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Advanced Data Analytics - D213 Task 2

Part I: Reasearch Question

A1: Can neural networks be used to predict the sentiment of a review based on previous reviews.

A2: The goal of this analysis is to build a model that can predit the sentiment of a customer review to determine if the review was favorable or not.

A3: I will be using Recurrent Neural Networks (RNN) for this assessment; specificially a Long Short-Term Memory (LSTM) model.

Import Libararies

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import string
import re
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 Input, Embedding, LSTM, Dense
from keras.callbacks import EarlyStopping
from keras.optimizers import Adam
from wordcloud import STOPWORDS
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
from nltk.corpus import wordnet
from sklearn import model_selection

import nltk
nltk.download('punkt_tab')
nltk.download('averaged_perceptron_tagger_eng')
nltk.download('wordnet')
nltk.download('omw-1.4')

pd.set_option('display.max_rows', None)
```

```
[nltk_data] Downloading package punkt_tab to /root/nltk_data...
[nltk_data]   Package punkt_tab is already up-to-date!
[nltk_data] Downloading package averaged_perceptron_tagger_eng to
[nltk_data]     /root/nltk_data...
[nltk_data]   Package averaged_perceptron_tagger_eng is already up-to-
[nltk_data]       date!
[nltk_data] Downloading package wordnet to /root/nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package omw-1.4 to /root/nltk_data...
[nltk_data]   Package omw-1.4 is already up-to-date!
```

Read the text files

In [2]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.
mount("/content/drive", force_remount=True).
```

In [3]:
```
#files downloaded from (UCI Machine Learning Repository, n.d.)

df1 = pd.read_csv("/content/drive/My Drive/Colab Notebooks/D213/amazon_cells_labell


# IMDb file needed to be parsed differently to avoid panda's structure.
with open("/content/drive/My Drive/Colab Notebooks/D213/imdb_labelled.txt", "r", en
    raw_text = df2.read()


df3 = pd.read_csv("/content/drive/My Drive/Colab Notebooks/D213/yelp_labelled.txt",
```

In [4]:
```
# Extract reviews and sentiments using regex becuase the imdb data wasnt splitting
imdb_data = re.findall(r"(.*?)(?:\t([01])(?:\n|$))", raw_text)
```

In [5]:
```
df2 = pd.DataFrame(imdb_data, columns=['Review', 'sentiment'])
df2['sentiment'] = df2['sentiment'].astype(int)
```

In [6]:
```
# concatonating all the three dataframes.
reviews = pd.concat([df1, df2, df3], ignore_index=True)#(Sewell, n.d.)
```

In [7]:
```
reviews.head()
```

Out[7]:

	Review	sentiment
0	So there is no way for me to plug it in here i...	0
1	Good case, Excellent value.	1
2	Great for the jawbone.	1
3	Tied to charger for conversations lasting more...	0
4	The mic is great.	1

Part II: Data Preperation

B1. I began the exploratory data analysis (EDA) process by looking at the shape of the data, checking for sentiment counts, and ensuring there were no missing values.

In [8]:
```
reviews.shape
```

Out[8]:
```
(3000, 2)
```

In [9]:
```
#looking for counts of each sentiment
reviews.sentiment.value_counts()
```

Out[9]:

sentiment	count
0	1500
1	1500

dtype: int64

In [10]:
```
#checking for missing values
reviews.isna().sum()
```

Out[10]:

	0
Review	0
sentiment	0

dtype: int64

Before and after cleaning the data, I calculated the vocabulary size using keras `tokenizer`. Before cleaning, the vocabulary contained all uniqe tokens including the puncutuation and non-english characters that will be shown in the next section. The total vocabulary size before cleaning was 5271.

In [11]:
```
#Tokenize to get the vocabulary size across all reviews
tokenizer = Tokenizer()
tokenizer.fit_on_texts(reviews.Review)
print("Vocabulary size: ", len(tokenizer.word_index))
```

```
Vocabulary size:  5271
```

To check for non-english characters or emojies, I extracted all the unique values from the three concatonated dataframes using a for loop. The full list of unique characters can be found below. Later I removed all of the non-english characters as part of the cleaning process.

