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Sentiment Analysis of Musical Instruments Customer Reviews Using Machine Learning Techniques with Novel Hybrid Approach

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Abstract. Nowadays the Customer reviews are becoming more and more important to businesses in the market because they have a significant impact on consumer behavior and marketing strategy. Purchase decisions can be greatly influenced by the insightful information provided by customer reviews regarding product performance and customer satisfaction. As a result, companies leverage various techniques to analyze and interpret these reviews. A branch of Natural Language Processing (NLP) called sentiment analysis is essential to comprehending the feelings conveyed in consumer reviews. By automating the classification of sentiments such as positive, negative, or neutral, businesses can gain a deeper understanding of customer opinions and enhance their marketing efforts. Customer reviews of a variety of musical products make up the musical instruments customer reviews dataset, which was obtained from Kaggle. Several conventional preprocessing techniques, such as lowercase conversion, stopword removal, stemming, punctuation and symbol removal, and lemmatization, were used to get the data ready for sentiment analysis. Following cleaning, the data was converted to numerical form and divided into two sets: 80% for training and 20% for testing. The sentiments were then divided into positive, negative, and neutral categories using a number of well-known machine learning algorithms, such as Naive Bayes, Support Vector Machine (SVM), Random Forest, and Decision Tree and NSRD (Naïve + Support Vector Machine + Random Forest + Decision Tree) proposed algorithm. Accuracy, precision, recall, and F1-score metrics were used to assess these models' performance, offering a thorough examination of their efficacy in sentiment classification.

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Keywords; Natural Language Processing, Naïve Bayes Algorithm, Random Forest Algorithm, Support Vector Machine, Decision Tree Algorithm, NSRD (hybrid algorithm)

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1. Introduction

A subfield of Artificial Intelligence (AI) called Natural Language Processing (NLP) is concerned with how computers and human language interact. It makes it possible for machines to meaningfully and practically comprehend, interpret, and produce human language. One important use of NLP is sentiment analysis, which identifies the emotional tone of a text and classifies it into sentiments like positive, negative, or neutral. Sentiment analysis has become a vital tool for companies looking to obtain a competitive edge due to the growing amount of user-generated content, particularly in the form of customer reviews. When it comes to musical instruments, knowing consumer sentiment can yield insightful information about the usability, quality, and general satisfaction of the product. Businesses can quickly evaluate enormous volumes of reviews and obtain actionable insights by automating the sentiment analysis process, which would otherwise require a significant investment of time and resources to extract manually.

Businesses can better understand customer opinions and make data-driven decisions by using sentiment analysis in the context of customer reviews.

A rich source of feedback, customer reviews offers important insights into customer satisfaction and product performance. However, to make sure the text is clear and appropriate for analysis, the raw text data from reviews needs to undergo a thorough preprocessing process that includes lowercase conversion, stopword removal, stemming, lemmatization, and punctuation and symbol removal. Figure 1 shows that the several machine learning algorithms, including Naive Bayes, Support Vector Machine (SVM), Random Forest, and Decision Tree and hybrid algorithm of NSRD are used to accurately classify sentiments after the data has been preprocessed. Through performance metrics like accuracy, precision, recall, and F1-score, these algorithms aid in assessing the efficacy of sentiment classification. This research investigates the application of these methods to evaluate musical instrument reviews from consumers, providing insightful information about the sentiment of both the product and the consumer.

The structure of this research is as follows: Chapter 2 provides a review of the related literature, Chapter 3 offers a detailed description of the dataset, Chapter 4 outlines the materials and methods employed, Chapter 5 presents the experimental results, and Chapter 6 concludes the study with key findings and insights.

