



Determining Customer Sentiment in Fashion Product Reviews using Lexicon-based Approach and Machine Learning Techniques

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ABSTRACT

Nowadays, E-commerce websites use online reviews to know what and how customers feel about their products. These reviews are essential to the growth and improvement of these companies. The fashion industry thrives on the feedback and perception of the user. Hence, the need to know the user's feelings and opinions after using their products. Sentiment analysis evaluates people's opinions from the reviews and helps the business make decisions based on its results. The analysis process involves natural language processing, text analysis, and opinion classification. The sentiment analysis in this project using a fashion review dataset was done using the lexicon-based approach and machine learning algorithms. The lexicon-based approach classified the sentiments as negative, neutral, and positive. The classification was done using the polarity score of reviews, and the NLP techniques used are TextBlob and VADER sentiments. The machine learning algorithms used are Logistic Regression, SVM, and AdaBoost. The logistic regression model and AdaBoost showed higher accuracy and precision than the SVM model.

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INTRODUCTION

Sentiment Analysis, also known as opinion mining, studies people's opinions about products or services expressed through spoken or written communication. Online reviews are crucial in the e-commerce industry, particularly fashion, where businesses use sentiment analysis to determine customer opinions and feelings. According to a survey by Wankhade et al. (2022), sentiment analysis is an effective tool for automating customer sentiment in online reviews. The information gathered from customer reviews can be processed using sentiment analysis to provide valuable insights for organisational growth (Jain, Pamula, & Srivastava, 2021).

Three categorization levels are involved in sentiment analysis: sentiment analysis at the document, phrase, and aspect levels. Every sentence in a document communicates the feeling. The sentence's objectivity or subjectivity must be determined in the first phase. The aspect-level sentiment analysis classifies the sentiment

using the specific aspect of the entity. (Medhat, Hassan and Korashy, 2014a) (Sentiment Analysis and Opinion Mining - Bing Liu - Google Books, 2022)

Lexicon-based approaches like TextBlob and the Vader Sentiment NLP algorithms can perform sentiment analysis. These methods determine the polarity score of a sentence or document to identify the sentiment type contained. Moreover, traditional supervised machine-learning algorithms can also specify the sentiment linked to an entity. These algorithms classify reviews based on user recommendations of a product. Machine learning approaches use a training set to develop a sentiment classifier that classifies sentiment.

Statement of Problem

Customer reviews are vital for fashion brands to grow and improve. Businesses make informed decisions based on user feedback to enhance their products. However, issues can arise during the review analysis process. There may be

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numerous reviews to sift through, as well as emotional biases on the part of humans, and other factors that can impede accurate sentiment prediction in studies. This is a problem for the e-commerce store because when they cannot determine the intention and meaning the user is trying to communicate, thus do not fulfill the need for the online review system.

Using machine learning alongside lexicon-based NLP techniques to help determine the sentiment in customer reviews will help create a robust hybrid system.

Objectives of the Study

This research aims to determine customer sentiment in fashion product reviews using a lexicon-based approach and machine learning techniques. This study aims to empower fashion businesses to make data-driven decisions, improve product offerings, and enhance customer satisfaction by developing an accurate and domain-specific sentiment analysis model.

The research objectives are as follows:

1. To determine the sentiment types that appear most frequently in evaluations of clothing.
2. To assist companies in finding opportunities for development and assisting those in making decisions based on customer feedback.
3. To assist companies in identifying consumer groups that have favorable reviews and using information for focused marketing initiatives.
4. To create fresh machine learning techniques for categorising reviews of fashion merchandise.
5. To publish the study's findings in a journal that has undergone peer review.

JUSTIFICATION OF THE STUDY

This research utilises a combined methodology of lexicon-based analysis and advanced machine learning algorithms to analyse customer sentiment in fashion product reviews. By comprehending the emotions conveyed in these reviews, fashion firms can make informed decisions, improve customer satisfaction, and

align their offerings with market expectations. The study aims to provide contextually aware and accurate sentiment analysis through developing a domain-specific lexicon and applying state-of-the-art machine-learning models. (Shivaprasad and Shetty, 2017). The findings of this research will contribute to the field of sentiment analysis and assist clothing retailers in making well-informed decisions.

LITERATURE REVIEW

Natural Language Processing

Natural Language Processing (NLP) is a subfield of artificial intelligence (AI) that focuses on the interaction between computer and human language like speech and text. It is concerned with enabling computers with the ability to understand text and spoken words the way a human can – in a way that is both meaningful and valuable. (Chowdhary, 2020) In essence, NLP combines computational linguistics with machine learning and deep learning models to enable computers to process human language and to understand its full meaning, complete with the writer's or speaker's intent and sentiment. (Christopher and Hinrich 1999). NLP has a wide range of uses in a variety of industries, including education, healthcare, fashion industry and finance. Deep learning models have been at the forefront of recent developments in natural language processing, achieving cutting-edge outcomes in a variety of NLP tasks, such as sentiment analysis and machine translation. For instance, a study by Zhang et al. (2018) found that deep learning models have significantly improved the accuracy of sentiment analysis, a task that involves identifying the sentiment or emotion expressed in each text. Similarly, another study by Vaswani et al. (2018) demonstrated the effectiveness of deep learning models in machine translation, which involves translating text from one language to another.

