IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 26, Issue 2, Ser. 1 (Mar. – Apr. 2024), PP 01-09
www.iosrjournals.org

Machine Learning Models For Forecasting Customer Satisfaction

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Abstract:
The dynamic nature of the global business environment, especially in the e-commerce domain, demands that improving customer satisfaction be given careful consideration. The intense rivalry within the e-commerce sector highlights the necessity for creative methods in order to satisfy customer demands. This study, which focuses on Jumia in Nigeria specifically, examines how machine learning can be used to improve the customer experience on business-to-consumer (B2C) e-commerce platforms.
E-commerce platforms must contend with fierce competition while maintaining client happiness as important participants in the digital economy. A smart way to analyze customer data thoroughly, create predictive models, and improve consumer sentiment analysis is to apply machine learning techniques, namely the BERT (Bidirectional Encoder Representations from Transformers) model.
The study uses the BERT model, which has been refined through a methodical process to examine consumer opinion.
The model is trained on a dataset that has been specially selected for Jumia's context as part of the fine-tuning phase. The BERT model's deployment produced encouraging outcomes, as seen by its remarkable 96% accuracy rate in forecasting Customer sentiment. This result confirms that the goals of the research were successfully met. The high accuracy rate indicates how well the algorithm interprets and discerns user sentiment on the Jumia platform.
This study offers a solid method for improving consumer experiences, which is a significant contribution to the e-commerce sector. The BERT model's precision in interpreting consumer attitudes enables e-commerce platforms, such as Jumia, to customize services and marketing campaigns more efficiently. This strategy has consequences for enhanced brand perception, higher sales, and customer loyalty. The report also emphasizes the advantages for producers and suppliers, allowing them to better match consumer preferences.
The implementation of sophisticated machine learning algorithms, such as BERT, highlights the e-commerce sector's dedication to technical advancement. To sum up, the thorough framework and model created in this study give manufacturers, suppliers, investors, online retailers, and technology providers with useful information. Having these insights is crucial to staying competitive.
Keyword: *BERT; e-commerce; customer experience; natural language processing; machine learning model.*

Date of Submission: 22-02-2024 Date of Acceptance: 02-03-2024

I. Introduction

Commerce has been more prevalent in the global period, and its expansion is based on extensive transformation of the current business landscape and reshaping the way people engage in commerce and consumption. In the rapid advancement of technology, the economy, and society, e-commerce has emerged as an essential retail model, with online shopping being a pivotal method of purchase (1). The simplification of trade processes, better logistics systems, lower transaction costs, increased trading opportunities, and corporate and economic restructuring are all advantages of business-to-consumer (B2C), business-to-business (B2B), and business-to-business to customer (B2B2C) e-commerce (2). E-commerce refers to the exchange of products and services over a computer network, the internet, or a mobile device. This involves the application of information and communication technology (ICT) and electronic funds transfer (EFT) to facilitate trade between businesses and customers, businesses and other businesses, or businesses and other businesses. Electronic Data Interchange (EDI), which has grown significantly with the widespread usage of the internet's world wide web (www), has also generated e-commerce with the innovative virtual internet bazaar within the virtual world that is appropriately referred to as EMalls (3). The e-commerce business in Nigeria has grown significantly in recent years, with more people choosing to purchase online for their necessities. As industry competition grows, firms must focus on offering a great customer experience and assuring customer satisfaction to retain customers and achieve a competitive edge (4). The B2C concept includes transactions between corporations and consumers. It applies to any company that sells goods or services to customers via the internet. These websites preserve a database of product details in an online catalogue. Online banking, tourism services, health information, supermarkets, and other services are also included in the B2C model. Furthermore, B2C e-commerce relies on the customer as the core entity, who browses the online store, selects products, and makes purchases. A successful B2C business caters to customer needs and preferences, providing a seamless shopping experience through the online store. Products are available for purchase, and offers are discounts, promotions, or special deals. Clear product descriptions, images, and offers capture customer interest. Payment options, such as credit and debit cards and digital wallets, are crucial for smooth transactions. The process of preparing and shipping products involves order processing, packaging, shipping, and tracking, with reliable and efficient delivery services meeting customer expectations. A positive customer experience relies on a user-friendly platform, a wide range of quality products, attractive offers, secure payment methods, and timely product delivery.

