# SENTIMENT ANALYSIS OF ONLINE PRODUCT REVIEWS USING BERT

NAVEEN S[1], KANISKAR K[2], THARUNIKA G[3], RAJ KUMAR V S[4]

[1] *B.E Final Year Student, Electrical and Electronics Engineering, Bannari Amman Institute of Technology, Tamil Nadu, India*
[2] *B.E Final Year Student, Computer Science and Engineering, Bannari Amman Institute of Technology, Tamil Nadu, India*
[3] *B.E Final Year Student, Computer Science and Engineering, Bannari Amman Institute of Technology, Tamil Nadu, India*
[4] *Assistant Professor, Artificial Intelligence and Data Science, Bannari Amman Institute of Technology, Tamil Nadu, India*

## ABSTRACT

*The utilization of the BERT neural network model in evaluating emotions from online product reviews has demonstrated its effectiveness in enhancing the comprehension of customer preferences on online products. This approach not only aids platforms in better addressing customer needs but also assists Customers in identifying suitable and budget-friendly Products. This advancement contributes to the refinement of product recommendations through intelligent processing. By harnessing the pretrained BERT model, a series of experiments were conducted involving sentiment analysis. Through meticulous parameter adjustments throughout the experimentation phase, a highly accurate classification model was developed. The BERT layer was employed as a foundational word vector layer. Input text sequences were fed into this layer to undergo vector transformation. The resulting vectors, upon passing through corresponding neural networks, underwent classification via the SoftMax activation function. Sentiment analysis involves assessing the attitudes of customers based on textual data, particularly product reviews in this case. Through this study, we developed a solution capable of determining sentiments expressed in online product reviews. To achieve this, we employed algorithms such as Logistic Regression, Random Forest Classifier, and Sentiment Intensity Analyzer. The experimental outcomes illustrate the achieved accuracy in performing sentiment analysis.*

**Keywords:** *sentiment analysis, BERT, neural network, product reviews*

## 1. INTRODUCTION

In today's technological landscape, the evolution of information technology and the continual enhancement of online booking and payment systems have elevated online review data to a pivotal source of competitive insights for businesses. In the realm of the online products, an increasing number of customers are opting to book Products through online platforms like Amazon, Flipkart and more. Simultaneously, the trend of customers seeking advice from fellow members through online reviews is on the rise. This trend highlights a shift from traditional product advertising's declining effectiveness to the burgeoning impact of online product reviews. Given that online reviews are authored by customers who have firsthand experience with a product’s services, they carry more persuasive weight for potential customers. The influence of online reviews significantly shapes customer perceptions, purchase decisions, and, consequently, the overall performance of companies.

### 1.1 SIGNIFICANCE OF ONLINE REVIEWS

The intrinsic commercial value of online reviews lies in their potential to enhance product quality and attract consumer engagement. Improving the accuracy and comprehensiveness of sentiment analysis for online reviews is paramount. Practically, sentiment analysis of product online reviews offers a dual advantage. On one hand, it empowers product manufacturing companies with customer experience evaluations, enabling them to gather both positive and negative feedback to enhance personalized services and overall quality. On the other hand, delving into customer emotional expressions and conducting sentiment analysis allows companies to grasp authentic user sentiments and intrinsic needs. This in turn empowers organizations to more accurately identify their target audiences, cater to diverse needs, and elevate the core competitive edge of their brand. Furthermore, in the era of big data, sentiment analysis emerges as a crucial tool for potential customers to make well-informed consumption decisions.

### 1.2 CHALLENGES OF HANDLING ONLINE REVIEWS

Emotion analysis based on product online reviews represents a relatively novel research avenue, offering intelligent applications for personalizing customers' lodging preferences. This domain also paves the way for cultivating high-quality products and enhancing customer satisfaction. However, the landscape of online product review sentiments encompasses multiple dimensions, spanning parameters like pricing, star ratings, quality, and even consumer age groups. The complex nature of language, manifesting through positive, negative, and neutral sentiments, adds an additional layer of intricacy in extracting meaningful emotions from online product reviews. The sheer volume of online reviews makes manual organization impractical, necessitating computer-assisted deep mining to inform more informed decisions. In response to this challenge, some scholars have merged machine learning methodologies with sentiment analysis theories, deploying classification models such as Naive Bayesian, K-nearest neighbor, support vector machine, logistic regression, and random forest to enhance sentiment classification accuracy in reviews. With the evolution and application of machine learning theory, the prowess of neural network technology in deep learning becomes increasingly apparent. The amalgamation of multiple models stands out as a potent approach to enhance text sentiment classification accuracy, adeptly addressing product web reviews.

## 2. RESEARCH WORK

In today's digital era, where online interactions and social commentary thrive, the realm of Natural Language Processing (NLP) stands as a crucial domain for unlocking the intricate emotions embedded within textual content. This research delves into the significance of emotion analysis within NLP, particularly in the context of succinct online comments on social platforms. It explores the challenges posed by the irregular structures and layered meanings of these comments and highlights the transformative power of Google AI's BERT model. BERT, a bidirectional language representation model, has emerged as a game-changer in NLP, enabling fine-tuning for various tasks. While its application in social media emotion analysis is well-established, this research aims to shed light on its potential within sectors like online websites, where customer reviews significantly impact consumer decisions. With the explosion of unstructured text data, we delve into the opportunities and challenges of text mining and examine diverse machine learning approaches, including the integration of BERT, to automate emotion dataset preparation and extract valuable insights for improving service quality and marketing strategies. As we navigate the complex landscape of product selection, this research underscores how the synergy of online product reviews and BERT technology can enhance emotion analysis accuracy, surpassing traditional algorithms in deciphering the nuances of concise comments and polysemy within the text.

