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# EXPERIMENT - 6

**AIM**: To implement spam detection on relevant dataset

**Spam Detection**

Messaging spam, sometimes called SPIM, is a type of spam targeting users of instant messaging (IM) services, SMS, or private messages within websites. Spam detection can be performed using neural networks or transformer based deep learning networks.

Steps for detecting spam:

1. Categorically encode input dataset to 0 and 1 for binary classification.
2. Use TF AutoTokenizer to convert the input data into standard tokens. This also generates the attention mask used by BERT.
3. Load Distilled BERT (base and uncased) pretrained from huggingface
4. Setup accuracy as monitoring metric and Adam as the optimizer
5. Compile the model
6. Evaluate batch_size, no of epochs and the learing rate for the model hyperparameters.
7. Train the models on train data and plot loss/accuracy curves.
8. Calculate precision, recall and F1 scores on test data
9. Perform Hyperparameter tuning to improve metrics
10. Plot confusion matrix and verify on unseen data

**SMS Spam Collection Dataset**

The SMS Spam Collection v.1 is a public set of SMS labeled messages that have been collected for mobile phone spam research. It has one collection composed by 5,574 English, real and non-encoded messages, tagged according being legitimate (ham) or spam. It has a total of 4,827 SMS legitimate messages (86.6%) and a total of 747 (13.4%) spam messages.

**CODE:**

```
import os

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

from tensorflow.keras.optimizers import Adam
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report
from transformers import AutoTokenizer, TFAutoModelForSequenceClassification

for dirname, _, filenames in os.walk("/content/input"):
    for filename in filenames:
        print(os.path.join(dirname, filename))

df = pd.read_csv("/content/input/SPAM text message 20170820 - Data.csv")

df.head()
df.info()
df.isnull().sum()

df["Category"]
df["Category"].value_counts()
df["Category"].value_counts().plot(kind="bar")
df["Category"] = pd.get_dummies(df["Category"], drop_first=True)

pred_dict = {0: "Ham", 1: "Spam"}

df.head()
```

```
X = df["Message"]
y = df["Category"]

X = list(X)
y = list(y)

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42
)

tokenizer = AutoTokenizer.from_pretrained("distilbert-base-uncased")
tokenized_train_data = tokenizer(X_train, return_tensors="np", padding=True)
tokenized_test_data = tokenizer(X_test, return_tensors="np", padding=True)
labels = np.array(y_train)

model =
TFAutoModelForSequenceClassification.from_pretrained("distilbert-base-uncased"
)

model.summary()

model.compile(optimizer=Adam(3e-5), metrics=["accuracy"])

history = model.fit(
    dict(tokenized_train_data), labels, batch_size=16, epochs=2, shuffle=True
)

pd.DataFrame(history.history["loss"]).plot(figsize=(8, 5))
plt.xlabel("No of Epochs")
plt.ylabel("Loss")
plt.legend(["loss"])
plt.show()

pd.DataFrame(history.history["accuracy"]).plot(figsize=(8, 5))
plt.xlabel("No of Epochs")
```

```
plt.ylabel("Accuracy")
plt.legend(["accuracy"])
plt.show()

dict(tokenized_train_data)

# Predicting our values

y_pred = model.predict(dict(tokenized_test_data))

y_pred

# Converting our values intoı 0 and 1 labels

logits = y_pred.logits
softmax = tf.nn.softmax(logits)
predictions = np.argmax(softmax.numpy(), axis=1)

y_test = np.array(y_test)

predictions

y_test

# Evaluating our results

cm = confusion_matrix(y_test, predictions)
cr = classification_report(y_test, predictions)

print("Confusion Matrix:\n", cm)
print("\nClassification Report:\n", cr)

sns.heatmap(cm, annot=True, cmap="BuPu", fmt="g")

"""## Unseen Data Test"""
```