However, service quality evaluation has always been important for businesses, but it has typically been hampered by obstacles in gathering consumer feedback. Moreso, with the development of user-generated material over the last decade, as well as the ease with which online customers may express their thoughts on providers' websites, online review platforms, and social media, new techniques to measuring service quality have emerged. Individuals willingly and intentionally exchange socialised data over digital computer networks. Online reviews are a common type of socialised data, representing users' spontaneously shared thoughts on review systems. Meanwhile, marketing is constantly changing due to consumers' changing wants and aspirations, which are heavily impacted by global trends and culture. Additionally, marketing is undergoing continual evolution because of changing customer preferences driven by global trends and culture. Marketing has evolved from old approaches to electronic applications for transactions in the digital arena, often known as electronic marketing (5). The benefits of this digital world are enormous, particularly for African small and medium enterprises. These advantages enable firms, particularly small-scale enterprises in Nigeria such as Jumai, to compete with online merchants from other countries if they provide unique products and services. While B2C e-commerce has made rapid advancements, there remain substantial concerns that require resolution. The growth of the internet has propelled the development of e-commerce, encompassing online payments, product purchases, network security, and logistics as critical components.

A significant e-commerce company confronts challenges in effectively managing customer satisfaction. This is attributed to the enormous volume of user comments, ratings, and reviews related to product quality, customer service, and the overall shopping experience. The software grapples with difficulties in analyzing and extracting insights from this extensive data. Specialists such as design researchers, interface designers, and business executives are diligently addressing concerns regarding user experience, which encompasses emotional responses to website interfaces, functionality, and information, striving continuously to enhance it. The emotional response of the user to the e-commerce platform, user interface, functionality, and pertinent information throughout the visit is referred to as the user experience. As a result, evaluating and improving the quality of product purchase services in B2C e-commerce is critical for identifying development defects and improving overall service quality (6).

Considering the foregoing, this study examines how to improve the purchasing product offer on an e-commerce platform, utilizing Jumai as a case study. A model including particular machine learning algorithms will be constructed to find crucial aspects influencing customer experience and happiness, product quality, and correct order fulfilment. The collection of feedback via the Jumai platform will aid in the collection of crucial data that can be utilized to develop an accurate prediction model that will improve the overall user experience and happiness on their websites. Improving the user experience is critical for e-commerce platforms wanting to boost customer loyalty, retention, and market share. This research is so critical for creating a terrific shopping experience for consumers, increasing customer happiness, and increasing sales and earnings on e-commerce platforms. A Natural language processing was proposed using BERT approach base on transfer learning, though to determine the class of text, the literature review explored a range of classifiers based on Supervised Learning, such as Random Forest Classifier, Logistic Regression Classifier, and Support Vector Machine, which were deemed the most prevalent algorithm groupings. Pretrained.

