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OPTIMIZING SENTIMENT ANALYSIS IN MOVIE REVIEWS: COMPARATIVE STUDY OF MACHINE LEARNING ALGORITHMS

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Abstract:
Reviews of movies, in particular, are produced in large quantities by a variety of reviewers who base their opinions on their subjective experiences and perceptions. To extract useful insights from the analysis of these reviews from the social media like twitter, one must employ sophisticated data mining techniques, which is a challenging task. To guarantee data quality and relevance, the study entails a thorough pre-processing of the review data, which includes stop word removal, stemming, part-of-speech tagging, tokenization, and named entity recognition. After processing the data, the classification algorithms are run through an evaluation process to determine how well they performed in terms of accuracy, precision, recall, and F1 score. These algorithms' comparative analysis demonstrates how well they work in recommendation and sentiment analysis systems. This study analyzes movie reviews using data mining techniques such as Support Vector Machine, Random Forest, and Logistic Regression. The main objective is to determine the films' merits and faults by analyzing reviews, and then to recommend the best film based on these algorithms' accuracy and efficiency. The study intends to improve knowledge of film reception through comparative analysis and offer a trustworthy technique for recommending movies to prospective viewers based on the sentiment conveyed in social media reviews.

Keywords:
Support Vector Machine, Random Forest, Logistic Regression, Tokenization, Stemming.

1. Introduction

The artificial intelligence field of natural language processing, or NLP, is concerned with how people and computers interact using natural language. NLP's ultimate goal is to read, interpret, comprehend, and usefully make sense of human languages. To help machines comprehend and react to text or audio data, natural language processing (NLP) integrates machine learning, deep learning, and computational linguistics. NLP is used in speech recognition, sentiment analysis, language translation, and text summarization. The entertainment industry, especially the movie industry, produces a lot of data in the digital age because of the reviews that viewers post on different social media platforms. The audience's subjective opinions and perceptions are reflected in these reviews. Sentiment analysis is a branch of natural language processing (NLP) that focuses on identifying the sentiment of text by removing subjective elements from the data. Sentiment analysis is useful in the context of movie reviews because it can be used to predict box office success, understand audience preferences, and assess public opinion. Filmmakers, marketers, and other stakeholders must analyse these attitudes in order to make wise decisions.

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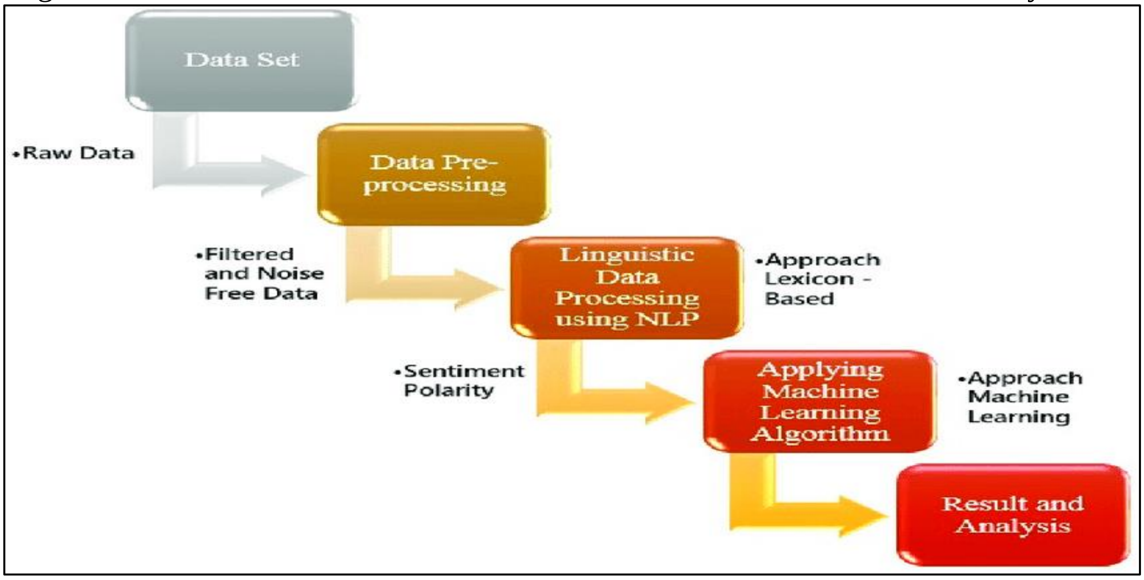

