

DETECTING STRESS BASED ON SOCIAL INTERACTIONS IN SOCIAL NETWORK

Miss. Sandhyarani Sonwane¹, Miss. Pratima Bade², Miss. Bhumi Ratnani³,
Miss. Maitreyee Kshirsagar⁴,

B.E. Student, at Computer Dept. BSIOTR, Wagholi, Maharashtra, (India)

Prof. R. A. Badgular

Asst. Professor, at Computer Dept. BSIOTR, Wagholi, Maharashtra, (India)

ABSTRACT

Traditional mental health studies rely on data essentially gathered through individual contact with a medicinal services proficient. Late work has demonstrated the utility of online social information for contemplating despondency, be that as it may, there have been limited assessments of other mental well being conditions. We present investigation of emotional wellness phenomena in openly accessible social networking sites. . We first define a set of stress-related textual, visual, and social attributes from various aspects, and then propose a novel hybrid model. By additionally investigating the social communication information, we likewise find a few fascinating phenomena.

Keywords: Stress detection, factor graph model, social media, healthcare

I. INTRODUCTION

Psychological wellness conditions influence a noteworthy level of the world's adult population every year. Including depression, eating disorders like anorexia and bulimia, bipolar disorder and post traumatic stress disorder (PTSD). Endless anxiety expands the danger of creating medical issues, for example, a sleeping disorder, corpulence, heart ailments so on. Hence, there is noteworthy significance to identify stress some time before it transforms into serious issues. Conventional mental stress recognition is predominantly based on interviews, self-report surveys or wearable sensors. With the increase the use of social networks individual's shares their day to day occasions, inclinations, and interact with companions through the social media. As these online networking information auspicious mirror's client's genuine states and feelings in an auspicious way.

II. RELATED WORK

Existing methods for stress detection are numerous endeavours have been given to creating convenient devices for singular anxiety recognition late years. Analysts are endeavouring to use unavoidable gadgets like PCs and cell phones for routine anxiety discovery.

Researches on using social media for healthcare are with the quick spread of social networks, looks into on utilizing online social information for physical and mental human healthcare are likewise progressively developing.

Deep learning approaches for cross-media data modelling. Micro-blog information is common cross-media information. Things may originate from assorted sources and modalities. It is hard to deal with the heterogeneous cross-media information. Late years, broad examines on profound learning show predominant capacity of profound neural networks (DNN) in taking in highlights from expansive scale unlabeled information

III.SYSTEM ARCHITECTURE

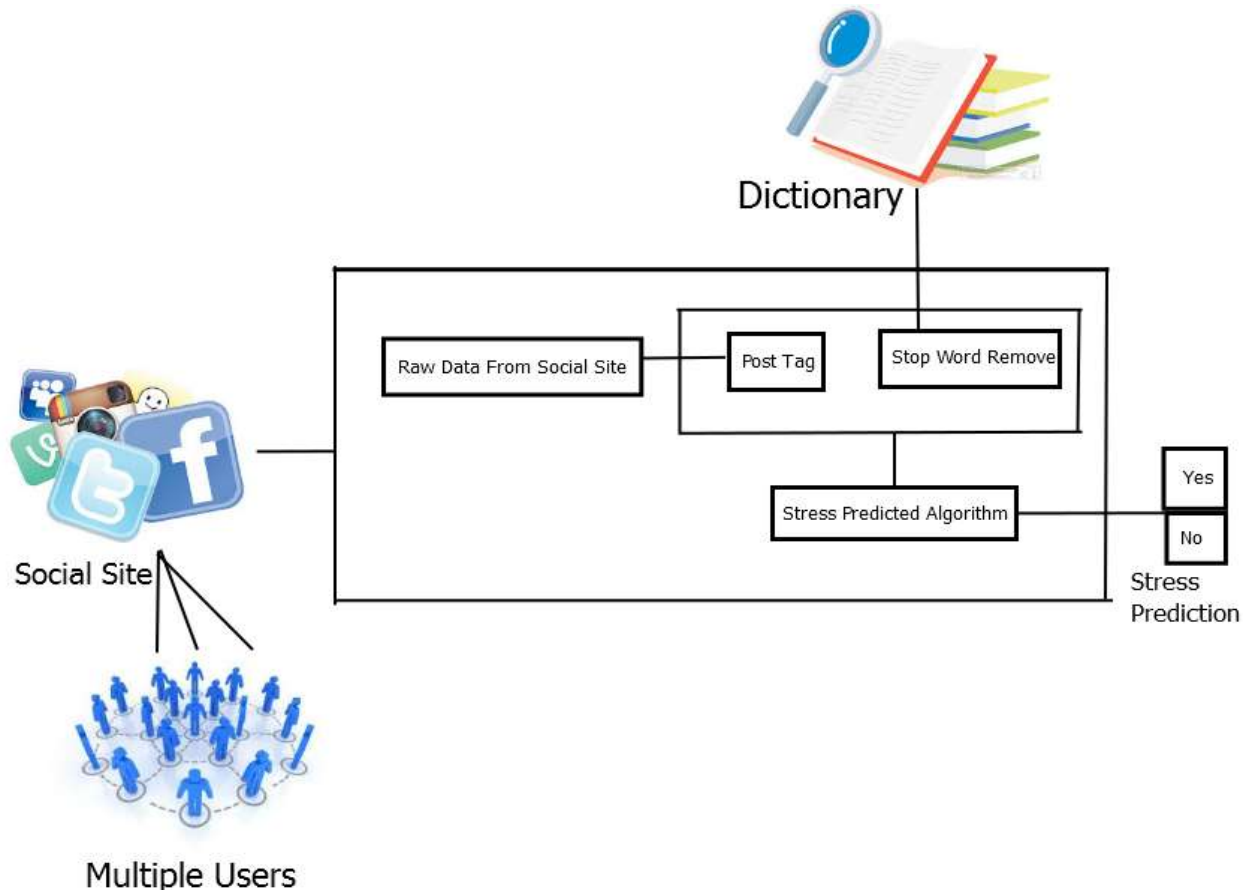


Fig. 1 System Architecture

IV.METHODOLOGY

Modules:

