A System on Stress Detection Based On Social Interactions On Social Networks

Prof. Indu Dokare
Computer Department, VESIT
Mumbai, India
indu.dokare@ves.ac.in

Gayatri Pawar
Computer Department, VESIT
Mumbai, India
gayatri.pawar@ves.ac.in

Shreya Narsapur
Computer Department, VESIT
Mumbai, India
shreya.narsapur@ves.ac.in

Kajal Rajani
Computer Department, VESIT
Mumbai, India
kajal.rajani@ves.ac.in

Manisha Mirchandani
Computer Department, VESIT
Mumbai, India
manisha.mirchandani@ves.ac.in

***Abstract*— Psychological stress is threatening people's health. It is non-trivial to detect stress timely for proactive care. With the popularity of social media, people are used to sharing their daily activities and interacting with friends on social media platforms, making it feasible to leverage online social network data for stress detection. In this paper, we find that users stress state is closely related to that of his/her friends in social media, and we employ a large-scale dataset from real-world social platforms to systematically study the correlation of users' stress states and social interactions. We first define a set of stress-related textual, visual, and social attributes from various aspects, and then propose a novel hybrid model - a factor graph model combined with Convolutional Neural Network to leverage tweet content and social interaction information for stress detection. Experimental results show that the proposed model can improve the detection performance by 6-9% in F1-score. By further analyzing the social interaction data, we also discover several intriguing phenomena, i.e. the number of social structures of sparse connections (i.e. with no delta connections) of stressed users is around 14% higher than that of non-stressed users, indicating that the social structure of stressed users' friends tend to be less connected and less complicated than that of non-stressed users.**

Keywords—convolutional neural network; sparse connection; delta connection

I. INTRODUCTION

Psychological stress is becoming a threat to people's health nowadays. With the rapid pace of life, more and more people are feeling stressed. According to a worldwide survey reported by Newbusiness in 2010, over half of the population have experienced an appreciable rise in stress over the last two years. Though stress itself is non-clinical and common in our life, excessive and chronic stress can be rather harmful to people's physical and mental health. Researches reveal that the rapid increase of stress has become a great challenge to human health and life quality. Thus, there is significant importance to detect stress before it turns into severe problems.

Inspired by psychological theories, we first define a set of attributes for stress detection from tweet-level and user-level aspects respectively: 1) tweet-level attributes from content of user's single tweet, and 2) user-level attributes from user's weekly tweets. The tweet-level attributes are mainly composed of linguistic, visual, and social attention (i.e., being liked, retweeted, or commented) attributes extracted from a single-tweet's text, image, and attention list. The user-level attributes however are composed of: (a) posting behavior attributes as summarized from a user's weekly tweet postings; and (b) social interaction attributes extracted from a user's social interactions with friends. In particular, the social interaction attributes can further be broken into: (i) social interaction content attributes extracted from the content of users' social interactions with friends; and (ii) social interaction structure attributes extracted from the structures of users' social interactions with friends. To maximally leverage the user-level information as well as tweet-level content information, we propose a novel hybrid model of factor graph model combined with a convolutional neural network (CNN).

This is because CNN is capable of learning unified latent features from multiple modalities, and factor graph model is good at modeling the correlations. The overall steps are as follows: 1) we first design a convolutional neural network (CNN) with cross auto encoders (CAE) to generate user-level content attributes from tweet-level attributes; and 2) we define a partially labeled factor graph (PFG) to combine user-level social interaction attributes, user-level posting behavior attributes and the learnt user-level content attributes for stress detection. We evaluate the proposed model as well as the contributions of different attributes on a real-world dataset from Twitter. The proposed model can also efficiently combine tweet content and social interaction to enhance the stress detection performance. • We propose a unified hybrid model integrating CNN with FGM to leverage both tweet content attributes and social interactions to enhance stress detection.

II. Problems in the Existing Systems

In the existing system, the research on user-level emotion detection in social networks has been studied. While tweet-level emotion detection reflects the instant emotion expressed in a single tweet, people's emotion or psychological stress states are usually more enduring, changing over different time periods. In recent years, extensive research starts to focus on user-level emotion detection in social networks.