Figure 1: Architecture of the Research work

A thorough process for utilizing data mining techniques to analyze movie reviews is depicted in the figure 1. The first step is gathering raw data, or the "Data Set," which consists of reviews of movies from different sources. The following stage is called "Data Pre-processing," in which noise is filtered out of the raw data to produce clean, pertinent data. After filtering the data, it is subjected to "Linguistic Data Processing using NLP," which uses natural language processing techniques to ascertain the reviews' sentiment polarity. After that, the sentiment data is put through a process called "Applying Machine Learning Algorithm," which uses machine learning techniques to evaluate and categorize the data. "Result and Analysis," the last step, involves analyzing the machine learning algorithms' outputs to produce insightful findings. The figure emphasizes how these processes flow sequentially and how methodical processing and analysis turn raw data into insightful analytical findings.

The process of analyzing user reviews through text processing is shown visually in the figure. The "User Review" section is where users first contribute their opinions about movies or other topics. These evaluations are gathered as "Text data," which is then organized and saved. In the following step, "Processing text," the text data is subjected to a variety of natural language processing (NLP) methods. Gears are used to represent this processing step, which shows how raw text is transformed into structured information in a methodical and intricate way. Ultimately, the text has been processed, assessed, and divided into "Reviews," which are grouped according to their sentiment, for example, positive (thumbs up) or negative (thumbs down) shown in figure 2.

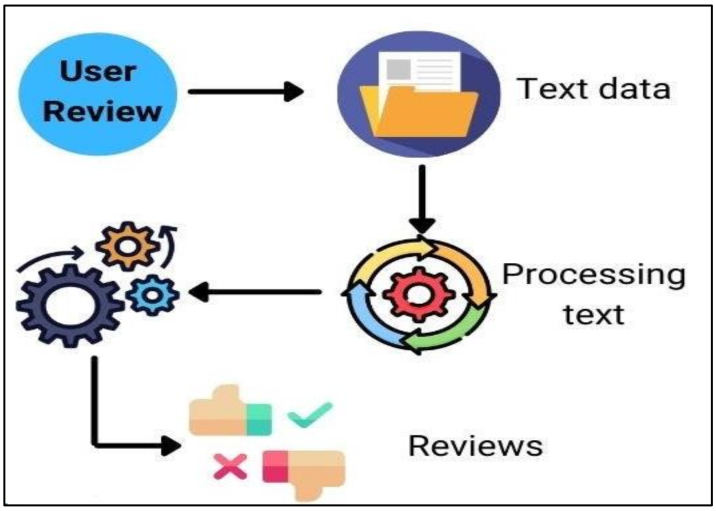

Figure 2: Sentiment Analysis of Movie Reviews Using Machine Learning Algorithms

The process from unstructured user input to final structured and analyzed reviews is depicted in this figure, emphasizing the role text processing plays in extracting valuable insights from user feedback.

2. Review of Literature

Reviews of the literature offer insights into the different techniques and strategies employed by other researchers. This enables academics to select the most appropriate techniques for their research questions, improve their own methods, and learn from existing approaches. Comprehending prior research facilitates the contextualization of researchers' own findings. They can more effectively compare the results, talk about the similarities and differences, and assess the implications.

