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Sentiment Analysis of Facebook Posts using Hybrid Method

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Abstract: Social Media is a popular medium of communication amongst youngsters to remain connected with their friends. Facebook is one of the most preferred Social Media Sites which store the gigantic amount of data which can be explored for Sentiment Analysis. In this study, we have applied hybrid analysis approach which combines the best features of a lexical analysis and SVM machine learning classification algorithm on Facebook Posts. The analysis is further improved by incorporating language discourse features to detect intensity of sentiment and the prominent emotions expressed through these posts.

Index Terms: Emotion lexicons, Hybrid Analysis, Sentiment Analysis, Social Networking Sites, Support Vector Machine.

I. INTRODUCTION

Nowadays, enormous information is available on Social Networking Sites due to the penetration of the Internet amongst 4.2 billion users worldwide[1]. People use Social Networking Sites as the most popular and fast communication medium to remain in touch with their friends, family, and peer. There are 3.03 billion active Social Networking Sites users[1], most of them range in the age group of 18-49 years who share their emotions, photos, daily life activities, chats, opinions about products, politics, social issues, movies and many more. These sites play a vital role in spreading mass opinion thus can be used to build a positive public opinion about different societal issues [1]. Sentiments spread through Social Networking Sites are contagious which can be used as a tool for the well-being of mankind [2], [3], [4]. Sentiment analysis is the systematic process of collecting and analyzing emotions from the enormous volume of unstructured online data in real time. People, through the medium of the Internet, use various Social Networking Sites, blogs forums etc., to express their feelings and thoughts. Their sentiments can include a situation, event or object [5].

[1]https://www.brandwatch.com/blog/amazing-social-media-statistics-and-facts/ Sentiment analysis is described as a process that classifies information mostly found in the textual form to evaluate feelings, mindsets, and sentiments towards an issue or an object. The description emphasizes the working of sentiment analysis and the need to categorize emotions as per their polarity as positive, negative or neutral [6]. Sentiment analysis generally uses a lexical method or machine learning method for detecting sentiment polarity of data. The lexical analysis uses lexicons to identify the semantic orientation of the textual data while machine learning classifier requires a labeled dataset for classification. In our study, we have tried to identify the basic emotions underlying Facebook Posts of youngsters. In a nutshell, the progression of our research begins by collecting user-generated posts from Facebook. The extracted posts are cleaned, transformed, and accordingly classified into positive or negative sentiments. We recommend a hybrid method for sentiment analysis which combines features of both methods. Each sentence is evaluated, and the overall score is combined to predict the sentiment polarity, the degree of sentiment and the basic emotions exhibited by him. In the end, the inclination of a youngster towards negativity is identified through the level of negativity found in his posts. Section II reviews the related work carried out by the researchers in this area. Section III describes the methodology used to detect emotions using a hybrid approach. Section IV gives information about experimental setup. Section V highlights the results and comparative analysis of different approaches used. The conclusion is discussed in section VI.

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II. RELATED WORK

Sentiment analysis incorporates several tasks to generate contextual knowledge from a huge textual data starting with systematically gathering data and concluding with the concrete results which can be useful in the design of opinion mining system [7]. Self-articulation is an imperative use of social media, in the form of sharing comments, activities, and happenings of daily life, sharing the opinion about different things, etc. Social media is penetrated in our lives in such a way that it has started dominating face to face interaction with virtual communication. The reason behind this changing dynamic is the widespread use of Social Media by young users. Facebook is immensely helpful in keeping touch with family and friends that live at distant. With its unique features of providing posts, photos, and profile information, it makes you aware of day to day happenings of your circle of friends and family. On Facebook, you can have thousands of friends as it offers you with a facility to add friends without any complicated technicalities.

