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Sentiment Analysis of Online Customer Feedbacks Using NLP and Supervised Learning Algorithm

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Abstract: E-Commerce is now an integral part of our everyday lives because of the proliferation of computers and the lightning-fast growth of the Internet. Numerous reviews are available for widely used products. In addition to making it harder for consumers to make an educated purchase choice, this also makes it harder for the product's producer to monitor and respond to customer feedback. One of the fastest-growing subfields in social media analysis is sentiment analysis and opinion mining. It's crucial since it gives companies a chance to concentrate on enhancing the company plan and learn more about the comments buyers have about their product. This research suggests using sequential Bayesian linear regression (SBLR) for Sentiment analysis of electronic customer comments. It includes mining a person's thoughts and feelings about a firm via computer analysis of customer purchasing patterns. The dataset used in this article has been gathered from Amazon and consists of customer opinions on various electrical products. We used machine learning (ML) techniques after analyzing the reviews to determine whether they were favorable or negative. The findings of this article indicate that ML Techniques provide the best outcomes for categorizing online Reviews.

Keywords: *Machine learning, natural language processing, sentiment analysis, product reviews, sequential Bayesian linear regression (SBLR)*

1. Introduction

Sentiment analysis is an ML processing approach for identifying emotions, which may be used by company owners to glean insights into their customers' points of opinion by channels, including social media, polls, and e-commerce site evaluations. This information may be obtained via various online media, such as social media. With this newfound information, we will be better able to comprehend the factors that contribute to the commodity's deterioration. Data may be analyzed on the aspect level of sentiment, genuine intent or emotion can be detected, and fine-grained sentiments can be classified using a scale from severely negative to reasonably positive [1]. All of these can be done within the realm of sentiment analysis, which encompasses a variety of fields and types of sentiment classification. Many approaches to classifying sentiments, such as the paper level and document category methodologies. The examination of feelings and the categorization of feelings served as the foundation for their research. In particular, throughout the last decade, rapidly expanding e-commerce platforms have started to take control of the whole corporate sector [2]. Customers started to feel more at ease with e-commerce than with traditional commerce, thanks to the many options provided by these platforms. Customers could find products experienced by others, which were reviewed and rated by many people expressing and sharing their feelings and thoughts about any products. As a result, consumers' views started playing a significant part in the choices about purchases, business intelligence, and maintaining the availability of any product or service [3]. Companies have carried out a great number of research and polls, and the results of these endeavors have shown that sentiment analysis is a field that is continuously expanding. Specifically, in e-commerce platforms, sentiment analysis in reviews is the practice of analyzing, monitoring and classifying unstructured language expressing ideas and sentiments about a product or service. The opinion or sentiment of consumers is gleaned from sources like reviews, survey answers, online social media, healthcare media, and other such sources. Sentiment analysis, in its broadest sense, is the process of determining the emotional tone of a piece of writing, a conversation, an online forum thread, a published article, or any other kind of material [4]. One of the most important tasks in sentiment analysis is identifying the overall tone of the text at the feature, phrase, and document levels. Opinionated data has been created on the internet due to the rise in the number of people using the internet, which has led to each user having an interest in putting their viewpoint on the internet