II. Related Work

Over the past few years, the idea of customer experience and pleasure has drawn a lot of attention in the world of e-commerce. Businesses must now recognise the importance of customer experience and pleasure due to the escalating competition in the e-commerce sector. Several researchers have investigated the potential for applying various machine learning algorithms to address various e-commerce difficulties to better understand how to improve customer satisfaction and experience. (1) investigated the utilization of user experience evaluation to enhance the design and development of B2C e-commerce systems. The study explored essential factors that influenced consumer satisfaction in the realm of B2C e-commerce logistics and proposed strategies for enhancing and gauging user satisfaction with logistics distribution in this sector. Based on their findings, the study employed user-centred evaluation methods for B2C e-commerce logistics distribution. To assess the performance of B2C websites in terms of user experience within e-commerce platforms and construct relevant metrics, the researchers utilized the Analytic Hierarchy Process (AHP) and the fuzzy comprehensive evaluation approach. However, the research also aimed to bridge the gap by incorporating advanced machine learning techniques, particularly deep learning, along with statistical approaches. These methods were employed for data validation and data visualization to enhance the accuracy of the evaluation process. Furthermore, (7) The importance of big data in today's world is highlighted by the requirement for customer-reviewed analysis for effective marketing analytics. Their identification does not guarantee increased marketing because features demand feature development and analysis. Six different machine learning algorithms were used to discover and build features in the authors' study on sentiment categorization in the hotel industry. The results showed that emotion prediction accuracy was high. As a result, the proposed research will forecast the acquired items and compare advanced techniques that use deep learning for improved accuracy due to the heterogeneous dataset.

(8), focused on social media was adopted and utilized within organizations. The research presented a model that analysed various factors influencing the extent of social media usage within organizations. These factors included both external and internal readiness, projected benefits, and strategic objectives. Furthermore, the research investigated the impact of trends in social media usage on constituent satisfaction and performance outcomes. The study contributed valuable insights by uncovering data on the determinants of an organization's adoption of social media and the consequences of its utilization. It built upon prior research in the field by delving into social media usage trends and their effects on constituent satisfaction and performance outcomes. However, there were limitations in the study. Notably, the use of a single respondent from each organization limited the breadth of perspectives considered. The proposed study seeks to address this limitation by gathering responses from multiple individuals within each organization. Additionally, the study acknowledged that the amount of data collected might not fully capture the significance of the research topic it aimed to address. In their study conducted, (9) observed stable curves in the context of intelligent computing and fuzzy statistical methods. Among these methods, intelligent computing stood out as the most efficient. The study also identified several second-level indicators that played a significant role in assessing logistic satisfaction. These indicators included a merchant's reputation, customer service philosophy, and after-sale support. Other factors like speed, safety, customer attitude, and cost were considered secondary to logistical satisfaction in their findings. However, a limitation of the study was its failure to provide a clear rationale for focusing solely on accuracy measurements while overlooking other critical criteria such as efficiency, scalability, and the practicality of implementation. Due to time constraints, the authors of the study did not delve into comprehensive details regarding the smart computing technique or the development of a logistic satisfaction evaluation index system. In the current proposed study, there will be a deliberate effort to address the measurement accuracy of metrics, considering the broader spectrum of evaluation criteria and the practical implications of implementing these methods.

In their study, (10) analysed online sales during the COVID-19 pandemic and examined the factors that influenced customer behaviour and customer satisfaction in e-commerce. The researchers emphasized the importance of online purchases and government initiatives in preventing the spread of the virus. The study employed both traditional and contemporary data analysis techniques, survey methods, and structural equation modelling to analyse the factors that affected customer satisfaction. The findings from their research have contributed valuable insights for businesses. These insights have helped optimize supply chains, improve order execution processes, and identify key components of e-commerce value, all of which have led to enhanced customer satisfaction and improved business performance. As such, it was imperative to address specific aspects of the research process, including data collection methods, sample size, and sample representativeness. In this context, the proposed research aimed to provide a detailed account of the data collection process and to establish the validity of the data. In addition to quantitative ratings, (11) showed how socialised textual data can also provide helpful information for evaluating service quality. They also demonstrated how considerably the distribution of participants between judgements of good and negative vary. Particularly negative evaluations typically draw attention to problems with merchant reaction. The study finds consistent disparities between good and unfavourable consumer perceptions that have not previously been shown using either cutting-edge text mining or conventional methods like polls. The study ignores other variables and merchant responses that may have an impact on overall service quality and instead relies solely on online reviews from a single Italian pricing comparison site. The current proposed will consider factors that it currently overlooks, and which may have an impact on overall service quality. The current proposed study will include additional elements into their study, such as location, pricing, consumer demographics, and other pertinent contextual aspects, to create a more thorough picture.

