



Sentiment Classification for Film Reviews in Gujarati Text Using Machine Learning and Sentiment Lexicons

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Abstract. In this paper, two techniques for sentiment classification are proposed: Gujarati Lexicon Sentiment Analysis (GLSA) and Gujarati Machine Learning Sentiment Analysis (GMLSA) for sentiment classification of Gujarati text film reviews. Five different datasets were produced to validate the machine learning-based and lexicon-based methods' accuracy. The lexicon-based approach employs a sentiment lexicon known as GujSentiWordNet, which identifies sentiments with a sentiment score for feature generation, while in the machine learning-based approach, five classifiers are used: logistic regression (LR), random forest (RF), k-nearest neighbors (KNN), support vector machine (SVM), naive Bayes (NB) with TF-IDF, and count vectorizer for feature selection. Experiments were carried out and the results obtained were compared using accuracy, precision, recall, and F-score as performance evaluation criteria. According to the test results, the machine learning-based technique improved accuracy by 3 to 10% on average when compared to the lexicon-based approach.

Keywords: Gujarati text; lexicon; machine classifier; movie reviews; sentiment analysis.

1 Introduction

Text categorization is a subset of opinion classification for the evaluation of people's views and attitudes toward various subjects. Usage of social media platforms has increased in recent years, which has resulted in the generation of a huge amount of data on the web. Many different online platforms are available, such as retail, entertainment and content communities, messaging, and blogging services, where users can express their opinions. This results in large data that cannot be analyzed manually, necessitating the use of a method such as sentiment analysis, which offers atomization.

Individual users' perspectives differ from one another. Therefore, it is critical to evaluate many different opinions to offer more realistic thoughts about a topic and a large number of opinions must be analyzed. The bulk of the material on the

internet is in English, but owing to the increased awareness of online media, information in regional languages is also increasing quickly. So far, not much attention has been paid in the literature to Indian languages, particularly languages like Gujarati [1].

According to our literature survey, lexicon-based and machine learning-based approaches have been utilized for sentiment classification. Machine learning (ML) algorithms are used to predict sentiment in ML-based methods [2]. On the other hand, sentiment lexicons are utilized in lexicon-based sentiment analysis. Lexicons are characterized as either lexicon-based or corpus-based, based on the resources used to determine sentiment polarity. Lexicon-based methods begin with seed emotion words and then proceed with synonyms and antonyms. Corpus-based methods start with sentiment seed words and then build a huge corpus of opinion words in the same context [3].

Due to a lack of resources for Gujarati, the authors propose an algorithm that relies on a machine-learning classifier as well as a sentiment lexicon. Because there was no widely available dataset of movie reviews written in Gujarati, a dataset of movie reviews in Gujarati was generated. Both suggested methods were evaluated on this dataset. It was determined that ML-based classification produced more accurate results than lexicon-based classification. The same approaches were applied to five unique datasets, comprising various real-world data, to test the accuracy of the suggested method.

2 Related Work

The relevant literature can be categorized into two types according to the approach applied: lexicon-based and ML-based. Supervised methods are often used in ML-based systems using TF-IDF and count vectorizer as feature generators [4]. Lexicon-based approaches need the development of a lexicon [5], which may be generated from an existing lexicon or derived from opinion words in a corpus. Using the lexicon's polarity values, the general mood of the document is predicted. Table 1 shows the lexicon technique as well as the prediction model used for sentiment analysis in the Indian language.

The point of convergence of this research was to perform sentiment analysis from review data related to movies. A previous study [6], has proposed the Senti-lexical algorithm to find the furthest point of a study as positive, negative, or neutral. The authors furthermore proposed a procedure to manage words that affect studies, while the effect of emoticons can similarly be inspected.

Table 1 Prediction classifier and lexicon-based sentiment analysis of Indian language.