The research work titled as "Sentiment Analysis Based on Performance of Linear Support Vector Machine and Multinomial Naïve Bayes Using Movie Reviews with Baseline Techniques" carried out by Danyal et. al. in [1]. In order to better understand public sentiment, this research paper explores the field of sentiment analysis and focuses on obtaining subjective data from movie reviews. In order to assist consumers in making decisions without having to read every review, the study attempts to compile movie reviews. Using the IMDB dataset of 50,000 reviews and the Sentiment Polarity Dataset Version 2.0, it compares a number of machine learning classifiers, such as Logistic Regression, Random Forest Classifier, Decision Tree, K-Nearest Neighbor, Gradient Boosting Classifier, Passive Aggressive Classifier, Linear Support Vector Machines (SVM), and Multinomial Naïve Bayes. To improve the performance of the models, pre-processing actions like data cleaning, duplicate removal, and handling chat words are carried out. According to the results, the Passive Aggressive Classifier achieves the highest accuracy of 90.27% after hyperparameter tuning, while the Linear SVM achieves the highest accuracy of 89.48% on the IMDB dataset. Multinomial Naïve Bayes achieves the highest accuracy of 70.69% on the Sentiment Polarity Dataset Version 2.0; after tuning, this accuracy rises to 71.04%. With the Passive Aggressive Classifier emerging as the best method post-tuning, this study highlights the importance of sentiment analysis for assessing emotions and attitudes in movie reviews and predicting a movie's performance based on the average sentiment of all reviews. A research work titled as "Movies Rating Prediction Using Supervised Machine Learning Techniques" done by Siddique et. al. in [2], In order to create a movie recommendation system, this research study investigates the use of supervised machine learning techniques, making use of the enormous and quickly expanding amounts of data produced by social media. Three machine learning models are the subject of the study: Random Forest (RF), Support Vector Machine (SVM), and K-nearest neighbors (KNN). Using the MovieLens 100k and 1M datasets, the study compares these models to assess how well they perform in terms of accuracy, precision, recall, and F1 score. The paper starts off by giving a summary of previous machine learning methods that were applied to item recommendations. After that, it explores the creation and assessment of the predictive models, emphasizing how well they predict movie ratings. The Random Forest model proves to be the most successful approach for movie recommendation in this study, as the results show that it performs better than the other models. In order to further advance the field, the paper also addresses open issues, future research directions, and current challenges.

Another research paper examines how well different machine learning (ML) models handle sentiment analysis (SA) on a dataset of 50,000 movie reviews that is equally divided between favorable and unfavorable ratings done by Jassim et. al. in [3]. Random Forest, K-Nearest Neighbor, Artificial Neural Network, Gradient Boosting, Support Vector Machine (SVM), AdaBoost, Extreme Gradient Boosting, Decision Tree, Light GBM, Stochastic Gradient Descent, and Bagging are among the simple and ensemble ML techniques that are compared in the study. In order to create a new method for rating prediction based on textual customer reviews, the research will use term frequency and term frequency-inverse document frequency for feature extraction. Using precision, accuracy, recall, F-score, AUC, and Kappa-measure, the models' performance was assessed. With a precision rate of 88.33%, the Support Vector Machine (SVM) classifier proved to be the most effective approach among those put to the test, according to the results. The research work titled as "Prediction of movie success based on machine learning and twitter sentiment analysis using internet movie database data" carried out by Tripathi et. al. in [4], uses a hybrid approach that combines sentiment analysis of review reviews with movie features to predict the box office success of new films. To train supervised machine learning models, important movie attributes from IMDb are gathered and preprocessed, including the title, director, star cast, and writer. Metrics such as mean squared error, root mean square error, and r2 score are used to compare the performance of different models. Furthermore, sentiment analysis is done on tweets pertaining to movies, and the best sentiment analysis model has an accuracy of 88.47%. The hybrid model, which incorporates sentiment analysis and movie features, performs well in predicting the box office success of movies. With an accuracy of 88.47%, the sentiment analysis model stands out as the most effective approach for this task among the methods evaluated. A research work carried out by Jassim et. al. in [5], the advancements in sentiment mining are examined in this paper, with a particular emphasis on automating sentiment analysis through the use of machine learning, data mining, and natural language processing methods. It addresses the difficulties in precisely identifying and categorizing sentiments in movie reviews caused by language structure, especially grammar and dictionary management. The suggested approach uses "Term Frequency" and "Term Frequency-Inverse Document Frequency" techniques to create vectors after pre-processing and word extraction based on frequency. We apply and assess four Naive Bayes models: Gaussian, Multinomial, Bernoulli, and Complement. With an accuracy of 86.46%, the results show that the Naive Bayes Multinomial model performs better than the other models, making it the most successful technique for sentiment classification in this investigation.

Table 1: Comparison of various methods used by the researchers

Reference	Author Name	Methods Used	Best Method Used	Accuracy
[1]	Danyal et al.	Logistic Regression, Random Forest, Decision Tree, K-Nearest Neighbor, Gradient Boosting, Passive Aggressive Classifier, Linear SVM, Multinomial Naïve Bayes	Passive Aggressive Classifier	90.27% (IMDB), 71.04% (Sentiment Polarity)
[2]	Siddique et al.	Random Forest, Support Vector Machine (SVM), K-nearest neighbors (KNN)	Random Forest	(Performance metrics not specified)
[3]	Jassim et al.	Random Forest, K-Nearest Neighbor, Artificial Neural Network, Gradient Boosting, Support Vector Machine (SVM), AdaBoost, Extreme Gradient Boosting, Decision Tree, Light GBM, Stochastic Gradient Descent, Bagging	Support Vector Machine (SVM)	88.33% (Precision)
[4]	Tripathi et al.	Supervised ML models, sentiment analysis on Twitter data	Sentiment analysis model	88.47% (Accuracy)
[5]	Jassim et al.	Naive Bayes (Gaussian, Multinomial, Bernoulli, Complement)	Naive Bayes (Multinomial)	86.46% (Accuracy)

