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A Novel Method to Reduce False Positives and Negatives in Sentiment Analysis

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Abstract: Sentiment analysis focuses on the prediction of sentiment of the data by text processing, feature extraction, vectorization and classification techniques. The research areas in Sentiment analysis used to focus on the model that gives more accurate positive prediction. Reduction of False Positives and Negatives which are called Type I and II errors are not much dealt with. The best model may not be the best in reducing false positives and negatives. In this work rule-based and machine-learning algorithms are experimented to create a suitable model that gives equal importance to the reduction of positive and negative false values and accuracy. Experimented studies revealed that the model suggested using Linear Regression classifier that gave an overall accuracy of 62.35 % is the one that gives a better reduction in Type I and II error along with a competitive accuracy than SVM based model which was having the highest accuracy of 62.4%.

Keywords: *Machine Learning, Sentiment Analysis, Natural Language Processing.*

1. Introduction

Over the past several years' information and communication technology have undergone rapid change. The key development in the change is the emergence of social media content. The emergence of mobile technology enhanced the growth of social media content across the globe. People started using social media for commercial purposes as well as individual interests. It can be a desire to reveal valuable and entertaining content to others, define themselves, and grow and nourish. The influence of social media in political news and campaigns has increased tremendously. As the social networks are focusing on interactions among people they are becoming more powerful. This paved the way for unstructured and unorganized data that is scattered throughout the cloud. Sentiment analysis has essentially evolved out of this context to properly organize, cluster, classify and output the polarity of textual data which is expressed in different forms in social media [1]. It is a technique combining natural language processing, and data analysis techniques which in turn derive an objective quantitative result from a raw text.The primary building block of the classification model, which is implemented in sentiment analysis, is categorised under four, true positive, true negative, false positive, and false negative. A true positive is a model that correctly predicts the positive class and a true negative predicts the negative polarity [11]. A false positive is arrived at when the model incorrectly predicts the positive class. A false negative is an outcome when an incorrect prediction is made in the negative class. The reliability of sentiment analysis can be increased by reducing false negatives and false positives.

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In [12], SVM models experimented from 2012 to 2017 were compared efficiently and it was found that this classifier obtained good results on different matrices. The authors of [13] have done a detailed study on the SVM method using a chi-square classifier and claimed to achieve a better prediction. Amrani et al. [14] proposed a hybrid model that combines random forest and SVM to improve prediction in positive and negative binary classification. Yang & Shih. in [15] discussed the accuracy of a rule-based method in identifying the polarity of product features. In [16], the authors worked out a classification with the lexical rule-based models VADER and Text blob. These unsupervised models were used to analyse customer perceptions of products, and they proved to be more accurate. An aspect-based sentiment analysis approach was suggested in [17] by implementing syntactic rules on aspect, opinion pairs using a Linear Regression model. For this experimental work, they took a product review dataset and attained an improved classification accuracy .Indra et al. in [18] worked with the bag of words featurization method on the LR model for valuating 1800 tweets. They attained an accuracy of 92%, which is a very high prediction accuracy. In [19], the authors compared different machine learning models on three manually compiled datasets. The Naïve Bayes model made a better classification by giving an accuracy of about 92%. [20] proposed a Twitter sentiment analysis method based on the Naive Bayes and SVM models. This model proved to give a more accurate analysis of the feelings of the dataset.

Referring to the literature studies conducted, it is obvious that research was done on accuracy. Little care was given to the reduction of Type I and Type II errors. The model that gives the best accuracy may not always be the apt one. Even a false identification of a positive case or a faulty identification of a

negative case may become more relevant than the total accuracy. A better model should be one that also focuses on the reduction of these errors. Moreover, the sample dataset chosen was small. Predictions on accuracy are made in the majority of cases by classifying the dataset into positive and negative cases. Neutral
cases are not considered or given sufficient importance.

