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Automated Sentiment Analysis Of Product Reviews Using Machine Learning Techniques

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ABSTRACT
Over the last few years, the rapid growth of e-commerce has increased the significance of customer reviews in influencing decisions about what to buy. Reviews not only help potential customers make informed decisions, but they also give businesses invaluable insight and lend your business credibility and trust. For this research, we conducted an analysis of a dataset containing reviews from Amazon that covers a wide range of product categories. This SA project's goal is to use a BERT model to categorize reviews from Amazon that are either positive, negative, or neutral. Important steps in an investigation include preprocessing, gathering, dividing, training, and assessing data. Amazon-sold items, written in JSON, were amalgamated as devices which included Video security systems, tablets, laptops, televisions, and cell phones. For data preparing, we applied lowercasing, stop word removing, punctuation removal, contraction removal, tokenization and tagging of parts of speech. An opinion lexicon was used to generate sentiment scores, and word embeddings were used of numerical vectorization. A BERT model was then implemented for sentiment categorization using a training a cross-entropy loss function in the PyTorch framework. We used evaluation criteria for performance measurement including recall, F1-score precision, and accuracy. In October 2018, BERT was released, and it outperformed logistic regression and decision tree model, thanks to its effectiveness in capturing long-term dependencies of text. These findings have significant real-world implications and will instill confidence in their strategy by enabling e-commerce sites to make informed choices and solidify their service provisions.
Keywords: *Sentiment Analysis, Amazon Reviews, Machine Learning, BERT, NLP, Classification*

INTRODUCTION

In the recent few decades, a proliferation of the online marketplaces has occurred and the trend of asking customers for reviews about products purchased has become the norm to improve the overall consumer experience. Every day millions of reviews are published on the web for different products, services, and locations [1]. This results in that information and opinions on products and services are now largely available on the Internet.

The great number of product reviews together with multiple viewpoints for consideration may lead to complicated decision-making which then results in uncertainty and confusion. Buyers struggle to gather adequate information about products since several opinions and ratings appear for every item. The evaluation of this information by e-commerce businesses enables them to gather customer product feedback while improving purchasing choices for their consumers [2]. During the upcoming several years sentiment analysis technologies will prove essential for future operations. Opinion processing enables us to differentiate content quality from inferior to high-quality. The available modern technologies help us detect the review sentiment patterns and their underlying reasons for a particular movie. In the early phase of research about this field scientists mostly analyzed user-generated content such as Amazon.com reviews to identify neutral or positive or negative sentiments [3]. Research in sentiment analysis now focuses on social media sites platforms including IMDB, Facebook, and Twitter although these sites require suitable approaches to address text requirements [4]. The language analysis in cinema report assessments proves to be a complex task. The procedure known as Research Sentiment Mining extracts a

broad spectrum of author opinions through data mining techniques based on information extraction (IE) or Natural Language Processing (NLP).
The text analysis adopts both IR and machine etymology methods as explained in [5]. Text or brief communications require polarity identification as the fundamental step for sentiment analysis. Text opinion which consists of negative or neutral or impartial sentiments is easily recognized. The execution of emotion mining requires the following three successive actions. The first phase involves identifying sentences at the document level by assigning them either positive or neutral classifications. Sentences should be classified according to "yes, “no" and "unbiased" categories. 3) Sensitivity classification identifies features through universal word elements that classify texts as either positive or negative or non-partisan. [6,7]. The Figure 1 below demonstrates how customers interact with sentiment analysis programs.

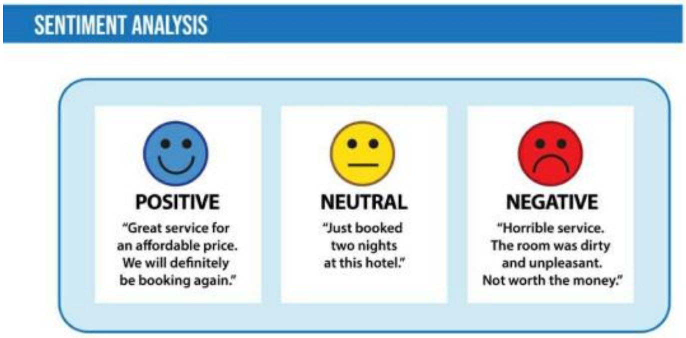

Figure 1: Customer Behavior during Sentiment Analysis

Modern semantic and review analysis fields have experienced increasing popularity through the use of ML methods during recent years. Amazon held a position among the leading online retailers based on research findings [8]. Users can review hundreds of recorded feedback about products through available online platforms [9]. The evaluations collected provide buyers essential information to understand the main features of the product. The outcome benefits consumers and helps businesses understand their client demands better [10].
This research addressed the sentiment classification issue for online reviews through the implementation of ML algorithms. The task focused on positive or negative categorization of customer reviews and retrieving their overall relevance. The research source for product evaluations was Amazon's online platform. The aim was to split customer assessments into positive or negative segments for relevance determination.

