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

In [9]:
```
data = data.drop_duplicates()
```

In [10]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 5169 entries, 0 to 5571
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype 
---  ------  --------------  ----- 
 0   Class   5169 non-null   int64 
 1   Text    5169 non-null   object
dtypes: int64(1), object(1)
memory usage: 121.1+ KB
```

In [11]:
```
# Viewing values in 'v1' column
data['Class'].value_counts()
```

Out[11]:
```
Class
0    4516
1     653
Name: count, dtype: int64
```

In [12]:
```
data.groupby('Class').describe()
```

Out[12]:

	Text			
	count	unique	top	freq
Class				
0	4516	4516	Go until jurong point, crazy.. Available only ...	1
1	653	653	Free entry in 2 a wkly comp to win FA Cup fina...	1

In [13]:
```
# Viewing the imbalanced rate
653/4516
```

Out[13]: 0.1445969884853853

In [14]:
```
# Viewing unique values in 'v2'
data['Text'].nunique()
```

Out[14]: 5169

Exploratory Data Analysis (EDA)

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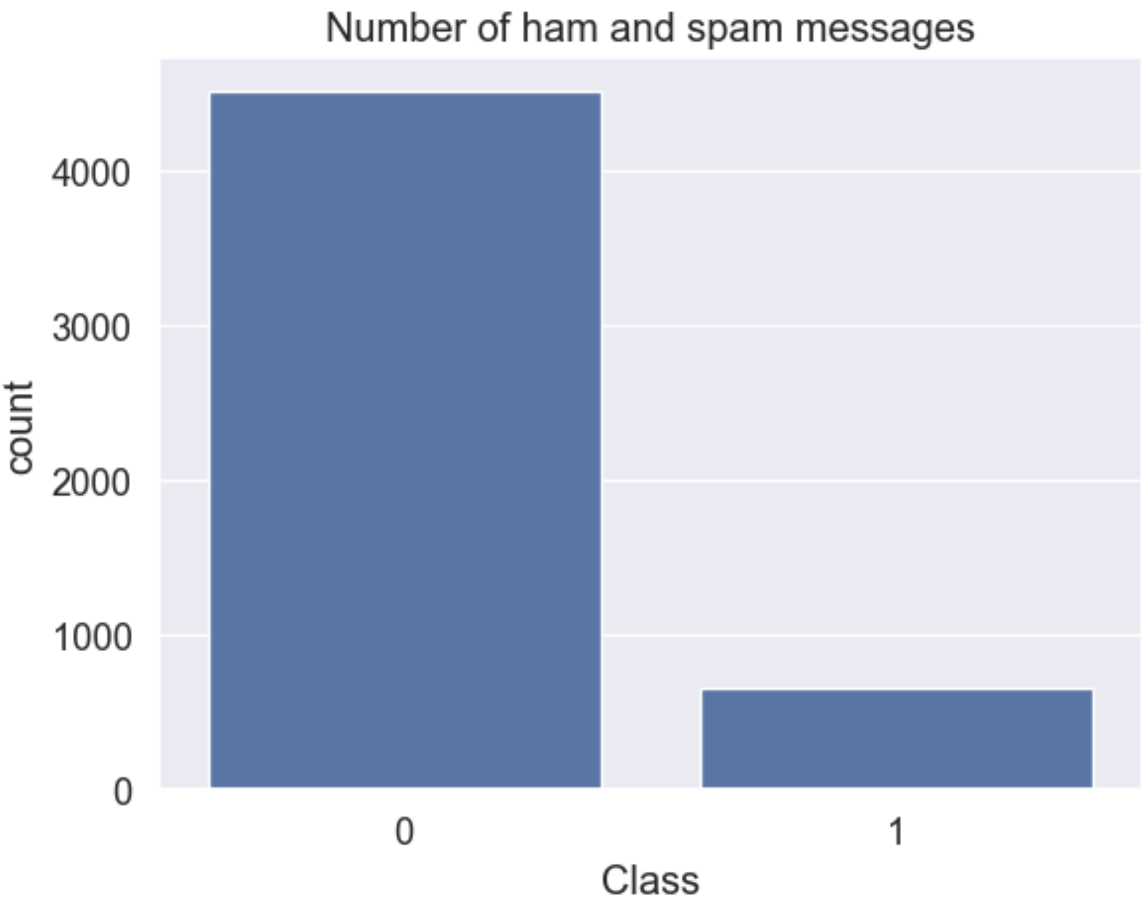
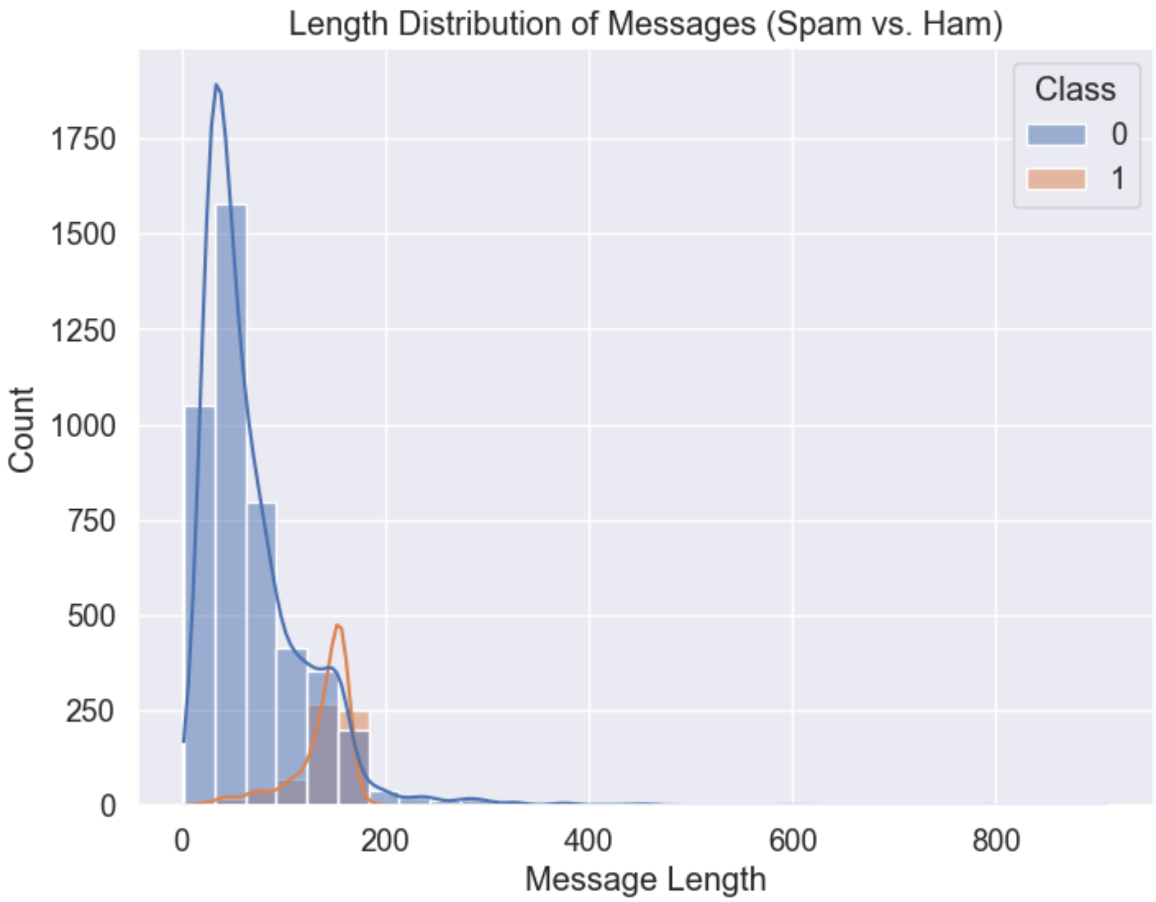
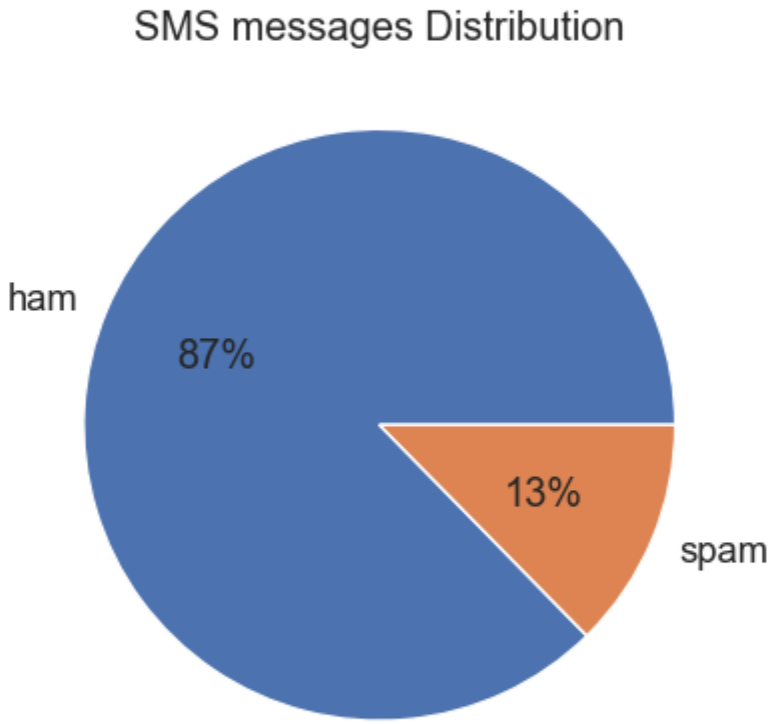
In [15]:
```
sns.set(style = "darkgrid" , font_scale = 1.2)
sns.countplot(data=data, x= 'Class').set_title("Number of ham and spam messages"
plt.show()
```



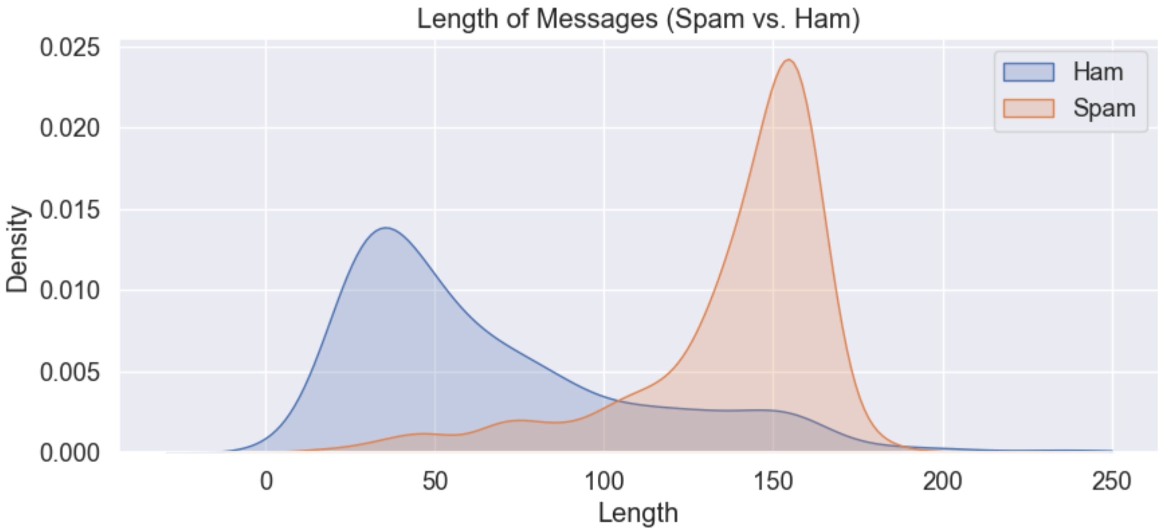
In [16]:
```
# Plot the distribution of message lengths
plt.figure(figsize=(8, 6))
sns.histplot(x=data['Text'].str.len(), bins=30, hue=data['Class'], kde=True)
plt.title('Length Distribution of Messages (Spam vs. Ham)')
plt.xlabel('Message Length')
plt.ylabel('Count')
plt.show()
```



In [17]:
```
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 [18]:
```
# 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 [19]:
```
X = data['Text']
y = data['Class']
```

In [20]:
```
X.shape
```

Out[20]: (5169,)

In [21]:
```
y.shape
```

Out[21]: (5169,)

In [22]:
```
print(f'Length of X: {len(X)}')
print(f'Length of y: {len(y)}')
```

```
Length of X: 5169
Length of y: 5169
```

In [23]:
```
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: 3618, 3618
Validation data: 775, 775
Testing data: 776, 776
```

Model Building

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In [24]:
```
%%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: 11.9 s
Wall time: 13 s
```

In [25]:
```
%%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)
embbed = bert_encoder(encoder_inputs)

# Neural Network layers
dropout1 = Dropout(0.1, name='Dropout1')(embbed['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: 656 ms
Wall time: 784 ms
```

In [26]:

```
model.summary()
```

```
Model: "model"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 Inputs (InputLayer)            [(None,)]            0           []

 keras_layer (KerasLayer)       {'input_type_ids':   0           ['Inputs[0][0]']
                                (None, 128),
                                 'input_word_ids':
                                (None, 128),
                                 'input_mask': (Non
                                e, 128)}

 keras_layer_1 (KerasLayer)     {'sequence_output':  109482241   ['keras_layer[0]
[0]',
                                 (None, 128, 768),                'keras_layer[0]
[1]',
                                 'default': (None,                'keras_layer[0]
[2]']
                                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)],
                                 'pooled_output': (
                                None, 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 [27]:
```python
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 [28]:
```python
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 [29]:
```python
%%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
114/114 [==============================] - 70s 535ms/step - loss: 0.4402 - accura
cy: 0.8237 - precision: 0.4103 - recall: 0.9059 - val_loss: 0.2324 - val_accuracy
: 0.9058 - val_precision: 1.0000 - val_recall: 0.2551 - lr: 0.0010
Epoch 2/20
114/114 [==============================] - 61s 532ms/step - loss: 0.1881 - accura
cy: 0.9514 - precision: 0.7728 - recall: 0.8709 - val_loss: 0.1466 - val_accuracy
: 0.9755 - val_precision: 0.9540 - val_recall: 0.8469 - lr: 0.0010
Epoch 3/20
114/114 [==============================] - 61s 536ms/step - loss: 0.1200 - accura
cy: 0.9682 - precision: 0.8717 - recall: 0.8775 - val_loss: 0.0974 - val_accuracy
: 0.9665 - val_precision: 0.9615 - val_recall: 0.7653 - lr: 0.0010
Epoch 4/20
114/114 [==============================] - 60s 530ms/step - loss: 0.1058 - accura
cy: 0.9696 - precision: 0.8881 - recall: 0.8687 - val_loss: 0.0834 - val_accuracy
: 0.9729 - val_precision: 0.9639 - val_recall: 0.8163 - lr: 0.0010
Epoch 5/20
114/114 [==============================] - 60s 530ms/step - loss: 0.0985 - accura
cy: 0.9671 - precision: 0.8894 - recall: 0.8446 - val_loss: 0.0669 - val_accuracy
: 0.9819 - val_precision: 0.9468 - val_recall: 0.9082 - lr: 0.0010
Epoch 6/20
114/114 [==============================] - 60s 530ms/step - loss: 0.0893 - accura
cy: 0.9704 - precision: 0.8995 - recall: 0.8621 - val_loss: 0.0717 - val_accuracy
: 0.9794 - val_precision: 0.9100 - val_recall: 0.9286 - lr: 0.0010
Epoch 7/20
114/114 [==============================] - 60s 526ms/step - loss: 0.0947 - accura
cy: 0.9685 - precision: 0.9016 - recall: 0.8425 - val_loss: 0.0777 - val_accuracy
: 0.9806 - val_precision: 0.9278 - val_recall: 0.9184 - lr: 0.0010
Epoch 8/20
114/114 [==============================] - 60s 525ms/step - loss: 0.0802 - accura
cy: 0.9718 - precision: 0.9236 - recall: 0.8468 - val_loss: 0.0686 - val_accuracy
: 0.9768 - val_precision: 0.9651 - val_recall: 0.8469 - lr: 2.0000e-04
CPU times: total: 10min 24s
Wall time: 8min 12s
```

