Springer

INTERNATIONAL CONFERENCE ON MULTI-STRATEGY LEARNING ENVIRONMENT

iCMSLE

Graphic Era Hill University

DEHRADUN • BHIMTAL • HALDWANI

Certificate of Presentation

This is to certify that

Dr. V Ramu

has presented a paper titled

Sentiment Forecasting in Women's Fashion E-Commerce: A Machine Learning Perspective

at the International Conference on Multi-Strategy Learning Environment (ICMSLE-2024) held on 12th and 13th January 2024 at Graphic Era Hill University, Dehradun, India.

Session Chair

Prof. Dibyahash Bordoloi
Conference Chair

Prof. Dr. Mahesh Manchanda
Convener

INTERNATIONAL CONFERENCE ON MULTI-STRATEGY LEARNING ENVIRONMENT

ICMSLE

International Conference on Multi-Strategy Learning Environment (ICMSLE-2024)

12-13, January 2024 | Dehradun, India

Proceedings

Springer

Organized by

Graphic Era Hill University

DEHRADUN · BHIMTAL · HALDWANI

Graphic Era Hill University
Dehradun, India.

Sentiment Forecasting in Women's Fashion E-Commerce: A Machine Learning Perspective

*V. Shobha Rani[1], K. Deepthi[2], Dr. V. Ramu[3], and G. Shirisha[4]
[1]Assistant Professor, School of CS&AI, SR University, Telangana, India
[1]shobhareddy19@gmail.com
[2]Assistant Professor, School of CS&AI, SR University, Telangana, India
[2]deepthivaishu18@gmail.com
[3]Assistant Professor, Depatment of CSE-DS, Mallareddy Engineering College, Telangana, India
[3]ramuds@mrec.ac.in
[4]Lecturer, Depatment of CS, Govt. Degree college(Men) Gajwel,Telangana, India
[4]shirishasiri55@gmail.com

*Corresponding Author: Dr. V. Ramu

Abstract. Sentiment analysis is a technique that uses natural language processing to determine whether a piece of text has a negative, positive, or neutral sentiment. It is also known as emotional AI or opinion mining. It proves invaluable when dealing with noisy, unstructured customer data from diverse channels, where manual processing is impractical. This technique is widely applied across social media posts, blogs, surveys, reviews, and news articles to derive sentiment scores and extract valuable insights. The study in question focuses on analysis of sentiment in the field of reviews for women's clothes, applying Naive Bayes, Support vector machine, Neural networks, Logistic Regression, and other machine learning approaches. Evaluation parameters similar to precision, accuracy, F1-score, recall and (AUC) Area under the Curve is employed to assess the model performance. The research concludes that Logistic Regression and Neural Network models yield the best results, achieving a remarkable 92% accuracy. Notably, Naive Bayes demonstrates efficiency, particularly in handling larger datasets. This study contributes valuable insights into sentiment analysis, classifying women's clothing opinions as positive, neutral, or negative with practical implications for predictive modeling.

Keywords: Sentiment Rating, Machine Learning, Word Embeddings, Customer Reviews, Ensemble Models, Sentiment Analysis.

1 Introduction

Sentiment analysis helps figure out if people like or dislike the main thing in a text [1]. For instance, if a mother would like to purchase clothing for the sake of her children online, she is able to read the reviews.Some may claim that they have a strong preference for clothing that flatters them. Others say bad things and make you look more grown up. Some may say it's comfy and fits well, but has some small issues. And some may claim that it makes you the most stylish person on the street. For a new customer, all these reviews can be confusing, and they might get tired of reading them all and give up on buying. But sentiment analysis can make it simple by saying if the overall feeling is positive, neutral, or negative. It can also give a clear suggestion like recommending or not recommending the product to customers.

Online reviews from people are a terrific approach to learn what clients think; especially when it comes to women's clothing [2]. Customers look at everything, from how good the product is to the services it comes with [3]. With more internet communities and review websites, there are lots of online reviews in different areas. This makes it easier to see what customers think by using text mining methods to analyze the reviews. Two popular techniques for this are sentiment analysis and topic modeling. Topic modeling groups reviews into main issues using certain models. These results are put together to understand what customers overall feel about something.Sentiment analysis focuses on the emotions expressed in the text by analyzing words to determine if they are good or negative [4].

