AN OVERVIEW OF SENTIMENT POLARITY AND SUBJECTIVITY DETECTION IN TEXT ALONG EMPIRICAL TESTING

KHAN, S. N.[1*] – KHAN, S. U.[2] – ZAHRA, A.[3] – WASIM, N.[3] – SAJID, I.[3] – SHAFIQUE, O. B.[3] – NOREEN, T.[3]

[1] *Department of Graphics Computer Vision and Digital Systems, Silesian University of Technology, Gilwice, Poland.*

[2] *Department of Electrical Engineering Technology, Punjab University of Technology, Punjab, Pakistan.*

[3] *Department of Information and Technology, University of the Punjab Jhelum Campus, Punjab, Pakistan.*

**Corresponding author*
e-mail: sndskhan87[at]gmail.com

(Received 20th May 2023; accepted 30th August 2023)

Abstract. Sentiment analysis start through lexicon and corpuses in which words keep semantic orientation called polarity. The level of positivity or negativity in a text is referred to as its polarity. In the current era, detection patterns have been viewed as a bright career in research. The reason behind that is rapid growth in online textual data day by day. Turn over toward at the present; the focus is polarity detection according to the subjectivity while subjectivity remains multiple directions. As a result, an intrinsic relationship is considered between them. Subjectivity detection performs prevention about sentiment classifier. Sentiment analysis through MC dataset along experimental testing provides the better results. This article argues on the difference between polarity and subjectivity detection among subjectivity terms. Many state-of-the-art algorithms talk about their important features. For sentiment polarity detection, SentiWordNet used utmost for training in which terms organized in the set of synonyms. Comparison between supervised and semi-supervised approaches is also displayed in detail.
Keywords: *sentiment, semantics, polarity, subjectivity, detection, synonym*

Introduction

Now days, a huge volume of data in the form of text are easily accessible as on web sites, web pages, blogs in the form of macro and micro and rapidly increase. This textual form of data can be considered as an input and researchers get this form of input from the users or reviewers about products, features, exchange market, events, services conversational boards and different types of fields. Researchers used these reviews for their research and try to enhance the research area in the field of text mining. These reviews source collection representatives are advertising intellectuals, communal psychologists, educationists, market exchange workers, and some other authentic companies and institutes. They try to work on mining the useful reviews or comments on accessories. They try to catch up the thoughts, state of mind, approach and judgment of the users or reviewers such as a comment keep polar (positive and negative) or neutral review. Therefore, the art of world calls this process of digging the reviews about anything in the form of views or comments from the users or reviewers is sentiment analysis. When they accomplish their settled objectives about sentiment analysis is called sentiment detection. An important task of opinion mining is to perceive the valuable information from text. Sentiment analysis divided into two forms such as subjectivity and polarity detection. Subjectivity related toward accepting of individual views in addition to opinions at the same time as contrasting information based on fact. Polarity main goal is focusing on the analysis report of the subjectivity. Dimensions, magnitudes, or rankings are different in subjectivity according to the environmental structure (Ullah et al., 2023). Sentiment recognition is slightly different field as compared to conventional topic detection. In fact, topic detection is an area in which keywords or some type of reserve words perform important role while discovery of sentiments can explain in the form of polarity or dimensions of sentiments. Detection of sentiments up-to-date now only have two focused and concerned approaches based on machine learning and semantic analysis in the authentic world applications such as documents. Sentiment detection originated from Natural Language Processing (NLP) and Information Retrieval (IR) while this area of interest is also contributing their features with some other important tasks like information extraction and text mining. Studies regarding polarity detection from the text are in English communication (Khan et al., 2018; Cambria, 2016). According to the social media report, 28.6% users used English1 language and rest of used other languages of the world. Now in subjectivity, written material is more important and valuable for detection and indication of the accurate performance. This considering point of view about subjectivity have a great control on text analysis applications.