Facebook post helps you to express freely without any hassles. It can be classified easily because it contains more characters as compared to a tweet. It also conveys emotions better than other Social Networking Site [8]. You can update photos, selfies, links to songs, music, movies and anything that you want to inform about. These days the younger generation finds it very easy to communicate and be in touch with their peer through Facebook than the traditional mode of communication [9]. A lot of research using lexicon-based analysis has been carried out by different researchers from the past decade. Subsequently, it has been advanced a lot from matching input text with prior polarity lexicons to the incorporation of the semantic orientation of text based on negation, intensifiers apart from adjectives which are mainly used as emotion depicting words [10] to achieve better results. The context in which an emotion lexicon is used also plays an important role in depicting polarity of the post. The humongous volume of Facebook posts, along with comments statistics, presents an opportunity for human sentiment analysis and behavioral study. Using machine learning techniques, Facebook posts can also be used to find the personality traits of a user [11]. Some authors used Naïve Bayes classifier to identify how people feel about certain topics [12] while others used Support Vector Machine and Naïve Bayes classifiers, to classify Facebook posts of Tunisian users for studying their behavior and state of minds during Arabic Spring Era [13]. In very few studies, the hybrid analysis approach which combines both lexical and machine-based techniques are used to detect the emotions of the user from the contents posted on Facebook. The authors have applied hybrid analysis to create an application called SentBuk and used it for effective e-learning [14]. In another study, the authors have used regular expression-based rules and statistical text mining techniques to predict sentiments expressed in suicide notes [15].

III. HYBRID SENTIMENT ANALYSIS

The hybrid analysis combines both lexical and machine learning analysis techniques and compensates shortcomings of each technique to generate better results [16]. In our study, the analysis is based on the combination of the algorithm used to calculate the aggregate sentiment score of lexicons expressed by the post and Support Vector Machine classifier. The score works as a new feature for the SVM's training dataset. The proposed approach has the advantage of having the improved score of the lexicons obtained by applying the aggregate sentiment scoring algorithm which takes into consideration the language discourse features and the flexibility of the SVM. Fig. 1 shows the proposed method's flow.

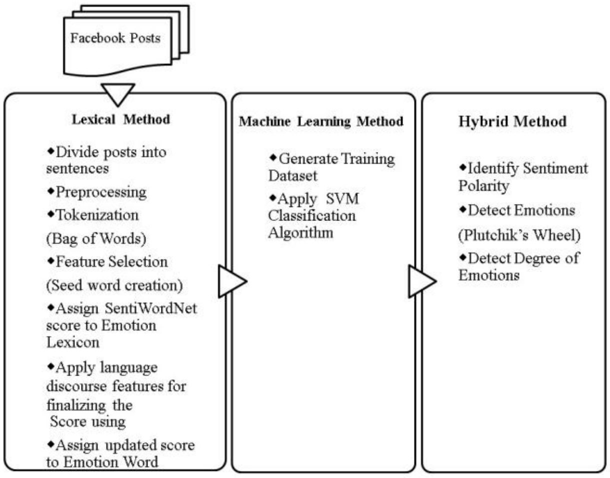

Fig. 1. Proposed architecture of Hybrid Analysis

A. *Phase I using Lexical Analysis method*

The lexical analysis begins with the creation of seed words i.e. emotion lexicons. The seed words are precompiled, context-oriented emotion lexicons and incorporate emotion lexicons related to the domain of analysis. Each time a new post is incorporated, it is tokenized, and each token is matched against the seed words. The user post is analyzed using seed words and the sentiment of data is decided based on the combined polarity of each emotion lexicon found in the post [17] [18].

a. Preprocessing

To get more accurate results, the unstructured data is subjected to preprocessing before being used for finding sentiment polarity. It involves the removal of unwanted special symbols except '!' or '?', removal of repeated characters, unnecessary spaces, spelling corrections, conversion of data to lowercase, conversion of abbreviations to full forms, changing Internet slangs to their respective full forms, stemming etc. The entire post which is in the form of a paragraph is segregated into sentences. Each sentence is then tokenized into its constituent tokens. Hence each token can be analyzed individually.

b. Emotion Lexicon creation

The emotion lexicons are the words which represent strong semantic orientation. They are context specific words used to express human feelings. The research work centers on eight basic emotions given by Plutchik's wheel of emotions [19]. Hence, we have stored the emotion lexicons (Seed Words) depicting emotions like joy, trust, surprise, anticipation fear, anger, disgust, and sadness in a database. Sentiment polarity and weight associated with each emotion word are assigned using SentiWordNet[2] and Hindi SentiWordnet[3].

c. Feature Selection

In sentiment analysis, feature selection is considered as one of the most important tasks. Once the dataset is tokenized and brought to a stage where one can identify individual token, features are selected by matching the tokens with the emotion lexicons stored in the database exclusively created for storing lexicons expressing emotions. The features can be selected based on their presence or frequency.

