INDIAN JOURNAL OF SCIENCE AND TECHNOLOGY

RESEARCH ARTICLE

Check for updates

OPEN ACCESS

Received: 04-11-2022

Accepted: 26-12-2022

Published: 11-03-2023

Aspect Based Sentiment Analysis and Opinion Mining on Twitter Data Set Using Linguistic Rules

Rayees Ahmad[1]*, Yasmin Shaikh[2], Sanjay Tanwani[3]

1 Research Scholar, International Institute of Professional Studies, DAVV, Indore (M. P.), India
2 Assistant Professor, International Institute of Professional Studies, DAVV, Indore (M. P.), India
3 Professor & Head, School of CS & IT, DAVV, Indore (M. P.), India

Citation: Ahmad R, Shaikh Y, Tanwani S (2023) Aspect Based Sentiment Analysis and Opinion Mining on Twitter Data Set Using Linguistic Rules . Indian Journal of Science and Technology 16(10): 764-774. https://doi.org/10.17485/IJST/v16i10.2138

* **Corresponding author**.

raees.u.zaman@gmail.com

Funding: None

Competing Interests: None

Published By Indian Society for Education and Environment (iSee)

ISSN
Print: 0974-6846
Electronic: 0974-5645

Abstract

Objectives: To propose the most effective machine learning technique for aspect based sentiment analysis of consumer feedback reviews by correlating people's emotions of different aspects of a product or service with word importance, linguistic rules, tagging, dependency relations and filtering to enhance the classification accuracy and to explore the different machine learning approaches in order to determine their significance and to spark interest in this field of study. **Methods:** The dataset has been taken from the most popular networking site twitter using twitter API. A total of 33,036 tweets were retrieved for this study from16 July 2022 to 16 Sept. 2022, but were only able to include 7570 tweets after data cleaning and then proposes a model named SVMS (SVM using Spacy) for sentiment Analysis. To measure the performance of a particular model, numerous analyses are conducted on the dataset and then the effectiveness of proposed model is compared with 4 basic classifiers LR, NB, RF and SVM. The parameters used in this study are accuracy, precision, recall, and F1 score. **Findings:** It is found that the Proposed SVMS model shows better results than all other algorithms by having 96% accuracy which is 1% faster than LR, 2% faster than NB, 5% faster than RF, and 4% faster than SVM, 96% precision, 98% recall and 97% F1 score. SVMS is recommended in this research context for the classification of the text and has a great significance for future researchers in sentences and text classification. **Novelty:** In this paper the performance of sentiment analysis classifiers is evaluated. In addition to general opinions, the work examines specific aspects such as product, quality, service, price, and ease of use. Comparing the proposed model with the existing models, it has been found that it outperformed the other models in most of the aspects.

Keywords: Aspect; Sentiment Analysis; NLP; Spacy; Linguistics

1 Introduction

The most important task in aspect-based sentiment analysis (ABSA) is the aspect and sentiment word extraction[(1)]. Previously, sentiment analysis was used to analyze reviews in a variety of fields such as hotels, restaurants, movies, and online shopping. Suhariyanto et al.[(2)] analyze the sentiment of the movie reviews on RottenTomatoes using SentiWordnet. Bagus et al.Dewi et al. and Reza et al.[(3,4)] conduct an experiment on aspect based sentiment analysis on hotel reviews using topic modelling and machine learning methods. In aspect-based sentiment analysis, it is generally divided into three sub-processes. The processes are aspect extraction, aspect aggregation, and sentiment analysis[(5)]. Aspect extraction is the process to extract the candidate aspects from reviews. These candidate aspects can be explicitly written or implicitly contained in a sentence[(6)]. Aspect aggregation is the process to group the candidate aspects into pre-defined aspect[(7)].

This work used belief maximization for the SVM model using spacy pipeline for aspect recognition and overall sentiment prediction. Pipelines are used to launch the spacy implementation and grant access to various properties. This makes model building process faster and easier since all the stages are bundled together into one unit process. The models are loaded into the pipeline. The package that contains language-related data offers a variety of models, including vocabularies, trained vectors, syntaxes, and entities. A wide range of document attributes, including tokens, token's reference indexes, part-of-speech tags, entities, vectors, sentiment, vocabulary, etc., are output by these pipelines. The researchers evaluated these models on different tweets or reviews of different products and the results revealed that the SVM model outperformed the on hand algorithm in terms of aspect identification and overall sentiment prediction.