The results of several research studies on sentiment analysis in film reviews are compiled in the table 1. The most accurate classifier, according to a comparison by Danyal et al. of several, was the Passive Aggressive Classifier, which scored 90.27% on IMDB data and 71.04% on Sentiment Polarity data. Without mentioning any metrics, Siddique et al. preferred Random Forest for movie recommendation. According to Jassim et al., the precision of the Support Vector Machine was 88.33%. Tripathi et al. combined sentiment analysis with machine learning models to predict movie success with an accuracy of 88.47%. According to Jassim et al., Naive Bayes (Multinomial) is an efficient method for classifying sentiment with an accuracy rate of 86.46%.

3. Description of Dataset

The 676 movie reviews in the dataset were gathered from real-time Twitter social media. Review attributes are as follows: Month, Movie Name, and Reviews. Taken as a whole, these characteristics offer an impression of the general opinion and responses to the film "Indian 2" as they were tweeted during the designated time frame.

Table 2: Sample Dataset of Movie Reviews

Month	Movie Name	Review Text
July	Indian 2	I would give 2 Stars for guts to release this movie. Otherwise, ordinary movie. I would watch old Kamal's movie which are more entertaining.
July	Indian 2	Story first half very good, second half needs to be fast, bgm score may be need to be worked out. story, dialogue, director, thiru kamal hassan, thiru siddharth, thiru jagan, cinemaphotography hunt the story. screenplay needs to be much more concentrated in second half. Lot of star artist more potential, used potential may be less.If star artist is reduced, it might reached finance target with in a weekIn my point of view slow hit. movie will reach the target after a week....
July	Indian 2	All the reviews read on this movie were negative and hencewent for the movie with least expectations. But I realised that all the reviews were totally biased. Movie is worth watching for its plot - though not strongly projected. Some scenes like the patient's daughter peeping into an operation theatre, surgery procedure and the last thirty minutes chase are absurd and lacks any logic. On the whole movie is watchable and definitely better than Kalki.
July	Indian 2	Horrible movie. Even after so much acting experience, Kamal's facial expression is the worst. Today the new comers in OTT are doing much better than him. He is fightimg against corruption but in real life colluding with the most corrupt party and politicians in the world. Its auch a contradiction, so not able to relate at all..
July	Indian 2	Could not believe it's a Shankar's movie. Not even worth a one time watch...
July	Indian 2	Worst nothing in the movie waste of time no story
July	Indian 2	Ones watchable
July	Indian 2	The filming technique is very unassuming
July	Indian 2	This was the worst movie and it also received the least amount of applause after few weeks
July	Indian 2	Neither boring nor interesting.

The table 2 shows an overview of the movie reviews that were gathered for the movie "Indian 2" in July. A distinct review is represented by each row, expressing a range of feelings and viewpoints regarding the film. Reviews range from critical evaluations emphasizing problems with the acting, direction, and coherence of the plot to more complimentary comments on particular aspects such as the narrative or cinematography. While some reviews argue the film isn't worth seeing despite its flaws, others express disappointment with the way it was done and with its apparent lack of entertainment value. The table presents a wide array of viewpoints from viewers, which is indicative of the varied reactions that "Indian 2" elicited during its month of release.

4. Materials and Methods

In order to guarantee the accuracy and repeatability of scientific research, the "Materials and Methods" section is essential. It makes it possible for additional researchers to comprehend the study, possibly repeat it, confirm the accuracy of the findings, and expand on the research to further the field's understanding [6][7]. Support vector machines (SVM), logistic regression (LR), and random forests (RF) are a few examples of machine learning techniques that are the subject of research papers. Each technique is important for handling various aspects of classification and prediction tasks.

4.1 Preprocessing Techniques

The preprocessing workflow for a dataset of movie reviews is shown in the figure. First, unfiltered film reviews are gathered and kept in a dataset. This dataset underwent a number of preprocessing procedures to get it ready for additional analysis. These actions are:

Lowercase Conversion: To maintain consistency and get rid of case sensitivity issues, all text should be converted to lowercase.