The key contribution of this research paper is a new methodology to decrease the presence of false negatives and false positives by giving due consideration to neutral cases, without compromising accuracy. To reduce the number of false positive and negative cases, instead of performing individual word analysis, a contextual analysis is suggested [9]. This helps to decide the polarity based on the meaning of the text. In this research, various classification experiments were performed to analyse the sentiment of movie reviews, which consists of about 8,500 reviews. A system is developed starting from the pre-processing stages like tokenization, feature extraction, part of speech tagging, stemming, lemmatization, stop word removal, etc. In each stage, applications are designed in such a way that the totality of the meaning is considered in spite of word-by-word classification. After implementing these NLP techniques and extracting the essential features, vectorization is done with the help of the TF-IDF method. Rule-based as well as supervised machine learning classifier models are created to train and classify data.

2. Methodology

An algorithm that mainly focuses on the false positive and false negative is formulated. Figure. 1 shows the suggested framework for conducting experiment at the word level. According to Algorithm I the main stages of the experimental research are collection of multiclass classifiable dataset and annotation, text preprocessing and cleaning, extracting the essential features, classifying the opinions and measuring the performance.

Algorithm I.

Input:A complex multi class classifiable dataset.
Output :Class Label and Accuracy measures.
Process

1. Import a non-linear dataset
2. Identify /Extract the features
3. Implement trimming vocabulary methods to remove unnecessary terms, which are irrelevant for identifying polarity.
4. Perform multilingual stemming and reduce all variants of a term into a single term followed by lemmatization.
5. Tokenise the data
6. Vectorize the data
7. Split the dataset into a training set and testing set
8. Fit the nonlinear classifier to the training set
9. Predict the result
10. Calculate accuracy using precision,recall and F measure
11. Compute confusion matrix
12. Evaluate False positives and False Negatives.

On collecting the data set proper identification of features and cleaning of data is done. NLP techniques like trimming, stemming, and stop word removal are implemented to clean and properly extract the features [5]. After cleaning the data and getting only the essential components needed for polarity classification the next step is clustering and classification. Proper vectorization method is applied to find the vector values corresponding to the features extracted. In vectorization, values will be associated with each word that has to be classified based on which final polarity can be calculated. After performing the vectorization, we move on to the final stage which classifies the data based on polarity. The accuracy of the system is tested using various matrices like precision, recall, f-measures and confusion matrix. False negative and positive values are obtained from the confusion matrix and compared with different models.

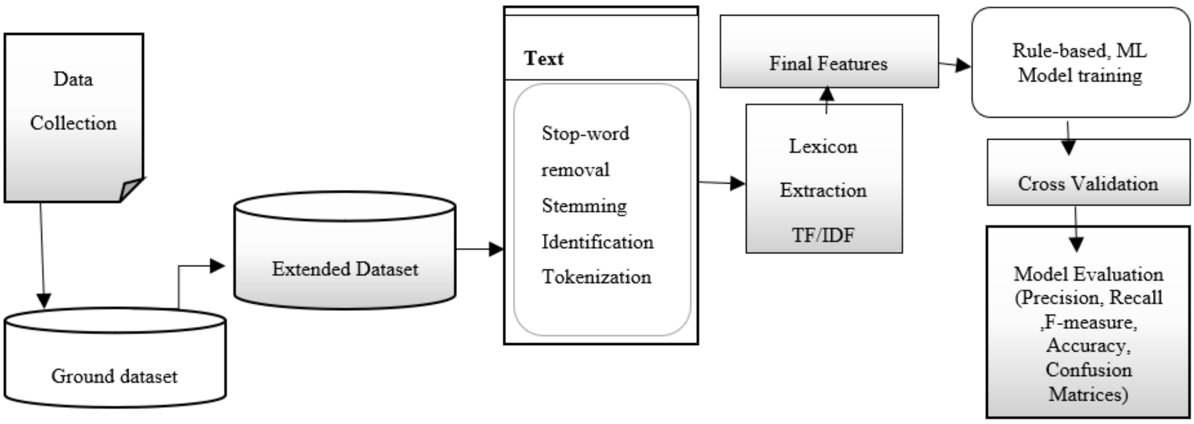

Fig 1. Outline of the proposed methodology.