According to an argument made in machine learning via the lens of e-commerce initiatives (12), machine learning (ML) is quickly changing the e-commerce industry by allowing user-friendly, secure, and profitable platforms. To remain competitive and deliver individualised experiences, brands are embracing ML. Popular ML approaches include Random Forest and Neural Networks, with Neural Networks being both powerful and difficult. They are becoming increasingly important in e-commerce due to their wide range of applications and possible influence on corporate profit and fraud detection.

III. Procedure methodology

This research is focuses on collecting and evaluating a customer feedback dataset on products purchased from the Jumia an online store website. The dataset includes information such as the product name, price, rating, review, category, and URL. To collect this data, first become acquainted with the Jumia website design and identify the target data, then analyse the website's URL structure, inspect the HTML, and develop pagination to manage the enormous volume of purchased products included in this study. Aspects such as handling missing data, data formatting, data preparation, and data quality checks were also addressed. The obtained data was securely stored in CSV files, which may be found in the CSV folder connected to this dissertation document. Throughout the data gathering procedure, ethical considerations were given top priority. researcher obtained the necessary permissions and consent from the appropriate authorities.

In total, we collected 1835 customer's feedback entries per feature. For model development, 80% of the dataset was allocated for training, and the remaining 20% for testing, following tokenization of the dataset.

Data analysis

The machine learning model is put to the test, and its performance accuracy is evaluated. Based on product ratings, the model is reliable and capable of providing the desired results. Another component of testing is identifying and correcting any potential faults or weaknesses in the model's implementation. The product rating, which is the target variable, is represented by a 0 for a positive rating, a 1 for a neutral rating, and a 2 for a negative rating, using a pretrained BERT model for classification with a dropout layer and a linear layer with a size of 3 for the three categories. Cross-entropy-loss was used as the loss function and Adam as the optimizer.

The BERT model has 96% accuracy after training. To meet the research's goal, the evaluation and testing phases were critically examined using the selected model with the highest accuracy. This phase was divided into two sections: explanatory data analysis, model development, and EDA was used to learn more about how the data was distributed, to uncover links between qualities, and to look for trends that could affect customer experience and satisfaction. Visualization is used to demonstrate the explanatory data analysis and model for customer experience and satisfaction of e-commerce on the Jumai B2C platform.

A pretrained BERT model was employed in the model development phase. BERT stands out as the most successful model, boasting the highest accuracy which signifies its exceptional generalization and performance on the given questions. However, it is important to highlight that when a comprehensive analysis is undertaken, BERT demonstrates complexity owing to its contextual understanding. The impressive accuracy achieved by BERT indicates its capacity to manage intricate language patterns effectively. Therefore, Following training in the Scikit-Learn environment, the model was tested using a variety of methods. For fine-tuning, the same optimizer that BERT was trained with, "Adaptive Moments" (Adam), is used. This optimizer reduces prediction loss while also performing weight decay regularization, to evaluate the model. Two values will be returned, accuracy and loss (a number representing inaccuracy; lower values are preferable) The training and validation losses, as well as the training and validation accuracy, are plotted on the graph for comparison.

IV. Result

An in-depth exploration of the experimental outcomes pertaining to the machine learning model and its accompanying Explanatory Data Analysis (EDA) is presented. The discussion encompasses the model's evaluation, the process of model selection, and the challenges encountered throughout the development journey. Additionally, the section delves into the assessment of the model's efficacy in predicting the determinants of customer satisfaction within an e-commerce platform. By examining these facets, a comprehensive understanding of the model's performance and its ability to elucidate the factors influencing customer satisfaction in the e-commerce realm is established.

Explanatory data analysis (EDA) was used to learn more about how the data was distributed to uncover links between qualities, and to look for trends that could affect customer experience and satisfaction. Visualization is used to demonstrate the explanatory data analysis and model for customer experience and satisfaction of e-commerce on the Jumai B2C platform. Feature selection and extraction also aid in identifying the most relevant features to predict consumer experience and enjoyment. This covers techniques such as feature selection and dimensionality reduction, in which we reduced six characteristics to the three most important elements.

