Improving Accuracy of Sentiment Analysis for Depression Recommendation using Multi-Domain Fuzzy Rules

Roopal Mamtora, Lata Ragha

Abstract: ***Social media & e-commerce has opened up the doors for human behavioral analysis in ways which were not possible before. Companies have the ability to track user's mood and suggest advertisements which can trigger buying decisions based on it. This is possible due to user's real time social media updates. Users nowadays are willing to provide information like their location, their age, nearby friends information, their mood, their buying patterns, etc. Companies do not intentionally collect all this information, but it has become a matter of social pride to post it as social media status and updates. The information available can be put to use in multiple forms- predict election results, movie success, product liking/disliking, travel destination recommendation, health care, etc. In our work, we utilize this textual information posted by different users and analyze their depression level focusing on negative sentiments. In order to perform this task, we have considered user's tweets, any links which they might have posted, the time of the tweet, their age group and any previous depression history of the user. All these parameters are given to a novel fuzzy decision tree that uses sentiment analysis and game theory-based scoring in order to evaluate the depression score for the user. We analyzed the system on different real-time users, and observed that the system predicts depression level with more than 90% accuracy. Our work can be used to generate a prototype to identify if a person is in a depressive state and figure out the intensity of his/her depression.***

Keywords: ***Depression, Fuzzy Decision, Game Theory, Sentiment Analysis.***

I. INTRODUCTION

In today's digital era, people know each other majorly via social media updates. There is a huge tectonic shift from personal communication to social status-based observation due to which personal communication has taken a big hit. Different classes of people are seen on social media like observers, moderate users and active users. Observers are mute spectators, affected by social insecurity, whose buying & outing patterns are directed by what they see.

Revised Manuscript Received on February 28, 2020.
* Correspondence Author
Roopal Mamtora*, Information Technology Department, Terna Engineering College, Navi Mumbai, India. Email: roopal.mamtora@gmail.com
Dr. Lata Ragha, Computer Engineering Department, FCRIT, Vashi, Navi Mumbai, India. Email: lata.ragha@gmail.com

Moderate or low-profile users post less frequently but get depressed when others follow them. Active users, post minute-to-minute updates and get depressed if their posts do not get enough attention on social media. Apart from these social media-based depression, personal and professional problems also lead to depression. In depression, users isolate themselves and resort to social media for attention and comfort. Posts from such people showcase their mood and actions, while in depression. Twitter and Snapchat, are new micro-blogging platforms for showcasing emotions. Thus, in our work, we utilize the textual information posted by different users and analyze their depression level focusing on negative sentiments. Thereafter, we combine the concepts of sentiment analysis, game theory and rule engine in order to develop an accurate state-of-the-art depression analysis algorithm. The details of the algorithm are given in section 3 of this paper. Section 4 deals with result of the proposed algorithm and comparison with state of art methods. Finally, we conclude with some interesting observations about the proposed algorithm and suggest methods to improve the same.

II. LITERATURE REVIEW

Previously various researchers have worked towards improving the performance of depression recommendation. One of these works is mentioned in [1], where authors have used speech, textual data with support vector machines (SVM) to perform sentiment analysis. They use WordNet Affect and SentiWordNet for language processing and pitch, energy, formants, intensity & zero crossing rate (ZCR) features for sound processing to claim 81% accuracy, which can be further improved using deep learning algorithms like deep-nets and Q-learning. Their work can be used for depression analysis by appending their results to our fuzzy rule base. Another interesting work in this field is done in [2], wherein YouTube movie reviews are used to perform sentiment analysis. Using multi-modal analysis system, they achieved an accuracy of more than 60% for a large dataset. Their research can therefore be used for moderate to large datasets in order to predict sentiment values.

The work done in [3] uses visual information with textual features in order to improve the accuracy of sentiment analysis and audio data to analyze user's emotional state. They have used convolutional neural networks (CNN) for classification which further uses a multi-kernel model in order to perform effective classification. Their work is able to detect emotions like angry, happy, sad & neutral with a high accuracy of more than 70% which can be further improved by using spiking neural networks. An interesting review about different accuracy improvement techniques can be read from [4].

From their review it is inherent that radial basis function neural network combined with conditional random field theory can be an effective combination for classifying any signal source and attaining high accuracy levels. In [5], a deep learning model - Deep Boltzmann Machine (DBM) is utilized to classify textual data, audio data, visual data and improve the accuracy of sentiment analysis. These 3 analyses are then merged and a final result is generated and compared. The proposed method outperforms all with an accuracy of more than 75%. Hence designers must use DBM method to design their systems.