2.1 Real Time Dataset

For the experimental application a dataset having a multi class classification is fetched. Social media platforms are the storehouses of a plethora of emotions expressed by users under different media. Considering the relevance of the opinion expressed and the influence of more real-time information, movie reviews are taken as the data set. It helped to design a system for making a real-time analysis. By scraping movie reviews, there were a total of 8543 inputs out of which 3609 were positive cases, 3310 were negative cases, and 1624 were neutral cases. The graphical representation of the data statistics is given in Fig. 2 with 1 representing positive cases, 0 for neutral, and -1 for negative sentiments A word cloud that extract the frequent word used by those with positive, negative or neutral sentiments is created and analyzed. Here the most commonly used words are presented in varied sizes depending on the frequency of occurrence of the word in the dataset. The larger text are the more frequent ones in the corpus. A sample of created word cloud for the experimented dataset is shown Fig. 3

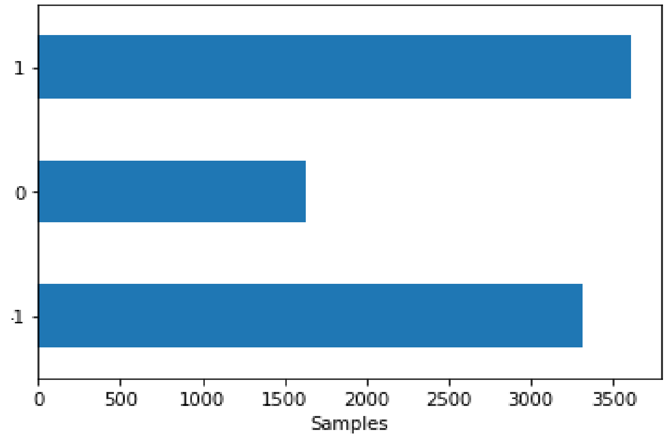

Fig. 2. Data statistics.

2.2 Feature Extraction

Feature extraction analyzes the different opinions posted by the reviewers from different points of view. In this state, several preprocessing techniques with the help of NLP are applied for cleaning the data and extracting the essential features for polarity classification. Unwanted and unnecessary punctuations, email IDs, user names, punctuations, HTML tags, URLs, etc. are removed and essential features are extracted and passed on for further analysis. Table 1 shows the initial preprocessing stage

Fig 3. Word cloud of the Movies dataset

Table 1.A sample of original review from the dataset and its processed form.

Sample Review	Processed Review
The gorgeously elaborate continuation of `` The Lord of the Rings '' trilogy is so huge that a column of words can not adequately describe co-writer/director Peter Jackson 's expanded vision of J.R.R. Tolkien 's Middle-earth .	the gorgeously elaborate continuation of the lord of the rings trilogy is so huge that a column of words can not adequately describe cowriterdirector peter jackson s expanded vision of jrr tolkien s middleearth
Singer/composer Bryan Adams contributes a slew of songs -- a few potential hits , a few more simply intrusive to the story -- but the whole package certainly captures the intended , er , spirit of the piece .	singercomposer bryan adams contributes a slew of songs a few potential hits a few more simply intrusive to the story but the whole package certainly captures the intended er spirit of the piece
You 'd think by now America would have had enough of plucky British eccentrics with hearts of gold .	you d think by now america would have had enough of plucky british eccentrics with hearts of gold

Preprocessing methods are usually done to make a comparative analysis of the opinion more specifically from a syntactical point of view. For better clarity in the output and getting more accuracy preprocessing should be done without changing the original meaning of the sentence. Parts of speech tagging or POS tagging is a preprocessing method that assigns a tag to each piece of text and further classifies that into categories such as noun, verb, adjective etc. A probabilistic stochastic approach including frequency probability and statistics is recommended in this research work. The probabilistic approach helps to find the most frequently used tag for a specific word in the given training data and this information is used to tag that word that is in the unannotated text.

Stemming changes the words present in the text to the stem that is to the root. Stemming is very important in preprocessing stages as it helps to avoid duplication when the words are subjected to polarity classification. The important aspect that should be considered while performing stemming on any social media data is to have a consideration of multilingual language operability. Taking into account this particular feature, the Snowball Stemmer algorithm which can map non-English words as well is applied for converting the inflected words to their root. Finally stop words are identified and removed from the dataset.