Figure No 1: *Visualization of Category Product on Purchased Product.*

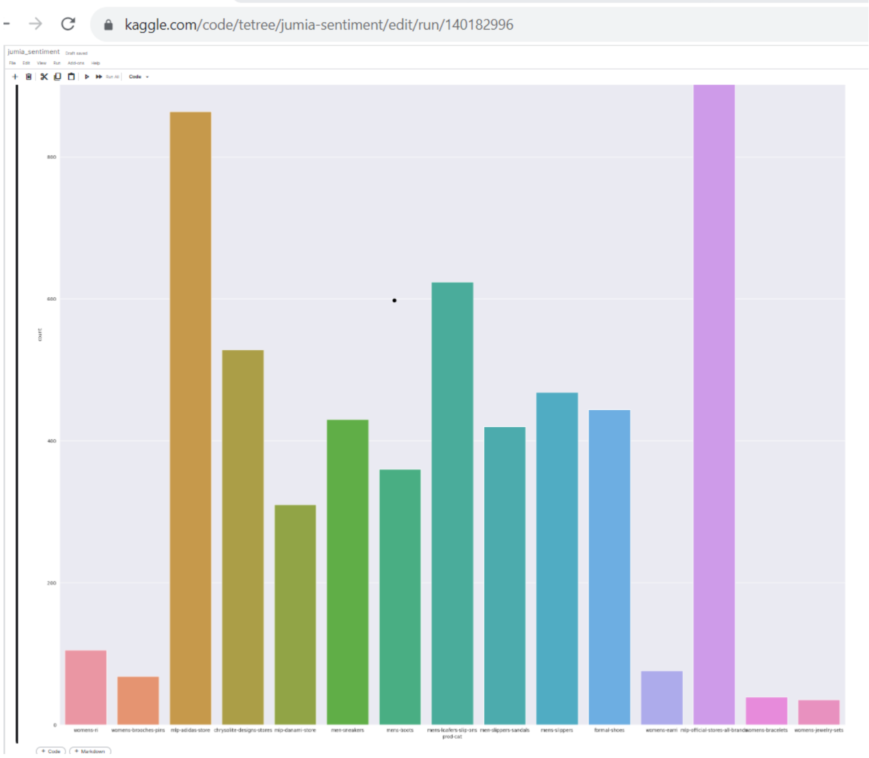

Figure No 2: *Visualization of Customer Ratings for Purchased Product.*

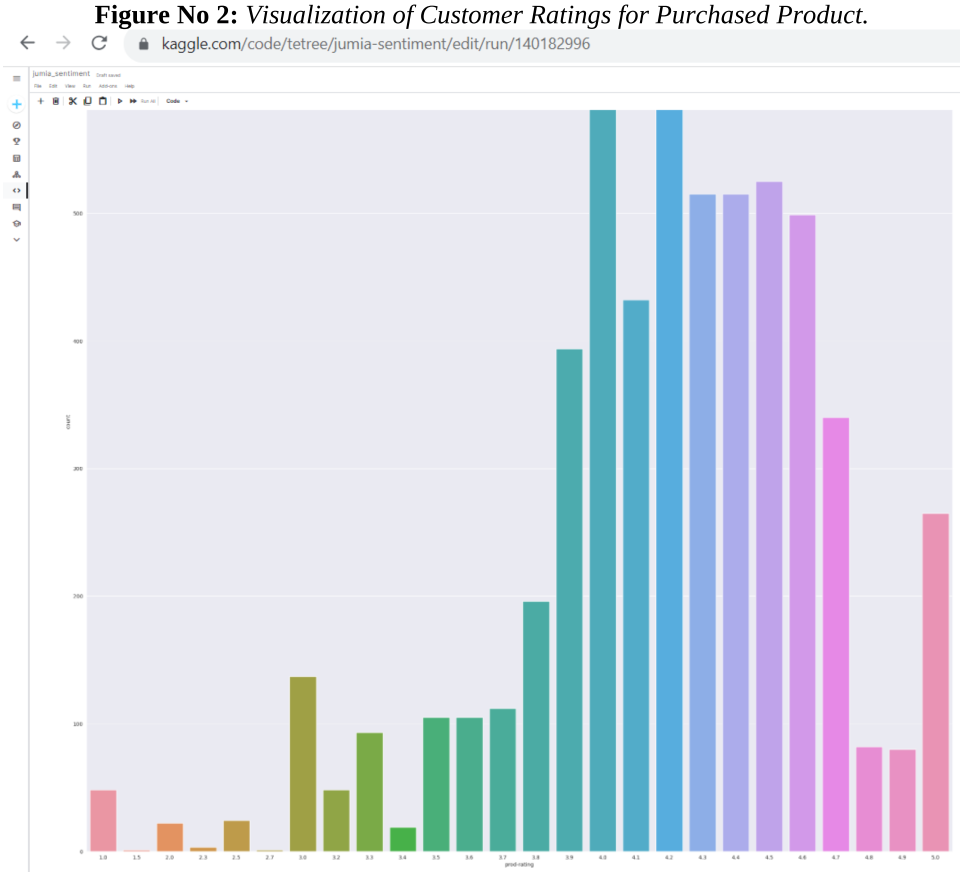

Figure No 3: *Visualization of Word Count on Customer Review for Purchased Product*

```
In [89]: sns.barplot(y=common_wrd['word'],x=common_wrd['count'])

Out[89]: <Axes: xlabel='count', ylabel='word'>
```

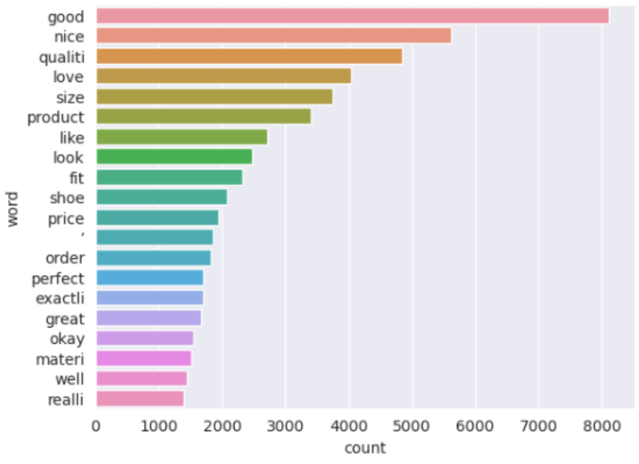

Figure No 4: *Output Showing the Epoch Accuracy Of Model Used (BERT).*

```
Epoch 1/10
----------
Train loss 0.4579465036691094 accuracy 0.8345729212239751
Val   loss 0.3958756912034005 accuracy 0.8661725344863084

Epoch 2/10
----------
Train loss 0.32825713732136824 accuracy 0.8968010911804823
Val   loss 0.3355411872708876 accuracy 0.8949969116738727

Epoch 3/10
----------
Train loss 0.2601806047066169 accuracy 0.9259335512262913
Val   loss 0.22613703257918946 accuracy 0.9248507309038501

Epoch 4/10
----------
Train loss 0.2014764507206064 accuracy 0.9420953753506447
Val   loss 0.18294829648986802 accuracy 0.9493514515132797

Epoch 5/10
----------
Train loss 0.17206596607398342 accuracy 0.951025555241012
Val   loss 0.16113621448197304 accuracy 0.9507926703726579

Epoch 6/10
----------
Train loss 0.14304507562481159 accuracy 0.9570476362045449
Val   loss 0.15724033818543448 accuracy 0.9584105414865143

Epoch 7/10
----------
Train loss 0.13305409385507544 accuracy 0.9604961782947732
Val   loss 0.13957179373889966 accuracy 0.9596458719374099

Epoch 8/10
----------
Train loss 0.1190783508641403 accuracy 0.9632756002779422
Val   loss 0.13330833277187162 accuracy 0.9602635371628576

Epoch 9/10
----------
Train loss 0.11543310378140782 accuracy 0.9640991327173998
Val   loss 0.1284694698019609 accuracy 0.9606753139798229

Epoch 10/10
----------
Train loss 0.10971198361952658 accuracy 0.9649484005455903
Val   loss 0.12961711903814208 accuracy 0.9610870907967881
```

