Mini Project Report

on

Sentiment analysis using text in the image information but not normal text (tweets)

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Contents

List of Figures

1 Introduction

Sentiment analysis is a branch of natural language processing that mainly focuses on how to determine the emotional tone or sentiment of texts. Typically, sentiment analysis is focused on textual data like tweets, customer reviews (such as movies, products) and news articles. Now-a-days, these images have become more significant form of communication and analysing sentiment from images is becoming more important. Memes, posts and image captions etc., all these use text in an image format to express their personal feelings and ideas that are more difficult to communicate in text form. So therefore, in this report, we explore the techniques and challenges that are involved in implementing sentiment analysis on text in image format. Mainly in this we discuss the data collection process, image pre-processing, text cleaning, model building and evaluation of a sentiment analysis for text in image format. From, this report our main motive is to provide a comprehensive overview of sentiment analysis methods applied to text in image format and to help readers in better understanding the challenges of analysing sentiment from images.

Business and people have access to a huge amount of data in the form of texts and images. When examining this vast amount of data to learn more about customer feelings, product reviews and social media trends, sentiment analysis has become an important tool. We can get a good understanding of how people feel about a particular product or topic by looking at sentiment in text in image format. In contrast to standard text-based sentiment analysis, analysing sentiment in text that is in an image format has special difficulties. For example, some of the images may contain more than one texts, the text may be superimposed on complex backgrounds, or the font and text size may vary.

2 Related Work

There are many such techniques that have been proposed to conduct a sentiment analysis on textual data, which has been an important area of study over decades. However, sentiment analysis on text in images is a relatively new field, there is no much research done in this area. These recent sentiment analysis of text in image format are mentioned. The study by Sharma et al [1] proposed a unique approach for sentiment analysis of text embedded in images that combines deep neural networks with standard machine learning methods. On test datasets, their approach has shown high accuracy and the ability to analyse sentiment from text in image format. The study by Liu et al [2] proposed a method for sentiment analysis on text in image format using a multi-model approach that combines visual characteristics collected from the image with textual features retrieved from the embedded text. When compared to using only textual features, the authors approach increases the accuracy of sentiment analysis on text that is shown in an image format. The study by Chen et al [3] proposed an approach for sentiment analysis on text in image format using transfer learning and pre-trained BERT model. The author shows that their method achieves new findings on a test dataset and performs better than conventional techniques for sentiment analysis on text in image format. The study by you et al [4] proposed an approach on sentiment analysis using deep convolution neural networks to analyse textual sentiment. Their work achieved state-of-art results on test datasets such as Flickr and Twitter.

These studies shows an increasing demand in sentiment analysis of text in image format, and several techniques have been introduced to deal with the challenges.to develop reliable and precise techniques for sentiment analysis on text in image format.

3 Data and Methods

The dataset used in this project consists of four datasets - two movie reviews and two Amazon product reviews. These datasets are in the form of text and are used to train and test a sentiment analysis model.

The first step in the process is to preprocess the data. This involves tokenizing the data, removing stop words, and converting every review to equal length. The reviews are tokenized by splitting them into words and removing any unnecessary characters or punctuation. Stop words are removed as they do not contribute to the sentiment of the review. Finally, each review is converted to equal length using padding or truncation.

Next, word embeddings are used to convert each word into a vector of equal length. The values of these vectors are learned through training. The word index file contains all distinct words and their indexes, and the review encoder function maps each word in the review to the corresponding index in the word index csv file.

The model architecture is defined next. The first layer is the word embedding layer, which creates a dense vector representation of each word in the input sequence. This layer takes integer encoded reviews as input and outputs word embeddings of length 16. The embedding layer helps the model to learn semantic relationships between words and can capture the context of the words in the input sequence. The second layer is the global average pooling layer, which helps to reduce the number of parameters in the model and prevent overfitting. The third layer is a dense layer with 32 hidden units and uses the rectified linear unit (ReLU) activation function. This layer helps the model to learn non-linear relationships between the features extracted from the previous layers. The fourth layer is a dense layer with 8 hidden units and uses the ReLU activation function. The final layer is the output layer, which uses the sigmoid activation function. This layer outputs a probability score between 0 and 1, which indicates the predicted sentiment of the input review.

