Original Article

Comparative Performance of Machine Learning Techniques for Sentiment and Insight Analysis in Amazon Product Reviews

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Abstract

The sentiment analysis of online product review has been a pressing concern in perception and support of sound decision-making using information provided by e-commerce portals. Through a random forest (RF) classifier and a sophisticated preprocessor pipeline, this paper proposes a useful sentiment classification model of Amazon product reviews. The data collection is made in the beginning of the research process with Amazon Reviews (2018). It is pre-processed in several stages, such as special character removal, stop-word removal, tokenization and part-of-speech (POS) tagging to normalize and standardize the textual data. TF-IDF is an extraction tool which converts text into meaningful numerical processes. RF model is then trained to predict customer sentiment and its ensemble structure is employed to overfitting and maximize predictive stability. The measures of performance in the model include accuracy, precision, recall, F1-score and loss. RF classifier is an excellent accuracy (ACC) rate of 98.83, a high precision (PRE) rate of 97.70, a high recall (REC) rate of 98.64, and a balanced F1-score (F1) rate of 98.17 compared to other traditional and deep learning classifiers such as the Logistic Regression, SVM, NB-SVM, and CNN-RNN. Overall, the RF-based sentiment analysis model is a highly trustworthy, scalable and efficient way of obtaining insights using a huge volume of e-commerce reviews data.

Keywords:

Sentiment Analysis, TF-IDF, Amazon Product Reviews, Consumer Behavior, Machine Learning.

1. Introduction

The online marketplace has expanded rapidly, and it has become a dynamic realm where customers continuously leave in-depth product reviews. Amazon, which is one of the biggest online retailers in the world, boasts of millions of reviews that condense customer experiences, expectations and level of customer satisfaction [1]. These textual reviews can be a crucial source of information to the business to know more about the user behavior, product weaknesses and better service delivery [2]. However, the size and the nature of this unorganized data make analyzing this information manually useless and imprecise, and thus call for the use of automated

computation techniques. In this respect, sentiment analysis is significant because this factor classifies the emotional polarity of sentiments posted in reviews so that the companies can easily understand how individuals feel about their products.

Despite the fact that sentiment analysis is applied to ascertain whether the feedback was favorable, negative, or neutral, latent patterns, behavioral trends, and the key subjects in the text hold greater value towards improved comprehension of the consumer [3]. The broader perspective or rather what can be termed as an insight analysis, is the one that goes beyond mere superficial sentiment to unearth the intentions of customers, recurrent issues and the unspoken expectations [4]. Sentiment and insight analysis, when combined, provide an overview of customer responses, which can be used during decision-making in product refinement, targeted marketing, optimization of the supply chain, and customer relationship management.

The general model in the modern place is AI, which combines data-driven reasoning, pattern recognition, and automated decision support. ML is a sub-field of AI that learns using data to carry out sentiment analysis and derive insights. Conversely, DL is a more dedicated field, where neural architectures facilitate an in-depth, abstract comprehension of complex subtleties of linguistic concepts [5]. The three technologies related to one another, AI, ML and DL complement each other to enhance the ACC, scalability and the quality of sentiment and insight analysis on e-commerce mega places like Amazon.

Machine learning (ML) has emerged as a prevailing paradigm of textual analysis of large and heterogeneous sets of text. ML techniques are also good to detect linguistic structures, semantic relations and context-specific patterns in text [6]. Noise, ambivalence, colloquialisms, and category-specific language are the key issues that can be successfully addressed with the help of Amazon product review models. There are different ML methods, such as probabilistic and ensemble, as well as the vector-based classifier, which offer varying degrees of accuracy, generalization, and robustness [7]. In that regard, their performance should be contrasted to determine the most consistent method of deriving the real-life sentiments and insights.