2.3 Vectorization of data

In vectorization, words and phrases in the input dataset are mapped into the corresponding vector format. This conversion is necessary to calculate the polarity of input text data. For implementing vectorization among the different methods like count vectorization and TF-IDF vectorization, the TF-IDF method is implemented. Along with word embedding, this method also focuses on the significance of the words [8]. This helps to include only the important features for further analysis removing the less significant parts thus making the model building process less complex. In this model, each individual term is counted with the help of the unigram approach. Term frequency is the frequency of a specific word in a text. Inverse document frequency is the process of lessening the importance of terms that are seen more frequently throughout the text. In Table 2 the vectorized polarity values are noted in the sentiment column.

Table 2. Review sample from the dataset preprocessed and vectorized

Index	Sentiment	Reviews
0	2	the gorgeously elaborate continuation of the lord of the rings trilogy is so huge that a column of words can not adequately describe cowriterdirector peter jackson s expanded vision of jrr tolkien s middleearth
1	2	singercomposer bryan adams contributes a slew of songs a few potential hits a few more simply intrusive to the story but the whole package certainly captures the intended er spirit of the piece
2	1	you d think by now america would have had enough of plucky british eccentrics with hearts of gold
3	2	yet the act is still charming here
4	2	whether or not you re enlightened by any of derrida s lectures on the other and the self derrida is an undeniably fascinating and playful fellow

2.4 Rule-based sentiment analysis

In the rule-based method instead of using machine learning techniques word count method is used to find the sentiment polarity. Class predictions of data are done using if-then rules. If-then rules are formulated using human logic usually done by the developer. Rule-based algorithms usually work based on a three-step logic. The first part is the analysis of data which is then conditionally processed with human-formulated and embedded if-then rules. The final step will be to trigger follow-up actions. The main drawback of the system is that it won't work for itself without human intervention and in turn lags behind in the quality of making intelligent decisions [6].

2.4.1 Text blob

Text blob is a rule-based method for text data processing. It implements major NLP tasks such as noun-phase extraction, part–of–speech tagging, classification, tokenization, parsing, word, and phrase frequencies, etc. The polarity output for Text blob range from [-1.0 to 1.0] where the least limit indicates a negative outcome and higher the value it tends to be more positive while a 0 indicates a neutral case. Text blob is using an integrated Sentiment Analysis model making use of Subjectivity and polarity. Though the method seems to be powerful, in terms of speed, the Text blob is more dependent on external sources. The polarity value indicates the positive and negative sentiment of a text while subjectivity deals with the objectivity of a text. The principle behind the algorithm is to rate each and every individual word in the lexicon. The averaging technique is implemented to find the polarity of a single word and the same principle is applied to the whole text to get the net sentiment. Text blob has a fascinating feature called intensifiers that escalate the sense of the text based on the swatch. Table 3 shows the classes predicted by Text blob.

Table 3. Classification done with Text Blob

Index	Sentiment	Reviews	Polarity	Prediction
0	1	the gorgeously elaborate continuation of the lord of the rings trilogy is so huge that a column of words can not adequately describe cowriterdirector peter jackson s expanded vision of jrr tolkien s middleearth	0.244444444	0
1	1	singercomposer bryan adams contributes a slew of songs a few potential hits a few more simply intrusive to the story but the whole package certainly captures the intended er spirit of the piece	0.073469388	0
2	0	you d think by now america would have had enough of plucky british eccentrics with hearts of gold	0	0
3	1	yet the act is still charming here	0.7	1
4	1	whether or not you re enlightened by any of derrida s lectures on the other and the self derrida is an undeniably fascinating and playful fellow	0.2875	0