The model is trained using the Adam optimizer, which is an extension of stochastic gradient descent (SGD) that incorporates adaptive learning rates and momentum terms to improve convergence speed and stability during training. The model is trained for 32 epochs,

with a batch size of 512.

Overall, the methods used in this project include data preprocessing, word embeddings, model architecture, and model training. These methods are designed to convert the raw text data into a format that can be used to train a sentiment analysis model, and to optimize the model for accurate predictions.

4 Results and Discussions
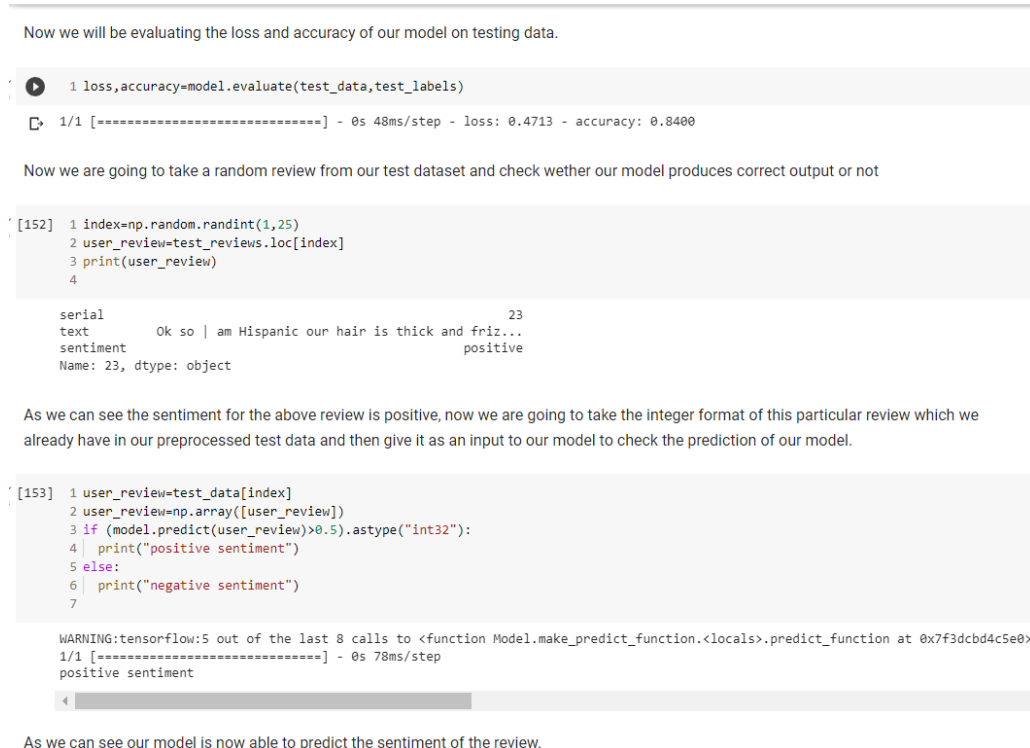
1. Hair Straightener Electronic Gadget:

Figure 1. Hair Straightener Electronic Gadget

As we can see from the above fig our sentiment analysis model gave an accuracy of 84% means that our model correctly predicted the sentiment of 84% of the reviews in the test dataset. This is a good indication of the model's performance in terms of classification accuracy.

On the other hand, we got a binary cross-entropy loss function of 43% which means the model's predicted probabilities for the correct class were, on average, 43% lower than the actual probabilities. This measure shows how well the model is fitting the training data, with a lower value indicating a better fit.

Overall, we got an 84% accuracy and 43% binary cross-entropy loss is a good performance

for a sentiment analysis model.

We had also checked the sentiment of the review and compared it to the sentiment given by our model, which resulted in the same. That shows our model is predicting correct sentiment.