Sentiment Analysis

Sentiment analysis is an NLP technique that extracts subjective information from a document related to an entity and helps businesses understand social sentiment. (Liu

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2022) In simple terms, sentiment analysis involves identifying positive, negative, or neutral connotations in text to determine emotional tone. (Mohammed 2016) The analysis can provide valuable insights into how people feel about various subjects, including people, events, topics, and brands, allowing businesses, individuals, and organizations to make more informed decisions.

Sentiment analysis has been widely recognised as a valuable tool for businesses looking to improve their customer experience. It is used in various fields, such as politics, business, and market research. It helps understand customer opinions, identify trending topics, gauge public reactions to events, and assess public sentiment towards social issues.

A study by Harvard Business Review (2007) found that companies that actively manage

customer experience have higher customer satisfaction rates and increased revenue. Sentiment analysis can also be useful for fashion brands looking to improve their customer experience. By analysing customer reviews and social media posts, fashion brands can gain insights into the emotions and opinions expressed about their products and brand (Lang and Zhaobrand, 2020). This can help them identify areas of improvement, track trends, and make data-driven decisions to enhance the overall customer experience. With sentiment analysis, fashion brands can ensure they meet customer expectations and stay ahead of the competition. As NLP technology advances, sentiment analysis will play a significant role in understanding human emotions and opinions.

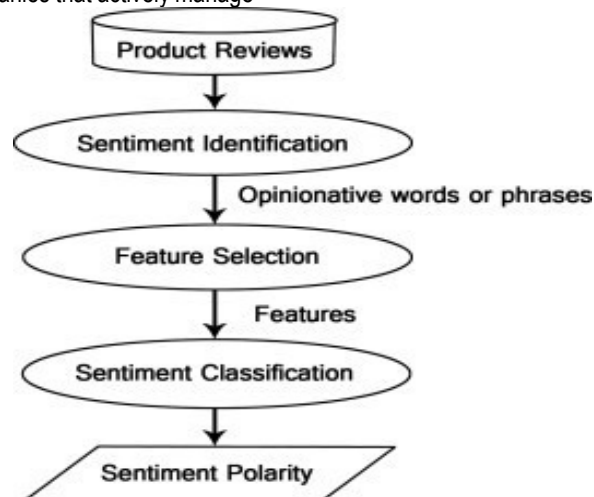


Fig 1: Steps of sentiment analysis in product reviews (Medhat, Hassan and Korashy, 2014b)

Types of Sentiment Analysis

Emotions can be represented in various ways, with positive, negative, or neutral being the most common. Different types of sentiment analysis can capture, meet consumer needs, and categorise emotions, with previous research focusing mostly on these categories:

- i. Document-Level Sentiment Analysis: This is the most basic form of sentiment analysis, where the overall sentiment of an entire document (such as a review, article, or tweet) is classified as positive, negative,

or neutral. (Behdenna, Barigou, and Belalem, 2018).

- ii. Sentence-Level Sentiment Analysis: In this type, sentiment analysis is performed in a document sentence-by-sentence basis. Each sentence is classified as positive, negative, or neutral, providing a more fine-grained analysis. (Bongirwar, 2015).
- iii. Entity-Level Sentiment Analysis: Here, the focus is on specific entities within the text, such as people, products, or places. The

sentiment towards each entity is analysed, allowing for a deeper understanding of opinions.

- iv. Aspect-Based Sentiment Analysis: This analysis goes beyond entities and focuses on specific aspects or features. Its purpose is to determine the sentiment associated with each aspect. For instance, idea is analyzed separately for attributes such as design, performance, and customer services in a product review.

Lexicon-Based Sentiment Analysis

Lexicon-based sentiment analysis is a technique that uses predefined lexicons or dictionaries to classify sentiments based on associated words' sentiment scores. This approach is helpful in dealing with specialised text data with distinct sentiment implications, such as fashion product reviews (Kumaresh et al., 2019). The lexicon used in this sentiment analysis contains a vast list of words, phrases, and expressions, each annotated with sentiment scores that capture the polarity of the associated word. (Taboada et al., 2011).

During the analysis, the text is broken down into smaller units, such as individual words or sentences. The lexicon is then used to look up each word's sentiment score. The sentiment scores of all the words in each text are aggregated to determine the overall sentiment of the text. The final sentiment classification is often based on a threshold value, where scores above a certain threshold are classified as positive, scores below

another threshold as unfavourable, and scores in between as neutral (Khan et al., 2014).

Machine Learning

A branch of artificial intelligence known as machine learning focuses on creating computer programmes that automatically get more efficient at what they do as they gain more experience. The goal of machine learning is more application systems with more robust learning capabilities (Jordan and Mitchell, 2015). Machine learning involves building systems that learn independently and can make informed decisions based on what they have learned. A domain-independent enabling technology for a wide variety of computer applications is what machine learning research aims to create. Robotics, intelligent databases, computer-aided design, sentiment analysis, and knowledge-based consultant systems are just a few of the computer-related fields where an enormous advancement in machine learning could have a big influence.