Spacy an open source Natural language processing library for python offers a clear API to access its machine learning-trained methods and properties[(8)]. Spacy comes up with three different language models, namely en_core_web_sm (small), en_core_web_md (medium) and en_core_web_lg(large). All the three models consists of Vocabulary, syntax, tagger, parser and entities. In contrast to Small model, Medium and large models consists of vectors. The vectors in medium one consists of 514K keys and 20k unique vectors while as the large one consists of 514k Keys and 514k unique vectors. The language model used in this experiment is the en_core_web_sm which provides a variety of linguistic annotations that gives insights into a text's grammatical structure.

2 Methodology

The process of opinion extraction and sentiment prediction from the online reviews plays an important role in business analytics. Texts from social networking sites like twitter gain much more importance due to the fact they reflect the current events. The architecture for sentiment analysis using Spacy pipeline is depicted in Figure 1.

The remaining section describes the proposed architecture in detail. The process of sentiment analysis starts with preparing the review database then processing pipeline is used for processing text. The output of processing pipeline is Doc object which is a sequence of tokens. The doc object is used to create documents with linguistic annotations and various natural language properties. The next step is extraction of opinion words and identification of word polarity. Finally the polarity of sentence is identified that makes the complete sense of sentiment.

2.1 Preparing Review Database

This work is carried out using online tweeter data set. Firstly the reviews and ratings of different products and services are extracted from the most popular networking sites, twitter via Twitter API and then storing them into review database.

2.2 Processing Pipeline

Spacy is an open-source NLP processing library for python particularly designed for production use and helps us to build applications that process large volumes of text efficiently. Spacy is implemented by creating pipelines and grant access to various properties which makes model building process faster and easier since all the stages are bundled together into one unit process.

When an nlp is called on a text, spacy first tokenizes the text to produce a Doc object. The Doc is then processed in pipeline components. Each component returns the Processed Doc, which is then passed on to the next pipeline component. This is referred to as Processing Pipeline. The diagrammatic representation preprocessing pipeline is shown in Figure 2 below:

Preprocessing in NLP consists of tokenization, Parsing, POS tagging, NER, chunking, Dependency Relations. These are explained below:

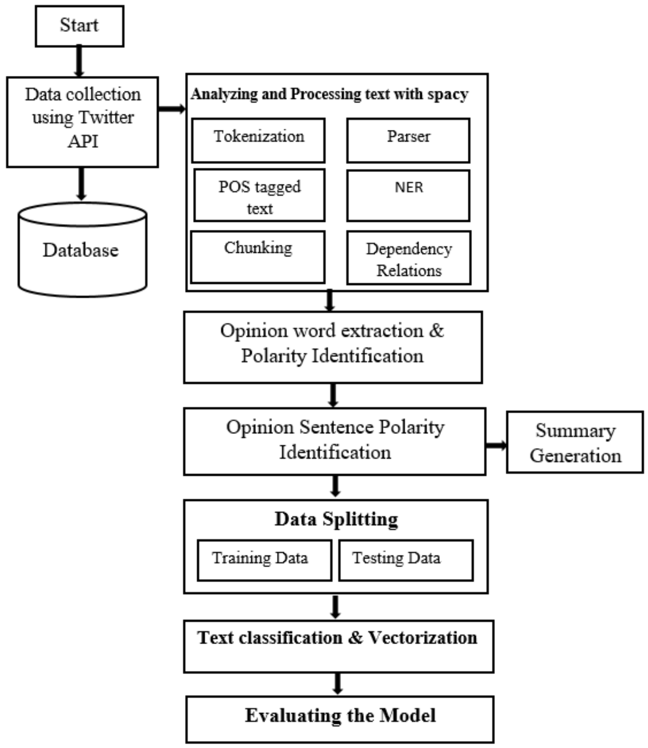

Fig 1. Architecture of Aspect Sentiment Analysis using spacy

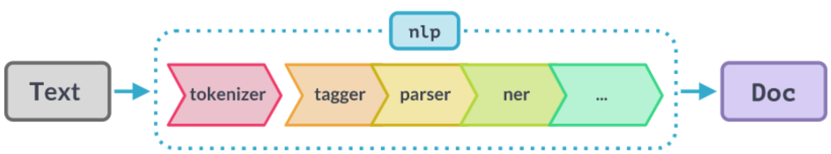

Fig 2. Preprocessing pipeline

2.2.1 ***Tokenization***

Tokenization is the process of dividing the text into its individual items known as tokens and ignoring space and punctuation marks. Spacy's tokenizer takes input in the form of Unicode characters and produces results in the form of token objects. After creating the doc object (contains sequence of token objects) which uses preprocessing pipeline components and from this pipeline using sentencizer component sentence tokens have been accessed.