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via various mediums. It is possible to analyze this opinionated data using sentiment analysis, extracting some crucial insights that might assist other users in making decisions [5]. The information gleaned from social media platforms may come from various sources, including but not limited to “Product Reviews, Movie Reviews, Reviews from Airlines, Cricket Reviews, Hotel Reviews, Employee Interactions, Healthcare Reviews, News and Articles”, etc. The feedback that companies get from their customers online is a rich data source, and using methods from natural language processing (NLP) makes it possible to gain more comprehension. Using NLP, companies can analyze the feedback left by customers and extract useful information from the content of those comments. The procedure starts with acquiring data from various internet sources, such as social media platforms and review websites. The raw text data are next subjected to text preprocessing, which involves cleaning and transforming the data [6]. This requires doing activities such as eliminating stop words, tokenizing, and information that is unrelated to the work at hand. After that, approaches for analyzing sentiment may be utilized to figure out the attitude that was communicated in the feedback, such as whether it was good, negative, or neutral. Aspect-based sentiment analysis goes this one step further by identifying certain elements or characteristics that were highlighted in the feedback and then analyzing the sentiment that was associated with each aspect individually. This gives them a far better knowledge of the issues that are influencing the emotion of their customers. The topic modeling approaches may expose hidden themes or subjects included within the feedback, which can assist in discovering issues or interests that are shared by consumers. Using Named Entity Recognition (NER), it is possible to extract relevant entities from the feedback, such as product names or brand mentions, which provides deeper insights into consumer preferences [7]. The approaches of data visualization help to show the gleaned insights in an aesthetically attractive way, which makes the comprehension of the data much simpler. In addition, feedback summary strategies may provide condensed and insightful summaries of the information included in the client feedback. Companies can get significant insights into consumer feelings, preferences, and areas for development when they use natural language processing (NLP) for online customer feedback. In this study, the sequential Bayesian linear regression (SBLR) technique was created for the express goal of assessing the tone of online consumer comments. This enables the companies to make choices based on the data and improve their goods or services by the data. Online customer reviews serve as a resource for information, comments, and insights that benefit both customers and companies. The reviews that are available online provide customers with a source of knowledge and direction when it comes to making purchase selections.

The following is an example of the document's structure. In Section 2, the collected consumer comments are analyzed in depth. In Section 3, we detail the full scope of the suggested methodology. The outcomes of the implementation are shown and discussed in Section 4. In Section 5, we analyze the article's main contributions and consider the prospects for expanding the suggested framework.

2. Related Work

It includes a variety of procedures, and its conclusions apply to MOOC programs at institutions all around the globe. First, this research distinguishes two distinct course types focused on learners' result intent, which are known as knowledge-seeking MOOCs and skill-seeking MOOCs. This is accomplished via exploratory analysis of student reviews and the judgment of subject matter experts [8]. To analyze ML, deep learning (DL), and explainable artificial intelligence (XAI) models, as well as approaches for predicting client attitudes within the FDS domain. An examination of the relevant literature indicated that lexicon-based and ML techniques are used extensively in FDS to predict sentiments gleaned from customer evaluations. However, because of the absence of the model's interpretability and the explainability of the judgments taken, we could only find a small number of research that used DL approaches [9]. A methodology for classifying emotions is called LeBERT, which combines BERT, N-grams, and CNN with the sentiment lexicon. Words are vectorized in the model by using a sentiment lexicon, N-grams, and BERT. These are all taken from a portion of the input text. To map features and determine the output sentiment class, a deep neural network classifier known as CNN is used [10]. The vast majority of the existing strategies on SA that are geared at these online items have an incredibly low rate of accuracy and also involve a greater amount of time when training. Using an Improved Adaptive Neuro-Fuzzy Inferences System (IANFIS), a proposed technique is aimed at the future prediction of online products. This is done to combat the problems that have been outlined above. The Deep Learning Modified Neural Network (DLMNN) is utilized in the first technique [11]. To provide the community of researchers working on aspect-based sentiment analysis with an in-depth understanding of the domain of implicit and explicit aspect extraction, it is necessary to adopt a systematic literature technique. The key results acquired from the review are provided based on methodologies, strategies, assessment metrics, data domains, languages, and considerable difficulties. This is because of the vast number of included publications [12]. A generic framework that, to produce new scores based on customer feelings for various product aspects, employs NLP methods such as sentiment analysis, text data mining, and clustering approaches. This is done to acquire these ratings. While many SA systems classify comments as either positive or negative, a review may nonetheless include statements with a variety of polarity because a user may feel differently about each aspect of the product [13].