Motivation and Contribution of the Paper

The study investigators began their study to monitor the rising number of online reviews in e-commerce platforms. The research adopts BERT technology to enhance sentiment analysis precision after text preprocessing for detecting exact model outputs. The current natural-language customer review interpretation methods demonstrate poor results due to this research initiative. The research project uses BERT contextual embedding research in conjunction with preprocessing approach evaluation methods to enhance sentiment analysis performance through better natural language processing workflow methodology. This work delivers three fundamental results which will be fully discussed later in the paper.

- The application of a BERT model for SA received validation through research utilizing a big 13,057 product reviews from different categories on Amazon which confirmed both model scalability and operational reliability.
- An opinion lexicon enabled the system to generate sentiment scores which improved the detection precision for both positive and negative and neutral sentiments.
- The text data preprocessing sequence consisted of multiple steps that started with lowercasing then stopped each word and punctuation before handling contractions to produce tokenized sentences for subsequent part-of-speech tagging analysis.
- The research application of BERT to Amazon product review SA demonstrated how BERT's deep learning strategy provides better performance compared to traditional models.

- BERT proves superior to both logistic regression and decision tree models according to the research which shows BERT outperforms at capturing long-term dependencies while clarifying the evaluation results through F1 score, recall, precision and accuracy metrics.

Structure of the Paper

This paper follows the structure which starts with Section I Introduction setting up the study background. The second section of this work reviews previous research combined with existing methodologies. The experimental system with employed methodologies appears in Section III Materials and Methods. Results and their discussion along with model comparison occur in Section IV. The paper ends with a recommendation section for future development in Section V.

LITERATURE REVIEW

The methods of sentiment dictionaries together with ML algorithms evaluate previous sentiment analysis research in this section. The integration of sentiment polarity classification together with topic modelling has occurred yet researchers have not developed efficient methods for sentiment analysis.

The authors developed an integrated sentiment analysis system which mines online product experience through unification of textual analysis approaches with ML algorithms [11]. The SVM algorithm determines the sentiment polarity a reviewer expresses. Such foundations allow the LDA model to find sentiment themes within reviews. After prevention of emotional information loss through semantic similarity the analysis expands its lexical range. Research about Amazon.com customer reading experiences has verified both the validity and functionality of this method. Research demonstrates how this method achieves effective review pattern identification and works to retrieve elements which affect reading experiences.

By creating a recommendation model that makes use of natural language processing such as Vectorizers for TF-IDF and Count to analyze customer comments, the study takes into account the food industry. The classification techniques LR combined with dummy classifier and RF classifier utilize ML to predict consumer sentiments according to the provided data [12].

The research performs a performance-based evaluation that measures the accuracy of various classifiers using mobile product dataset sizes [13]. The analytic methods from this dataset established its accuracy during categorization processes using data obtained from Amazon and Flipkart as well as Snapdeal online stores. The best method emerges through testing how four classification systems namely NB, RF, DT and SVM perform against each other.

The research project plans to implement Artificial Basics (ABSA) on annotated data to transform present rating-based recommendation systems into aspect-based ones [14].

ABSA will be applied to mobile phone consumer evaluations through Basics (ABSA) to provide an aspect-based review system which would replace the current rating-based system [14]. The dataset quality was verified through multiple ML methods including LR, NB, SVM, RF, KNN, and MLP. Keras Sequential API enabled the construction of the MLP model that reached 67.45% accuracy while K-nearest neighbour achieved 49.93%.

The research establishes an optimal methodology through classifier evaluations of the present techniques [15]. The team conducted their queries against Rokomari.com which is the best e-commerce website in Bangla for user reviews.

The researchers applied their built and tested ML and DL classifier models to evaluate their effectiveness with this dataset. LSTM together with SGD demonstrated higher accuracy in comparison to alternative ML and based classifier models based on the experimental results.

The information about female online clothing sales was extracted from Kaggle's user evaluation database that includes 23486 entries [16]. This paper aims to study customer perceptions between purchasing products through Internet stores and traditional retail outlets. The study developed an analysis in Python by running simulations of ANN, SVM, and LR which are three ML algorithms. The accuracy rate of ANN amounts to 88% while both SVM and LR achieve accuracy rates of 80% and 75% respectively.

Multiple researchers have studied advanced customer evaluation monitoring techniques across various business sectors. The solution includes implementing text analysis tools alongside ML algorithms to extract online product information. The solution implements SVM to determine sentiment polarity and LDA to perform topic extraction. The research examines food industry sentiment analysis using TF-IDF and Count Vectorizer under NLP methods in combination with classifier evaluation of LR and RF. Researchers evaluated different classifiers on mobile products available across various online shopping websites through a performance evaluation of NB, RF, DT, and SVM to identify the best approach. Multiple ML techniques alongside aspect-based SA have been researched on mobile phone reviews thus producing Multi-Layer Perceptron as the most accurate method. A research study of women's clothing e-commerce reviews revealed ANN as the most accurate model among SVM and LR. Multiple research examples illustrate sentiment analysis development as well as favorable performances of various ML techniques across different e-commerce domains.