1.1. Significance and Contribution of the Study
The study is highly significant because it presents an exceptionally effective and scalable approach to researching customer opinions using extensive amounts of Amazon product reviews and enables a more in-depth analysis of the user experience and purchase patterns. The high effectiveness of the model as illustrated through its high performance of the model implies that it can be applied in the real world of e-commerce to support other practical e-commerce solutions, including recommendation systems, market analysis, product improvement and decision-making. In addition, the study would contribute to the research on sentiment analysis by demonstrating that more complicated DL designs are not always more effective than simpler ML models, as long as they are properly backed by great pre-processing. The key significant contributions of this work are the following:

➤ A complex pre-processing technique that involved the following steps was used to improve the quality of the text greatly: tokenization, POS tagging, stop word reduction, and elimination of special characters.
➤ TF-IDF feature extraction, which is applied in practice to generate meaningful numerical textual review representations and at the same time make them computationally efficient.
➤ Developed a powerful sentiment classification system with the help of the RF algorithm to guarantee the high level of ACC and the minimized level of overfitting.
➤ All key evaluation metrics ACC, PRE, REC, and F1 thereby demonstrating balanced classification, high reliability, and improved effectiveness compared to existing ML and DL approaches.

1.2. Justification of the Study
This study is motivated by the need for a highly accurate, scalable, and interpretable sentiment analysis framework that can handle massive volumes of user-generated content within the existing e-commerce system. Although DL models have become popular, they often require substantial computational resources and complex architectures, making them less practical for many real-world applications. The novelty of this work is that, even with a traditional ML approach carefully engineered with a strong pre-processing pipeline and TF-IDF feature extraction, it can perform better than complex models such as CNN-RNN, SVM, and NB-SVM on the large Amazon review dataset. This paper presents an optimized RF setup that not only has outstanding ACC (98.83) but is also robust, stable, and interpretable. Also, POS tagging and effective stop-word management contribute to the uniqueness of the pre-processing phase, leading to higher-quality feature representation and improved sentiment detection.

1.3. Structure of the Paper

The paper is organized as follows Section II contains important studies on sentiment analysis in Amazon product ratings; Section III discusses the approach; Section IV presents findings and model comparisons; and Section V offers conclusions and suggestions for additional investigation.

2. Literature Review

This section looks at the study that has been done on analyzing how people feel about Amazon product reviews. The analyzed literature revealed several recurring themes, including:

Alrehili and Albalawi (2019) tested the proposed model across six scenarios using five classifiers. The circumstances entail the use of trigram, bigram, and unigram (with or without the stop of word elimination). When using unigram and stop-word removal, the RF methodology achieves the highest ACC of 89.87%, while the voting method performs best in other circumstances [8].

Ahmed and Muhammad (2019) describe a method for locating these fake reviews in the Amazon Review Dataset. To increase the ACC of the conventional method, and have employed boosting techniques instead of conventional ML classifiers. By boosting the performance of poor learners, this method has produced a notable increase in ACC. When attempting to identify fraudulent reviews, up to 93% ACC has been attained, compared to up to 89% ACC with traditional ML methods [9].

Hossain et al (2019) use the NB technique to ascertain the document's phrase frequency. Following that, they classify words as positive or negative using SVM. For investigation, used Amazon customer review data that was available online. The manuscript is being preprocessed and cleaned using specific methods, leaving only the words. Trained model using 24,000 data points. Consequently, it provides us the best PRE. Using the optimal technique, develop this model, which has an ACC of 98.39% [10].

Wijayanto and Sarno (2018) use customer feedback on IMDb for movies and Amazon for goods. The firm has received several reviews. Sentiment analysis was therefore used to accelerate the viewing of client evaluations. The supervised method converts words into features using TF-IDF. The training data determines how well the guided method works. Making the training data better leads to more accurate results. About the CHI2: To improve the quality of the training data, this method uses selection and stop word removal. To obtain reliable results in this investigation, employ K-fold cross-validation. This study demonstrates how the results may be enhanced by using context-based stop words [11].