The features selected are assigned binary values (0 or 1) when selected based on presence or absence of sentiment in the feature vector or it can be stored as an integer or decimal value used to depict the intensity of sentiment in the data. The core of accurate sentiment polarity depends on the extraction of emotion-oriented words called features from this informal data. Better the selection of emotion words accurate would be the result of the sentiment polarity.

d. Prediction of Sentiment Polarity and Sentiment Degree

Each emotion word is assigned the corresponding value of its emotion score using SentiWordNet 4.0. When an emotion word is detected in the post corresponding score of its emotion value is assigned to the word. The emotion score of all lexicons present in the sentence is added to calculate the total score of the sentence. Based on the total score of the emotion lexicons, the polarity of the sentence is identified as Negative, Positive or Neutral. The degree of sentiment expressed through the sentence is calculated by summing the individual score of emotion lexicon along with the other details of emotion score as mentioned below.

1. Identifying domain specific emotion keywords: The accuracy of the classifier is greatly influenced by the context in which words are used in the sentence. Emotion words change with respect to a domain. Hence taking this into consideration only domain-specific words are selected.
2. Negation: When negation occurs in a sentence it mainly influences the original meaning of positive or negative emotion words by inverting their polarities [20], [21], [22], [23].
3. Double negation: It is observed that, if negation is used more than once in a sentence then it invalidates the effect of negation on emotion words. The emotion words in such sentences are generally adjectives or adverbs [24], [25].

[2] sentiwordnet.isti.cnr.it/
[3] http://www.cfilt.iitb.ac.in/wordnet/webhwn/downloaderInfo.php

4. Effects of conjunctions: Conjunctions are used to connect words, clauses or sentences. They provide meaningful information about the sentence.
5. The presence of conjunction in a sentence makes the calculation of polarity difficult. When it appears in a sentence, we need to find which part of the sentence contributes more to the final emotional polarity of the sentence [26].
6. Intensifiers and Diminishers: They increase or decrease the polarities of negative or positive emotion words. They do not have their own sentiment orientation, but their presence strongly conveys the sentiments which they are associated with. They never invert polarities of the emotion words [27].
7. Punctuation marks: The punctuations like an exclamation mark and question mark are used to further increase or decrease the strength of the emotion expressed. An exclamation mark used in a sentence conveys strong emotions such as surprise, astonishment and any other such emotions. It adds additional emphasis to the emotion expressed. In contrast, the question mark indicates confusion.
8. Slang: The weight of the original word for the corresponding slag word used is taken into consideration.

Algorithm: Aggregate Facebook Post
Input: Facebook Post
Output: Emotion Score

1. Begin
   //Scan Facebook Post
2. While (Facebook Post) Do
3. Call **PreProcessing** (Facebook Post)
4. Call **SeedWordGeneration** (Facebook Post)
5. Search Facebook Post in SeedWord Database
6. If (Facebook Post contains Emotion Lexicon)
7. Call **EmotionScoring** (Facebook Post)
8. Go to Step 1 to scan next Facebook Post
9. Else
10. Go to Step 1 to scan next Facebook Post
11. End if
12. End While
13. End Function

//**Pre-Processing**

1. Begin
   //Scan dataset
2. While (Facebook Post) Do
3. token=tokenize (Facebook Post)
4. For each token
5. Conversion to lowercase
6. Conversion of abbreviation to full form
7. Conversion of Internet slang to full form
8. Remove special symbol
9. Remove URL
10. Remove repeated characters
11. Remove URL
12. Remove multiple spaces
13. Spelling corrections
14. Search token in StopWord Database
15. If found then
16. Remove stop word
17. Endif
18. Next token
19. End while
20. End function

//Seed Word Generation

1. Collect emotion lexicons related to eight basic emotions (Plutchik's wheel) and store in a database
2. Collect synonyms of emotion lexicons related to eight emotions and store in a database
3. Assign SentiWordNet score to emotion lexicon
4. Begin
5. While (Facebook Post) Do
6. For each token
7. Search token in SeedWord Database
8. If not found then
9. If occurrence of emotion lexicon > 3 then
10. Store emotion lexicon in a database
11. Assign SentiWordNet score of emotion lexicon to token
12. End if
13. End if
14. Next token