Reference	Language	Method Used	Dataset	Accuracy
[7]	Hindi	Naive Bayes	Movie Review	80% (Hindi)
[8]	Hindi, Tamil, Bengali	POS using SentiWordnet	SAIL2015	34% (Bengali), 56.7% (Hindi), 39.3% (Tamil)
[9]	Konkani	Konkani WordNet	Not Specified	Not Specified
[10]	Malayalam	Malayalam WordNet	Movie Reviews	85%
[11]	Punjabi	Punjabi WordNet	Blogs and News Papers	Not Specified
[12]	Kannada	Kannada WordNet	General Document	Not Specified
[5]	Gujarati	Synset Replacement Algorithm (Guj SentoWordNet), WordNet, Bag-of words	Tweets	52.72%
[13]		Support vector Machine	Normal total 40 Tweets	92%
[14]	Hindi	Machine Translation Hindisentiwordnet Support vector Machine	Movie Reviews	65.96% 60.31% 78.14%
[15]	Bengali	NB, SVM, KNN, Decision tree, SVM, RF.	Bengali Horoscope	98.7% (SVM)
[16]	Tamil	Maximum entropy, NB, SVM, decision tree.	Movie	75.9% (SVM)
[17]	Punjabi	Naive bayes	Blogs and News Papers	Not specified
[18]	Kannada	Decision Tree (ID3)	Kannada movie reviews	79%
[19]		Naive bayes	Hindi Tweets	56%
[20]	Hindi	Decision Tree	Hindi tweets (weka)	45%
[21]	Malayalam	Lexicon based	Malayalam text	87.5%
[22]	Hindi	Lexicon based	Movie review	75%
[23]	Hindi and Bengali	Lexicon based	Hindi and Bengali tweets	50.75% (Hindi) 48.82% (Bengali) 78% (lexicon- based)
[24]	Kannada	Lexicon based Maximum entropy Naïve Bayes	Kannada documents	90% (NB) 93% (ME)

The goal of Ref. [25] was to extract opinions from movie reviews and to group the opinions communicated at various levels using sentiment lexicons. This paper offers exploratory outcomes utilizing a technique inspired by nature (molecule swarm streamlining) for marking. This improvement strategy repeatedly marks all words in a lexicon and evaluates the accuracy of the assessment

characterization utilizing a lexicon until the ideal names for words in the lexicon are found. A helper approach using an AI strategy is incorporated into the technique presented in [26]. This method could classify over 90% of the texts and accomplished preferable outcomes compared to the lexicon-based method. A crossover model can be utilized for sentiment analysis in human-robot communications.

Opinion mining, a subdiscipline of information mining and computational etymology, refers to computational methods for extracting, characterizing, understanding, and evaluating sentiment. Each article presents an unique imaginative examination structure, computational techniques, and selected results and models. The authors in Ref. [28] explored opinion mining and sentiment classification and concentrated on three non-English dialects to study the characterization techniques and the proficiency of every algorithm utilized. It was discovered that most of the non-English research followed techniques employed for the English language, with only little use of unambiguous linguistic features such as morphological variation. According to all reports, the field of application appears to be confined to specified topics.

In another paper, [29], the author presented a technique for producing an area-explicit lexicon utilizing a probabilistic approach together with monetary-based information, i.e., stock value weight. This work is different from common approaches in that it builds area-explicit dictionaries and the opinion scores are processed by considering the earlier stock value change, achieving an average of 50% of accuracy.

In the overview in [30], several potential computation enhancements and many SA applications are explored and briefly described. These items were categorized according to their function among the various SA processes. Disciplines related to SA that have recently attracted specialists are discussed. The primary goal of this research was to provide a nearly complete picture of SA techniques and related disciplines.

3 Materials and Methods

To apply sentiment analysis to Gujarati, a text dataset had to be created by the authors of the present paper due to the unavailability of a standard dataset, which required effort, research, and time from the authors' end. The authors had to perform text processing to generate more accurate results. To apply the lexicon-based and machine learning-based techniques without a valid dataset for result analysis was a challenging task, even though the authors overcame these challenges and managed to produce satisfactory results by applying the lexicon-based and machine learning-based techniques.