MATERIALS AND METHODS

The research establishes and evaluates an e-commerce product evaluation sentiment analysis system which relies on ML techniques. The study aims to deploy the BERT model as an advanced ML technique for accurate sentiment classification between neutral and positive and negative sentiments in reviews

Data Collection represents the starting step where JSON data formats are acquired from multiple Amazon testing categories while Data Preprocessing follows with lowercasing operations, stopword elimination and punctuation removal leading to opinion scoring through both opinion lexicon and word embedding systems for number-based conversion. The data splitting method uses an 80:10:20 split where 70 percent goes for training purposes along with 10 percent for validation while the test portion amounts to 20 percent; After splitting the data we utilized the BERT network to create continuous patterns in dependencies then applied it through PyTorch to analyze the collected reviews while cross-entropy loss was employed to boost accuracy Figure 2 displays the suggested methodology's flowchart.

Data Collection

All system testing datasets come from JSON file format reviews discovered on Amazon's web page. There are several reviews in the JSON files. The dataset collection includes evaluations of video surveillance equipment, TVs, tablets, smartphones, and PCs. The reviews are sorted by product type and their corresponding quantities in Table 1.

Table 1: The quantity of reviews for each category of products

Product Name	Review Count
Laptops	1,846
Video Surveillance Products	2,587
Tablets	1,884
Mobile Phones	1,928
Televisions	1,595

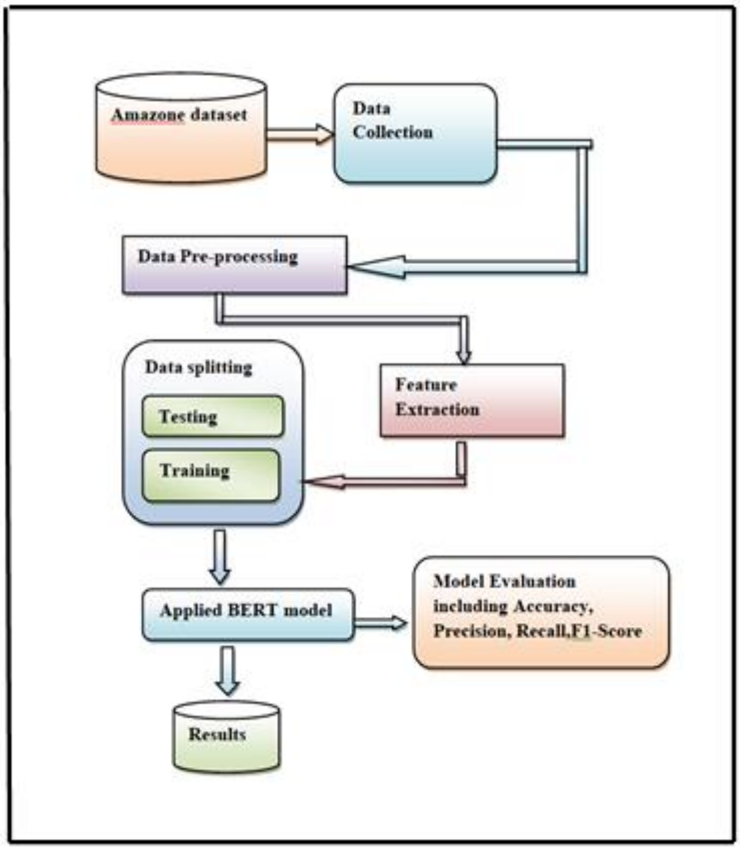

Figure 2: Methodology Flowchart for Sentiment Analysis

This segment provides an outline of the sequential established procedure to conduct SA on reviews on Amazon. The strategy consists of multiple sequential steps that can be observed in Figure 2.

Data Preprocessing

The effectiveness of discovering useful knowledge relies heavily on proper data preparation work within NLP activities. The computing system transforms raw data through preprocessing processes for subsequent evaluations. The steps involved in preprocessing serie as follows:

- **Lowercase:** This means changing all the words in the review to lowercase.
- **Stop word removal:** Common words that don't add much meaning, such as the, a, and is, are taken out of the review text.
- **Punctuation removal:** All punctuation was taken out. Also, any review that was only one word long was removed.
- **Contraction removal:** This process changes short forms of words into their full forms. For instance, when've changes to when have."
- **Tokenization:** Review texts include tokens or different words in each sentence.
- **Part-of-Speech Tagging:** Every word in the sentence has a POS tag added to it. A verb is denoted by VB, an adjective by AJJ, and a noun by NN.
- **Score Generation:** I did a review's sentiment analysis and came up with a score. To figure out the score, I compared a dataset to a list of opinions that had 4,500 negative and 5,000 positive words using principles attached[17]. Each review's sentiment score was determined using these values. If the score was below zero, the review was labeled negative; if not, it was labeled positive.
- **Word Embeddings:** During the word embeddings stage of our product-review dataset, we calculated number vectors corresponding to each pre-processed word. To create word indices, we transformed

each review text phrase into a list of words. We obtain these indices using text Tokenizer for Keras. We made certain that each term or word inside The function of the tokenizer is given some non-zero value index and that the tokenizer's The size of the vocabulary is appropriately capped. Next, in the training and testing sets for every word, the first unique index is determined.

