights)

Table of Contents

In [115…
```
%%time
# Initialize Keras Tuner with the existing model
```

```python
tuner = kt.Hyperband(
    compile_model,
    objective='val_accuracy',
    max_epochs=5,
    factor=3,
    directory=os.getcwd(),
    project_name='clw_model'
)

# Perform hyperparameter tuning
tuner.search(X_train, y_train, epochs=5, validation_data=(X_val, y_val))

# Get the best model
best_model_clw = tuner.get_best_models(num_models=1)[0]
```

```
Trial 3 Complete [00h 02m 15s]
val_accuracy: 0.9844497442245483

Best val_accuracy So Far: 0.9844497442245483
Total elapsed time: 00h 06m 52s
CPU times: total: 4min 45s
Wall time: 6min 53s
```

In [116…

```python
# Evaluate the best model on the validation set
hp_results_val_clw = best_model_clw.evaluate(X_val, y_val)
print(f"\nValidation Loss: {hp_results_val_clw[0]}")
print(f"Validation Accuracy: {hp_results_val_clw[1]}")
```

```
27/27 [==============================] - 12s 413ms/step - loss: 0.0379 - accuracy
: 0.9844 - precision: 0.9760 - recall: 0.9062

Validation Loss: 0.03790128976106644
Validation Accuracy: 0.9844497442245483
```

In [117…

```python
# Evaluate the best model on the test set
hp_results_test_clw = best_model_clw.evaluate(X_test, y_test)
print(f"\Test Loss: {hp_results_test_clw[0]}")
print(f"Test Accuracy: {hp_results_test_clw[1]}")
```

```
27/27 [==============================] - 11s 410ms/step - loss: 0.0407 - accuracy
: 0.9844 - precision: 0.9806 - recall: 0.9018
\Test Loss: 0.04074835404753685
Test Accuracy: 0.9844497442245483
```

Model Building

Table of Contents

In [118…

```python
%%time
# Fitting best model on X_train, y_train, X_val, y_val, X_test, y_test
best_model_clw.fit(X_train, y_train, epochs=20,
                   validation_data=(X_val, y_val),
                   callbacks=[early_stopping, lr_scheduler])
```

```
Epoch 1/20
122/122 [==============================] - 66s 522ms/step - loss: 0.0699 - accura
cy: 0.9767 - precision: 0.9390 - recall: 0.8834 - val_loss: 0.0334 - val_accuracy
: 0.9868 - val_precision: 0.9810 - val_recall: 0.9196 - lr: 0.0010
Epoch 2/20
122/122 [==============================] - 64s 527ms/step - loss: 0.0674 - accura
cy: 0.9751 - precision: 0.9193 - recall: 0.8929 - val_loss: 0.0356 - val_accuracy
: 0.9856 - val_precision: 0.9808 - val_recall: 0.9107 - lr: 0.0010
Epoch 3/20
122/122 [==============================] - 64s 525ms/step - loss: 0.0822 - accura
cy: 0.9708 - precision: 0.9098 - recall: 0.8681 - val_loss: 0.0361 - val_accuracy
: 0.9856 - val_precision: 0.9808 - val_recall: 0.9107 - lr: 0.0010
Epoch 4/20
122/122 [==============================] - 65s 531ms/step - loss: 0.0761 - accura
cy: 0.9731 - precision: 0.9098 - recall: 0.8872 - val_loss: 0.0350 - val_accuracy
: 0.9844 - val_precision: 0.9714 - val_recall: 0.9107 - lr: 2.0000e-04
CPU times: total: 2min 59s
Wall time: 4min 19s
```

Out[118…

```
<keras.callbacks.History at 0x1be90e2a680>
```

Model Evaluation

Table of Contents

In [119…

```
y_predict_hp_clw = best_model_clw.predict(X_test)
y_predict_hp_clw = y_predict_hp_clw.flatten()
```

```
27/27 [==============================] - 12s 430ms/step
```

In [120…

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

Out[120…

```
array([0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1])
```

In [121…

```python
cm_hp_clw = confusion_matrix(y_test, y_predict_hp_clw)
cm_hp_clw
```