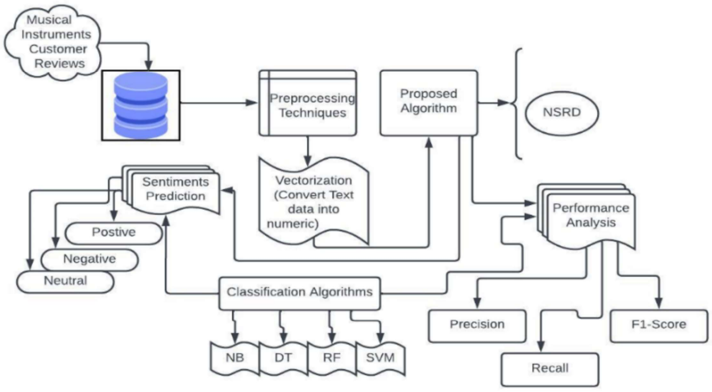

Figure 1. Architecture of Research work

2. Review of Literature

The literature review examines current research on sentiment analysis and natural language processing (NLP), emphasizing how these fields are used to analyze customer feedback in a variety of fields. Along with developments in hybrid approaches, it looks at the application of conventional machine learning algorithms such as Naive Bayes, SVM, Random Forest, and Decision Tree. There is also discussion of studies that concentrate on preprocessing methods like punctuation removal, lemmatization, and stemming. The basis for determining research gaps and developing innovative techniques for sentiment analysis in customer reviews is provided by this review.

A research paper carried out by Loukili et al. [1] states that the effectiveness of artificial intelligence techniques, such as Machine Learning and Natural Language Processing, in evaluating various algorithms, including KNN, Random Forest, Logistic Regression, and CatBoost Classifier. Their findings indicate that Logistic Regression achieved the highest accuracy, scoring 90% (0.900). Another research work done by Mujawar et al. [2] explored sentiment analysis techniques applied to user reviews of wireless earphones from the Indonesian online retailer Tokopedia. Their research concluded that the Naïve Bayes classifier outperformed other methods across several evaluation metrics, making it the most effective approach overall.

A research work titled as "A Combined Approach of Sentiment Analysis Using Machine Learning Techniques" done by Gupta et al. [3], in which that the Random Forest classifier emerged as the most effective model with the accuracy exceeding 78% among those evaluated and proved to be the most practical for sentiment analysis in this work. Another research carried out by Elangovan Durai, and Varatharaj Subedha [4] utilized the Deep Belief Network (DBN) for sentiment classification in their proposed methodology. Their APGWO-DLSA technique was identified as the most efficient approach, achieving peak accuracy rates of 94.77% on the Cell Phones and Accessories (CPAA) dataset and 85.31% on the Amazon Products (AP) dataset following rigorous testing.

A research paper done by Tabany, Myasar, and Meriem Gueffal [5], in which that the SVM model initially achieved 70% accuracy, outperforming Naive Bayes, Logistic Regression and Random Forest classifiers. The performance of the SVM model was significantly improved through hyperparameter optimization, ultimately attaining 93% accuracy in sentiment analysis.

The literature review offers a thorough grasp of the body of research, stressing the advantages and disadvantages of the different sentiment analysis and natural language processing techniques. It finds gaps in the existing research while highlighting efficient approaches like preprocessing methods and machine learning algorithms.

3. Description of Dataset

The musical instruments customer reviews dataset, gathered from the Kaggle repository, contains 10,235 entries with 9 attributes shown in Figure 2. For sentiment analysis, the reviewText column is preprocessed and used to extract insights into customer sentiments.

- **reviewerID:** Unique identifier for the reviewer.
- **asin:** Amazon Standard Identification Number, a unique identifier for the product.
- **reviewerName:** Name of the reviewer.
- **helpful:** The number of helpful votes received for the review.
- **reviewText:** The text of the review written by the customer. This column is selected for sentiment analysis.

- **overall:** The overall rating given by the reviewer, typically on a scale from 1 to 5.
- **summary:** A brief summary or title of the review.
- **unixReviewTime:** The timestamp of when the review was submitted, in Unix format.
- **reviewTime:** The date and time when the review was submitted.