Khurshid et al. (2017) refer to this phenomenon as spam. The classification of reviews as benign or malicious is known as review spam detection. As a result, rather than using a dataset specifically designed for Amazon Mechanical Turkers (AMT), the purpose is to assess the efficacy of supervised ML systems for review spam identification based on multiple feature sets obtained from real-life datasets. Test several parameters, including PRE, REC, and the Receiver Operating Characteristic (ROC). With an ACC of 0.83, AdaBoost outperforms all others, accurately identifying all spam while ignoring a very small percentage of valid reviews [12].

Singla, Randhawa, and Jain (2017) extracted usable data from a large collection of assessments, which were classified as positive or negative sentiment. A computational method for obtaining subjective information from text is termed sentiment analysis. The suggested study uses sentiment analysis to categorize over 4,000,000 reviews as good or unfavorable. Among other techniques, reviews have been categorized using NB, SVM, and DT. The model is evaluated using 10-Fold Cross-Validation [13].

Ejaz et al. (2017) used a lexical dictionary-based method that combines an n-gram RF learner with word vectors, a decision tree learner with document vectors, and an RF with n-grams to compare three well-known machine learning algorithms. Using information from Amazon product reviews, both positive and bad comments have been predicted. To determine which approach performs better on a specific Amazon dataset, the ROC curve is used to calculate the ACC for each algorithm [14].

A comparative analysis of the background study, based on its methodology, Dataset/Environment, Problem Addressed, Performance, and Future Work/Limitations, is provided in Table I.

Table 1. Literature Review on Sentiment Analysis in Amazon Product Reviews

Author	Methodology	Environment / Tools Used	Problem Addressed	Limitations / Future Work
Alrehili and Albalawi (2019)	analyzed RF and voting algorithms in six scenarios, compared five classifiers, and assessed unigrams, bigrams, and trigrams with and without stop-word removal.	Text preprocessing, N-gram models, Stop-word removal, Multiple ML classifiers	Improving classification accuracy for spam review detection	Accuracy varies across scenarios; deeper feature engineering and hybrid models needed
Ahmed and Muhammad (2019)	Boosting applied to weak learners for fraudulent review detection; used Amazon Review Dataset	Boosting algorithms, Amazon Review Dataset	Enhanced fraud review detection accuracy beyond conventional ML	Boosting models may still overfit; requires testing on multi-domain datasets
Hossain et al. (2019)	Used Naïve Bayes for frequency extraction; SVM for sentiment classification; extensive preprocessing	Amazon Review Dataset, Naïve Bayes, SVM, Text-cleaning techniques	High-accuracy sentiment classification using 24,000 reviews	Requires evaluation on multilingual datasets; limited by dataset size
Wijayanto and Sarno (2018)	Sentiment analysis using supervised learning; TF-IDF, CHI^2 Feature Selection, Stop word optimization; K-fold Cross-Validation	IMDb and Amazon datasets, TF-IDF, CHI^2, Cross-Validation	Improve sentiment classification by enhancing training data quality	Context-based stopwords need further refinement; may not generalize well across domains
Khurshid et al. (2017)	Compared supervised ML algorithms (AdaBoost, etc.) on real-life datasets rather than AMT datasets; evaluated using Precision, Recall, ROC	Supervised ML models, Real-life review datasets	Detection of review spam in authentic datasets	Requires handling class imbalance; limited feature sets restrict model generalization
Singla, Randhawa and Jain (2017)	Classified 4M reviews into positive/negative using NB, SVM, Decision Tree; Ten-Fold Cross Validation	Large-scale review data, NB, SVM, DT, Cross-Validation	Large-scale sentiment classification	Does not address spam reviews; limited to binary sentiment only
Ejaz et al. (2017)	Comparing ROC for assessment, RF with n-gram lexicon-based method, DT with document vectors, and RF with word vectors	Amazon Product Review data, Word vectors, Document vectors, N-gram lexicon	Identify most effective ML approach for sentiment prediction	Limited comparison of deep learning methods; feature engineering could be expanded