3.1 Data Extraction

Data extraction is a critical step in big data analysis. The Beautiful Soup library, which is a free and open-source library, was used to collect data from various movie review websites. It is possible to retrieve reviews automatically based on a single seed URL. A seed URL allows us to navigate across all web pages of a domain. After extracting reviews, a sentiment score of 0 or 1 was assigned to each review based on the ratings given on the website for the movie by critics/users; if the rating of the movie was greater than 3, a score of 1 was assigned, meaning ‘good movie’; if the rating was less than 3, a score of 0 was assigned, meaning ‘terrible film’, as stated in Figure 1.

	text	experience
0	વાર્તા એક સમયે નાની વકીલ મીરા કપૂર પરિણીતી યો...	1
1	જીવનની વિવિધ પસંદગીઓ ધરાવતા નિશ્ચિત પરિવારન...	1
2	બદનામ આઇએએસ અધિકારી ચંચલ ચૌહાણ માટે વાર્તા જી...	1
3	વાર્તાસોલસીથી અણધારી જગ્યાએ જોવા મળે છે જે સા...	1
4	વાર્તા તેને કબૂતરનો અનાસતો કહે છે પરંતુ મધુ મ...	0
5	વાર્તા જ્યારે પીટીના એક યુવાન શિક્ષકને નવા કો...	1
6	વાર્તા વિવિધ પાત્રો સાથેની અનેક વાર્તાઓ એક સા...	1
7	લક્ષ્મી વાર્તા રશ્મિ કિયારા અડવાણી તેને સંબંધ...	1
8	કોઈ રોમેન્ટિક ભૂતકાળ સાથે લગ્ન કરવા માટે તલપા...	1
9	એક કમનસીબ રાત્રે સ્થાનિક કેબી બ્લેકી ઇશાન ખટ્...	0
10	દલિત પરિવારની વાર્તા આયં મણિ નવાજુદ્દીન સિદ્ધ...	0
11	વાર્તા કાજલ સ્વતંત્ર જીવન જીવવા ઇચ્છતી એક યુવ...	1
12	હોમો રાક્ષસ ો લા હોમો સેપિયન્સ અને વડા પ્રધાન...	1
13	રહસ્યમય સંજોગોમાં તેની માતા શકુંતલા દેસાઈના મ...	0
14	વાર્તા જ્યારે એક ટોચના પોલીસને પોલીસ તાલીમ એક...	1
15	ખુદા હાફિઝ વાર્તા નવદંપતી નરગિસ શિવાલીકા ઓબેર...	1
16	વાર્તા આ ફિલ્મમાં ભારતીય વાયુસેનાના ભૂતપૂર્વ ...	1
17	વાર્તા જીવન પ્રિન્ટિંગ પ્રેસના કર્મચારી નંદન ...	1
18	વાર્તા રહસ્યમય સંજોગોમાં તેના લગ્નની રાત્રે પ...	1
19	શકુંતલા દેવીના જીવન પર એક જીવનચરિત્રાત્મક નાટ...	1

Figure 1 Movie review dataset.

Based on reviews from various websites, the datasets were named Gujwebiduniya, Hungama, Times of India, User, and FilmFare. These names are used in this paper to refer to these datasets. Table 2 lists the sources the reviews were retrieved from.

Table 2 Details of extracted reviews.

Sr.no.	Website URL	No. of reviews
01.	https://gujarati.webdunia.com/movie-review (the source language of this website is Gujarati)	232
02.	https://www.bollywoodhungama.com (machine translation was used to convert reviews from English to Gujarati)	592
03.	https://www.filmfare.com/reviews (machine translation was used to convert reviews from English to Gujarati)	396
04.	https://timesofindia.indiatimes.com/entertainment/movie-reviews (machine translation was used to convert reviews from English to Gujarati)	572
05.	Manual collection of reviews from users in the Gujarati language	293

3.2 Data Preprocessing

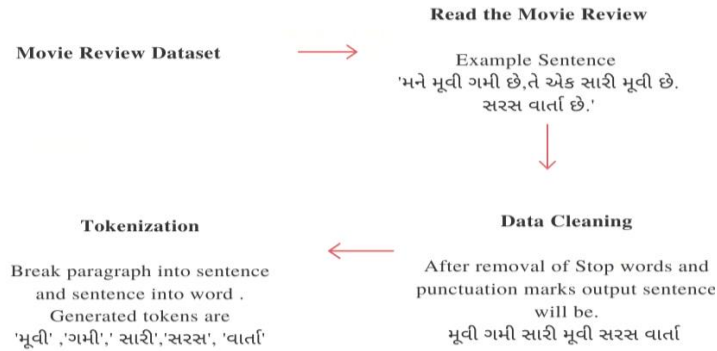
Data preparation entails adequate data fragmentation and data cleaning. In this study, we utilized NLP preparation techniques [6], such as stopword removal, tokenization, and so on. Data preparation results in more robust data with reduced noise.