In [30]:

```python
# Extract loss and accuracy for training and validation from the history object
train_loss = history.history['loss']
val_loss = history.history['val_loss']
train_accuracy = history.history['accuracy']
val_accuracy = history.history['val_accuracy']

# Create a range object for the number of epochs
epochs = range(1, len(train_loss) + 1)

# Plot training and validation loss
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(epochs, train_loss, 'b', label='Training Loss')
plt.plot(epochs, val_loss, 'r', label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Plot training and validation accuracy
plt.subplot(1, 2, 2)
plt.plot(epochs, train_accuracy, 'b', label='Training Accuracy')
plt.plot(epochs, val_accuracy, 'r', label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
```

```python
plt.ylabel('Accuracy')
plt.legend()

# Display the plots
plt.tight_layout()
plt.show()
```

Model Evaluation

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In [31]:

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

```
25/25 [==============================] - 10s 419ms/step - loss: 0.0521 - accuracy
: 0.9858 - precision: 0.9485 - recall: 0.9388
Test Loss: 0.05211685970425606
Test Accuracy: 0.9858247637748718
```

In [32]:

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

```
25/25 [==============================] - 11s 421ms/step
```

In [33]:

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

Out[33]:

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

In [34]:

```python
from sklearn.metrics import confusion_matrix

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

Out[34]:

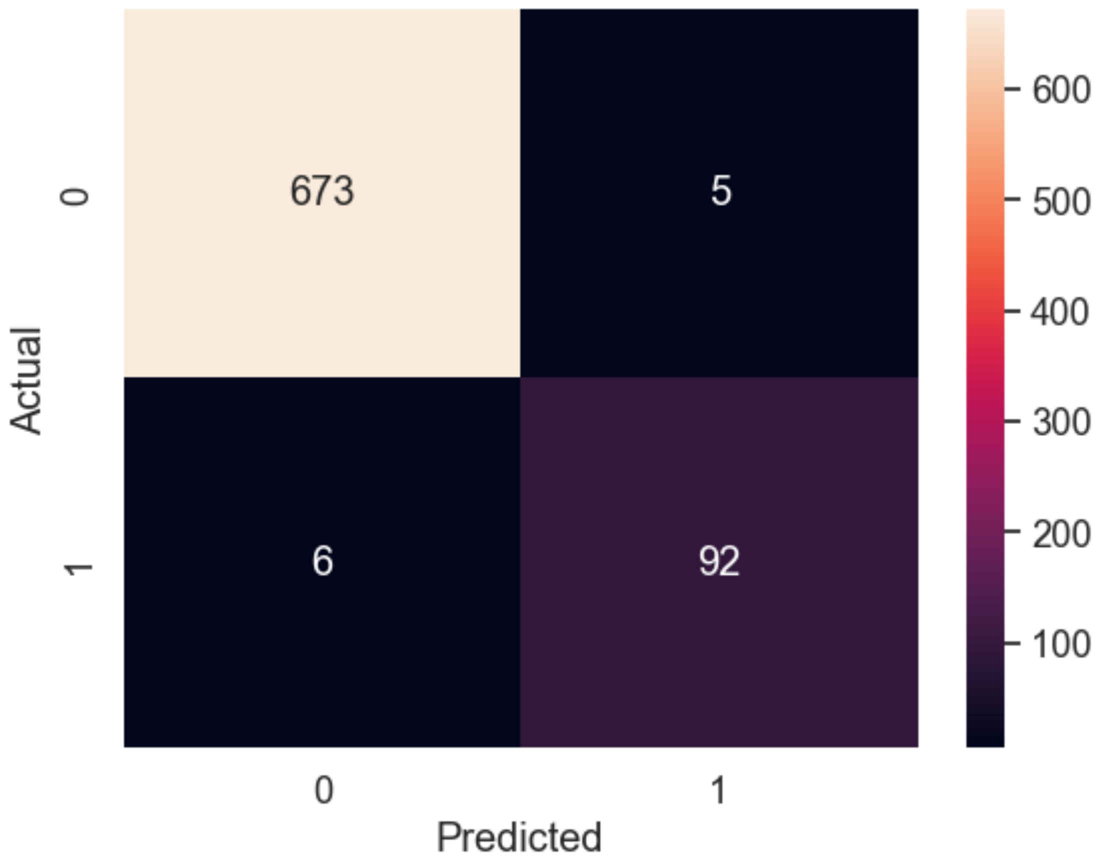
```
array([[673,   5],
       [  6,  92]], dtype=int64)
```

In [35]:

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

Out[35]:

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



In [36]:
```
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      0.99      0.99       678
        Spam       0.95      0.94      0.94        98

    accuracy                           0.99       776
   macro avg       0.97      0.97      0.97       776
weighted avg       0.99      0.99      0.99       776
```

Inference

In [37]:
```
# 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 783ms/step
```

Out[37]:
```
array([[0.04189568],
       [0.52800953],
       [0.04187298],
       [0.29887256],
       [0.00634511]], dtype=float32)
```

Hyperparameter Tuning with Keras Tuner (Original Data)

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In [38]:
```
%%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: 1.53 s
Wall time: 2.2 s
```

In [39]:
```
# 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]}")
```

```
25/25 [==============================] - 12s 418ms/step - loss: 0.0490 - accuracy
: 0.9865 - precision: 0.9581 - recall: 0.9337

Validation Loss: 0.04902127757668495
Validation Accuracy: 0.9864603281021118
```

In [40]:
```
# 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]}")
```

```
25/25 [==============================] - 11s 421ms/step - loss: 0.0315 - accuracy
: 0.9910 - precision: 0.9789 - recall: 0.9490
\Test Loss: 0.03152916207909584
Test Accuracy: 0.9909793734550476
```

Model Building

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In [41]:

```
%%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
114/114 [==============================] - 63s 524ms/step - loss: 0.0713 - accura
cy: 0.9793 - precision: 0.9321 - recall: 0.9015 - val_loss: 0.0498 - val_accuracy
: 0.9832 - val_precision: 0.9670 - val_recall: 0.8980 - lr: 1.0000e-04
Epoch 2/20
114/114 [==============================] - 60s 525ms/step - loss: 0.0702 - accura
cy: 0.9760 - precision: 0.9243 - recall: 0.8818 - val_loss: 0.0479 - val_accuracy
: 0.9845 - val_precision: 0.9674 - val_recall: 0.9082 - lr: 1.0000e-04
Epoch 3/20
114/114 [==============================] - 60s 530ms/step - loss: 0.0604 - accura
cy: 0.9807 - precision: 0.9428 - recall: 0.9015 - val_loss: 0.0473 - val_accuracy
: 0.9845 - val_precision: 0.9674 - val_recall: 0.9082 - lr: 1.0000e-04
Epoch 4/20
114/114 [==============================] - 59s 515ms/step - loss: 0.0630 - accura
cy: 0.9798 - precision: 0.9384 - recall: 0.8993 - val_loss: 0.0478 - val_accuracy
: 0.9845 - val_precision: 0.9674 - val_recall: 0.9082 - lr: 1.0000e-04
Epoch 5/20
114/114 [==============================] - 59s 521ms/step - loss: 0.0678 - accura
cy: 0.9776 - precision: 0.9372 - recall: 0.8818 - val_loss: 0.0461 - val_accuracy
: 0.9858 - val_precision: 0.9677 - val_recall: 0.9184 - lr: 1.0000e-04
Epoch 6/20
114/114 [==============================] - 60s 523ms/step - loss: 0.0642 - accura
cy: 0.9798 - precision: 0.9486 - recall: 0.8884 - val_loss: 0.0471 - val_accuracy
: 0.9858 - val_precision: 0.9677 - val_recall: 0.9184 - lr: 1.0000e-04
Epoch 7/20
114/114 [==============================] - 59s 522ms/step - loss: 0.0663 - accura
cy: 0.9771 - precision: 0.9174 - recall: 0.8993 - val_loss: 0.0479 - val_accuracy
: 0.9832 - val_precision: 0.9293 - val_recall: 0.9388 - lr: 1.0000e-04
Epoch 8/20
114/114 [==============================] - 59s 519ms/step - loss: 0.0622 - accura
cy: 0.9787 - precision: 0.9279 - recall: 0.9015 - val_loss: 0.0459 - val_accuracy
: 0.9858 - val_precision: 0.9677 - val_recall: 0.9184 - lr: 2.0000e-05
Epoch 9/20
114/114 [==============================] - 59s 519ms/step - loss: 0.0621 - accura
cy: 0.9807 - precision: 0.9469 - recall: 0.8972 - val_loss: 0.0464 - val_accuracy
: 0.9858 - val_precision: 0.9677 - val_recall: 0.9184 - lr: 2.0000e-05
Epoch 10/20
114/114 [==============================] - 59s 515ms/step - loss: 0.0624 - accura
cy: 0.9804 - precision: 0.9509 - recall: 0.8906 - val_loss: 0.0465 - val_accuracy
: 0.9858 - val_precision: 0.9677 - val_recall: 0.9184 - lr: 2.0000e-05
Epoch 11/20
114/114 [==============================] - 60s 524ms/step - loss: 0.0680 - accura
cy: 0.9771 - precision: 0.9269 - recall: 0.8884 - val_loss: 0.0464 - val_accuracy
: 0.9858 - val_precision: 0.9677 - val_recall: 0.9184 - lr: 4.0000e-06
CPU times: total: 13min 49s
Wall time: 10min 56s
```

Out[41]:
```
<keras.callbacks.History at 0x1db3d02d150>
```

Model Evaluation

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In [43]:
```
y_predict_hp = best_model_nml.predict(X_test)
y_predict_hp = y_predict_hp.flatten()
```

```
25/25 [==============================] - 11s 406ms/step
```

In [44]:
```
y_predict_hp = np.where(y_predict_hp > 0.5,1,0)
```

```python
y_predict_hp
```

Out[44]:

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

In [45]:

```python
cm_hp = confusion_matrix(y_test, y_predict_hp)
cm_hp
```

Out[45]:

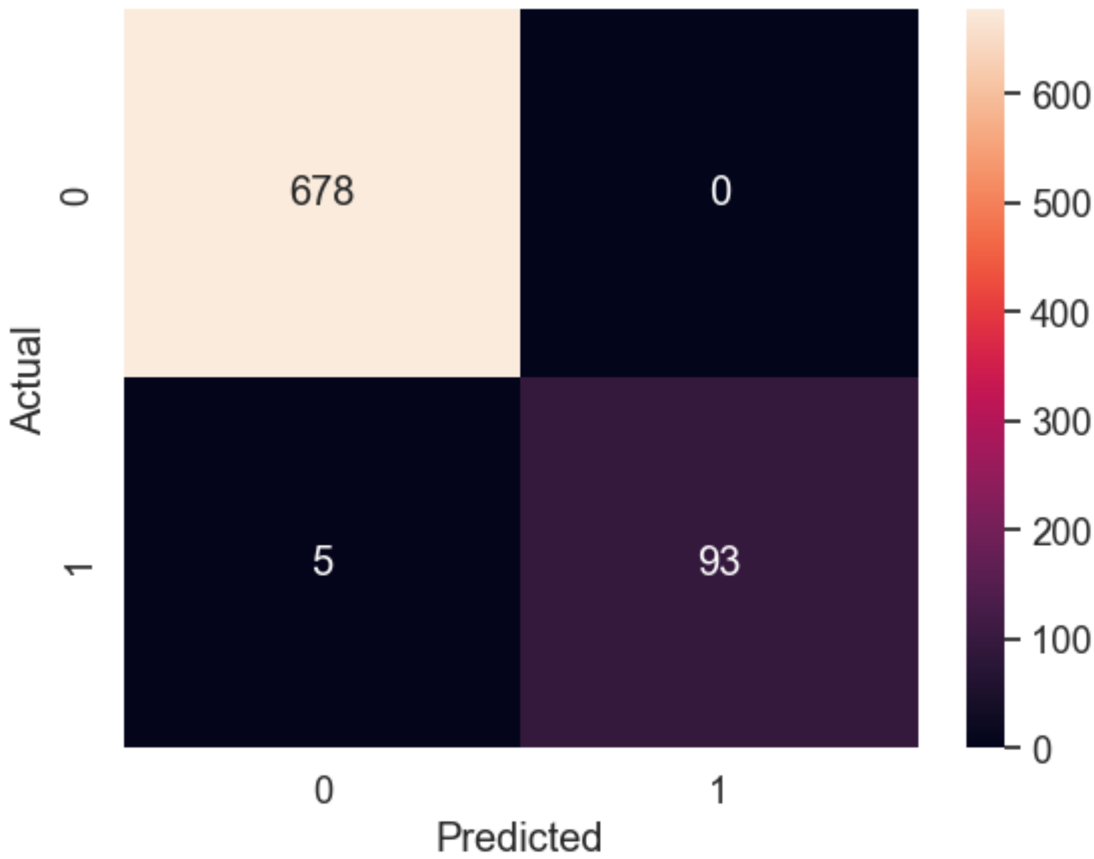
```
array([[678,   0],
       [  5,  93]], dtype=int64)
```

In [46]:

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

Out[46]:

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



In [47]:
```
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      1.00       678
        Spam       1.00      0.95      0.97        98

    accuracy                           0.99       776
   macro avg       1.00      0.97      0.99       776
weighted avg       0.99      0.99      0.99       776
```

Additional Metrics (ROC-AUC) for BERT

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In [48]:
```
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}')
```

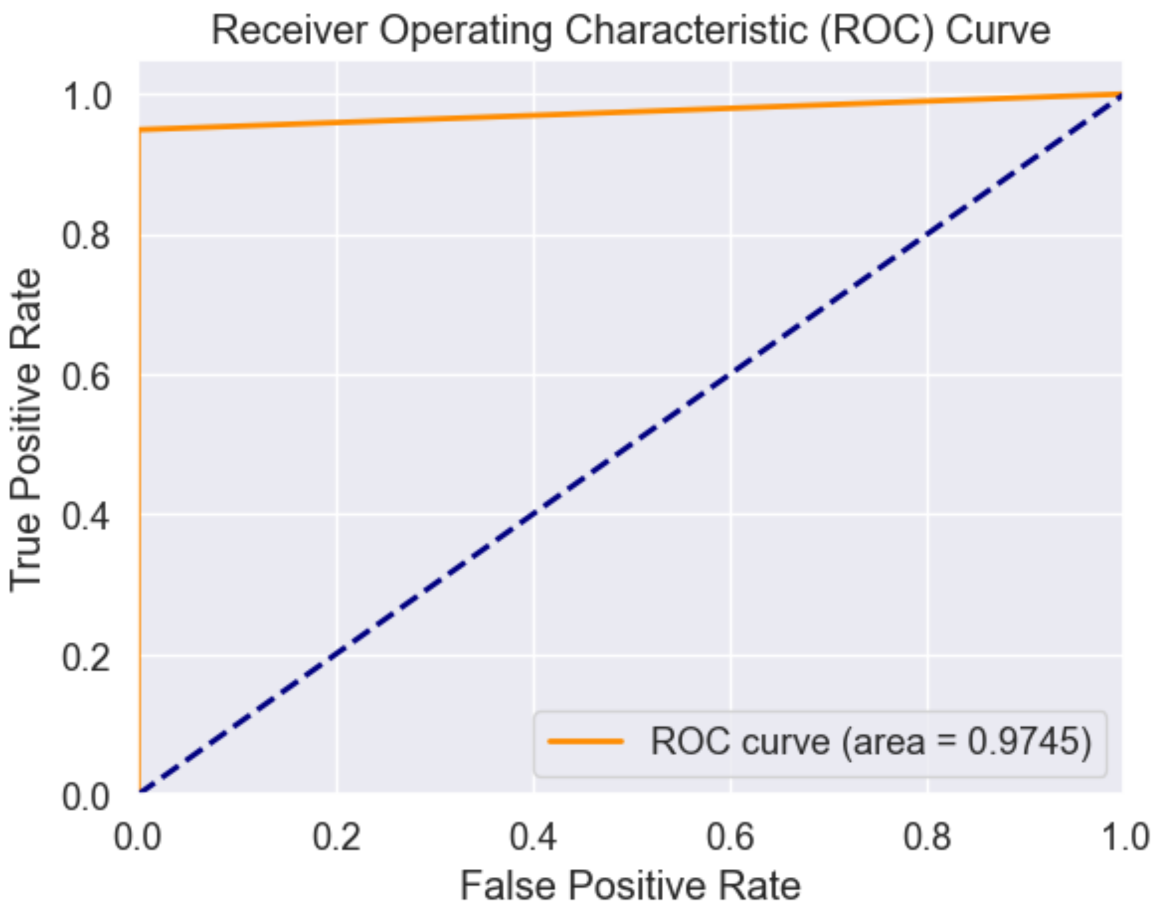
```
ROC-AUC Score on Test Set: 0.9745
```

In [49]:
```
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 [50]:
```
# Detection of examples
nml_inf_hp = best_model_nml.predict(reviews)
nml_inf_hp
```

```
1/1 [==============================] - 1s 705ms/step
```