Yet, when it comes to analyzing free-form reviews, sentiment analysis faces some challenges. Using pre-made sentiment dictionaries doesn't always capture the specific details of the reviews. This happens because the unique aspects of the topic or product being reviewed may not be fully considered during the classification of words based on sentiment. Let's take words with positive and negative meanings that are commonly used in customer reviews as an example. Imagine we have seven words: 'terrific,' 'good,' 'interesting,' 'acceptable,' 'tolerable,' 'bad,' and 'terrible.' Now, 'terrific' and 'good' are clearly positive, and 'bad' and 'terrible' are definitely negative. However, 'interesting,' 'acceptable,' and 'tolerable' fall in the middle, and their meaning could change based on the situation. For instance, if a teacher describes a student's report as 'interesting,' it might mean it's almost excellent, or it could mean it's just average without wanting to be too critical.

But, when people make not-so-good comments, it doesn't just make the product look bad; it might also make others not want to buy it [5] (Shah et al., 2018). So, it's crucial to accurately figure out what customers really feel in their reviews. Thi

Main aim of the study is to discover a trustworthy way to categorize customer reviews, especially those about women's clothing online and to predict how customers rate their reviews about women's clothing using computer programs. We're working with a set of reviews from an online store. To make our predictions better, we're preparing the data and adding more details to it. Then, we're checking how well our predictions work using different computer methods like Support Vector Machine (SVM), Logistic Regression,Naïve Bayes and Neural network. The goal is to determine the most effective method to predict customer sentiments by comparing different methods and using both the original and enhanced data.

2 Literature Review

Analyzing how customers feel about women's online clothing can be really helpful, thanks to something called sentiment analysis. But it's crucial to know that how well this analysis works depends on how good the data is and the specific methods used. Sentiment analysis is a way of figuring out people's opinions from written words. It's part of a bigger field called natural language processing (NLP) that has become quite popular lately [6]

The paper helps us to grasp different levels of sentiment analysis, various models for emotions, and how we go about detecting sentiments and emotions in text. It also talks about the difficulties we encounter when trying to analyze sentiments and emotions in text. By using sentiment analysis, you can find out how customers feel about different parts of your organization without having to go through a large number of comments all at once. If you receive a lot of feedback each month, it's impossible for one person to read all the responses. However, you can focus on specific customer categories within your organization and better understand their sentiments by using sentiment analysis and automating this process [7]

Customers' level of satisfaction with a company's products and services is the main indicator of customer satisfaction. It's a big clue about whether customers will keep buying from that company in the future [8]. For businesses in today's competitive market, keeping an eye on and managing customer satisfaction is super important. Sentiment analysis (SA) is a handy tool that can automate a big part of this job [9]. That's why there's been a lot more research on SA in the past fifteen years. People use it for all sorts of things in business, like predicting stock markets, figuring out how well a movie will do, and estimating how many customers might leave.

This study focuses on sentiment analysis, which involves figuring out if a piece of text is negative, positive or neutral. It explores a unique way of doing sentiment analysis using statistical data compression models. This approach has shown to be successful for various text classification tasks like subject classification and authorship attribution. The paper highlights the advantages of this method, such as its ability to recognize non-word or meta word properties, not needing pre-processing, and being tolerant of slang and informal language. The paper uses three different datasets to demonstrate how well the compression-based method works. [10].

In the corpus-based way, figuring out feelings in text is like putting the text into categories. They make a special tool (called a sentiment classifier) using sentences that already show if they're positive or negative. People can mark these sentences themselves or use things like emoticons or star ratings to help. The first study to use this method was by [11], and they tried different machine learning techniques- like Naïve Bayes, Maximum entropy, and Support Vector Machines (SVM) to see how well they work for finding feelings. Now, there's a trend to use deep learning methods. These methods do three things: first, they learn what words mean from a bunch of text. Then, they put these meanings together to understand what a whole sentence means. Lastly, they determine whether every word of the writing is good or negative [12].