3.2.1 Removing Stop Words, Special Characters, and Hyperlinks

Stop words do not have any effect on the opinion expressed, so they must be removed for normalization.

3.2.2 Tokenization into Sentence and Word

Delimiters are used to split textual material into sentences, which are then broken down into words.

**Figure 2** Gujarati text pre-processing steps.

3.3 GLSA (Gujarati Sentiment Lexicon (Lexicon) based approach)

Sentiment classification based on a lexicon approach was used to help to identify sentiments related to film reviews in the Gujarati language, where overall review polarity was graded as positive or negative using Gujarati SentiWordNet. The Synset Replacement Algorithm was used instead of accuracy enhancement for Gujarati words that are not available in Gujarati SentiWordNet. Figure 3 represents the lexicon-based method [31].

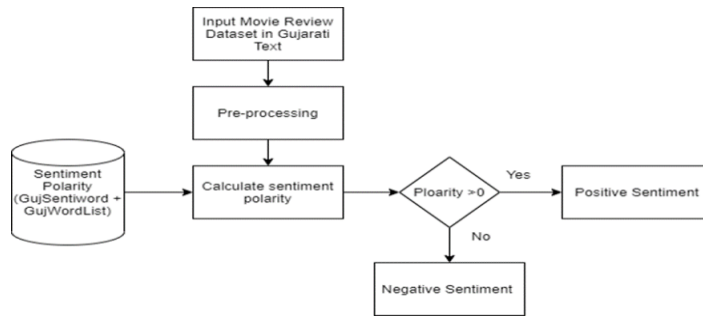


Figure 3 Lexicon learning-based proposed architecture.

Sentiment resources were generated for Gujarati text, called GujaratiSentiWordNet, as shown in Figure 4. To generate GujaratiSentiWordNet, the Indowordnet interface was used by mapping the synset of HindiWordNet to GujaratiWordNet. The features that are crucial to determining sentiments regarding movie reviews accessible in Gujarati were selected based on sentiment polarity in this technique.

POS_TAG	ID	POS	NEG	\	LIST_OF_WORDS
0	a	10363	0.000	0.000	અનોપચારિક
1	a	2627	0.000	0.750	મૃત, મૃએલું, મૃતક, મુડદું, શબ, વૈકુંઠવાસી, પરલોકવાસી...
2	a	11476	0.125	0.000	પરવર્તી
3	a	28106	0.250	0.375	સારી, સાઈ, અચ્છા, યોગ્ય, વાજબી, ઠીક
4	a	11156	0.875	0.000	ભાગ્યશાળી, નસીબદાર, સદ્ભાગી, સુભાગી, ખુશનસીબ, ખુશકિ...
5	a	2279	0.000	1.000	અભાગી, દુભાગી, કમનસીબ, મનદુઃસ, બદકિસ્મત, દુભાગ્ય...
6	a	2384	0.000	0.875	બેઘર, આવાસહીન, ઘરવિહોણું, અનિકત, નિવાસ_રહિત
7	a	4714	0.250	0.125	સુગંધિત, સુવાસિત, સુગંધીદાર, ખુશબોદાર, ખુશબુદાર, સ...
8	a	1488	0.000	0.750	દુગંધિત, દુગંધિવાળું, ગંધાતું
9	a	29150	0.000	0.000	વાગેલું, લગાવેલું

Figure 4 Sentiment resource generation for Gujarati text.

3.4 GMLSA (Gujarati Sentiment Analysis with Machine Learning Approach)

A prediction-based approach was applied to movie reviews that were prepared in the Gujarati Language, as shown in Figure 5. An experiment was conducted on a different dataset and showed that language-specific enhanced results were achieved.