In [12]:
```
#Create list of characters to see if there are non english characters included in t
text = reviews['Review']
char_list = []
for i in text:
    for char in i:
        if char not in char_list:
            char_list.append(char)
print(char_list)
```

```
['S', 'o', ' ', 't', 'h', 'e', 'r', 'i', 's', 'n', 'w', 'a', 'y', 'f', 'm', 'p',
'l', 'u', 'g', 'U', 'I', 'b', 'c', 'v', '.', 'G', 'd', ',', 'E', 'x', 'j', 'T', '4',
'5', 'M', 'A', 'J', 'O', 'R', 'P', 'B', 'L', '!', 'z', 'N', 'W', 'q', 'H', '+', 'V',
'"', 'Y', 'D', 'F', 'k', "'", 'K', 'C', '/', '7', '3', '6', '8', '0', '2', '?', 'Z',
'-', '1', ':', ')', '(', 'Q', '&', '$', '*', ';', 'X', '%', '9', '#', '[', ']', '\x9
6', 'é', '\x85', 'å', '\x97', 'ê']
```

To determine the maximum sequence length, I created a word_count column and identified the longest review based on tokens. I found that the IMDB data would combine several reviews into one line, resulting in a very long review. This was fixed by using special parcing to avoid pandas structure as it would not seperate by `"\t"` like the other two dataframes.

B2. The goal of tokenization is to convert each review into a numeric value that can be traced back to a unique word in the dataset.

To ensure that the data was clean and standardized before tokenization, I applied the following steps:

1. Converted to lowercase
2. Removed punctuation
3. Removed stropwords
4. lemmatization

In [13]:
```
#convert to lowercase
reviews.Review = reviews.Review.str.lower()

#remove punctuation
reviews.Review = reviews.Review.apply(lambda x: re.sub(r'[^a-z]', ' ', x))
reviews.Review = reviews.Review.apply(lambda x: re.sub(r'\s+[a-z]\s+', ' ', x))

#remove stopwords
reviews.Review = reviews.Review.apply(lambda x: ' '.join([word for word in x.split(

#lemmatization
def get_wordnet_pos(word):
    #Map POS tag to first character lemmatize() accepts
    tag = nltk.pos_tag([word])[0][1][0].upper()
    tag_dict = {"J": wordnet.ADJ,
                "N": wordnet.NOUN,
                "V": wordnet.VERB,
```

```
                "R": wordnet.ADV}
    return tag_dict.get(tag, wordnet.NOUN)
lemmatizer= WordNetLemmatizer()
reviews.Review = \
    reviews.Review.apply(lambda x: ' '.join([lemmatizer.lemmatize(w, get_wordnet_po
```

I added a column to store the word counts, and removed reviews in which the word count was less than 3 words as they will not likely contribute anything meaningful to the model.

In [14]:
```
#Create a column for word count
reviews['Word_Count'] = reviews['Review'].apply(lambda x: len(str(x).split()))
```

In [15]:
```
#Remove entires with 3 words or less to remove noise
reviews = reviews[reviews['Word_Count'] > 3]
```

Now that the data is ready for tokenization, I run the following code to generate a vocabulary that essentially maps each word to a unique number. The vocabulary before clenaning was 5271 and is now 3995 after cleaning.

In [16]:
```
#Tokenizing after cleaning
tokenizer = Tokenizer()
tokenizer.fit_on_texts(reviews.Review)
vocab_size = len(tokenizer.word_index) + 1
print("Vocab size after text cleaning: ", vocab_size)
```

```
Vocab size after text cleaning:  3998
```

In [17]:
```
#The longest review
print(reviews.loc[reviews['Word_Count'].idxmax(), 'Review'])
```

```
masterful piece film make many theme simmer occasionally boil wart study poet bohemi
an self indulgent wartime year span aerial bombardment london outward tranquillity w
elsh coastal retreat borderline friendship lust love dedication art experience versu
s practical concern jealousy rivalry cowardice egotism versus heroism self sacrifice
```

B3. Because each review has different lengths, it is important to pad each sequence to make them all the same length.

In [18]:
```
#Set max length based on word count of longest review
max_length = max(reviews['Word_Count'])
print("Number of words in longest review: ", max_length)
```

```
Number of words in longest review:  44
```

In [19]:
```
#The longest review
index_of_longest_sentence = reviews['Word_Count'].idxmax()
longest_sentence = reviews.loc[index_of_longest_sentence, 'Review']
print(longest_sentence)
```


```
masterful piece film make many theme simmer occasionally boil wart study poet bohemi
an self indulgent wartime year span aerial bombardment london outward tranquillity w
elsh coastal retreat borderline friendship lust love dedication art experience versu
s practical concern jealousy rivalry cowardice egotism versus heroism self sacrifice
```

I am using the longest reivew to be the 'padding length' for the rest of the reviews. The padding also occurs before the training split but after tokenization.