a. Modules 1: Data collection

To lead perceptions and assess our successive model, we initially gather a set of datasets utilizing diverse naming techniques

b. Module 2: CNN+ FGN

We propose a bound together hybrid model incorporating CNN with FGM to use both tweet content properties and social connections to upgrade stress discovery.

c. Module 3: Tweet Classification

we utilize a cross auto-encoder (CAE) to take in the methodology invariant representation of each single tweet with various modalities. Indicating the content, visual, and social traits of a tweet by v_T , v_I , and v_S , the CAE is planned.

d. Module 4: Attribute Categorization

To address the issue of stress recognition, we initially characterize two arrangements of ascribes to quantify the distinctions of the stressed and non-stressed on user via web-based networking media stages.

V.GENERATE DECISION TREE

1. Check if algorithm satisfies termination criteria
2. Computer information-theoretic criteria for all attributes
3. Choose best attribute according to the information-theoretic criteria
4. Create a decision node based on the best attribute in step 3
5. Induce (i.e. split) the dataset based on newly created decision node in step 4
6. For all sub-dataset in step 5, call C4.5 algorithm to get a sub-tree (recursive call)
7. Attach the tree obtained in step 6 to the decision node in step 4
8. Return tree

Input: an attribute valued dataset D

Tree={ }

If D is "Pure" OR other stopping criteria met then

Terminate

End if

For all attribute $a \in D$ do

Compute information theoretic criteria if we split on a

End for

a_{best} = Best attribute according to above computed criteria

Tree = Create a decision node that tests a_{best} in the root

D_v = Induced sub-Datasets from D based on a_{best}

For all D_v do

Tree_v = C4.5(D_v)

Attach Tree_v to the corresponding branch of Tree

End for

Return Tree

VI.APPLICATIONS

1. The patterns that emerge through collective human mobility behavior are now understood for wide ranging and important.

VII.CONCLUSION

In this system, we displayed a system for distinguishing users' psychological stretch states from clients' week after week online networking information, utilizing tweets' substance and additionally clients' social associations. Utilizing true online networking information as the premise, we contemplated the connection between client mental anxiety states and their social communication practices. To completely use both substance and social communication data of clients' tweets, we proposed a half and half model which joins the factor diagram display (FGM) with a convolution neural system (CNN).

REFERENCES

- [1] AndreyBogomolov, Bruno Lepri, MichelaFerron, Fabio Pianesi,and Alex Pentland. Daily stress recognition from mobile phone data, weather conditions and individual traits. In ACM InternationalConference on Multimedia, pages 477–486, 2014.
- [2] Chris Buckley and EllenM Voorhees. Retrieval evaluation with incomplete information. In Proceedings of the 27th annual internationalACM SIGIR conference on Research and development in informationretrieval, pages 25–32, 2004.
- [3] Xiaojun Chang, Yi Yang, Alexander G Hauptmann, Eric P Xing,and Yao-Liang Yu. Semantic concept discovery for large-scale zero-shot event detection. In Proceedings of International JointConference on Artificial Intelligence, pages 2234–2240, 2015.
- [4] WanxiangChe, Zhenghua Li, and Ting Liu. Ltp: A Chinese language technology platform. In Proceedings of International Conferenceon Computational Linguistics, pages 13–16, 2010.
- [5] Chihchung Chang and Chih-Jen Lin. Libsvm: a library for support vector machines. ACM TRANSACTIONS ON INTELLIGENTSYSTEMS AND TECHNOLOGY, 2(3):389–396, 2001.
- [6] Dan C Ciresan, Ueli Meier, Jonathan Masci, Luca Maria Gambardella, and J " urgenSchmidhuber. Flexible, high performance convolutional neural networks for image classification. In Proceedingsof International Joint Conference on Artificial Intelligence, pages 1237–1242, 2011.
- [7] Sheldon Cohen and Thomas A. W. Stress, social support, and the buffering hypothesis. Psychological Bulletin, 98(2):310–357, 1985.
- [8] Glen Coppersmith, Craig Harman, and Mark Dredze. Measuring post traumatic stress disorder in twitter. In Proceedings of theInternational Conference on Weblogs and Social Media, pages 579–582, 2014.
- [9] Rui Fan, Jichang Zhao, Yan Chen, and KeXu. Anger is more influential than joy: Sentiment correlation in weibo. PLoS ONE, 2014.
- [10] Zhanpeng Fang, Xinyu Zhou, Jie Tang, Wei Shao, A.C.M. Fong, Longjun Sun, Ying Ding, Ling Zhou, , and JarderLuo. Modeling paying behavior in game social networks. In In Proceedings of theTwenty-Third Conference on Information and Knowledge Management(CIKM'14), pages 411–420, 2014.
- [11] GolnooshFarnadi, GeethaSitaraman, ShanuSushmita, Fabio Celli, Michal Kosinski, David Stillwell, Sergio Davalos, Marie Francine Moens, and Martine De Cock. Computational personality recognition in social media. User Modeling and User-Adapted Interaction, pages 1–34, 2016.