Machine learning models can be used to predict the sentiment contained in a document or sentence. Machine learning-based sentiment analysis is an advanced approach that uses the power of artificial intelligence (AI) and statistical modelling to classify sentiments in text data automatically. Unlike lexicon-based methods, machine learning techniques do not rely on predefined sentiment scores, and text dictionaries but instead learn from vast amounts of labelled data to identify patterns and relationships between words and sentiments. (Hasan et al., 2018).

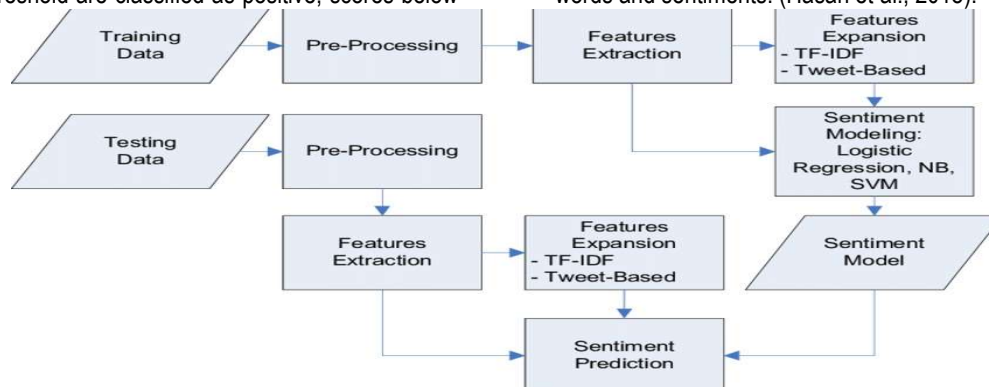


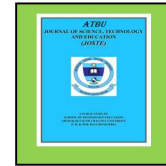
Fig 2: Sentiment-Analysis-Model-machine-learning-classifier-for-polarity-detection in sentences (Setiawan, Widyantoro and Surendro, 2018)

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The process of machine learning-based sentiment analysis begins with a labeled dataset, where human annotators have assigned sentiments (positive, negative, or neutral) to various text samples. This labelled data serves as the training set for the machine learning model. The model then undergoes a training process where it iteratively adjusts its internal parameters to minimize errors and optimize sentiment predictions.

When the model has been trained, it can be applied to analyse new, unexplored text data. To prepare the text for analysis, it may involve tokenization, lemmatization, removing stop words, and other text-cleaning techniques. The model then applies its learned knowledge to classify the sentiment of the text accurately.

Classification of Machine Learning

Machine learning algorithms are grouped into three categories: supervised, unsupervised, and reinforcement learning. A supervised machine learning algorithm learns from labelled training data to make predictions or decisions (Osisanwo et al., 2017). Examples include support vector machines (SVM), Naïve Bayes, and Nearest Neighbour.

In contrast to supervised learning, unsupervised learning deals with unlabelled data. The algorithm's objective is to uncover the underlying structure or patterns in the data without any explicit guidance in the form of labelled examples. Instead, the algorithm seeks to identify similarities, clusters, or relationships within the data points (Alloghani et al., 2020). Examples include clustering, K-means, and many more. Recommender systems and anomaly detection.

Finally, reinforcement learning describes machine learning algorithms that aim to train an agent to relate appropriately, considering its defined environment based on the correct rules that govern such an agent, the environment, and its behaviour in the background.

REVIEW OF RELATED WORKS

Nguyen et al. (2018) used a comparative study of text sentiment classification models using frequency-inverse document

frequency vectorization in supervised machine learning and lexicon-based techniques. A combination of Lexicon-based and traditional supervised machine-learning algorithms will detect sentiment in customer feedback. Support Vector Machines (SVM), Gradient Boosting (GB), and Logistic Regression (LR) are the supervised machine learning algorithms. Likewise, three lexicon-based techniques are employed: the Pattern Lexicon, the SentiWordNet Lexicon, and the Valence Aware Dictionary and Sentiment Reasoner (VADER). The study used data from the Amazon website, consisting of 43,620 product reviews from 1,000 products. The performance of the models was determined using a classification report, which gives the number of wrong and right predictions for each model. (Tasnim 2020). It also used other metrics like accuracy, precision, and F1 score. The findings demonstrate that the Logistics Regression, SVM, and Gradient Boosting models, respectively, have an F1-score of 94%, 92%, and 94%, and accuracy of 89%, 87%, and 90%; precision of 90%, 88%, and 91%; and recall of 98%, 98%, and 97%. Pattern, VADER, and SentiWordNet models had accuracy of 69%, 83%, and 80%, recall of 72%, 89%, and 88%, precision of 88%, 90%, and 90%, and F1-scores of 79%, 89%, and 88%, respectively. The supervised machine-learning models performed slightly better compared to the lexicon-based models.

The study by Yerpude et al. (2019) focused on using Natural Language Processing (NLP) and SentiWordNet to analyze the positive, negative, or neutral sentiment toward products. The research performed sentiment analysis on product reviews of electronic products and feature-based sentiment analysis on product reviews on mobile phones. It employs a lexicon-based methodology that tokenizes text to determine the sentiment of product reviews on an online marketplace.

In this study, sentiment analysis of customer reviews is carried out, and the results are presented as bar graphs and pie charts. The overall favourable and negative reviews of a product are depicted in the pie chart. It examined the polarity of each feature in each review of a

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particular product, and it generated a bar graph showing the total number of positive and negative comments of each item.

