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Optimized Machine Learning framework for Sentiment Analysis for Amazon Product Reviews



Abstract

Sentiment Analysis (SA) commonly referred to as opinion mining, is a subset of natural language processing that focuses on identifying views and attitudes inside a document. Currently, this paper examines the SA of the Amazon product reviews where Machine Learning (ML) algorithms will be employed to categorize the user sentiments as positive, negative, or neutral. The authors of the research use a dataset of Amazon product reviews for the text analysis to avoid featuring insignificant words, the text data is tokenized, stop-words are removed, and PoS. Here, KNN, SVM, RF are used for the development of models based on machine learning algorithms. Moreover, there are text preprocessing applied method such as the TF-IDF and Bag of Word. Metrics used to measure accuracy of the models are; $A_{accuracy}$, $P_{precision}$, R_{recall} , $F1_{score}$. The results of the KNN and SVM models were compared with the findings of the RF model. Using the data set, the complementary RF model achieved higher $A_{accuracy}$ of 98.83%, $P_{precision}$ of 97.70%, R_{recall} of 98.64%, and $F1_{score}$ of 98.17%.

Keywords: Sentiment Analysis, Amazon, NLP, Machine Learning.

1. INTRODUCTION

Consumers get products from several e-commerce platforms because global commercial sites are mostly online (Figure 1) [1]. Inspection of goods before purchase is another protected condition. Ratings and comments from actual customers increase a product's sales. Many online stores and wholesalers encourage customers to provide their feedback on sold products. On a daily basis, millions of reviews are posted online on various goods, services, and locations [2]. Because of this, the internet becomes the principal information source for a product or service. Reviews provide helpful information about a company, including its location, prices, and recommendations, so clients can make decisions about all aspects of their experience [3]. This is beneficial to customers and motivates marketers to understand.



Figure 1: Online shopping sites in India

Sentiment Analysis (SA) is the technique of ascertaining the emotions or sentiments expressed in a text. This could be performed for customer reviews, social media postings, or other text categories [4,5]. SA can help you learn from product reviews by sorting comments into three categories: positive, negative, and neutral (Figure 2). This information could assist them enhance your product, find areas for development, and understand what your consumers want. SA confronts significant hurdles when it comes to interpreting the various emotions expressed in customer feedback. This is due to the fact that individuals have diverse modes of expression and that adjectives like "good" and "bad" could have various meanings based on context [6]. It might be challenging to get reliable data on consumer happiness, which in turn complicates product improvement efforts. Today, when user evaluations are so valuable in the digital world, it is crucial to have the opportunity to quickly analyze many of them. The existing techniques fail to properly define human feelings at this time, and it becomes difficult to decide whether one is more positive or even a bit negative. That is why the need to construct a system able to perform the contextual emotion understanding arises, which will guarantee stable prediction and long-term strength.

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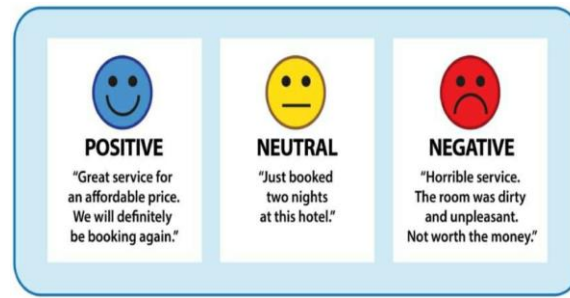


Figure 1: Customer behavior during Sentiment Analysis [7].

In this work, the authors outlined the identification of SA on product reviews on Amazon using artificial intelligence in machine learning. This approach will define sentiment as something positive, negative, or neutral towards the product reviewed. With the help of data mining, reviewing thousands of product reviews allows businesses as well as researchers to understand the satisfaction level, preferences, and even possible flaws of the product. Techniques like logistic regression, support vector machines and so on are easily employable in large scale sentiment analysis due to the Machine Learning (ML) characteristic of them. Here is potential research objectives for studies are:

- Build and train an ML model to classify Amazon product reviews into positive, negative, or neutral sentiments.
- Evaluate the performance of various ML algorithms (e.g., SVM, Random Forest, KNN etc.) for sentiment classification.
- Examine the impact of preprocessing steps like stop-word removal, Part-of-Speech (POS) tagging, and tokenization on model performance.
- To explore and compare different feature extraction techniques, such as bag-of-words and TF-IDF for optimizing sentiment classification.
- To assess the efficiency of distinct kinds of ML algorithms including Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and DL algorithms like neural networks for sentiment analysis

Following this, the papers other sections are structured as follows: A survey of relevant literature is provided in section 2 of the research. Explanation of the problem is given in Section 3. The formulation of the suggested model and SA is discussed in Section 4. The results and analysis of the study are then presented in Section 5. This research subject is brought to a conclusion in section 6.