Comparative Analysis and Summary

In a comparative analysis of sentiment analysis algorithms, the study [13] focused on general reviews and found Logistic Regression to be the most accurate at 87%. In a subsequent investigation on women's clothing reviews, both Logistic Regression and Support Vector Machine (SVM) surpassed this accuracy, achieving an impressive 92%.

Study [14], analyzing data from internet retailers, identified SVM as the most accurate at 98.2%, outperforming Maximum Entropy and Naive Bayes. Similarly, a study [15] concentrating on technological accessories on Amazon revealed Naive Bayes with the highest accuracy at 98.17%. In contrast, the current study on women's clothing reviews found Logistic Regression and SVM to be consistently accurate at 92%. Notably, a study [16] on eBay app store reviews favored SVM, while the current analysis of 27,126 datasets demonstrated that Logistic Regression was the most accurate.

Another study [17] with a massive dataset of 35 million Amazon.com reviews found Linear SVC to be the most accurate at 88.11%, whereas Logistic Regression and SVC outperformed with a higher accuracy of 92% in the present work. This analysis underscores the consistent prowess of Logistic Regression and SVM across various studies and domains, emphasizing their robust performance in sentiment analysis tasks, while also recognizing the influence of dataset characteristics and domain-specific considerations on algorithm preference.

3 Proposed Methodology

The planed methodology involves collecting a diverse dataset of women's clothing reviews from various sources, preprocessing the text data, and extracting features utilizing methods such as TF-IDF (Term frequency-Inverse document frequency). Sentiment labeling will be done through a combination of manual annotation and leveraging pre-trained sentiment lexicons. Machine learning models, including Naive Bayes, Logical Regression, neural network and Support Vector Machines, will be explored and fine-tuned for sentiment analysis. The goal is to provide actionable insights for improving product offerings and customer satisfaction in the women's clothing industry. I'm trying different methods to predict what customers feel from their reviews. **Naive Bayes is a quick and important method in understanding text**, but if you don't have a huge amount of data or a powerful computer, other methods might be helpful too. I started by looking at the data and making some charts to understand it better. Then, I tested different models and compared them in different ways.

3.1 Dataset Description

The custom datset is used in this study consists of Ten feature variables and 27,126 rows.
Each row contains the following variables and reflects a customer review:
Clothing ID: It is a categorical variable consisting of integers that indicates the particular article under review.
Title: Title of the review is stored in a string variable.
Age: A positive integer variable representing theage of the reviewer.
Review Text: Review's primary body text, stored in a string variable.
Rating: The customer's rating of the product is represented as a positive ordinal integer variable with a range of1 for the poorest and 5 for the best.
Class name: A classification name that designates the product's class.
Recommended IND: The customer's recommendation of the product is shown by a binary variable (0 indicates it is not advised, while 1 indicates it).
Positive Feedback Count: Count of the customers, who thought this review was positive, expressed as an integer.
Department Name: A category name designating the product department.
Division Name: A classification name designating the product's upper tier division.

3.2 Reading the Dataset and Importing Modules

To conduct our analysis, the first step is setting up our environment. I accomplished this by importing necessary modules and reading the data. Below is the initial snapshot of the data. Afterwards, I determined that certain columns were unnecessary for our analysis. Subsequently, I created a new dataset that includes only the columns relevant to our analysis.

	Unnamed: 0	Clothing ID	Age	Title	Review Text	Rating	Recommended IND	Positive Feedback Count	Division Name	Department Name	Class Name
0	0	862.0	63.0	NaN	This is my new favorite sweater. it is lightwe...	5.0	1.0	0.0	General Petite	Tops	Knits
1	1	1094.0	57.0	Perfect except slip	This is my new favorite dress! my only complai...	4.0	1.0	3.0	General Petite	Dresses	Dresses
2	2	1078.0	34.0	Such high hopes!	I purchased this for a very good price and i t...	3.0	0.0	0.0	General	Dresses	Dresses
3	3	262.0	49.0	Comfortable but not super-flattering on me	I tried these on at the store and the fit was ...	4.0	1.0	1.0	General Petite	Intimate	Lounge
4	4	999.0	24.0	Its okay	The pattern of this skirt is adorable and look...	3.0	1.0	0.0	General	Bottoms	Skirts

Fig.1: Sample Dataset

3.3 Including word counts in the data frame and determining the frequency of specific words

Adding word counts in a data frame is a highly beneficial practice as these counts can be utilized to derive valuable information. To achieve this, I created a function named "word counts".