3. Proposed Methodology

The importance of online customer evaluations in today's digital world is vital since they provide invaluable insights into the quality, performance, and consumer happiness of items. There is usually a multi-step process involved when analyzing evaluations left by customers online. E-commerce sites, review sites, and social media are just some places where consumers have been found to voice their ideas. Next, a representative sample is acquired manually or automatically, scraping websites for information. After that, the data is cleaned and preprocessed to eliminate extraneous or duplicate reviews and to make the text format consistent. Each review's tone is analyzed using sentiment analysis methods, determining whether it is favorable, negative, or neutral. Numerous social media data sets may be generated from various Data Sources for use in Sentiment Analysis and Opinion Mining. People may share their thoughts on many topics on this website.

3.1 Dataset

The json-formatted dataset was obtained from Amazon. The total amount of ratings are included in each json file. Camera, laptop, mobile phone, tablet, TV, and security camera user evaluations are included in the dataset [14].

3.2 Preprocessing

Tokenization, stop word elimination, stemming, punctuation mark removal, etc., have all been completed during preprocessing. It has been transformed into a wordy bag. In opinion mining and sentiment analysis, preprocessing is crucial.

Tokenization: It is the process of splitting a text into a group of manageable units called tokens, which may be anything from a single word or phrase to a whole sentence, allowing for more efficient processing. Due to its significance as a prerequisite for further processing, this step is highly valued in natural language processing. Tokens are generated from whitespace, punctuation, and line breaks. White space is used almost exclusively. A framework for working with human language data called Natural Language Toolkit (nltk) has a few tokenizers. Tokenizer for Regexp is one of them. Using regular expressions to find matching tokens, this tokenizer divided a phrase. For example, if we use RegexpTokenizer("[w ′] + ") for a statement like "Tokenization is an important NLP task," we would receive a result similar to this: ["Tokenization is an important NLP task."]. The second one is a tokenizer called TreebankWord. While treating punctuation as words, this tokenizer divides the phrase according to the regular expression, splitting commas, apostrophes, quote marks, etc. For example, if we use TreebankWordTokenizer() for the same text as before, the output would look like this: ["Tokenization"; ""; "is"; "is an"; "is important;" "NLP"; "task"]. WordPunct tokenizer comes in third. This tokenizer divided the text into two parts based on the regular expression w + |[ws]+. For example, the outcome of using WordPunctTokenizer() for the same text as before would be something like ["Tokenization", "' ", "is ", "an ", "important", "NLP ", "task", "."]. As can be observed, for the provided text, we obtained the same outcome as the TreebankWord tokenizer. The nltk utility has a variety of tokenizers that may be used as necessary.

Stop word elimination: Stop words are often the most prevalent words in a language, such as "and," "an," and "at" in English, which is seen as excessive and pointless in text mining applications. Pronouns, prepositions, conjunctions, articles, and auxiliary verbs are some examples of these terms. Most research demonstrates that stop words should be eliminated from the corpus without sacrificing important data before the feature selection because of their detrimental impacts on sentiment classifier performance. Nevertheless, in other cases, deleting the stop words might make it more difficult to accurately classify documents or texts that include prepositions, conjunctions, or auxiliary verbs. As a result, eliminating stop words may make matching difficult, although, as we've already said, text mining generally benefits from the smaller feature set. Normally, text mining technologies supply prepared lists for researchers to utilize. However, researchers sometimes develop pre-configured lists and then use them, depending on the application. While using nltk tools for this research, we adjusted the stop words list to fit the organization of our text.

Stemming: The goal of stemming is to reduce words in a text to their base forms by eliminating grammatical affixes like prefixes (removing the beginning of the term) and suffixes (removing the end of the word). They may thus serve as a standard indexing unit for researchers in the same field. Due to changes in language structure, it is necessary to do appropriate editing according to the language being studied, even if stemming algorithms in most application tools are generally created for English. Numerous algorithms developed for one language may now be adapted to work with another. There are many applications for stemming. One way to improve classification accuracy is to eliminate redundant information by using just the most basic representations for words that have a similar root. Reducing the number of dimensions is another motivation for shrinking the feature set.