2. LITERATURE REVIEW

Recent studies on sentiment analysis of Amazon product reviews highlight significant advancements in ML and Deep Learning (DL) methodologies. These studies emphasize a range of techniques, datasets, and feature extraction methods to evaluate sentiment classification performance. They focusing on evaluation metrics such as Accuracy ($A_{accuracy}$), Precision ($P_{precision}$), Recall (R_{recall}), and F1-score ($F1_{score}$).

Several studies have utilized DL techniques for sentiment analysis on Amazon product reviews, showing promising results. **Study [8]** explored DL models like BERT, XL-Net, and bidirectional LSTM, finding that BERT achieved an impressive 89% $A_{accuracy}$. Similarly, **study [9]** employed BERT and T5 for aspect-based sentiment detection, achieving $A_{accuracy}$ of 92% and 91%, respectively. **Study [10]** also applied LSTM and CNN-LSTM models, achieving $A_{accuracy}$ of 94% and 91%, with LSTM showing superior sequential learning capabilities. Similarly, **study [11]** reported that LSTM and GRU models performed exceptionally well, with $F1_{score}$ of 0.91 and 0.90, indicating a strong balance between precision and recall. Utilized Recurrent Neural Networks (RNN) for sentiment classification of Amazon product reviews, with the model achieving an $A_{accuracy}$ of 85%, demonstrating RNN's ability to process sequential data effectively [12].

ML methods such as SVM, RF, LR, DT, and Naïve Bayes (NB) have been widely used in sentiment classification tasks. For instance, **study [13]** tested SVM with hyper-parameter optimization, achieving an $A_{accuracy}$ of 93% on sentiment classification, and 88% accuracy in detecting fraudulent reviews. **Study [14]** employed Decision Tree (DT) and LR for sentiment analysis, with DT outperforming LR at 99% $A_{accuracy}$. **Study [15]** compared ML methods such as Multinomial NB (MNB) and RF, with LSTM achieving the highest $A_{accuracy}$ of 97%. Similarly, **study [16,17]** explored ML classifiers (MNB, MLP, DT, RF, SVM, ME, LR) to get impressive results on the Amazon electronic products reviews dataset and reported an $A_{accuracy}$ range from 73% to 78%, with SVM and LR performing similarly. **Study [17]** they have tested three separate preprocessing methods: TF-IDF, Bag of Words, and Word2Vec. With Bag of Words preprocessing, the MLP classifier obtained 92% $A_{accuracy}$, which is ideal.

3. PROBLEM STATEMENT

SA has evolved as an important tool to analyze customer feedback in the e-commerce context. Amazon as a prominent e-Commerce marketplace offering its services worldwide provides customers with the opportunity to leave their comments about products, and millions of people write comments every day. These reviews therefore include beneficial information about the customer’s satisfaction, expectation, and possible loopholes. Although the number of such reviews is relatively high, and the structure and presentation of these reviews are unformatted, the analysis of such messages cannot be conducted manually. Therefore, the development of an automatic system to classify the given reviews as positive, negative, or neutral is required. This research is specifically concerned with the use of ML technologies for purposes of sentiment analysis of the Amazon product reviews. Its purpose is to build a model that can successfully categorize textual data into positive or negative, according to the sentiments expressed by the customers. These are first, the ability to analyze noisy and unbalanced data sources, second, the ability to capture the context of the customers’ feedback, and finally, to develop high accuracy in sentiment analysis. Using several machine learning techniques, this research proposes a reliable and efficient solution to transform customer reviews into useful business intelligence for businesses.