	Review Text	Rating	Class Name	Age	Word Counts
0	This is my new favorite sweater. it is lightwe...	5.0	Knits	63.0	{'and': 1, 'be': 1, 'can': 1, 'casual': 1, 'dr...
1	This is my new favorite dress! my only complai...	4.0	Dresses	57.0	{'and': 1, 'as': 1, 'be': 2, 'but': 1, 'can': ...
2	I purchased this for a very good price and i t...	3.0	Dresses	34.0	{'add': 1, 'and': 4, 'appropriate': 1, 'at': 1...
3	I tried these on at the store and the fit was ...	4.0	Lounge	49.0	{'and': 2, 'are': 1, 'as': 1, 'at': 1, 'attent...
4	The pattern of this skirt is adorable and look...	3.0	Skirts	24.0	{'adorable': 1, 'an': 1, 'and': 2, 'best': 1, ...

Fig2: Determining the frequency of speific words

3.4 Using a Word Cloud to Show the Densities of Selected Words, Class Names, and All Words in the Reviews

I demonstrated word density in this area, which can provide insightful information. Firstly, I identified specific words reflecting customer sentiments, such as love, hate, fantastic, or regret. Second, I decided to look at the product class names instead of the product names because there were none. This way, we can gain insights into the most favored classes. Additionally, I found it intriguing to explore the overall word densities in the reviews. At last, I employed the Word Cloud module to present the first five rows of tables that showed word counts for particular words together with the class names that corresponded to those words.

The tables and figures below indicate that positive expressions like super, great and love were frequently used. Analyzing classes with in the structure of sentiment analysis using women's clothing reviews involves understanding the distribution of sentiments across different classes or categories. When analyzing the classes, it becomes evident that customers predominantly favored dress, knits, and blouses. Notably, the words dress and love emerged as frequently used terms across all reviews.

Selected Words

super 1726
glad 615
great 6119
happy 706
love 8955
dtype: int64

Class Names

Dresses 6324
Sweaters 1428
Empty 6514
Knits 4843
Blouses 3098
Name: Class Name, dtype: int64

Analysis of Sentiments

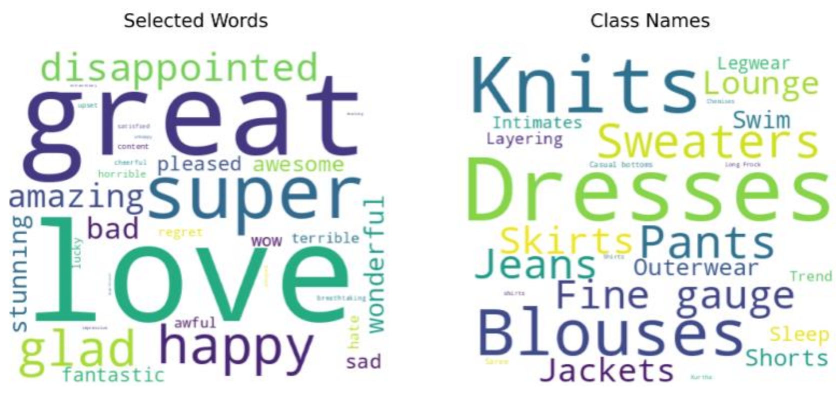


Fig.3: selected words and class names

Fig.4: all words in reviews

3.5 Examining the Relationship among Age, Class Name, and Rating

I considered it worthwhile to explore the connection between the rating, class names, and age, as certain age groups might consistently provide low ratings, write negative reviews, or lean towards products in the same class. To investigate this correlation, I employed the dynamic charts presented below.