15. End while
16. End function

//**Emotion Scoring**

1. Begin
2. While (Facebook Post) Do
3. For each token
4. Search token in SeedWord Database
5. If found then
6. Assign SentiWordNet score of emotion lexicon to token
7. End if
8. If token is used with negation then
9. Assign inverted SentiWordNet score of emotion lexicon to token
10. End if
11. If token is used with intensifier then
12. Add SentiWordNet score of emotion lexicon and SentiWordNet score of intensifier
13. Assign combined score to token
14. End if
15. If token is used with diminisher then
16. Add SentiWordNet score of emotion lexicon and SentiWordNet score of diminisher
17. Assign a combined score to token
18. End if
19. If token is used with double negation then
20. Assign SentiWordNet score of emotion lexicon to token
21. End if
22. If token is used with conjunction then
23. Assign SentiWordNet score of emotion lexicon to token depending upon the position of conjunction in a sentence
24. End if
25. If token is used with symbols like '!' or '?' then
26. Assign SentiWordNet score of emotion lexicon to token coupled with 0.1 increment or decrement depending upon the symbol used
27. End if
28. Calculate Sentence Score by adding score of each token found in the sentence
29. Calculate Aggregate Facebook Post Score by adding Sentence Score of each sentence found in Facebook Post
30. Next token
31. End while

B. *Phase II using Machine learning method*

Lexical analysis generates better results when used for small datasets. If the emotion lexicon is not found in the Seed word database, then the dataset cannot be evaluated properly. In contrast to this, Machine Learning analysis works on many labeled training datasets and produces better results [28], [29], [30]. There are various popular classification algorithms which outperform lexical analysis. In Machine learning sentiment analysis, the bag-of-words feature selection method is used predominantly. The entire dataset is treated as a bag (group) of words where the sequence of words in a sentence is retained even after the removal of stop words and stemming. Support Vector Machine (SVM) is a dominant linear classification algorithm. It treats the dataset as the points plotted in space. They are expected to be separated by enough space. It calculates a maximum margin hyperplane which divides the data points into two classes. In text classification, Support Vector Machine is considered the best classification algorithm [31], [32]. SVM algorithm generally divides the training dataset into minimum of two classes. These classes are separated from each other by the maximum possible distance drawn by the hyperplane. The sum of the distances of the closest points of the two classes from the hyperplane defines the margin of the classes.

The linear equation is given as under.

$$Y=BX+A \qquad (1)$$

Where the point (X, Y) has two-dimensional values X, Y and A is a constant value.

A point with value X will be classified in which class is given by equation 2.

$$W=\sum_{j=0}^{n} \alpha_j y_j x_j \qquad (2)$$

Among the advantages of SVM is that it achieves excellent results in high-dimensional data with very few samples. It is robust to outliers and noise. It can learn both simple linear and very complex nonlinear functions by using kernel function. We are using multiclass SVM to classify multiple sentiment levels and different emotions exhibited by the posts. SVM applies a technique of one-versus-all to select the class which classifies the test data with optimal possible distance.

IV. EXPERIMENTAL SETUP

The methodology of this study is divided into two phases. The first phase begins with the lexical analysis method which includes various sub-steps like data extraction from Facebook Posts of youngsters collected over a period of three months. The next step is the creation of Emotion Lexicons (Seed Words). The third step is the selection of relevant features from the group of tokenized data and the last step is assigning final weights to selected features (emotion lexicons) by taking into consideration their discourse relation like negation, double negation, conjunction, use of intensifiers and diminishers present in the sentence. The second phase starts by feeding this training dataset to SVM classifier for identifying underlying sentiments as well as the degree of sentiments. Emotion scoring, and the results obtained after this phase are used to find the level of emotional distress. The degree of emotional distress is further divided as positive, medium, negative and neutral. To perform our experiment, we have used WEKA machine learning toolkit, version 3.8. The data is divided into training dataset with 60% data and test dataset with 40% data. Information Gain and Ranker algorithms are used for feature selection. The dataset is trained using Support Vector Machine (SMO) classification algorithm implemented with 10-fold validation. We evaluated the performance of the hybrid analysis using various parameters like the presence of emotion lexicons, frequency of emotion lexicons, and the discourse relation. These features are the deciding factors for predicting the level of sentiments expressed through the Facebook post.