Out[121…

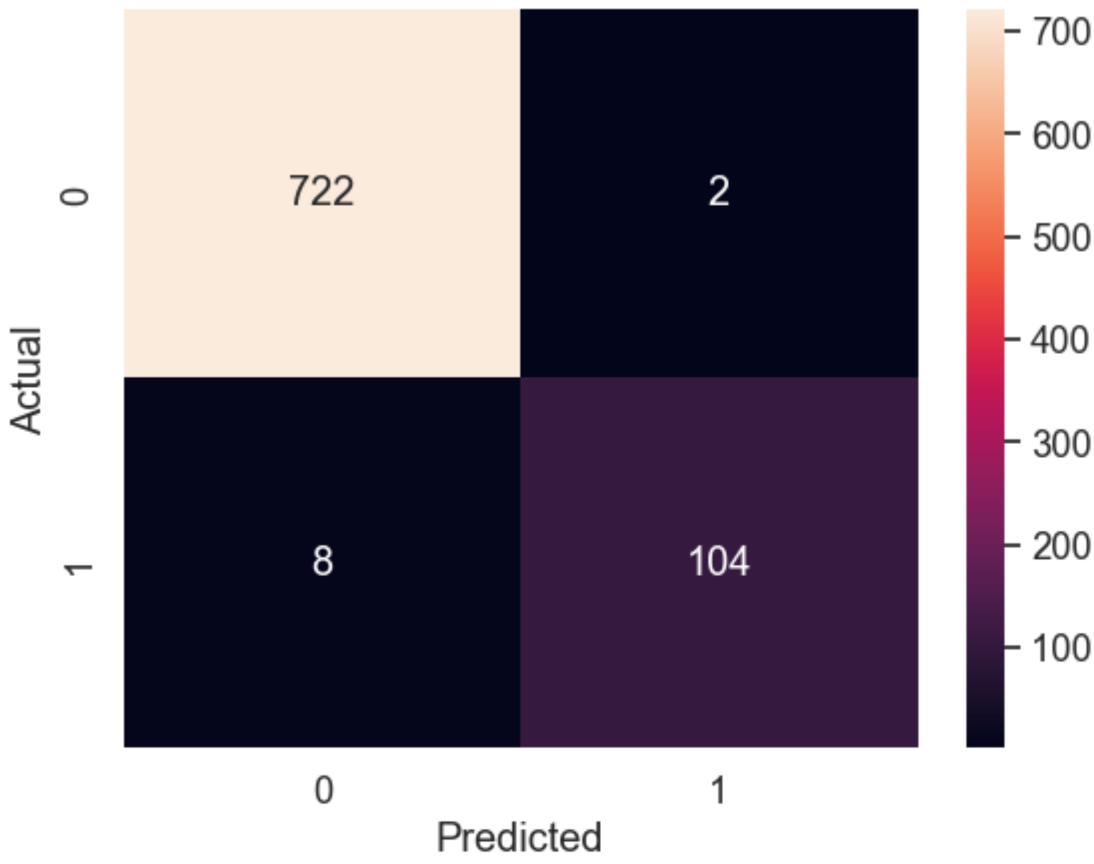
```
array([[722,   2],
       [  8, 104]], dtype=int64)
```

In [122…

```python
sns.heatmap(cm_hp_clw, annot=True, fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

Out[122…

```
Text(43.25, 0.5, 'Actual')
```



In [123…
```
cus_hp = classification_report(y_test, y_predict_hp_clw, target_names=['Ham', 'S
print(cus_hp)
```

```
              precision    recall  f1-score   support

         Ham       0.99      1.00      0.99       724
        Spam       0.98      0.93      0.95       112

    accuracy                           0.99       836
   macro avg       0.99      0.96      0.97       836
weighted avg       0.99      0.99      0.99       836
```

Additional Metrics (ROC-AUC) for BERT

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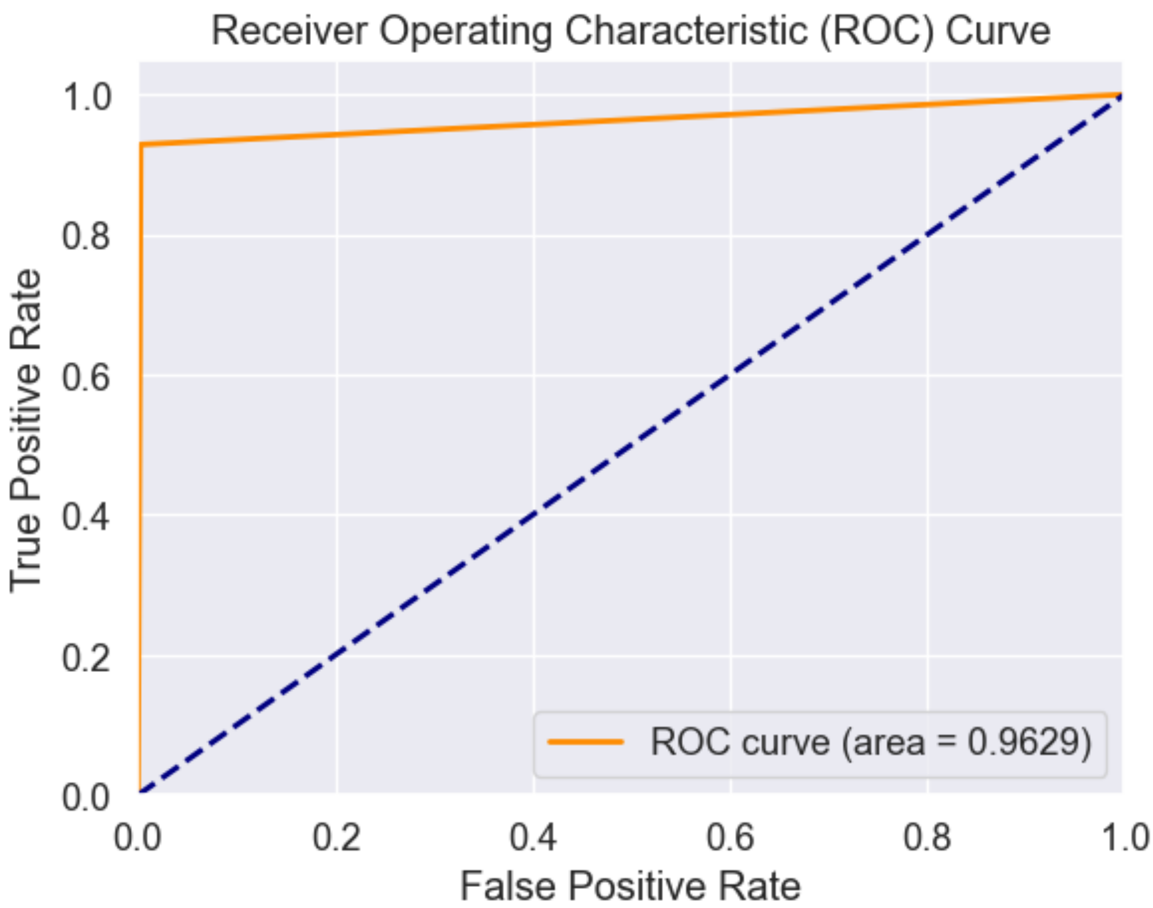
In [124…
```
roc_auc_test = roc_auc_score(y_test, y_predict_hp_clw)
print(f'ROC-AUC Score on Test Set: {roc_auc_test:.4f}')
```