Stop-word Removal: Eliminating common words like "and" and "the" that don't significantly add meaning to the text is known as stopword removal.

Tokenization: Tokenization is the process of dividing the text into discrete words or units.

Lemmatization: Keeping the text representation consistent by breaking words down to their most basic or root form.

Remove punctuation: Remove punctuation to prevent it from interfering with text analysis. Managing Missing Values: In order to guarantee a comprehensive and error-free dataset, address any missing data points.

These preprocessing methods prepare the processed dataset for the next stages of the pipeline for analysis or machine learning. The data is guaranteed to be clear, consistent, and ready for precise analysis thanks to this structured approach [8][9][10]. Pre-processing improves the quality of textual data before it is fed into algorithms for analysis or modelling, which is crucial for tasks involving natural language processing and machine learning shown in figure 3.

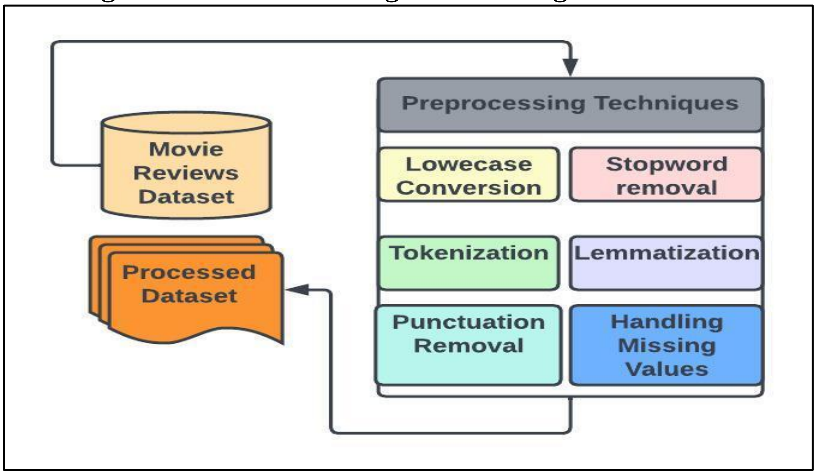

Figure 3: Preprocessing techniques

Tokenization, stop word removal, stemming or lemmatization, and normalization are some of the critical processes that are involved. Tokenization divides text into smaller units called tokens; stop word removal removes frequently used words with little meaning; lemmatization and stemming reduce words to their most basic form to handle variations; and normalization guarantees uniform formatting (e.g., lowercase text). By cleaning and preparing the data in this way, algorithms are better able to extract meaningful patterns and relationships from the data, increasing accuracy and efficiency in tasks like information retrieval, sentiment analysis, and classification.

4.2 Support Vector Machines (SVM)

SVM is an effective supervised learning algorithm that can be applied to regression and classification problems [11][12]. The way it operates is by determining which hyperplane best divides data points into distinct classes. SVMs work well in high-dimensional spaces and are especially helpful when there is a distinct class boundary [13][14]. Through kernel functions, they can handle both linear and non-linear relationships, which makes them adaptable to different kinds of data distributions.

Maximize (in a_i)

$$L(\alpha)\sum_{i=1}^{n} ai - \frac{1}{2}\sum_{i,j} a_i\, a_j y_i y_j x_i^T x_j = \sum_{i=1}^{n} a_i a_j y_i y_j k(x_i, x_j) \quad \ldots\ldots\ldots\ldots\ldots(1)$$

The equation you've presented is a part of the mathematical formulation of the Support Vector Machine (SVM) optimization problem, specifically in its dual form. By directly computing the inner product in a higher-dimensional feature space, the kernel function $k\ (x_{i,j})$ enables SVMs to function in a higher-dimensional feature space and facilitates the classification of non-linearly separable data. This equation essentially captures the dual form optimization goal of support vector machines (SVMs), which is to identify the set of Lagrange multipliers α that define the optimal hyperplane in the feature space (or, alternatively, in the kernel-induced feature space) with the maximum margin between classes.