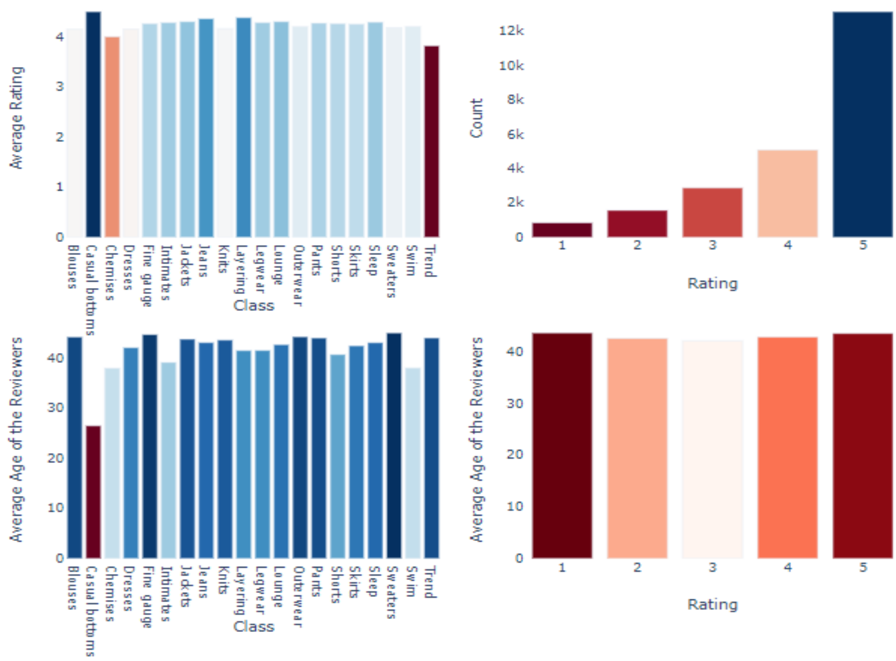


Fig.5: Relationship among age, class name and rating

The majority of ratings appear to be positive, and the average rating across different classes appears relatively consistent. However, when examining age groups, there isn't a significant change in the average age based on the rating. Similarly, the average age shows only minor variations among different class names, except for casual bottoms. It's worth noting that the chart below indicates only two reviews for casual bottoms, making it unreliable for drawing meaningful conclusions.

3.6 Creating a Classifier for Sentiment

I added a new column for sentiment because the dataset doesn't have one that indicates if a sentiment is positive or negativeThrough this procedure, I classified evaluations as either favorable (**True in the new data frame**) or negative (**False in the new data frame**) based on ratings of four or higher. Reviews with neutral ratings, equal to 3, were excluded. I then separated the data into test and training sets.

Then I continued to fit each model separately. Given that some models require substantial processing time, it is more efficient to run each of them in separate cells.

Neural Network

```
start_time = dt.datetime.now()
neural_network = MLPClassifier()
neural_network.fit(X_train, y_train)
elapsed_time = dt.datetime.now() - start_time
print('Execution time: ', str(elapsed_time))
```

Elapsed time: 0:03:38.877403

Logistic Regression

```
start_time = dt.datetime.now()
logistic_regression = LogisticRegression()
logistic_regression.fit(X_train, y_train)
elapsed_time = dt.datetime.now() - start_time
print('Execution time: ', str(elapsed_time))
```

Elapsed time: 0:00:01.945027

Support Vector Machine (SVM)

```
start_time = dt.datetime.now()
support_vector_machine = SVC()
support_vector_machine.fit(X_train, y_train)
elapsed_time = dt.datetime.now() - start_time
print('Execution time: ', str(elapsed_time))
```

Elapsed time: 0:01:13.701644

Naive Bayes

```
start_time = dt.datetime.now()
naive_bayes = MultinomialNB()
naive_bayes.fit(X_train, y_train)
elapsed_time = dt.datetime.now() - start_time
print('Execution time: ', str(elapsed_time))
```

Elapsed time: 0:00:00.035304

4 Evaluating Models

Initially, I included predicted outcomes in my training set.