4. RESEARCH METHODOLOGY

The flowchart in Figure 3 shows the steps to undergo sentiment analysis of the Amazon product reviews under the application of ML based solution. It starts with an input on the dataset provided as Amazon product reviews. Data preprocessing is performed on this dataset that includes step such as, stop word removal, tokenization and POS tagging on the text data. After preprocessing, in feature extraction the text data was transformed by applying techniques such as TF-IDF. TF-IDF measures the relevance of the particular word in the reviews regarding the whole set of documents and transforms textual information into numeric form that can be launched in the ML algorithms. The processed data is divided into training data (80%) and testing data (20%). In the training phase, different ML techniques as pre-processing steps including, SVM, RF, and KNN are trained for the purpose of sentiment classification: positive or negative. The performances of the testing phases are measured based on metrics such as $A_{accuracy}$, $P_{precision}$, R_{recall} , $F1_{score}$ to see how beneficial the models in the aspect of sentiment classification.

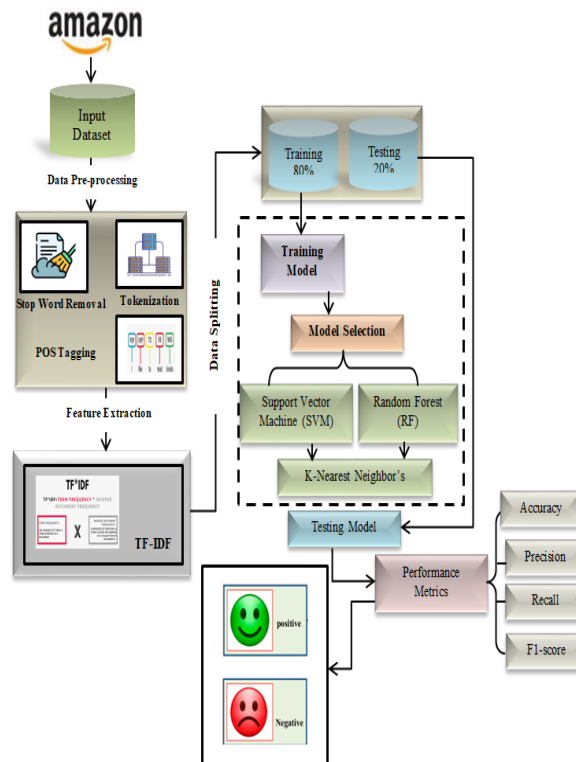


Figure 3: Flowchart of proposed work

4.1 Dataset

We use the dataset including reviews of Amazon products [18]. The dataset comprises 80,000 reviews in total. The product name, brand, price, rating, review content, and evaluation of the device's performance are included. We will assess the review column to optimize the use of the data for the first phase, because they are the most crucial elements of this project. We categorize reviews into positive and negative. Figure 4 pertains to positive and negative reviews. All reviews use a 5-star rating system, with 3-star ratings being neutral, indicating they are neither negative nor positive. We exclude reviews with a three-star rating from the required dataset and go to the subsequent stage, where a rating of 1 is deemed positive and a rating of 0 is regarded as negative [19].

	Reviews	Rating
0	I feel so LUCKY to have found this used (phone...	5
1	nice phone, nice up grade from my pantach revu...	4
2	Very pleased	5
3	It works good but it goes slow sometimes but i...	4
4	Great phone to replace my lost phone. The only...	4

Figure 4: Review dataset

4.2 Data Pre-processing

- **Tokenization:** Tokenization is the act of splitting a string into segments such as word, phrases, symbols, keywords, and the like. Tokens can be single words, individual phrases, or whole sentences or even a set of phrases.
- **Removing Stop Words:** Stop words are elements in a phrase that are unnecessary in any domain of text mining. Consequently, exclude these terms to improve the precision of the analysis.
- **POS tagging:** Parts of Speech tagging is the process of labeling a word with a certain part of speech. Nouns, verbs, adjectives, pronouns, conjunctions, and subcategories of these words make up the majority of a language's parts of speech.

4.3 Feature Extraction

Sentiment categorization relies on representation as a crucial stage. Many pre-processing procedures are necessary to filter out the noise that is inherent in raw data. Next, the preprocessed data is transformed into a Term Document Matrix (TDM), which counts the occurrences of each word. The TDM is compatible with a number of feature extraction techniques, including the TF-IDF and the bag of words. Checking the product of TF and IDF yields a word's TF-IDF score; this score could be discovered by examining these two components. Priority is given to the most frequently occurring keywords in the review dataset for calculating the TF score. Due to the IDF scaling factor, the dataset's least frequent terms are given greater weight. The score for unusual and common words is lower than that for other categories of words. It can eliminate them by excluding phrases with low TF-IDF values [20].