Removing common words: While it is not certain that a classifier's accuracy would improve after removing popular terms, this strategy often yields excellent results. Stop words are seldom used and should not be mistaken for common terms. Even though stop words are the most often used words, it just implies they appear frequently in many different types of academic writing. As a result, popular terms vary considerably within fields of study, but stop words are consistent across disciplines.

3.3 Score Generation

Here, the emotional weight of each phrase is determined. The sentiment score for each phrase was determined by comparing the dataset with opinion lexicons, which included 2007 positive terms and 4781 negative words.

3.4 Sentiment Classification

A method for incrementally learning and analyzing a dataset via regression, sequential Bayesian linear regression is an algorithm. It works sequentially, letting you add new data points to your model without retraining it from scratch. Prior distributions for the regression coefficients and the noise variance are initialized at the beginning of the process to represent the initial views about the parameters. The procedure changes the prior distributions when additional data points are added, using Bayes' theorem, leading to posterior distributions that account for the observed data. The model's predictions are iteratively improved with each additional observation. Algorithm predictions for new input values may be made using the updated posterior distributions. Sequential Bayesian linear regression uses the Bayesian framework to allow flexible learning and uncertainty quantification through posterior distributions. This method deals with streaming or time-series data, allowing for continuous analysis and prediction as new data points are collected.

Following the methodology provided, we simulate the SBLR in online customer feedback. We consider a 2-class situation where a specific viewer offers a favorable or negative total assessment of the subject product, denoted by $y \epsilon \{0,1\}$; Here, 1 and 0 stand for generally good and unfavorable product reviews, respectively. We consider a product that has n perceived qualities according to its reviewers. These qualities are correspondingly by x_{ij}, that denotes the score that reviewer i gave the target product for attribute j. These x_{ij} values are chosen to have a strong positive correlation with the reviewer's total rating. Feedback is supposed to depend on a combination of the reviewer's experience with the product and earlier reviews submitted by other reviewers.

The correlation between the real value of an attribute and the original class score is $P(x_{ij} > 0|y_i = 1) = P(x_{ij} > 0|y_i = 1) = \theta_{ij}$ for some $\theta_{ji} \epsilon$ (0.5,1). Let a_{ij} and b_{ij} stand in for $x_{ij} > 0$ and $x_{ij} < 0$, respectively. We presume that a reviewer (let's say, i) is free of any preconceived prejudice towards the subject product. Specifically, $P(x_{ij} = 1) = P(x_{ij} = 1) = 0.5$ at t=0. Idealistically, it ought to be the case that are represented in equations (1) and (2),

$$y_i = 0 \frac{1}{n} \sum_{j=1}^{n} \quad p(a_{ij}) > 0.5 \tag{1}$$

and

$$y_i = 0 \frac{1}{n} \sum_{j=1}^{n} \quad p(a_{ij}) > 0.5 \tag{2}$$

It is expected that the reviewer will perceive evidence incorrectly if it contradicts what they now opinion. When the reviewer's opinion that $x_{ij} > 0$ is true, we represent by α_{ij}; conversely, when the reviewer opinion that $x_{ij} < 0$ is true, we express by β_{ij}. For the jth characteristic, we refer to such seen views or signals by reviewer i as sij. When $y_i = 1, s_{ij} = \alpha_{ij}$ and $y_i = 0, s_{ij} = \beta_{ij}$ denotes $x_{ij} > 0$ and $x_{ij} < 0$, respectively. $s_j^i = (s1_j, s2_j, , \dots . s_{ji},)$ represents a series of signals or attribute scores supplied by different reviewers for attribute j of the product of interest.