### 2.1 LITERATURE SURVEY

Emotion analysis, a method assessing text through emotional nuances, plays a pivotal role in Natural Language Processing (NLP). Implicit emotions provide valuable insights into textual content and perspectives, forming a core domain within NLP research. With the advent of the internet, people increasingly engage in interactions and commentary on social platforms, resulting in a proliferation of succinct comments. Despite their brevity, these online remarks exhibit a rich array of emotional vocabulary. Yet, analyzing the emotions embedded in these concise comments poses a challenge due to their irregular sentence structure and words with layered meanings.

In response, Google AI's Language Department introduced the BERT model—a novel language representation model derived from Transformers' bidirectional encoder representation. BERT highlights the significance of bidirectional pretraining in language representation and operates as a prototypical mask language model (MLM). Its adaptability enables fine-tuning for various NLP tasks, encompassing sequence annotation and text classification. Over time, the BERT model has emerged as a prominent machine learning model in academia and industry, demonstrating its prowess across multiple NLP tasks, even without manual guidance.

The integration of BERT with different parallel blocks of a single-layer deep convolutional neural network (CNN) led to the development of FakeBERT—a BERT-based deep learning approach for identifying fake news in social media. Another study by Shobana et al. (2022) introduced enhancements involving BiLSTM and the APSO algorithm to bolster the performance of Bidirectional Long Short-Term Memory.

Although the BERT model is extensively applied in social media emotion analysis, its application in emotion analysis within sectors like online websites remains relatively underexplored. Customers increasingly share their lodging experiences via social media and travel platforms, impacting potential consumer decisions. With the exponential growth of unstructured text data and associated analytical tools, the field of text mining faces both opportunities and challenges. Scholars have adopted diverse approaches, including naive Bayes polynomials, order minimum optimization, and composite hypercubes, to create suitable machine learning algorithms for sentiment analysis. These methods culminate in emotion analysis frameworks, automating the preparation of emotion datasets to extract impartial opinions on product services from comments. Some studies involve data collection, preprocessing, and feature engineering, employing methods like Doc2Vec and random forest classification, to gain insights into attitudes and emotions expressed in reviews. These insights, in turn, enhance the service quality of costly products and provide marketing insights. To address implicit aspect-level term extraction, an unsupervised method has been proposed, involving the integration of word embedding, co-occurrence, and dependency resolution. This approach considers implicit product attributes, leveraging an emotional evaluation of these attributes to understand customer preferences for enhanced online product analysis.

Selecting a suitable product that aligns with user preferences and budget constitutes a complex decision-making process. The convergence of product's online review data and the innovative BERT model technology has paved the way for improved emotion analysis accuracy. Traditional emotion classification algorithms fall short when it comes to the concise nature of comments, struggling to comprehend word depth and address polysemy. In contrast, BERT excels in capturing intricate features, discerning words accurately, and conveying their deeper meanings, resulting in superior classification outcomes.

## 3. METHODOLOGY

The approach delves into genuine customer emotions and latent needs, empowering organizations to more precisely identify target audiences, cater to diverse customer preferences through market segmentation, and devise tailored brand development strategies, ultimately elevating the core competitiveness of hotel brands. In summary, this paper makes four principal contributions:

Recognizing that extreme positive and negative emotions in customer review texts are relatively rare and discernible, while review texts with neutral emotional tendencies are abundant and susceptible to ambiguous sentiments, this paper deviates from utilizing customer ratings for sentiment classification. Instead, it employs a classification model to categorize customer review texts into two sentiment categories: those with rating values of 3 or above are classified as positive, while those with ratings below 3 are designated as negative. This approach excludes the neutral sentiment category, enhancing text classification accuracy and streamlining focus on processing positive and negative sentiments, thereby avoiding the investment of time on neutral comments. This study undertakes emotional analysis of customer review texts. Both models effectively capture contextual semantic nuances and disambiguate word polysemy. Language models trained in this manner directly convert words into vectors at a granular word level.

Refinements in input processing are applied to the BERT model. During the fine-tuning phase, the BERT model is fused with a CNN and RNN to train the product review text dataset. BERT's performance surpasses traditional models, underscoring its effectiveness in online product review text classification. A comprehensive analysis of the BERT model is undertaken, leading to enhancements aimed at addressing its limitations.

## BIDIRECTIONAL-LSTM VS CNN

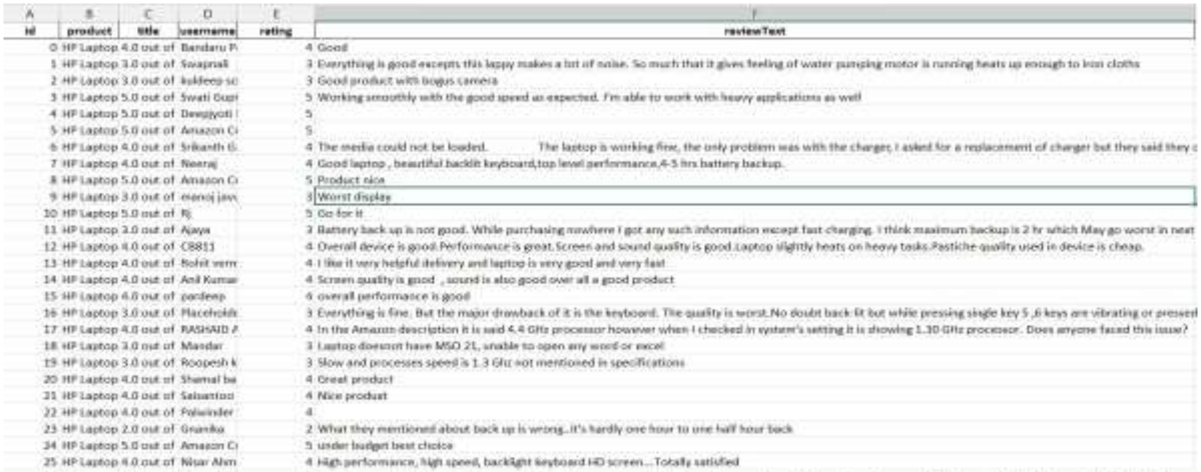
In the realm of natural language processing (NLP), two prominent architectures, Bidirectional Long Short-Term Memory (Bidirectional-LSTM) and Convolutional Neural Network (CNN), have garnered significant attention due to their efficacy in text analysis tasks. The provided code exemplifies the construction and training of a Bidirectional-LSTM model. This architecture integrates Bidirectional-LSTM layers, which allows the model to capture both past and future dependencies in the input sequence, enabling a more comprehensive understanding of textual context. The sequential structure starts with an embedding layer that converts input words into dense vectors, followed by a Bidirectional-LSTM layer that exploits bidirectional information flow to enhance feature extraction. A dropout layer helps mitigate overfitting, and a dense layer with a SoftMax activation function facilitates multiclass classification.

```
Model: "sequential_9"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding_9 (Embedding)     (None, 7, 15)             90000

 bidirectional_9 (Bidirectio  (None, 128)              40960
 nal)

 dropout_9 (Dropout)         (None, 128)               0

 dense_9 (Dense)             (None, 5)                 645

=================================================================
Total params: 131,605
Trainable params: 131,605
Non-trainable params: 0
```