- **Feature Extraction:** Feature extraction is a core step in NLP and really means taking raw words and turning them into numbers so that more powerful, they are easily understood by ML algorithms. In my project, I employed BOW extraction techniques.

Since it transforms input of text in a manner which machine learning systems can comprehend, the Bag-of-Words (BoW) method is crucial to sentiment analysis [18,19].

To make reviews easier for computers to analyze, we use a trick and treat those reviews very simply by treating the document like a big bag full of words. Junk the words we say in the order they appear and just count how many are there instead. Our algorithm for analyzing sentiment is based on a technology we created to convert unstructured and diverse customer input into vectors of numbers.

The BoW method for this research serves as a helpful instrument for us to evaluate and spot important patterns in the reviews' term frequency. We would like to analyze a great deal of reviews of products on Amazon and although it won't be able to recognize sophisticated relationships between words, it is a method that is straightforward to apply to virtually all texts, which enhances discerning important information easier. The first formula 1, for BOW is as follows:

$$P(\omega_t|context) = \text{softmax}\left(W_{out}\cdot\frac{1}{n}\sum_{i=1}^{n} W_{in}\,[\omega_{t-i}] + b_{in}\right)\dots(1)$$

where the conditional probability of a target word wt in relation to its context is described by the formula P(wt |context).

- Win is the input word embedding matrix.
- The output's word matrix is called Wout. The term "bin" is biased.
- For i = 1, 2,..., n, wt−i is a context word.
- The sum term of a specified formula establishes a mean of the Words that are embedded for context words.

Data Partitioning At this stage, the dataset containing 13,057 product reviews was repartitioned into 70% training, 10% validation, and 20% testing sets. Using BERT models, each review text was evaluated and classified as either positive or negative. Proposed Machine Learning Framework Classification refers to the technique for arranging data into various categories. In Sentiment Analysis (SA), classification is performed to divide data into binary (positive and negative) or ternary (positive, negative, and neutral) categories. Subsequently, the sentiment analysis procedure is performed [20]. The BERT model was used for sentiment analysis of customer reviews in this research.

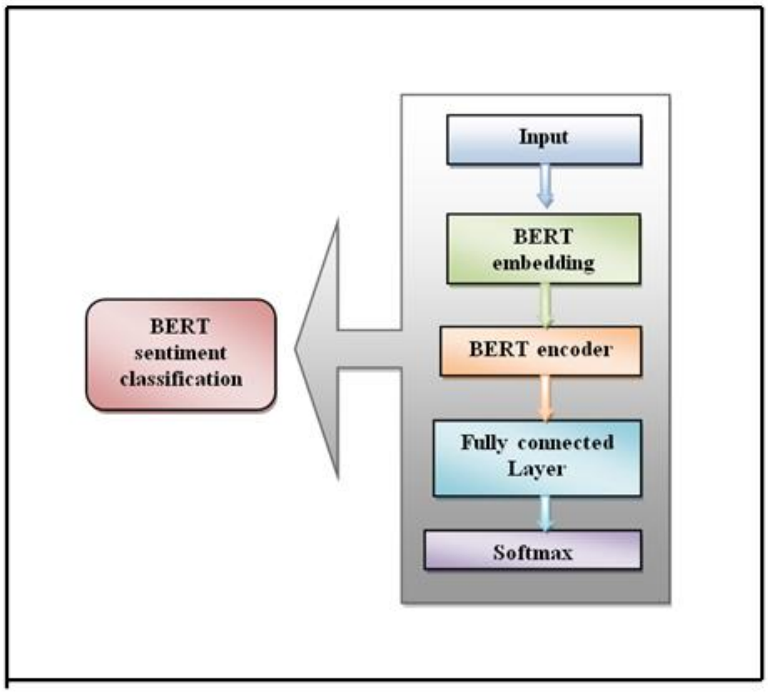

Figure 3: The Flow Chart of BERT Model for Sentiment Classification

A flow diagram illustrating the BERT model of sentiment classification is presented in Figure 3. The The embedding layer of the BERT model is composed of segment-vector, word-vector, and position-vector. Representation of words, segments and locations are converted to vectors using three different embedding functions. After the embedding procedure, both the location vector, the segment vector, and the word vectors are of 768 dimensions.

The dimension of three vectors' values together illustrate an representation of an emotional document that integrates discursive, segmentonal, and positional features of the words. This gives us the pretrained model, which will return a vector of words [21, 22]. The segment vector could

have elements whose value will either be one or zero. The corresponding dimension of a sentiment document is represented as 0 if it is shorter than the maximum sentiment length, and as 1 if it is longer [23–25]. In this case we can add the position vector where the word is in the text (1 -> max length). Using 255 to fill the position vector suggests that this is a short document. The BERT encoder layer consists of a 12-layer Transformer model that fully encodes the semantics of the context. Finally, to output a hidden layer to a emotion category and another hidden layer to another hidden layer completely linked behind encoder model. The final step of the classification process is to apply the layer of softmax to obtain the likelihood of every sentiment category

.