2.4.2 Vader

Valence Aware Dictionary for sEntiment Reasoning is a method intuitive in text data polarity calculation as well as to judge the intensity of emotions. Vader is a component custom-built to process social media text. Unlike the traditional system where the algorithm demands a labelled dataset for prediction, the Vader predicts the polarity of unlabeled data. It creates a vocabulary of opinion words with their score for assessing the total polarity of the text [10]. VADER depends on a vocabulary of text that maps directly opinion intensities to sentiment scores. The algorithm categorizes the analyzed string into four categories, positive, negative, neutral, and compound. The far-fetched thing about this method is that heaps of pre-processing stages are needless. Vader is self-contained enough to understand the degree of emojis, capitals, punctuations, etc. This feature makes it an adaptable tool for analyzing the polarity of textual data. VADER's developing principle is a Wisdom of the Crowd approach. WotC reckons on the thought that collective knowledge expressed by a group of people can be taken as an alternative to expert knowledge. The valence score of the text is calculated by VADER using the Five Heuristics, Punctuation, Capitalization, Degree Modifiers, Polarity shift, and Catching Polarity Negation. The emotional score in VADER is measured in the range of -4 to +4, where the least tend to be more negative and the highest to be more positive. While the above score is valid for tokens, the final score of polarity ranges between -1 to +1. This is achieved with the help of normalization implemented using the Eq. (1) where x is the aggregate of valance score and alpha, the normalization constant with a default value of 15.In Table 4. depicts classification score by Vader.

$$x = x/\sqrt{(x^2+\alpha)} \quad (1)$$

Table 4. Polarity Classification by Vader

Index	Sentiment	Reviews	Scores	compound	Pred
0	1	the gorgeously elaborate continuation of the lord of the rings trilogy is so huge that a column of words can not adequately describe cowriterdirector peter jackson s expanded vision of jrr tolkien s middleearth	{'neg': 0.0, 'neu': 0.772, 'pos': 0.228, 'compound': 0.8069}	0.8069	1
1	1	singercomposer bryan adams contributes a slew of songs a few potential hits a few more simply intrusive to the story but the whole package certainly captures the intended er spirit of the piece	{'neg': 0.0, 'neu': 0.845, 'pos': 0.155, 'compound': 0.631}	0.631	1
2	0	you d think by now america would have had enough of plucky british eccentrics with hearts of gold	{'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}	0	0

2.5 Supervised ML algorithms

In supervised machine learning, the samples are trained with labelled data. The final predictions are done more accurately using this well-trained data. The dataset that is trained acts as the trainer or supervisor for making the predictions. These ML algorithms execute to find a mapping from the input variable to an output variable. The processes in supervising ML start from determining the size of the dataset to be trained. After collecting the labelled trained data, it is split into, dataset, training data and validation data [3]. The features of training data should be identified correctly in order to make an accurate prediction. After implementing regression or classification algorithms based on the requirement, the final accuracy is calculated. Supervised algorithms can fall into regression and classification types. Regression algorithms can be implemented in case of the existence of a relationship between input and output variables as well as if the predictions need to be continuous.LR is a linear regression supervised ML algorithm which is subjected to the analysis and prediction of the dataset selected for this particular work. Supervised ML facilitates an experience-based prediction which in turn results in a dynamic way of decision analysis. Classification algorithms are implemented when the output is categorical [7]. Category classification can be a linear one like a binary classification or a non-linear one that cannot be separated by a single decision boundary line.SVM is one of the machine learning classification algorithms that is experimented for polarity classification.

2.5.1. Linear Regression

LR algorithm is based on statistical principles to predict the polarity based on the relationship of an existing dataset. The whole dataset is converted to a vector and its value should correlate with the size of the vocabulary. As the vocabulary size increases vector will be more scattered. This will increase the training and prediction time. Because of that, a prevalence dictionary is made and the prevalence of each word is extricated. The entire training set is subjected to a binary classification of positive and negative sentiments. The aggregate word count is taken and a dictionary is built with the frequencies of positive and negative polarity. Preprocessing of the text is done by eliminating the URLs, tokenizing the dataset to words, removing the stop words, stemming the tokens, and finally converting the entire corpus to lower case. Calculation of polarity is done in the LR model with the help of a sigmoid function. It outputs a value between -1 and +1. A sigmoid function with weight value ɵ is as defined in Eq. (2). The cost function in LR is computed as in Eq. (3). Cost function is to be brought down by upgrading the value of ɵ by implementing the equation as in Eq. (4) using the learning factor α.