Consequently, most of the researcher’s main focus is sentiment detection along polarity on Twitter data. The messages placed on Twitter are frequently informal while this category of text is abnormal nature. Because informal text kept symbolic codes, terrible sentence structure, mockery, sometimes abusive words etc. On the other hand, formal text requires fewer early step processing. Therefore, informal text preprocessing and investigation is very tricky as compared to formal text. Twitter data is used according to different aspects in applications like calculation (Bollen et al., 2011), user feelings (Mohammad, 2012) and derision (Reyes et al., 2013).

Related work

There are many tasks in which researchers perform sentiment analysis according to their branches such as polarity and subjectivity detection. So, review is about any text divided into polar forms like positive/negative or neutral. Some are analyzed according to human feelings (Cambria et al., 2014). As per reference, Volkova et al. (2013) introduced an innovative technique for subjectivity with its evaluation in three different communication languages while Cui et al. work is structure of emotion in the form of tokens, recurrent punctuations, and letters in Cui et al. (2011). For Hindi product reviews, Bakliwal (2012) promote a subjective lexicon for the classification of polarity. In reference to Agarwal et al. (2011) used semi-supervised approach to add up polarity of words in tweets. Bahrainian and Dengel (2013) gives a solution to resolve the issue of domain dependent lexicon with the help of topic detection algorithms. Chung et al. (2014) performs polarity detection on concepts of documents through SVM classifier because this classifier is good for binary classification. According to the Irish General Elections in February 2011, subjectivity lexicon (Bakliwal et al., 2013) used with supervised learning method to solve the polarity issue in sentiment classification. Montejo-Ráez et al. (2012) designs a new method for sentiment polarity detection of tweets. According to the Twitter data, empirical tests shows the result of tweets to check as a polarity is subjective. Zhang et al. (2011) propose method is a combination of SVM and corpus that is used to classify the tweets according to their polarities.

Materials and Methods

The method which is used for evaluation of polarity and subjectivity of sentiment is classification. On the basis of classification, researchers divided sentiments into a single entity/object and an opinion holder (reviewer). Opinionated data is having beneficial information and this information is further divided into two parts such as objective statement (Facts) and sentiments. Consequently, classification of sentiments is based on polarity and this polarity explores the polar and neutral forms of the documents, sentences, words etc. Classification of polarity and subjectivity detection is presented according to the following measures along their accuracy metric which have accuracy, precision, recall and F-measures and the pseudo code which shows the flow of, how to allocate the polarity to twitter messages. Characteristically, statistical analysis is used for classification task according to the evaluation metrics. In these metrics, True-Positive (TP) and True-Negative) play an important role in considering the performance on the basis of a classifier (Sokolova et al., 2006).

Accuracy measures

$$\text{Acc} = \frac{TN+TP}{TN+TP+FP+FN} \qquad \text{Eq. (1)}$$

$$\text{Prec} = \frac{TP}{TP+FP} \qquad \text{Eq. (2)}$$

$$\text{Rec} = \frac{TP}{TP+FN} \qquad \text{Eq. (3)}$$

$$\text{F-1} = \frac{2\,[Prec*Rec]}{Prec+Rec} \qquad \text{Eq. (4)}$$

Confusion matrix

***Table 1**. The categories description in positive and negative behavior.*

Category		Positive	Negative
Human	Positive	TP	FN
Data	Negative	FP	TN

Pseudo code for assigning polarity to tweets

Analyse polarity (content):

If an item from the lexicon is found…Extract the polarity…
If an item from the negation list is found…If it is before any item from the lexicon… Reverse the polarity
For each tweet in the tweet list…If an item from the adversative list is found… Analysepolarity(second section of the tweet)…Else…Analysepolarity(whole tweet)… If polarity is consistent…Assign the final polarity…Else if both polarities found… Assign "both"…Else… Assign "-"

Figure 1 shows the generic framework for sentiment polarity and subjectivity detection. SentiWordNet used in this framework as a collection of tweets. It keeps data related to polarity classification with detected subjectivity in (Sokolova et al., 2006). After performing preprocessing, calculate each tweet score for further processing such as classified tweet is objective or subjective on the basis of threshold (value=0). Moreover, if tweet find as a subjective tweet than apply machine learning method and detection process will be completed.