Term Frequency - Inverse Document Frequency (TF-IDF)

TF-IDF is a prominent weighting approach used in feature extraction and selection, often employed in information retrieval due to its efficacy [21]. This technique evaluated the significance of a pre-existing term. A word's contribution value increases with its frequency in a text. However, if the term only appeared in a few publications, then the resultant contribution's value was reduced. TF-IDF integrates two distinct methodologies: TF, which quantifies the frequency of a word inside a text, and IDF, which assesses the prevalence of documents containing certain terms [22]. The TF-IDF formula is shown in Equation 1

$$TF - IDF(t, d) = tf_{t,d} \times \log\left(\frac{N}{df_t}\right) \quad (1)$$

Then, df_t is the number of documents that include the word t , N is the number of documents in the dataset, and $tf_{t,d}$ is the frequency of the word t occurring in dataset d . The TF-IDF method gives more weight to words that occur more often in a text and gives less weight to terms that appear less frequently [23].

4.4 Machine Learning (ML) Classifier

In this section, the authors provide classifiers for SA of Amazon product review including SVM, RF, and KNN. Figure 5 shows the images of ML classifiers.

Support Vector Machine (SVM)

One supervised ML approach that has seen extensive application is SVM, which primarily deals with classification issues but can also handle regression. It has the capacity to identify intricate concealed patterns. SVMs are an optimized option for classification issues because of their stability and their ability to interact with kernel-based learning [24]. SVMs attempt to partition two-dimensional data into two classes using a hyper-plane that optimally divides the classes.

Random Forest (RF)

One kind of supervised learning method is RF, which uses a mix of tree predictors to make predictions. Classification and regression are two of its main uses [25]. Among general-purpose learning approaches, it is thought to be among the most accurate. With its simple implementation and ability to handle many input variables without over-fitting, the RF is a great choice [26]. RF adds unpredictability to the model as the trees develop. It finds the best feature from a random selection of characteristics rather than the most important feature when splitting a node.

K-Nearest Neighbors (KNN)

KNN is a method for supervised ML that can handle regression and classification tasks. Among the simplest and most basic categorization algorithms, it requires little in the way of processing power and time to run [27]. The principle behind the procedure is that items that are similar tend to cluster together; in other words, the closer the two samples are, the more likely they are to belong to the same group. To begin, they need to know how many neighbors a particular point has, which is represented by the *k* parameter. Subsequently, it determines the distance of the newly added data to the sample data set using distance functions [28].

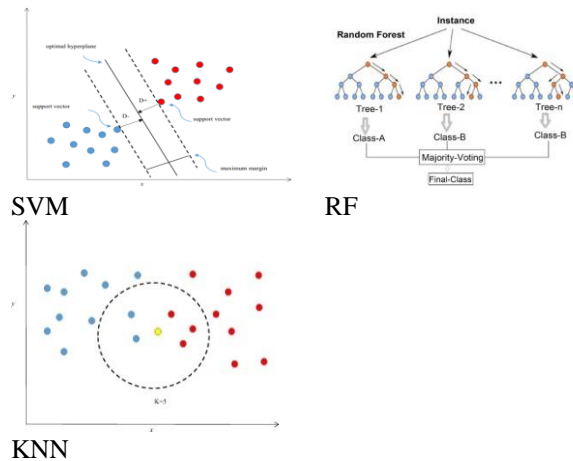


Figure 5: ML classifiers [29].

4.5 Evaluation Metrics of the Model

The following metrics are used to assess the proposed methodology:

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (2) \text{ Recall} = \text{Sensitivity} = \frac{TP}{TP+FN} \quad (3)$$

$$Precision = \frac{TP}{TP+FP} \quad (4) \text{ F1 - score} = \frac{2 * Precision * Recall}{Precision + Recall} \quad (5)$$

5. RESULT AND ANALYSIS

This paper offers the data set used to implement the suggested model and evaluate its effectiveness. The model is separated into two parts: the first part deals with the results of the suggested model's training phase, where the training data is used, and the second part deals with the results of the evaluation phase, where the test data set is used to test the performance of the proposal method that was trained with the training data.