$$h(x^{(i)}, \theta) = 1/(1 + e^{(-\theta^T * x^{(i)})}) \quad (2)$$

$$J(\theta)=(-1/m)*\sum_{i=1}^{m}[y(i)\log(h(x(i),\theta)+(1-y(i))\log(1-h(x(i),\theta))] \quad (3)$$

$$\theta j:=\theta j-\alpha*\partial J(\theta)/\theta j \quad (4)$$

2.5.2 Support Vector Machine

Support Vector Machine is a supervised Machine Learning algorithm that is used frequently for classification and regression problems. The decision boundary is set in SVM with the help of a hyperplane. An n-dimensional space classification is done and data points are put into the correct grouping. Hyperplanes are created using extreme points which are termed support vectors. The main objective of SVM is to maximize the interspace between vector values and hyperplane. SVM can be linear as well as nonlinear. In linear SVM a binary classification is done using a linearly separable straight line. If the given input cannot be classified using a single straight line that means the data is not linearly separable. In that cases, a nonlinear SVM is implemented. In non-linear SVM we need one more dimension, which is calculated as in Eq. (5).

$$z=x2+y2 \quad (5)$$

$$a \cdot b = xa \cdot xb + ya \cdot yb + za \cdot zb \quad (6)$$

$$a \cdot b = xa \cdot xb + ya \cdot yb + (xa^2 + ya^2) \cdot (xb^2 + yb^2) \quad (7)$$

SVM completes its classification in a non-linear model using the dot product instead of vector values as in Eq. (6) and Eq. (7). This is implemented with the help of the kernel function.SVM begins with text classification in which textual data is converted to a vector value. The texts are handled as a bag of words. For every word, there will be a frequency feature associated with the word. The clarity of the training dataset and prediction can be improved by implementing the preprocessing NLP techniques. SVMs proved to be very dependable in multi-scale spaces. A clear indentation of separation can be done beyond the scope of binary classification.

2.6 Accuracy Analysis

Precision, Recall and F1 score measures provide a fragile idea of how accurate the classification is. In contrast to just looking at the overall accuracy of the methods, these quantification methods will look into fragmented accuracy analysis [4]. The cornerstone of these quantification techniques is the classification into labelled True positive, (TP), True Negative (TN), False positive(FP) and False Negative(FN) cases. TPs are the positive predictions, FPs indicate an erroneous prediction, TNs are negative and error-free predictions while FNs are predictions that turned negative while actually being positive. Precision can be calculated using the formula in Eq. (8). It gives an idea of how precisely positive predictions are done. It is actually a ratio of True positives to aggregate predicted positive cases. A higher value in precision indicates fewer FPs which in turn gives better accuracy.

Precision=TP/ (TP+FP) (8)

Recall=TP/ (TP+FN) (9)

The recall is the sensitivity of the classification technique. It is a quantifying technique that quantifies the value of true positives to the total number of true positive predictions that could have been done. Recall can be calculated using the formula given in Eq. (9). Recall points out missed positive predictions.

F1 score computes the accuracy using both precision and recall. The f1 score related to each class will give an idea of how accurately data is classified by the classifier. It can be calculated by finding the harmonic mean between precision and recall as in Eq. (10).

F Measure=2*((precision*recall)/ (precision+recall)) (10)

Along with the above measures, a comparative analysis on the Type I and Type II errors are done with the help of confusion matrices for each model.

3. Results and Discussion

The dataset consisting of the movie reviews is text processed and feature reduced. During the vectorization technique, TF-IDF is implemented to extract and vectorize the features and finally subjected to rule-based and machine learning algorithms. The dataset is divided into training and testing before implementing supervised machine learning algorithms. The ratio followed is 70:30 where 70% of data is trained and 30% is tested. The precision, recall and F measure of the rule-based methods and two supervised methods are analyzed. The results obtained are as illustrated in the Table 5. In the table SVM proved to show a better accuracy. The models are again tested for Type I and II errors.