Out[50]:
```
array([[0.03139546],
       [0.5518679 ],
       [0.19162832],
       [0.44041386],
       [0.00502677]], dtype=float32)
```

Downsampling Data

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In [51]:
```
data_dwn = data.copy(deep=True)
```

In [52]:
```
data_dwn.head()
```

Out[52]:

	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 [53]:
```
data_spam = data_dwn[data_dwn['Class']==1]
data_spam.shape
```

Out[53]: (653, 2)

In [54]:
```
data_ham = data_dwn[data_dwn['Class']==0]
data_ham.shape
```

Out[54]: (4516, 2)

In [55]:
```
data_ham_downsampled = data_ham.sample(data_spam.shape[0])
data_ham_downsampled.shape
```

Out[55]: (653, 2)

In [56]:
```
data_balanced_dwn = pd.concat([data_spam,data_ham_downsampled])
data_balanced_dwn.shape
```

Out[56]: (1306, 2)

In [57]:
```
data_balanced_dwn['Class'].value_counts()
```

Out[57]:
```
Class
1    653
0    653
Name: count, dtype: int64
```

Train/Test Splitting

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In [58]:
```
X_dwn = data_balanced_dwn['Text']
y_dwn = data_balanced_dwn['Class']
```

In [59]:
```
# 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: 914, 914
Validation data: 196, 196
Testing data: 196, 196
```

Model Building

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In [60]:
```
%%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
29/29 [==============================] - 15s 520ms/step - loss: 0.8676 - accuracy
: 0.7287 - precision: 1.0000 - recall: 0.4573 - val_loss: 0.1464 - val_accuracy:
0.9592 - val_precision: 1.0000 - val_recall: 0.9184 - lr: 4.0000e-06
Epoch 2/20
29/29 [==============================] - 15s 511ms/step - loss: 0.8376 - accuracy
: 0.7298 - precision: 1.0000 - recall: 0.4595 - val_loss: 0.2046 - val_accuracy:
0.9337 - val_precision: 1.0000 - val_recall: 0.8673 - lr: 4.0000e-06
Epoch 3/20
29/29 [==============================] - 15s 509ms/step - loss: 0.8209 - accuracy
: 0.7188 - precision: 1.0000 - recall: 0.4376 - val_loss: 0.2596 - val_accuracy:
0.9133 - val_precision: 1.0000 - val_recall: 0.8265 - lr: 4.0000e-06
Epoch 4/20
29/29 [==============================] - 15s 515ms/step - loss: 0.8396 - accuracy
: 0.7254 - precision: 1.0000 - recall: 0.4508 - val_loss: 0.3261 - val_accuracy:
0.8980 - val_precision: 1.0000 - val_recall: 0.7959 - lr: 8.0000e-07
CPU times: total: 1min 15s
Wall time: 59.3 s
```

In [61]:
```
# Extract loss and accuracy for training and validation from the history object
train_loss = history_dwn.history['loss']
val_loss = history_dwn.history['val_loss']
train_accuracy = history_dwn.history['accuracy']
val_accuracy = history_dwn.history['val_accuracy']

# Create a range object for the number of epochs
epochs = range(1, len(train_loss) + 1)

# Plot training and validation loss
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(epochs, train_loss, 'b', label='Training Loss')
plt.plot(epochs, val_loss, 'r', label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Plot training and validation accuracy
plt.subplot(1, 2, 2)
plt.plot(epochs, train_accuracy, 'b', label='Training Accuracy')
plt.plot(epochs, val_accuracy, 'r', label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
```

```
plt.legend()

# Display the plots
plt.tight_layout()
plt.show()
```

Model Evaluation

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In [62]:
```
# 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]}")
```

```
7/7 [==============================] - 3s 361ms/step - loss: 0.1266 - accuracy: 0
.9592 - precision: 1.0000 - recall: 0.9184
Test Loss: 0.1266266405582428
Test Accuracy: 0.9591836929321289
```

In [63]:
```
y_predict_dwn = model.predict(X_test_dwn)
y_predict_dwn = y_predict_dwn.flatten()
```

```
7/7 [==============================] - 3s 402ms/step
```

In [64]:
```
y_predict_dwn = np.where(y_predict_dwn > 0.5,1,0)
y_predict_dwn
```

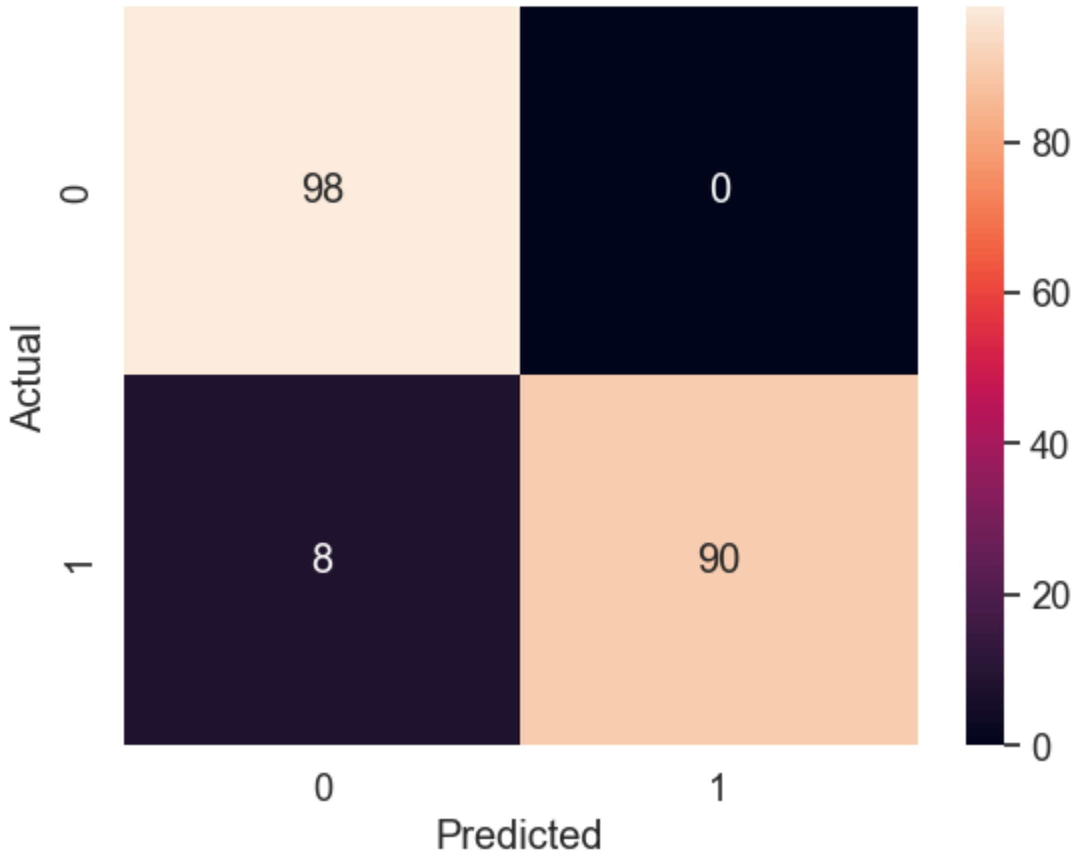
Out[64]:
```
array([1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1,
       0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0,
       0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1,
       0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1,
       0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0,
       0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 1, 0,
       1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0])
```

In [65]:
```
cm_dwn = confusion_matrix(y_test_dwn, y_predict_dwn)
cm_dwn
```

Out[65]:
```
array([[98,  0],
       [ 8, 90]], dtype=int64)
```

In [66]:
```python
sns.heatmap(cm_dwn, annot=True, fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

Out[66]:
```
Text(43.25, 0.5, 'Actual')
```



In [67]:
```python
dwn = classification_report(y_test_dwn, y_predict_dwn, target_names=['Ham', 'Spa
print(dwn)
```

```
              precision    recall  f1-score   support

         Ham       0.92      1.00      0.96        98
        Spam       1.00      0.92      0.96        98

    accuracy                           0.96       196
   macro avg       0.96      0.96      0.96       196
weighted avg       0.96      0.96      0.96       196
```

In [68]:
```python
# Detection of examples
dwn_inf = model.predict(reviews)
dwn_inf
```

```
1/1 [==============================] - 0s 52ms/step
```

Out[68]:
```
array([[0.01022932],
       [0.23287717],
       [0.07121247],
       [0.19026127],
       [0.00284273]], dtype=float32)
```

Hyperparameter Tuning with Keras Tuner (Downsampled Data)

Table of Contents

In [69]:
```
%%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: 1.27 s
Wall time: 1.69 s
```

In [70]:
```
# 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 366ms/step - loss: 0.0994 - accuracy: 0
.9566 - precision: 0.9786 - recall: 0.9337

Validation Loss: 0.04902127757668495
Validation Accuracy: 0.9864603281021118
```

In [71]:
```
# 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]}")
```

```
7/7 [==============================] - 3s 367ms/step - loss: 0.0629 - accuracy: 0
.9796 - precision: 0.9896 - recall: 0.9694
\Test Loss: 0.06288964301347733
Test Accuracy: 0.9795918464660645
```

Model Building

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In [72]:
```
%%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
29/29 [==============================] - 18s 531ms/step - loss: 0.2720 - accuracy
: 0.9289 - precision: 0.9712 - recall: 0.8840 - val_loss: 0.2406 - val_accuracy:
0.9235 - val_precision: 0.8739 - val_recall: 0.9898 - lr: 0.0010
Epoch 2/20
29/29 [==============================] - 15s 519ms/step - loss: 0.2761 - accuracy
: 0.9201 - precision: 0.9444 - recall: 0.8928 - val_loss: 0.1539 - val_accuracy:
0.9541 - val_precision: 0.9238 - val_recall: 0.9898 - lr: 0.0010
Epoch 3/20
29/29 [==============================] - 15s 519ms/step - loss: 0.1566 - accuracy
: 0.9573 - precision: 0.9686 - recall: 0.9453 - val_loss: 0.4503 - val_accuracy:
0.8316 - val_precision: 0.7519 - val_recall: 0.9898 - lr: 0.0010
Epoch 4/20
29/29 [==============================] - 15s 533ms/step - loss: 0.1556 - accuracy
: 0.9540 - precision: 0.9705 - recall: 0.9365 - val_loss: 0.1310 - val_accuracy:
0.9490 - val_precision: 0.9400 - val_recall: 0.9592 - lr: 0.0010
Epoch 5/20
29/29 [==============================] - 15s 516ms/step - loss: 0.1424 - accuracy
: 0.9540 - precision: 0.9642 - recall: 0.9431 - val_loss: 0.3061 - val_accuracy:
0.9337 - val_precision: 1.0000 - val_recall: 0.8673 - lr: 0.0010
Epoch 6/20
29/29 [==============================] - 15s 518ms/step - loss: 0.1478 - accuracy
: 0.9475 - precision: 0.9596 - recall: 0.9344 - val_loss: 0.1392 - val_accuracy:
0.9490 - val_precision: 0.9231 - val_recall: 0.9796 - lr: 0.0010
Epoch 7/20
29/29 [==============================] - 15s 533ms/step - loss: 0.1517 - accuracy
: 0.9584 - precision: 0.9604 - recall: 0.9562 - val_loss: 0.1065 - val_accuracy:
0.9541 - val_precision: 0.9495 - val_recall: 0.9592 - lr: 2.0000e-04
Epoch 8/20
29/29 [==============================] - 15s 527ms/step - loss: 0.1391 - accuracy
: 0.9584 - precision: 0.9666 - recall: 0.9497 - val_loss: 0.1024 - val_accuracy:
0.9541 - val_precision: 0.9406 - val_recall: 0.9694 - lr: 2.0000e-04
Epoch 9/20
29/29 [==============================] - 16s 540ms/step - loss: 0.1550 - accuracy
: 0.9486 - precision: 0.9496 - recall: 0.9475 - val_loss: 0.0980 - val_accuracy:
0.9643 - val_precision: 0.9596 - val_recall: 0.9694 - lr: 2.0000e-04
Epoch 10/20
29/29 [==============================] - 15s 522ms/step - loss: 0.1229 - accuracy
: 0.9562 - precision: 0.9603 - recall: 0.9519 - val_loss: 0.1031 - val_accuracy:
0.9592 - val_precision: 0.9412 - val_recall: 0.9796 - lr: 2.0000e-04
Epoch 11/20
29/29 [==============================] - 15s 535ms/step - loss: 0.1080 - accuracy
: 0.9683 - precision: 0.9714 - recall: 0.9650 - val_loss: 0.0955 - val_accuracy:
0.9643 - val_precision: 0.9691 - val_recall: 0.9592 - lr: 2.0000e-04
Epoch 12/20
29/29 [==============================] - 15s 516ms/step - loss: 0.1418 - accuracy
: 0.9431 - precision: 0.9374 - recall: 0.9497 - val_loss: 0.0961 - val_accuracy:
0.9592 - val_precision: 0.9592 - val_recall: 0.9592 - lr: 2.0000e-04
Epoch 13/20
29/29 [==============================] - 15s 516ms/step - loss: 0.0977 - accuracy
: 0.9650 - precision: 0.9754 - recall: 0.9540 - val_loss: 0.1163 - val_accuracy:
0.9592 - val_precision: 0.9412 - val_recall: 0.9796 - lr: 2.0000e-04
Epoch 14/20
29/29 [==============================] - 15s 520ms/step - loss: 0.1242 - accuracy
: 0.9519 - precision: 0.9579 - recall: 0.9453 - val_loss: 0.1056 - val_accuracy:
0.9643 - val_precision: 0.9505 - val_recall: 0.9796 - lr: 4.0000e-05
CPU times: total: 4min 32s
Wall time: 3min 34s
```

Out[72]: <keras.callbacks.History at 0x1db3d11a290>

Model Evaluation

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In [73]:
```
y_predict_hp_dwn = best_model_dwn.predict(X_test_dwn)
y_predict_hp_dwn = y_predict_hp_dwn.flatten()
```