```
ROC-AUC Score on Test Set: 0.9629
```

In [125…
```
# Assuming y_test and y_predict_hp are already defined
fpr, tpr, _ = roc_curve(y_test, y_predict_hp_clw)
roc_auc = auc(fpr, tpr)

# Plotting the ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {roc_auc:
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
```

```python
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```



In [126…

```python
# Detection of examples
clw_inf_hp = best_model_clw.predict(reviews)
clw_inf_hp
```

```
1/1 [==============================] - 1s 824ms/step
```

Out[126…

```
array([[0.03164164],
       [0.43615294],
       [0.15338531],
       [0.39281282],
       [0.00118425]], dtype=float32)
```

Custom Loss

Table of Contents

In [127…

```python
%%time
cus_model = tf.keras.models.clone_model(model)  # Cloning the custom model archi
```

```
CPU times: total: 11.1 s
Wall time: 12.1 s
```

In [128…

```python
def custom_loss(y_train, y_predict):
    # Convert y_train to float
    y_train = tf.cast(y_train, tf.float32)
```

```
    # Apply label smoothing
    y_train_smoothed = y_train * 0.9 + 0.05

    # Compute binary cross-entropy
    bce_loss = tf.keras.losses.binary_crossentropy(y_train_smoothed, y_predict,

    return bce_loss
```

In [129…

```
%%time
cus_model.compile(optimizer=Adam(learning_rate=0.001),
                  loss = custom_loss,
                  metrics = metrics)
```

```
CPU times: total: 0 ns
Wall time: 4.35 ms
```

Model Building

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In [130…

```
%%time
# Fit the model
history_cus = model.fit(X_train, y_train, epochs=20,
                    validation_data=(X_val, y_val),
                    callbacks=[early_stopping, lr_scheduler])
```

```
Epoch 1/20
122/122 [==============================] - 66s 543ms/step - loss: 0.0699 - accura
cy: 0.9751 - precision: 0.9128 - recall: 0.9006 - val_loss: 0.0343 - val_accuracy
: 0.9868 - val_precision: 0.9810 - val_recall: 0.9196 - lr: 2.0000e-04
Epoch 2/20
122/122 [==============================] - 65s 532ms/step - loss: 0.0725 - accura
cy: 0.9736 - precision: 0.9070 - recall: 0.8948 - val_loss: 0.0343 - val_accuracy
: 0.9868 - val_precision: 0.9810 - val_recall: 0.9196 - lr: 2.0000e-04
Epoch 3/20
122/122 [==============================] - 65s 532ms/step - loss: 0.0744 - accura
cy: 0.9762 - precision: 0.9216 - recall: 0.8987 - val_loss: 0.0343 - val_accuracy
: 0.9868 - val_precision: 0.9633 - val_recall: 0.9375 - lr: 2.0000e-04
Epoch 4/20
122/122 [==============================] - 65s 534ms/step - loss: 0.0619 - accura
cy: 0.9790 - precision: 0.9473 - recall: 0.8929 - val_loss: 0.0342 - val_accuracy
: 0.9868 - val_precision: 0.9720 - val_recall: 0.9286 - lr: 4.0000e-05
Epoch 5/20
122/122 [==============================] - 66s 539ms/step - loss: 0.0640 - accura
cy: 0.9774 - precision: 0.9290 - recall: 0.9006 - val_loss: 0.0341 - val_accuracy
: 0.9856 - val_precision: 0.9717 - val_recall: 0.9196 - lr: 4.0000e-05
Epoch 6/20
122/122 [==============================] - 65s 533ms/step - loss: 0.0696 - accura
cy: 0.9769 - precision: 0.9270 - recall: 0.8987 - val_loss: 0.0343 - val_accuracy
: 0.9868 - val_precision: 0.9810 - val_recall: 0.9196 - lr: 4.0000e-05
Epoch 7/20
122/122 [==============================] - 65s 533ms/step - loss: 0.0680 - accura
cy: 0.9744 - precision: 0.9188 - recall: 0.8872 - val_loss: 0.0344 - val_accuracy
: 0.9868 - val_precision: 0.9810 - val_recall: 0.9196 - lr: 8.0000e-06
Epoch 8/20
122/122 [==============================] - 65s 532ms/step - loss: 0.0730 - accura
cy: 0.9754 - precision: 0.9261 - recall: 0.8872 - val_loss: 0.0343 - val_accuracy
: 0.9856 - val_precision: 0.9717 - val_recall: 0.9196 - lr: 8.0000e-06
CPU times: total: 5min 51s
Wall time: 8min 41s
```