	Review Text	Rating	Class Name	Age	Word Counts	Sentiment	Logistic Regression	Naive Bayes	SVM	Neural Network
13914	I love these jeans! their fit is fabulous and ...	4.0	Jeans	68.0	{'and': 1, 'are': 1, 'brand': 1, 'comfortable'...	True	True	True	True	True
21394	Saw this online, but it said the store was out...	5.0	Blouses	57.0	{'and': 2, 'at': 1, 'be': 1, 'bigger': 1, 'bit...	True	True	True	True	True
24142		NaN	NaN	NaN	{}	False	False	True	False	False
11111	These run so small!! i was dissapointed with h...	5.0	Jeans	56.0	{'are': 1, 'back': 1, 'can': 1, 'dissapointed'...	True	True	True	True	True
1428	Very cute dress but the skirt flares out more ...	4.0	Dresses	43.0	{'above': 1, 'also': 1, 'alteration': 1, 'at':...	True	True	True	True	True

Fig.6: Embedding Results in the Data Frame

ROC Curves and AUC

I initiated the evaluation process by examining the ROC curve and AUC. While the results may seem favorable, they offer limited insights. To determine the best model, it's crucial to also scrutinize additional evaluation metrics.

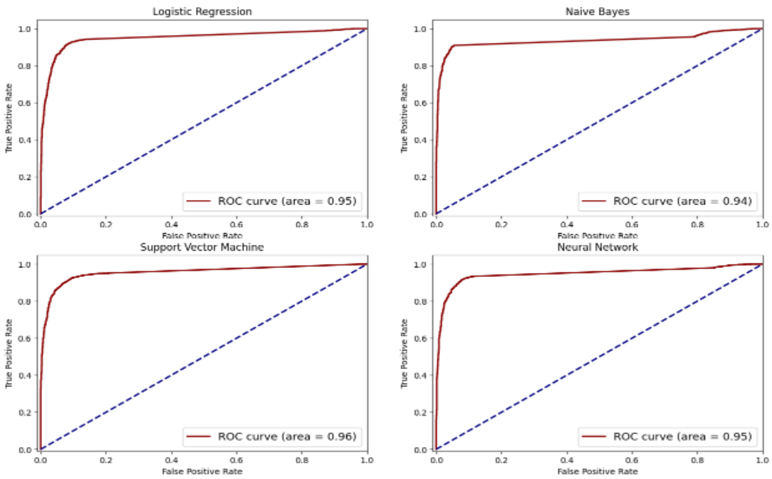
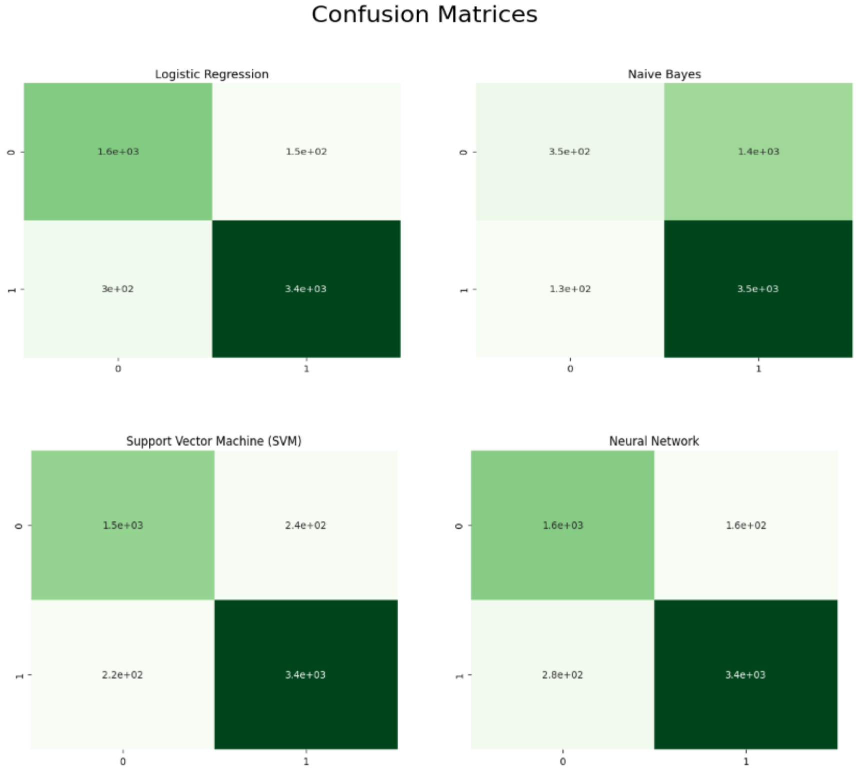