Rajeswari et al. (2020) used a hybrid approach combining lexicon-based and machine-learning techniques. It was claimed that the main flaw in existing systems was their exclusive concentration on classifying feedback as either positive or negative. A customer's opinion of a product or movie will be misinterpreted if the unbiased evaluation isn't taken into consideration, which will harm the industry or trend. The study uses machine learning algorithms like Support Vector Machine, Decision Tree, Logistic Regression, and Naive Bayes for sentiment analysis to resolve neutral opinions beyond the binary categorization of the customer's review.

SentiWordNet is a lexicon-based technique. The authors concluded that the third-class neutral can be predicted using a hybrid strategy that uses the lexical approach to help solve the binary classification problem.

RESEARCH DESIGN

Machine Learning Models

Supervised machine learning models are employed in this project to help determine the sentiment associated with the customers' reviews. The machine learning algorithms adopted in this project are logistic regression, support vector machine, and AdaBoost.

The machine learning algorithms are trained with the review sparse matrix as the set of features, and the customer recommendation as the target variable.

Logistic Regression Model

The already processed reviews which are now in the form of a sparse matrix are trained using the logistic regression algorithm. The logistic regression is trained using a class weight of balanced, and max iteration of 1000. The resulting model is then used to make predictions on the test dataset. The logistic regression prediction is then compared to the original customer recommendation to see how the model performs.

```
In [170]: print("Logistic Regression confusion matrix")
          print(logConfusionMatrix)
```

```
Logistic Regression confusion matrix
[[ 515 382]
 [ 655 3393]]
```

Fig. 3. Logistic Regression Confusion Matrix

Classification Report for the Logistic Regression Model				
	precision	recall	f1-score	support
0	0.44	0.57	0.50	897
1	0.90	0.84	0.87	4048
accuracy			0.79	4945
macro avg	0.67	0.71	0.68	4945
weighted avg	0.82	0.79	0.80	4945

Fig. 4. Logistic Regression Classification Report

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As seen in fig. 4.0. The logistic regression model has a true positive value of 3393 and a true negative value of 655. The false negative is 515, and the false positive is 382. This model seems to have performed better in classifying the positive reviews compared to classifying the negative reviews. In comparison to the other two models, the logistic regression model appears to have the truest positive results. Also, from the classification report, the logistic regression model has a 79%

accuracy, 82% precision, a recall of 79%, and an f1-score of 80%.

Support Vector Machine Model

The SVM model is trained using a linear kernel and a balanced class weigh, and a C value of 1.0. The result from using the support vector machine classifier model to predict the sentiment analysis of is shown below in fig. 4.2 below.

```
In [195]: print("SVM Classifier confusion matrix")
          print(svcConfusionMatrix)

SVM Classifier confusion matrix
[[ 493  404]
 [ 714 3334]]
```

Fig. 5. SVM Classifier Confusion Matrix

```
In [196]: print("SVM Classifier Classification Report")
          print(svcClassificationReport)
```

SVM Classifier Classification Report				
	precision	recall	f1-score	support
0	0.41	0.55	0.47	897
1	0.89	0.82	0.86	4048
accuracy			0.77	4945
macro avg	0.65	0.69	0.66	4945
weighted avg	0.80	0.77	0.79	4945

Fig. 6: SVM Classifier Classification Report

The SVM classifier handles classifying negative sentiments better compared to the logistic regression model as it has a true negative value of 714. It appears to be the model with the highest number of true negatives among the 3 models. The SVM model has a 77% accuracy, 80% precision, 77% recall, and a f1-score of 79%, according to the classification report.

is the decision tree classifier algorithm. The reason for using decision tree as the base estimator is because it is versatile and creates a robust ensemble model.

AdaBoost Model

The AdaBoost Model is a boosting algorithm and the base algorithm used in this case

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This algorithm creates a balance between the negative and positive predictions.

```
[197]: print("AdaBoost confusion matrix")
print(adaBoostConfusionMatrix)

AdaBoost confusion matrix
[[ 554  343]
 [ 689 3359]]
```

Fig. 7: AdaBoost Confusion Matrix

```
In [198]: print("AdaBoost Classification Report")
print(adaBoostClassificationReport)

AdaBoost Classification Report
      precision    recall  f1-score   support

     0       0.45     0.62     0.52       897
     1       0.91     0.83     0.87      4048

 accuracy          0.79     4945
 macro avg          0.68     0.72     0.69     4945
 weighted avg          0.82     0.79     0.80     4945
```

Fig. 8: AdaBoost Classification Report

The accuracy score for the model is 79%, the precision is 82%, the recall is 79%, and the f1- score is 80%.