Work done in [6] proves that only text-based depression analysis systems can also provide good accuracy, when used in proper contexts. Researchers used Google Cloud Natural API to obtain results that were more than 80% accurate across both real-time and static datasets. This engine can be recommended as a validation engine. Researchers in [7] have used Distributional Semantic Models for effectively analyzing depression from input data along with bi-grams, tri-grams, and N-grams to improve the accuracy of sentiment analysis to more than 80%.

Fusion-based systems are also prevalent in sentiment analysis. For instance, the work done in [8], utilizes a text, speech along with SVM-based classifier for evaluation of depression to achieve more than 45% accuracy. The work is very basic, but can be used as a start-point for any research in this area. In [9] also, text, audio and video are combined together in order to train a CNN. Features like N-grams, mel-frequency components, color maps are evaluated for text, audio and video respectively. They attained worst-case accuracy as 70% and more than 85% in some cases. Thus, can be used with DBN to further improve the worst-case performance. A similar work is done in [10], wherein bio-inspired algorithms with multi-modal data use a cognitive and a perception module to get same accuracy as [9]. As application-specific systems, work done in [11] uses tweets with audio and visual data to detect depressive traits. This work closely matches the work done by us in this paper. The authors in [11] have used same algorithms as in [10], learned and tried to improve the accuracy to be more than 90% at times. A detailed survey about multi-modal systems is presented in [12], which makes it clear that deep-learning and machine-learning models pave the way for further development. In fact, our work on fuzzy rules is also inspired by [10] & [11], which have proved the effectiveness of machine learning for sentiment analysis.

Video-based sentiment analysis is done in [13] using deep-learning techniques to gain accuracy of more than 60%. Multi-modal and application specific systems are studied in details in [14-16]. Tensor fusion-based approaches are discussed in [17], on the basis of intra-modality and inter-modality dynamics which allow for real-time applications in sentiment analysis with an accuracy of more than 65%. Further, the tensor-based systems can be improved with the help of DBN and CNNs for a better accuracy. Similar studies are done in [18-20], wherein methods like anxiety analysis, deep-learning and AI are proposed. From the review, we are able to identify that deep-learning and machine-learning techniques like DBN & CNN are most effective for depression analysis, but limited work has been done on fuzzy-rule-based systems. Thus, this work proposes a machine learning-based fuzzy-rule-based system. The system and its details are described in the next section.

III. PROPOSED FUZZY-RULES-BASED DEPRESSION ANALYSIS PROTOCOL

The proposed fuzzy-rules-based depression analysis algorithm uses twitter text data, links posted by users during tweeting, their age group and other user-specific parameters. The algorithm can be explained using the following steps:

1. Read the tweets from the dataset, and obtain the following parameters for the tweet,
    a. Tweet text (Tt)
    b. Any links which the tweet is referring to, and the title of that particular page (Lt)
    c. Timestamp of the tweet (Ts)
    d. Age group of the user (Ag)
    e. Previous user depression score (Sd)
2. Combine Tt and Lt into a single entity, let this combined tweet be called as Ct
3. Apply Fuzzy Decision tree (FDT) on Ct, in order to check the emotional state of the user during the tweet Ct, let this emotional state be called as Es
4. Due to the nature of FDT, the emotional state will have the following 5 classes,
    a. Not depressed (C1)
    b. Somewhat depressed (C2)
    c. Moderately depressed (C3)
    d. Depressed (C4)
    e. Highly depressed (C5)
5. The classes C1 to C5 are evaluated based on the occurrence of depressive words in the entity Ct
6. Divide the age group into the following categories (the age division is done on the basis of general trends of person's sensitivity to take things casually),
    a. Highly sensitive group (G3, from 13 to 18, and 55 & above)
    b. Moderately sensitive group (G2, from 19 to 25, and 48 to 54)
    c. Lower sensitive group (G1, from 26 to 47)
7. Divide the tweet time into the following groups,
    a. Non-depressive tweet timing (T1, 5:00 A.M. to 3:00 P.M.)
    b. Slightly depressive tweet timing (T2, 3:00 P.M. to 6:00 P.M.)
    c. Moderately depressive tweet timing (T3, 6:00 P.M. to 11:00 P.M.)
    d. Highly depressive tweet timing (T4, 11:00 P.M. to 5:00 A.M.)