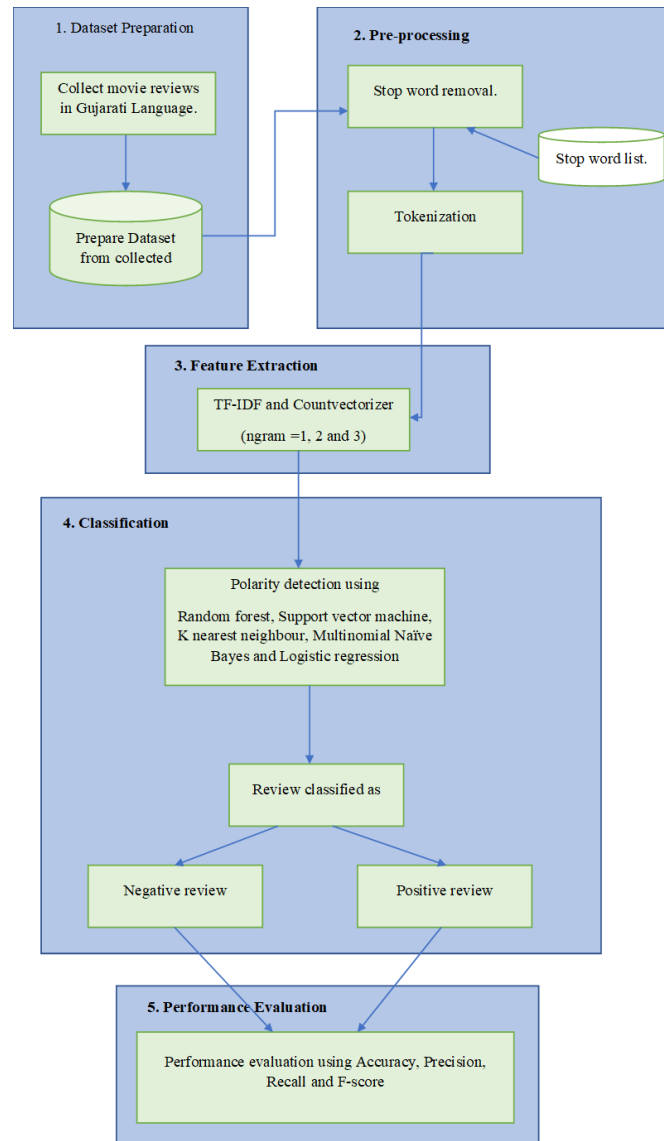


Figure 5 Proposed machine learning-based architecture.

To achieve the desired results, we performed data preprocessing, which provides a list of tokens that are helpful in the feature selection task. A feature vector generated using TF-IDF and the count vectorizer technique was used as input for different machine learning based classifiers, which generated a confusion matrix, based on which the accuracy of the different classifiers was measured. Minor accuracy variations may occur after applying the same model to a different dataset, however, the model generated adequate results [32-35].

4 Results and Discussion

Five different datasets were created to perform these experiments, as shown in Table 2. These datasets were subjected to preprocessing methods to balance them to achieve more accurate results. The assessment metrics used were correctness, precision, recall, and F-measure. GujaratiSentiwordnet was created for the evaluation of the proposed lexicon-based architecture to classify the sentiments of the reviews as positive or negative. Figure 6 shows the resource-based classification technique used with GujaratiSentiWordNet for evaluating the proposed method to identify the sentiments for each movie and classify them as 0 (negative) or 1 (positive).

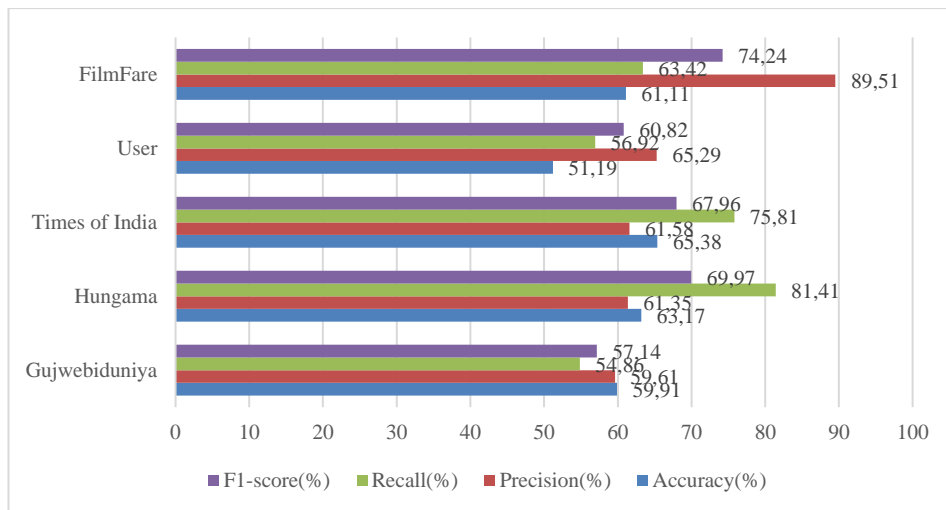


Figure 6 Dataset-wise performance evaluation based on sentiment score.