reviewerID	asin	reviewerName	helpful	reviewText	overall	summary	unixReviewTime	reviewTime
A2IBPI20UZIR0U	1384719342	cassandra tu "Yeah, well, that's just like, u...	[0, 0]	Not much to write about here, but it does exactly what it's supposed to. filters out the pop sounds. now my recordings are much more crisp. it is one of the lowest prices pop filters on amazon so might as well buy it, they honestly work the same despite their pricing,	5	good	1393545600	02 28, 2014
A14VAT5EAX3D9S	1384719342	Jake	[13, 14]	The product does exactly as it should and is quite affordable.I did not realized it was double screened until it arrived, so it was even better than I had expected.As an added bonus, one of the screens carries a small hint of the smell of an old grape candy I used to buy, so for reminiscent's sake, I cannot stop putting the pop filter next to my nose and smelling it after recording. :DIf you needed a pop filter, this will work just as well as the expensive ones, and it may even come with a pleasing aroma like mine did!Buy this product! :]	5	Jake	1363392000	03 16, 2013
A195EZSQDW3E21	1384719342	Rick Bennette "Rick Bennette"	[1, 1]	The primary job of this device is to block the breath that would otherwise produce a popping sound, while allowing your voice to pass through with no noticeable reduction of volume or high frequencies. The double cloth filter blocks the pops and lets the voice through with no coloration. The metal clamp mount attaches to the mike stand secure enough to keep it attached. The goose neck needs a little coaxing to stay where you put it.	5	It Does The Job Well	1377648000	08 28, 2013
A2C00NNG1ZQQG2	1384719342	RustyBill "Sunday Rocker"	[0, 0]	Nice windscreen protects my MXL mic and prevents pops. Only thing is that the gooseneck is only marginally able to hold the screen in position and requires careful positioning of the clamp to avoid sagging.	5	GOOD WINDSCREEN FOR THE MONEY	1392336000	02 14, 2014
A94QU4C90B1AX	1384719342	SEAN MASLANKA	[0, 0]	This pop filter is great. It looks and performs like a studio filter. If you're recording vocals this will eliminate the pops that gets recorded when you sing.	5	No more pops when I record my vocals.	1392940800	02 21, 2014

Figure 2. Sample dataset of Musical Instruments Reviews

4. Experimental results or Performance evaluation: Using The Template

The research materials and methodologies include and preprocessing methods numerical format such as vectorization. To categorize sentiments and forecast accuracy, machine learning algorithms such as Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), and Naive Bayes (NB) are used. Furthermore, NSRD (Naive SVM Random Decision), a hybrid approach, is presented to improve performance by fusing the advantages of several algorithms to forecast polarity and accuracy.

*1) **Pre-processing Methods***

The pre-processing of the musical instruments customer reviews dataset involves several key steps to clean and prepare the text for sentiment analysis shown in Figure 3. First, the text is converted to lowercase to ensure uniformity, eliminating discrepancies between capitalized and lowercase words. Stop-word removal follows, eliminating common words like "and," "the," and "is," which do not add significant meaning to the analysis.

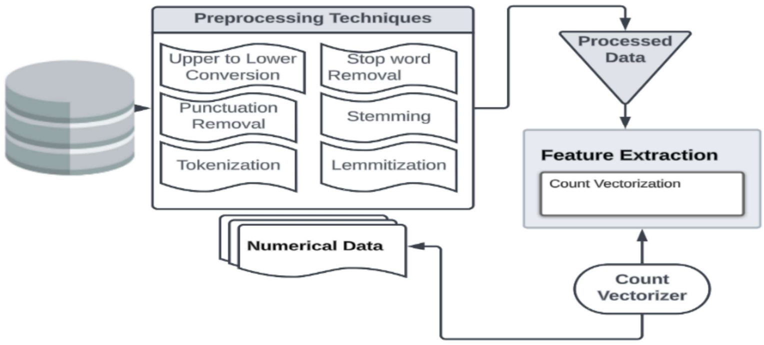

Figure 3. Workflow of Preprocessing Techniques

Stemming and lemmatization are applied to reduce words to their root forms, with stemming focusing on removing prefixes and suffixes, while lemmatization ensures words are reduced to their correct base form based on context[6][7]. Tokenization then splits the text into individual words or tokens, which helps in breaking down the data for further processing. Finally, the cleaned text is transformed into numerical data using count vectorization, where the frequency of each word is represented as a feature vector, making the dataset suitable for machine learning models.