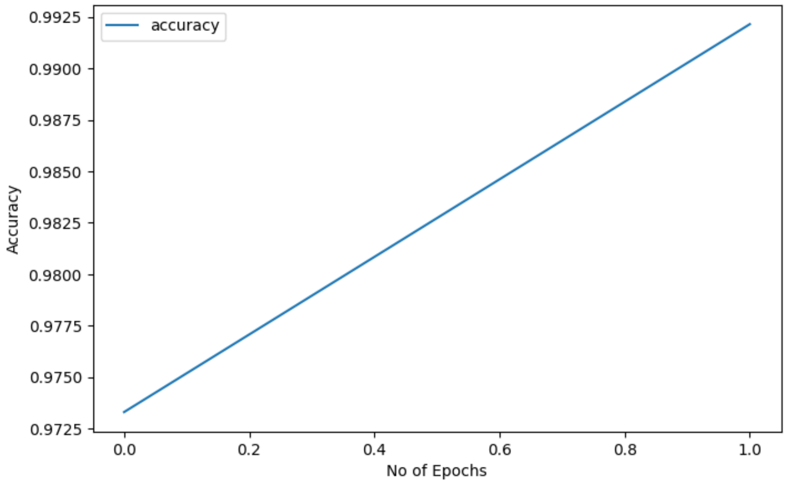
```
def run(input: str):
    tokenized_irl = tokenizer([input], return_tensors="np", padding=True)
    y_irl = model.predict(dict(tokenized_irl))
    new_logits = y_irl.logits
    new_softmax = tf.nn.softmax(new_logits)
    new_predictions = np.argmax(new_softmax.numpy(), axis=1)
    print("Input: ", input)
    print("Prediction: ", pred_dict[new_predictions[0]])


run("Hi I am Jarvis")
run("Special Offer for you from bank")
```

**OUTPUT:**

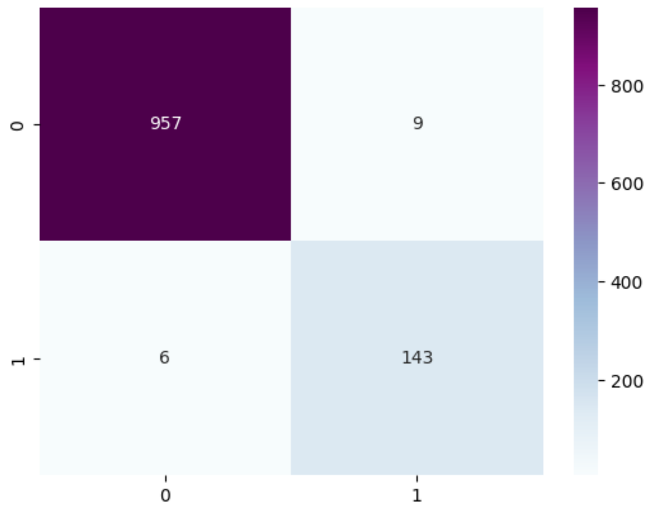
```
Model: "tf_distil_bert_for_sequence_classification"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 distilbert (TFDistilBertMai  multiple                 66362880
 nLayer)

 pre_classifier (Dense)      multiple                  590592

 classifier (Dense)          multiple                  1538

 dropout_19 (Dropout)        multiple                  0

=================================================================
Total params: 66,955,010
Trainable params: 66,955,010
Non-trainable params: 0
_________________________________________________________________
```

```
Epoch 1/2
279/279 [==============================] - 150s 399ms/step - loss: 0.0833 -
accuracy: 0.9733
Epoch 2/2
```

279/279 [==============================] - 104s 372ms/step - loss: 0.0287 - accuracy: 0.9921




```
Confusion Matrix:
 [[957   9]
 [  6 143]]

Classification Report:
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       966
           1       0.94      0.96      0.95       149

    accuracy                           0.99      1115
   macro avg       0.97      0.98      0.97      1115
weighted avg       0.99      0.99      0.99      1115
```




```
1/1 [==============================] - 2s 2s/step
Input:  Hi I am Jarvis
Prediction:  Ham
```

```
1/1 [==============================] - 0s 50ms/step
Input:  Special Offer for you from bank
Prediction:  Spam
```

**CONCLUSION**: Transformer networks allow for context-based spam classification. Unlike majority of the methods transformer models like BERT model complex semantic relationships in the language and accurately classify sequences. In this experiment, we achieved a maximum accuracy of 99.21%.