Existing work also implemented to detect users psychological stress states from social media by learning user-level presentation via a deep convolution network on sequential tweet series in a certain time period. Motivated by the principle of homogeneity, the system incorporated social relationships to improve user-level sentiment analysis in Twitter.

Though some user level emotion detection studies have been done, the role that social relationships plays in one's psychological stress states, and how we can incorporate such information into stress detection have not been examined yet.

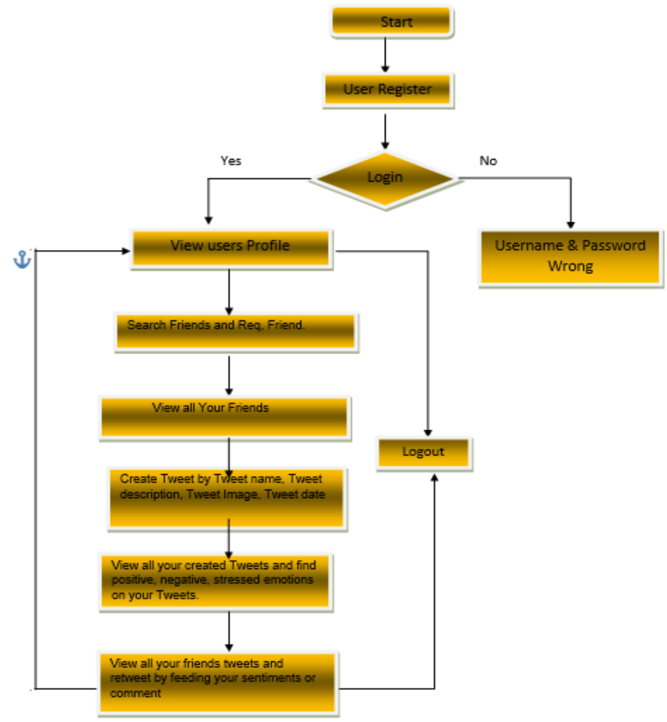
III. Advantages of Our System

In the proposed system, the system finds that users stress state is closely related to that of his/her friends in social media, and we employ a large-scale dataset from real-world social platforms to systematically study the correlation of users' stress states and social interactions. The system first defines a set of stress-related textual, visual, and social attributes from various aspects, and then proposes a novel hybrid model - a factor graph model combined with Convolutional Neural Network to leverage tweet content and social interaction information for stress detection. Experimental results show that the proposed model can improve the detection performance by 6-9% in F1-score. By further analyzing the social interaction data, we also discover several intriguing phenomena, i.e. the number of social structures of sparse connections (i.e. with no delta connections) of stressed users is around 14% higher than that of non-stressed users, indicating that the social structure of stressed users' friends tend to be less connected and less complicated than that of non-stressed users.

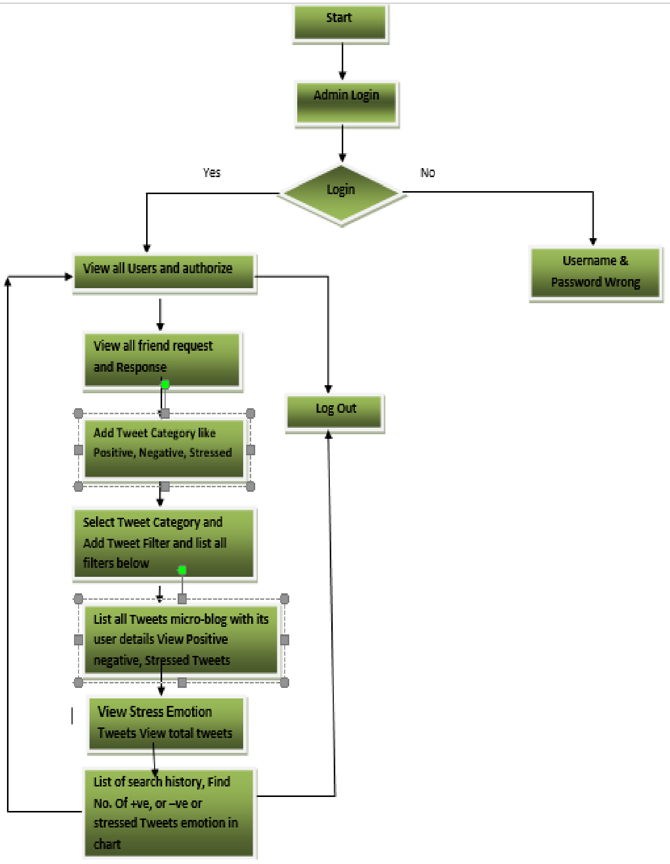
Advantages of our system are that it can analyze bulk tweet data at a time and users can tweet based on human emotions, actions and stress.