Using Spacy Preprocessing is done in order remove the unwanted text like URL's, stop words, special characters, punctuation, numbers etc. This unwanted text add no value to text-understanding and cause algorithmic noise. As a result, this noise is removed in order to reduce feature space complexity.

2.2.2 ***Parsing***

In this step The Stanford NLP parser is used which takes a digital sentence as an input and decomposes into its basic grammatical structure (Phrase Structure Trees) and dependency relations also known as Stanford dependencies[9]. These structures define the relationships between the words and identifies the subject and object of the sentence.

*2.2.3 **POS Tagging***

POS stands for Parts of Speech also known as word classes or lexical categories is a process of classifying words into their POS and labeling them accordingly.

Table 1. POS tags and their descriptions

Tag	Description	Tag	Description
CC	Coordinating conjunctions	**PRPS**	Possessive pronoun
CD	Cardinal number	**RB**	Adverb
DT	Determiner	**RBR**	Adverb, comparative
EX	Existential there	**RBR**	Adverb, superlative
FW	Foreign word	**RP**	Particle
IN	Preposition or subordinating conjunction	**SYM**	Symbol
JJ	Adjective	**TO**	To
JJR	Adjective, comparative	**UH**	Interjection
JJS	Adjective, superlative	**VB**	Verb, base form
LS	List item marker	**VBD**	Verb, past tense
MD	Modal	**VBG**	Verb, gerund or present participle
NN	Noun, singular or mass	**VBN**	Verb, past participle
NNS	Noun, plural	**VBP**	Verb, noun 3rd person singular present
NNP	Proper noun, singular	**VBZ**	Verb, 3rd person singular present
NNPS	Proper noun, plural	**WDT**	Whdeterminer
PDT	Predeterminer	**WP**	Whpronoun
POS	Possessive ending	**WPS**	Possessive whpronoun
PRP	Personal pronoun	**WRB**	Whadverb

The Table 1 shows the set of tags and their descriptions. The set of tags used for a particular task is known as tag set. It is very useful in text realization, helps in distinguishing the sense of a word and indicates how a word functions in meaning as well as grammatically within the sentence. Now a word can have one parts of speech on the context it is being used. E.g., Google something on the internet. Now here Google is used as a verb although it is a proper noun. The reviews matching with the query are passed to the parser. The parser scans the sentence word by word and with the help of POS tagging each word in sentence is tagged with its part-of-speech from the standard list. After Part-of-speech tagging, now it is possible to retrieve product features (Nouns) and opinion words (adjectives).

Consider the following example

"The Picture quality of canon camera is very good"

In tagged sentence, canon (product feature) is tagged with NN, while as Good (adjective) is tagged with JJ.

Product features are generally NN so each NN is extracted from sentence.

ions the featuresexplicitlyimplicitlyExare mentioned directly by the reviewerImplicit features are those whmentioned directly by the reviewer. E.g.,Picture quality

Now consider another example,

"This laptop requires multiple charges per day"

In this review, the reviewer is talking about battery life but it is not directly mentioned in the sentence. So battery is implicit feature.

Opinions are generally JJ so every JJ is extracted from sentence. Opinions are divided into two types namely regular and comparative. An opinion which expresses a sentiment about a particular entity (aspect of the entity) is called a regular opinion. e.g., "HP laptop looks good" expresses a positive opinion on the look of HP.

While as an opinion which compares more than one entities based on some of their shared aspects, is called comparative opinion. E.g., "HP looks better than Acer" compares HP and Acer based on their look (aspect) and expresses a preference for HP. Opinions can also be categorized as direct or indirect. In the above sentences, picture quality is direct opinion while as battery life is indirect opinion.

2.2.4 ***Named Entity Recognition***

Named entity recognition also known as NER is the information retrieval task to locate and classify named entities into predefined categories such as Persons, location, organizations, movie, medical codes, quantities, monetary values, percentages etc. There are three particular steps in Named Entity Recognition

1. Noun Phrase Identification: extracting all the Noun Phrases from the text using dependency, Parsing and POS tagging.
2. Phrase Classification: extracting all the Noun Phrases and classifies them into respective categories which are location, Names etc.
3. Entity Disambiguation: sometimes it is possible that the entities are misclassified. Hence creating a validation layer on the top of the result is very useful and the use of knowledge graphs can be plotted for this purpose. Popular knowledge graphs are the Google knowledge graph, IBM Watson, and Wikipedia.