When the SBLR is present, it is assumed that the reader's observed views are neither independently nor uniformly distributed. The likelihood that reviewer i will give the jth attribute a score that verifies a false opinion is denoted by the symbol θ_{ij}^* as $P(s_{ij} = \alpha_{ij}|P(y_j = 1|s_j^{i-1}) > 0.5, x_{ij} > 0) = P(s_{ij} = \beta_{ij}|P(y_j = 0|s_j^{i-1}) > 0.5, x_{ij} > 0)$. We represent θ_{ij}^{**}, the likelihood that reviewer i will provide a value for the jth characteristic that supports a genuine opinion, as $P(s_{ij} = \alpha_{ij}|P(y_j = 1|s_j^{i-1}) > 0.5, x_{ij} < 0) = P(s_{ij} = \beta_{ij}|P(y_j = 0|s_j^{i-1}) > 0.5, x_{ij} < 0)$. Reviewer i's observed signals θ_{ij}^* and θ_{ij}^{**} are when the reviewer thinks it is feasible to categorize the product of interest into one of the two categories $y_j = 1 \; or \; 0$.

The reviewer analyses the information that contradicts learned opinion incorrectly with a probability of $\gamma > 0$ and proof that supports learned opinion correctly. We adjust this likelihood for the number of feedback, with the lowest discount applied to the first review and the biggest discount applied to the last. Since most readers of online product evaluations only read the first feedback and a diminishing number of subsequent feedback, this kind of discounting is acceptable. The explanation for this decline in readership for feedback farther down the line might be that a reader creates a fair judgment depending on the first feedback, and the little alteration of this first-formed belief from reading subsequent feedback is the likely source of the decline.

Due to the reviewer's error in reading the evidence, which has probabilities $\gamma, \theta_{ij}^{*} = (1 - \theta_{ij}) + \gamma^{i-1}\theta_{ij}$ and $\gamma, \theta_{ij}^{*} = (1 - \theta_{ij}) + \gamma^{i-1}(1 - \theta_{ij})$. When the value is $\gamma = 0$, the reviewer is not biassed; however, when the score is $\gamma = 1$, the first reviewer's score for that characteristic impacts the ratings of all subsequent reviewers.

We consider the situation where the reviewer's opinion is that they have $n_{\alpha ij}\alpha j$ value and $n_{\beta ij}\beta j$ scores after reading i of the prior evaluations of the attribute j of the product of interest. The revised posterior opinion under these circumstances is provided by equation (3)

$$P(a_{ij}|n_{\alpha ij}, n_{\beta ij}) = \frac{\theta^{n_{\alpha ij} - n_{\beta ij}}}{\theta^{n_{\alpha ij} - n_{\beta ij}} + (1-\theta)^{n_{\alpha ij} - n_{\beta ij}}} \quad (3)$$

In equation (4), According to the relative probability ratio, the following is how we define the observer's opinions:

$$\Lambda(n_{\alpha ij}, n_{\beta ij}) = \frac{P(a_{ij}|n_{\alpha ij}, n_{\beta ij})}{P(b_{ij}|n_{\alpha ij}, n_{\beta ij})} = \frac{\theta^{n_{\alpha ij} - n_{\beta ij}}}{(1-\theta)^{n_{\alpha ij} - n_{\beta ij}}} \quad (4)$$

The bias that the reviewer is said to have dependent on the order in which the various reviews are viewed is thereby offset by the Bayesian observer. The Bayesian observer's and the reviewer's likelihood ratios are not identical because of the bias introduced by the reader's choice of reading sequence. We have only focused on one of the many attributes that could be present in each evaluation so far. The outcomes would be the same for each of the other qualities due to symmetry. Additionally, after all of the variables are considered, the general dynamic need to continue to be the same to decide the review's outcome.