GRAPHICAL REPRESENTATION OF THE MACHINE LEARNING MODEL RESULTS

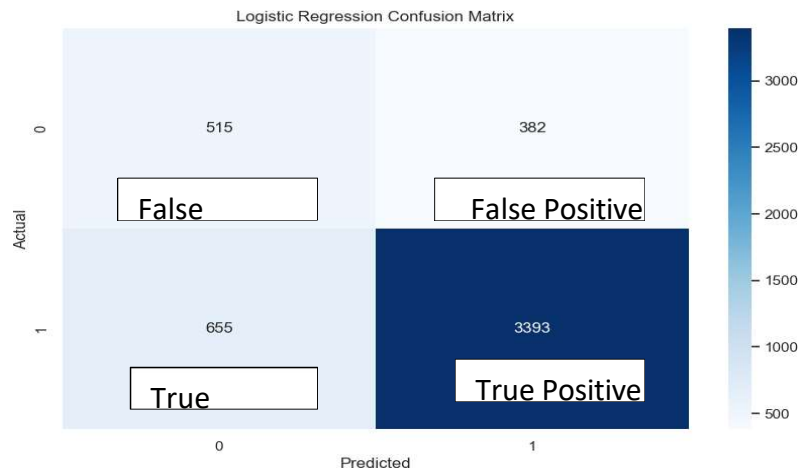


Fig. 9: Confusion Matrix of the Logistic Regression Model

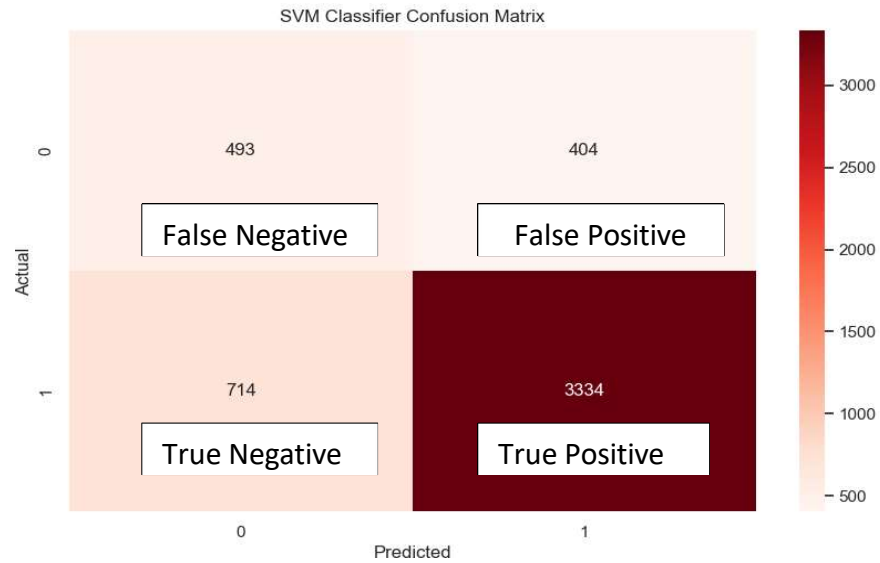


Fig. 10. Precision-Recall Curve of the Logistic Regression Model

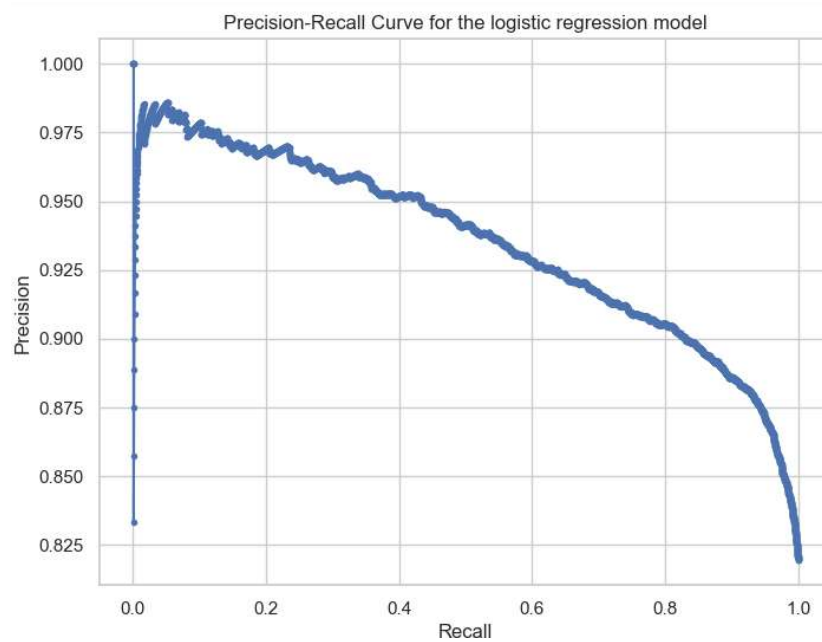


Fig. 11: Confusion Matrix of the SVM Classifier Model

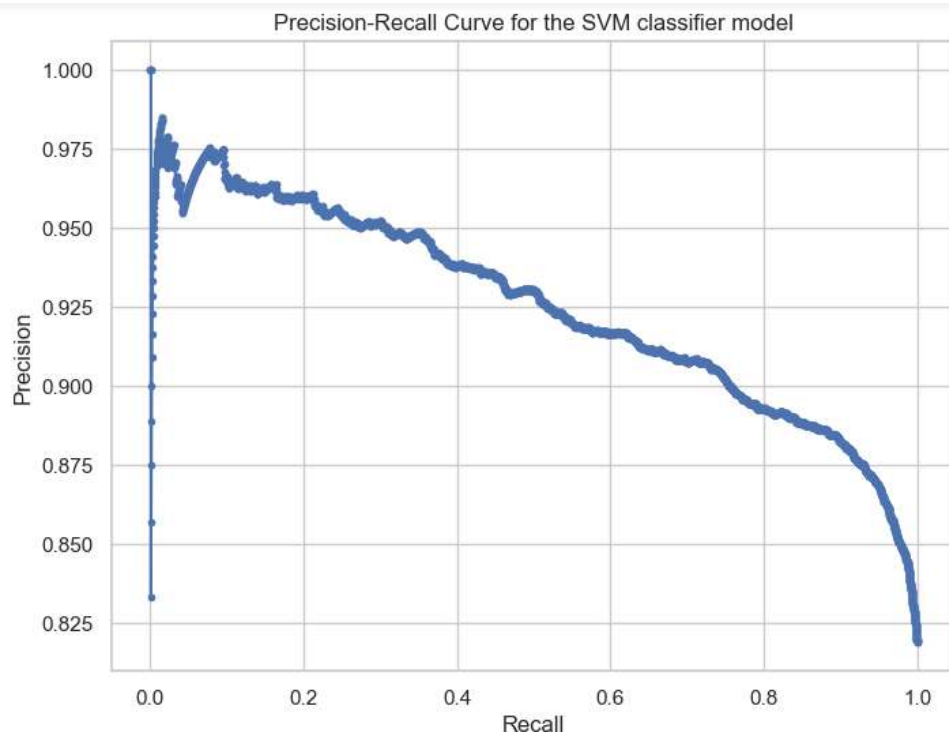


Fig. 12: Precision Recall Curve of the SVM Classifier Model

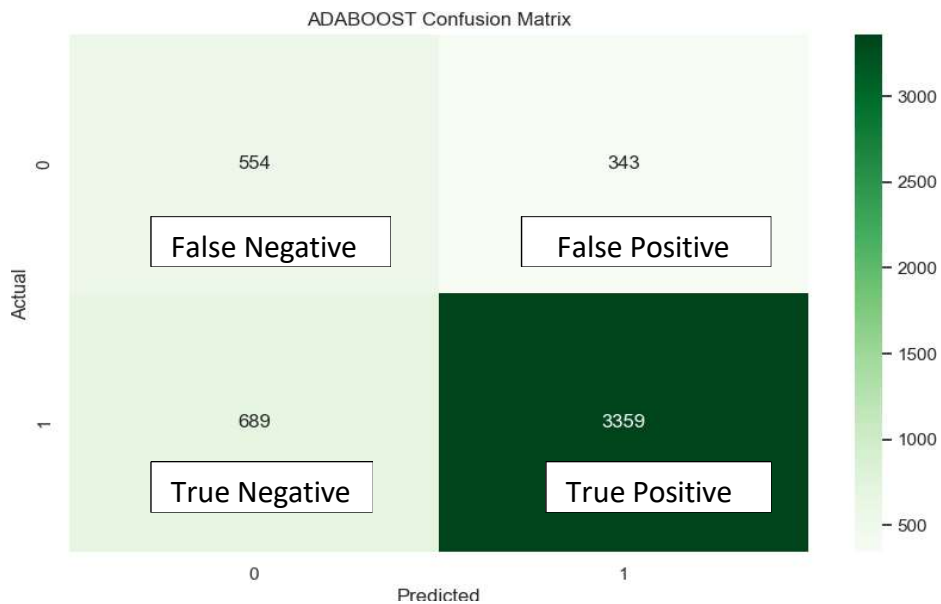