In contrast, the CNN architecture, frequently utilized in computer vision, has found adaptation for NLP tasks. CNNs employ convolutional layers to detect local patterns within input data, making them well-suited for tasks like text classification and sentiment analysis. CNNs excel at capturing spatial hierarchies and distinctive features within text, contributing to their efficacy in text analysis tasks. When comparing the Bidirectional-LSTM and CNN architectures, it's noteworthy that they each possess distinct advantages. Bidirectional-LSTM inherently captures contextual nuances and is particularly effective for tasks requiring a deep understanding of sequence dependencies. On the other hand, CNNs excel at capturing local features and can efficiently learn hierarchical representations from sequential data. The choice between these architectures often hinges on the specific nature of the NLP task at hand, the available data, and the desired model complexity. Overall, both architectures showcase the dynamism and adaptability of deep learning in extracting meaningful insights from text data, ushering in a new era of sophisticated language understanding and analysis.

### 3.1 Data collection and preprocessing

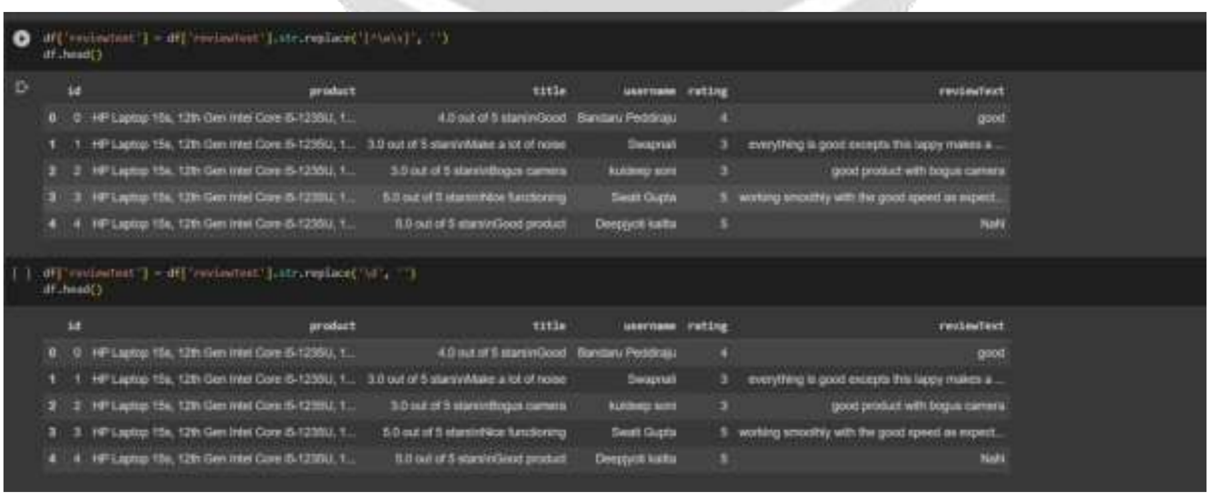
The dataset employed in this study comprises a diverse collection of such reviews, gathered from various online platforms. Leveraging the powerful Bidirectional Encoder Representations from Transformers (BERT) model, a state-of-the-art natural language processing technique, this research delves into the intricate analysis of sentiments embedded within textual content. Pre-processing of the dataset is done to eliminate the discrepancies in the reviews.