4. Result and Discussion

In this section, we will discuss the findings that we received by reading online consumer evaluations of various items. To analyze the sentiment of online customer feedback, the sequential Bayesian linear regression (SBLR) method has been developed. The approach that we have created is contrasted with various methodologies already in use, such as the naive Bayes method [15] and the Bidirectional Encoder Representations from Transformers - Dilated Convolutional Neural Networks (BERT-DCNN) [16] approach. The criteria include characteristics like accuracy and precision and F-Score.

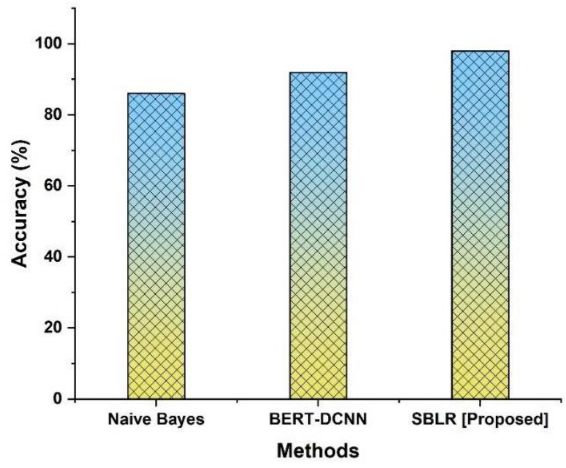

Fig. 1. Comparison of accuracy

Accuracy may be determined by contrasting the comments' actual labels with those predicted by the system. A forecast is regarded as accurate if it accurately predicts the exact mood. The accuracy is then expressed as a percentage by taking that number and dividing it by the total number of forecasts. The precision of the suggested approach is shown in figure 1. Compared to other techniques, such as Naive Bayes (86%) and BERT-DCNN (92%), the recommended method scores 98%. Accuracy of both the proposed and current approaches is compared in Table 1.

Table 1. Accuracy

Methods	Accuracy (%)
Naive Bayes	86
BERT-DCNN	92
SBLR [Proposed]	98

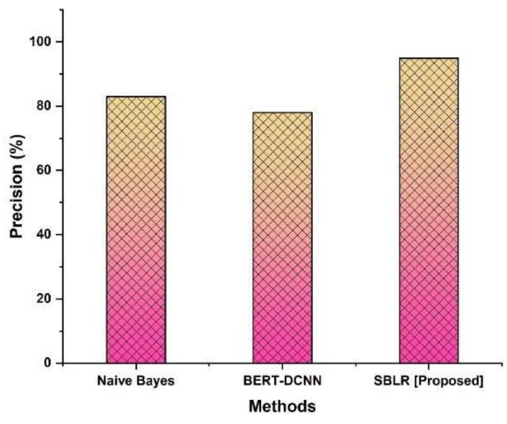

Fig. 2. Comparison of precision

Precision is the percentage of accurately anticipated positive occurrences relative to the total number of expected positive cases. Concerning online reviews, precision may provide light on whether or not a sentiment analysis model's optimistic outlook is well-founded. Figure 2 illustrates the precision of the suggested approach. Comparing the proposed method's score of 95% to other techniques, such as Naive Bayes (83%) and BERT-DCNN (78%), shows that the latter two fall short. Table 2 displays a comparison of the precision of proposed and current approaches.