```
7/7 [==============================] - 3s 407ms/step
```

In [74]:
```
y_predict_hp_dwn = np.where(y_predict_hp_dwn > 0.5,1,0)
y_predict_hp_dwn
```

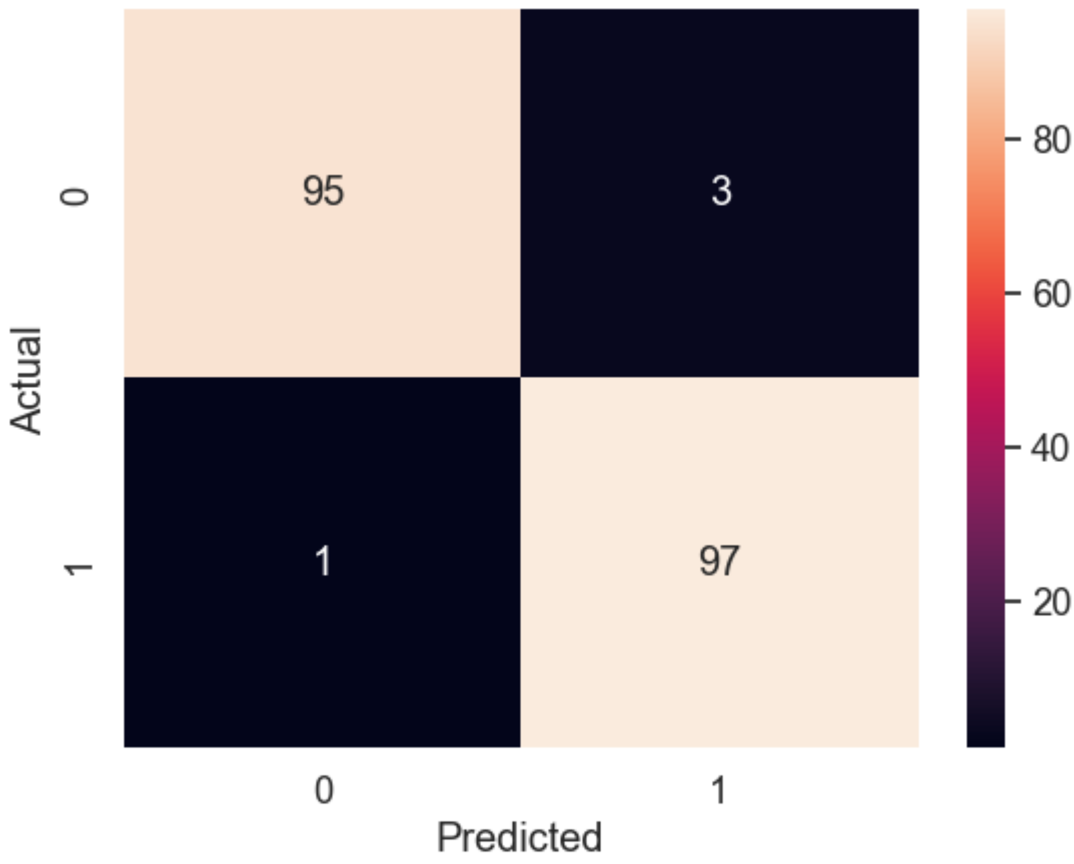
Out[74]:
```
array([1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1,
       0, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 0,
       0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1,
       0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1,
       0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0,
       0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0,
       1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0])
```

In [75]:
```
cm_hp_dwn = confusion_matrix(y_test_dwn, y_predict_hp_dwn)
cm_hp_dwn
```

Out[75]:
```
array([[95,  3],
       [ 1, 97]], dtype=int64)
```

In [76]:
```
sns.heatmap(cm_hp_dwn, annot=True, fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

Out[76]:
```
Text(43.25, 0.5, 'Actual')
```



In [77]:
```
dwn_hp = classification_report(y_test_dwn, y_predict_hp_dwn, target_names=['Ham'
print(dwn_hp)
```

```
              precision    recall  f1-score   support

         Ham       0.99      0.97      0.98        98
        Spam       0.97      0.99      0.98        98

    accuracy                           0.98       196
   macro avg       0.98      0.98      0.98       196
weighted avg       0.98      0.98      0.98       196
```

Additional Metrics (ROC-AUC) for BERT

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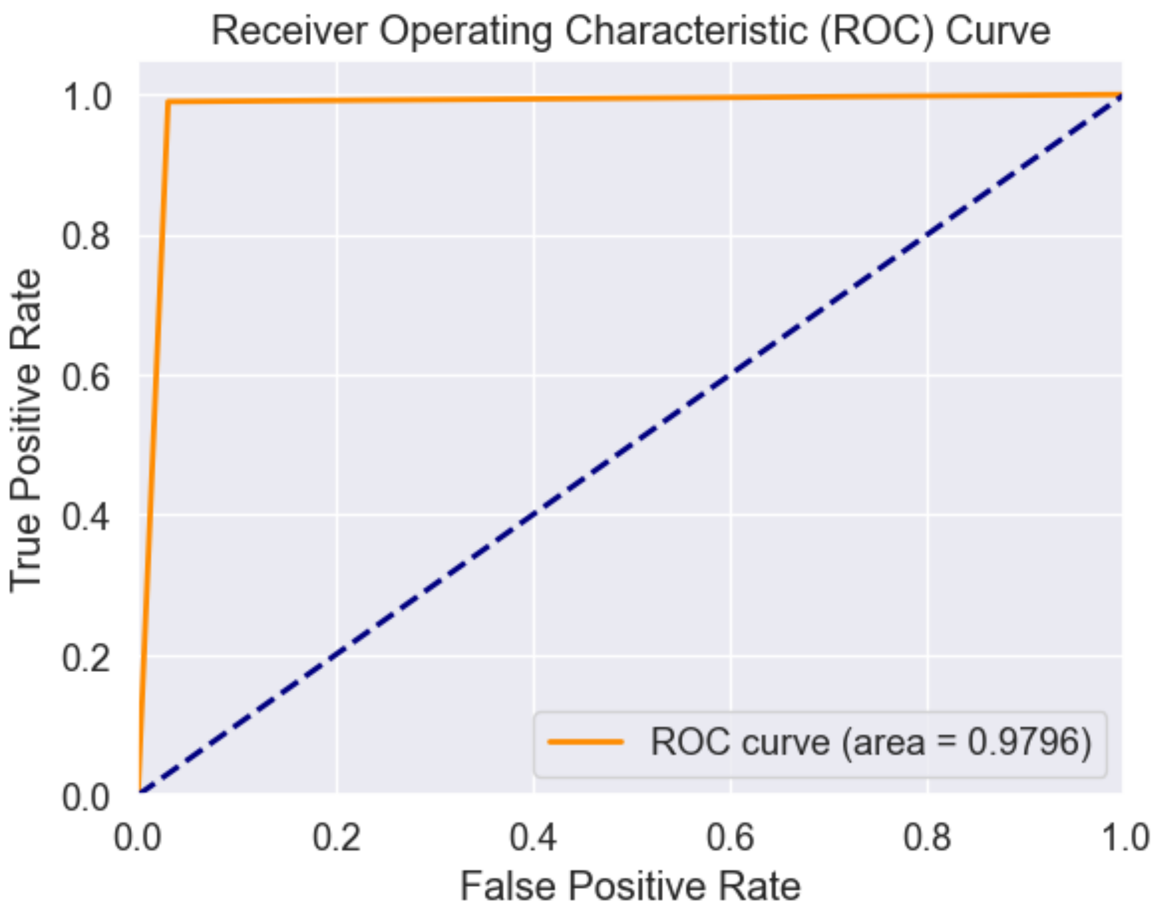
In [78]:
```
roc_auc_test = roc_auc_score(y_test_dwn, y_predict_hp_dwn)
print(f'ROC-AUC Score on Test Set: {roc_auc_test:.4f}')
```

```
ROC-AUC Score on Test Set: 0.9796
```

In [79]:
```
# 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 [80]:

```
# Detection of examples
dwn_inf_hp = best_model_dwn.predict(reviews)
dwn_inf_hp
```

```
1/1 [==============================] - 1s 729ms/step
```

Out[80]:

```
array([[0.23240902],
       [0.72064584],
       [0.83650786],
       [0.9270451 ],
       [0.00124681]], dtype=float32)
```

Upsampling Data

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In [81]:

```
data_up = data.copy(deep=True)
data_up
```

Out[81]:

	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

5169 rows × 2 columns

In [82]:

```
data_spam_up = data_up[data_up['Class']==1]
data_spam_up.shape
```

Out[82]:

```
(653, 2)
```

In [83]:

```
data_ham_up = data_up[data_up['Class']==0]
data_ham_up.shape
```

Out[83]:

```
(4516, 2)
```

In [84]:

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

Out[84]:

```
(4516, 2)
```

In [85]:

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

Out[85]:

```
(9032, 2)
```

In [86]:

```
data_balanced_up['Class'].value_counts()
```

Out[86]:

```
Class
0    4516
1    4516
Name: count, dtype: int64
```

Train/Test Splitting

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In [87]:

```
X_up = data_balanced_up['Text']
```

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

In [88]:
```
# 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: 6322, 6322
Validation data: 1355, 1355
Testing data: 1355, 1355
```

Model Building

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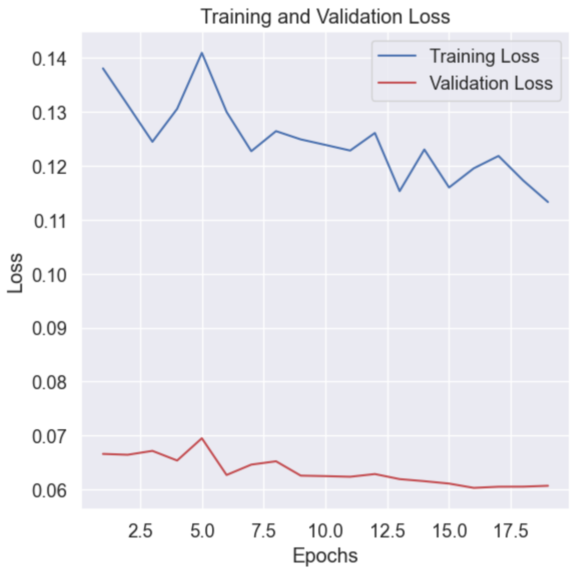
In [89]:
```
%%time
# Fit the model
history_up = model.fit(X_train_up, y_train_up, epochs=20,
                       validation_data=(X_val_up, y_val_up),
                       callbacks=[early_stopping, lr_scheduler])
```

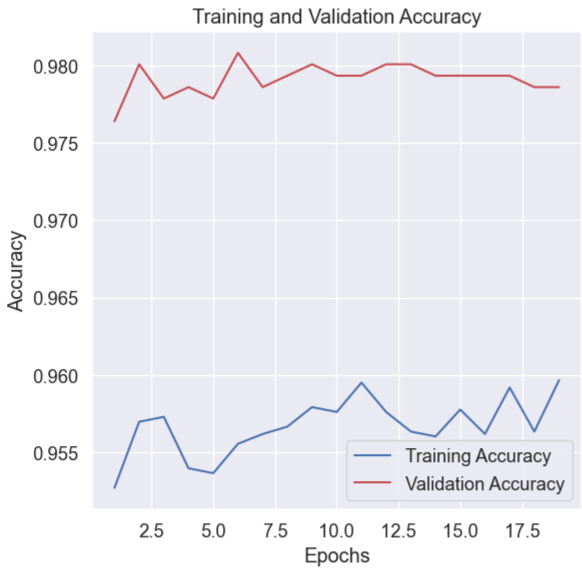
```
Epoch 1/20
198/198 [==============================] - 104s 528ms/step - loss: 0.1381 - accur
acy: 0.9527 - precision: 0.9563 - recall: 0.9488 - val_loss: 0.0666 - val_accurac
y: 0.9764 - val_precision: 0.9695 - val_recall: 0.9838 - lr: 4.0000e-05
Epoch 2/20
198/198 [==============================] - 103s 521ms/step - loss: 0.1313 - accur
acy: 0.9570 - precision: 0.9590 - recall: 0.9548 - val_loss: 0.0664 - val_accurac
y: 0.9801 - val_precision: 0.9766 - val_recall: 0.9838 - lr: 4.0000e-05
Epoch 3/20
198/198 [==============================] - 103s 519ms/step - loss: 0.1245 - accur
acy: 0.9573 - precision: 0.9590 - recall: 0.9554 - val_loss: 0.0672 - val_accurac
y: 0.9779 - val_precision: 0.9723 - val_recall: 0.9838 - lr: 4.0000e-05
Epoch 4/20
198/198 [==============================] - 102s 518ms/step - loss: 0.1306 - accur
acy: 0.9540 - precision: 0.9533 - recall: 0.9548 - val_loss: 0.0654 - val_accurac
y: 0.9786 - val_precision: 0.9737 - val_recall: 0.9838 - lr: 4.0000e-05
Epoch 5/20
198/198 [==============================] - 105s 530ms/step - loss: 0.1410 - accur
acy: 0.9537 - precision: 0.9552 - recall: 0.9519 - val_loss: 0.0695 - val_accurac
y: 0.9779 - val_precision: 0.9709 - val_recall: 0.9853 - lr: 4.0000e-05
Epoch 6/20
198/198 [==============================] - 105s 530ms/step - loss: 0.1300 - accur
acy: 0.9556 - precision: 0.9586 - recall: 0.9522 - val_loss: 0.0627 - val_accurac
y: 0.9808 - val_precision: 0.9780 - val_recall: 0.9838 - lr: 4.0000e-05
Epoch 7/20
198/198 [==============================] - 106s 538ms/step - loss: 0.1227 - accur
acy: 0.9562 - precision: 0.9578 - recall: 0.9544 - val_loss: 0.0646 - val_accurac
y: 0.9786 - val_precision: 0.9723 - val_recall: 0.9853 - lr: 4.0000e-05
Epoch 8/20
198/198 [==============================] - 107s 542ms/step - loss: 0.1264 - accur
acy: 0.9567 - precision: 0.9578 - recall: 0.9554 - val_loss: 0.0652 - val_accurac
y: 0.9793 - val_precision: 0.9738 - val_recall: 0.9853 - lr: 4.0000e-05
Epoch 9/20
198/198 [==============================] - 104s 528ms/step - loss: 0.1249 - accur
acy: 0.9579 - precision: 0.9568 - recall: 0.9592 - val_loss: 0.0626 - val_accurac
y: 0.9801 - val_precision: 0.9766 - val_recall: 0.9838 - lr: 8.0000e-06
Epoch 10/20
198/198 [==============================] - 105s 532ms/step - loss: 0.1239 - accur
acy: 0.9576 - precision: 0.9591 - recall: 0.9560 - val_loss: 0.0625 - val_accurac
y: 0.9793 - val_precision: 0.9751 - val_recall: 0.9838 - lr: 8.0000e-06
Epoch 11/20
198/198 [==============================] - 104s 526ms/step - loss: 0.1228 - accur
acy: 0.9595 - precision: 0.9607 - recall: 0.9582 - val_loss: 0.0624 - val_accurac
y: 0.9793 - val_precision: 0.9751 - val_recall: 0.9838 - lr: 8.0000e-06
Epoch 12/20
198/198 [==============================] - 105s 531ms/step - loss: 0.1261 - accur
acy: 0.9576 - precision: 0.9559 - recall: 0.9595 - val_loss: 0.0629 - val_accurac
y: 0.9801 - val_precision: 0.9752 - val_recall: 0.9853 - lr: 8.0000e-06
Epoch 13/20
198/198 [==============================] - 105s 531ms/step - loss: 0.1153 - accur
acy: 0.9563 - precision: 0.9561 - recall: 0.9567 - val_loss: 0.0619 - val_accurac
y: 0.9801 - val_precision: 0.9752 - val_recall: 0.9853 - lr: 8.0000e-06
Epoch 14/20
198/198 [==============================] - 104s 525ms/step - loss: 0.1230 - accur
acy: 0.9560 - precision: 0.9583 - recall: 0.9535 - val_loss: 0.0615 - val_accurac
y: 0.9793 - val_precision: 0.9738 - val_recall: 0.9853 - lr: 8.0000e-06
Epoch 15/20
198/198 [==============================] - 105s 529ms/step - loss: 0.1160 - accur
acy: 0.9578 - precision: 0.9582 - recall: 0.9573 - val_loss: 0.0611 - val_accurac
y: 0.9793 - val_precision: 0.9738 - val_recall: 0.9853 - lr: 8.0000e-06
```