8. Use Table- I rules to evaluate the actual user's depression score:

Table- I: Fuzzy Rules Table

Sr. No.	Emotional State	Age group	Tweet Time	Sd(i+1)
1	C1	X	X	Sd
2	C2	G1	T1	Sd
3	C2	G1	T2	Sd
4	C2	G1	T3	Sd
5	C2	G1	T4	Sd+1 [a]
6	C2	G2	T1	Sd
7	C2	G2	T2	Sd+1 [a]
8	C2	G2	T3	Sd+1 [a]
9	C2	G2	T4	Sd+2 [a]
10	C2	G3	T1	Sd+1 [a]
11	C2	G3	T2	Sd+1 [a]
12	C2	G3	T3	Sd+2 [a]
13	C2	G3	T4	Sd+2 [a]
14	C3	G1	T1	Sd
15	C3	G1	T2	Sd
16	C3	G1	T3	Sd+1 [a]
17	C3	G1	T4	Sd+1 [a]
18	C3	G2	T1	Sd
19	C3	G2	T2	Sd+1 [a]
20	C3	G2	T3	Sd+2 [a]
21	C3	G2	T4	Sd+2 [a]
22	C3	G3	T1	Sd+1 [a]
23	C3	G3	T2	Sd+1 [a]
24	C3	G3	T3	Sd+2 [a]
25	C3	G3	T4	Sd+3 [a]
26	C4	G1	T1	Sd
27	C4	G1	T2	Sd+1 [a]
28	C4	G1	T3	Sd+1 [a]
29	C4	G1	T4	Sd+2 [a]
30	C4	G2	T1	Sd+1 [a]
31	C4	G2	T2	Sd+1 [a]
32	C4	G2	T3	Sd+2 [a]
33	C4	G2	T4	Sd+2 [a]
34	C4	G3	T1	Sd+1 [a]
35	C4	G3	T2	Sd+2 [a]
36	C4	G3	T3	Sd+2 [a]
37	C4	G3	T4	Sd+3 [a]
38	C5	G1	T1	Sd+1 [a]
39	C5	G1	T2	Sd+2 [a]
40	C5	G1	T3	Sd+3 [a]
41	C5	G1	T4	Sd+4 [a]
42	C5	G2	T1	Sd+2 [a]
43	C5	G2	T2	Sd+3 [a]
44	C5	G2	T3	Sd+3 [a]
45	C5	G2	T4	Sd+4 [a]
46	C5	G3	T1	Sd+3 [a]
47	C5	G3	T2	Sd+4 [a]
48	C5	G3	T3	Sd+4 [a]
49	C5	G3	T4	Sd+5 [a]

[a] Increment in the depression score (Sd) takes place with increasing levels of emotional state classes/age group/time zones considered for the algorithm

9. Repeat steps 1 to 8 for all the 'n' tweets pertaining to the user
10. Evaluate the final score for the user using following equations:

$$S_{DN} = \sum S_d \qquad (1)$$

$$S_{final} = \frac{S_{DN}}{n} \qquad (2)$$

11. Decide a threshold value for the score, and check if the given score is above that threshold (generally this should be around 1.5)
12. Divide the score level which are above threshold into further ranges in order to evaluate the depression level as given in Table II.

Table- II: Final score thresholds for depression analysis

Score	Depression Level
Below 2	On the verge of depression
Between 2 to 3	Depressed
Between 3 to 4	Highly depressed
Above 4	Needs counselling

The above algorithm was tested on different number of tweets and on different age groups of people, and it was observed that the algorithm is able to detect depression levels with good accuracy. The result analysis of the proposed algorithm is given in the next section.

IV. RESULT EXAMINATION

In order to perform result examination, we took data from different users, and analyzed their tweets when they were in different moods. Based on this analysis, we evaluated the depression score of the users via our algorithm and evaluated the precision and recall values. These values were averaged, and compared with other standard algorithms in order to evaluate the performance of our algorithm.

The dataset was collected manually, by using the Twitter API for tweet fetching of tweeter users/well-known personalities, and based on that the true depression class was added to the dataset. For validation, we collected data for Shaheen Bhatt who recently came out with her book "I've never been (Un)happier". Her book narrates her fight with Depression throughout her life. She is more of an Instagram user than a twitter user which made us collect messages from Instragram, twitter and transcript her interviews available on social media.

Also, we extracted her age via Google, in order to collect the complete data required for our algorithm to function. Our proposed algorithm, correctly predicts Shaheen Bhatt to be "on the verge on depression" since depression has affected her on and off, which is in-line with her medical condition as well. Fig. 1. graphically depicts the result for Shaheen Bhatt's tweets being analyzed with a final score to be "Below 2".