3. Methodology

The proposed strategy of analyzing sentiment regarding Amazon products reviews starts with obtaining the review data on Kaggle and moves to a difficult stage of data-cleansing. These cleaning operations involve a number of processes that include: special character removal, stop word removal, tokenization, and POS tagging that are all aimed at cleaning and organizing the text to be analyzed. Feature extraction is then performed through the TF-IDF approach. The RF model has been trained to identify sentiments with a high ACC. The overall effectiveness of the sentiment analysis technique is then assessed by evaluating the model's performance using a range of metrics, including ACC, PRE, REC, F1, and loss. Figure 1's flowchart illustrates the suggested methodology:

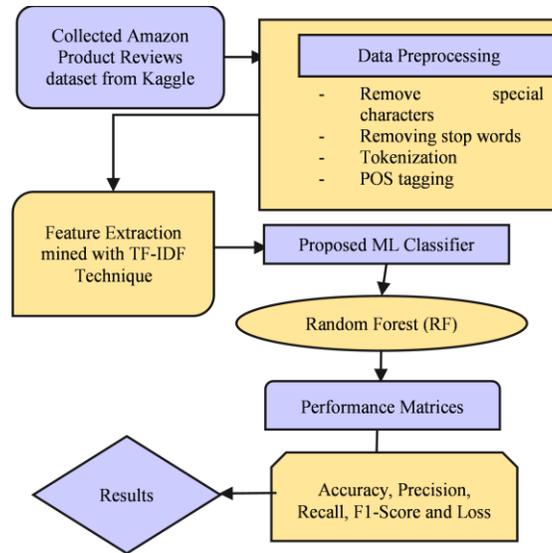Each step of the flowchart is explained in the section below:

Figure 1. Flowchart of Sentiment Analysis in Amazon Product Reviews

3.1. Data Collection

Amazon Reviews (2018) contains 233.1 million Amazon product reviews (text, ratings, and supplemental votes), along with product metadata and connections. A dataset was created using the electronic subset of this dataset, which included 7,824,482 reviews, for this purpose. This section contains more data visualizations for sentiment analysis of Amazon product reviews:
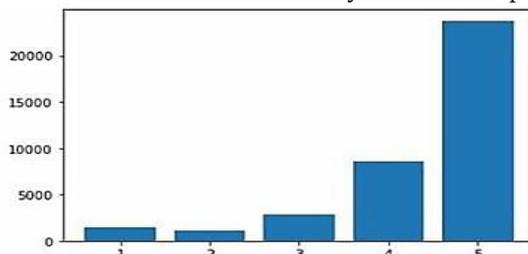

Figure 2. Number of Reviews vs. Rating Visualization

The distribution shown in Figure 2 appears to be ratings or scores, with a range of 1-5. These categories (1, 2, 3, 4, 5) are represented on the x-axis, and the frequency or count for each category is represented on the y-axis. The distribution is highly concentrated at the top end, with category 5 recording the largest number, over 22500. The number of categories 4 is also high and it is nearly 9,000. On the other hand, categories 1, 2, and 3 are significantly lower, with category 1 at approximately 1,500, category 2 slightly lower, and category 3 at approximately 2,500. This trend indicates a strong tendency toward higher ratings/scores in the data, with underrepresentation.
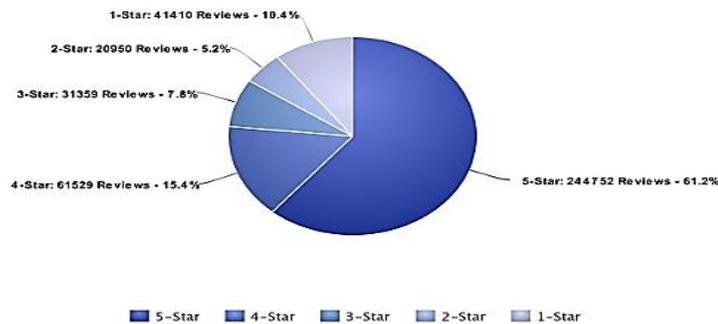