Table 5. Experiment with different classifier on vectorized data

Classifier	Accuracy	Precision	Recall	F1-Score
Text Blob	32.44%	0.65	0.3	0.31
Vader	46.17%	0.61	0.6	0.61
LR	62.35%	0.64	0.80	0.71
SVM	62.39%	0.67	0.75	0.71

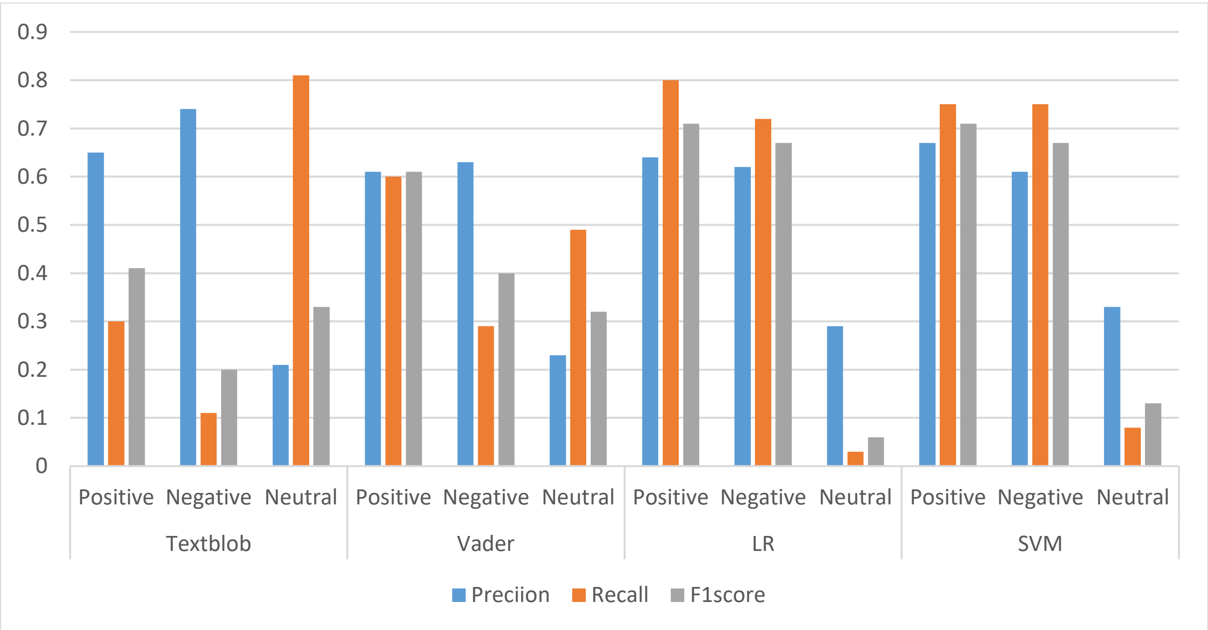

Fig 4. Precision, Recall and F1score of all the three classes using the rule based and ML algorithms

From Figure 4, it can be observed that both the ML classifiers outperformed the rule-based models in reducing false cases. Though LR and SVM show a similarity in predictions, more false classifications are avoided by LR. Figure 5. clearly depicts the comparison of false positives(Type I error) and false negatives(Type II error) in positive, negative, as well as neutral classifications by using rule-based and machine-learning models. From the comparison chart, it's clear that although the positive prediction accuracy is higher for SVM , Type I and Type II errors are reduced in a three-class classification(positive, negative, neutral) by the model suggested with TF/IDF feature extraction and LR classifier. An average of positive and negative false values is taken for a clear analysis of the above result. The comparative analysis of the same is illustrated in Table 6. The total accuracy implementing the five models is given in Table 5, where it is clear that SVM gave a better accuracy in prediction