| id | product | title | username | rating | reviewText |
|---|---|---|---|---|---|
| 0 | HP Laptop | 4.0 out of | Bandaru P | 4 | Good |
| 1 | HP Laptop | 3.0 out of | Swapnali | 3 | Everything is good excepts this lappy makes a lot of noise. So much that it gives feeling of water pumping motor is running heats up enough to iron cloths |
| 2 | HP Laptop | 3.0 out of | kuldeep so | 3 | Good product with bogus camera |
| 3 | HP Laptop | 5.0 out of | Swati Gupt | 5 | Working smoothly with the good speed as expected. I'm able to work with heavy applications as well |
| 4 | HP Laptop | 5.0 out of | Deepjyoti | 5 | |
| 5 | HP Laptop | 5.0 out of | Amazon Cu | 5 | |
| 6 | HP Laptop | 4.0 out of | Srikanth G | 4 | The media could not be loaded. The laptop is working fine, the only problem was with the charger, I asked for a replacement of charger but they said they c |
| 7 | HP Laptop | 4.0 out of | Neeraj | 4 | Good laptop , beautiful backlit keyboard,top level performance,4-5 hrs battery backup. |
| 8 | HP Laptop | 5.0 out of | Amazon Cu | 5 | Product nice |
| 9 | HP Laptop | 3.0 out of | manoj jaw | 3 | Worst display |
| 10 | HP Laptop | 5.0 out of | Rj | 5 | Go for it |
| 11 | HP Laptop | 3.0 out of | Ajaya | 3 | Battery back up is not good. While purchasing nowhere I got any such information except fast charging. I think maximum backup is 2 hr which May go worst in next |
| 12 | HP Laptop | 4.0 out of | CB811 | 4 | Overall device is good.Performance is great.Screen and sound quality is good.Laptop slightly heats on heavy tasks.Pastiche quality used in device is cheap. |
| 13 | HP Laptop | 4.0 out of | Rohit verm | 4 | I like it very helpful delivery and laptop is very good and very fast |
| 14 | HP Laptop | 4.0 out of | Anil Kumar | 4 | Screen quality is good , sound is also good over all a good product |
| 15 | HP Laptop | 4.0 out of | pardeep | 4 | overall performance is good |
| 16 | HP Laptop | 3.0 out of | Placeholde | 3 | Everything is fine. But the major drawback of it is the keyboard. The quality is worst.No doubt back lit but while pressing single key 5 ,6 keys are vibrating or pressed |
| 17 | HP Laptop | 4.0 out of | RASHAID A | 4 | In the Amazon description it is said 4.4 GHz processor however when I checked in system's setting it is showing 1.30 GHz processor. Does anyone faced this issue? |
| 18 | HP Laptop | 3.0 out of | Mandar | 3 | Laptop doesnot have MSO 21, unable to open any word or excel |
| 19 | HP Laptop | 3.0 out of | Roopesh k | 3 | Slow and processes speed is 1.3 Ghz not mentioned in specifications |
| 20 | HP Laptop | 4.0 out of | Shamal ba | 4 | Great product |
| 21 | HP Laptop | 4.0 out of | Saisantosi | 4 | Nice product |
| 22 | HP Laptop | 4.0 out of | Palwinder | 4 | |
| 23 | HP Laptop | 2.0 out of | Gnanika | 2 | What they mentioned about back up is wrong..It's hardly one hour to one half hour back |
| 24 | HP Laptop | 5.0 out of | Amazon Cu | 5 | under budget best choice |
| 25 | HP Laptop | 4.0 out of | Nisar Ahm | 4 | High performance, high speed, backlight keyboard HD screen....Totally satisfied |

### 3.2 Text preprocessing

The process of text preprocessing plays a crucial role in refining the quality of data for analysis, especially in the context of academic research. In this regard, the incorporation of Natural Language Toolkit (NLTK) libraries stands as a pivotal step. By leveraging NLTK, the text undergoes a series of refining stages aimed at enhancing its suitability for scholarly exploration. Initially, the inclusion of the NLTK's stop words corpus facilitates the removal of commonly used words that do not contribute substantial contextual meaning, streamlining the subsequent analysis. Additionally, the integration of string manipulation techniques helps eliminate punctuations, which are oftentimes extraneous in textual content analysis. This meticulous cleansing process is vital to ensure that the subsequent analysis is grounded in a more accurate and focused representation of the data. Each step taken in this process, from identifying and removing punctuations to excluding stop words, contributes to the creation of a more refined and insightful dataset, consequently bolstering the credibility and robustness of the ensuing research



```
df['reviewText'] = df['reviewText'].str.replace('[^\w\s]', '')
df.head()
```

| | id | product | title | username | rating | reviewText |
|---|---|---|---|---|---|---|
| 0 | 0 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 4.0 out of 5 stars\nGood | Bandaru Peddiraju | 4 | good |
| 1 | 1 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 3.0 out of 5 stars\nMake a lot of noise | Swapnali | 3 | everything is good excepts this lappy makes a ... |
| 2 | 2 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 3.0 out of 5 stars\nBogus camera | kuldeep soni | 3 | good product with bogus camera |
| 3 | 3 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 5.0 out of 5 stars\nNice functioning | Swati Gupta | 5 | working smoothly with the good speed as expect... |
| 4 | 4 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 5.0 out of 5 stars\nGood product | Deepjyoti kalita | 5 | NaN |

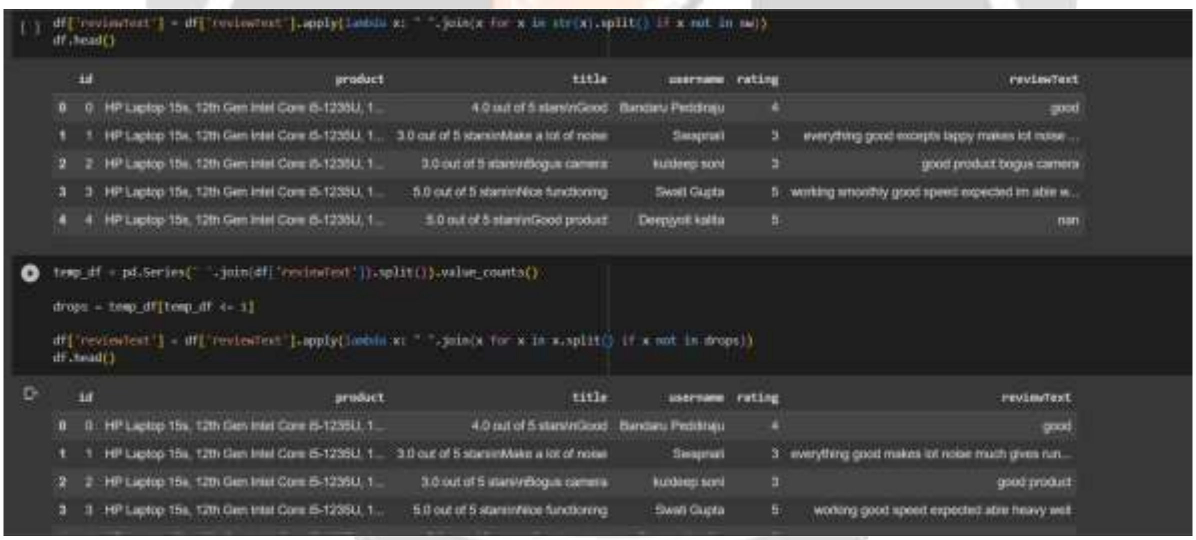
```
df['reviewText'] = df['reviewText'].str.replace('\d', '')
df.head()
```