```
Epoch 16/20
198/198 [==============================] - 106s 535ms/step - loss: 0.1195 - accur
acy: 0.9562 - precision: 0.9526 - recall: 0.9601 - val_loss: 0.0603 - val_accurac
y: 0.9793 - val_precision: 0.9751 - val_recall: 0.9838 - lr: 8.0000e-06
Epoch 17/20
198/198 [==============================] - 107s 543ms/step - loss: 0.1218 - accur
acy: 0.9592 - precision: 0.9560 - recall: 0.9627 - val_loss: 0.0605 - val_accurac
y: 0.9793 - val_precision: 0.9751 - val_recall: 0.9838 - lr: 8.0000e-06
Epoch 18/20
198/198 [==============================] - 104s 527ms/step - loss: 0.1173 - accur
acy: 0.9563 - precision: 0.9561 - recall: 0.9567 - val_loss: 0.0605 - val_accurac
y: 0.9786 - val_precision: 0.9737 - val_recall: 0.9838 - lr: 8.0000e-06
Epoch 19/20
198/198 [==============================] - 104s 527ms/step - loss: 0.1133 - accur
acy: 0.9597 - precision: 0.9595 - recall: 0.9598 - val_loss: 0.0607 - val_accurac
y: 0.9786 - val_precision: 0.9737 - val_recall: 0.9838 - lr: 1.6000e-06
CPU times: total: 42min 9s
Wall time: 33min 9s
```

In [90]:

```python
# Extract loss and accuracy for training and validation from the history object
train_loss = history_up.history['loss']
val_loss = history_up.history['val_loss']
train_accuracy = history_up.history['accuracy']
val_accuracy = history_up.history['val_accuracy']

# Create a range object for the number of epochs
epochs = range(1, len(train_loss) + 1)

# Plot training and validation loss
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(epochs, train_loss, 'b', label='Training Loss')
plt.plot(epochs, val_loss, 'r', label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Plot training and validation accuracy
plt.subplot(1, 2, 2)
plt.plot(epochs, train_accuracy, 'b', label='Training Accuracy')
plt.plot(epochs, val_accuracy, 'r', label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

# Display the plots
plt.tight_layout()
plt.show()
```





Model Evaluation

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In [91]:
```
# 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]}")
```

```
43/43 [==============================] - 18s 427ms/step - loss: 0.0520 - accuracy
: 0.9845 - precision: 0.9781 - recall: 0.9911
Test Loss: 0.05197938531637192
Test Accuracy: 0.984501838684082
```

In [92]:
```
y_predict_up = model.predict(X_test_up)
y_predict_up = y_predict_up.flatten()
```

```
43/43 [==============================] - 19s 441ms/step
```

In [93]:
```
y_predict_up = np.where(y_predict_up > 0.5,1,0)
y_predict_up
```

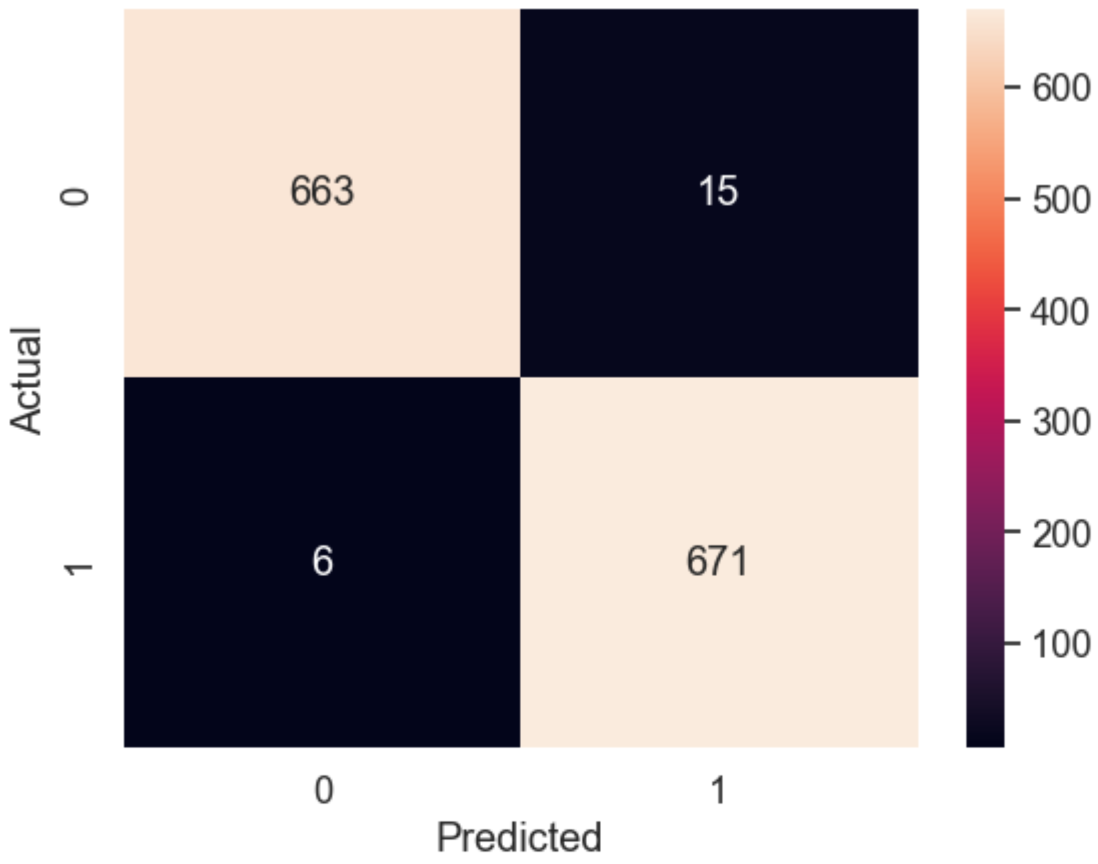
Out[93]:
```
array([0, 1, 0, ..., 1, 1, 1])
```

In [94]:
```
cm_up = confusion_matrix(y_test_up, y_predict_up)
cm_up
```

Out[94]:
```
array([[663,  15],
       [  6, 671]], dtype=int64)
```

In [95]:
```
sns.heatmap(cm_up, annot=True, fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

Out[95]:
```
Text(43.25, 0.5, 'Actual')
```



In [96]:
```
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       678
        Spam       0.98      0.99      0.98       677

    accuracy                           0.98      1355
   macro avg       0.98      0.98      0.98      1355
weighted avg       0.98      0.98      0.98      1355
```

In [97]:
```
# Detection of examples
up_inf = model.predict(reviews)
up_inf
```

```
1/1 [==============================] - 0s 52ms/step
```

Out[97]:
```
array([[0.35127744],
       [0.808034  ],
       [0.7271071 ],
       [0.90419203],
       [0.00117756]], dtype=float32)
```

Hyperparameter Tuning with Keras Tuner (Upsampled Data)

Table of Contents

In [98]:
```
%%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: 1.73 s
Wall time: 2.12 s
```

In [99]:

```
# 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]}")
```

```
43/43 [==============================] - 19s 423ms/step - loss: 0.3446 - accuracy
: 0.9528 - precision: 0.9819 - recall: 0.9225

Validation Loss: 0.344561904668808
Validation Accuracy: 0.952767550945282
```

In [100…

```
# 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]}")
```

```
43/43 [==============================] - 19s 433ms/step - loss: 0.2795 - accuracy
: 0.9314 - precision: 0.9883 - recall: 0.8730
\Test Loss: 0.27953922748565674
Test Accuracy: 0.9313653111457825
```

Model Building

Table of Contents

In [101…

```
%%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
198/198 [==============================] - 108s 528ms/step - loss: 0.1900 - accur
acy: 0.9296 - precision: 0.9333 - recall: 0.9253 - val_loss: 0.1852 - val_accurac
y: 0.9365 - val_precision: 0.9983 - val_recall: 0.8746 - lr: 0.0100
Epoch 2/20
198/198 [==============================] - 104s 525ms/step - loss: 0.1497 - accur
acy: 0.9440 - precision: 0.9434 - recall: 0.9446 - val_loss: 0.9622 - val_accurac
y: 0.6339 - val_precision: 0.5775 - val_recall: 1.0000 - lr: 0.0100
Epoch 3/20
198/198 [==============================] - 104s 527ms/step - loss: 0.1427 - accur
acy: 0.9502 - precision: 0.9529 - recall: 0.9472 - val_loss: 0.2732 - val_accurac
y: 0.8886 - val_precision: 0.9981 - val_recall: 0.7788 - lr: 0.0100
Epoch 4/20
198/198 [==============================] - 106s 536ms/step - loss: 0.1211 - accur
acy: 0.9548 - precision: 0.9633 - recall: 0.9456 - val_loss: 0.0632 - val_accurac
y: 0.9786 - val_precision: 0.9880 - val_recall: 0.9690 - lr: 0.0020
Epoch 5/20
198/198 [==============================] - 105s 532ms/step - loss: 0.1142 - accur
acy: 0.9562 - precision: 0.9575 - recall: 0.9548 - val_loss: 0.0681 - val_accurac
y: 0.9793 - val_precision: 0.9738 - val_recall: 0.9853 - lr: 0.0020
Epoch 6/20
198/198 [==============================] - 105s 529ms/step - loss: 0.1047 - accur
acy: 0.9605 - precision: 0.9625 - recall: 0.9582 - val_loss: 0.0647 - val_accurac
y: 0.9830 - val_precision: 0.9895 - val_recall: 0.9764 - lr: 0.0020
Epoch 7/20
198/198 [==============================] - 105s 531ms/step - loss: 0.1009 - accur
acy: 0.9619 - precision: 0.9671 - recall: 0.9563 - val_loss: 0.0573 - val_accurac
y: 0.9838 - val_precision: 0.9809 - val_recall: 0.9867 - lr: 4.0000e-04
Epoch 8/20
198/198 [==============================] - 106s 538ms/step - loss: 0.0975 - accur
acy: 0.9617 - precision: 0.9647 - recall: 0.9586 - val_loss: 0.0551 - val_accurac
y: 0.9838 - val_precision: 0.9896 - val_recall: 0.9779 - lr: 4.0000e-04
Epoch 9/20
198/198 [==============================] - 107s 540ms/step - loss: 0.1001 - accur
acy: 0.9639 - precision: 0.9666 - recall: 0.9611 - val_loss: 0.0656 - val_accurac
y: 0.9793 - val_precision: 0.9710 - val_recall: 0.9882 - lr: 4.0000e-04
Epoch 10/20
198/198 [==============================] - 105s 529ms/step - loss: 0.0988 - accur
acy: 0.9639 - precision: 0.9651 - recall: 0.9627 - val_loss: 0.0569 - val_accurac
y: 0.9852 - val_precision: 0.9867 - val_recall: 0.9838 - lr: 4.0000e-04
Epoch 11/20
198/198 [==============================] - 103s 518ms/step - loss: 0.0988 - accur
acy: 0.9624 - precision: 0.9671 - recall: 0.9573 - val_loss: 0.0556 - val_accurac
y: 0.9845 - val_precision: 0.9852 - val_recall: 0.9838 - lr: 8.0000e-05
CPU times: total: 24min 27s
Wall time: 19min 17s
```

Out[101…

```
<keras.callbacks.History at 0x1db6a6ad1b0>
```

Model Evaluation

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In [102…

```
y_predict_hp_up = best_model_up.predict(X_test_up)
y_predict_hp_up = y_predict_hp_up.flatten()
```

```
43/43 [==============================] - 18s 415ms/step
```

In [103…

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

```
y_predict_hp_up
```

Out[103…

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

In [104…

```
cm_hp_up = confusion_matrix(y_test_up, y_predict_hp_up)
cm_hp_up
```

Out[104…

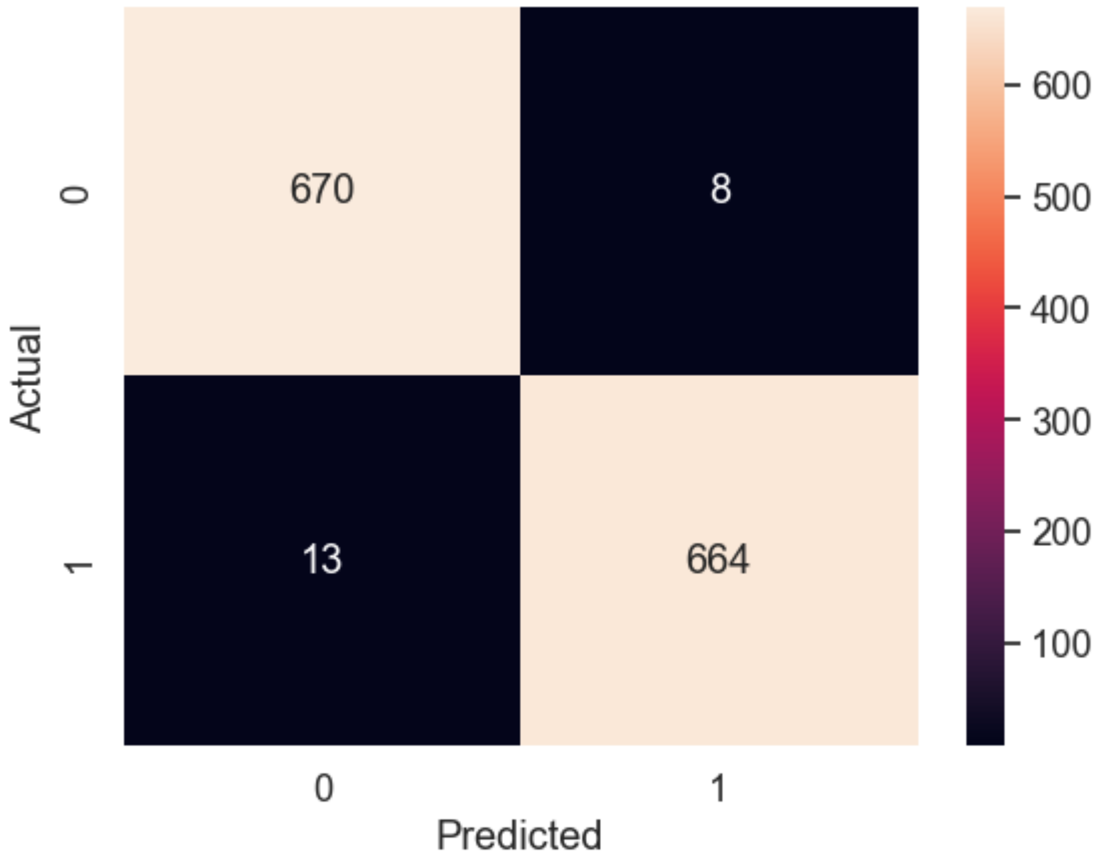
```
array([[670,   8],
       [ 13, 664]], dtype=int64)
```