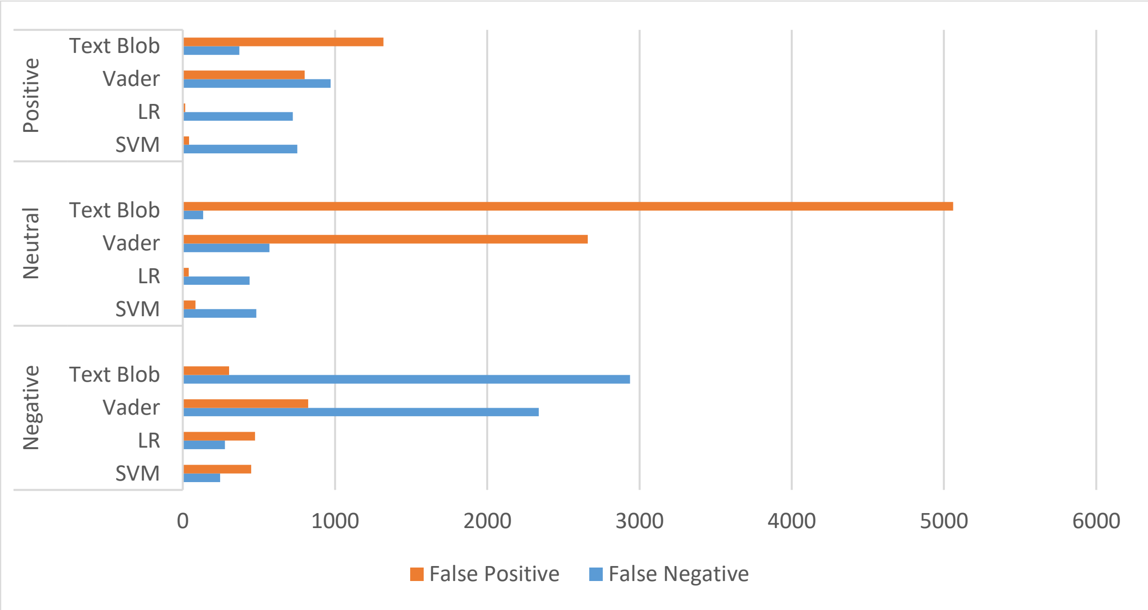

Fig 5. Comparison of false positives (Type I error) and false negatives (Type II Error)

Table 6. Comparion on the averages of Type I and II errors

	Average_False Negative	Average_False Positive
SVM	493	191
LR	479	176
Vader	1293	1428
Text Blob	1148	2228

According to the experimental results, Text Blob has a 32.44% accuracy while Vader has a 44% accuracy. The analysis and prediction done by Vader are found to be more accurate as its algorithm is designed to be social media-friendly and capable of making Vader handle social media language more efficiently than rule-based algorithms. The F1 Measure of Text Blob is.31, while that of Vader is.44. The closer the F Measure to 1, the better the prediction. Compared to the rule-based model, the supervised ML algorithms proved to give a better result. The prediction based on the experience done in the supervised ML model is found to make more accurate predictions in terms of polarity. A better prediction is achieved by implementing linear SVM with a centred kernel. The accuracy using LR is found to be 62.35% while that of SVM is 62.39%. But in spite of the accuracy in positive predictions achieved by SVM, a better result in reducing false positives and false negatives, along with a competitive result in accuracy, is obtained by implementing the proposed model with TF/IDF feature extraction and LR classification.

4. Conclusion

This paper presented sentiment analysis on a multiclass dataset. Instead of the usual cases of neglecting the neutral classification, a three-class classification is implemented by using the proposed system. A dataset big enough was subjected to study. Different models were applied to the dataset, which contains 8543 reviews. In the conducted experiments, the main focus was on reducing the false values and thereby increasing the accuracy. Experimental analysis was done using a real-time benchmark dataset, which consisted of positive, negative, and neutral cases. Different algorithms, including Text Blob, Vader, Logistic Regression methods, and SVM, were considered for analysis. The use of the stochastic Hidden Markov Model for POS tagging increased the accuracy of pattern recognition. Implementation of more aggressive algorithms like snowball stemmer at the initial stages of data preprocessing helped in getting cleaner and optimised data, which resulted in better accuracy of prediction. The TF/IDF increased the importance of factorization. Amongst SVM showed a better performance in the prediction of true positivity by giving an accuracy of 62.39% . But the LR model created a better accurate model by reducing the false positives and negatives (Type I and II errors) in a three-class classification by taking a contextual evaluation of the features. False negative and positive values in SVM were 493 and 191, while in LR they were 479 and 176.

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CONFLICT OF INTEREST: The authors have no competing interests.

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