V. Discussion

The displayed result illustrates the progression of a machine learning model's training across multiple epochs. Each epoch corresponds to a complete iteration over the training dataset. The training process is conducted over 10 epochs, indicating 10 full cycles over the training dataset. The information presented encompasses details regarding both the training loss and training accuracy for each epoch.

Throughout the training phase, the train loss serves as an indicator of how closely the model's predictions align with the actual target values. A diminishing train loss suggests that the model is enhancing its capacity to effectively fit the data. The proportion of correctly categorized examples in the training dataset is represented by train accuracy. Increasing train accuracy indicates that the model's performance on training data is improving. The loss calculated on a separate validation dataset is known as validation loss. It is useful to track the model's performance on data that was not encountered during training. A decreased validation loss suggests that the model generalizes well to previously unseen data. The validation accuracy of a model indicates how well it performs on the validation dataset. It is useful in determining whether the model is overfitting (doing well on training but not on validation data).

The model has a train accuracy of around 83% and a validation accuracy of around 87% at the start (Epoch 1). This indicates that the model is learning from the data but may not be performing optimally. Both train and validation accuracy improve as the epochs advance, demonstrating that the model is learning and generalizing successfully. The train and validation losses continually decrease with each epoch, indicating that the model's predictions are becoming more accurate. As indicated by rising accuracy and decreased loss over epochs, the model appears to be learning effectively. The validation accuracy is slightly lower than the train accuracy, as expected, indicating some degree of generalization. There is no evidence of overfitting because the validation accuracy is improving in line with the training accuracy.

Figure No 5: *Graph Output Showing the Train Loss Of Proposed Model (Bert).*

```
plt.plot(history['train_loss'], label='train loss')
plt.plot(history['val_loss'], label='validation loss')

# Graph chars
plt.title('Training history')
plt.ylabel('Losses')
plt.xlabel('Epoch')
plt.legend()
plt.ylim([0, 1]);
```

In the above plot, the red lines represent the training loss, and the blue lines are validated loss.

Figure No 6: *Graph Output Showing the Train Accuracy of Proposed Model (BERT).*

```
plt.plot(train_acc, label='train accuracy')
plt.plot(val_acc, label='validation accuracy')

# Graph chars
plt.title('Training history')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend()
plt.ylim([0, 1]);
```

In the above plot, the red lines represent the training accuracy, and the blue lines are validating accuracy.

Figure No 7: *The Model Output Evaluating Customer Satisfaction and Experience on Purchased Product*

```
review_text1 = "the women earing I just bought is of good quality, Best ever!!!"
predict_review(review_text1)
```

```
Review text: the women earing I just bought is of good quality, Best ever!!!
Sentiment  : positive
```

```
review_text2 = "it is ok"
predict_review(review_text2)
```

```
Review text: it is ok
Sentiment  : neutral
```

Considering the foregoing, the pretrained BERT model for classification with a dropout layer and a linear layer of size 3 for the three categories, positive rating, neutral rating, and bad rating, was adopted. The Adam optimizer is used, and cross-entropy-loss is used as the loss function. The model has 96% accuracy after training, and a graph showing the number of epochs vs. the training loss, test loss, training accuracy, and test accuracy was generated to check for overfitting. It also demonstrates that there is no overfitting. The graph below illustrates that the test loss and training loss decreased concurrently, while the training accuracy and test accuracy increased concurrently. Finally, the fabricated review and model work and predict accurately.