| | id | product | title | username | rating | reviewText |
|---|---|---|---|---|---|---|
| 0 | 0 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 4.0 out of 5 stars\nGood | Bandaru Peddiraju | 4 | good |
| 1 | 1 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 3.0 out of 5 stars\nMake a lot of noise | Swapnali | 3 | everything is good excepts this lappy makes a ... |
| 2 | 2 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 3.0 out of 5 stars\nBogus camera | kuldeep soni | 3 | good product with bogus camera |
| 3 | 3 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 5.0 out of 5 stars\nNice functioning | Swati Gupta | 5 | working smoothly with the good speed as expect... |
| 4 | 4 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 5.0 out of 5 stars\nGood product | Deepjyoti kalita | 5 | NaN |

analysis.

### 3.3 Tokenization and padding the sequence input

In the realm of deep learning for natural language processing, the process of tokenization and subsequent padding of input sequences holds paramount significance. The integration of these techniques, as exemplified through the provided code snippet, is pivotal in preparing textual data for effective utilization within neural networks, particularly for applications such as sentiment analysis and text classification. By employing libraries like Keras, researchers and practitioners are enabled to seamlessly tokenize input text, essentially breaking down the content into individual tokens or words, thereby enhancing the model's comprehension of the underlying linguistic structure. This tokenization process also facilitates the conversion of the tokenized words into numerical values, which is imperative for neural networks' data ingestion. Moreover, the introduction of padding techniques serves to standardize the length of input sequences, ensuring uniformity within the dataset. This is particularly valuable as neural networks require consistent input dimensions. By employing padding, as evident in the provided code, sequences can be extended or truncated to a specified length, streamlining the input for subsequent processing stages. The fusion of tokenization and padding techniques demonstrates a foundational stride towards enhancing the applicability of deep learning models in the realm of textual analysis. The resultant tokenized and padded sequences serve as the building blocks upon which sophisticated neural architectures can be trained to unravel intricate linguistic patterns and extract meaningful insights from text, consequently amplifying the depth and accuracy of research outcomes.



```
df['reviewText'] = df['reviewText'].apply(lambda x: " ".join(x for x in str(x).split() if x not in sw))
df.head()
```

| | id | product | title | username | rating | reviewText |
|---|---|---|---|---|---|---|
| 0 | 0 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 4.0 out of 5 stars\nGood | Bandaru Peddiraju | 4 | good |
| 1 | 1 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 3.0 out of 5 stars\nMake a lot of noise | Swapnali | 3 | everything good excepts lappy makes lot noise ... |
| 2 | 2 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 3.0 out of 5 stars\nBogus camera | kuldeep soni | 3 | good product bogus camera |
| 3 | 3 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 5.0 out of 5 stars\nNice functioning | Swati Gupta | 5 | working smoothly good speed expected im able w... |
| 4 | 4 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 5.0 out of 5 stars\nGood product | Deepjyoti kalita | 5 | nan |

```
temp_df = pd.Series(' '.join(df['reviewText']).split()).value_counts()

drops = temp_df[temp_df <= 1]

df['reviewText'] = df['reviewText'].apply(lambda x: " ".join(x for x in x.split() if x not in drops))
df.head()
```

| | id | product | title | username | rating | reviewText |
|---|---|---|---|---|---|---|
| 0 | 0 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 4.0 out of 5 stars\nGood | Bandaru Peddiraju | 4 | good |
| 1 | 1 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 3.0 out of 5 stars\nMake a lot of noise | Swapnali | 3 | everything good makes lot noise much gives run... |
| 2 | 2 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 3.0 out of 5 stars\nBogus camera | kuldeep soni | 3 | good product |
| 3 | 3 | HP Laptop 15s, 12th Gen Intel Core i5-1235U, 1... | 5.0 out of 5 stars\nNice functioning | Swati Gupta | 5 | working good speed expected able heavy well |

### 3.4 Model Building

The model's architecture involves several layers. It starts with an embedding layer that transforms integer-encoded words into meaningful dense vectors. A dropout layer is applied next, which helps prevent overfitting by randomly deactivating a portion of the neural units. A 1D convolutional layer follows, utilizing 32 filters of size 3, which could be useful for capturing local patterns in the data. A max-pooling layer reduces the dimensionality of the data. More dropout is used for regularization. The model also incorporates a bidirectional LSTM layer, which is a type of recurrent layer capable of capturing sequence dependencies in both forward and backward directions. Additional dropout is included. The final layer is a densely connected layer with a SoftMax activation function, intended for multi-class classification into 5 categories. This architecture aims to effectively learn patterns and relationships in sequential data for accurate classification.

```
[ ] from nltk.sentiment import SentimentIntensityAnalyzer
    from tqdm.notebook import tqdm
    sia = SentimentIntensityAnalyzer()
```

```
[ ] #implement sia in example
    sia

    <nltk.sentiment.vader.SentimentIntensityAnalyzer at 0x7b460408b8e0>
```

```
[ ] sia.polarity_scores(example)

    {'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}
```

```
[ ] #str(['reviewText']).encode('utf-16')
    #str(['id']).encode('utf-16')
```