Table 3, shows the accuracy, precision, recall, and F-score generated by the lexicon-based method on the movie review dataset. According to Figure 5, the accuracy scores were satisfactory, which means GujaratiSentiWordNet could be used as a benchmark.

Table 3 Result generated based on sentiment score.

Dataset Name	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Gujwebiduniya	59.91	59.61	54.86	57.14
Hungama	63.17	61.35	81.41	69.97
Times of India	65.38	61.58	75.81	67.96
User	51.19	65.29	56.92	60.82
Filmfare	61.11	89.51	63.42	74.24

The proposed AI-based system was tested for execution utilizing a split rate to decide the preparation and test sets. By and large, the system performed better with 70% preparation information and 30% testing information. The examination was finished utilizing five unique classifiers on the five different datasets. Table 4 shows the exact correlation of the five different classifiers in the various datasets utilizing TF-IDF and CV as element choices.

Table 4 Dataset-wise accuracy comparison of all classifiers using TF-IDF and CV.

Dataset Name	Gujwebiduniya		Hungama		Times of India		User		Filmfare	
	TFIDF-Accuracy (%)	Gram-Accuracy (%)	TFIDF-Accuracy (%)	N-Gram-Accuracy (%)	TFIDF-Accuracy (%)	N-Gram-Accuracy (%)	TFIDF-Accuracy (%)	N-Gram-Accuracy (%)	TFIDF-Accuracy (%)	N-Gram-Accuracy (%)
Model Name										
Multinomial Naive										
Bayes	77.14	75.51	91.57	86.4	98.26	86.67	57.95	69.35	86.55	95.24
Random Forest	88.57	75.51	96.63	92.8	91.86	92.5	57.95	72.58	96.64	95.24
Logistic regression	80	75.51	93.26	86.4	97.09	89.17	57.95	70.97	86.55	95.24
Support Vector										
Machine	88.57	73.47	95.51	82.4	97.09	85.83	57.95	64.52	96.64	95.24
KNeighborsClassifier	58.57	65.31	74.16	73.6	75.58	58.33	54.55	46.77	85.71	59.52

Figure 7 shows the effectiveness-based correlation of the classifiers. All classifiers performed well on the various datasets and achieved a precision of over 75%, except for KNN.

Five different datasets of movie reviews created in the Gujarati language were tested using the two proposed framework architectures. The results are shown in Table 5. All five classifier generated higher accuracy result compared to the lexicon-based approach. Considering the Hungama, Times of India, and Filmfare datasets, the machine learning strategy had 10% greater accuracy when compared to the lexicon method. The ML-based technique outperformed the lexicon-based approach by 10% on the Hungama, Times of India, and Filmfare datasets. On the datasets with reviews from users and Gujwebiduniya, both approaches got nearly identical results. Based on the generated and compared findings, it was determined that the proposed ML-based framework produced more accurate results than the proposed lexicon-based approach.