V. PERFORMANCE EVALUATION

With lexical analysis, we have received 78.05% accuracy in sentiment polarity and 70.41% accuracy in sentiment degree. When we have analyzed the dataset using the SVM algorithm without considering the discourse features found in the post, we have got sentiment polarity with an accuracy of 96% and sentiment degree with 95.41% accuracy. After applying the hybrid analysis for various parameters, we have achieved the results as shown below.

Table I. Comparison of Hybrid Analysis with presence and frequency of emotion lexicons for predicting Sentiment Polarity

Metric	Sentiment Polarity	Degree of Sentiment
Hybrid analysis by considering the presence of emotion lexicon	94.54%	-
Hybrid analysis by considering the frequency of emotion lexicon	94.50%	90.17%

The results shown are in Table I indicate that the mere presence of emotion lexicon or its frequency in the post does not affect the polarity of sentiment expressed through the post. Based on the presence of emotion lexicon alone, it is difficult to predict the degree of sentiment.

Table II. Comparison of Hybrid Analysis with emotion lexicon score and different features for predicting Sentiment Polarity

Metric	Sentiment Polarity	Degree of Sentiment
Hybrid analysis by considering negation, double negation, and conjunction	87.95%	85.58%
Hybrid analysis by considering negation, double negation, conjunction, intensifier, and diminishers	88.15%	85.21%

The hybrid analysis approach has detected sentiment polarity with 87.95% accuracy when improved lexicon scores coupled with language discourse relation are taken into consideration. These results are further improved with the incorporation of intensifiers and diminishers.

Improvement in the prediction of True Positives

Table III. depicts that there is a decrease in false negatives with the incorporation of the frequency of emotion lexicons than just their presence in the posts.

Table III. Confusion Matrix with presence and frequency of emotion lexicons for predicting Sentiment Polarity

Metric	Hybrid analysis by considering negation, double negation, and conjunction			Hybrid analysis by considering negation, double negation, conjunction Intensifier, and diminishers		
	Positive	Negative	Neutral	Positive	Negative	Neutral
Positive	2355	38	437	2351	42	437
Negative	29	**139**	75	37	**145**	61
Neutral	39	38	2296	29	39	2305

Improvement in the prediction of True Negatives

It is observed that false positives are reduced with the incorporation of discourse relation than just the presence or

Metric	Hybrid analysis with the presence of emotion lexicon			Hybrid analysis with the frequency of emotion lexicon		
	Positive	Negative	Neutral	Positive	Negative	Neutral
Positive	2757	**59**	14	2765	**51**	14
Negative	21	201	21	29	193	21
Neutral	215	65	2093	219	61	2093

the frequency of emotion lexicons. The following Table IV depicts the results obtained by using these parameters.

Table IV. Confusion Matrix with emotion lexicon score and different features for predicting Sentiment Polarity

Predicting Degree of Sentiment using different sentiment levels

To predict the degree of sentiment exhibited by the post, we have categorized sentiments into five different levels namely very positive, positive, neutral, negative and very negative. The results are shown in Table V also depict that the degree of sentiment is better predicted by sentiment frequency than its score. On the contrary, the results obtained using frequencies are misleading because they simply represent the occurrence of emotion lexicons in the given post. They do not consider the SentiWordNet score assigned to these lexicons. It is also noted that classifier is not able to categorize posts into very positive or very negative categories successfully because of their very less percentage in the dataset. Hence, we have decided to consider only four levels namely positive, moderate, negative and neutral for further analysis.

The new results obtained in Table VI exhibits significant improvement in the performance of the classifier for depicting the degree of sentiment.