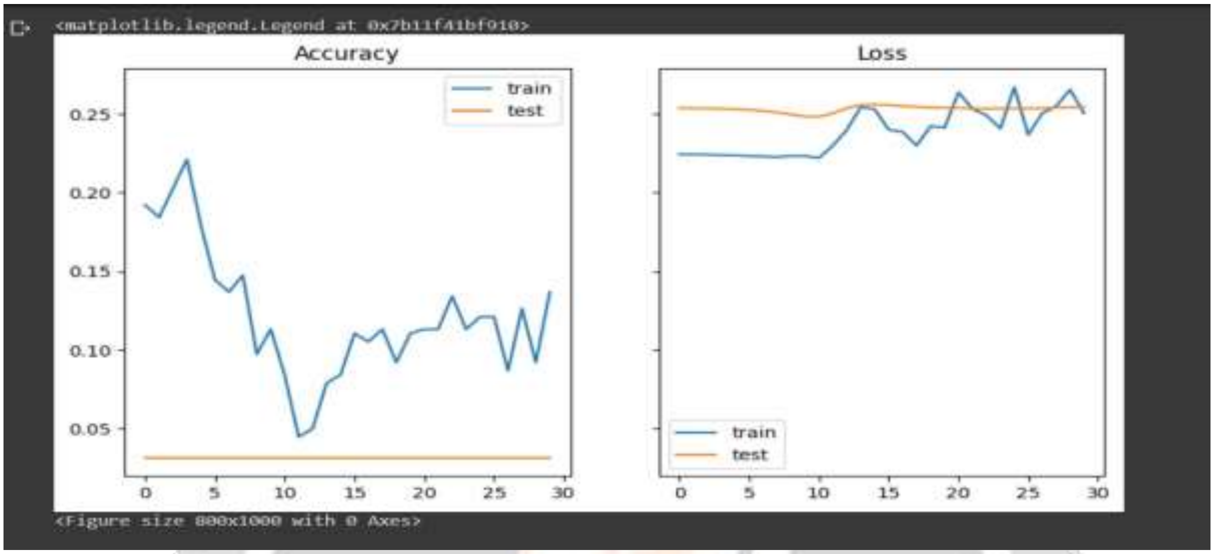
```
#run the polarity score on the entire dataset
res = {}
for i, row in tqdm(df.iterrows(), total=len(df)):
    text = row['reviewText']
    myid = row['id']
    res[myid]= sia.polarity_scores(str(text))

100% 100/100 [00:00<00:00, 817.91it/s]
```

```
model1 = keras.Sequential([
    keras.layers.Embedding(6000, 15, input_length=7),
    keras.layers.Bidirectional(keras.layers.LSTM(64)),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(5, activation='softmax')
])

# compiles model
model1.compile(loss='categorical_crossentropy',
               optimizer='adam',
               metrics=['accuracy'])

# model summary
model1.summary()

num_epochs = 30
history1 = model1.fit(x_train,y_train, epochs=num_epochs, batch_size = 128, verbose=1, validation_split=0.2)

Epoch 2/30
3/3 [==============================] - 0s 95ms/step - loss: 0.2242 - accuracy: 0.1842 - val_loss: 0.2536 - val_accuracy: 0.0316
Epoch 3/30
3/3 [==============================] - 0s 80ms/step - loss: 0.2241 - accuracy: 0.2026 - val_loss: 0.2535 - val_accuracy: 0.0316
Epoch 4/30
3/3 [==============================] - 0s 77ms/step - loss: 0.2238 - accuracy: 0.2211 - val_loss: 0.2533 - val_accuracy: 0.0316
Epoch 5/30
3/3 [==============================] - 0s 76ms/step - loss: 0.2237 - accuracy: 0.1789 - val_loss: 0.2530 - val_accuracy: 0.0316
Epoch 6/30
3/3 [==============================] - 0s 72ms/step - loss: 0.2233 - accuracy: 0.1447 - val_loss: 0.2526 - val_accuracy: 0.0316
Epoch 7/30
```

```
[4] # load the model and the tokenizer
    tokenizer = AutoTokenizer.from_pretrained('nlptown/bert-base-multilingual-uncased-sentiment')

    model = AutoModelForSequenceClassification.from_pretrained('nlptown/bert-base-multilingual-uncased-sentiment')

    Downloading (…)okenizer_config.json: 100% 39.0/39.0 [00:00<00:00, 608B/s]
    Downloading (…)lve/main/config.json: 100% 953/953 [00:00<00:00, 3.30kB/s]
    Downloading (…)solve/main/vocab.txt: 100% 872k/872k [00:00<00:00, 4.52MB/s]
    Downloading (…)cial_tokens_map.json: 100% 112/112 [00:00<00:00, 5.64kB/s]
    Downloading pytorch_model.bin: 100% 669M/669M [00:09<00:00, 73.0MB/s]
```

### 3.5 Model Evaluation

Once the model is trained, it is evaluated on dataset of reviews. This is to measure the accuracy of the model.




## 4. CONCLUSIONS

In conclusion, this research journey delves into the realm of sentiment analysis within the context of online product reviews, harnessing the transformative power of the BERT neural network model. The utilization of BERT demonstrates its efficacy in unravelling the intricate fabric of customer emotions hidden within textual content. Through a meticulously curated dataset, preprocessing techniques, and the integration of BERT's bidirectional contextual understanding, sentiments within online product reviews are deciphered with remarkable accuracy. The significance of this study extends beyond academia, influencing both businesses and consumers alike. By comprehensively assessing sentiments expressed in online product reviews, companies can gain valuable insights into customer preferences, allowing them to tailor their products and services for improved customer satisfaction. This understanding contributes to the refinement of product recommendations, fostering a more personalized and fulfilling shopping experience. Moreover, consumers stand to benefit from the enhanced product transparency facilitated by sentiment analysis. Armed with a clearer understanding of fellow shoppers' sentiments, individuals can make informed decisions that align with their preferences and budget. BERT's proficiency in deciphering complex linguistic nuances further augments its value as a tool for enhancing language understanding and emotion analysis in the digital era. As future research directions, the exploration of sentiment analysis could extend to other domains beyond online product reviews. The BERT model's adaptability opens doors to applications across various industries, from social media sentiment analysis to customer feedback interpretation. By advancing the integration of deep learning models like BERT, the field of sentiment analysis continues to evolve, enabling a deeper understanding of human emotions expressed through language, ultimately transforming the way businesses and consumers engage in the digital landscape.