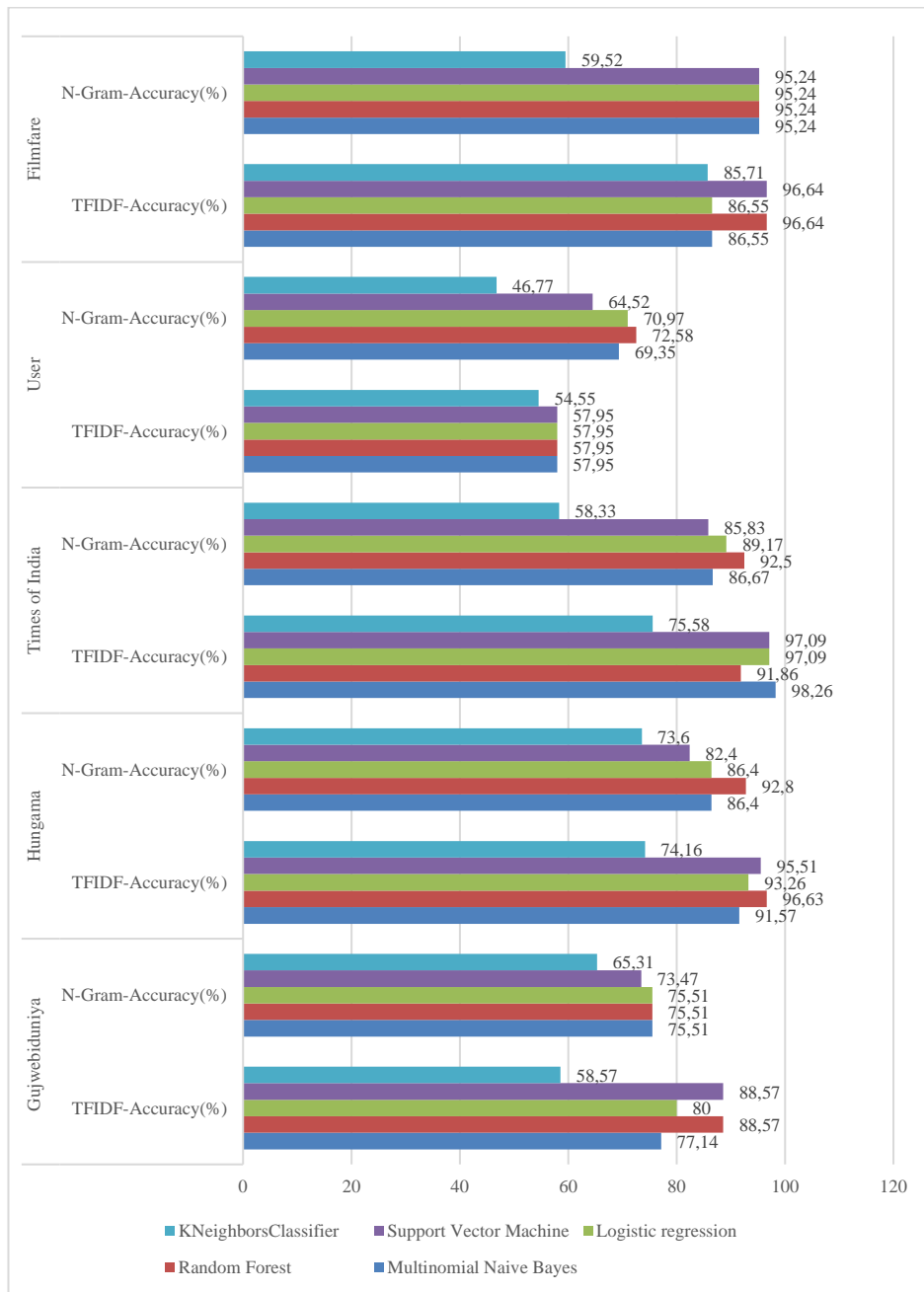


Figure 7 Dataset-wise accuracy comparison of all classifiers using TF-IDF and CV.

Table 5 Overall performance-based comparison of the ML-based and lexicon-based methods.