This section provides a graphic representation of the research methodologies. The data distribution of class labels is shown in Figure 6. It is clear that there are 30,000 reviews with a negative class label and over 50,000 reviews with a positive class label.

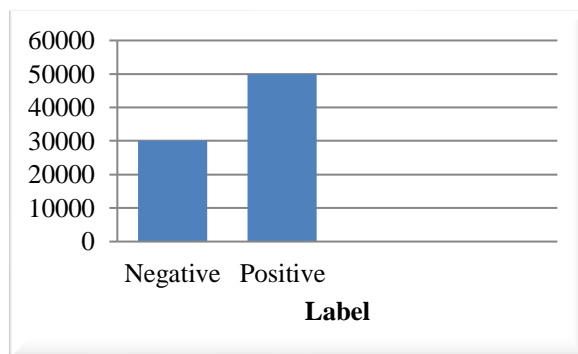


Figure 6: Actual class label counts

5.1 KNN Model

The batch size was set to 32, the learning rate was set to 0.001, the optimizer was set to Ada-grade, and categorical cross-entropy was chosen as a loss function. They were able to achieve the best set of model training parameters. They trained and verified the KNN model for a total of 50 epochs, and the graphs that represent the model's accuracy are shown in Figure 7. A representation of the KNN model loss at each epoch is shown in Figure 8.

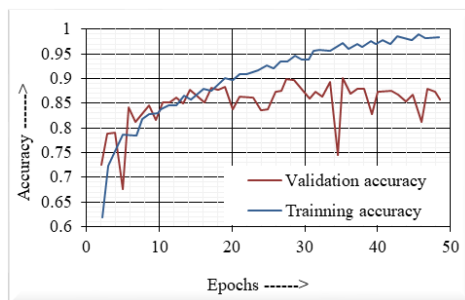


Figure 7: Accuracy of the KNN model

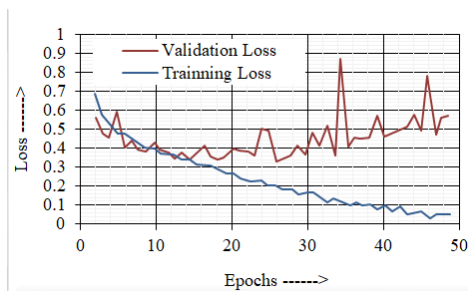


Figure 8: Loss of the KNN model

Figure 9 illustrates the confusion matrix that is generated by using the KNN model. The matrix has the following elements: TP = 19, FP = 1, TN = 19, and FN = 1.

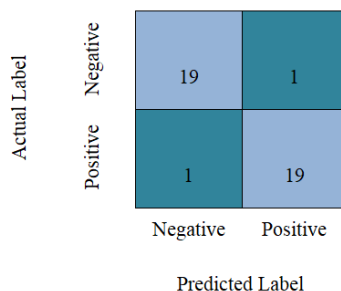


Figure 9: Confusion Metrics of the KNN model

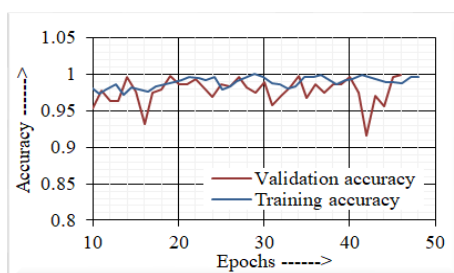
There is a report on the categorization using KNN in Table 1.

Table 1: The result of the KNN model

Model	$A_{accuracy}$	$P_{precision}$	R_{recall}	$F1_{score}$
KNN	97.50%	95.25%	100%	97.56%

5.2 SVM Model

Figure 10 shows the results of SVM validation and training/learning accuracies. The training accuracy, shown by the blue line, grows as the epoch count rises and reaches 100% after 50 epochs. The validation accuracy is shown by the brown curve, which starts at 96.56% and rises to 98.02% after 50 epochs. They stopped training after 50 epochs due to over-fitting in the learning curve. Optimal training/validation accuracy was achieved by fine-tuning the number of training epochs. The training and validation loss for the SVM model is shown in Figure 4.6. A score of 0.0 would imply that the whole learning process was outstanding and there were no errors observed. After 50 epochs, the training loss reached 0.0030 and the validation loss, which started at 0.110 and decreased to 0.01, both decreased steadily with an increasing epoch count.