In [105…

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

Out[105…

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



In [106…

```
up_hp = classification_report(y_test_up, y_predict_hp_up, target_names=['Ham', '
print(up_hp)
```

```
              precision    recall  f1-score   support

         Ham       0.98      0.99      0.98       678
        Spam       0.99      0.98      0.98       677

    accuracy                           0.98      1355
   macro avg       0.98      0.98      0.98      1355
weighted avg       0.98      0.98      0.98      1355
```

Additional Metrics (ROC-AUC) for BERT

Table of Contents

In [107…

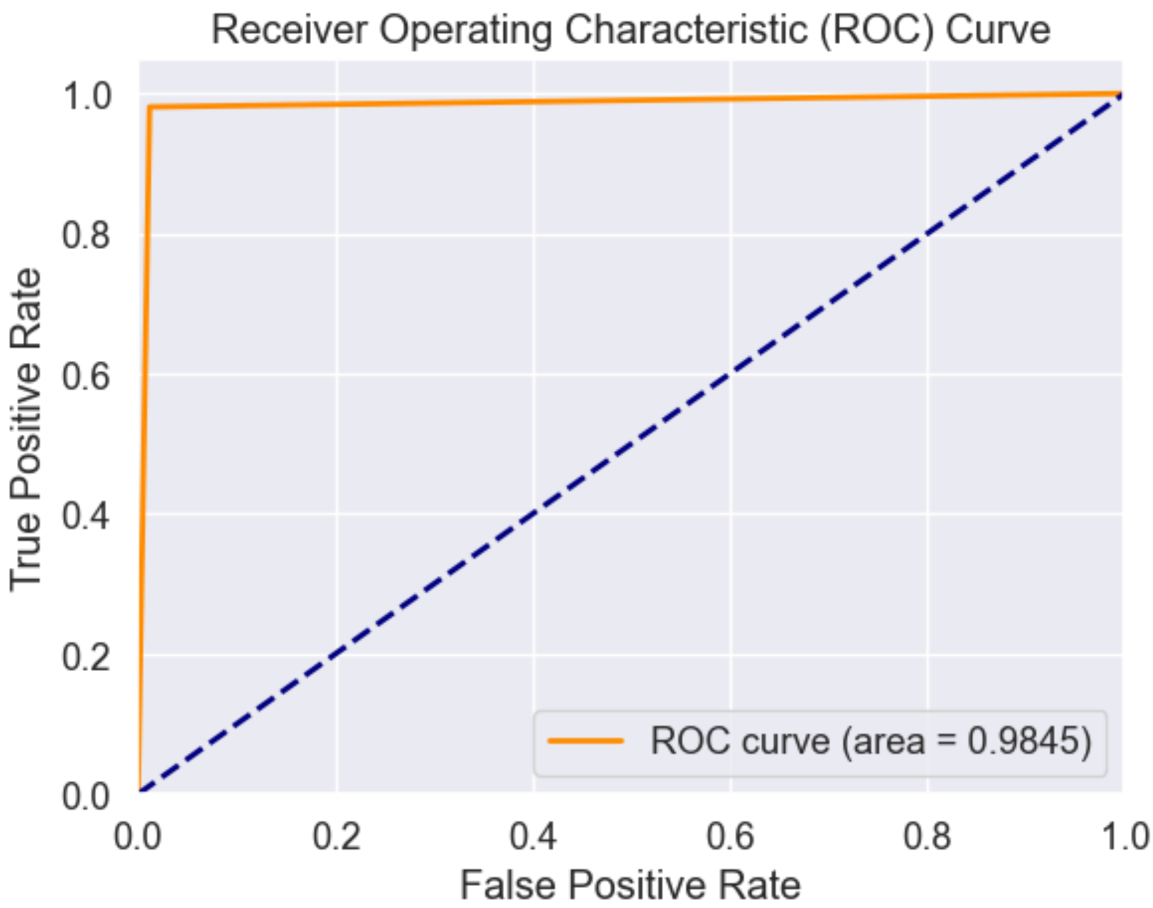
```
roc_auc_test = roc_auc_score(y_test_up, y_predict_hp_up)
print(f'ROC-AUC Score on Test Set: {roc_auc_test:.4f}')
```

```
ROC-AUC Score on Test Set: 0.9845
```

In [108…

```
# 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 [109…

```
# Detection of examples
up_inf_hp = best_model_up.predict(reviews)
up_inf_hp
```

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

Out[109…

```
array([[0.25089422],
       [0.8353094 ],
       [0.631627  ],
       [0.85261863],
       [0.00646944]], dtype=float32)
```

Class Weights

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In [110…

```
# 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 [111…

```
%%time
clw_model = tf.keras.models.clone_model(model)
```

```
CPU times: total: 10.6 s
Wall time: 10.9 s
```

In [112…

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

Model Building

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In [113…

```
%%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
114/114 [==============================] - 63s 536ms/step - loss: 0.4238 - accura
cy: 0.7424 - precision: 0.3288 - recall: 0.9978 - val_loss: 0.2310 - val_accuracy
: 0.9097 - val_precision: 0.5833 - val_recall: 1.0000 - lr: 8.0000e-05
Epoch 2/20
114/114 [==============================] - 61s 535ms/step - loss: 0.3342 - accura
cy: 0.7905 - precision: 0.3757 - recall: 0.9956 - val_loss: 0.3326 - val_accuracy
: 0.8645 - val_precision: 0.4828 - val_recall: 1.0000 - lr: 8.0000e-05
Epoch 3/20
114/114 [==============================] - 60s 526ms/step - loss: 0.2719 - accura
cy: 0.8259 - precision: 0.4198 - recall: 0.9912 - val_loss: 0.3327 - val_accuracy
: 0.8671 - val_precision: 0.4876 - val_recall: 1.0000 - lr: 8.0000e-05
Epoch 4/20
114/114 [==============================] - 59s 520ms/step - loss: 0.2606 - accura
cy: 0.8328 - precision: 0.4298 - recall: 0.9912 - val_loss: 0.3512 - val_accuracy
: 0.8619 - val_precision: 0.4780 - val_recall: 1.0000 - lr: 1.6000e-05
CPU times: total: 5min 9s
Wall time: 4min 3s
```

In [114…

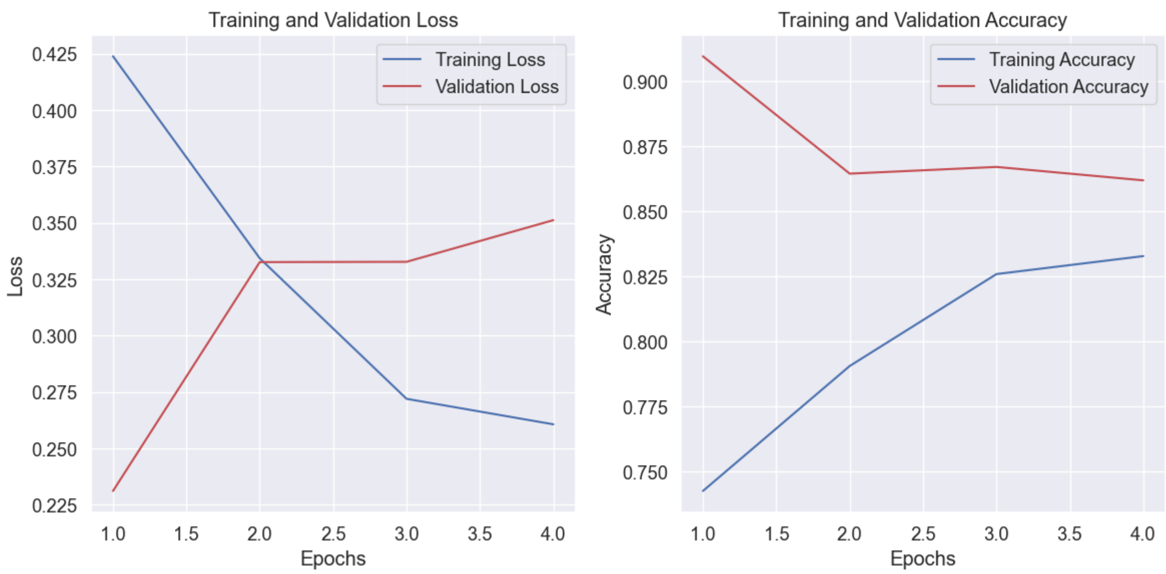
```
# Extract loss and accuracy for training and validation from the history object
train_loss = history_clw.history['loss']
val_loss = history_clw.history['val_loss']
train_accuracy = history_clw.history['accuracy']
val_accuracy = history_clw.history['val_accuracy']

# Create a range object for the number of epochs
epochs = range(1, len(train_loss) + 1)

# Plot training and validation loss
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(epochs, train_loss, 'b', label='Training Loss')
plt.plot(epochs, val_loss, 'r', label='Validation Loss')
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Plot training and validation accuracy
plt.subplot(1, 2, 2)
plt.plot(epochs, train_accuracy, 'b', label='Training Accuracy')
plt.plot(epochs, val_accuracy, 'r', label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

# Display the plots
plt.tight_layout()
plt.show()
```



Model Evaluation

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In [115…

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

```
25/25 [==============================] - 10s 413ms/step - loss: 0.2001 - accuracy
: 0.9137 - precision: 0.5939 - recall: 1.0000
Test Loss: 0.05211685970425606
Test Accuracy: 0.9858247637748718
```

In [116…

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

```
25/25 [==============================] - 11s 424ms/step
```

In [117…

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

Out[117…

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

In [118…

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

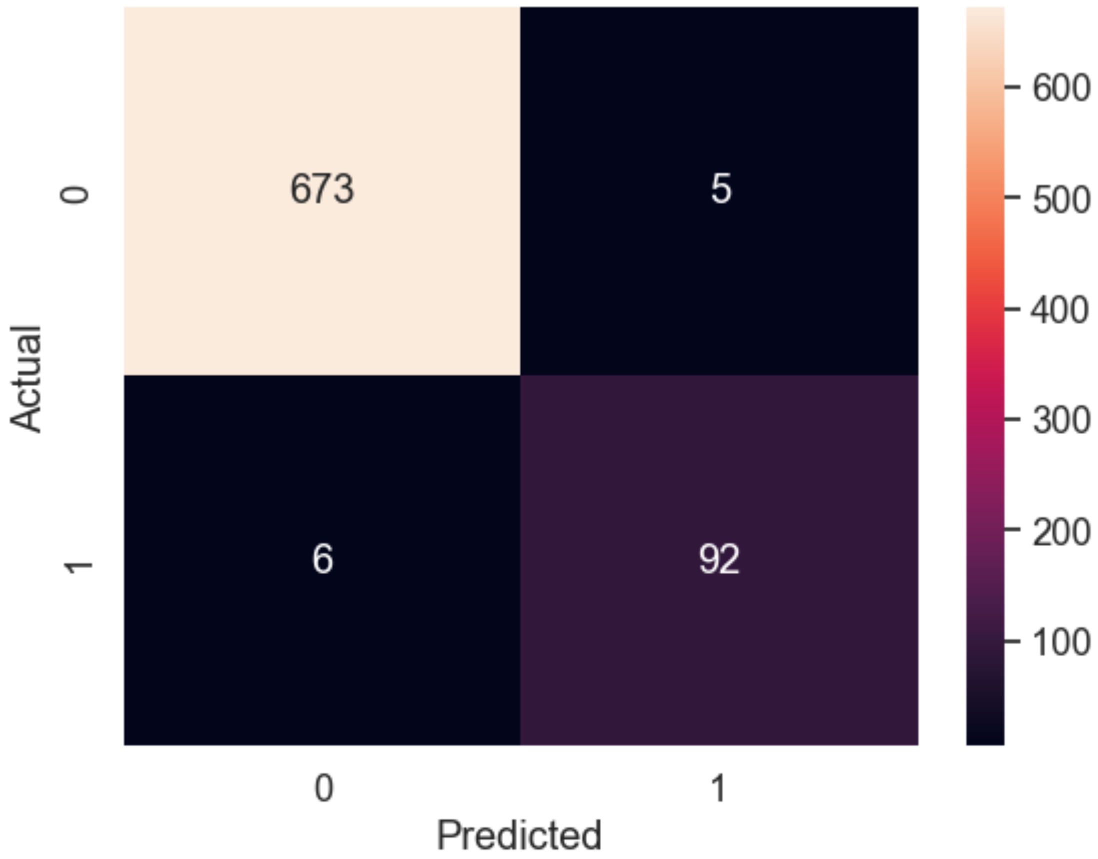
Out[118…

```
array([[673,   5],
       [  6,  92]], dtype=int64)
```

In [119…

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

Out[119… Text(43.25, 0.5, 'Actual')



In [120…
```
clw = classification_report(y_test, y_predict_clw, target_names=['Ham', 'Spam'])
print(clw)
```

```
              precision    recall  f1-score   support

         Ham       0.87      1.00      0.93       678
        Spam       0.00      0.00      0.00        98

    accuracy                           0.87       776
   macro avg       0.44      0.50      0.47       776
weighted avg       0.76      0.87      0.81       776
```

In [121…
```
# Detection of examples
clw_inf = clw_model.predict(reviews)
clw_inf
```

```
1/1 [==============================] - 1s 896ms/step
```

Out[121…
```
array([[0.31555504],
       [0.33709228],
       [0.34629753],
       [0.34160677],
       [0.3247794 ]], dtype=float32)
```

Hyperparameter Tuning with Keras Tuner (Class Weights)

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In [122…
```
%%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='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]
```

```
Reloading Tuner from C:\Users\sathi\Career\Internship\AFAME\Spam SMS Detection\BE
RT\clw_model\tuner0.json
CPU times: total: 1.52 s
Wall time: 2.01 s
```

In [123…
```
# 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]}")
```

```
25/25 [==============================] - 12s 447ms/step - loss: 0.0446 - accuracy
: 0.9484 - precision: 0.7266 - recall: 0.9490

Validation Loss: 0.044625263661146164
Validation Accuracy: 0.9484203457832336
```

In [124…
```
# 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]}")
```

```
25/25 [==============================] - 11s 430ms/step - loss: 0.0337 - accuracy
: 0.9910 - precision: 1.0000 - recall: 0.9286
\Test Loss: 0.03372407332062721
Test Accuracy: 0.9909793734550476
```

Model Building

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In [125…
```
%%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
114/114 [==============================] - 64s 539ms/step - loss: 0.0672 - accura
cy: 0.9760 - precision: 0.9263 - recall: 0.8796 - val_loss: 0.0423 - val_accuracy
: 0.9832 - val_precision: 0.9670 - val_recall: 0.8980 - lr: 0.0010
Epoch 2/20
114/114 [==============================] - 61s 532ms/step - loss: 0.0691 - accura
cy: 0.9732 - precision: 0.9206 - recall: 0.8621 - val_loss: 0.0416 - val_accuracy
: 0.9832 - val_precision: 0.9670 - val_recall: 0.8980 - lr: 0.0010
Epoch 3/20
114/114 [==============================] - 61s 534ms/step - loss: 0.0636 - accura
cy: 0.9768 - precision: 0.9287 - recall: 0.8840 - val_loss: 0.0480 - val_accuracy
: 0.9845 - val_precision: 0.9300 - val_recall: 0.9490 - lr: 0.0010
Epoch 4/20
114/114 [==============================] - 61s 533ms/step - loss: 0.0724 - accura
cy: 0.9735 - precision: 0.9188 - recall: 0.8665 - val_loss: 0.0549 - val_accuracy
: 0.9794 - val_precision: 0.9881 - val_recall: 0.8469 - lr: 0.0010
Epoch 5/20
114/114 [==============================] - 62s 546ms/step - loss: 0.0667 - accura
cy: 0.9765 - precision: 0.9366 - recall: 0.8731 - val_loss: 0.0424 - val_accuracy
: 0.9832 - val_precision: 0.9670 - val_recall: 0.8980 - lr: 2.0000e-04
CPU times: total: 6min 32s
Wall time: 5min 8s
```