The above conclusion is based on the results obtained :

**Sentiment Intensity Analyzer**

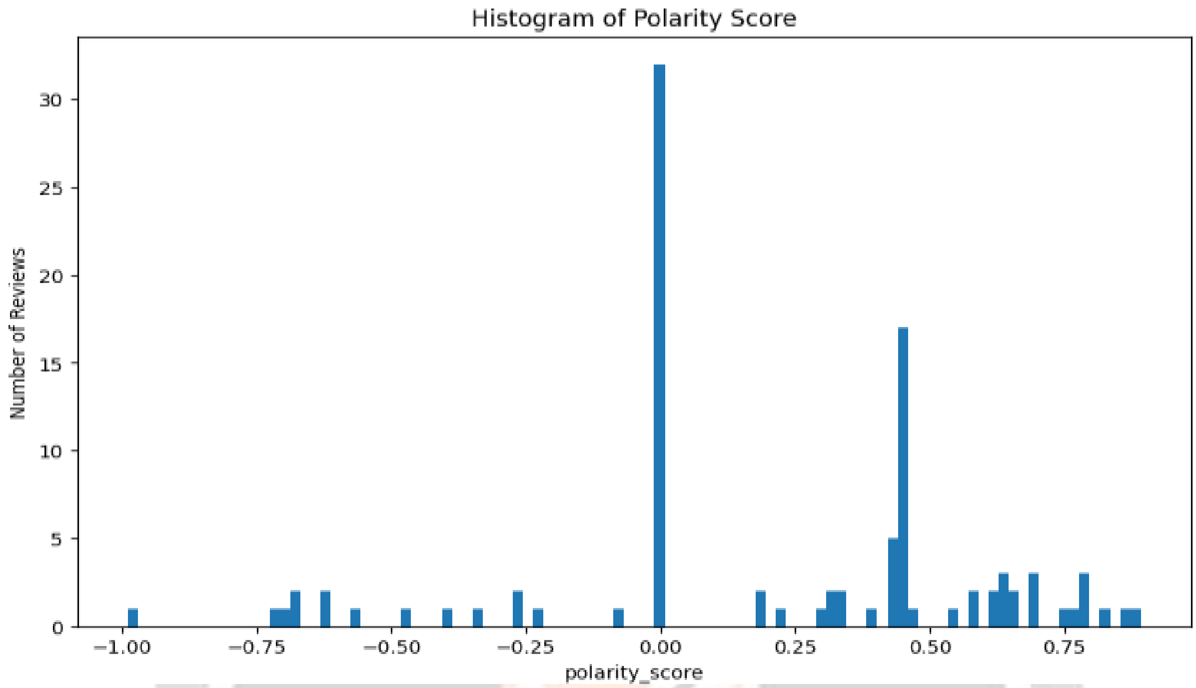



**Figure 4.1 Sentiment Intensity Analyzer.**

**Vader Model**

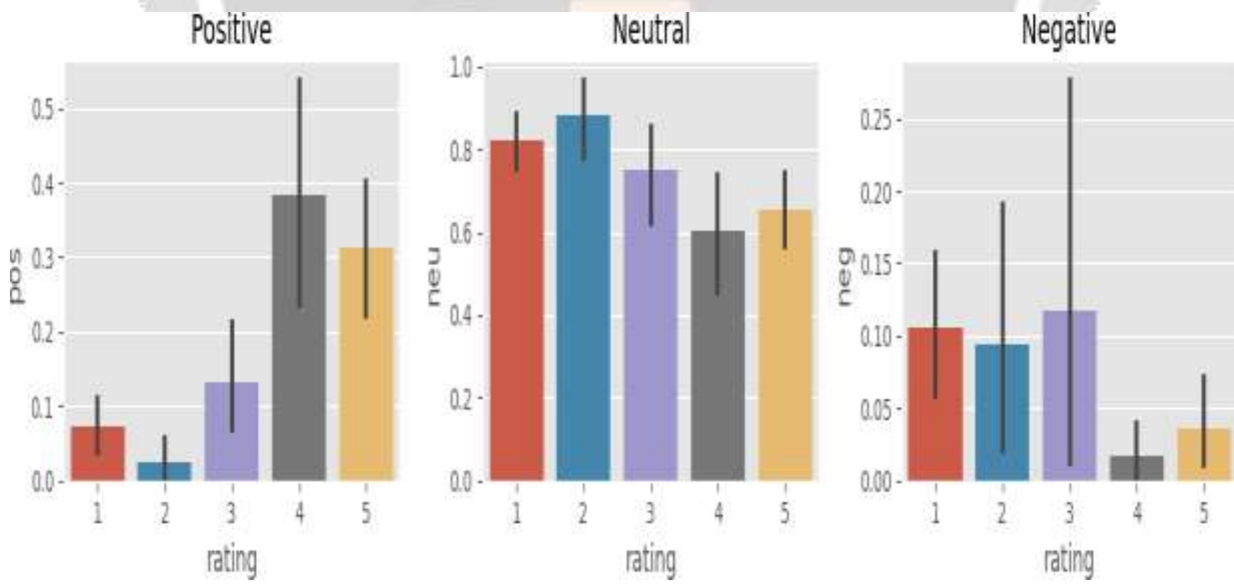



**Figure 4.2 Vader model.**

## Roberta Model

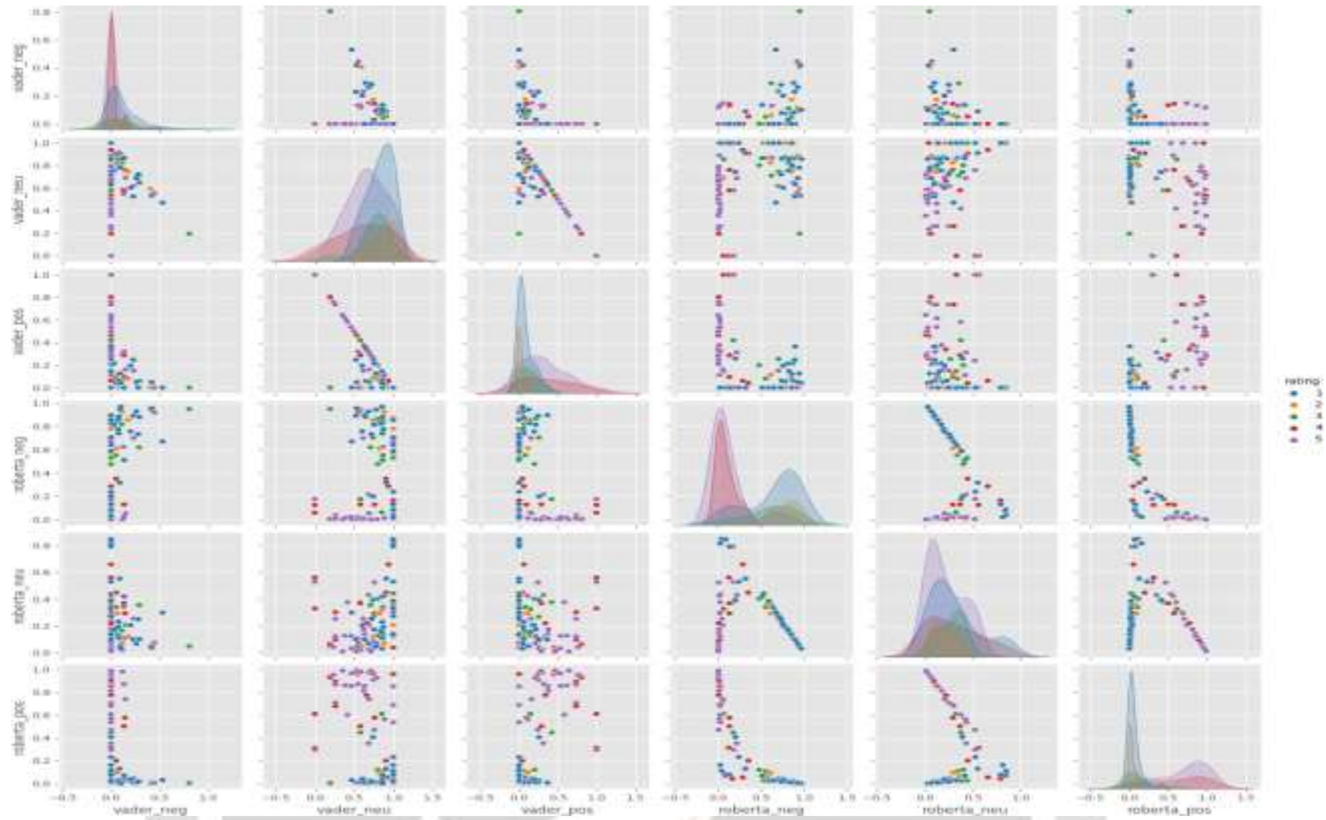


Figure 4.3 Roberta Model

## 5. REFERENCES

[1] Kim W. G., & Park S. A. (2017): Investigated the impact of social media review ratings on customer satisfaction. Compared social media review ratings with traditional customer satisfaction measures. Explored the relationship between online reviews and customer perceptions in the hospitality industry.

[2] Park Do-Hyung, Kim Sara (2008): Examined how consumer knowledge influences the processing of electronic word-of-mouth through online consumer reviews. Investigated the role of consumer knowledge in the evaluation of online reviews.

[3] Wang Yonggui, Tariq Samia, Alvi Tariq Hameed (2021): Explored the influence of primary and supplementary online reviews on consumer decision-making. Investigated the psychological and managerial mechanisms that mediate the impact of online reviews on consumer choices.

[4] Yan X., Han X. (2021): Explored optimal pricing and remanufacturing entry strategies for manufacturers in the presence of online reviews. Investigated how online reviews affect pricing and entry decisions in the context of remanufacturing.

[5] Mauri Aurelio G., and Minazzi Roberta (2013): Studied the influence of web reviews on the expectations and purchasing intentions of potential hotel customers. Explored the role of online reviews in shaping consumer perceptions in the hospitality industry.