RESULTS AND DISCUSSION

Here we show the final visualisation results of the dataset along with the outcomes of the best evergreen machine learning (ML) model for Amazon goods review sustainability. Metrics like F1 score, recall, accuracy, and precision will be employed, to help gauge how well our machine learning models do.

Exploratory data analysis(EDA)

It employs several charts to visualise and evaluate hidden information within its columns and rows in hope of illuminating the most from a dataset: Exploratory data analysis (EDA). According to the sentiment score used in this paper, reviews are divided into three classes, positive negative as well as neutral reviews on Amazon.

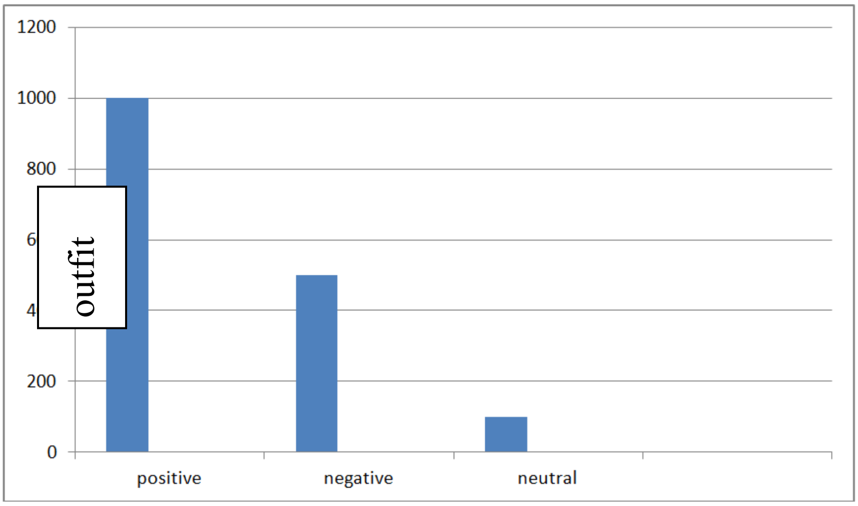

Figure 4: Categories of Reviews Distribution outfit

Figure 4 shows a visual representation of a text data of a Word Cloud program of Python made according to review categories. The graph displays the most often used terms in reviews, separated into sentiments that are positive and negative.

Figure 5: Most Frequent terms Employed in the Evaluations

The word cloud in Figure 5 displays the text data, where the size of each word indicates how frequently or how important it is. Highlighting important textual passages may be aided by word clouds, a widely used tool for text mining social network data. Researchers made word clouds for this analysis to show the most frequently used phrases among reviewers.

Model Evaluation Matrix

It is possible to assess categorization algorithms using metrics such as recall, precision, accuracy, and F-score. These parameters are quite helpful when evaluating supervised ML algorithms. The confusion matrix or contingency table data which gives a detailed study of the performance of the model forTP, TN, FP, and FN is the basis for their evaluation of the effectiveness of a model [26,27].

Accuracy

The accuracy measurement calculates the ratio between correctly predicted incidents and all observed incidents as per Equation 2.

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + TN + FP} \ldots\ldots (2)$$

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In this scenario True Positive gets denoted by TP while False Positive stands for FP and True Negative equals TN along with False Negative represented by FN.

True Negative, and FN for False Negative. The study's models' Table 1 displays the information about accuracy measurements.

Precision

The ratio of clearly detected positive reviews compared to the entire population of real favorable reviews defines accuracy as demonstrated in Equation 3.

$$\textbf{Precision: } \frac{\textbf{True Positive}}{\textbf{False Positive} + \textbf{True Positive}} \ldots..(3)$$

Recall

Equation 4 represents the measure of correctly classified positive reviews among all reviews flagged as positive

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \ldots..(4)$$

F1 Score

The calculation method for F-Measure combines the notions of recall and precision into a unified measurement point (Equation 5).

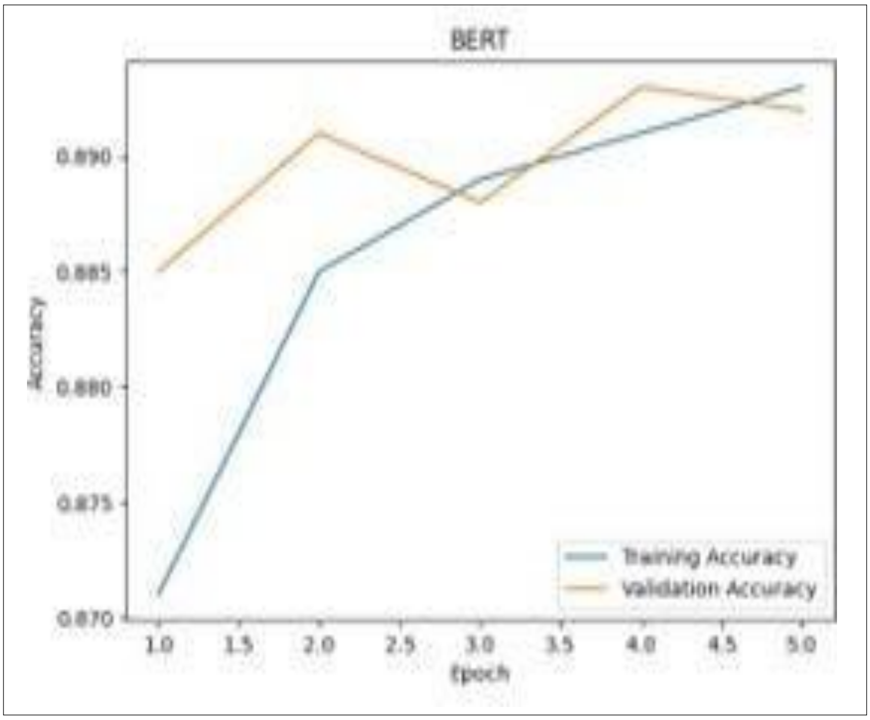
$$\mathbf{F - measure} = \frac{\mathbf{2. Precision. Recall}}{\mathbf{Precision\ +\ Recall}} \ldots..(5)$$