Model Evaluation

Table of Contents

In [131…

```
# Evaluate the model
results_cus = model.evaluate(X_test, y_test)
print(f"Test Loss: {results_cus[0]}")
print(f"Test Accuracy: {results_cus[1]}")
```

```
27/27 [==============================] - 12s 431ms/step - loss: 0.0346 - accuracy
: 0.9892 - precision: 0.9813 - recall: 0.9375
Test Loss: 0.034644171595573425
Test Accuracy: 0.989234447479248
```

In [132…

```
y_predict_cus = cus_model.predict(X_test)
y_predict_cus = y_predict_cus.flatten()
```

```
27/27 [==============================] - 12s 440ms/step
```

In [133…

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

Out[133…

```
array([1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1,
       1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1,
       0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1,
       1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1,
       0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1,
       0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1,
       0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1,
       1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1,
       0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1,
       1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1,
       1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0,
       1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1,
       1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,
       1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1,
       1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,
       0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1])
```

In [134…

```
cm_cus = confusion_matrix(y_test, y_predict_cus)
cm_cus
```

Out[134…

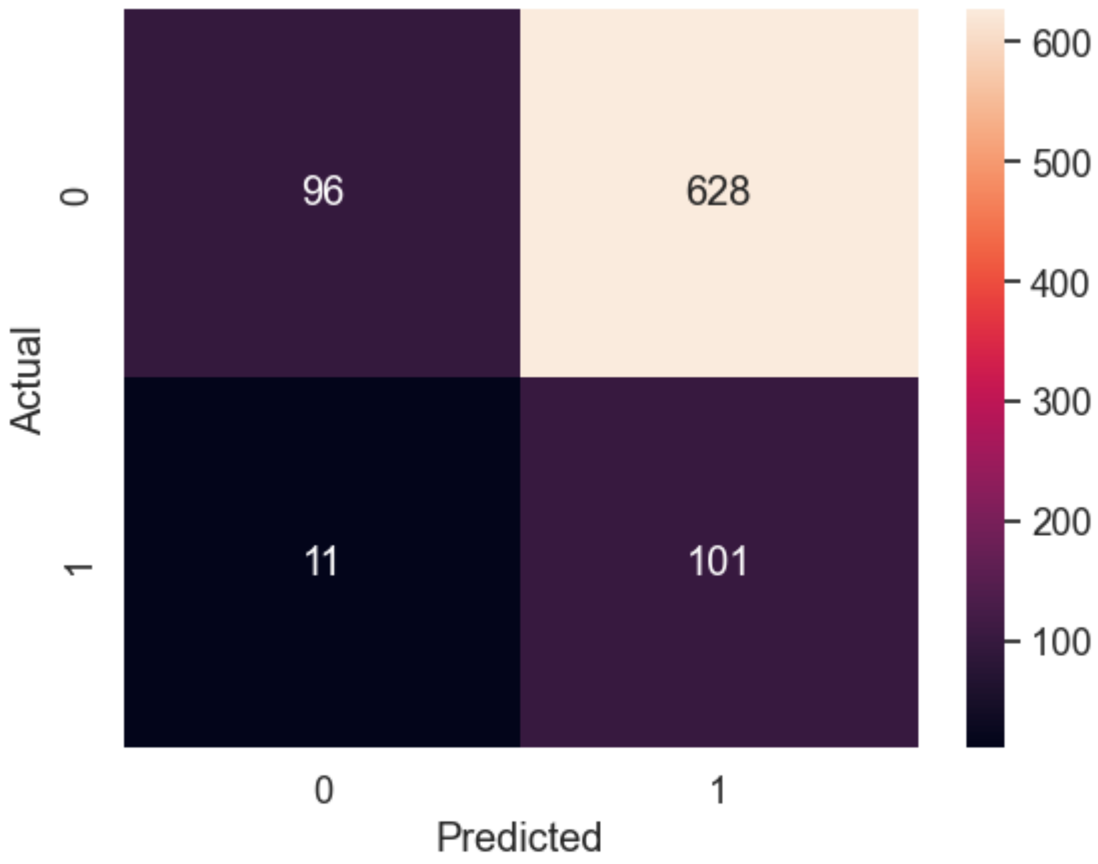
```
array([[ 96, 628],
       [ 11, 101]], dtype=int64)
```

In [135…

```
sns.heatmap(cm_cus, annot=True, fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

Out[135…

```
Text(43.25, 0.5, 'Actual')
```



In [136…

```
cus = classification_report(y_test, y_predict_cus, target_names=['Ham', 'Spam'])
print(cus)
```

```
              precision    recall  f1-score   support

         Ham       0.90      0.13      0.23       724
        Spam       0.14      0.90      0.24       112

    accuracy                           0.24       836
   macro avg       0.52      0.52      0.24       836
weighted avg       0.80      0.24      0.23       836
```

In [137…

```
# Detection of examples
cus_inf = cus_model.predict(reviews)
cus_inf
```

```
1/1 [==============================] - 1s 947ms/step
```

Out[137…

```
array([[0.50201404],
       [0.5446488 ],
       [0.52540606],
       [0.53057665],
       [0.52335185]], dtype=float32)
```

Hyperparameter Tuning with Keras Tuner (Custom Loss)

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In [138…

```
%%time
# Initialize Keras Tuner with the existing model
```

```
tuner = kt.Hyperband(
    compile_model,
    objective='val_accuracy',
    max_epochs=5,
    factor=3,
    directory=os.getcwd(),
    project_name='cus_model'
)