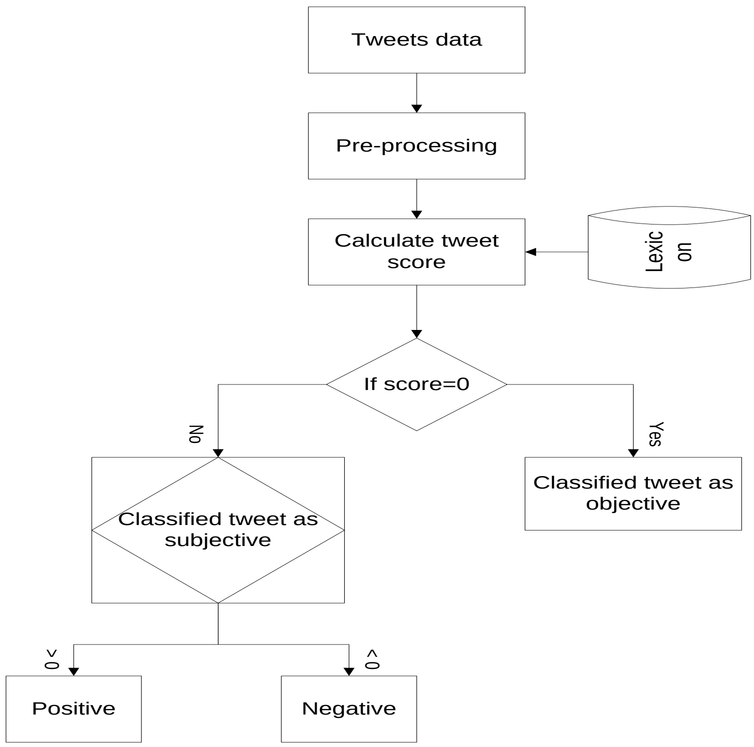

Figure 1. *Generic sentiment polarity and subjectivity detection framework.*

Results and Discussion

In *Table 2*, we try to explain the results about sentiment detection from different researchers. Most of the researchers used supervised and some of them used unsupervised learning methods along different types of methodologies. So, the difference between results is capture in this observation according to the higher performance of level. In this era, sentiment detection research used for generating the classes and dimensions of the under reviewed documents, sentences, even single unit words. In fact, single unit words are more important than other preservers due to its single entity. Polarity detection process performs on this list of words for their classification. For polarity check, subjectivity detection is most established unit. For the empirical tests, researchers required corpus or lexicon or any type of dictionary for their prior communication source. Statistical tests also perform along classifiers in which sometimes data training is the first step of test.

Table 2. *Summary of sentiment polarity detection approaches with accuracy*.

Category of learning methods	References	Approaches	Results
Supervised	Lin et al. (2012)	Mutual Information (MI)	Multiple product reviews with

		with SVM classifier	88% accuracy
	Xu et al. (2012)	Sentiment Hyperspace Analogue to Language (S-HAL)	Chinese communication source corpus with 85% accuracy
	Chikersal et al. (2015)	Bing Liu word list with emoticons, SenticNet and SentiWordNet	Twitter data with 79.81% F-1
	Habernal et al. (2015)	MI with Information Gain and statistical tests	Multiple product reviews with 79% F-1
	Dhande and Patnaik (2014)	NB, Neural Network and Naïve Baysian Neural classifiers	Movie review data with 62.3%, 49.9% and 80.6% accuracy respectively
	Sharma and Dey (2012)	Rule based approach	Movie review data with 62.9% accuracy
	He and Zhou (2011)	Lexicon based approach with self-learner features	Movie and multi domain data with 74.70% accuracy
	Khan et al. (2016)	SentiMI	Movie review data with 84% accuracy
Semi-supervised	Montejo-Ráez et al. (2012)	Random walk algorithm with SentiWordNet	Twitter data with 63% accuracy
	Ortega et al. (2013)	Rule based labeling with SentiWordNet	Twitter and SMS data from SemEval2013 with 50% accuracy
	Jain and Pandey (2013)	SentiWordNet with only adjectives	Study on customer reviews with 69% accuracy
	Park et al. (2015)	Lexicon coverage algorithm with Latent Dirichlet Allocation (LDA)	Multiple domain dataset with 80% F-1
	Saif et al. (2016)	Lexicon based approach with SentiCircles	Twitter dataset with 87.50% accuracy and 85.45% F-1
	Socher et al. (2011)	Recursive Autoencoder (RAE) method	Self-collected experience project data with 50.1% accuracy
	Lin et al. (2010)	Latest Sentiment Model (LSM) with and without prior information, Joint Sentiment Topic (JST) and Reverse-JST models	Movie and multi domain data with 70.35% accuracy