This can be explained with the help of following examples:

```
Example 1:

#Python code
NE_sent1= "The Picture quality of canon camera is very good"
NE_tokens = word_tokenize(NE_sent1)
NE_tags = nltk.pos_tag(NE_tokens)
NE_NER = ne_chunk(NE_tags)
print(NE_NER)

(S
  The/DT
  (ORGANIZATION Picture/NNP)
  quality/NN
  of/IN
  canon/NN
  camera/NN
  is/VBZ
  very/RB
  good/JJ)
```

```
Example 2:

#Python code
NE_sent2= "The voice quality of the Apple's iPhone is amazing"
NE_tokens = word_tokenize(NE_sent2)
NE_tags = nltk.pos_tag(NE_tokens)
NE_NER = ne_chunk(NE_tags)
print(NE_NER)

(S
  The/DT
  voice/NN
  quality/NN
  of/IN
  the/DT
  (ORGANIZATION Apple/NNP)
  's/POS
  (ORGANIZATION iPhone/NN)
  is/VBZ
  amazing/VBG)
```

2.2.5 ***Chunking***

Chunking basically means picking up individual pieces of information together and Grouping them into bigger pieces. The bigger pieces are known as chunk. Chunking is the basic technique used for entity detection, means grouping up of tokens. Figure 3 explains the process of chunking.

The	price	of	iPhone	is	very	high	but	overall	it	is	a	great	phone
DT	**NNP**	**IN**	**NNP**	**VBZ**	**RB**	**JJ**	**CC**	**JJ**	**PRP**	**VBZ**	**DT**	**JJ**	**NN**
				VP							**NP**		

Fig 3. Segmentation and labelling at both the token and chunk levels

The two most commonly used techniques used in chunking are NP-chunking, VP chunking.

1. Noun phrase chunking also known as NP- chunking is the process of searching for chunks corresponding to individual noun Phrases. NP-Phrase chunking of examples (1) can be represented graphically by the Phrase structured tree and grammar as shown in Figure 4 (a, b).
2. Verb Phrase chunking also known as VP chunking is the process of searching for chunks corresponding to individual verb phrases. NP-Phrase chunking of example (1) can be represented graphically by the Phrase structured tree and grammar as shown in Figure 4(c, d).

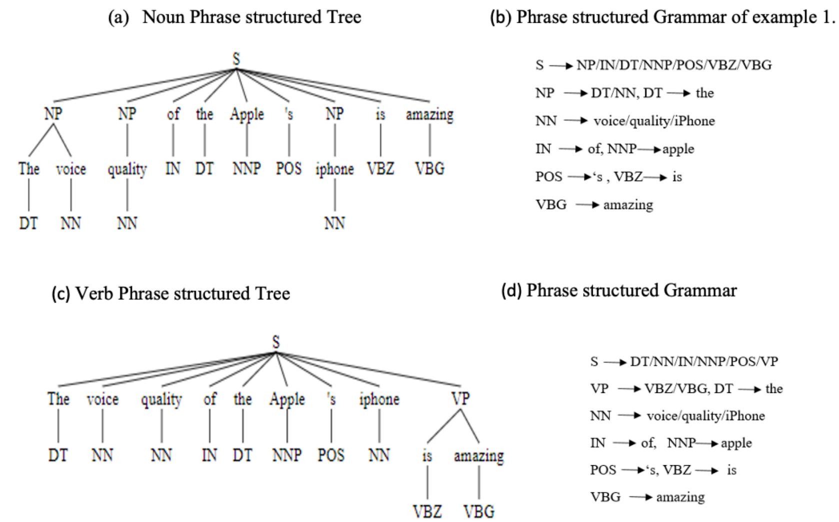

Fig 4. Structured Trees and grammars of example 1

2.2.6 ***Dependency Relations***

The dependency parsing problem is to take the sentence as an input and produce the dependency structures as the output. A Dependency relation is a grammatical relation or a binary relation between a governor (reagent or head) and a dependent. Each dependency is a pair (h, m) where h is the index of a head word, m is the index of a modifier word. In the figures, a dependency (h, m) is presented by a directed edge from h to m. Root is a special root symbol. 0 is taken to be the root symbol. The relation dependencies can be graphically represented in different ways, i.e. with labels and without labels. Consider the following example.