In [20]:
```
#Tokenize to encode to numeric values
tokenizer= Tokenizer(num_words= vocab_size)
tokenizer.fit_on_texts(reviews.Review)
encoded_reviews= tokenizer.texts_to_sequences(reviews.Review)
padded_reviews= pad_sequences(encoded_reviews, maxlen= max_length)
```

The following is the padded sequence of the longest review that was displayed earlier.

In [21]:
```
#taking a look at the padded review of the longest review
padded_reviews[1620]
```

Out[21]:
```
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,   85, 1742, 1743,  845, 3618],
      dtype=int32)
```

B4. In this assessment the data is represented as binary values of `0` for negative sentiment and `1` for positive sentiment. Becuase I am classifying into two categories, the the activation function is `sigmoid` and there is `1` output.

`model.add(Dense(1, activation= 'sigmoid'))` (Sewell, n.d.)

In [22]:
```
#Sentiment categories and their count
reviews.sentiment.value_counts()
```

Out[22]:

sentiment	count
0	1039
1	1021

dtype: int64

B5. I split the data into the industry standard, 80/20 split into training and test.

In [23]:
```
#Splitting 80/20
X_train, X_test, y_train, y_test = model_selection.train_test_split(
    padded_reviews,
    reviews['sentiment'],
    test_size=0.20,
    random_state=386,
    stratify=reviews['sentiment']
)
```

In [24]:
```
train_shape = X_train.shape[0]
print("Input shape: ", train_shape)
```

```
Input shape:  1648
```

B6. The following files will be included in the submission files:

- `reviews_training.csv`
- `reviews_test.csv`
- `labels_training.csv`
- `labels_test.csv`

Prepping the data for the model

In [25]:
```
#exporting the files for B6
pd.DataFrame(X_train).to_csv('/content/drive/My Drive/Colab Notebooks/D213/reviews_
pd.DataFrame(X_test).to_csv('/content/drive/My Drive/Colab Notebooks/D213/reviews_t

pd.DataFrame(y_train).to_csv('/content/drive/My Drive/Colab Notebooks/D213/labels_t
pd.DataFrame(y_test).to_csv('/content/drive/My Drive/Colab Notebooks/D213/labels_te
```

Part III: Network Architecture

C1. The following is the `model.summary()` of the function from tensorflow.

In [26]:
```
#(Sewell, n.d.)
model= Sequential()
model.add(Input(shape= (train_shape, )))
model.add(Embedding(vocab_size, 100))
model.add(LSTM(128, dropout= 0.5, recurrent_dropout= 0.5, activation= 'tanh'))
model.add(Dense(1, activation= 'sigmoid'))
model.compile(loss= 'binary_crossentropy', optimizer= Adam(learning_rate= 0.0001),
print(model.summary())
```

Model: "sequential"

Layer (type)	Output Shape	Param #
embedding (Embedding)	(None, 1648, 100)	399,800
lstm (LSTM)	(None, 128)	117,248
dense (Dense)	(None, 1)	129

Total params: 517,177 (1.97 MB)

Trainable params: 517,177 (1.97 MB)

Non-trainable params: 0 (0.00 B)

None

C2. This is a seqential model with three layers. The first layer is an `embedding` layer, which has 399,800 pparameters, which are learned during training. The second layers is an `LSTM` layer to help the model process sentences. The third layer is a `dense` layer with 1 unit, which outputs a binary prediction of either `0` or `1` for positive or negative.

C3. The activation functions were `tanh` for the LSTM layer, and `sigmoid` in the dense layer to allow for the binary output of 0 or 1. The loss function is `binary_crossentropy` because this task is a binary classificaiton of 1 and 0 as mentioned before. This model used the `Adam` optimizer with a 0.0001 learning rate for smooth training (GeeksforGeeks, 2025). The stopping criteria was set to a patience of 3 epochs since the total epochs in the `model.fit()` was set to 15. Lastly, the evaluation metric was set to `accuracy`.