Table 2. Precision

Methods	Precision (%)
Naive Bayes	83
BERT-DCNN	78
SBLR [Proposed]	95

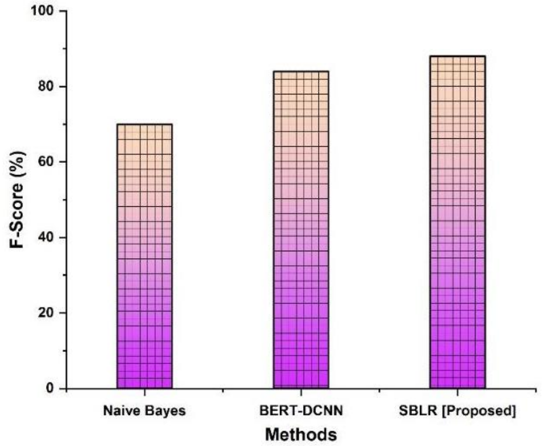

Fig. 3. Comparison of F-Score

In binary classification tasks like online review sentiment analysis, the F-score (the F1 score) is a common assessment statistic. The mean harmonic recall is a balanced metric considering accuracy and how well a model can remember information. The f-score for the suggested strategy is shown in Figure 3. Naive Bayes received a 70% score, and BERT-DCNN received an 84% score, whereas the proposed technique scored 88%. As shown in Table 3, the f-score is compared to new and established approaches.

Table 3. F-Score

Methods	F-Score (%)
Naive Bayes	70
BERT-DCNN	84
SBLR [Proposed]	88

Camera, laptop, mobile phone, tablet, TV, and video surveillance data set compiled from Amazon customer reviews [17]. It is in the form of json files, and each file has the same information shown in figure 4 and Table 4 on the total number of reviews.

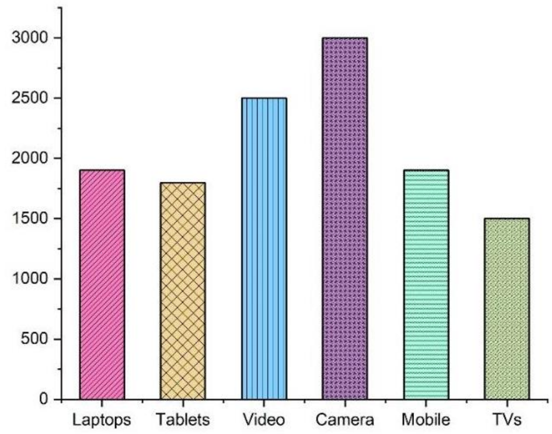

Fig. 4. Review count

Table 4. Dataset and reviews count

Laptops	**1900**
Tablets	1800
Video	2500
Camera	3000
Mobile	1900
TVs	1500

5. Conclusion

The study of sentiment analysis and opinion mining has become more vital in recent years. Most sectors generate a wide range of data that need analysis before choices that are in the best interests of the industry as a whole. There is a growing need to analyze and glean insights from the vast amounts of data being produced by the proliferation of social media. This article uses a dataset of Amazon customer evaluations for six electronic categories: cameras, laptops, cellphones, tablets, televisions, and video surveillance systems. The sequential Bayesian linear regression (SBLR) technique was created for the express goal of assessing the tone of online consumer comments. All of the reviews for this product have been analyzed for sentiment and categorized using ML techniques. Future research using the same dataset may benefit from using Aspect level sentiment analysis to narrow down precisely what individuals liked and disliked.

Reference

[1] Wassan, S., Chen, X., Shen, T., Waqar, M. and Jhanjhi, N.Z., 2021. Amazon product sentiment analysis using machine learning techniques. Revista Argentina de Clínica Psicológica, 30(1), p.695.

[2] Pahwa, B., Taruna, S. and Kasliwal, N., 2018. The sentiment is analysis-strategy for text pre-processing. Int. J. Comput. Appl, 180(34), pp.15-18.

[3] Abualigah, L., Alfar, H.E., Shehab, M. and Hussein, A.M.A., 2020. Sentiment analysis in healthcare: a brief review. Recent advances in NLP: the case of Arabic language, pp.129-141.

[4] Dhar, S., Pednekar, S., Borad, K. and Save, A., 2018, April. Sentiment analysis using neural networks: A new approach. In 2018 Second international conference on inventive communication and computational technologies (ICICCT) (pp. 1220-1224). IEEE.