Out[125…

```
<keras.callbacks.History at 0x1db762b0df0>
```

Model Evaluation

Table of Contents

In [126…

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

```
25/25 [==============================] - 11s 424ms/step
```

In [127…

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

Out[127…

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

In [128…

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

Out[128…

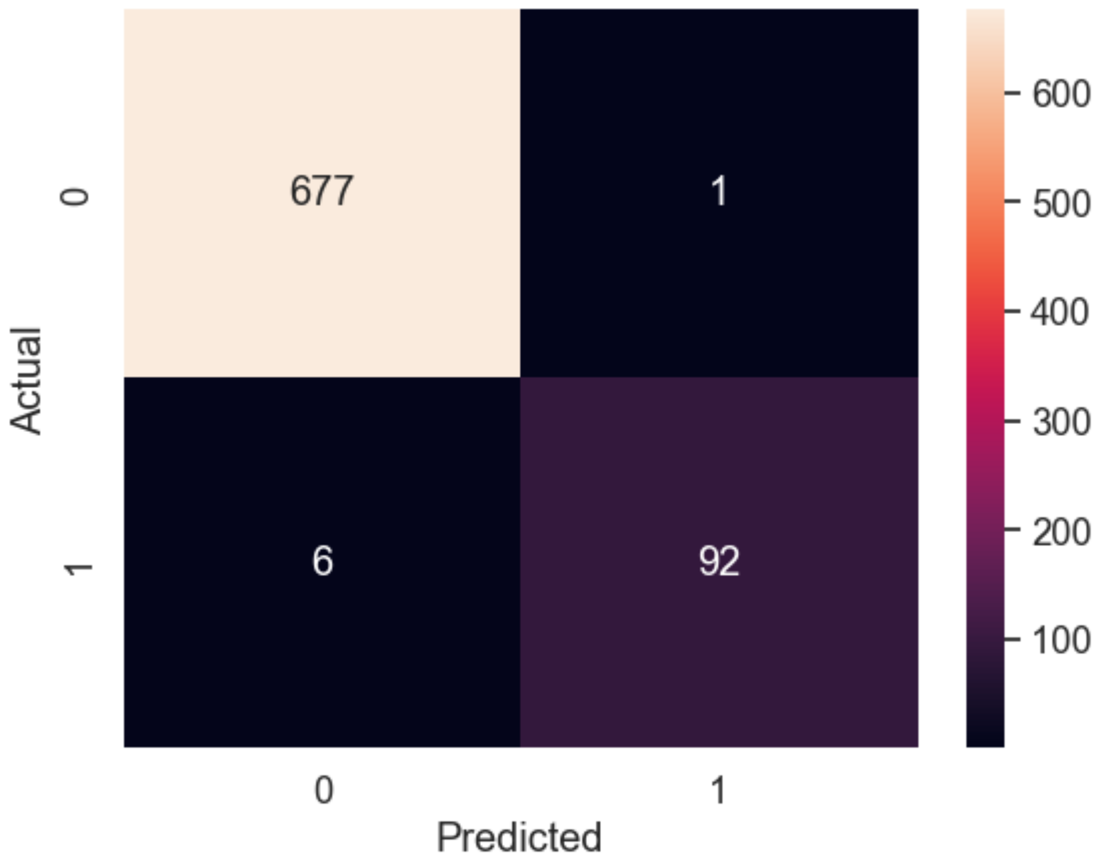
```
array([[677,   1],
       [  6,  92]], dtype=int64)
```

In [129…

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

Out[129…

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



In [130…

```
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       678
        Spam       0.99      0.94      0.96        98

    accuracy                           0.99       776
   macro avg       0.99      0.97      0.98       776
weighted avg       0.99      0.99      0.99       776
```

Additional Metrics (ROC-AUC) for BERT

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In [131…

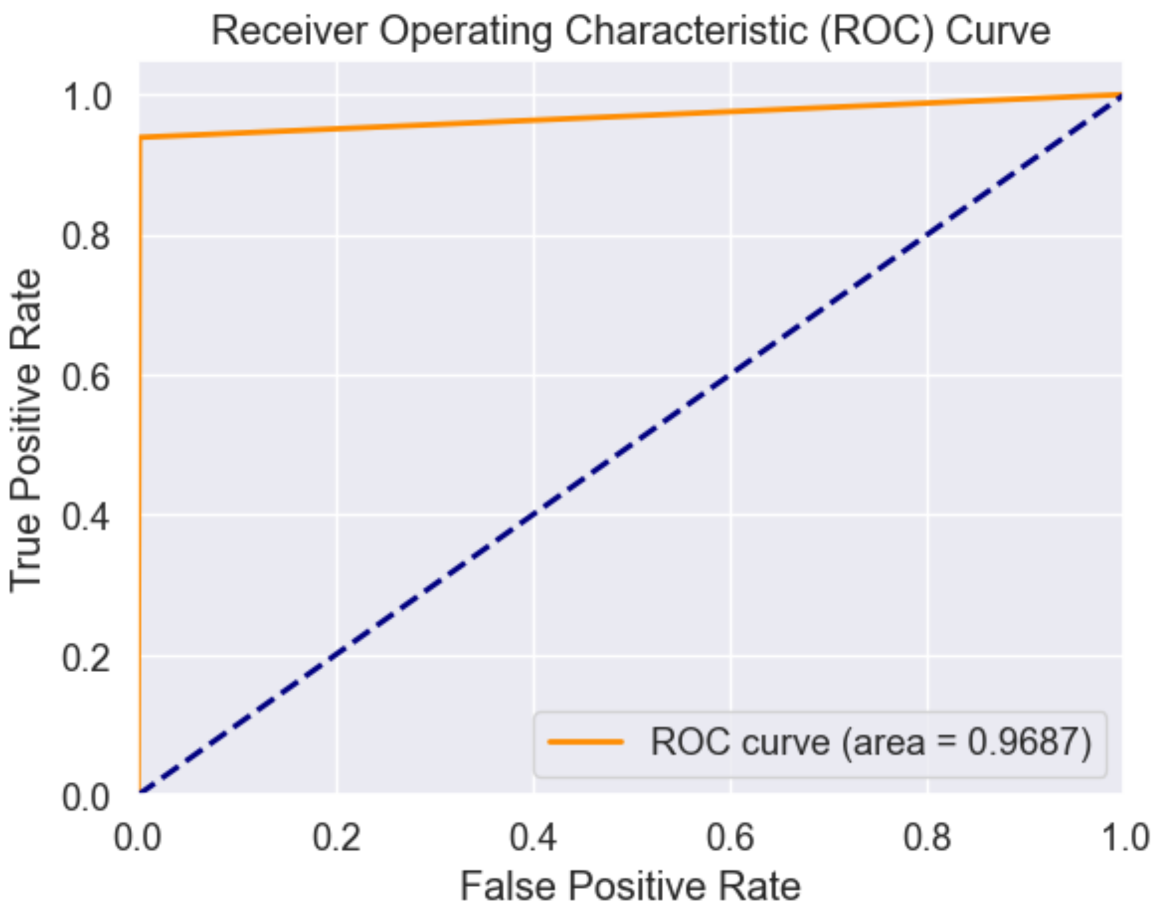
```
roc_auc_test = roc_auc_score(y_test, y_predict_hp_clw)
print(f'ROC-AUC Score on Test Set: {roc_auc_test:.4f}')
```

```
ROC-AUC Score on Test Set: 0.9687
```

In [132…

```
# 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])
```

```
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 [133…

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

```
1/1 [==============================] - 1s 750ms/step
```

Out[133…

```
array([[0.04296187],
       [0.42120916],
       [0.17502187],
       [0.41391   ],
       [0.0019341 ]], dtype=float32)
```

Custom Loss

Table of Contents

In [134…

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

```
CPU times: total: 10.9 s
Wall time: 11.3 s
```

In [135…

```
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 [136…

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

```
CPU times: total: 31.2 ms
Wall time: 5 ms
```

Model Building

Table of Contents

In [137…

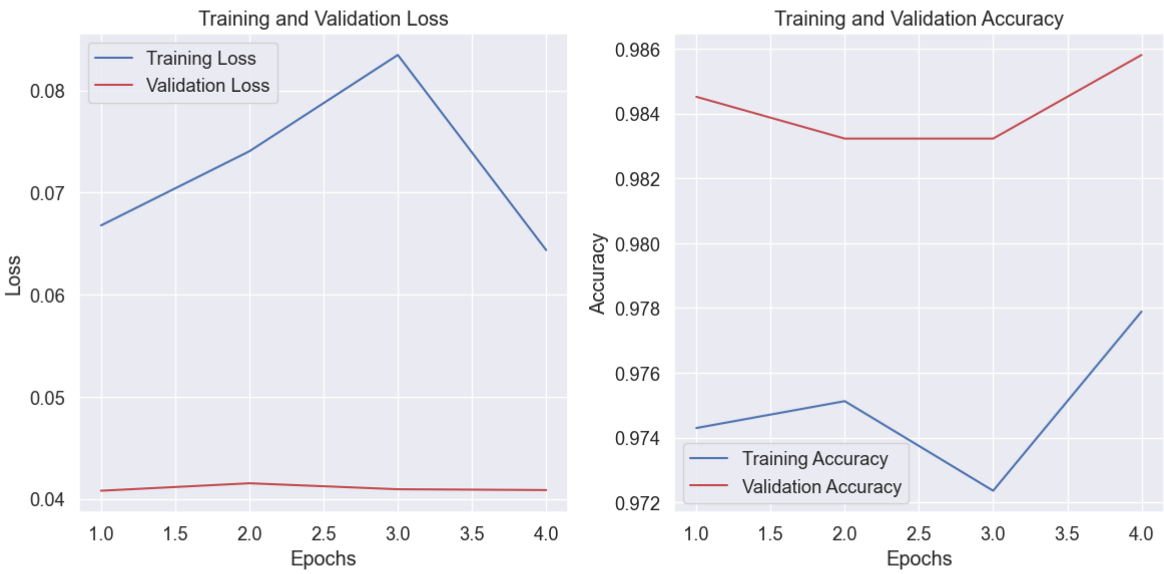
```
%%time
# Fit the model
history_cus = model.fit(X_train, y_train, epochs=20,
                    validation_data=(X_val, y_val),
                    callbacks=[early_stopping, lr_scheduler])
```

```
Epoch 1/20
114/114 [==============================] - 61s 532ms/step - loss: 0.0668 - accura
cy: 0.9743 - precision: 0.9118 - recall: 0.8818 - val_loss: 0.0408 - val_accuracy
: 0.9845 - val_precision: 0.9674 - val_recall: 0.9082 - lr: 2.0000e-04
Epoch 2/20
114/114 [==============================] - 60s 528ms/step - loss: 0.0740 - accura
cy: 0.9751 - precision: 0.9124 - recall: 0.8884 - val_loss: 0.0415 - val_accuracy
: 0.9832 - val_precision: 0.9670 - val_recall: 0.8980 - lr: 2.0000e-04
Epoch 3/20
114/114 [==============================] - 60s 524ms/step - loss: 0.0835 - accura
cy: 0.9724 - precision: 0.9142 - recall: 0.8621 - val_loss: 0.0409 - val_accuracy
: 0.9832 - val_precision: 0.9670 - val_recall: 0.8980 - lr: 2.0000e-04
Epoch 4/20
114/114 [==============================] - 59s 520ms/step - loss: 0.0644 - accura
cy: 0.9779 - precision: 0.9294 - recall: 0.8928 - val_loss: 0.0409 - val_accuracy
: 0.9858 - val_precision: 0.9677 - val_recall: 0.9184 - lr: 4.0000e-05
CPU times: total: 5min 3s
Wall time: 4min
```

In [138…

```
# Extract loss and accuracy for training and validation from the history object
train_loss = history_cus.history['loss']
val_loss = history_cus.history['val_loss']
train_accuracy = history_cus.history['accuracy']
val_accuracy = history_cus.history['val_accuracy']

# Create a range object for the number of epochs
epochs = range(1, len(train_loss) + 1)

# Plot training and validation loss
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(epochs, train_loss, 'b', label='Training Loss')
plt.plot(epochs, val_loss, 'r', label='Validation Loss')
```

```python
plt.title('Training and Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()

# Plot training and validation accuracy
plt.subplot(1, 2, 2)
plt.plot(epochs, train_accuracy, 'b', label='Training Accuracy')
plt.plot(epochs, val_accuracy, 'r', label='Validation Accuracy')
plt.title('Training and Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()

# Display the plots
plt.tight_layout()
plt.show()
```



Model Evaluation

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In [139…

```python
# 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]}")
```

```
25/25 [==============================] - 10s 414ms/step - loss: 0.0288 - accuracy
: 0.9923 - precision: 0.9894 - recall: 0.9490
Test Loss: 0.028787437826395035
Test Accuracy: 0.9922680258750916
```

In [140…

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

```
25/25 [==============================] - 11s 414ms/step
```

In [141…

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

Out[141…

```
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, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 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 [142…

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

Out[142…

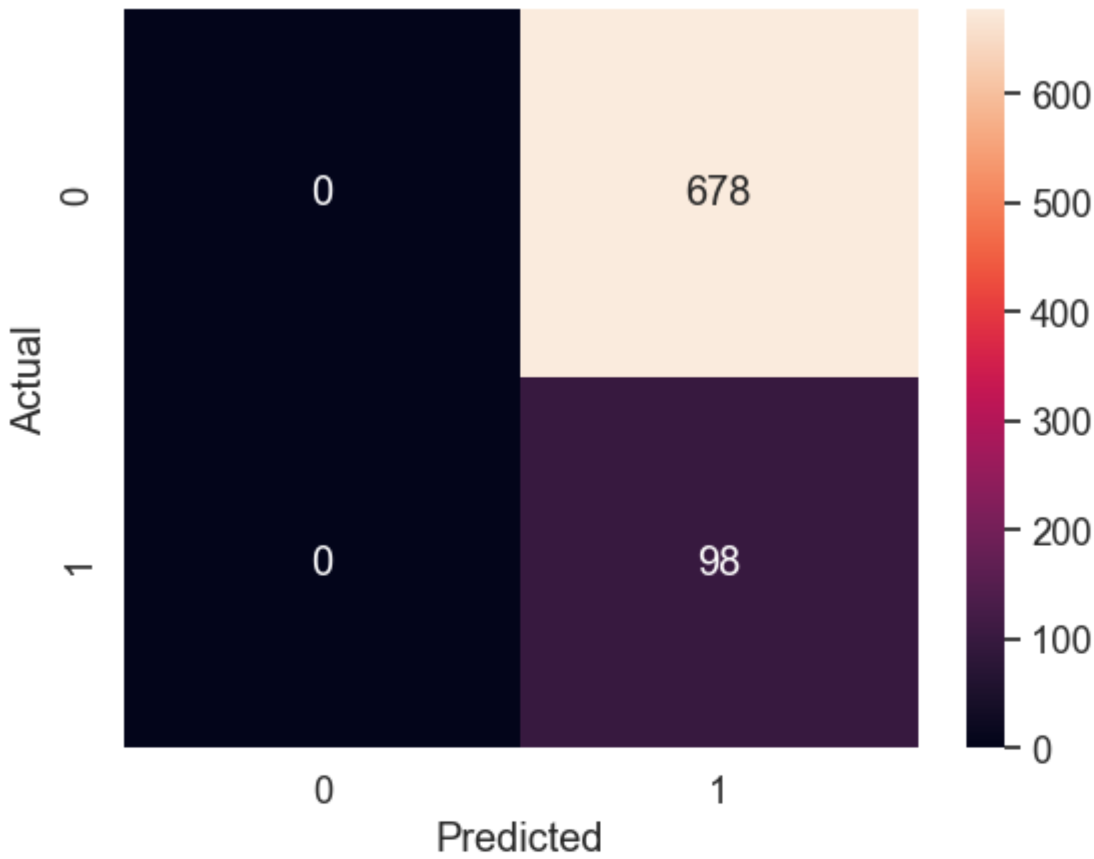
```
array([[  0, 678],
       [  0,  98]], dtype=int64)
```

In [143…

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

Out[143…

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



In [144…

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