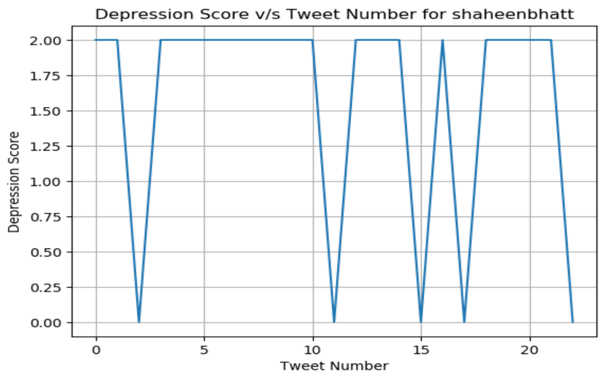

Fig. 1.Depression Score vs. Tweet Number for user

Parameters like precision and recall were evaluated for the proposed algorithm using the following formulas:

$$Precision = \frac{Number\ of\ correct\ outputs}{Total\ number\ of\ outputs} \quad (3)$$

$$Recall = \frac{Number\ of\ correct\ outputs}{Total\ number\ of\ obtained\ results} \quad (4)$$

The following results were obtained after running the algorithm for different number of tweets:

Table- III: Comparison of precision and recall values for different number of tweets

Number of Tweets	Precision	Recall
10	0.8	0.8
20	0.85	0.8
30	0.85	0.85
50	0.90	0.88
100	0.91	0.9
150	0.93	0.9
200	0.94	0.91
250	0.94	0.91
300	0.95	0.93

Based on these values, we can observe that the precision of the proposed algorithm increases linearly with an increase in the number of tweets. We evaluated the mean values of the precision and recall parameters, & compared it with the existing algorithms [CMP1] [CMP2], and obtained the following results:

Table- IV: Performance comparison with other algorithms

Algorithm	Precision	Recall
Multinomial Naïve Bayes [CMP1]	0.77	0.77
Random Forest [CMP1]	0.81	0.8
Gradient Boosting [CMP1]	0.79	0.77
Ensemble Vote [CMP1]	0.85	0.85
Multinomial Naïve Bayes 2 [CMP2]	0.836	0.83
Support Vector Machine [CMP2]	0.8	0.79
Proposed Fuzzy rule-based	0.95	0.93

V. CONCLUSION

From the results shown in Table-IV, it is clear that the proposed algorithm performs at-least 10% better than the existing state-of-the-art techniques, and thus can be used for real-time social media-based depression analysis. The performance of the system can be improved by considering large number of tweets and allowing the model to learn.

VI. FUTURE WORK

Presence of AI and machine learning (ML) in the current work will improve upon the overall accuracy and precision values. The ML based techniques like Q-learning and re-enforcement learning will allow for better performance due to the incentive-based classification mechanism, while deep-nets will get better precision and recall values due to their superior pattern analysis and classification performance.

REFERENCES

1. Jasmine Bhaskar, K. Sruthi, Prema Nedungadi, "Hybrid Approach for Emotion Classification of Audio Conversation Based on Text and Speech Mining", Elsevier Science, Procedia Computer Science, Volume 46, 2015, pp. 635-643.
2. Martin Wöllmer, Felix Weninger, Tobias Knaup, Björn Schuller, Congkai Sun, Kenji Sagae, Louis-Philippe Morency, "YouTube Movie Reviews: Sentiment Analysis in an Audio-Visual Context", IEEE Intelligent Systems, Volume: 28, Issue: 3,2013, pp. 46 – 53.
3. S Poria, I Chaturvedi, E Cambria, A Hussain," Convolutional MKL based multimodal emotion recognition and sentiment analysis", 2016 IEEE 16th International Conference on Data Mining (ICDM), 2374-8486/16.
4. Kumar Ravia and Vadlamani Ravia, "A survey on opinion mining and sentiment analysis: Tasks, approaches and applications", Elsevier Science, Journal Knowledge-Based Systems, Volume 89 Issue C,2015, pp. 14-46.
5. Lei Pang; Shiai Zhu; Chong-Wah Ngo,"Deep Multimodal Learning for Affective Analysis and Retrieval",IEEE Transactions on Multimedia, Volume: 17, Issue: 11, 2015, pp. 2008 – 2020.
6. Ashwath Kumar Salimath, Robin K Thomas, Sethuram Ramalinga Reddy, Yuhao Qiao, "Detecting Levels of Depression in Text Based on Metrics", 9 Jul 2018, arXiv:1807.03397v1 [cs.CL].
7. Nikolaos Malandrakis, Alexandros Potamianos, Elias Iosif, Shrikanth Narayanan, "Distributional Semantic Models for Affective Text Analysis", IEEE Transactions on Audio, Speech, and Language Processing, Volume: 21, Issue: 11 ,2013, pp. 2379 – 2392.
8. A. Houjeij, L. Harnieh, N. Mehdiand, H. Hajj, "A novel approach for emotion classification based on fusion of text and speech", 2012,19th International Conference on Telecommunications (ICT).
9. S Poria, H Peng, A Hussain, N Howard, E Cambria,"Ensemble application of convolutional neural networks and multiple kernel learning for multimodal sentiment analysis", Neurocomputing 261 (2017), Elsevier, pp. 217–230.