Example 3. “ *I like Apple phones' user interface*”

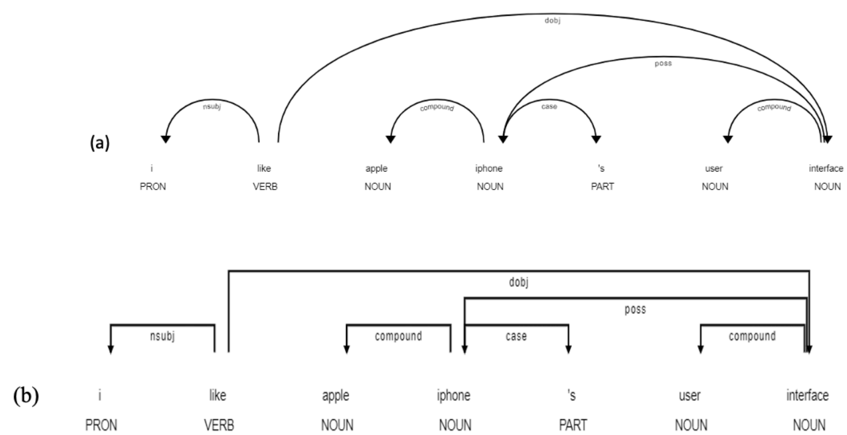

Fig 5. Dependencyrelations (a) and (b)

The above representation can also be represented with the help of Dependency table. Dependency Table 2 describes the dependencies between POS, Dep, and text.

The dependency relations of the above example is given below:

root(root-0, like 2), nsubj(like-2, i-1), dobj(like-2, interface-7)
compound(interface-7, user-6), poss(interface-7, iphone-4)
compound(iphone-4, apple-3), case(iphone-4, 's-5)
Where,

Table 2. Dependencytable of example 3

Text	POS	TAG	Explain Tag	Dep	Shape	is_alpha	Is_stop
I	PRON	PRP	pronoun, personal	nsubj	x	1	1
Like	VERB	VBP	verb, non-3rd person singular present	ROOT	xxxx	1	0
apple	NOUN	NN	noun, singular or mass	compo und	xxxx	1	0
iPhone	NOUN	NN	noun, singular or mass	poss	xxxx	1	0
‘s		POS	possessive ending	case	’x		1
User	NOUN	NN	noun, singular or mass	compo und	xxxx	1	0
interface	NOUN	NN	noun, singular or mass	dobj	xxxx	1	0

nsubj: nominal subject, dobj: direct object and poss: possession modifier

2.3 Opinion word extraction & Polarity Identification

In this step firstly opinion words are identified and after that semantic orientation (Positive, negative and Neutral) of each opinion word is identified. An opinion sentences consists of one or more than one product features (NN) and opinion words (JJ).

2.4 Opinion Sentence Polarity Identification

In this step, the orientation of an opinion sentence is predicted. Consider the following sentence

“This picture quality of this phone is not bad”

The above sentence contains the opinion word “bad” which expresses negative opinion. But the sentence expresses negative opinion because of negation (not).

So, after finding the polarity of opinion word, it is necessary to find Opinion sentence Polarity. Also a list of negation words (no, not, but) can be prepared and negation rules can be formed.

2.5 Summary Generation

Summary is based on product features and can be generated with the help of tables, charts and graphs.

3 Results and Discussion

The Data set for this experiment was gathered from the most popular social networking site twitter using twitter API. A total of 33,036 tweets were retrieved for this study from16 July 2022 to 16 Sept. 2022, but were only able to include 7570 tweets after data clean. In this stage, Spacy package of python is used to remove stop words, lemmatize and normalize the text from the obtained dataset. The labelled online Twitter data was subjected to sentiment analysis utilizing natural language processing. The data set contains tweets related to different products or services which are labelled as 1 for favorable and 0 for negative. The Figure 6 shows the cleaned tweets with their corresponding sentiment labels.

About 7570 online tweets from the Twitter API are included in the data set; 4100 of these tweets were classified as favorable ratings and 3470 as negative tweets. Each individual tweet has been tokenized, filtered for stop words, vectorized, and preprocessed using the Python spacy package in order to make the data suitable for the machine learning model.

For implementing SVMS Machine learning model, Python Jupyter Notebook, NLP with spacy language model are used. Experiments are conducted using the Scikit, spacy and NLTK libraries. The Figure 7 depicts how generally a classifier is being trained by using the training data set and then predicts labels for inputs by using testing data set.