On the other hand, subjectivity term is used as a mystifying expression in any case of detection. From literature, subjectivity divided into five different meanings such as affect, feeling, emotion, sentiment and opinion. In the form of affect, subjectivity is abstractive and complicated in communication source or in any language. According to feeling, subjectivity test through stored facts such as lexicon or corpus while feeling and affect meanings directly associated with emotions. Therefore, emotions are a combination of subjective and objective factors. Feelings generate cognition and affect create awareness. Now sentiments are just like patterns in which impression, communicative gestures and civilizing aspect encircled with subjective manners. Opinion is thinking such as what a person thinks? If a person thinking power is strong than that is called logic. Opinion in term of subjectivity is knowledge about something. Liu [58] give an idea about an opinion is in mathematical language like illustration of symbols as ⟨o,f,so,h,t⟩. In this mathematical demonstration where ‘o’ indicate object while ‘f’ is working as a feature and ‘so’ show the polarity opinion, ‘h’ is act like opinion holder or carrier and ‘t’ used in terms of time. *Figure 2* described every step of subjectivity in terms of its meanings where every important term is directly or indirectly linked with each other. *Figure 3*, *Figure 4* and *Figure 5* shows the schematic structures of an emotion, sentiment and an opinion according to subject detection respectively

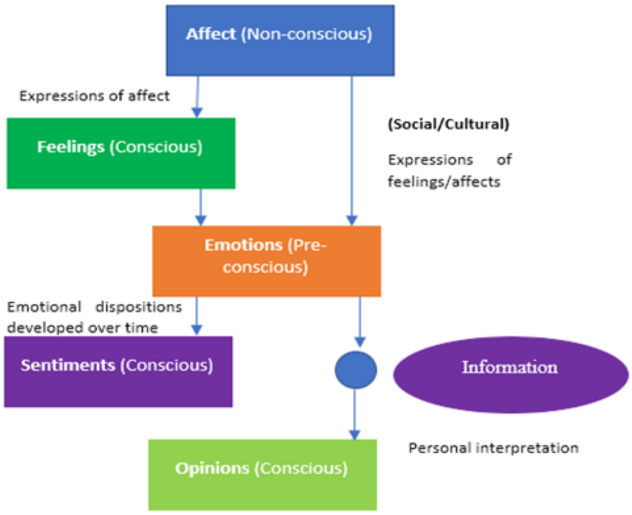

Figure 2. *Important factors according to the subjectivity.*

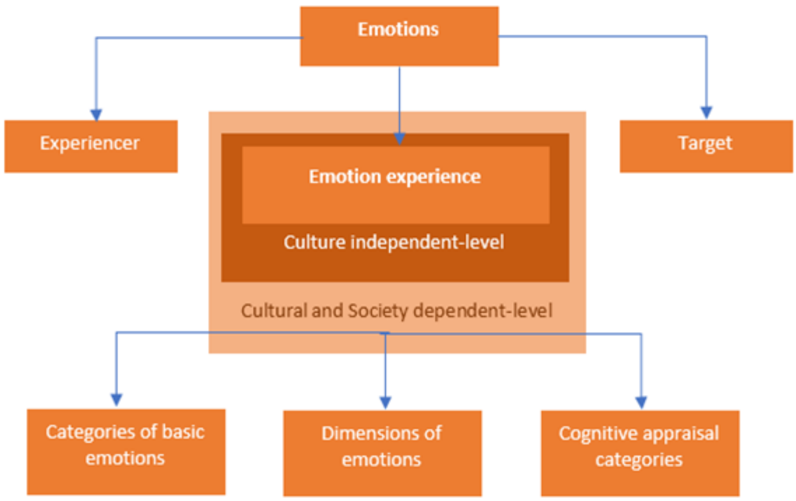