[5] Jagdale, R.S., Shirsat, V.S. and Deshmukh, S.N., 2019. Sentiment analysis on product reviews using machine learning techniques. In Cognitive Informatics and Soft Computing: Proceeding of CISC 2017 (pp. 639-647). Springer Singapore.

[6] Tammina, S. and Annareddy, S., 2020, January. Sentiment analysis on customer reviews using convolutional neural network. In 2020 International Conference on Computer Communication and Informatics (ICCCI) (pp. 1-6). IEEE.

[7] Shafin, M.A., Hasan, M.M., Alam, M.R., Mithu, M.A., Nur, A.U. and Faruk, M.O., 2020, December. Product review sentiment analysis using NLP and machine learning in the Bangla language. In 2020 23rd International Conference on Computer and Information Technology (ICCIT) (pp. 1-5). IEEE.

[8] Li, L., Johnson, J., Aarhus, W. and Shah, D., 2022. Key factors in MOOC pedagogy based on NLP sentiment analysis of learner reviews: What makes a hit. Computers & Education, 176, p.104354.

[9] Adak, A., Pradhan, B. and Shukla, N., 2022. Sentiment analysis of customer reviews of food delivery services using deep learning and explainable artificial intelligence: Systematic review. Foods, 11(10), p.1500.

[10] Mutinda, J., Mwangi, W. and Okeyo, G., 2023. Sentiment analysis of text reviews using lexicon-enhanced bert embedding (LeBERT) model with the convolutional neural network. Applied Sciences, 13(3), p.1445.

[11] Sasikala, P. and Mary Immaculate Sheela, L., 2020. Sentiment analysis of online product reviews using DLMNN and future prediction of online product using IANFIS. Journal of Big Data, 7, pp.1-20.

[12] Maitama, J.Z., Idris, N., Abdi, A., Shuib, L. and Fauzi, R., 2020. A systematic review on implicit and explicit aspect extraction in sentiment analysis. IEEE Access, 8, pp.194166-194191.

[13] Kauffmann, E., Peral, J., Gil, D., Ferrández, A., Sellers, R. and Mora, H., 2019. Managing marketing decision-making with sentiment analysis: An evaluation of the main product features using text data mining. Sustainability, 11(15), p.4235.

[14] Jagdale, R.S., Shirsat, V.S. and Deshmukh, S.N., 2019. Sentiment analysis on product reviews using machine learning techniques. In Cognitive Informatics and Soft Computing: Proceeding of CISC 2017 (pp. 639-647). Springer Singapore.

[15] Kewsuwun, N. and Kajornkasirat, S., 2022. A sentiment analysis model of agritech startup on Facebook comments using naive Bayes classifier. International Journal of Electrical & Computer Engineering (2088-8708), 12(3).

[16] Jain, P.K., Quamer, W., Saravanan, V. and Pamula, R., 2022. Employing BERT-DCNN with sentic knowledge base for social media sentiment analysis. Journal of Ambient Intelligence and Humanized Computing, pp.1-13.

[17] Thakur, S. S. & Dela Cruz, G. B. (2022). Contribution of Social Robots to Interact with Humans and Others in Taking over Entire Job Functions, Such as Greeting and Basic Customer Service in the Workplace. Technoarete Transactions on Industrial Robotics and Automation Systems (TTIRAS), 2(2): 30–36.

[18] C. S., S., Kunju, N. ., & Shahul Hameed, T. A. . (2023). Design and Simulation of Two Stage Wideband CMOS Amplifier in 90 NM Technology. International Journal on Recent and Innovation Trends in Computing and Communication, 11(2s), 249–258. https://doi.org/10.17762/ijritcc.v11i2s.6144

[19] Garcia, P., Martin, I., Garcia, J., Herrera, J., & Fernández, M. Enhancing Cyber security with Machine Learning-Based Intrusion Detection. Kuwait Journal of Machine Learning, 1(4). Retrieved from http://kuwaitjournals.com/index.php/kjml/article/view/157