Scenario 2:

An online fashion retailer wants to develop a machine learning model that can classify customer reviews into different sentiment categories. The model will take as input a customer review and output a prediction of the review's sentiment, such as positive, negative, or neutral. Develop a ML model for aforesaid classification with an example Dataset.

Import Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from wordcloud import WordCloud
import tensorflow as tf
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Embedding, LSTM, Dense
```

Import the data

```
data = pd.read_csv('/content/drive/MyDrive/DRDO assesment/Womens Clothing E-Commerce Reviews.csv')
```

```
data.head()
```

	Unnamed: 0	Clothing ID	Age	Title	Review Text	Rating	Recommended IND	Positive Feedback Count	Divisi Na
0	0	767	33	NaN	Absolutely wonderful - silky and sexy and comf...	4	1	0	Initmat
1	1	1080	34	NaN	Love this dress! it's sooo pretty. i	5	1	4	Gene

New column

Make a new column named "sentiment". We will use this column as our target variable to train the mode. Where rating is 4 or 5, sentiment is positive (2), for rating 3 sentiment is neutral (1), and for rating 1 and 2 sentiment is 0 (negative).

```
data['sentiment'] = np.where(data['Rating'] >= 4, 2, np.where(data['Rating'] == 3, 1, 0))
```

```
data.head()
```

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1	1	1080	34	NaN	Love this dress! it's sooo pretty. i happene...	5	1	4	Gene

Data Cleaning

```
data = data.dropna(subset=['Review Text'])
print(data.shape)
```

```
(22641, 12)
```

EDA

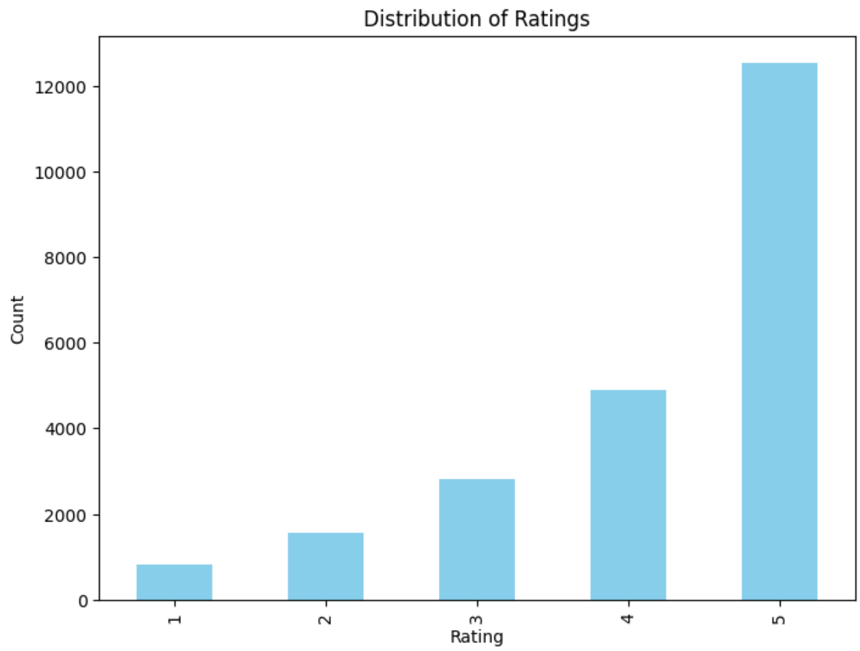
```
print("Shape of the dataset:", data.shape) # shape of the dataset

print("Basic Statistics:")  # Basic statistics
print(data.describe())
```

```
Shape of the dataset: (22641, 12)
Basic Statistics:
         Unnamed: 0   Clothing ID           Age        Rating  \
count  22641.000000  22641.000000  22641.000000  22641.000000
mean   11740.849035    919.332362     43.280376      4.183561
std     6781.957509    202.266874     12.326980      1.115762
min        0.000000      1.000000     18.000000      1.000000
25%     5872.000000    861.000000     34.000000      4.000000
50%    11733.000000    936.000000     41.000000      5.000000
75%    17621.000000   1078.000000     52.000000      5.000000
max    23485.000000   1205.000000     99.000000      5.000000

       Recommended IND  Positive Feedback Count     sentiment
count     22641.000000             22641.000000  22641.000000
mean          0.818868                 2.630582      1.665960
std           0.385136                 5.786164      0.657139
min           0.000000                 0.000000      0.000000
25%           1.000000                 0.000000      2.000000
50%           1.000000                 1.000000      2.000000
75%           1.000000                 3.000000      2.000000
max           1.000000               122.000000      2.000000
```

```
# Distribution of ratings
plt.figure(figsize=(8, 6))
data['Rating'].value_counts().sort_index().plot(kind='bar', color='skyblue')
plt.xlabel('Rating')
plt.ylabel('Count')
plt.title('Distribution of Ratings')
plt.show()
```



```
# Word cloud for positive reviews
positive_reviews = " ".join(data[data['sentiment'] == 2]['Review Text'])
wordcloud_positive = WordCloud(width=800, height=400, background_color='white').generate(positive_reviews)

plt.figure(figsize=(10, 5))
plt.imshow(wordcloud_positive, interpolation='bilinear')
plt.axis('off')
plt.title('Word Cloud for Positive Reviews')
plt.show()
```


```
tokenizer = Tokenizer()  # initialise a tokeniser
tokenizer.fit_on_texts(data['Review Text'])
X = tokenizer.texts_to_sequences(data['Review Text'])  # text to sequence
X = pad_sequences(X)  # pad the sequences for uniform lenght
y = data['sentiment'] # labels
```

Train Test Split