Figure 3. *Graphical representation of an emotion.*

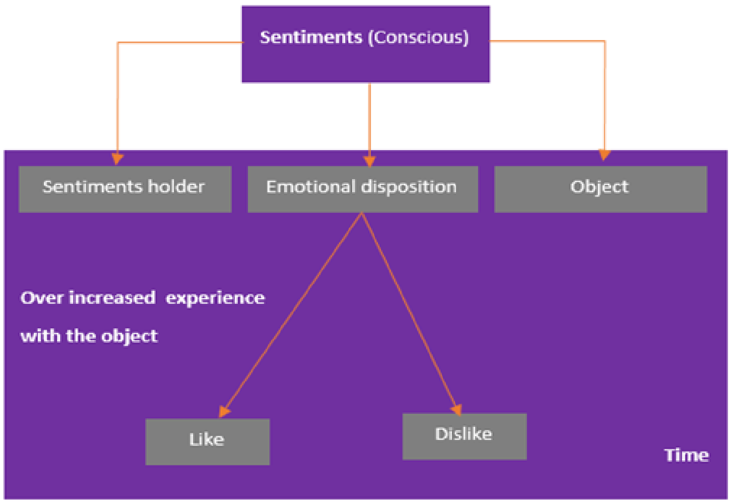

Figure 4. *Graphical presentation of sentiment.*

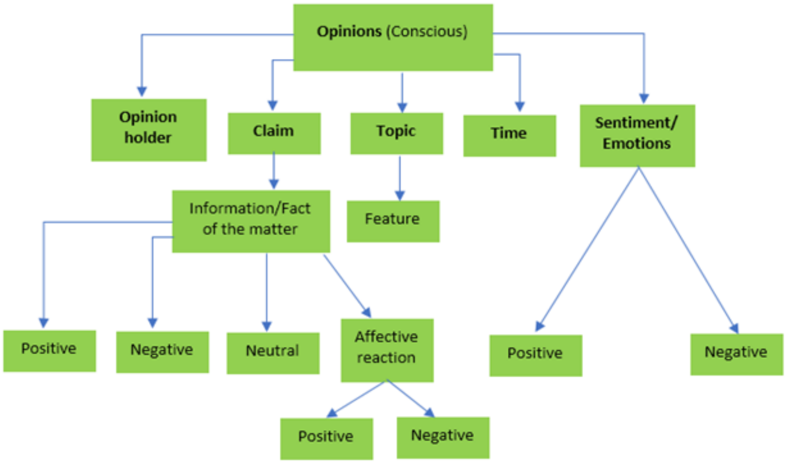

Figure 5. *Graphical representation of an opinion.*

In polarity detection, first step is to check the subjectivity of the document that's why author emphasis on subjectivity according to their terms. But in different theoretical backgrounds, its definition is going to be changed. So, this is the major problem of subjectivity while the solution of this issue is, must mention research area before using subjectivity. *Figure 6* presented the detailed results of supervised and semi-supervised approaches by using different sets or combination of sets of data. Performance calculated with the help of accuracy and F-1 measuring factors. *Table 3* depicts the MC dataset with scores obtained by a similarity measure. This visualizes Spearman's rank correlation between these human judgments and scores provided by a semantic similarity measure. As this evaluation is widely used by the community, the results may be compared with other published methods. However, the MC, RG and WordSim have a small vocabularies. Imagine a measure which performs well only on the 39 words of the MC dataset. Then, it may achieve the same correlation as a measure with coverage of 390.000 words. Main characteristics of this evaluation task are the following: (1) (+) These datasets are widely used. Numerous publications during the last 20 years, make it easy to compare the results with the baselines; (2) (−) Small vocabulary size makes it impossible to assess coverage or recall of a similarity measure; and (3) (−) The datasets provide no relation types.