Part IV: Model Evaluation

D1. As noted in the previous section, the pattience is set to 3 becuase the total epochs to be ran is set to 15. The following code demonstrates that the early_stopping was never activated since the model continously improved through the 15 epochs. However, the validation accuracy did appear to plateau around 8 epochs.

D2. The model appeared to perform well with the training and validation accuracy closely alligned. I orginally ran the model with 20 epochs and a patience of 5 but the validation accuracy platteued around 7 epochs, suggesting overfitting. Making these changes impoved accuracy and vaidation accuracy.

In [27]:
```
early_stopping = EarlyStopping(patience= 3)
```

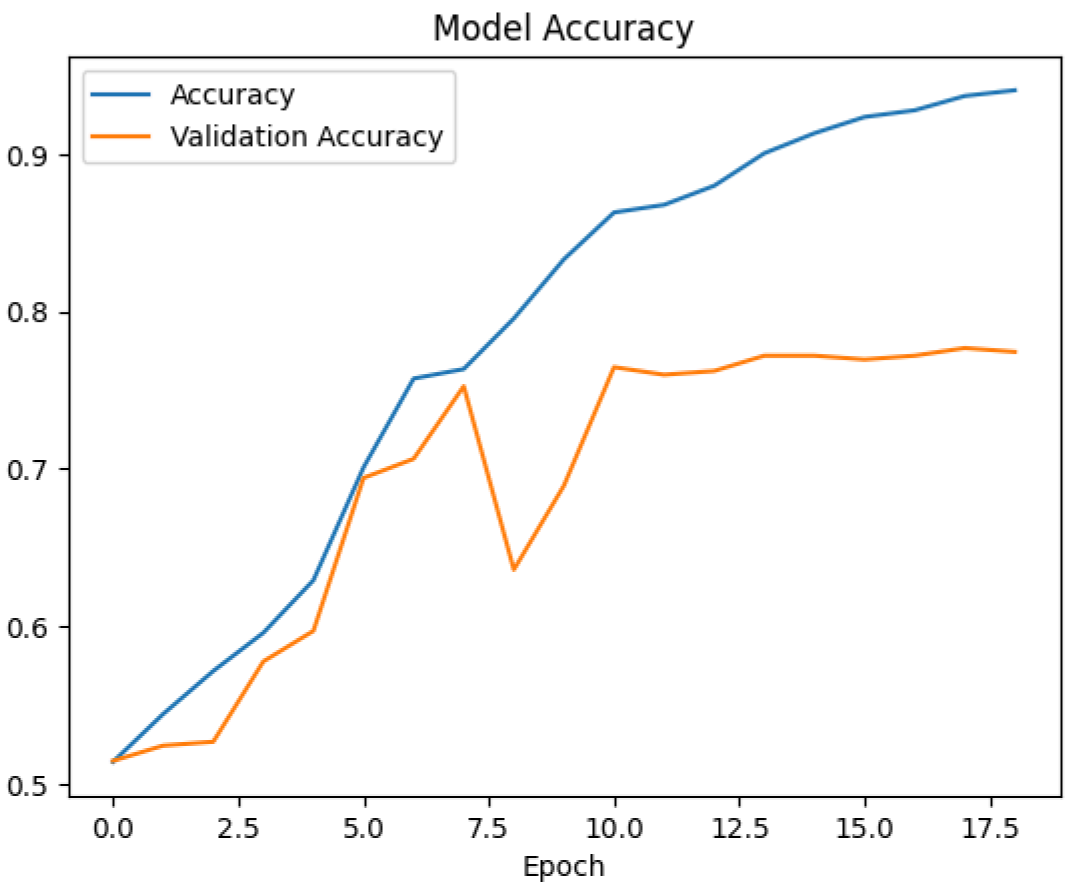
In [28]:
```
history = model.fit(X_train, y_train, epochs= 20, validation_data= (X_test, y_test)
```

```
Epoch 1/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 13s 135ms/step - accuracy: 0.5018 - loss: 0.6938 - val_ac
curacy: 0.5146 - val_loss: 0.6923
Epoch 2/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 10s 131ms/step - accuracy: 0.5267 - loss: 0.6922 - val_ac
curacy: 0.5243 - val_loss: 0.6914
Epoch 3/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 11s 157ms/step - accuracy: 0.5914 - loss: 0.6892 - val_ac
curacy: 0.5267 - val_loss: 0.6902
Epoch 4/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 6s 118ms/step - accuracy: 0.5885 - loss: 0.6883 - val_acc
uracy: 0.5777 - val_loss: 0.6886
Epoch 5/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 8s 157ms/step - accuracy: 0.6236 - loss: 0.6854 - val_acc
uracy: 0.5971 - val_loss: 0.6859
Epoch 6/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 6s 117ms/step - accuracy: 0.6720 - loss: 0.6802 - val_acc
uracy: 0.6942 - val_loss: 0.6816
Epoch 7/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 12s 147ms/step - accuracy: 0.7468 - loss: 0.6713 - val_ac
curacy: 0.7063 - val_loss: 0.6736
Epoch 8/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 11s 156ms/step - accuracy: 0.7658 - loss: 0.6538 - val_ac
curacy: 0.7524 - val_loss: 0.6593
Epoch 9/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 6s 116ms/step - accuracy: 0.8027 - loss: 0.6275 - val_acc
uracy: 0.6359 - val_loss: 0.6406
Epoch 10/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 8s 155ms/step - accuracy: 0.8150 - loss: 0.5893 - val_acc
uracy: 0.6893 - val_loss: 0.6101
Epoch 11/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 6s 116ms/step - accuracy: 0.8464 - loss: 0.5384 - val_acc
uracy: 0.7646 - val_loss: 0.5736
Epoch 12/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 8s 157ms/step - accuracy: 0.8614 - loss: 0.4757 - val_acc
uracy: 0.7597 - val_loss: 0.5454
Epoch 13/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 6s 116ms/step - accuracy: 0.8823 - loss: 0.3983 - val_acc
uracy: 0.7621 - val_loss: 0.5261
Epoch 14/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 8s 155ms/step - accuracy: 0.9026 - loss: 0.3503 - val_acc
uracy: 0.7718 - val_loss: 0.5208
Epoch 15/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 8s 117ms/step - accuracy: 0.9225 - loss: 0.3166 - val_acc
uracy: 0.7718 - val_loss: 0.5148
Epoch 16/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 8s 156ms/step - accuracy: 0.9310 - loss: 0.2732 - val_acc
uracy: 0.7694 - val_loss: 0.5139
Epoch 17/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 6s 115ms/step - accuracy: 0.9211 - loss: 0.2737 - val_acc
uracy: 0.7718 - val_loss: 0.5143
Epoch 18/20
52/52 ━━━━━━━━━━━━━━━━━━━━ 8s 155ms/step - accuracy: 0.9394 - loss: 0.2390 - val_acc
uracy: 0.7767 - val_loss: 0.5204
Epoch 19/20
```