Fig. 13: Confusion Matrix of the AdaBoost Model

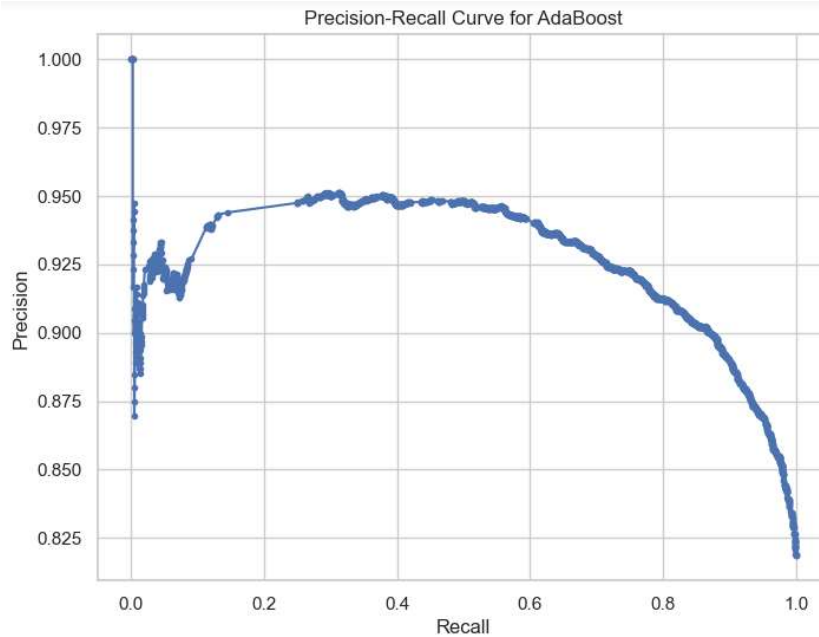


Fig. 14: Precision Recall Curve of the AdaBoost Model

COMPARISON OF MODEL RESULT

Table 1: Comparative analysis of the machine learning models

	LOGISTIC REGRESSION	SUPPORT VECTOR MACHINE	ADABOOST
ACCURACY (%)	79	77	79
PRECISION (%)	82	80	82
RECALL (%)	79	77	79
F1 SCORE (%)	80	79	80
TRUE POSITIVE	3393	3334	3359
TRUE NEGATIVE	655	714	689
FALSE POSITIVE	382	404	343
FALSE NEGATIVE	515	493	554