Fig.7: Evaluation process by examining ROC and AUC curves

4.2 Confusion Matrices

I also utilized confusion matrices to get more information. It is evident that while SVM has excellent ROC values, it does not produce outcomes that are healthy



4.3 Experimental Results and Analysis

Neural Network
Comparable to the SVM and LR, the accuracy of the Neural Network approach is 92%. Naive Bayes has a 71% precision rate and an 82% F1 score.

	Precision	Recall	F1-score	Support
False	0.85	0.91	0.88	1774
True	0.95	0.92	0.94	3652
Accuracy			0.92	5426
Macro avg	0.90	0.92	0.91	5426
Weighted avg	0.92	0.92	0.92	5426

Table1: performance measures of Neural network

Logistic Regression

The Recall, precision score, and f1 scores are 92%, 94%, and 96%, respectively. Conversely, the logistic regression and SVM precision values are 96% and 94%, respectively. When compared to the other two classifiers, the AUC exhibits the highest value. Compared to SVM, it performs better. Its accuracy rate is 92%.

	Precision	Recall	F1-score	Support
False	0.85	0.91	0.88	1774
True	0.96	0.92	0.94	3652
Accuracy			0.92	5426
Macro avg	0.90	0.92	0.91	5426
Weighted avg	0.92	0.92	0.92	5426

Table2: performance measures of Logistic Regression

Support Vector Machine (SVM)
The table below shows that the SVM's accuracy is 92%, an extremely good number. At 88%, the precision value is comparable to that of logistic regression.

	Precision	Recall	F1-score	Support
False	0.88	0.87	0.87	1774
True	0.94	0.94	0.94	3652
Accuracy			0.92	5426
Macro avg	0.91	0.90	0.90	5426
Weighted avg	0.92	0.92	0.92	5426

Table3: performance measures of Support Vector Machine

Naive Bayes

Naive Bayes technique accuracy is 71%, which is comparable to that of the LR and support vector machine (SVM). Naive Bayes has a 73% precision rate and an 82% F1 score.

	Precision	Recall	F1-score	Support
False	0.73	0.20	0.31	1774
True	0.71	0.96	0.82	3652
Accuracy			0.71	5426
Macro avg	0.72	0.58	0.57	5426
Weighted avg	0.72	0.71	0.65	5426

Table4: performance measures of Naive Bayes

5 Conclusion

Sentiment analysis was used to evaluate whether the product is recommended, employing various machine learning algorithms to enhance prediction accuracy. We also integrated a deep learning algorithm to assess how well it performed in contrast to conventional machine learning techniques. The classification algorithms involved Logistic Regression, Support Vector Machine (SVM),and Naive Bayes and Neural Network.

When comparing these models, it becomes challenging to single out the best among the top 5, as their scores are very close. However, upon reviewing all evaluation metrics in the model evaluation section, Logistic Regression and Neural Network emerged as the top performers for our analysis. Both models prove highly effective in predicting sentiment. Conversely, Naive Bayes demonstrates a quicker runtime, and this efficiency might become a notable advantage, especially with larger datasets.