Table 3. *Miller-Charles (MC) dataset and scores obtained with a similarity measure.*

Word (ci)	Word (cj)	Human score (sk)	Score (s^k)	Human rank (rk)	Rank (r^k)
Automobile	Car	3.92	0.884	1	1
Journey	Voyage	3.84	0.592	2	8
Gem	Jewel	3.84	0.581	3	3
Boy	Lad	3.76	0.325	4	2
Coast	Shore	3.70	0.440	5	7
Asylum	Madhouse	3.61	0.190	6	5
Magician	Wizard	3.50	0.556	7	4
Midday	Noon	3.42	0.692	8	10
Furnace	Stove	3.11	0.296	9	9
Food	Fruit	3.08	0.300	10	13
Bird	Cock	3.05	0.145	11	16
Bird	Crane	2.97	0.190	12	12
Implement	Tool	2.95	0.260	13	6
Brother	Monk	2.82	0.174	14	21
Crane	Implement	1.68	0.016	15	14
Brother	Lad	1.66	0.219	16	11
Car	Journey	1.16	0.124	17	25

Monk	Oracle	1.10	0.057	18	17
Cemetery	Woodland	0.95	0.056	19	24
Food	Rooster	0.89	0.027	20	26
Coast	Hill	0.87	0.186	21	28
Forest	Graveyard	0.84	0.069	22	23
Shore	Woodland	0.63	0.076	23	22
Monk	Slave	0.55	0.101	24	18
Coast	Forest	0.42	0.145	25	19
Lad	Wizard	0.42	0.083	26	20
Cord	Smile	0.13	0.020	27	29
Glass	Magician	0.11	0.078	28	27
Noon	String	0.08	0.026	29	15
Rooster	Voyage	0.08	0.005	30	30