Figure 3. Star Rating Distribution of the Reviews

Figure 3 presents a pie chart of the distribution of customer reviews by 5-star rating. The highest percentage of reviews, 61.2 is 5-star rating, which includes 244,752 reviews. Subsequently, there are 4-star reviews (15.4% 61,529 reviews). The percentages are much lower for lower ratings: 3-star reviews are 7.8% (31,359 reviews), 2-star reviews are 5.2% (20,950 reviews), and 1-star reviews are 10.4% (41,410 reviews).

3.2. Data Preprocessing

This phase involves data cleaning. Extraneous words and symbols are eliminated. This is done to make processing easier. This phase includes eliminating hyperlinks, repetitious sentences, emoticons, and special characters. There is also tokenization. Ultimately, the classifier receives a condensed collection of features. The main steps in text normalization are as follows:

- ➢ Remove special characters: As a preventive measure, eliminate the characters usually known as accent marks since they lead to numerous issues throughout the preprocessing stages, including lemmatization and contraction expansion. Emojis and other special characters are also removed in this stage.
- ➢ Remove stop words: Words with little to no meaning, like "I," "to," and "the," are known as stop words. "No," "not," and "cannot" are not excluded from the NLTK stop words corpus.
- ➢ Tokenization: It includes breaking up a string sequence into individual tokens, including words, phrases, keywords, symbols, and other items. Tokens could be single words, phrases, or sentences. Punctuation marks are one of the characters deleted during the tokenization process. The tokens serve as input for several activities, including parsing and text mining.
- ➢ POS Tagging: Speech sections Tagging is the technique of identifying a specific element of speech for a sentence. The term "POS tagging" is commonly used. Adjectives, nouns, verbs, pronouns, conjunctions, and subclasses of these are the building blocks of language. One application that can help with this is the Parts of Speech Tagger, sometimes known as POS tagger.

3.3. Feature Extraction

Feature extraction is one of the primary stages in a classifier's operation. Among the various methods of feature extraction, one very important yet difficult task is the elimination of unsuitable and extraneous words to achieve better classification results. For text data feature extraction, the following method is used:

3.3.1. TF-IDF

A word-frequency-based metric known as When applied to a given text, TF-IDF determines how significant a phrase is in relation to the whole collection of documents. When calculating TF-IDF, the frequency of a phrase is considered both inside and across texts. Finding the TF and the IDF are the two phases involved in computing TF-IDF. Equation (1) provides the TF-IDF equation for a term t in a document d from the corpus:

$$TF - IDF = IDF(t, d) = TF(t, d) \times IFD(t) \tag{1}$$

TF-IDF only generates lexical-level features and is unable to capture a word's contextual meaning.

3.4. Classification with Random Forest Model

The RF algorithm, an ensemble learning technique, replaced the DT. To accomplish this, it constructs numerous DTs during the training phase and then uses the majority vote from each tree to identify the class [15]. One of RF's primary benefits is that it is less likely to overfit while simultaneously providing a measure of feature relevance, which, in this instance, has been used to identify the most influential terms in Amazon reviews.

The Equation provides the mode of the classes as its forecast Equation (2):

$$\hat{y} = \text{mode}\left(\widehat{y_1}, \widehat{y_2}, \dots, \widehat{y_{n_{estimators}}}\right) \tag{2}$$

$n_{estimators} = 100$ This parameter manages the quantity of trees in the forest. Based on cross-validation results, a value of 100 was selected to balance overfitting and underfitting.