*a) **Lowercase Conversion***

At this point, the text in every review has been converted to lowercase. By helping to standardize the text and making sure that terms like "Excellent" and "excellent" are treated as the same term by the analysis, it reduces variability and improves consistency in text processing.

$$\mathrm{T_{lower}} = \mathrm{F_{lower}}\,(\mathrm{T_{original}}) \qquad \ldots\ldots(1)$$

$\mathrm{T_{original}}$: The set of original tokens (words) in the text.

$\mathrm{F_{lower}}$: The lowercase conversion function that transforms each token to its lowercase equivalent.

T_{lower}: *The resulting set of tokens with all characters in lowercase.*

b) **Stopwords Removal**

Since stopwords don't substantially contribute to sentiment analysis, they are usually removed from texts[8]. These words include "and," "the," and "is." By reducing noise in the data, removing these stopwords enables the model to focus on more important terms.

$$T_{clean} = T_{original} - S \ldots\ldots\ldots\ldots(2)$$

$T_{original}$: The set of all tokens (words) in the original text.

T_{clean} : The set of predefined stopwords.

c) ***Tokenization***

Tokenization produces distinct words, or tokens, within the text[9]. This step is crucial for breaking down the continuous text into discrete units that can be analyzed or utilized as input for machine learning models.

$$T = f(S) \ldots\ldots\ldots\ldots(3)$$

S : The input text; f is the function that splits the input text into individual components (words, phrases, or sentences) based on a delimiter such as spaces, punctuation, or custom rules. T -The output set or sequence of tokens (words or components).

d) ***Stemming***

The base or root form of a stemmed word is derived [10][11]. For example, "working" might be stemmed to "work." This method can assist the model in more efficiently identifying and analyzing related terms by fusing different word forms into a single representation.

$$T_{Stemmed} = f_{stem}(T_{original}) \ldots\ldots\ldots\ldots(4)$$

($T_{original}$)- The set of original tokens (words) extracted from the text. f_{stem} - The stemming function that reduces each token to its root or base form by applying linguistic rules or truncation. $T_{Stemmed}$ -The resulting set of stemmed tokens.

e) ***Lemmatization***

Lemmatization more accurately reduces words to their base or root form than stemming because it considers the word's context and meaning [12][13]. Words like "better" would be lemmatized to "good." This method provides more accurate text normalization, which improves text analysis and sentiment prediction.

$$T_{lemma} = f_{lemma}(T_{original}, C) \ldots\ldots\ldots\ldots(5)$$

$T_{original}$: The set of original tokens (words) in the text.

f_{lemma} : The lemmatization function that maps each token to its base or dictionary form (lemma).

C: The context or part of speech (POS) of each token, which guides the lemmatization process.

T_{lemma}: The resulting set of tokens after applying lemmatization.

2) Machine Learning Algorithms

Several machine learning algorithms are used in this research to categorize and examine the sentiment contained in the dataset. Support Vector Machines (SVM) is excellent at handling high-dimensional data, while Naive Bayes (NB) is used because of its ease of use and probabilistic methodology[14][15]. Strong ensemble and tree-based classification capabilities are offered by Random Forest (RF) and Decision Tree (DT). Furthermore, NSRD (Naive Bayes, SVM, Random Forest, and Decision Tree) is a hybrid algorithm that combines the advantages of these techniques to improve accuracy and performance.

a) Naïve Bayes Algorithm

Based on Bayes' Theorem, the probabilistic machine learning algorithm Naive Bayes assumes feature independence [16][17]. It is easy to use, effective, and especially suitable for tasks involving text classification, such as sentiment analysis. Given the input data, the algorithm determines the probability of each class and chooses the one with the highest probability. It is a popular option for text mining and natural language processing because, in spite of its "naive" independence assumption, it works well in situations involving high-dimensional data.

b) Support Vector Machine

A popular supervised machine learning algorithm for classification and regression problems is the Support Vector Machine (SVM)[18]. It operates by locating the best hyperplane in a high-dimensional space that maximally divides data points of various classes. SVM is robust against overfitting, especially when there are fewer data points, and is especially good at handling high-dimensional data. For sentiment analysis and other text classification tasks, SVM is a flexible and dependable option because it can model intricate, non-linear relationships using kernel functions.

c) Decision Tree Algorithm

A supervised machine learning algorithm for classification and regression applications is called a decision tree. It creates a tree-like structure with decision nodes and leaf nodes by recursively dividing the dataset into subsets according to feature values [19]. While leaf nodes stand for class labels or results, each decision node represents a feature test. Decision trees are a popular option for tasks requiring explain ability because they are simple to comprehend, interpret, and visualize. They may, however, be susceptible to overfitting, which can be lessened by employing strategies like ensemble methods or pruning.