The findings from BERT analysis are evaluated against existing top literature approaches. The system-wide efficiency analysis employs standard assessment factors.

Results of BERT Model

The section includes all research outcomes from our investigation. The following results from BERT model SA are evaluated in the review of consumer product assessments.

Figure 6: Plotting of BERT Accuracy Curve



A BERT model performs review analysis through Figure 6 which shows its accuracy measurement pattern. Performance tracking during five epochs shows training accuracy data by the line in blue together with accuracy of validation data shown through the orange line. The Validation Accuracy shows significant fluctuations yet the Training Accuracy maintains its initial high value throughout the process. The model demonstrates prediction accuracy between 0.870 and 0.890 throughout training and validation periods. The graphical representation helps display how BERT models evolve to learn better generalization skills over time.

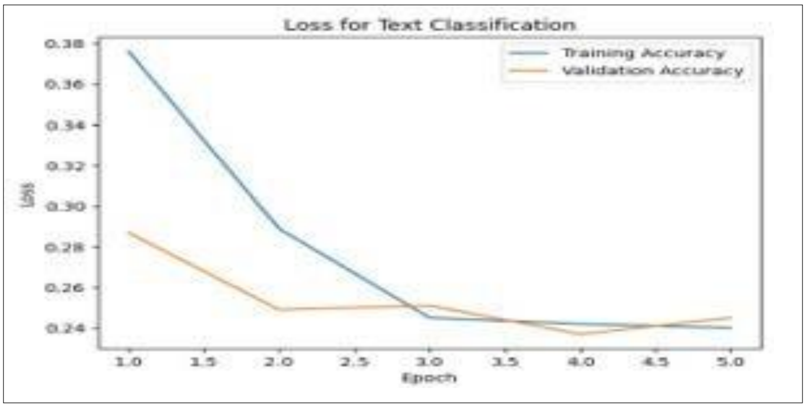


Figure 7: Plotting of BERT Accuracy Curve

The graph in figure 7 shows the product review analysis loss output by BERT. The figure 7 demonstrates loss values which decrease between 0.24 and 0.38 on the y-axis during epochs from 0 to 5 on the x-axis 0.24 to 0.38. The Training Accuracy line begins at 0.38 loss value until it quickly drops down to stabilize at 0.26 during epoch 3. The Validation Accuracy line begins its descent from 0.36 while dropping more slowly than the Training Accuracy line which it crosses between epoch 1 and epoch 2 and displays minimal fluctuation above it starting in epoch 3. The model demonstrates effective learning according to the loss metrics because the decrease in loss occurs steadily even though potential overfitting happens when validation loss becomes unstable.

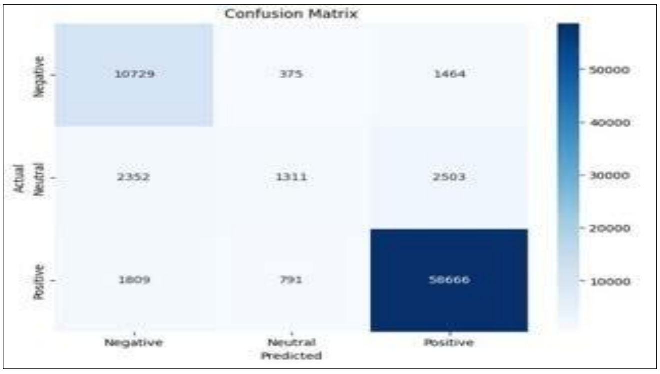


Figure 8: Confusion Matrix of BERT Model

The BERT model achieved classification success viewing a confusion matrix in Figure 8 showing its performance in categorizing events between negative and positive and neutral ranges. The model achieves effective predictions when classifying negative and positive results but demonstrates difficulty when handling neutral cases. The model displays a combination of 2503 false positives and 1311 false negatives in the neutral class because it tends to classify neutral instances incorrectly to other categories. The overall performance of the model requires refinement to enhance its capability in recognizing neutral instances.