# Perform hyperparameter tuning
tuner.search(X_train, y_train, epochs=5, validation_data=(X_val, y_val))

# Get the best model
best_model_cus = tuner.get_best_models(num_models=1)[0]
```

```
Trial 3 Complete [00h 02m 14s]
val_accuracy: 0.9844497442245483

Best val_accuracy So Far: 0.9868420958518982
Total elapsed time: 00h 06m 45s
CPU times: total: 4min 43s
Wall time: 6min 46s
```

In [139…

```
# Evaluate the best model on the validation set
hp_results_val_cus = best_model_cus.evaluate(X_val, y_val)
print(f"\nValidation Loss: {hp_results_val_cus[0]}")
print(f"Validation Accuracy: {hp_results_val_cus[1]}")
```

```
27/27 [==============================] - 12s 408ms/step - loss: 0.0333 - accuracy
: 0.9850 - precision: 0.9807 - recall: 0.9062

Validation Loss: 0.03334769606590271
Validation Accuracy: 0.9850478172302246
```

In [140…

```
# Evaluate the best model on the test set
hp_results_test_cus = best_model_cus.evaluate(X_test, y_test)
print(f"\Test Loss: {hp_results_test_cus[0]}")
print(f"Test Accuracy: {hp_results_test_cus[1]}")
```

```
27/27 [==============================] - 11s 408ms/step - loss: 0.0349 - accuracy
: 0.9880 - precision: 0.9811 - recall: 0.9286
\Test Loss: 0.03488761931657791
Test Accuracy: 0.9880383014678955
```

Model Building

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In [141…

```
%%time
# Fitting best model on X_train, y_train, X_val, y_val, X_test, y_test
best_model_cus.fit(X_train, y_train, epochs=20,
                   validation_data=(X_val, y_val),
                   callbacks=[early_stopping, lr_scheduler])
```

```
Epoch 1/20
122/122 [==============================] - 66s 518ms/step - loss: 0.0677 - accura
cy: 0.9759 - precision: 0.9231 - recall: 0.8948 - val_loss: 0.0350 - val_accuracy
: 0.9856 - val_precision: 0.9717 - val_recall: 0.9196 - lr: 0.0010
Epoch 2/20
122/122 [==============================] - 63s 517ms/step - loss: 0.0729 - accura
cy: 0.9744 - precision: 0.9273 - recall: 0.8776 - val_loss: 0.0329 - val_accuracy
: 0.9868 - val_precision: 0.9720 - val_recall: 0.9286 - lr: 0.0010
Epoch 3/20
122/122 [==============================] - 63s 514ms/step - loss: 0.0691 - accura
cy: 0.9767 - precision: 0.9219 - recall: 0.9025 - val_loss: 0.0341 - val_accuracy
: 0.9880 - val_precision: 0.9722 - val_recall: 0.9375 - lr: 0.0010
Epoch 4/20
122/122 [==============================] - 63s 515ms/step - loss: 0.0637 - accura
cy: 0.9769 - precision: 0.9287 - recall: 0.8967 - val_loss: 0.1094 - val_accuracy
: 0.9844 - val_precision: 0.9381 - val_recall: 0.9464 - lr: 0.0010
Epoch 5/20
122/122 [==============================] - 63s 515ms/step - loss: 0.0720 - accura
cy: 0.9751 - precision: 0.9277 - recall: 0.8834 - val_loss: 0.0343 - val_accuracy
: 0.9868 - val_precision: 0.9810 - val_recall: 0.9196 - lr: 2.0000e-04
CPU times: total: 3min 42s
Wall time: 5min 16s
```

Out[141…

```
<keras.callbacks.History at 0x1bea8e51270>
```

Model Evaluation

Table of Contents

In [142…

```
y_predict_hp_cus = best_model_cus.predict(X_test)
y_predict_hp_cus = y_predict_hp_cus.flatten()
```

```
27/27 [==============================] - 12s 413ms/step
```

In [143…

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

Out[143…

```
array([0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0,
       0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0,
       0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1])
```

In [144…