From Table 4.6 we can see the metrics of the various supervised machine-learning models.

i. **Accuracy:** Although accuracy is a crucial indicator in sentiment analysis, it may not always present a whole picture, particularly in cases where classes are unbalanced. The maximum accuracy is attained by AdaBoost and Logistic Regression, both at 79%. This indicates that they accurately categorise roughly 79% of evaluations, both positive and

negative.

ii. **Precision:** AdaBoost and Logistic Regression have a precision of 82%, which is the highest. This suggests that these models are accurate roughly 82% of the time when they predict a review to be positive. This accuracy is significant in situations when accurately identifying good evaluations in reviews.

iii. **Recall:** The recall rate for all models is 79%. Accordingly, they can recognise about 79% of the genuine favourable evaluations. When it's

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- critical not to miss positive reviews, a high recall is important.
- iv. **F1 Score:** The two models with the highest F1 scores, AdaBoost and Logistic Regression, both have 80%. This suggests a fair trade-off between recall and precision. While maintaining a healthy balance between false positives and false negatives, these models successfully categorise both positive and negative reviews with good accuracy.
 - v. **True Positive:** AdaBoost has the highest true positive count, which indicates that it forecasts most positive reviews with the most accuracy.
 - vi. **True Negative:** Support Vector Machine has the greatest true negative count, which

- suggests that it is more accurate in predicting bad reviews.
- vii. **False Positive:** Logistic Regression frequently predicts a review as positive when it is negative because it has the highest false positive rate.
- viii. **False Negative:** AdaBoost has the largest number of false negatives, which indicates that occasionally it forecasts a review as unfavourable when it is positive.

The image below – Fig 4.12 shows the comparisons between the 3 machine learning models. The recall and precision metrics is used for the comparisons.

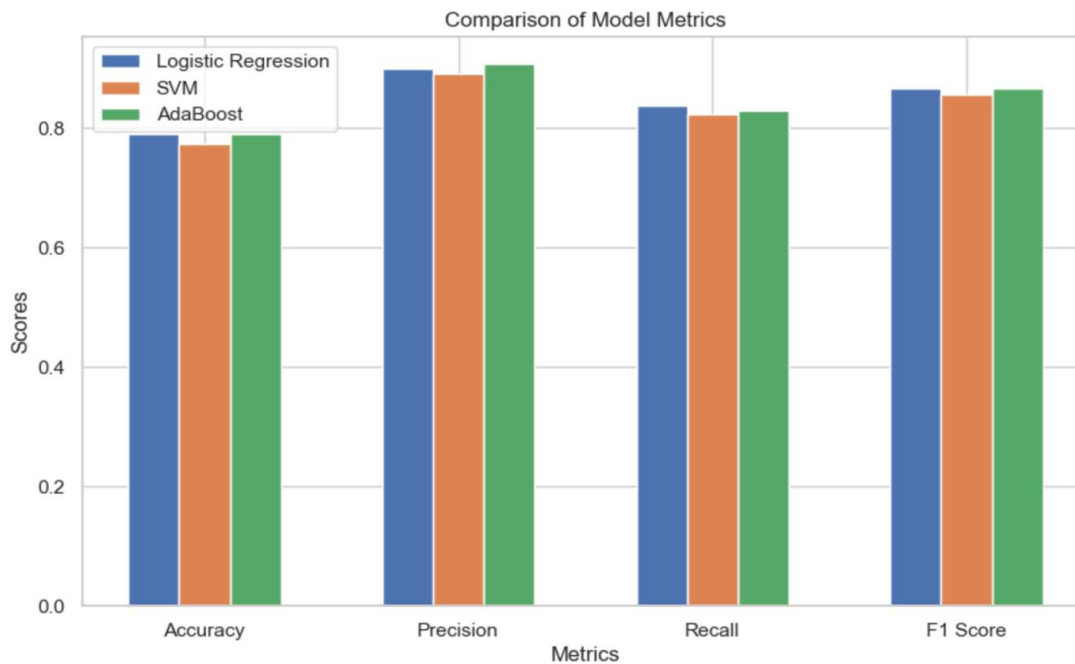


Fig. 15. Comparison of the Three Model

COMPARISON OF LEXICON-BASED TECHNIQUES RESULTS

This section is to analyze the results of the lexicon-based sentiment analysis techniques

used in the research. The two lexicon-based techniques used are Textblob and Vader sentiment.