Table V. Confusion Matrix with emotion lexicon score and different features for predicting Degree of Sentiment

Metric	Hybrid analysis with the frequency of emotion lexicon					Hybrid analysis by considering negation, double negation and conjunction					Hybrid analysis by considering negation, double negation, conjunction, intensifier and diminishers				
	Very Positive	Positive	Neutral	Negative	Very Negative	Very Positive	Positive	Neutral	Negative	Very Negative	Very Positive	Positive	Neutral	Negative	Very Negative
Very Positive	0	79	1	6	0	0	49	35	2	0	0	49	35	2	0
Positive	0	2681	12	44	0	0	2312	397	28	0	0	2297	410	30	0
Neutral	0	224	2094	63	0	0	45	2303	33	0	0	43	2309	29	0
Negative	0	24	19	136	0	0	23	110	46	0	0	30	114	35	0
Very Negative	0	7	2	54	0	0	11	28	24	0	0	10	29	24	0

Table VI. Confusion Matrix with new sentiment categories for predicting Degree of Sentiment

Hybrid analysis by considering intensifier and diminishers				
Metric	Positive	Moderate	Negative	Neutral
Positive	637	0	0	1
Moderate	0	1978	0	651
Negative	5	0	52	0
Neutral	0	0	0	2122

Our study also aims to analyze the predominant emotions expressed through these Facebook posts of young people. Generally, Facebook posts of youngsters of this age are found to express their feelings of love and affection apart from self-expression. Hence, we have also incorporated 'love', a complex emotion obtained by combining emotions of joy and trust in our study. Fig. 2 represents the distribution of emotions found in these posts. The emotion of love leads the other emotions which are mostly positive emotions. The other notable emotions are joy, sadness, and anger. The emotions of anticipation, trust, surprise, fear, and disgust are found in a handful of posts.

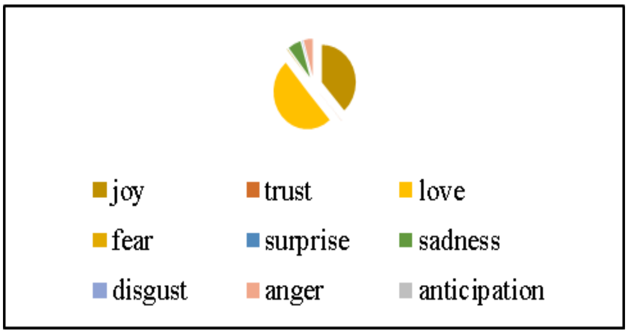

Fig. 2. Distribution of Emotions found in Facebook Posts

The underlying basic emotions found in Facebook Posts when detected using hybrid analysis are as shown in Table VII. The analysis is performed using various parameters like presence, frequency, language discourse features and the intensity of emotion lexicons.

Table VII. Comparison of Hybrid Analysis for predicting Emotions

Metric	Emotion Prediction
Hybrid analysis with the presence of emotion lexicon	94.69%
Hybrid analysis with the frequency of emotion lexicon	94.38%

Hybrid analysis with language discourse relation of emotion lexicon	71.25%
Hybrid analysis with language discourse relation of emotion lexicon and its intensity	86.52%

The emotions are predicted more accurately when the hybrid analysis is performed using language discourse relation along with the intensity of emotion lexicon present in the post. Table VIII represents the results using the confusion matrix. The results obtained based on the presence or frequencies of the emotion lexicon in the post are ambiguous. The classifier has not predicted emotions of anger and sadness accurately. The probable reason could be their lesser number in the dataset.

Table VIII. Confusion Matrix with different features for predicting Emotions

Metric	Hybrid analysis by considering negation, double negation, and conjunction					Hybrid analysis by considering negation, double negation, conjunction, intensifier, and diminishers			
	Joy	Love	Sadness	Anger	Neutral	Joy	Love	Sadness	Neutral
Joy	104	12	0	19	1207	**952**	12	1	360
Love	2	1419	5	1	63	10	1414	3	61
Sadness	4	17	30	7	94	11	17	28	92
Anger	38	11	8	6	27	34	13	6	35
Neutral	4	17	23	4	2324	15	18	20	2313

When posts with negative sentiment level were further analyzed they primarily showed the presence of two basic emotions like sadness and anger. Hence the aggregate score of emotional distress depends on the sum of weights of all emotion lexicons found in a sentence coupled with discourse relation. The comparison of all methods has revealed that hybrid method has generated the best results while the results obtained from lexical and machine learning methods were least.