```python
cm_hp_cus = confusion_matrix(y_test, y_predict_hp_cus)
cm_hp_cus
```

Out[144…

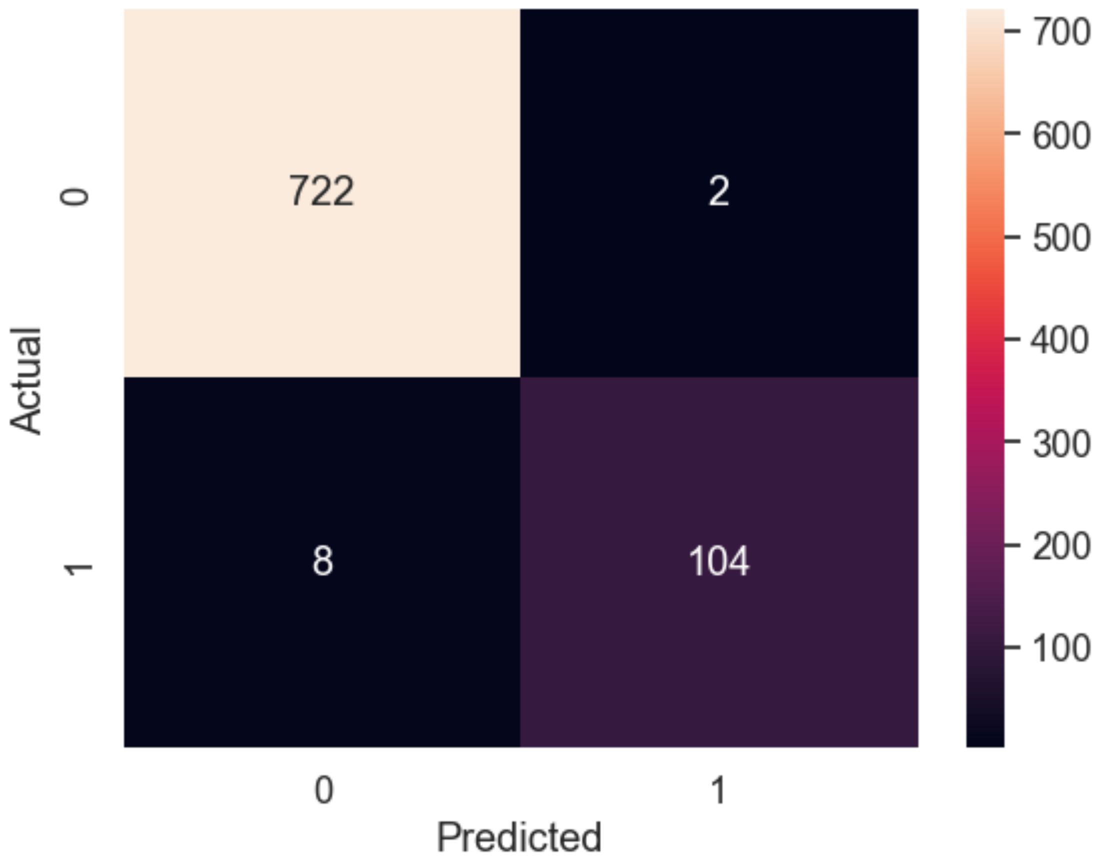
```
array([[722,   2],
       [  8, 104]], dtype=int64)
```

In [145…

```python
sns.heatmap(cm_hp_cus, annot=True, fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

Out[145…

```
Text(43.25, 0.5, 'Actual')
```



In [146…

```
cus_hp = classification_report(y_test, y_predict_hp_cus, target_names=['Ham', 'S
print(cus_hp)
```

```
              precision    recall  f1-score   support

         Ham       0.99      1.00      0.99       724
        Spam       0.98      0.93      0.95       112

    accuracy                           0.99       836
   macro avg       0.99      0.96      0.97       836
weighted avg       0.99      0.99      0.99       836
```

Additional Metrics (ROC-AUC) for BERT

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In [147…

```
roc_auc_test = roc_auc_score(y_test, y_predict_hp_cus)
print(f'ROC-AUC Score on Test Set: {roc_auc_test:.4f}')
```

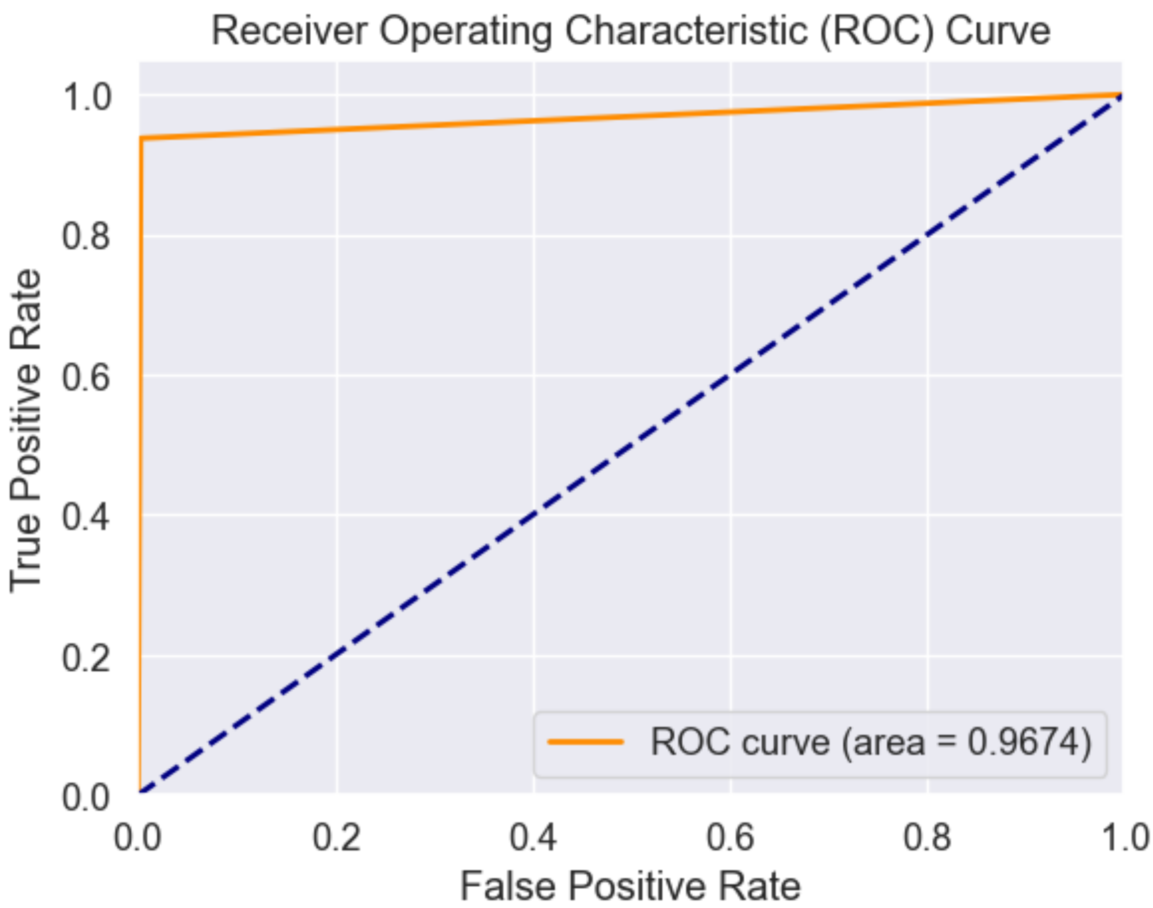
```
ROC-AUC Score on Test Set: 0.9629
```