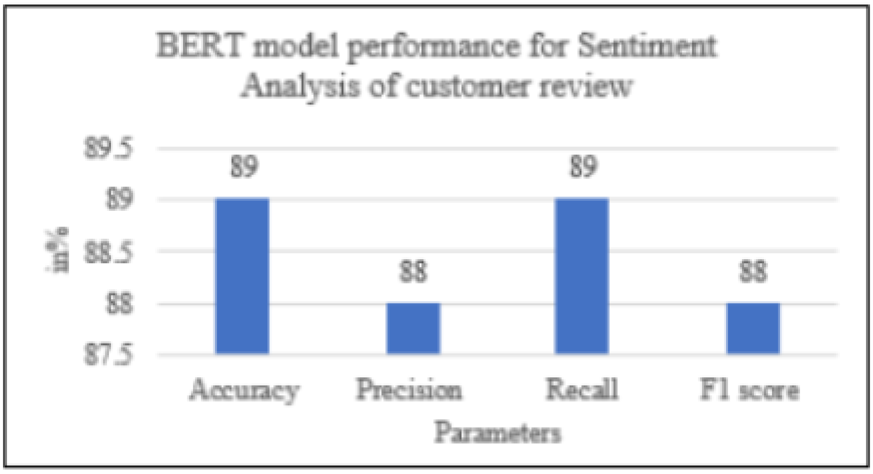


Figure 9: Performance of BERT Model for Customer Review

Figure 9 shows that a BERT model achieves a sentiment analysis of product customer reviews with 89% accuracy and recall but produces precision at 88% along with an f1-score of 88%.

Comparative Analysis

Together with logistic regression and decision tree models, Table 2 compares several machine learning models that are used for product review analysis using BERT.

Table 2: Comparing Different Machine Learning Models for Product Review Analysis [17, 28].

Models	Accuracy	Precision	Recall	F1 score
BERT	89	88	89	88

Logistic Regression Model	83.1 %	87.7 %	83.1%	84.9%
Decision Tree	75%	79%	73%	73%

Several machine learning models for sentiment analysis of product reviews show that BERT outperforms logistic regression and decision tree models in each assessment stage.

BERT delivered exceptional performance in sentiment analysis by obtaining review evaluation scores of 89% accuracy and 88% precision together with 89% recall and 88% F1 score. The LR model achieved assessment outcomes of accuracy 83.1% along with precision 87.7% and recall 83.1% and F1 score 84.9%. This performance remained below the superior level of BERT. The performance of the decision tree model in text-based sentiment analysis revealed the worst scores at 73% recall and 75% accuracy and 79% precision and an F1 score of 73%. BERT surpasses typical textual models in sentiment analysis because it effectively demonstrates superior capabilities for contextual representation of textual content relationships.

CONCLUSION AND FUTURE SCOPE

Sentiment classification functions as a NLP-based sentiment analysis job which evaluates text documents for positive and negative assessments. This research analyzes different ML techniques which analyze Amazon user reviews to detect sentiments. The BERT model demonstrates excellence in analyzing customer reviews for sentiment evaluation through this research work. The model achieves superior review classification performance when preprocessing methods are combined with an advanced neural network design. The BERT approach delivers superior results to traditional methods like LR and DT because it reaches an 89% performance mark in all measurement categories including recall and F1 score along with precision and accuracy. Large datasets benefit from using this model as an effective solution for sentiment analysis. The research outcome advances both online store sentiment prediction precision and provides valuable insights into customer comment evaluation.

The superior performance of BERT comes with decreased efficiency when applied to real-time applications or large datasets through smaller infrastructure. Research should focus on improving BERT model performance speed while adding neutral sentiment detection capabilities alongside expanding its product category application scope. The investigation should further examine combined model approaches as well as optimization methods which would improve performance and minimize processing requirements. The technique of feature engineering together with deep learning and class imbalance approaches operates effectively with ML models.

REFERENCES

1. Quyyam T, Ghous H (2021) Sentiment Analysis of Amazon Customer Product Reviews: A Review. Int J Sci Res Eng Dev 4: 564-595.
2. Fang X, Zhan J (2015) Sentiment analysis using product review data. J Big Data 2: 1-14.
3. Xia R, Zong C, Li S (2011) Ensemble of feature sets and classification algorithms for sentiment classification. Inf Sci 181: 1138-1152.
4. Singla Z, Randhawa S, Jain S (2018) Sentiment analysis of customer product reviews using machine learning. Proceedings of 2017 International Conference on Intelligent Computing and Control https://ieeexplore.ieee.org/document/8321910.
5. Sharma R, Nigam S, Jain R (2014) Opinion Mining of Movie Reviews At Document Level. Int J Inf Theory 3: 13-21.
6. Sharma R, Nigam S, Jain R (2014) Polarity Detection at Sentence Level. Int J ComputA ppl 86: 29-33.
7. Umarani V, Julian A, Deepa J (2021) Sentiment Analysis using various Machine Learning and Deep Learning Techniques. J Niger Soc Phys Sci 3: 385-394.
8. Sreenivasulu MT, Jayakarthik R (2020) A Reinforced Deep Belief Network with Firefly Optimization for Sentiment Analysis of Customer Product Review. Int J Adv Sci Technol 29: 1504-1516.