The data set is divided into training and testing datasets, which were used to train and test the machine learning model (support vector machine) and evaluate. Train test split is 80:20 where 80% of the data are used for training and 20% is used for testing. Table 3 shows the number of tweets in training and testing sets.

	Tweet	Label
0	the picture quality of canon camera is very good.	1
1	i like the apple iphone s user interface.	1
2	the price of iphone is very high but overall i...	1
3	this laptop requires multiple chargres per day.	0
4	this is a simple little phone to use but the ...	0
...	...	...
2971	the story which was told so eloquently by Fran...	1
2972	In a most wonderful location lies a story of c...	1
2973	All in all a beautiful directed film from Nico...	1
2974	I m translating movies for a living and this i...	0
2975	But when someone strives for greatness and poe...	0

2976 rows × 2 columns

Fig 6. Tweetswith sentiment labels

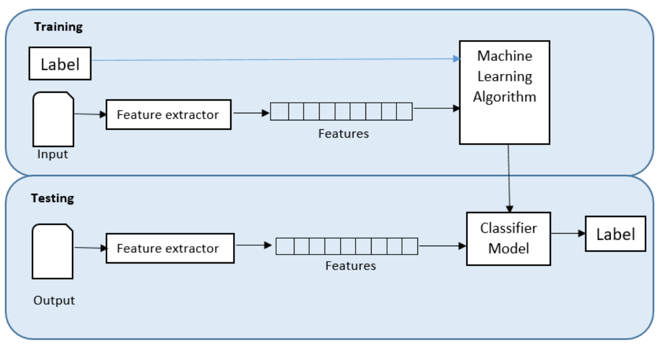

Fig 7. Supervised classification using Spacy

Table 3. Training and testing set size

Sentiment	Training set size	Test set size	Total
Positive	2595	1505	4100
Negative	2000	1470	3470
Total	4595	2975	7570

3.1 Evaluation Criteria

To evaluate the efficiency of this research, various measures were used, namely: accuracy, precision, recall and F1-Score. In this experiment, a twitter data set is taken that consists of reviews related to various products. So, these measures have been used in order to evaluate the relevance and irrelevance of the extracted features. Accuracy is a measure of how close the measured value is to the true value and is defined as the ratio of total number of correctly identified aspect polarities to the overall number of aspect polarities. Precision P is out of all positive predictions how many you got it right and is the ratio of correctly identified terms by the total terms while Recall R is out of all relevant predictions how many you got it right and is the ratio of correctly identified terms by the total identified terms. F1-Score, the most popular evaluation criterion and is the harmonic mean of precision and recall. There is a direct relationship between the F1-score and the value of Precision and recall and hence the value of F1-score will be high if the value of precision and recall are high and vice versa.

The formula for the above methods is as follows:

Accuracy = (TP+TN)/Total, Precision (P) = TP/ (TP+FP)

Recall(R) = TP/ (TP+FN), F1-Score = 2*P*R/ (P+R)

These measures were calculated using the confusion matrix which is shown in Table 4

Table 4. Confusion Matrix

	Observation	
Expectation	True Positive (TP)	False Positive (FP)
	False Negative (FN)	True Negative (TN)

The TP is the True positive, which means the relevant documents that are identified by the system. FP is the false positive, which means negative documents that are not relevant. FN is the false negative is the number of relevant reviews that the system failed to identify.TN is the true negative, relevant documents that are identified by the system.

Figure 8 shows the confusion matrix for machine learning models using the TF-IDF features. The confusion matrix for machine learning models utilizing TF-IDF features is displayed in Figure 5 (b). Using the TF-IDF characteristics, SVMS gives 2857 correct predictions and 89 wrong predictions. Logistic regression is the second best performer and predicts 2827 correctly while 152 predictions are wrong. Naïve Bayes the third best performer predicts 2798 correctly while 172 predictions are wrong. SVM predicts 2738 correctly while 216 predictions are wrong. Random Forest predicts 2708 correctly while 186 predictions are wrong.