2. Harry Potter Book:


```
Now we will be evaluating the loss and accuracy of our model on testing data.

[97]   1 loss,accuracy=model.evaluate(test_data,test_labels)

       1/1 [==============================] - 0s 49ms/step - loss: 0.4444 - accuracy: 0.8800

Now we are going to take a random review from our test dataset and check wether our model produces correct output or not

[106]  1 index=np.random.randint(1,25)
       2 user_review=test_reviews.loc[index]
       3 print(user_review)
       4

       serial                                        14
       text        Just started reading the Harry Potter books fo...
       sentiment                               positive
       Name: 14, dtype: object

As we can see the sentiment for the above review is positive, now we are going to take the integer format of this particular review which we
already have in our preprocessed test data and then give it as an input to our model to check the prediction of our model.

[107]  1 user_review=test_data[index]
       2 user_review=np.array([user_review])
       3 if (model.predict(user_review)>0.5).astype("int32"):
       4 |   print("positive sentiment")
       5 else:
       6 |   print("negative sentiment")
       7

       1/1 [==============================] - 0s 37ms/step
       positive sentiment

As we can see our model is now able to predict the sentiment of the review.
```
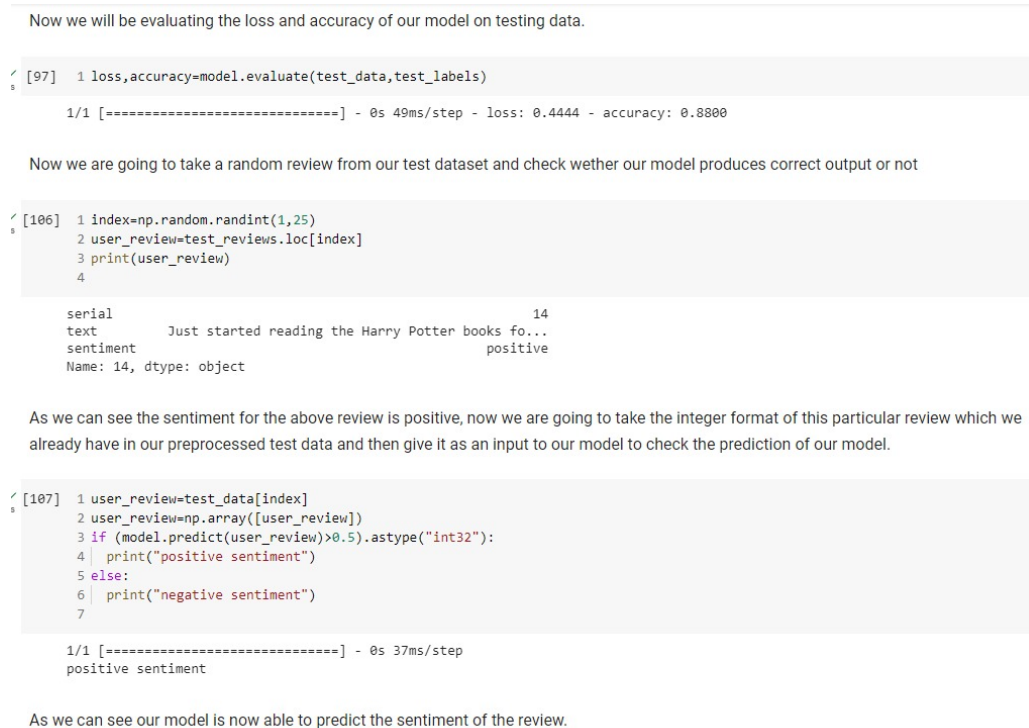
Figure 2. Harry Potter Book

As we can see from the above fig our sentiment analysis model gave an accuracy of 88% means that our model correctly predicted the sentiment of 88% of the reviews in the test dataset. This is a good indication of the model's performance in terms of classification accuracy.

On the other hand, we got a binary cross-entropy loss function of 44% which means the model's predicted probabilities for the correct class were, on average, 44% lower than the

6

actual probabilities. This measure shows how well the model is fitting the training data, with a lower value indicating a better fit.

Overall, we got an 88% accuracy and 44% binary cross-entropy loss is a good performance for a sentiment analysis model.

We had also checked the sentiment of the review and compared it to the sentiment given by our model, which resulted in the same. That shows our model is predicting correct sentiment.