```
              precision    recall  f1-score   support

         Ham       0.00      0.00      0.00       678
        Spam       0.13      1.00      0.22        98

    accuracy                           0.13       776
   macro avg       0.06      0.50      0.11       776
weighted avg       0.02      0.13      0.03       776
```

In [145…

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

```
1/1 [==============================] - 1s 715ms/step
```

Out[145…

```
array([[0.5919666 ],
       [0.61560005],
       [0.60953027],
       [0.6203045 ],
       [0.637023  ]], dtype=float32)
```

Hyperparameter Tuning with Keras Tuner (Custom Loss)

Table of Contents

In [146…

```
%%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]
```

```
Reloading Tuner from C:\Users\sathi\Career\Internship\AFAME\Spam SMS Detection\BE
RT\cus_model\tuner0.json
CPU times: total: 1.66 s
Wall time: 2.16 s
```

In [147…

```
# 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]}")
```

```
25/25 [==============================] - 11s 406ms/step - loss: 0.0396 - accuracy
: 0.9884 - precision: 0.9785 - recall: 0.9286

Validation Loss: 0.039572760462760925
Validation Accuracy: 0.988394558429718
```

In [148…

```
# 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]}")
```

```
25/25 [==============================] - 10s 410ms/step - loss: 0.0280 - accuracy
: 0.9923 - precision: 0.9894 - recall: 0.9490
\Test Loss: 0.027957065030932426
Test Accuracy: 0.9922680258750916
```

Model Building

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In [149…

```
%%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
114/114 [==============================] - 61s 515ms/step - loss: 0.0642 - accura
cy: 0.9765 - precision: 0.9227 - recall: 0.8884 - val_loss: 0.0391 - val_accuracy
: 0.9871 - val_precision: 0.9681 - val_recall: 0.9286 - lr: 0.0010
Epoch 2/20
114/114 [==============================] - 59s 517ms/step - loss: 0.0738 - accura
cy: 0.9748 - precision: 0.9236 - recall: 0.8731 - val_loss: 0.0404 - val_accuracy
: 0.9858 - val_precision: 0.9677 - val_recall: 0.9184 - lr: 0.0010
Epoch 3/20
114/114 [==============================] - 59s 518ms/step - loss: 0.0699 - accura
cy: 0.9743 - precision: 0.9194 - recall: 0.8731 - val_loss: 0.0479 - val_accuracy
: 0.9819 - val_precision: 0.9667 - val_recall: 0.8878 - lr: 0.0010
Epoch 4/20
114/114 [==============================] - 59s 521ms/step - loss: 0.0687 - accura
cy: 0.9776 - precision: 0.9541 - recall: 0.8643 - val_loss: 0.0421 - val_accuracy
: 0.9845 - val_precision: 0.9674 - val_recall: 0.9082 - lr: 2.0000e-04
CPU times: total: 5min 1s
Wall time: 3min 58s
```

Out[149…

```
<keras.callbacks.History at 0x1db79ee8580>
```

Model Evaluation

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In [150…

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

```
25/25 [==============================] - 11s 426ms/step
```

In [151…

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

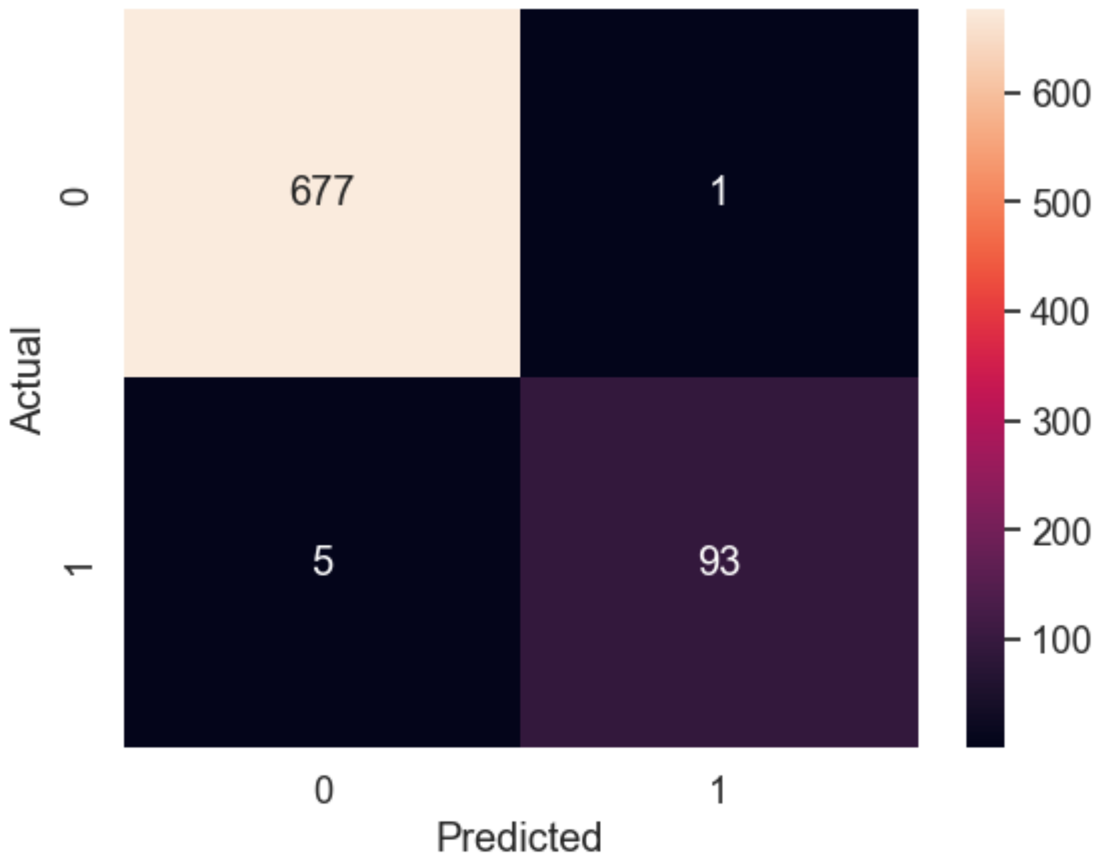
Out[151…
```
array([0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 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, 1, 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, 0, 0, 0, 0, 0, 0, 1, 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, 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, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 1, 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, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 1, 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, 1, 1,
       0, 0, 1, 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, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
       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, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 1, 0, 0, 1, 0, 0, 0, 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, 1, 0, 0, 1, 0, 1, 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, 1, 0, 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, 1, 0, 1, 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, 0, 1, 0, 0, 0, 1,
       0, 0, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 1, 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, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0])
```

In [152…
```python
cm_hp_cus = confusion_matrix(y_test, y_predict_hp_cus)
cm_hp_cus
```

Out[152…
```
array([[677,   1],
       [  5,  93]], dtype=int64)
```

In [153…
```python
sns.heatmap(cm_hp_cus, annot=True, fmt = 'd')
plt.xlabel('Predicted')
plt.ylabel('Actual')
```

Out[153…
```
Text(43.25, 0.5, 'Actual')
```



In [154…

```
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      1.00       678
        Spam       0.99      0.95      0.97        98

    accuracy                           0.99       776
   macro avg       0.99      0.97      0.98       776
weighted avg       0.99      0.99      0.99       776
```

Additional Metrics (ROC-AUC) for BERT

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In [155…

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

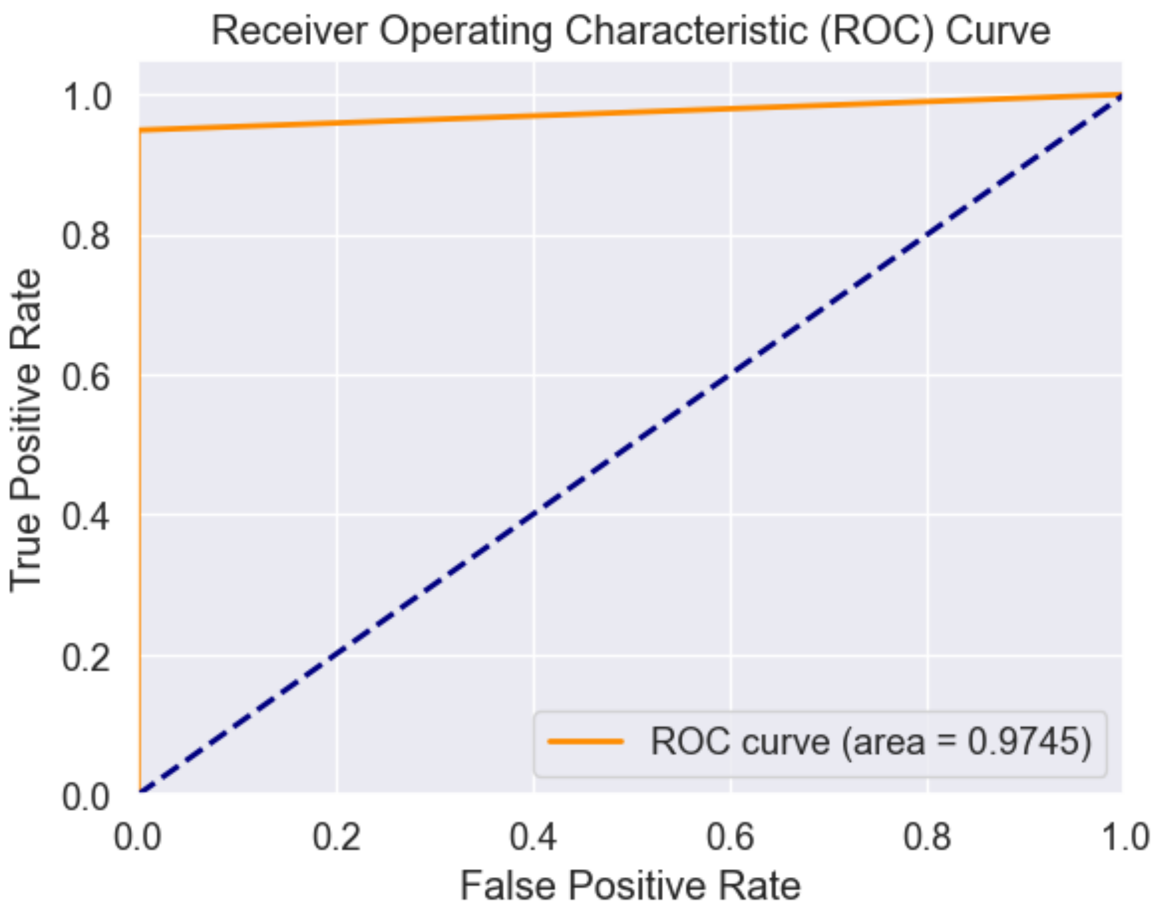
```
ROC-AUC Score on Test Set: 0.9738
```

In [156…

```
# 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 [157…

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

```
1/1 [==============================] - 1s 850ms/step
```

Out[157…

```
array([[0.0627556 ],
       [0.506941  ],
       [0.20083985],
       [0.4653539 ],
       [0.00232182]], dtype=float32)
```

Performance Comparison of Fine-Tuned BERT

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In [158…

```
# 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[158…

	Model	Accuracy	Precision (ham)	Precision (spam)	Recall (ham)	Recall (spam)	F1-score (ham)	F1-score (spam)	Sup (l
0	Original	0.985825	0.991163	0.948454	0.992625	0.938776	0.991894	0.943590	
1	Down Sampling	0.959184	0.924528	1.000000	1.000000	0.918367	0.960784	0.957447	
2	Up Sampling	0.984502	0.991031	0.978134	0.977876	0.991137	0.984410	0.984593	
3	Class Weights	0.873711	0.873711	0.000000	1.000000	0.000000	0.932600	0.000000	
4	Custom Loss	0.126289	0.000000	0.126289	0.000000	1.000000	0.000000	0.224256	

Performance Comparison of Hyperparameter-Tuned BERT

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In [159…

```
# 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']
})
```

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

Out[159…

	Model	Accuracy	Precision (ham)	Precision (spam)	Recall (ham)	Recall (spam)	F1-score (ham)	F1-score (spam)	Sup (l
0	Original	0.993557	0.992679	1.000000	1.000000	0.948980	0.996326	0.973822	
1	Down Sampling	0.979592	0.989583	0.970000	0.969388	0.989796	0.979381	0.979798	
2	Up Sampling	0.984502	0.980966	0.988095	0.988201	0.980798	0.984570	0.984433	
3	Class Weights	0.990979	0.991215	0.989247	0.998525	0.938776	0.994857	0.963351	
4	Custom Loss	0.992268	0.992669	0.989362	0.998525	0.948980	0.995588	0.968750	

Inference Comparison of Fine-Tuned BERT

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In [160…

```python
# 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[160…

	Normal Inference	Down Sampling Inference	Up Sampling Inference	Class Weights Inference	Custom Loss Inference
0	0.041896	0.010229	0.351277	0.315555	0.591967
1	0.528010	0.232877	0.808034	0.337092	0.615600
2	0.041873	0.071212	0.727107	0.346298	0.609530
3	0.298873	0.190261	0.904192	0.341607	0.620305
4	0.006345	0.002843	0.001178	0.324779	0.637023

Inference Comparison of Hyperparameter-Tuned BERT

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In [161…

```
# 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[161…

	Normal Inference	Down Sampling Inference	Up Sampling Inference	Class Weights Inference	Custom Loss Inference
0	0.031395	0.232409	0.250894	0.042962	0.062756
1	0.551868	0.720646	0.835309	0.421209	0.506941
2	0.191628	0.836508	0.631627	0.175022	0.200840
3	0.440414	0.927045	0.852619	0.413910	0.465354
4	0.005027	0.001247	0.006469	0.001934	0.002322

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 the Original configuration** demonstrates the highest F1-score for spam detection, achieving a value of **0.996326**. This indicates excellent performance in identifying spam messages while maintaining a perfect balance between precision and recall.

In contrast, the Hyperparameter-tuned BERT model with **Up Sampling** also performs well, with an F1-score of **0.984433**, but it slightly falls short compared to the Original configuration. The **Down Sampling** approach achieves an F1-score of **0.979798**, reflecting solid performance but less optimal than the Original and Up Sampling methods.

Other approaches, such as **Class Weights**, where weights are assigned to the data, show comparatively lower F1-scores for spam detection, achieving a value of **0.963351**. Similarly, the **Custom Loss** method, which involves label smoothing based on the data labels' ratio, achieves an F1-score of **0.968750** for spam detection. While these methods show promise, they are not as effective as the Original configuration.

These results indicate that using balanced data and maintaining the default class distribution (as in the Original configuration) yields the most accurate results for classifying text messages into ham or spam when applying Bidirectional Encoder Representation from Transformers (BERT). It highlights a superior balance between precision and recall for identifying spam, making the **Hyperparameter-tuned BERT model with the Original configuration** the most effective model among those tested.

Given these findings, the **Hyperparameter-tuned BERT model with the Original configuration** 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 [170…

```
# Save the entire model to a HDF5 file
best_model_nml.save('spam_detection_model.h5')
```

In [ ]:

```
# Save the model in SavedModel format
best_model_nml.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_nml.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

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