4.3 Logistic Regression

Despite its name, logistic regression (LR) is a linear model that is applied to binary classification problems. It simulates a binary outcome's probability depending on one or more predictor variables [15][16]. The influence of each variable on the likelihood of the result is represented by the predictor variable coefficients, which are estimated by LR [17]. Because of its ease of use, readability, and efficacy in situations where there is a linear relationship between predictors and outcomes, it is frequently employed.

$$l(w, b) = \sum_{i=1}^{n}[\, y_i(w^T X_i + b) - \log\left(1 + e^{(w^T x_i + b)}\right)] \text{ ....(2)}$$

Optimizing ℓ(z,b) ℓ(w,b) using techniques such as gradient descent guarantees that the values of w w and b b are adjusted to optimize the probability of the observed data in the context of the Logistic Regression model. This formulation makes Logistic Regression a potent tool for binary classification tasks in machine learning by enabling it to learn discriminative decision boundaries that divide the classes based on the input features.

4.4 Random Forests (RF)

During training, Random Forest builds a large number of decision trees. It then outputs a class that is the mean prediction (regression) or the mode of the classes (classification) of the individual trees [18][19]. Because each tree is trained using a random subset of features and data, Random Forests are resistant to overfitting and able to handle large, highly dimensional datasets. They are renowned for their exceptional precision and capacity to identify intricate connections within the data.

$$F(x; \{T_1, T_2, \dots \dots, T_B\}) = \frac{1}{B}\sum_{b=1}^{B} T_b(x) \text{....................(3)}$$

The final prediction for a new input x is obtained by averaging the predictions from all trees T_b. By combining multiple decision trees trained on bootstrapped samples with random feature subsets, Random Forest makes use of the power of ensemble learning [20][21]. This method produces a flexible and efficient model for machine learning tasks involving both regression and classification. In essence, equation (3) summarizes the fundamental idea of ensemble learning in Random Forests, utilizing the collective wisdom of several decision trees to produce predictions that are more accurate and dependable than those from a single tree acting alone.

These techniques are fundamental to machine learning research because they each have special advantages that researchers can take advantage of according to the demands and features of their tasks and datasets.

5. Experimental Results

The research's findings are presented in the "Results and Discussion" section, which also offers a forum for critical evaluation, interpretation, and contemplation of the findings' importance and ramifications. It contributes to the advancement of knowledge in the research domain by bridging the gap between empirical findings and theoretical insights.

5.1 Results of Preprocessing

Preprocessing included actions like cutting punctuation, changing the text's case, eliminating stop words, and, when necessary, stemming or lemmatizing words to their root forms [22][23][24]. This text has been cleaned up and normalized, making it ready for additional analysis like sentiment analysis or classification.

Table 3: Results of Preprocessing

Month	Movie Name	Review Text	Processed Text Reviews
July	*Indian 2*	*Could not believe it's a Shankar's movie. Not even worth a one time watch...*	*could believ 's shankar 's movi even worth one time watch ...*
July	*Indian 2*	*Worst nothing in the movie waste of time no story*	*worst noth movi wast time stori*
July	*Indian 2*	*Ones watchable*	*one watchabl*
July	*Indian 2*	*The filming technique is very unassuming*	*film techniqu unassum*
July	*Indian 2*	*This was the worst movie and it also received the least amount of applause after few weeks*	*worst movi also receiv least amount applaus week*

July	*Indian 2*	*Neither boring nor interesting.*	*neither bore interest*

The following movie review examples show some of the benefits of preprocessing text data before analysis shown in table 3. The reviews' varied word forms, punctuation, and capitalization prior to preprocessing make it difficult for algorithms to accurately interpret meaning [25][26]. However, following preprocessing, the text is standardized: words are changed to lowercase, punctuation is eliminated, and words are, when appropriate, reduced to their root forms using stemming techniques [27][28]. Normalization improves natural language processing tasks like sentiment analysis and classification in terms of accuracy and efficiency [29][30]. It enables algorithms to concentrate on the text's semantic content rather than its surface-level variations, increasing the validity of inferences made from the data.

5.2 Results of classification Algorithms

The classification algorithms' performance metrics, which include Random Forest, Support Vector Machine (SVM), and Logistic Regression, show differing degrees of predictive power. For this dataset, Random Forest performs similarly to random chance, as evidenced by its moderate results across metrics like TP Rate (True Positive Rate), Precision, Recall, and F-Measure, with a ROC Area of 0.5. With high TP Rate, Precision, Recall, and F-Measure values, a robust ROC Area of 0.8, and a high Precision-Recall Curve (PRC Area) of 0.939, SVM exhibits strong performance, demonstrating its efficacy in class distinction.