3.5. Performance Matrix

The proposed model was evaluated using four popular performance metrics: ACC, PRE, REC, F1, and loss. A table that categorizes the model's predictions to demonstrate the classifier's performance is called the confusion matrix. These variables are as follows:

TP are reviews that the model correctly identifies as positive. FP is the model that misclassifies a negative rating as favorable. FN refers to those that the model mistakenly labels as negative, whereas TN refers to those that the model correctly classifies as negative.

3.5.1. Accuracy

The percentage of reviews the model accurately categorizes. It illustrates how well the model performs overall in sentiment prediction. Equation (3) is used to determine the correctness of the entire model:

$$Accuracy = \frac{TP+TN}{(TP+TN+FP+FN)} \quad (3)$$

3.5.2. Precision

The proportion of favorable evaluations that the model projected would be favorable. A high PRE indicates that relatively few instances of positive feelings have been mislabeled as false positives by the algorithm. Equation (4) computes the PRE:

$$Precision = \frac{TP}{(TP+FP)} \quad (4)$$

3.5.3. Recall

The REC metric shows the number of real positive reviews the model correctly classified. A high REC indicates that the model can recognize nearly all genuine good emotions. Equation (5) provides a mathematical representation of the REC:

$$Recall = \frac{TP}{(TP+FN)} \quad (5)$$

3.5.4. F1-Score

The harmonic mean of PRE and REC is one of the metrics that produces a balanced result, particularly when working with an imbalanced dataset, because it accounts for both FP and FN. To calculate the F1, use Equation (6).

$$F_1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (6)$$

3.5.5. Loss

A numerical value represents the model's prediction error during training and validation. Lower loss in sentiment analysis indicates that the model's predicted sentiments are more closely aligned with the reviews' actual sentiments.

4. Results and Discussion

Python 2.7 was used to generate models in a Jupyter notebook. A 2.7 GHz Intel Core i5 with 8 GB of DDR3 RAM operating at 1867 MHz was deployed for the models' local training and validation. The Python libraries utilized were NLTK 3.3.1, pattern 2.4, spacy 2.0.12, pandas 0.23.1, NumPy 1.14.5, scikit-learn 0.19.1, and matplotlib 1.5.1. Table II indicates that the RF model performs remarkably well in sentiment analysis, with 98.83% ACC, high PRE (97.70%), REC (98.64%), and F1 (98.17%). This suggests that the model is quite reliable and well-balanced in its classification.

Table 2. Evaluation of RF Model on Sentiment Analysis in Amazon Product Reviews

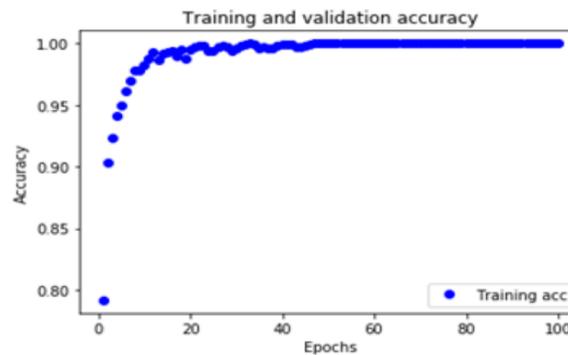| Model	Accuracy	Precision	Recall	F1-Score
RF	98.83	97.70	98.64	98.17

Figure 4. Accuracy of the RF Model

Figure 4 shows the training ACC curve of the RF model in 100 epochs and reveals a gradual increase in the ACC of the model as it is learning based on the data. The PRE begins at around 0.79 in the initial epoch and rises sharply through the initial 15-20 epochs which means that the process of learning is fast and the features have been differentiated successfully. The ACC also attains accuracy, and levels off on the training set to a more or less 1.00 value, which means that the model ACC on the training set is approaching perfection.
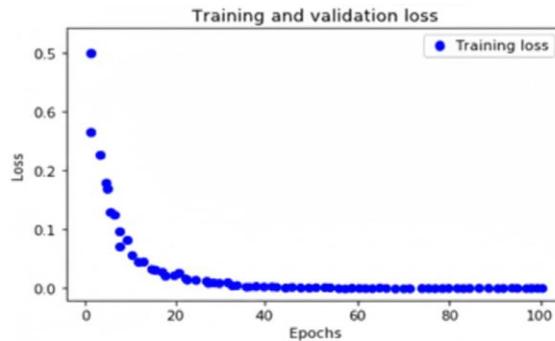