Table 2. Comparative analysis of the lexicon-based models

	TEXTBLOB	VADER SENTIMENT
NEGATIVE (%)	4.7	2.3
NEUTRAL (%)	13.3	1.1
POSITIVE (%)	82.0	96.6

The lexicon-based approach is not as robust as the traditional machine learning models as it has to depend on creating a threshold for positive, negative, and neutral sentiment based on

the polarity score, and that the result for this is different for the textblob and vader sentiment models.

TextBlob Polarity Pie Chart

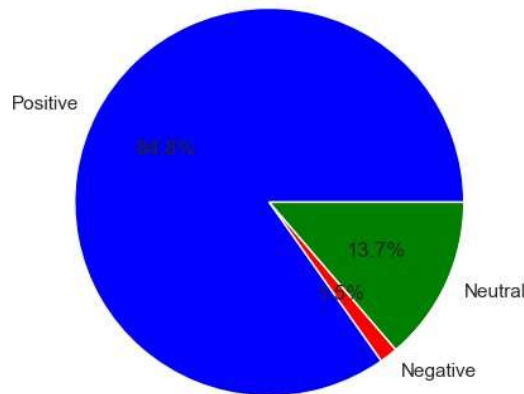


Fig. 16: TEXTBLOB Polarity Pie Chart

Vader Polarity Pie Chart

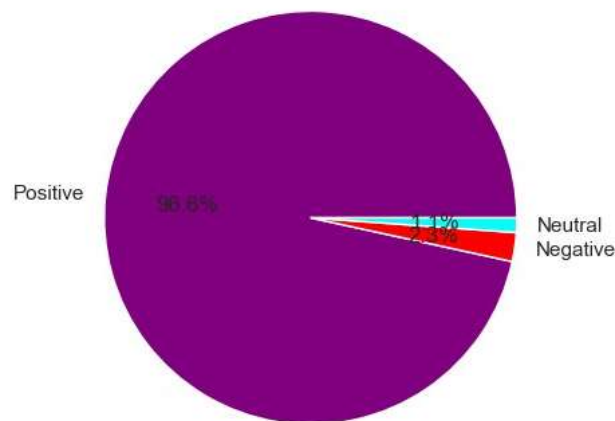


Fig. 17: Vader Sentiment Polarity Pie Chart

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Interesting conclusions are drawn from (Fig 4.12, Fig 4.13) the comparison of VADER with TextBlob for sentiment analysis. When it comes to identifying negative emotions, VADER outperforms TextBlob, classifying 2.3% of the text as negative versus 4.7% for TextBlob. This shows that VADER is better able than TextBlob in detecting positive attitudes. In contrast, although VADER only classifies 1.1% of the text as neutral, TextBlob classifies 13.3% of the material as neutral, demonstrating TextBlob's stronger propensity to do so. When it comes to positive feelings, VADER identifies 96.6% of the text as such, while TextBlob assigns 82.0%. This demonstrates how variable VADER's classification of positive sentiment is.

RESULT DISCUSSION, PROJECT MANAGEMENT AND RELEVANCE

The sentiment analysis done using the lexicon-based algorithms TextBlob and VADER, using the fashion review dataset, revealed some fascinating insights. The TextBlob and VADER techniques showed a very high percentage of 82% and 92.2% positive sentiments, respectively, while they showed minimal, neutral results of 13.3% and 1.1% and negative results of 4.7% and 2.3%.

The supervised machine learning algorithms also create valuable insights into sentiment analysis. The classification is binary; hence, there are only negative and positive sentiments. Logistic regression has a 79% accuracy, 82% precision, 79% recall, and an 80% f1 score. The SVM Classifier has a 77% accuracy, 80% precision, 77% memory, and a 79% f1-score. AdaBoost has a 79% accuracy, 82% precision, 79% memory, and an 80% F1 score.

IMPLICATIONS AND APPLICATIONS

Through the sentiment analysis project, the fashion product company can gain valuable insights into customer feedback, satisfaction, and preferences. This information can be used to improve products, develop effective marketing strategies, and better meet the needs of customers. Additionally, identifying positive sentiment towards certain features can help identify emerging trends and inform strategic

product development. The sentiment analysis can also be used for brand reputation management by monitoring real-time sentiments and swiftly responding to negative feedback. This project can serve as a foundation for future research on the use of machine learning models for sentiment analysis.

CONCLUSION

After examining the reviews using both a lexicon-based approach and supervised machine learning models, we found that the TextBlob and Vader tools mostly categorized the reviews as positive. However, there is still an imbalance present. The TextBlob method classified a significant number of reviews as neutral, but this isn't an accurate representation as the neutral category is based on the tradeoff between negative and positive reviews.

The machine learning algorithms, on the other hand categorized the reviews as either negative or positive and performed well in organizing them. We have concluded that the majority of the reviews are positive, with fewer negative reviews. This is expected due to the imbalanced dataset. Overall, we strive for fairness and accuracy in our analysis, regardless of the tool or method used.

RECOMMENDATIONS

In this project, we investigated sentiment analysis for a specific type of reviews. However, we suggest utilizing a wider range of data to evaluate the effectiveness of the models. Additionally, businesses that operate in international markets could expand the project to incorporate multi-lingual sentiment analysis and cross-domain assessment to determine the system's ability to adapt to different contexts.

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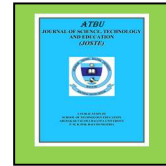
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