In [148…

```
# y_test and y_predict_hp_cus are already defined
fpr, tpr, _ = roc_curve(y_test, y_predict_hp)
roc_auc = auc(fpr, tpr)

# Plotting the ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (area = {roc_auc:
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
```

```
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```



In [149…

```
# Detection of examples
cus_inf_hp = best_model_cus.predict(reviews)
cus_inf_hp
```

```
1/1 [==============================] - 1s 697ms/step
```

Out[149…

```
array([[0.038733  ],
       [0.48401392],
       [0.21443476],
       [0.4764059 ],
       [0.00154567]], dtype=float32)
```

Performance Comparison of Fine-Tuned BERT

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In [151…

```
# Converting the actual classification report metrics into dictionaries
nml_metrics = classification_report(y_test, y_predict, target_names=['ham', 'spa
dwn_metrics = classification_report(y_test_dwn, y_predict_dwn, target_names=['ha
up_metrics = classification_report(y_test_up, y_predict_up, target_names=['ham',
clw_metrics = classification_report(y_test, y_predict_clw, target_names=['ham',
cus_metrics = classification_report(y_test, y_predict_cus, target_names=['ham',

# Create a DataFrame with the relevant metrics
metrics_df = pd.DataFrame({
```

```
    'Model': ['Original', 'Down Sampling', 'Up Sampling', 'Class Weights', 'Cust
    'Accuracy': [nml_metrics['accuracy'], dwn_metrics['accuracy'], up_metrics['a
    'Precision (ham)': [nml_metrics['ham']['precision'], dwn_metrics['ham']['pre
    'Precision (spam)': [nml_metrics['spam']['precision'], dwn_metrics['spam']['
    'Recall (ham)': [nml_metrics['ham']['recall'], dwn_metrics['ham']['recall'],
    'Recall (spam)': [nml_metrics['spam']['recall'], dwn_metrics['spam']['recall
    'F1-score (ham)': [nml_metrics['ham']['f1-score'], dwn_metrics['ham']['f1-sc
    'F1-score (spam)': [nml_metrics['spam']['f1-score'], dwn_metrics['spam']['f1
    'Support (ham)': [nml_metrics['ham']['support'], dwn_metrics['ham']['support
    'Support (spam)': [nml_metrics['spam']['support'], dwn_metrics['spam']['supp
})

# Display the comprehensive comparison table
metrics_df
```

Out[151…

	Model	Accuracy	Precision (ham)	Precision (spam)	Recall (ham)	Recall (spam)	F1-score (ham)	F1-score (spam)	Sup (l
0	Original	0.990431	0.991758	0.981481	0.997238	0.946429	0.994490	0.963636	
1	Down Sampling	0.960000	0.926230	1.000000	1.000000	0.919643	0.961702	0.958140	
2	Up Sampling	0.982735	0.987448	0.978112	0.977901	0.987569	0.982651	0.982818	
3	Class Weights	0.153110	1.000000	0.136585	0.022099	1.000000	0.043243	0.240343	
4	Custom Loss	0.235646	0.897196	0.138546	0.132597	0.901786	0.231047	0.240190	

Performance Comparison of Hyperparameter-Tuned BERT

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In [152…

```
# Converting the actual classification report metrics into dictionaries
nml_metrics_hp = classification_report(y_test, y_predict_hp, target_names=['ham'
dwn_metrics_hp = classification_report(y_test_dwn, y_predict_hp_dwn, target_name
up_metrics_hp = classification_report(y_test_up, y_predict_hp_up, target_names=[
clw_metrics_hp = classification_report(y_test, y_predict_hp_clw, target_names=['
cus_metrics_hp = classification_report(y_test, y_predict_hp_cus, target_names=['

# Create a DataFrame with the relevant metrics
metrics_hp_df = pd.DataFrame({
    'Model': ['Original', 'Down Sampling', 'Up Sampling', 'Class Weights', 'Cust
    'Accuracy': [nml_metrics_hp['accuracy'], dwn_metrics_hp['accuracy'], up_metr
    'Precision (ham)': [nml_metrics_hp['ham']['precision'], dwn_metrics_hp['ham'
    'Precision (spam)': [nml_metrics_hp['spam']['precision'], dwn_metrics_hp['sp
    'Recall (ham)': [nml_metrics_hp['ham']['recall'], dwn_metrics_hp['ham']['rec
    'Recall (spam)': [nml_metrics_hp['spam']['recall'], dwn_metrics_hp['spam']['
    'F1-score (ham)': [nml_metrics_hp['ham']['f1-score'], dwn_metrics_hp['ham'][
    'F1-score (spam)': [nml_metrics_hp['spam']['f1-score'], dwn_metrics_hp['spam
    'Support (ham)': [nml_metrics_hp['ham']['support'], dwn_metrics_hp['ham']['s
    'Support (spam)': [nml_metrics_hp['spam']['support'], dwn_metrics_hp['spam']
})
```