*d) **Random Forest***

In order to increase accuracy and decrease overfitting, the Random Forest ensemble learning algorithm constructs several decision trees and aggregates their predictions [20]. To ensure diversity among the trees, it selects features at random at each split and trains each tree on a random subset of the data. A majority vote from all trees is used for classification, or the outputs are averaged for regression, to arrive at the final prediction. Random Forest is a dependable option for classification and regression tasks because it is resilient, manages big datasets well, and works well in situations with noisy or missing data.

*e) **NSRD (A hybrid method)***

The strengths of four well-known machine learning algorithms—Naive Bayes (NB), Support Vector Machine (SVM), Random Forest (RF), and Decision Tree (DT)—are combined in NSRD, a hybrid algorithm. Through the integration of these disparate models, NSRD makes use of the interpretability of Decision Trees, the ensemble strength of Random Forest, the boundary optimization potential of SVM, and the probabilistic nature of Naive Bayes. This hybrid method increases prediction robustness, decreases overfitting, and improves classification accuracy. The combination makes NSRD an effective tool for tasks like text classification and sentiment analysis by enabling better handling of various data types and intricate patterns.

5. Results and Discussion

Metrics like accuracy, precision, recall, and F1-score are used in the results and discussion section to compare the performance of several machine learning algorithms, such as Naive Bayes, Support Vector Machine, Random Forest, Decision Tree, and the hybrid NSRD method. The hybrid NSRD algorithm performs better than the individual models, demonstrating increased robustness and classification accuracy. The advantages and disadvantages of each model are examined in relation to how well-suited they are for the given dataset and task. Furthermore, explanations of the performance variations are given, elucidating the ways in which feature selection, preprocessing, and algorithm selection affect the outcomes. The results show that a hybrid model that combines several algorithms performs better on text classification and sentiment analysis tasks.

Figure 4 shows the consistency of all text was standardized after lowercase conversion. Lemmatization and stemming efficiently handled morphological variances by reducing words to their root forms. Tokenization allowed for in-depth analysis by breaking the review text down into individual words. By removing non-informative words like "and," "the," and "is," stopword removal improved the clarity of the dataset. After completing these preprocessing steps, the dataset was cleaned and prepared for sentiment analysis and numerical representation.

```
                                              reviewText  \
Not much to write about here, but it does exac...
The product does exactly as it should and is q...
The primary job of this device is to block the...
Nice windscreen protects my MXL mic and preven...
This pop filter is great. It looks and perform...

                                         processed_lower  \
not much to write about here, but it does exac...
the product does exactly as it should and is q...
the primary job of this device is to block the...
nice windscreen protects my mxl mic and preven...
this pop filter is great. it looks and perform...

                                      processed_Stopword  \
much write here, exactly supposed to. filters ...
product exactly quite affordable.i realized do...
primary job device block breath would otherwis...
nice windscreen protects mxl mic prevents pops...
pop filter great. looks performs like studio f...

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much write here, exactli suppos to. filter pop...
product exactli quit affordable.i realiz doubl...
primari job devic block breath would otherwis ...
nice windscreen protect mxl mic prevent pops. ...
pop filter great. look perform like studio fil...

                                      processed_Stemming proc
much write here, exactli suppos to. filter pop...
product exactli quit affordable.i realiz doubl...
primari job devic block breath would otherwis ...
nice windscreen protect mxl mic prevent pops. ...
pop filter great. look perform like studio fil...
```

Figure 4. Results of pre-processing Techniques

The frequency of particular words in a dataset pertaining to reviews of musical instruments is highlighted in the Table 1 and Figure 5. Due to its prominence in the dataset, the word "7049" appears the most, followed by "Guitar" with 6,353 occurrences. Additionally, words like "Sound" (5,027) and "One" (4,753) are used a lot, which indicates how important they are in the context of the reviews. "Great" (4,127) and "Good" (3,819) are examples of positive descriptors that indicate a trend toward positive sentiments. Furthermore, words like "String" (3,660) and "Work" (3,430) draw attention to technical details, whereas "Get" (3,412) may stand for actions or results. Figure 6 offers insightful information about recurring themes and emotions in the dataset.