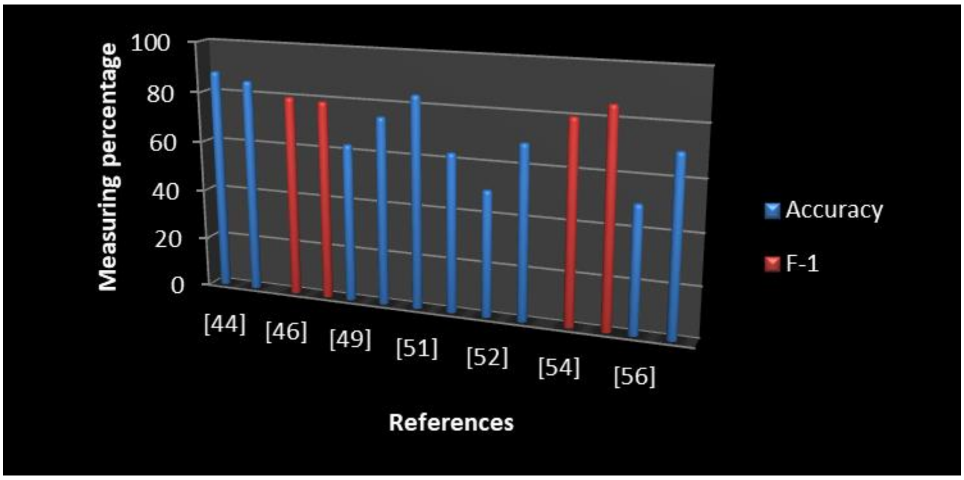

***Figure 6.** Measuring results of supervised and semi-supervised approaches according to multiple datasets.*

Conclusion

This paper main concern is to differentiate between polarity and subjectivity detection according to the sentiments. Therefore, we support the research community to continue their work but take care of the difference that is lie in between polarity and subjectivity. Being able to examine the polarity and subjectivity of the text on every level of given text such as document, comments, sentences and words. Polarity is not just a process of division. It is associated with subjectivity. Authors investigate a bundle of articles and take out the excellent results of sentiment polarity detection along subjectivity through appropriate term. A supervised approach used SVM as a classifier which gives the best accuracy results on multiple product reviews with MI. On the other hand, a semi-supervised approach among feature selection method performs 85.40% result according to F-1. Researches still unlock the gate to jump into the blue sea and analyze different levels. These levels involve in subjectivity directly as terms. Selection of correct term of subjectivity is also a big challenge. Finally, this research main goal is to understand the polarity detection with subjectivity. In future, the above mentioned approaches necessitate auxiliary improvement and enhancements. Sentiment detection victorious accounts give confidence to the upcoming versions and modifications of methods, techniques and algorithms.

Acknowledgement

This research study is self-funded.

Conflict of interest

The authors declare that there is no conflict of interest involve in this research study.

REFERENCES

[1] Agarwal, A., Xie, B., Vovsha, I., Rambow, O., Passonneau, R. (2011): Sentiment analysis of twitter data. – In Proceedings of the Workshop on Languages in Social Media, Association for Computational Linguistics 8p.

[2] Bahrainian, S.A., Dengel, A. (2013): Sentiment analysis and summarization of twitter data. – In Computational Science and Engineering (CSE), 2013 IEEE 16th International Conference, IEEE 7p.

[3] Bakliwal, A., Foster, J., van der Puil, J., O'Brien, R., Tounsi, L., Hughes, M. (2013): Sentiment analysis of political tweets: Towards an accurate classifier. – Association for Computational Linguistics 10p.

[4] Bakliwal, A., Arora, P., Varma, V. (2012): Hindi subjective lexicon: A lexical resource for hindi polarity classification. – In Proceedings of the Eight International Conference on Language Resources and Evaluation (LREC) 8p.

[5] Bollen, J., Mao, H., Zeng, X. (2011): Twitter mood predicts the stock market. – Journal of Computational Science 2(1): 1-8.

[6] Cambria, E. (2016): Affective computing and sentiment analysis. – IEEE Intelligent Systems 31(2): 102-107.

[7] Cambria, E., Olsher, D., Rajagopal, D. (2014): SenticNet 3: a common and common-sense knowledge base for cognition-driven sentiment analysis. – In Twenty-Eighth AAAI Conference on Artificial Intelligence 28(1): 7p.

[8] Chikersal, P., Poria, S., Cambria, E., Gelbukh, A., Siong, C. E. (2015): Modelling public sentiment in Twitter: using linguistic patterns to enhance supervised learning. – In International Conference on Intelligent Text Processing and Computational Linguistics, Springer, Cham 16p.

[9] Chung, J.K.C., Wu, C.E., Tsai, R.T.H. (2014): Improve polarity detection of online reviews with bag-of-sentimental-concepts. – Proceedings of the 11th ESWC, Semantic Web Evaluation Challenge, Crete, Springer 41p.

[10] Cui, A., Zhang, M., Liu, Y., Ma, S. (2011): Emotion tokens: Bridging the gap among multilingual twitter sentiment analysis. – In Asia Information Retrieval Symposium, Springer, Berlin, Heidelberg 12p.

[11] Dhande, L.L., Patnaik, G.K. (2014): Analyzing sentiment of movie review data using Naive Bayes neural classifier. – International Journal of Emerging Trends & Technology in Computer Science (IJETTCS) 3(4): 313-320.

[12] Habernal, I., Ptáček, T., Steinberger, J. (2015): Reprint of "Supervised sentiment analysis in Czech social media" – Information Processing & Management 51(4): 532-546.

[13] He, Y., Zhou, D. (2011): Self-training from labeled features for sentiment analysis. – Information Processing & Management 47(4): 606-616.

[14] Jain, A.K., Pandey, Y. (2013): Analysis and implementation of sentiment classification using lexical POS markers. – International Journal 2(1): 36-40.