(a) SVMS Confusion Matrix

	1	0	<----- Classified as
1	1445	60	1=Positive
0	29	1412	0=Negative

(b) LR Confusion Matrix

	1	0	<----- Classified as
1	1445	60	1=Positive
0	92	1382	0=Negative

(c) Naïve Bayes Confusion Matrix

	1	0	<----- Classified as
1	1460	45	1=Positive
0	127	1338	0=Negative

(d) RF Confusion Matrix

	1	0	<----- Classified as
1	1445	60	1=Positive
0	126	1263	0=Negative

(e) SVM Confusion Matrix

	1	0	<----- Classified as
1	1430	75	1=Positive
0	141	1308	0=Negative

Fig 8. Confusion matrix for classifiers using TF-IDF

3.2 Proposed model against Base classifiers

This work compares the proposed SVMS model against the base classifiers. The results revealed that this model outperformed the other models in most of the cases. The performance evaluation with the help of accuracy, precision, recall and F1 Score is shown in Table 5.

The results showed that the proposed model SVMS shows better results than all other algorithms by having 96% accuracy which is 1% faster than LR, 2% faster than NB, 5% faster than RF, and 4% faster than SVM, 96% precision which is same as LR and RF, enhanced by 1% compared to SVM and shortened by 1% compared to NB, 98% recall which is enhanced by 4% compared to LR, 6% when compared to NB and RF, and 7% compared to SVM and 97% f1 score which is fastest among all the algorithms.

Table 5. Comparative analysis of proposed model against base classifiers

Model	Accuracy	Precision	Recall	F1 Score
Proposed SVMS	96%	0.96	0.98	0.97
Logistic Regression	95%	0.96	0.94	0.95
Naïve Bayes	94%	0.97	0.92	0.94
Random Forest	91%	0.96	0.92	0.94
SVM	92%	0.95	0.91	0.93

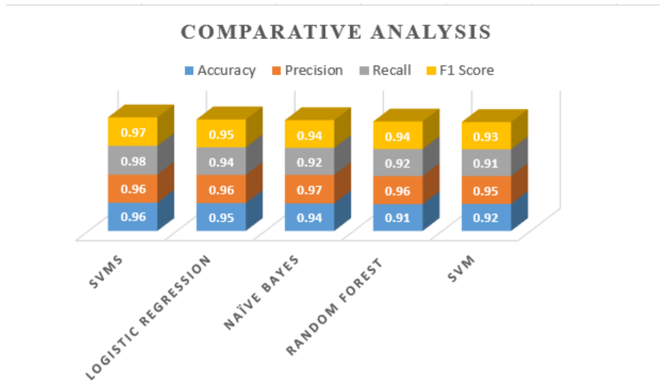

Fig 9. Comparative analysis of proposed model against base classifiers

Figure 9 shows the visualized comparative analysis of all the algorithms that are used in this work. It is clear from the above results the SVMS model performs better and when compared to the base classifiers in most of the aspects the Accuracy, Precision, Recall and F1 measure of Proposed SVMS Classifier has been improved.

3.3 Proposed model against Existing methods

This work compares the proposed SVMS model against the existing models. Table 6 compares five recent literature against the proposed model.

Table 6. Comparative analysis of proposed model against Existing models

Ref.	Model	Accuracy	Precision	Recall	F1 Score
(10)	Logistic Regression	78%	0.78	-	-
(11)	RVVC- BoW RVVC-TF-IDF Hybrid NB-SVM	93% 94% 87%	0.91 - -	0.85 - -	0.88 - -
(12)	SSentiA (SVM)	77%	0.77	0.77	0.77
(13)	Hybrid-SVM Hybrid LR	92% 92%	- -	- -	0.91 0.90
(14)	Fuzzy Logic	85%	0.95	0.91	0.93
Proposed SVMS		96%	0.96	0.98	0.97

The results showed that the proposed SVMS model outperforms well against the existing methods and provides better accuracy of 96%, 96% Precision, 98% Recall and 97% F1 score for aspects of different products.

4 Conclusion and Future Scope

In this study, an aspect based opinion analysis model is proposed which mines customer reviews and opinions and produce an aspect based opinion summary using linguistic annotations and dependency relations. A set of syntactic rules and relations is explored which were observed from twitter data set and effectiveness in the mapping of relationships between the aspect review and the corresponding opinions is demonstrated. Such type of analysis is useful in monitoring customer satisfaction levels regarding a particular topic, product or service, business analysis such as monitoring public opinions of companies, understanding how employees feel about their job and company and for decision makers or policy-makers for a country etc.

Various machine learning algorithms are used for classifying the reviews. After performing classification it was revealed that Proposed SVMS (support vector Machine with spacy) against the basic classifiers and existing models, it gives excellent results by having 96% Accuracy, precision 96%, recall 98% and F1-score 97%.