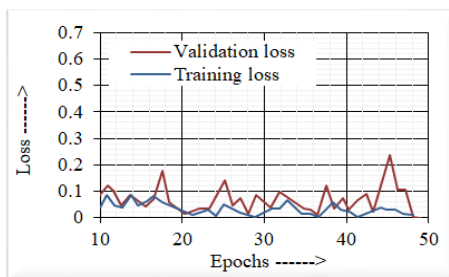


Figure 10: SVM model a) Accuracy b) Loss

Figure 11 illustrates the confusion matrix that is generated by using the SVM model. The matrix has the following elements: TP = 18, FP = 1, TN = 19, and FN = 2.

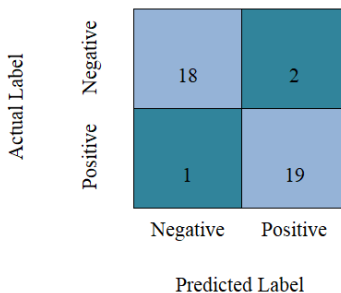


Figure 11: Confusion Metrics of SVM model

There is a report on the categorization using SVM in Table 2.

Table 2: The result of the SVM model

Model	$A_{accuracy}$	$P_{precision}$	R_{recall}	$F1_{score}$
SVM	97.29%	94.36%	97.29%	95.80%

5.3 RF Model

Figure 12 illustrates the performance of a RF model in terms of accuracy and loss during training and validation over 50 epochs. The accuracy curves show that training accuracy steadily increases, reaching nearly perfect values as the number of epochs progresses. This indicates that the model is effectively learning the patterns in the training data. On the other hand, the validation accuracy fluctuates between 0.9 and 0.95 after the initial few epochs. The training loss shows a consistent decline, indicating improved fitting of the model to the training data. Meanwhile, the validation loss decreases initially but then stabilizes with some fluctuations, suggesting variability in the model's performance on the validation set.

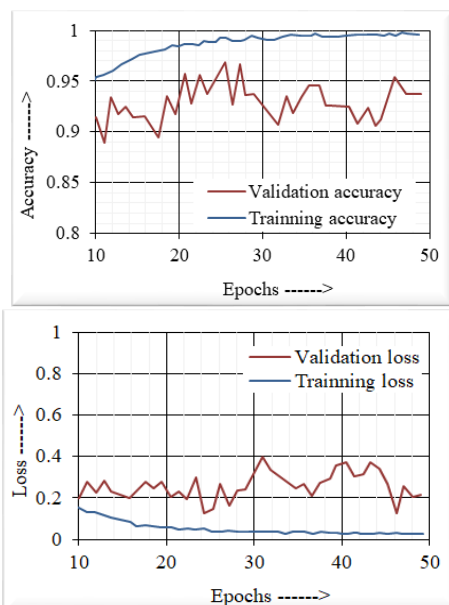


Figure 12: Accuracy curves of the RF model

Additionally, the data that was used for this matrix matched the data that was tested. The confusion matrix provides a visual representation of the method's efficacy (Figure 13). Table 3 displays the classification report that was generated by utilizing the suggested model. The confusion matrix of the proposed model has the following values: TP = 20, FP = 0, TN = 19, and FN = 1.

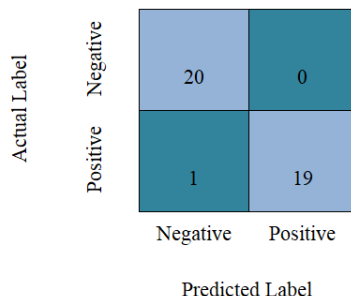


Figure 13: Confusion matrices of the RF model

Table 2: The result of the RF Model

Model	$A_{accuracy}$	$P_{precision}$	R_{recall}	$F1_{score}$
RF	98.83%	97.70%	98.64%	98.17%

5.4 Comparison analysis

They do comparative analysis in this section, which is divided into two parts. The first part is a comparison of the RF model with KNN and SVM. In the second part, a comparative analysis of the suggested model with the approaches done in the past.