Table 4: Performance Measure

	Random Forest	***Support Vector Machine***	***Logistic Regression***
TP Rate	0.638	0.838	0.767
FP Rate	0.648	0.868	0.298
Precision	0.404	0.787	0.698
Recall	0.628	0.838	0.78
F-Measure	0.489	0.699	0.765
ROC Area	0.5	0.8	0.826
PRC Area	0.538	0.939	0.832

The table 4 shows the overall, the performance of logistic regression is strong, with balanced metrics for TP Rate, Precision, Recall, and F-Measure. This is bolstered by a competitive PRC Area of 0.832 and a ROC Area of 0.826.

All of these metrics evaluate how well the algorithms classify instances, with SVM and Logistic Regression demonstrating especially promising performance. Based on what looks to be a confusion matrix or classification report, the table presents evaluation metrics for three different machine learning models

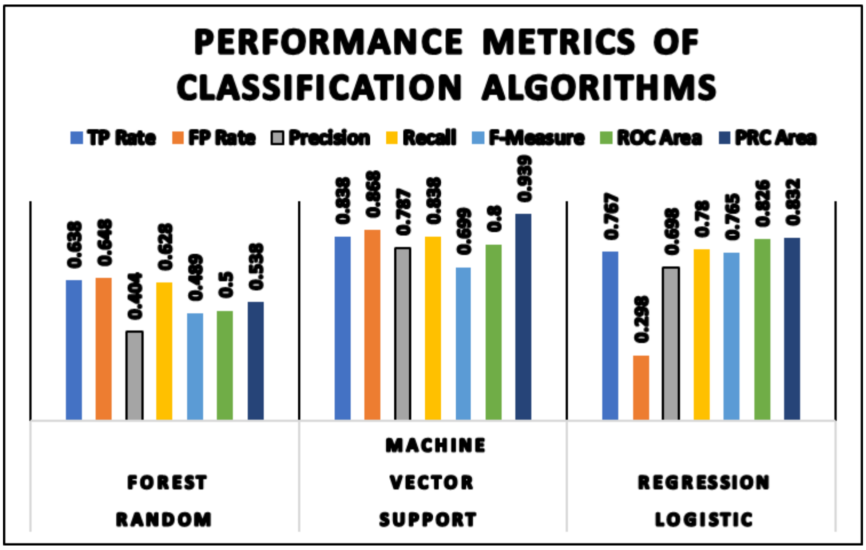

Figure 4: Performance Metrics of Classification Algorithms

Random Forest, Support Vector Machine (SVM), and Logistic Regression. Every row is associated with a particular metric: False Positive (FP) Rate shows the percentage of actual negative cases that are mistakenly identified as positive, while True Positive (TP) Rate quantifies the percentage of actual positive cases that are correctly identified. Precision gauges how well positive predictions come true. Sensitivity, or recall, quantifies how well the model recognizes positive instances.