Table 1. Frequency of words in Reviews

Word	Frequency
7049	Guitar
Guitar	6353
Sound	5027
One	4753
Like	4248
Great	4127
Good	3819
String	3660
Work	3430
Get	3412

```
Top 10 Most Frequent Words:
use         7049
guitar      6353
sound       5027
one         4753
like        4248
great       4127
good        3819
string      3660
work        3430
get         3412
dtype: int64
```

Figure 5. Number of Times Words Repeated

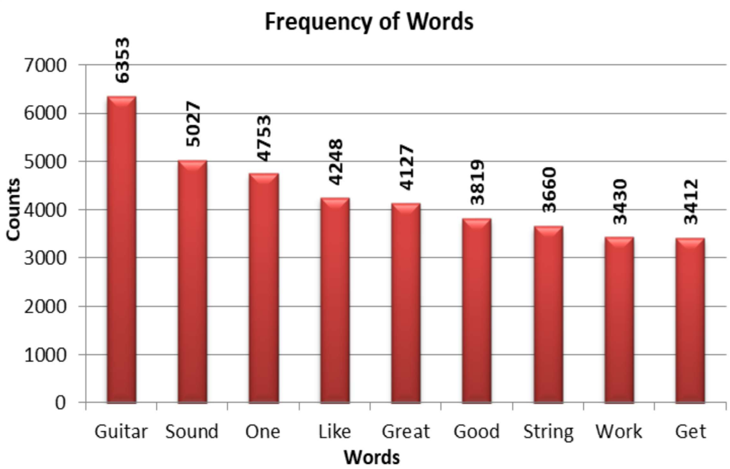

Figure 6. Frequency of Words in Customer Reviews

The progression of text lengths at different preprocessing stages for reviews is depicted in the Table 2, demonstrating how various techniques alter or reduce the text content. Since this step only standardizes text case, the "Lowercase Review" preserves the original text length while the "Review" column shows the original text length.

"Stopword Removal" drastically cuts down on text length by eliminating words like "the" and "is" that don't convey information. In certain instances, tokenization results in a slight increase in length, this reflects the division of text into discrete tokens or words. By combining words into their root forms or dictionary-based lemmas, stemming and lemmatization further condense the text. The Table 2 shows how preprocessing methodically keeps important content while streamlining and getting text ready for analysis.

Table 2. Length of Reviews in Preprocessing phase

Review	**Lowercas e review**	**Tokenized**	**Stopword Removal**	**Stemmin g**	**lemmatized**
442	442	428	392	386	385
477	477	413	392	386	385
226	226	216	146	134	131
299	299	260	184	174	172
213	213	213	198	186	182
112	112	158	148	134	131
215	215	246	238	213	213
476	476	546	509	498	496
58	58	72	64	53	50
45	45	51	48	42	41
152	152	152	148	125	123
35	35	47	46	32	31
219	219	235	209	198	196

This Figure 7 shows how different preprocessing methods affect textual data length at different stages. Since lowercase conversion does not change text length, the "Review" and "Lowercase Review" columns are the same length. "Tokenized" lengths, which represent the separation of text into discrete tokens (words), are either marginally longer or remain constant.