References

1. Gräbner, Dietmar, et al. "Classification of customer reviews based on sentiment analysis." *Information and communication technologies in tourism 2012*. Springer, Vienna, 2012. 460-470.
2. Chung, Wingyan, and Tzu-Liang Bill Tseng. "Discovering business intelligence from online product reviews: A rule-induction framework." *Expert systems with applications* 39.15 (2012): 11870-11879.
3. Moghaddam, Samaneh, and Martin Ester. "Aspect-based opinion mining from online reviews." *Tutorial at SIGIR Conference*. 2012.
4. Liu, Bing, and Lei Zhang. "A survey of opinion mining and sentiment analysis." *Mining text data*. Springer, Boston, MA, 2012. 415-463.
5. shah, A., karan shah, hridesh shah and dhruv shah. (2018). Research article data analysis on customer review., International Journal of advanced research(IJAR) 6(10): 1487– 1492.
6. Nandwani, P., Verma, R. A review on sentiment analysis and emotion detection

from text. *Soc. Netw. Anal. Min.* **11**, 81 (2021). https://doi.org/10.1007/s13278-021-00776-6 Nandwani, P., Verma, R. A review on sentiment analysis and emotion detection from text. *Soc. Netw. Anal. Min.* **11**, 81 (2021). https://doi.org/10.1007/s13278-021-00776-6

7. P. &. S. V. D. Sudhir, "Comparative study of various approaches, applications and classifiers for sentiment analysis.," Global Transitions Proceedings, vol. 2(2), no. 2021, pp. 205-211.

8. Capuano, Nicola, et al. "Sentiment analysis for customer relationship management: an incremental learning approach." *Applied Intelligence* 51 (2021): 3339-3352.
9. Hasan, Mehedi, et al. "Feedback or research: separating pre-purchase from post-purchase consumer reviews." *Advances in Information Retrieval: 38th European Conference on IR Research, ECIR 2016, Padua, Italy, March 20–23, 2016. Proceedings 38*. Springer International Publishing, 2016.

10. A. O. Opesade, "A Framework for Assessing E-Commerce Customers' Satisfaction based on Electronic Words of Mouth.," Covenant Journal of Informatics and Communication Technology

11. Chatterjee, Deb Prakash, et al. "A survey on sentiment analysis." *Emerging Technologies in Data Mining and Information Security: Proceedings of IEMIS 2020, Volume 2*. Springer Singapore, 2021.
12. Jurek, Anna, Maurice D. Mulvenna, and Yaxin Bi. "Improved lexicon-based sentiment analysis for social media analytics." *Security Informatics* 4.1 (2015): 1-13.
13. Jagdale, Rajkumar S., Vishal S. Shirsat, and Sachin N. Deshmukh. "Sentiment analysis on product reviews using machine learning techniques." *Cognitive Informatics and Soft Computing: Proceeding of CISC 2017*. Springer Singapore, 2019.
14. Alharbi, Ahmed Sulaiman M., and Elise de Doncker. "Twitter sentiment analysis with a deep neural network: An enhanced approach using user behavioral information." *Cognitive Systems Research* 54 (2019): 50-61.
15. Cheong, Hon-Sang, et al. "Hierarchical attention networks for different types of documents with smaller size of datasets." *Robot Intelligence Technology and Applications: 6th International Conference, RiTA 2018, Kuala Lumpur, Malaysia, December 16–18, 2018, Revised Selected Papers 6*. Springer Singapore, 2019.
16. C. M. Suryavanshi, "Sentiment Analysis of Product Reviews: Opinion Extraction and Display," 2021.
17. T. K. Shivaprasad and J. Shetty, "Sentiment analysis of product reviews: A review," in 2017 International Conference on Inventive Communication and Computational Technologies (ICICCT), Mar. 2017, pp. 298–301. doi: 10.1109/ICICCT.2017.7975207.
18. R. S. Jagdale, V. S. Shirsat, and S. N. Deshmukh, "Sentiment Analysis on Product Reviews Using Machine Learning Techniques," 2019, pp. 639–647. doi: 10.1007/978981-13-0617--4_61.
19. S. Moghaddam, "Beyond Sentiment Analysis: Mining Defects and Improvements from Customer Feedback," 2015, pp. 400–410. doi: 10.1007/978-3-319-16354-3_44.

20. A. Dhara, "Sentiment Analysis of Product-Based Reviews Using Machine Learning Approaches," 2017.