VI. CONCLUSION

We have proposed a hybrid method of SVM and lexical method coupled with language discourse relation to detect eight primary emotions from Facebook Posts based on Plutchik's wheel of emotions. We have analysed the performance of the proposed method by using different parameters and have found that it has given better results as compared to lexical or machine-based analysis. Detection of emotions from Facebook posts has given promising results when emotion scores of lexicons were taken into consideration.

REFERENCES

1. F. Cheong, and C. Cheong, "Social Media Data Mining: A Social Network analysis of Tweets during the 2010-2011 Australian floods," *Information Systems* (PACIS), 2011[*15th Pacific Asia Conf.*, July 7-11, 2011, pp. 1-16].
2. D.I. Kramer, J. E. Guillory, and J. T. Hancock, (2014, June). Experimental evidence of massive-scale emotional contagion through social networks. *PNAS*, 111 (24), pp. 8788-8790. Available: https://www.pnas.org/content/111/24/8788
3. R. Lin, S. Utz (2015, November). The emotional responses of browsing Facebook: Happiness, envy, and the role of tie strength. Computers in Human Behavior, 52, pp.29-38. Available: https://doi.org/10.1016/j.chb.2015.04.064
4. M. Settanni, D. Marengo (2015, July). Sharing emotion online: studying emotional well-being via automated text analysis of Facebook post. Frontiers in Psychology, 6, pp.1045. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4512028/
5. B. Liu, *"Sentiment Analysis and Subjectivity. Handbook of Natural Language Processing,", 2nd ed. Chapman and Hall: Florida, 2010.*
6. B. Liu, *Sentiment Analysis and Opinion Mining. Morgan & Claypool, 2012.*
7. E. Cambria, B. Schuller, Y. Xia, and C. Havasi (2013, March). New avenues in opinion mining and sentiment analysis. IEEE Intelligent Systems, 28(2), pp. 15-21.
8. J. K. Akhter, S. Soria, *Sentiment Analysis: Facebook Post Messages*. Final Project CS224N, Spring, 2010.
9. R. E. Wilson, S. D. Gosling, and L.T. Graham (2012, May). A Review of Facebook Research in the Social Sciences. Perspectives on Psychological Science, 7(3), pp. 203 –220.
10. S. Mukherjee, and P. Bhattacharyya, "Sentiment analysis in twitter with lightweight discourse analysis," Proceedings of COLING 2012: Technical Papers, Dec. 2012, pp.1847–1864 [24th Int. Conf. Computational *Linguistics*, Mumbai, 2012, pp. 1847-1864].
11. G. Farnadi, S. Zoghbi, M. Moens, and M. De Cock, "Recognizing personality traits using Facebook Posts," AAAI Workshop Technical Report, Computational Personality Recognition, 2013, pp.14-18 [7th Int. AAAI Conference on Weblogs and Social Media, 2013].
12. Troussas, M. Virvou, K. J. Espinosa, K. Llaguno, and J. Caro, *"Sentiment analysis of Facebook Postes using Naïve Bayes classifier for language learning," IEEE, Oct. 2013, pp. 1-6 [IISA 2013, Greece, 2013, pp. 1-6].*
13. S. B. Hamouda, and J. Akaichi (2013, May). *Social Networks' Text Mining for Sentiment Classification: The case of Facebook' Postes updates in the "Arabic Spring" Era". International Journal of Application or Innovation in Engineering & Management, 2(5), pp. 470-478. Available: https://pdfs.semanticscholar.org/aff6/bee30fcbafdc27132d5ad4e00a666f2fee3b.pdf*
14. Ortigosa, J. M. Martín, and R. M. Carro (2014). Sentiment analysis in Facebook and its application to e-learning. Computers in Human Behavior, Elsevier, 31, pp.527–541.
15. J. A. McCart , D. K. Finch, J. Jarman, E. Hickling, J. D. Lind, M. R. Richardson, D. J. Berndt, and S. L. Luther (2012, January). Using ensemble models to classify the sentiment expressed in suicide notes. Biomed Inform Insights, 5(Suppl. 1), pp. 77-85.
16. R. Prabowo, M. Thelwall (2009, April). Sentiment Analysis: A Combined Approach. Journal of Informetrics, Elsevier, 3(2), pp. 143-157.
17. M. El-Din *(2016). Enhancement Bag-of Lexicons Model for Solving the Challenges of Sentiment Analysis. International Journal of Advanced Computer Science and Applications, 7(1), pp.* 244-252.
18. P. D. Blinov, M. V. Klekovkina, E. V. Kotelnikov, and O. A. Pestov. Research of lexical approach and machine learning methods for sentiment analysis. Vyatka State Humanities University, Kirov, Russia.
19. R. Plutchik. *A general psychoevolutionary theory of emotion*, New York: Academic Press, 1980.
20. Asmi, and T. Ishaya, "Negation Identification and Calculation in Sentiment Analysis",2012, pp. 1-7 [*2nd Int. Conf. Advances in Information Mining and Management*, 2012, pp. 1-7].