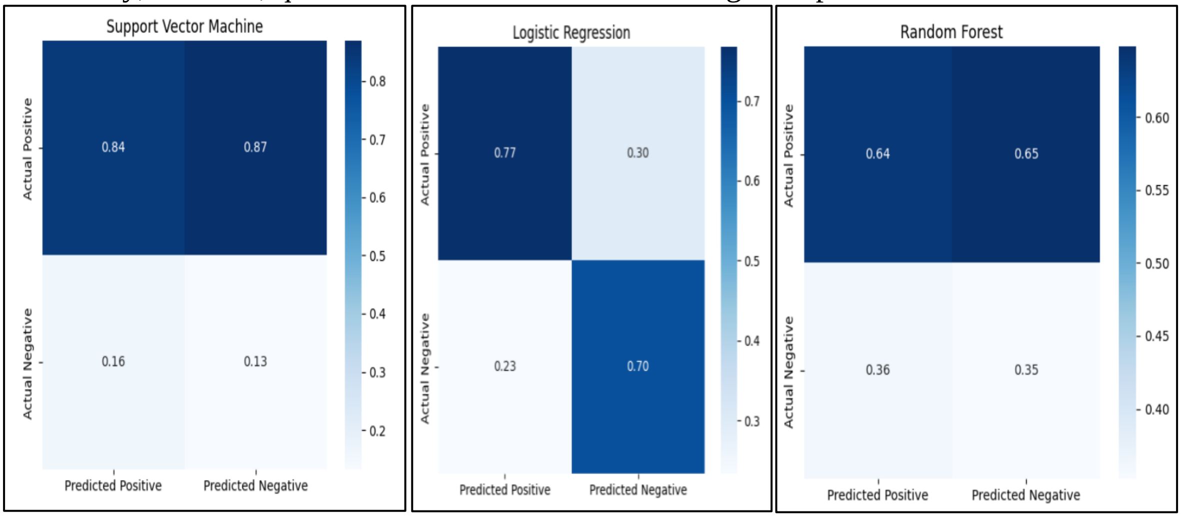

Figure 5: Confusion Matrix of classification algorithms

F-Measure is a metric that integrates recall and precision. The Area under the Precision-Recall Curve (PRC) is known as the Area Under the Receiver Operating Characteristic Curve (ROC Area) shown in figure 5. Three machine learning algorithms—Random Forest, Logistic Regression, and Support Vector Machine (SVM)—have their classification accuracy displayed in the table.

Table 5: Accuracy of Classification Algorithm

Classification Algorithm	Accuracy (%)
Support Vector Machine	92.61
Logistic Regression	96.24
Random Forest	95.98

The percentage of correctly classified instances out of all the predictions made by each model is known as accuracy. With an accuracy of 96.24%, Logistic Regression was found to be the most accurate, accurately classifying roughly 96.24% of the dataset's instances. With an accuracy of 95.98%, Random Forest trailed closely behind, showcasing its impressive ability to predict class labels with high accuracy using the ensemble of decision trees.

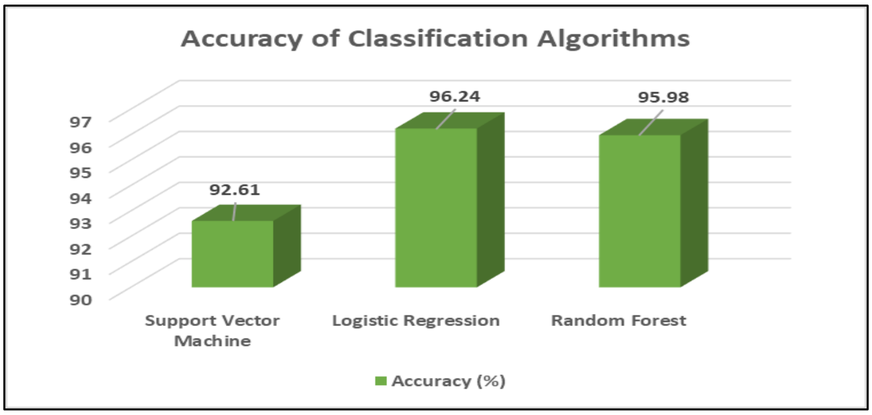

Figure 6: Accuracy of Classification of Classification Algorithm

SVM's accuracy of 92.61% shows that it is still quite successful in correctly classifying most cases, even though it is marginally less than that of Random Forest and Logistic Regression shown in figure 6. These findings imply that Logistic Regression performed exceptionally well in this specific classification task, most likely because of its capacity to accurately model intricate relationships between features and class labels. Random Forest's resilience in managing a wide range of datasets and SVM's capacity to divide classes using a margin-maximizing hyperplane came in second and third, respectively.

6. Conclusion

Several important conclusions about how well various machine learning algorithms perform in the context of sentiment analysis and classification tasks using data from product reviews can be made based on the research's findings. With an accuracy of 96.24%, Logistic Regression was the best performer, demonstrating its usefulness in correctly classifying sentiment based on product reviews. This suggests that the study benefited greatly from the capacity of logistic regression to represent intricate relationships between features and sentiment labels. Random Forest also performed admirably, achieving an accuracy rate of 95.98%. Its ensemble method, which combined predictions from several decision trees, worked well for identifying a variety of patterns and raising classification accuracy. Support Vector Machine (SVM) demonstrated its robustness in effectively separating classes with a margin-maximizing hyperplane, with an accuracy of 92.61%, slightly lower than that of Random Forest and Logistic Regression. The study's conclusion emphasizes the significance of choosing suitable machine learning models in accordance with the particular needs of sentiment analysis tasks, noting the noteworthy performance of Logistic Regression in this investigation in addition to the competitiveness of Random Forest and SVM. These discoveries advance our knowledge of and ability to use machine learning to analyze and classify sentiment from textual data in practical applications.

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