Dataset Name	Classifier	Feature Selection Method	TFIDF-Accuracy (%)	CV-Accuracy (%)	TF-IDF-Precision (%)	CV-Precision (%)	TF-IDF Recall (%)	CV-Recall (%)	TF-IDF F-Score (%)	CV-F-Score (%)
Gujwebiduniya	Multinomial Naive Bayes		77.14	75.51	100	66.67	58.97	80	74.19	72.73
	Random Forest	TF-IDF and CV	88.57	75.51	94.29	72.22	84.62	65	89.19	68.42
	Logistic regression		80	75.51	100	75.51	64.1	75.51	78.13	75.51
	Support Vector		88.57	73.47	100	62.96	79.49	85	88.57	72.34
	KNeighborsClassifier		58.57	65.31	65.63	54.29	53.85	95	59.15	69.09
	Lexicon Based		59.91		59.61		54.86		57.14	
Hungama	Multinomial Naive Bayes		91.57	86.4	87.25	90.32	97.8	83.58	92.23	86.82
	Random Forest	TF-IDF and CV	96.63	92.8	95.7	93.94	97.8	92.54	96.74	93.23
	Logistic regression		93.26	86.4	89.9	86.4	97.8	86.4	93.68	86.4
	Support Vector		95.51	82.4	93.68	89.47	97.8	76.12	95.7	82.26
	KNeighborsClassifier		74.16	73.6	70.27	80.36	85.71	67.16	77.23	73.17
	Lexicon Based		63.17		61.55		81.41		69.97	
Times of India	Multinomial Naive Bayes		91.57	86.4	87.25	90.32	97.8	83.58	92.23	86.82
	Random Forest	TF-IDF and CV	96.63	92.8	95.7	93.94	97.8	92.54	96.74	93.23
	Logistic regression		93.26	86.4	89.9	86.4	97.8	86.4	93.68	86.4
	Support Vector		95.51	82.4	93.68	89.47	97.8	76.12	95.7	82.26
	KNeighborsClassifier		74.16	73.6	70.27	80.36	85.71	67.16	77.23	73.17
	Lexicon Based		63.38		61.58		75.81		67.96	
User	Multinomial Naive Bayes		57.95	69.35	57.95	75	100	86.67	73.38	80.41
	Random Forest	TF-IDF and CV	57.95	72.58	57.95	72.58	100	100	73.38	84.11
	Logistic regression		57.95	70.97	57.95	70.97	100	70.97	73.38	70.97
	Support Vector		57.95	64.52	57.95	73.47	100	80	73.38	76.6
	KNeighborsClassifier		54.55	46.77	56.79	92.86	90.2	28.89	69.7	44.07
	Lexicon Based		51.19		65.29		56.92		60.82	
Filmfare	Multinomial Naive Bayes		86.55	95.24	86.55	95.06	100	100	92.79	97.47
	Random Forest	TF-IDF and CV	96.64	95.24	96.26	95.06	100	100	98.1	97.47
	Logistic regression		86.55	95.24	86.55	95.24	100	95.24	92.79	95.24
	Support Vector		96.64	95.24	96.26	95.06	100	100	98.1	97.47
	KNeighborsClassifier		85.71	59.52	86.44	93.88	99.03	59.74	92.31	73.02
	Lexicon Based		61.11		89.51		63.42		74.24	

5 Conclusion

The techniques proposed in this work attempted to improve the quality of sentiment analysis on textual movie reviews in Gujarati. For sentiment analysis on Gujarati text, lexicon and machine learning-based techniques were presented in this paper. The authors created GujSentiWordNet, a sentiment lexicon enhanced with a synonym lexicon, and deployed the two proposed classification methods to five different datasets to assess the accuracy of Gujarati text lexicon-based sentiment analysis (GLSA). On the ML side, five classifiers were employed, MNB, SVM, RF, KNN, and LR, on five different datasets to ensure reliable functioning Gujarati text machine learning-based sentiment analysis (GMLSA).

Based on the results of both proposed methods it can be concluded that the ML-based strategy provides greater accuracy than the lexicon-based approach. When compared to lexicon-based techniques, each of the five classifiers achieved good precision results. When compared to the lexicon-based strategy, the ML-based method had a 10% higher precision when using the Hungama, Times of India, and Filmfare datasets. With the Hungama, Times of India, and Filmfare datasets, the ML-based technique outperformed the lexicon-based methods by 10%. For the datasets with reviews from users and Gujwebiduniya, the two approaches got nearly identical results. Given the different findings, it is not certain that the

suggested ML-based approach produces more accurate results than the proposed lexicon-based methodology.

In our technological age, everyone expresses their opinions on social media platforms on a regular basis and because these perspectives are generally voiced in regional languages, most of the information created is in regional languages. As a result, to make reliable predictions, it is also important to target those audiences. We can assist the audience in using technology effectively for their benefit by generating evaluations, suggestions, or comments in their native language. The result of this research can be used as a baseline for applications such as agriculture helplines for farmers, tourism, voice assistance, question-answer systems, etc. In the future, lexicon-based algorithms can be applied to enormous amounts of data to provide more accurate results by developing domain-specific lexicons. Similarly, a machine learning-based method may be used on a huge dataset to get more accurate results.

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