Figure 5. Loss of the RF Model

Figure 5 shows the loss curve of the model with 100 epochs, which appears to have a clear negative slope since the model is tuning its learning. The first loss is also very large (more than 0.5), though it instantly decreases at the beginning of the epochs (the first 10-15 epochs), which means that the error-minimizing model is reaching rapid progress. The loss is minimally changing over time as the training goes on, towards zero and this indicates that the model is learning properly and converging.
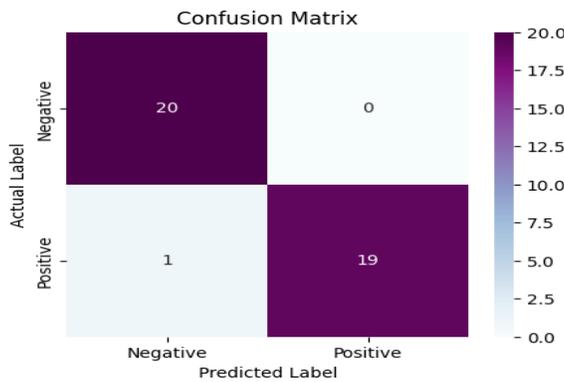

Figure 6. Confusion Matrix of the RF Model

Figure 6 presents the confusion table of the RF model of the test data. The model has a high predictive accuracy with 20/20 negative and 19/20 positive samples being correctly identified. The Positive category had one incorrectly classified Negative, and there were none in the Negative category which were incorrectly classified Positive.

4.1. Comparative Analysis

The Comparative analysis of various predictive models (Table III) indicates that the RF model has the best ACC value of 98.83, which is considerably superior to the other predictive methods. LR has a very good ACC of 90% with the hybrid CNN-RNN model having a superior ACC of 93.2 meaning that it is able to deal with complex patterns. Conversely, SVM and the NB-SVM are classic ML models that have lower accuracies of 81.20% and 73.51%, respectively, and are also poor at nonlinear correlation in the data.

Table 3. Comparative Analysis of Existing ML and DL Models on Sentiment Analysis In Amazon Product Reviews

Model	Accuracy
LR[16]	90
CNN-RNN[17]	93.2
SVM[18]	81.20

NB-SVM[19]	73.51
RF	98.83

5. Conclusion and Future Scope

Sentiment analysis refers to a text classification process that is dependent on the emotions and sentiments of the text. The present research is a very efficient, yet computationally efficient model of sentiment analysis of Amazon product review based on strict preprocessing of the data, the TF-IDF extraction of features, and the RF classification. The experimental results prove that the offered methodology shows excellent results; the RF model shows a higher performance than a number of traditional and DL approaches in ACC, PRE, REC, and F1. The stability of the ACC and loss curves, as well as the low misclassification in the confusion matrix, demonstrate the model's strength and reliability. In general, the suggested methodology will provide a scalable, interpretable way to extract sentiment information from large volumes of textual data to support decision-making on e-commerce platforms.

Future studies can use contextual word representations, such as Word2Vec, Glove, or transformer-based models (e.g., BERT), to reveal more semantically meaningful connections between reviews. ML and DL models may also be combined to create hybrid models that enhance classification performance. To improve the model's generalizability, it would be good to augment the dataset with multilingual reviews, domain-related sentiment categories, and aspect-based sentiment analysis. Analyzing real-time streaming data and implementing the model in a cloud-based setting can make it even more practical for large-scale e-commerce systems. "

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