The model was presented to stakeholders and tested to see how well it predicted consumer experience and happiness with each purchase of a product, and all functional and non-functional requirements were met. The task at hand determines the metric of choice. A standard statistic for binary sentiment tasks is the proportion of successfully predicted sentiments (positive, negative, and neutral) as a percentage of total predictions. The confusion matrix is a tabular representation of expected vs. actual statements that can help understand how true positives, true negatives, false positives, and false negatives are distributed. There are training, validation, and test datasets available that effectively represent the range of consumer experience and pleasure with purchased products. The stakeholder's overview of tests is as follows:

***Business Stakeholders*: It** was thoroughly described and tested to show them how sentiment analysis works, the model's correctness, and how the model is applied to new data.

***Technical Stakeholders*:** The insights into the model architecture, preprocessing pipeline, and training process were effectively explained and validated for the stakeholders. The data preprocessing pipeline and tokenization procedures underwent testing, revealing the necessity of converting text data into tokens for the model to comprehend distinct tokens and word occurrences. A significant outcome emerged from this process—an optimization that recognized the presence of 1883 unique words within the dataset. This discovery also shed light on the roles that specific words play in differentiating sentiments. Consequently, both business and technical stakeholders are now informed about the existence of a well-defined data preprocessing pipeline, poised to enhance efficiency and consistency in future processes. Furthermore, stakeholders have been apprised of the methodology employed to quantify sentiment. This entails translating the target variable to 0 for positive, 1 for neutral, and 2 for negative sentiment.

***Model Implementers*:** The model was tested for the technical stakeholder to demonstrate how a pretrained BERT model with a clear architecture involving dropout and linear layers, as well as how the optimizer (Adam) and loss function (cross-entropy), exhibit a comprehensive model setup. The model's accuracy of 96% and critical model efficacy were also described and tested for the technical stakeholder. As a result, graphs depicting training and testing loss, as well as training and testing accuracy, provide a visual picture of how the model improved over epochs. Meanwhile, the model was evaluated for prediction on an imaginary review, which lets technical stakeholders understand the model's real-world applicability. The analysis demonstrates the model's effectiveness, optimization phases, and practical utility in making predictions on new data, addressing all of the interests of diverse stakeholders.

VI. Conclusion

In conclusion, this research set out with a clear objective: to enhance consumer experience and satisfaction with products purchased on B2C e-commerce platforms using a machine learning model. These objectives were meticulously addressed through a systematic approach, yielding valuable insights and actionable outcomes. The successful development of a machine learning model, designed to predict and elevate consumer experiences on the Jumia e-commerce platform, represents a significant achievement. Key project stages, including data collection, preprocessing, exploratory data analysis, model development, and evaluation, played pivotal roles in achieving this goal. The incorporation of specific elements to assess consumer sentiment emerged as an effective strategy for enhancing overall satisfaction. Following training, the pretrained BERT model, enhanced with dropout and linear layers, demonstrated exceptional accuracy, reaching an impressive 96%.

Each of the research objectives was effectively met. The first goal involved a critical review of customer experience data, from collection to exploratory analysis, ensuring the data's suitability for model creation. The choice of a pretrained BERT model with additional layers proved to be a suitable deep learning algorithm for capturing customer sentiment. The architecture and evaluation of the model validated the successful accomplishment of this goal. Furthermore, the model's robust evaluation and testing, resulting in a 96% accuracy rate, confirmed the attainment of the second objective, emphasizing the model's reliability and effectiveness. In summary, this study not only delivered a robust machine learning model for predicting and enhancing user experiences on e-commerce platforms but also offered invaluable insights into the intersection of technology and business. The model's potential impact on customer service, online retailers, suppliers, manufacturers, and investors positions it as an asset in the ever-evolving e-commerce market.

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