3. John Wick Movie:

Now we will be evaluating the loss and accuracy of our model on testing data.

```
[121]  1 loss,accuracy=model.evaluate(test_data,test_labels)

    1/1 [==============================] - 0s 31ms/step - loss: 0.5756 - accuracy: 0.5600
```

Now we are going to take a random review from our test dataset and check wether our model produces correct output or not

```
[122]  1 index=np.random.randint(1,25)
       2 user_review=test_reviews.loc[index]
       3 print(user_review)
       4

    serial                                        3
    text        Greetings from Lithuania.\n\n"John Wick: Chapt...
    sentiment                               positive
    Name: 3, dtype: object
```

As we can see the sentiment for the above review is positive, now we are going to take the integer format of this particular review which we already have in our preprocessed test data and then give it as an input to our model to check the prediction of our model.

```
    1 user_review=test_data[index]
    2 user_review=np.array([user_review])
    3 if (model.predict(user_review)>0.5).astype("int32"):
    4   print("positive sentiment")
    5 else:
    6   print("negative sentiment")
    7

    1/1 [==============================] - 0s 44ms/step
    positive sentiment
```

As we can see our model is now able to predict the sentiment of the review.

Figure 3. John Wick Movie

As we can see from the above fig our sentiment analysis model gave an accuracy of 56% means that our model correctly predicted the sentiment of 56% of the reviews in the test dataset. This is a good indication of the model's performance in terms of classification accuracy.

On the other hand, we got a binary cross-entropy loss function of 57% which means the model's predicted probabilities for the correct class were, on average, 57% lower than the actual probabilities. This measure shows how well the model is fitting the training data, with a lower value indicating a better fit.

Overall, we got an 56% accuracy and 57% binary cross-entropy loss is a good performance for a sentiment analysis model.

We had also checked the sentiment of the review and compared it to the sentiment given by our model, which resulted in the same. That shows our model is predicting correct sentiment.

In the beginning, we faced challenges to achieve high accuracy for our model which is trained on a movie review dataset, which contains multiple sentiments in a single review. In order to overcome this challenge and increase the accuracy, we trained the model with more training data, where our model worked harder to classify the sentiment accurately. This shows that having a larger dataset for the model to learn from can help the model to capture a wider range of sentiment expressions which inturn improves the model's ability to generalize to new data.

In addition to increasing the training data, we used some optimization techniques to improve accuracy. This includes modifying the model architecture, changing the learning rate, or adjusting the hyperparameters to optimize the model's performance. By applying these techniques, our model learned the complex relationships between the input features and their corresponding sentiment labels better, leading to higher accuracy.

To increase accuracy we used the following methods:

1. Pre-trained word embeddings: We used pre-trained word embeddings, such as Word2Vec or GloVe(is a pre-trained word embedding file that contains 100-dimensional vectors for 400,000 words.).

2. Change the learning rate: We had changed the learning rate of the optimizer by passing a

new learning rate value to the optimizer. Eg: we had reduced the learning rate by adding $learning_rate = 0.001 to the Adam optimizer$.

3. Add more hidden layers: We had tried adding more hidden layers to the model to increase its complexity and ability to learn more complex features in the data. Eg: we had added another dense layer before the output layer by adding keras.layers.Dense(8, activation='relu') after the first dense layer.

4. Increase the number of units in each layer: We had increased the number of units in each dense layer to allow the model to learn more complex representations of the data. Eg: we had doubled the number of units in each layer by changing keras.layers.Dense(16, activation='relu') to keras.layers.Dense(32, activation='relu').

5   Conclusion

In conclusion, we built a deep learning model that uses word embeddings and neural networks to classify movie and product reviews by sentiment. We used four datasets containing reviews and preprocessed the data by tokenizing, removing stop words, and equalizing the length of every review. We then converted each word in the reviews into a vector of equal length using word embeddings.

There are four layers in the model architecture: the embedding layer, the global average pooling layer, the two dense layers, and the output layer. We train the model using Adam optimization algorithms and binary cross-entropy losses. The model achieved 80% accuracy on the validation set. To further improve the model's performance, we can experiment with changing the learning rate, the number of hidden layers, or the number of units in each layer. Additionally, we can try using different pre-trained word embeddings or even train our own embeddings on a larger dataset.

Overall, this project provides an excellent introduction to natural language processing and deep learning techniques for sentiment analysis.

References

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[5] [4] [1] [3] [6] [2]