10. Soujanya Poria, Erik Cambria , Newton Howard , Guang-BinHuang , Amir Hussain, "Fusing audio, visual and textual clues for sentiment analysis from multimodal content " , Elsevier Science, Neurocomputing , Volume 174, Part A,22 January 2016, pp. 50–59.
11. Keumhee Kang, Chanhee Yoon, Eun Yi Kim, "Identifying Depressive Users in Twitter Using Multimodal Analysis", 2016 Proc. International Conference on Big Data and Smart Computing (BigComp), Electronic ISSN: 2375-9356.
12. Mohammad Soleymani, David Garcia, Brendan Jou, Björn Schuller, Shih-Fu Chang, Maja Pantic,"Survey of multimodal sentiment analysis", Image and Vision Computing, Volume 65, September 2017, pp. 3-14.
13. Veronica Pérez Rosas, Rada Mihalcea, Louis-Philippe Morency, "Multimodal Sentiment Analysis of Spanish Online Videos", IEEE Intelligent Systems, Volume: 28, Issue: 3, 2013, pp. 38 -45.
14. Amir Zadeh; Rowan Zellers; Eli Pincus; Louis-Philippe Morency, "Multimodal Sentiment Intensity Analysis in Videos: Facial Gestures and Verbal Messages" , IEEE Intelligent Systems , Volume: 31, Issue: 6 , 2016, pp. 82 – 88.
15. Walaa Medhata,Ahmed Hassanb and Hoda Korashyb, "Sentiment analysis algorithms and applications: A survey", Elsevier Science, Ain Shams Engineering Journal , Volume 5, Issue 4,2014, pp.1093–1113.
16. Maria del Pilar Salas-Zarate, Jose Medina-Moreira, Katty Lagos-Ortiz, Harry Luna-Aveiga, Miguel Angel Rodríguez-Garcia, and Rafael Valencia-García , "Sentiment Analysis on Tweets about Diabetes: An Aspect-Level Approach" , Computational and Mathematical Methods in Medicine, Volume 2017 (2017), Article ID 5140631, 9 pages.
17. A. Zadeh, M. Chen, S. Poria, E. Cambria, L. Morency,"Tensor fusion network for multimodal sentiment analysis", Proc. Conf. Empirical Methods Natural Language Processing, 2017, pp. 1114-1125.
18. Christoph Kofler, Subhabrata Bhattacharya, Martha Larson, Tao Chen, Alan Hanjalic, Shih-Fu Chang , "Uploader Intent for Online Video: Typology, Inference, and Applications" , IEEE Transactions on Multimedia , Volume: 17, Issue: 8 , 2015,pp. 1200 – 1212.
19. Mandar Deshpande, Vignesh Rao,"Depression Detection using Emotion Artificial Intelligence" , 2017 International Conference on Intelligent Sustainable Systems (ICISS), 7-8 Dec. 2017, INSPEC Accession Number: 17858378.
20. Akshi Kumar, Aditi Sharma, Anshika Arora,"Anxious Depression Prediction in Real-time Social Data", proceeding of International Conference on Advanced Engineering, Science, Management and Technology – 2019 (ICAESMT19).

AUTHORS PROFILE

Roopal Mamtora is currently pursuing her PhD in Information Technology from Terna Engineering College, Mumbai University. She has done her MTech (CE) from MDU, Rohtak and BE (CSE) from Amravati University. She has approximately 15 years of experience in Academics. Published papers, one of them is available on IEEE Xplore. Completed NPTEL course with Elite grade.

Dr. Lata Ragha is currently Professor and HoD in the Department of Computer Engineering at Fr. C. Rodrigues Institute of Technology, Vashi, Navi Mumbai. She holds Doctorate in Computer Engineering with experience of more than 32 years. She has more than 93 publications in national and international journals and conferences. Her areas of specialization include Computer Networks and Security, Routing Protocols, Data Mining, Parallel and Distributed Computing, System/Information Security.