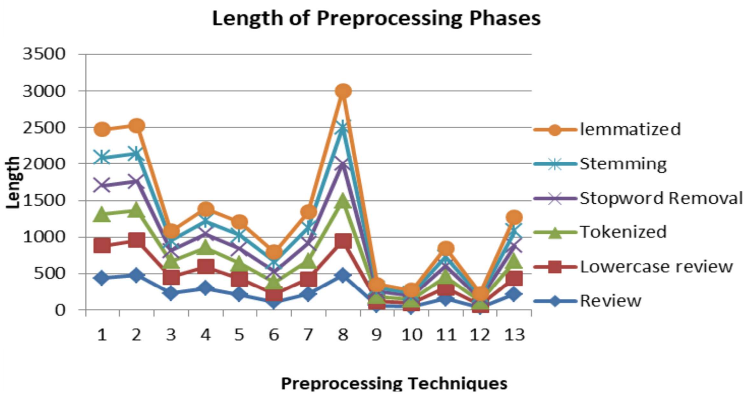

Figure 7. Length of Preprocessing Phases

The "Stopword Removal" step removes common, uninformative words, greatly reducing lengths. Additional reductions take place in the "Lemmatized" and "Stemming" columns, where words are transformed into dictionary-based lemmas or their root forms, respectively. These changes efficiently prepare the text for sentiment analysis or other text mining tasks by gradually condensing it while maintaining important content.

Table 3. Identification of Polarities

Sentiments	NB	RF	DT	SVM	NSRD
Positive	1846	1691	1676	1688	1745
Neutral	132	288	287	292	223
Negative	12	11	27	10	22

In order to classify reviews into Positive, Neutral, and Negative sentiments, the Table 3 shows how well five different classification algorithms performed on a sentiment analysis task: Naive Bayes (NB), Random Forest (RF), Decision Tree (DT), Support Vector Machine (SVM), and the hybrid NSRD algorithm. Out of all the models, NB has the most positive predictions (1,846), followed by NSRD (1,745).

SVM, RF, and DT have lower numbers in this category. SVM makes the most predictions for neutral sentiments (292), closely followed by RF (288) and DT (287), while NB makes the fewest predictions (132). With NB and SVM producing the fewest misclassifications (12 and 10, respectively), negative sentiment predictions are low across all models, suggesting their potential accuracy in handling extreme cases shown in Figure 8. Overall, the performance of the NSRD algorithm is balanced across all sentiments categories.

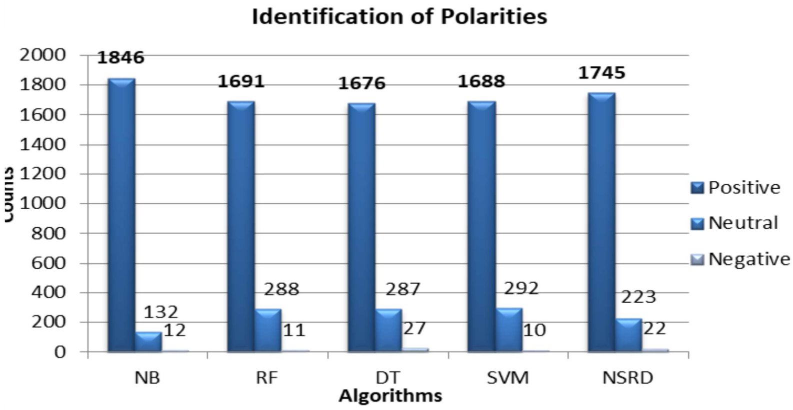

Figure 8. Identification of Polarities

Table 4. Performance Metrics of Algorithms

Decision Tree Algorithm			
Metrics	**Precision**	**Recall**	**F1-score**
Negative	0.80	0.74	0.84
Neutral	0.75	0.63	0.69
Positive	0.83	0.92	0.85
Naïve Bayes			
Negative	0.83	0.71	0.73
Neutral	0.72	0.62	0.63
Positive	0.92	0.92	0.94
Random Forest			
Negative	0.85	0.53	0.71
Neutral	0.73	0.75	0.72
Positive	0.84	0.91	0.93
Support Vector Machine			
Negative	0.82	0.74	0.81
Neutral	0.73	0.58	0.65
Positive	0.86	0.90	0.88
NSRD (Hybrid Algorithm)			
Negative	0.98	0.98	0.98
Neutral	0.95	0.90	0.92
Positive	0.96	0.96	0.96

The algorithms such as (Decision Tree, Naïve Bayes, Random Forest, Support Vector Machine, and the NSRD hybrid algorithm) are shown in the Table 4 and Figure 9 along with their precision, recall, and F1-score for predicting negative, neutral, and positive sentiments. With nearly flawless scores across all metrics and sentiment categories, the NSRD algorithm performs best overall. It excels with an F1-score of 0.98 for negative sentiments and 0.96 for positive sentiments. With an F1-score of 0.94, Naïve Bayes performs well as well, especially in the classification of positive sentiment, but it falls short in the predictions of neutral sentiment. Support vector machines and random forests produce competitive scores for positive sentiments but have trouble classifying negative and neutral sentiments consistently.