```
# Display the comprehensive comparison table
metrics_hp_df
```

Out[152…

	Model	Accuracy	Precision (ham)	Precision (spam)	Recall (ham)	Recall (spam)	F1-score (ham)	F1-score (spam)	Sup (I
0	Original	0.989234	0.990398	0.981308	0.997238	0.937500	0.993806	0.958904	
1	Down Sampling	0.964444	0.956522	0.972727	0.973451	0.955357	0.964912	0.963964	
2	Up Sampling	0.983425	0.988827	0.978142	0.977901	0.988950	0.983333	0.983516	
3	Class Weights	0.988038	0.989041	0.981132	0.997238	0.928571	0.993122	0.954128	
4	Custom Loss	0.988038	0.989041	0.981132	0.997238	0.928571	0.993122	0.954128	

Inference Comparison of Fine-Tuned BERT

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In [153…

```
# Reshape arrays to be 1-dimensional
nml_inf = nml_inf.reshape(-1)
dwn_inf = dwn_inf.reshape(-1)
up_inf = up_inf.reshape(-1)
clw_inf = clw_inf.reshape(-1)
cus_inf = cus_inf.reshape(-1)

inferences = {
    'Normal Inference': nml_inf,
    'Down Sampling Inference': dwn_inf,
    'Up Sampling Inference': up_inf,
    'Class Weights Inference': clw_inf,
    'Custom Loss Inference': cus_inf
}

inf = pd.DataFrame(inferences)

# Display the table
inf
```

Out[153…

	Normal Inference	Down Sampling Inference	Up Sampling Inference	Class Weights Inference	Custom Loss Inference
0	0.027743	0.007487	0.214065	0.627704	0.502014
1	0.462971	0.210188	0.780696	0.639677	0.544649
2	0.155890	0.087669	0.711345	0.524960	0.525406
3	0.420343	0.207842	0.766022	0.593533	0.530577
4	0.007806	0.002023	0.007855	0.594488	0.523352

Inference Comparison of Hyperparameter-Tuned BERT

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In [154…

```
# Reshape arrays to be 1-dimensional
nml_inf_hp = nml_inf_hp.reshape(-1)
dwn_inf_hp = dwn_inf_hp.reshape(-1)
up_inf_hp = up_inf_hp.reshape(-1)
clw_inf_hp = clw_inf_hp.reshape(-1)
cus_inf_hp = cus_inf_hp.reshape(-1)

inferences_hp = {
    'Normal Inference': nml_inf_hp,
    'Down Sampling Inference': dwn_inf_hp,
    'Up Sampling Inference': up_inf_hp,
    'Class Weights Inference': clw_inf_hp,
    'Custom Loss Inference': cus_inf_hp
}

inf_up = pd.DataFrame(inferences_hp)

# Display the table
inf_up
```

Out[154…

	Normal Inference	Down Sampling Inference	Up Sampling Inference	Class Weights Inference	Custom Loss Inference
0	0.021727	0.047020	0.368073	0.031642	0.038733
1	0.396931	0.444924	0.892845	0.436153	0.484014
2	0.200549	0.802365	0.759731	0.153385	0.214435
3	0.358744	0.768852	0.905011	0.392813	0.476406
4	0.004297	0.000901	0.006211	0.001184	0.001546

Conclusion

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Based on the comparison of the `Fine-tuned BERT model` and the `Hyperparameter-tuned BERT model` for spam detection, it is evident that the `Hyperparameter-tuned BERT model` with `Up Sampling` demonstrates the highest F1-score for spam detection, achieving a value of 0.983516. In contrast, the `Hyperparameter-tuned BERT model` with `Down Sampling` also performs well, with an F1-score of 0.963964, but it slightly falls short compared to the hyperparameter-tuned model. Other approaches, such as `Class Weights`, where weights are assigned to the data, show significantly lower F1-scores. Similarly, `Custom Loss`, which involves label smoothing according to the data labels ratio, decreases the classification report metrics, indicating less effectiveness in spam detection.

This indicates that balanced data will give more accurate results in the classification of text messages into ham or spam while applying Bidirectional Encoder Representation from Transformers (BERT). It also highlights a superior balance between precision and recall for identifying spam, making the `Hyperparameter-tuned BERT model` with `Up Sampling` the most effective model among those tested.

Given these results, the `Hyperparameter-tuned BERT model` with `Up Sampling` is recommended for optimal spam detection performance. This model is well-suited for real industry applications and is ready to be deployed. By saving this best-performing model, robust and reliable spam detection can be ensured in a production environment, enhancing the overall effectiveness and efficiency of the system.

Deployment

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In [ ]:
```
# Save the entire model to a HDF5 file
best_model_up.save('spam_detection_model.h5')
```

In [ ]:
```
# Save the model in SavedModel format
best_model_up.save('saved_model/spam_detection_model')
```

In [ ]:
```
message = input("Enter your message: ")

# Preprocess the message
preprocessed_message = bert_preprocessor([message])
encoded_message = bert_encoder(preprocessed_message)

# Predict using the best model
result = best_model_up.predict(encoded_message)
print(result)

if result[0] == 1:
    print("This has a high probability of being a spam message.")
else:
    print("This is not likely to be a spam message.")
```

References

Table of Contents

`www.google.com` `www.stackoverflow.com` `www.tensorflowhub.com` `www.geeksforgeeks.com` `www.youtube.com` `www.copilot.com` `www.chatgpt.com`