```
# train test split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Building the model

```
from tensorflow.keras.regularizers import l2
from tensorflow.keras.optimizers import Adam

optimizer = Adam(learning_rate=0.001)

vocab_size = len(tokenizer.word_index) + 1
embedding_dim = 75
max_length = len(X[0])

model = Sequential()
model.add(Embedding(input_dim=vocab_size, output_dim=embedding_dim, input_length=max_length))
model.add(LSTM(units=75))
model.add(Dense(units=64, activation='relu', kernel_regularizer=l2(0.01)))
model.add(Dense(units=3, activation='softmax'))
model.compile(optimizer=optimizer, loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

```
history = model.fit(X_train, y_train, epochs=10, batch_size=64, validation_split=0.1)
```

```
Epoch 1/10
255/255 [==============================] - 37s 137ms/step - loss: 0.7626 - accuracy: 0.7903 - val_loss: 0.5234 - val_accuracy: 0.798
Epoch 2/10
255/255 [==============================] - 38s 148ms/step - loss: 0.4108 - accuracy: 0.8318 - val_loss: 0.4926 - val_accuracy: 0.797
Epoch 3/10
255/255 [==============================] - 34s 134ms/step - loss: 0.3520 - accuracy: 0.8537 - val_loss: 0.5068 - val_accuracy: 0.791
Epoch 4/10
255/255 [==============================] - 35s 137ms/step - loss: 0.3149 - accuracy: 0.8684 - val_loss: 0.5346 - val_accuracy: 0.789
Epoch 5/10
255/255 [==============================] - 34s 132ms/step - loss: 0.2805 - accuracy: 0.8883 - val_loss: 0.5616 - val_accuracy: 0.786
Epoch 6/10
```

```
255/255 [==============================] - 35s 137ms/step - loss: 0.2574 - accuracy: 0.8996 - val_loss: 0.6480 - val_accuracy: 0.785
Epoch 7/10
255/255 [==============================] - 34s 132ms/step - loss: 0.2300 - accuracy: 0.9146 - val_loss: 0.6677 - val_accuracy: 0.772
Epoch 8/10
255/255 [==============================] - 35s 137ms/step - loss: 0.2072 - accuracy: 0.9260 - val_loss: 0.7455 - val_accuracy: 0.791
Epoch 9/10
255/255 [==============================] - 34s 133ms/step - loss: 0.1909 - accuracy: 0.9344 - val_loss: 0.7575 - val_accuracy: 0.783
Epoch 10/10
255/255 [==============================] - 35s 138ms/step - loss: 0.1702 - accuracy: 0.9438 - val_loss: 0.7297 - val_accuracy: 0.771
```

Accuracy

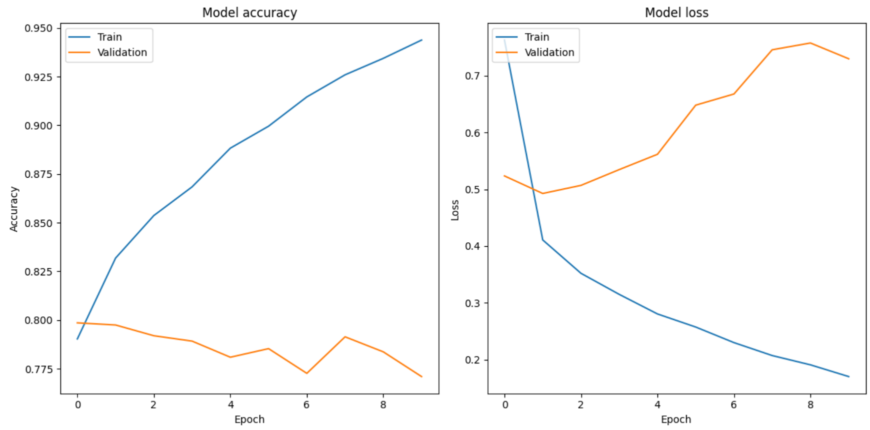
```
loss, accuracy = model.evaluate(X_test, y_test)
print(f'Accuracy: {accuracy * 100:.2f}%')
```

```
142/142 [==============================] - 3s 23ms/step - loss: 0.6772 - accuracy: 0.7885
Accuracy: 78.85%
```

```
# Plot training & validation accuracy values
plt.figure(figsize=(12, 6))
plt.subplot(1, 2, 1)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('Model accuracy')
plt.xlabel('Epoch')
plt.ylabel('Accuracy')
plt.legend(['Train', 'Validation'], loc='upper left')

# Plot training & validation loss values
plt.subplot(1, 2, 2)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('Model loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.legend(['Train', 'Validation'], loc='upper left')

plt.tight_layout()
plt.show()
```



Saving the model

Here, we will save the model as a pickle file.This file can be used for importing the model when we want to build application, we can do so using Flask.

```
model.save('sentiment_model.h5')
import pickle
with open('tokenizer.pkl', 'wb') as tokenizer_file:
    pickle.dump(tokenizer, tokenizer_file)
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/engine/training.py:3079: UserWarning: You are saving your model as an HDF5 file vi
  saving_api.save_model(
```

Conclusion:

The model is giving respectable accuracy (78.85%) but as we can see it is overfitting. To reduce the overfitting we can take the following measures:

1. Increase the training data.
2. Reduce the complexity of the model
3. Add a dropout layer.
4. Fine tune the model.

I could not work with the above solutions to make the val accuracy better due to shortage of time, but I plan on working on it eventually and try to increase the performance of the model.