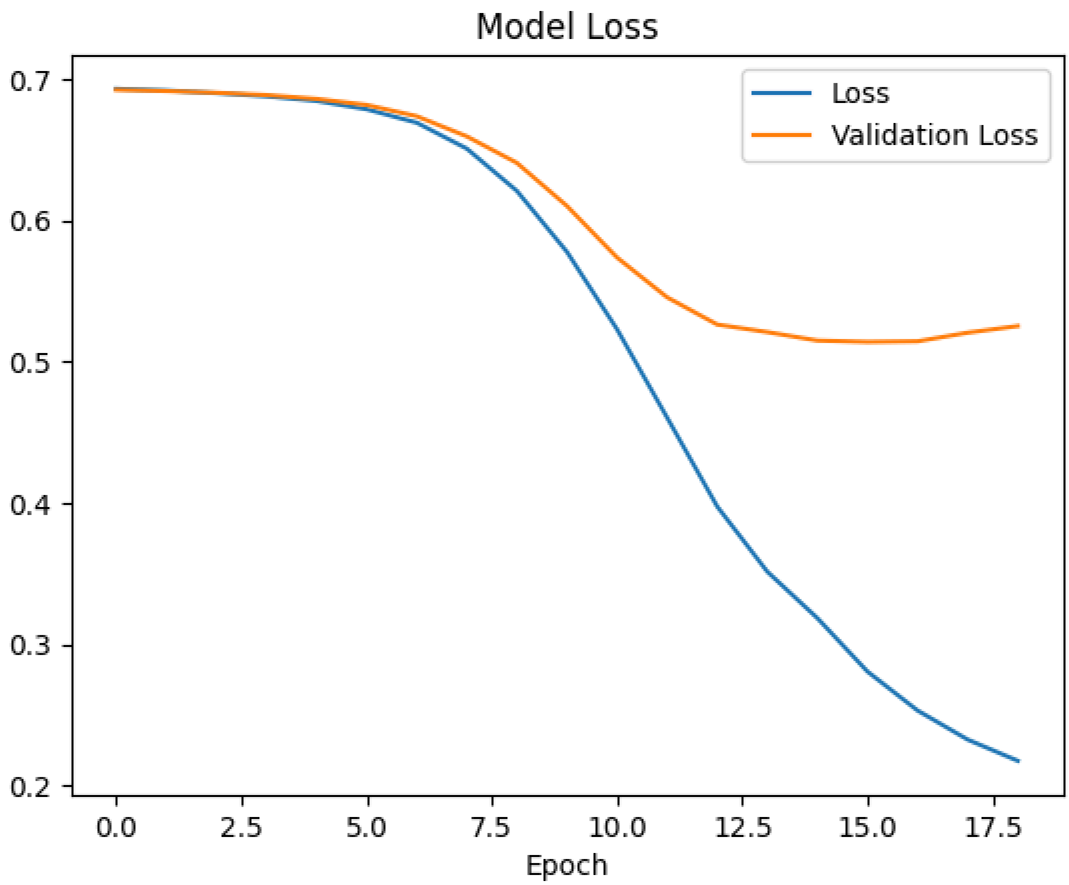
```
52/52 ━━━━━━━━━━━━━━━━━━━━ 9s 134ms/step - accuracy: 0.9355 - loss: 0.2265 - val_acc
uracy: 0.7743 - val_loss: 0.5251
```