[15] Khan, S.N., Nawi, N.M., Imrona, M., Shahzad, A., Ullah, A., Rahman, A.U. (2018): Opinion mining summarization and automation process: a survey. – International Journal on Advanced Science Engineering Information Technology 8(5): 1836-1844.

[16] Khan, F.H., Qamar, U.,Bashir, S. (2016): SentiMI: Introducing point-wise mutual information with SentiWordNet to improve sentiment polarity detection. – Applied Soft Computing 39: 140-153.

[17] Lin, Y., Zhang, J., Wang, X., Zhou, A. (2012): An information theoretic approach to sentiment polarity classification. – In Proceedings of the 2nd Joint WICOW/AIRWeb Workshop on Web Quality, ACM 6p.
[18] Lin, C., He, Y., Everson, R. (2010): A comparative study of Bayesian models for unsupervised sentiment detection. – In Proceedings of the Fourteenth Conference on Computational Natural Language Learning, Association for Computational Linguistics 9p.
[19] Mohammad, S. (2012): # Emotional tweets. – In * SEM 2012: The First Joint Conference on Lexical and Computational Semantics-Volume 1: Proceedings of the main conference and the shared task, and Volume 2: Proceedings of the Sixth International Workshop on Semantic Evaluation (SemEval 2012) 9p.
[20] Montejo-Ráez, A., Martínez-Cámara, E., Martín-Valdivia, M.T., Urena-Lopez, L.A. (2012): Random walk weighting over sentiwordnet for sentiment polarity detection on twitter. – In Proceedings of the 3rd Workshop in Computational Approaches to Subjectivity and Sentiment Analysis, Association for Computational Linguistics 8p.
[21] Ortega, R., Fonseca, A., Montoyo, A. (2013): SSA-UO: unsupervised Twitter sentiment analysis. – In Second Joint Conference on Lexical and Computational Semantics (SEM) 2: 501-507.
[22] Park, S., Lee, W., Moon, I.C. (2015): Efficient extraction of domain specific sentiment lexicon with active learning. – Pattern Recognition Letters 56: 38-44.
[23] Reyes, A., Rosso, P., Veale, T. (2013): A multidimensional approach for detecting irony in twitter. – Language Resources and Evaluation 47(1): 239-268.
[24] Saif, H., He, Y., Fernandez, M., Alani, H. (2016): Contextual semantics for sentiment analysis of Twitter. – Information Processing & Management 52(1): 5-19.
[25] Sharma, A., Dey, S. (2012): Performance investigation of feature selection methods and sentiment lexicons for sentiment analysis. – IJCA Special Issue on Advanced Computing and Communication Technologies for HPC Applications 3: 15-20.
[26] Socher, R., Pennington, J., Huang, E.H., Ng, A.Y., Manning, C.D. (2011): Semi-supervised recursive autoencoders for predicting sentiment distributions. – In Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing 10p.
[27] Sokolova, M., Japkowicz, N., Szpakowicz, S. (2006): Beyond accuracy, F-score and ROC: a family of discriminant measures for performance evaluation. – In Australasian Joint Conference on Artificial Intelligence, Springer, Berlin, Heidelberg 7p.
[28] Ullah, A., Khan, S.N., Nawi, N.M. (2023): Review on sentiment analysis for text classification techniques from 2010 to 2021. – Multimedia Tools and Applications 82(6): 8137-8193.
[29] Volkova, S., Wilson, T., Yarowsky, D. (2013): Exploring sentiment in social media: Bootstrapping subjectivity clues from multilingual twitter streams. – In Proceedings of the 51st Annual Meeting of the Association for Computational Linguistics 2: 505-510.
[30] Xu, T., Peng, Q., Cheng, Y. (2012): Identifying the semantic orientation of terms using S-HAL for sentiment analysis. – Knowledge-Based Systems 35: 279-289.
[31] Zhang, L., Ghosh, R., Dekhil, M., Hsu, M., Liu, B. (2011): Combining lexicon-based and learning-based methods for Twitter sentiment analysis. – HP Laboratories, Technical Report HPL-2011 89: 1-8.