[6] Kim T., Hwang S., & Kim M. (2022)-Journal of Business Research: Conducted text analysis of online customer reviews for products categorized in the FCB (Foote, Cone & Belding) quadrants. Examined the procedure, outcomes, and implications of analyzing customer reviews in different product categories.

[7] Blair-Goldensohn S., Hannan K., McDonald R., Neylon T., Reis G., & Reynar J. (2008)

[8] Tan S., & Zhang J. (2008)- Expert systems with applications: Conducted an empirical study of sentiment analysis for Chinese documents. Explored methods for sentiment analysis in Chinese text documents.

[9] Han W., Chen H., Gelbukh A., Zadeh A., Morency L. P., & Poria S. (2021): International Conference on Multimodal Interaction.

[10] Devlin J., Chang M. W., Lee K., & Toutanova K. (2018): - Introduced BERT, a pre-training model for deep bidirectional transformers for language understanding. - Described the architecture and pre-training process of BERT.

[11] Zheng J., Chen X., Du Y., Li X., & Zhang J. (2019): - Investigated short text sentiment analysis of microblogs using BERT. - Explored how BERT can be applied to analyze sentiment in short text data.

[12] Kaliyar R. K., Goswami A., & Narang P. (2021): - Developed "FakeBERT" for fake news detection in social media, a deep learning approach based on BERT. - Explored the use of BERT for identifying fake news in social media.

[14] Shobana J., & Murali M. (2022)-The computer journal: - Proposed an improved self-attention mechanism based on an optimized BERT-BiLSTM model for accurate polarity prediction. - Investigated enhancements to BERT-based models for sentiment analysis.