As the scope of future work, the efficiency of machine learning models can be improved by increasing the amount of data. For better results more feature engineering and deep learning approach is needed. In order to improve accuracy, various alternative optimization approaches, as well as different methods of data preprocessing, data normalization, is required for extracting more features from the dataset. And finally, this work shall be extended in order to implement it over neutral tweets and multi lingual.

References

1) Soni PK, Rambola R. Deep Learning, WordNet, and spaCy based Hybrid Method for Detection of Implicit Aspects for Sentiment Analysis. *2021 International Conference on Intelligent Technologies (CONIT)*. 2021;p. 1–6. Available from: https://doi.org/10.1109/CONIT51480.2021.9498372.
2) Firmanto A, Sarno R. Prediction of movie sentiment based on reviews and score on rotten tomatoes using sentiwordnet. 2018. Available from: https://doi.org/10.1109/ISEMANTIC.2018.8549704.
3) Suhariyanto RA, Sarno R. Aspect Based Sentiment Analysis for Explicit and Implicit Aspects in Restaurant Review using Grammatical Rules. *Hybrid Approach, and SentiCircle*. 2021;p. 294–305. Available from: https://doi:org/10.22266/ijies2021.1031.27.
4) Aljedaani W, Krasniqi R, Aljedaani S, Mkaouer MW, Ludi S, Al-Raddah K. If online learning works for you, what about deaf students? Emerging challenges of online learning for deaf and hearing-impaired students during COVID-19: a literature review. *Universal Access in the Information Society*. 2022;25. Available from: http://dx.doi.org/10.1007/s10209-022-00897-5.
5) Priyanka K, Janakiraman S, Priya MD. WITHDRAWN: Aspect level Sentimental Analysis of Opinion Mining – A Review. *Materials Today: Proceedings*. 2021. Available from: https://doi.org/10.1016/j.matpr.2021.02.183.
6) Turney PD. Thumbs up or thumbs down? Semantic orientation applied to unsupervised classification of reviews. arXiv preprint cs/0212032. 2002. Available from: https://doi.org/10.3115/1073083.1073153.
7) Carenini G, Ng RT, Zwart E, Huang X, Liu Y, Wang Y, et al. Feature extraction of search product based on multi-feature fusion-oriented to Chinese online reviews. Data Science and Management. . 2022. Available from: https://doi.org/10.1016/j.dsm.2022.04.002.
8) Singh AK, Verma A. An Efficient method for Aspect Based Sentiment Analysis Using SpaCy and Vader. *2021 10th IEEE International Conference on Communication Systems and Network Technologies (CSNT)*. 2021;p. 130–135. Available from: https://doi.org/10.1109/CSNT51715.2021.9509650.
9) Van Es B, Reteig LC, Tan SC, Schraagen M, Hemker MM, Arends SR, et al. . Negation detection in Dutch clinical texts: an evaluation of rule-based and machine learning methods. arXiv preprint arXiv:2209.00470. . Available from: https://doi.org/10.48550/arXiv.2209.00470.
10) Monica M, Ochani SD, Sawarkar M, Narwane S. A Novel Approach to Handle Class Imbalance in Machine Learning. *International Journal of Engineering Research & Technology (IJERT)*. 2019;8:2278–0181. Available from: https://doi.org/10.17577/IJERTV8IS110174.
11) Rupapara V, Rustam F, Shahzad HF, Mehmood A, Ashraf I, Choi GS. Impact of SMOTE on Imbalanced Text Features for Toxic Comments Classification Using RVVC Model. *IEEE Access*. 2021;9:78621–78634. Available from: https://doi.org/10.1109/ACCESS.2021.3083638.
12) Sazzed S, Jayarathna S. SSentiA: A Self-supervised Sentiment Analyzer for classification from unlabeled data. *Machine Learning with Applications*. 2021;4:100026–100026. Available from: https://doi.org/10.1016/j.mlwa.2021.100026.
13) Sazzed S. A Hybrid Approach of Opinion Mining and Comparative Linguistic Analysis of Restaurant Reviews. *Proceedings of the Conference Recent Advances in Natural Language Processing - Deep Learning for Natural Language Processing Methods and Applications*. 2021;p. 1281–1288. Available from: http://dx.doi.org/10.26615/978-954-452-072-4_144.
14) Vashishtha S, Susan S. Fuzzy Interpretation of Word Polarity Scores for Unsupervised Sentiment Analysis. *2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*. 2020. Available from: https://doi.org/10.1109/ICCCNT49239.2020.9225646.