21. U. Farooq, H. Mansoor, A. Nongaillard, Y. Ouzrout, and A.Q. Muhammad (2017, September). Negation Handling in Sentiment Analysis at Sentence Level. Journal of Computers, 12(5), pp. 470-478.
22. Hogenboom, P. V. Iterson, B. Heerschop, F. Frasincar, U. Kaymak, “Determining Negation Scope and Strength in Sentiment Analysis”, IEEE, Nov. 2011, pp. 2589-2594 [*IEEE Int. Conf. Systems, Man, and Cybernetics* (SMC), USA, 2011, pp. 2589-2594].
23. M. Dadvar, C. Hauff, and F. de Jong, “Scope of Negation Detection in Sentiment Analysis”, Jan. 2011, pp. 16-20 [*Dutch- Belgian Information Retrieval Workshop*,2011, pp. 16-20].
24. R. Rzepka, M.Takizawa, and K. Araki, “Emotion Prediction System for Japanese Language Considering Compound Sentences, Double Negatives and Adverbs”, IJCAI, July 2016 [*Workshop Language Sense on Computers*, 2016].
25. E. Dragut, and C. Fellbaum, “The Role of Adverbs in Sentiment Analysis”, Association for Computational Linguistics, June 2014, pp. 38-41 [*Workshop. France Semantics in NLP: A Workshop in Honor of Chuck Fillmore (1929-2014)*, USA, 2014, pp. 38-41].
26. U. Farooq, and A. Q. Muhammad, “Product reputation evaluation: the impact of conjunction on sentiment analysis”, SKIMA, Dec. 2013, pp. 590-602 [*7th Int. Conf. Software, Knowledge, Information Management and Applications* 2013, pp. 590-602].
27. *Whitelaw, N. Garg, and S. Argamon, “Using Appraisal Groups for Sentiment Analysis”, ACM, October 31 - November 05, 2005, pp. 625-631 [14th ACM Int. Conf. Information and knowledge management, 2005, pp. 625-631].*
28. *Le, H. Nguyen, “Twitter Sentiment Analysis Using Machine Learning Techniques,”, in Le Thi H., Nguyen N., Do T. (eds) Advanced Computational Methods for Knowledge Engineering. Advances in Intelligent Systems and Computing, vol. 358. Springer, Cham, 2015, pp. 279-289.*
29. Bo Pang, Lee Lillian, and S. Vaithyanathan, “Thumbs up? Sentiment Classification using Machine Learning Techniques”, EMNLP, July 2002 pp.79-86 [*Conf. Empirical Methods in Natural Language Processing*, 2002, pp. 79-86].
30. Xia Rui, Chengqing Zong, and Shoushan Li (2011, March). Ensemble of feature sets and classification algorithms for sentiment classification. Information Sciences-Informatics and Computer Science, Intelligent Systems, Applications: An International Journal, 181(6), pp. 1138–1152.
31. Y. Al-Amrani, M. Lazaar, K. E. Elkadiri (2018, May). Random Forest and Support Vector Machine based Hybrid Approach to Sentiment Analysis. Procedia Computer Science, 127, pp. 511-520.
32. N. Cristianini, J. Shawe-Taylor, *An Introduction to Support Vector Machines and Other Kernel-based Learning Methods*. Cambridge University Press, 2000.

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