9. Kabir M, Kabir MMJ, Xu S, Badhon B (2021) An empirical research on sentiment analysis using machine learning approaches. Int J Comput Appl https://www.researchgate.net/publication/334656958_An_empirical_research_on_sentiment_analysis_using_machine_learning_approaches.
10. Nandal N, Tanwar R, Pruthi J (2020) Machine learning based aspect level sentiment analysis for Amazon products. Spat Inf Res 28.
11. He H, Zhou G, Zhao S (2022) Exploring E-Commerce Product Experience Based on Fusion Sentiment Analysis Method. IEEE Access 10: 110248-110260.
12. Gupta D, Roup A, Gupta D, Ratre A (2022) Food Review Analysis and Sentiment Prediction using Machine Learning Models. 2022 2nd International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies https://ieeexplore.ieee.org/document/9807907.
13. Velmurugan T, Archana M, Latha U (2022) Sentiment Analysis of Customer Reviews Based Texts Using Classification Algorithms. Proceedings - 2022 8th Annual International Conference on Network and Information Systems for Computers https://ieeexplore.ieee.org/document/10045400.
14. Chehal D, Gupta P, Gulati P (2022) Evaluating Annotated Dataset of Customer Reviews for Aspect Based Sentiment Analysis. Journal of Web Engineering 21.
15. Jabin S, Suhi MS, Arefin MF, Hasib KM (2022) Comparison of Different Sentiment Analysis Techniques for Bangla Reviews. IEEE Region 10 Humanitarian Technology Conference, R10- HTC https://ieeexplore.ieee.org/document/9929495.
16. Sharma P, Kumar R, Gupta M (2021) Impacts of Customer Feedback for Online-Offline Shopping using Machine Learning. Proceedings - 2nd International Conference on Smart Electronics and Communication https://ieeexplore.ieee.org/document/9591939.
17. Al Qahtani ASM (2021) Product Sentiment Analysis for Amazon Reviews. Int J Comput Sci InfT echnol 13: 30.
18. George K, Joseph S (2014) Text Classification by Augmenting Bag of Words (BOW) Representation with Co-occurrence Feature. IOSR J Comput Eng 16: 34-38.
19. Deepu S, Raj P, Rajaraajeswari S (2016) A Framework for Text Analytics using the Bag of Words (BoW) Model for Prediction. Int J Adv Netw Appl https://www.ijana.in/ Special%20Issue/S71.pdf.
20. Bouazizi M, Ohtsuki T (2017) A Pattern-Based Approach for Multi-Class Sentiment Analysis in Twitter. IEEE Access https://ieeexplore.ieee.org/document/8013027.
21. Sun C, Qiu X, Xu Y, Huang X (2019) How to Fine-Tune BERT for Text Classification? Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 194-206.
22. Alaparthi S, Mishra M (2021) BERT: a sentiment analysis odyssey. J Mark Anal 9: 118-126.
23. Rohilla V, Chakraborty S, Kumar R (2022) Deep learning based feature extraction and a bidirectional hybrid optimized model for location based advertising. Multimedia Tools Appl81: 16067-16095.
24. Rohilla V, Chakraborty S, Kaur M (2022) An Empirical Framework for Recommendation-based Location Services Using Deep Learning. Eng Technol Appl Sci Res 12.
25. Sai Charan Reddy Vennapusa, Takudzwa Fadziso, Dipakkumar Kanubhai Sachani, Vamsi Krishna Yarlagadda, Sunil Kumar Reddy Anumandla (2018) Cryptocurrency-Based Loyalt Programs for Enhanced Customer Engagement. Technol Manag Rev 3: 46-62.
26. Sinnasamy T, Sjaif NNA (2022) Sentiment Analysis using Term based Method for Customers' Reviews in Amazon Product. Int J Adv Comput Sci Appl 13.
27. Purohit A (2021) Sentiment Analysis of Customer Product Reviews using deep Learning and Compare with other Machine Learning Techniques. Int J Res Appl Sci Eng Technol 16: 243-253.
28. Nabil S, Elbouhdidi J, Chkouri MY (2021) Sentiment analysis of amazon's reviews using machine learning algorithms. J Theor Appl Inf Technol 99: 5571-5581.
29. Pandey, G. K., & Srivastava, S. (2023, April). ResNet-18 comparative analysis of various activation functions for image classification. In 2023 International Conference on Inventive Computation Technologies (ICICT) (pp. 595-601). IEEE.
30. Pandey, G. K., & Srivastava, S. (2023, November). Investigating the Efficacy of a Newly Proposed Activation Function on Deep Neural Networks. In 2023 IEEE 3rd International Conference on Applied Electromagnetics, Signal Processing, & Communication (AESPC) (pp. 1-7). IEEE.
31. Pandey, G. K., Raj, V., Agarwal, A., Dixit, M., Chauhan, S. S., & Srivastava, S. (2025, February). Offline Signature Verification: An Extensive Survey of Deep Learning Methods. In 2025 4th International Conference on Sentiment Analysis and Deep Learning (ICSADL) (pp. 892-898). IEEE.