The accuracy percentages of five algorithms that were assessed for sentiment classification—Naïve Bayes, Support Vector Machine (SVM), Random Forest, Decision Tree, and the NSRD (Proposed Method)—are shown in the Table 5. With a substantially higher accuracy of 96.1%, the NSRD approach outperforms the other algorithms, demonstrating its efficacy and resilience in managing the dataset.

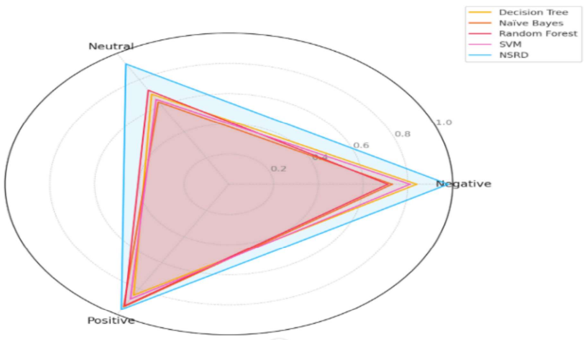

Figure 9. Metrics of Algorithms

Table 5. Accuracy of Algorithms

Algorithms	Accuracy %
Naïve Bayes	74.0
Support Vector Machine	83.3
Random Forest	84.1
Decision Tree	79.2
NSRD(Proposed method)	96.1

Additionally, Random Forest and SVM demonstrate their strong predictive abilities with accuracies of 84.1% and 83.3%, respectively. A moderate accuracy of 79.2% is attained by the Decision Tree algorithm, whereas Naïve Bayes performs relatively poorly with 74.0%, probably as a result of its feature independence assumptions. The outcomes highlight how the NSRD approach outperforms conventional models in terms of accurately classifying sentiment shown in Figure 10.

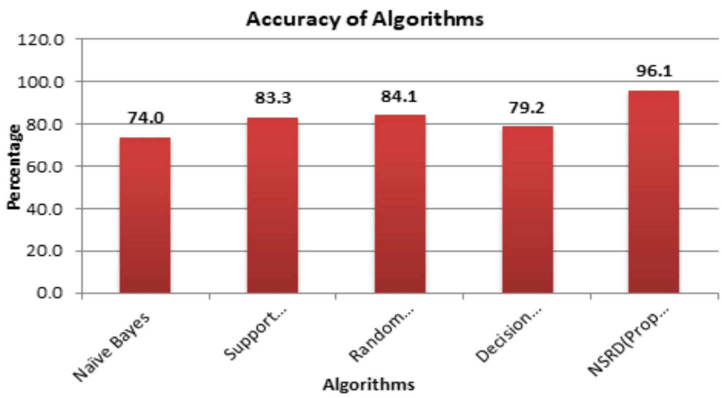

Figure 10. Accuracy of Algorithms

6. Conclusion

Social media data plays a crucial role in analyzing customer reviews and understanding their sentiments. In this study, reviews from the musical instruments dataset were used as input to evaluate the performance of selected machine learning algorithms, including Naïve Bayes, Support Vector Machine, Random Forest, Decision Tree, and a hybrid algorithm named NSRD. These algorithms were assessed based on metrics such as precision, recall, F1-score, and accuracy. Sentiment polarity analysis was conducted to classify customer reviews effectively. The experimental results demonstrated that the NSRD hybrid algorithm outperformed the existing algorithms in terms of both performance and efficiency. This superior accuracy and consistency highlight the hybrid algorithm's capability to provide enhanced sentiment analysis. It is concluded that the NSRD hybrid algorithm is a more effective tool for sentiment analysis compared to traditional algorithms. Future work will explore the application of additional machine learning algorithms on diverse datasets to further enhance sentiment classification and accuracy outcomes.

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