D3. Plotting model accuracy and loss

In [29]:
```
#Model Accuracy
plt.plot(history.history['accuracy'], label='Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.title("Model Accuracy")
plt.xlabel("Epoch")
plt.legend()
plt.show()
```



In [30]:
```
#Model Loss
plt.plot(history.history['loss'], label='Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title("Model Loss")
plt.xlabel("Epoch")
plt.legend()
plt.show()
```



Evaluating the model using the test set

D4. The models accuracy is 76.06%

In [31]:
```
model.evaluate(X_test, y_test)
```

```
13/13 ━━━━━━━━━━━━━━━━━━━━ 0s 21ms/step - accuracy: 0.7703 - loss: 0.5475
```

Out[31]:
```
[0.5250909924507141, 0.7742718458175659]
```

In [32]:
```
#saving the model
model.save('sentiment_analysis_model.keras')
```

In the following lines of code, I test two seperate sentences expecting to see a sentiment prediction of 1 or 0.

In [33]:
```
def predict_sentiment(text):
    tw= tokenizer.texts_to_sequences([text])
    tw= pad_sequences(tw)
    prediction= int(model.predict(tw).round().item())
    print("Predicted label: ", prediction)
```

In [36]:
```
#Expecting a prediction of 1
test_sentence1 = "I love this camera"
predict_sentiment(test_sentence1)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 38ms/step
Predicted label:  1
```

In [37]:
```
#Expecting a prediction of 0
test_sentence2 = "I hate this camera."
predict_sentiment(test_sentence2)
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 52ms/step
Predicted label:  0
```

Part VI: Reporting

H1. The PDF file of this report will be included in the submission files.

I1. Web Sources

- UCI Machine Learning Repository. (n.d.). Sentiment labelled sentences [Data set]. University of California, Irvine. https://archive.ics.uci.edu/dataset/331/sentiment+labelled+sentences

- GeeksforGeeks. (2025, March 10). Adam optimizer in TensorFlow. https://www.geeksforgeeks.org/adam-optimizer-in-tensorflow/#

J1. This code was adapted from the course webinar videos listed below.

- Sewell, W. (n.d.). D213 Webinar 3: Transition [Webinar]. Western Governors University. https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=ea04fe77-3e3a-4293-8e9f-af7a00f22a8c
- Sewell, W. (n.d.). D213 SA Webinar 4 [Webinar]. Western Governors University. https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=c2642337-7947-4e7c-aa8d-af7b01456876
- Sewell, W. (n.d.). Webinar 5 SA [Webinar]. Western Governors University. https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=8502edc2-27b3-46ed-ab9c-af89012040ed
- Sewell, W. (n.d.). D213 Webinar 6 SA [Webinar]. Western Governors University. https://wgu.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=c3890312-a194-4f3a-b579-af8901300903