Comparison of the RF with KNN and SVM

The results of the KNN and SVM models were compared with the findings of the RF model. The accuracy that is acquired with the use of the KNN model is 97.50%. The accuracy that is acquired with the use of the SVM model is 97.29%. When applied to the same dataset, the RF model attained an accuracy of 98.83%. Figure 14 is a bar chart that illustrates the comparison of all the metrics between KNN, SVM, and the RF model. Table 4 presents the results of this comparison.

Table 3: Comparison of the suggested model with KNN, SVM, and the RF model

Model	$A_{accuracy}$	$P_{precision}$	R_{recall}	$F1_{score}$
KNN	97.50%	95.25%	100%	97.56%
SVM	97.29%	94.36%	97.29%	95.80%
RF	98.83%	97.70%	98.64%	98.17%

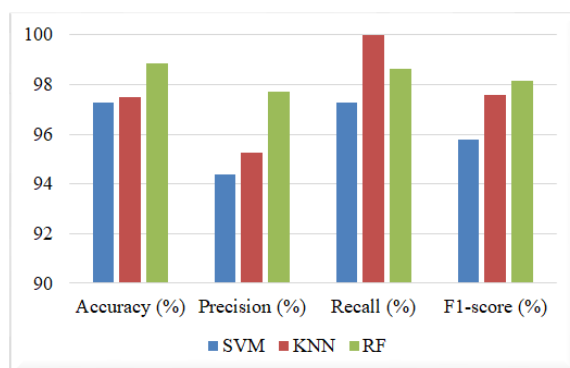


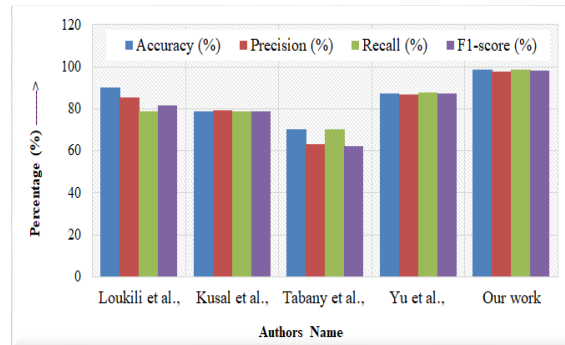
Figure 14: Graph of comparison of the Suggested Models

Comparison of the Suggested Model with Previous Work

Figure 15 provides a comparative analysis of performance metrics, including $A_{accuracy}$, $P_{precision}$, R_{recall} , $F1_{score}$, across various previous studies. Of all the methods examined in previous studies, the proposed method was the best with nearly perfect results in terms of $A_{accuracy}$, $P_{precision}$, R_{recall} , $F1_{score}$. This proves the efficiency of the proposed approach when reaching the highest possible points for all the critical parameters that allowed giving it an advantage compared to the previous work (Table 5).

Table 4: Comparison of the suggested model with previous work

Model	$A_{accuracy}$	$P_{precision}$	R_{recall}	$F1_{score}$
LR [30]	90	85.4	78.6	81.4
BERT [31]	78.91	79.08	78.75	78.86
SVM [32]	70	63	70	62
LR [33]	87.19	86.90	87.75	87.32
RF	98.83	97.70	98.64	98.17

**Figure 15:** Bar graph of comparison models

6. CONCLUSION

Machine learning sentiments used to make Amazon product reviews yield beneficial information to business decision makers and better user experiences. A classification of textual data and especially the customer reviews can be a part of such analytical activities where it is required to distinguish between the positive, negative, or neutral insights. Some of the usual data preprocessing techniques done before the analysis include tokenization, stop word removal, stemming and lemmatization in order to have a proper format of the review texts to feed on. In this study, the authors introduced the ML model for the sentimental analysis of the product reviews collected from Amazon. Several ML models have shown remarkable accuracy in sentiment categorization, including RF, KNN, and SVM. They finds the results based on the evaluation metrics such as $A_{accuracy}$, $P_{precision}$, R_{recall} , $F1_{score}$. The results of the KNN and SVM models were compared with the findings of the RF model. Using the data set, the complementary RF model achieved higher $A_{accuracy}$ of 98.83%, $P_{precision}$ of 97.70%, R_{recall} of 98.64%, and $F1_{score}$ of 98.17%.

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