IV. Flow of the System

A. *Admin:*



B. *Client:*



V. MODULES IN THE SYSTEM

A. Admin

In this module, the Admin has to login by using valid user name and password. After login successful he can do some operations such as View all End Users and Authorize, View all friend request and Response, Add Tweet Category like Positive, Negative, Stressed Select Tweet Category and Add Tweet Filter and list all filters below. List all Tweets micro-blog with its user details, View Positive (+) Emotion Tweets Emotions, View negative (-) Emotion Tweet Emotions, View Stressed Emotion Tweets, View total tweets and find number of positive, negative and stressed tweets, List of search history, Find Number of +ve,or –ve or stressed Tweets emotion in chart

B. Viewing All Positive and Negative, Stress Emotions

In this module, the admin can see all Positive and Negative Emotions posted by all users for cross domain Micro Blogs. The Review is considered either as Positive or Negative based on the Positive and Negative list of words which are used to find the review as positive or negative. In this the Positive and Negative words will be highlighted in blue color and in italics style.

C. View and Authorize Users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

D. View Chart Results

In this, the cross domain number of positive and negative Emotions for particular post will be shown in a chart by selecting particular Micro Blogs from a combo box.

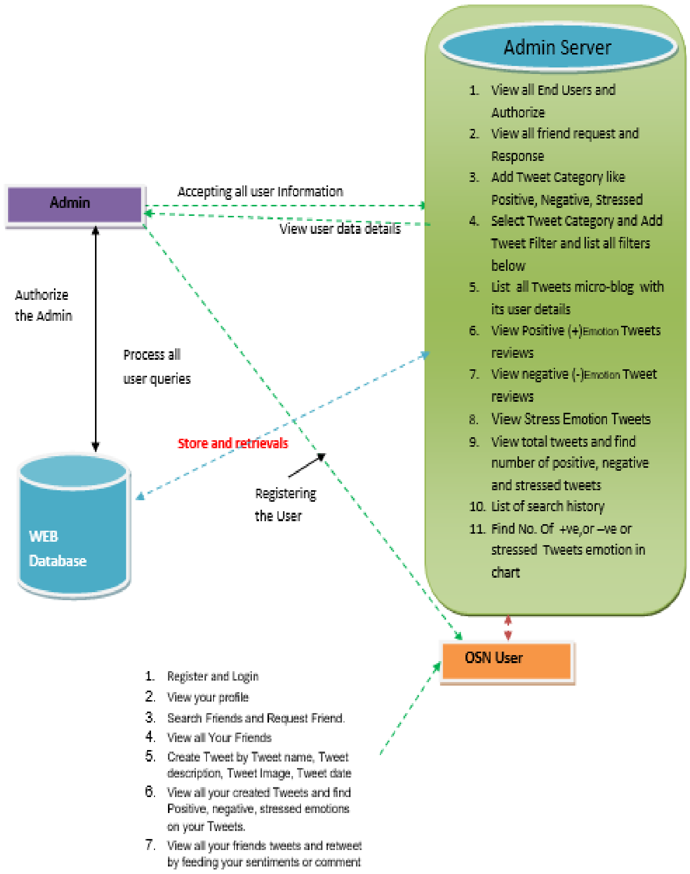
E. User

In this module, there are n numbers of users are present. User should register before doing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once Login is successful user will do some operations like View your profile, Search Friends and Request Friend. View all Your Friends, Create Tweet by Tweet name, Tweet description, Tweet Image, Tweet date, View all of your created Tweets and find positive, negative, Stress emotions on your Tweets, View all your friends tweets and retweet by feeding your sentiments or comment

F. Viewing All Micro Blogs Emotions and give Comment

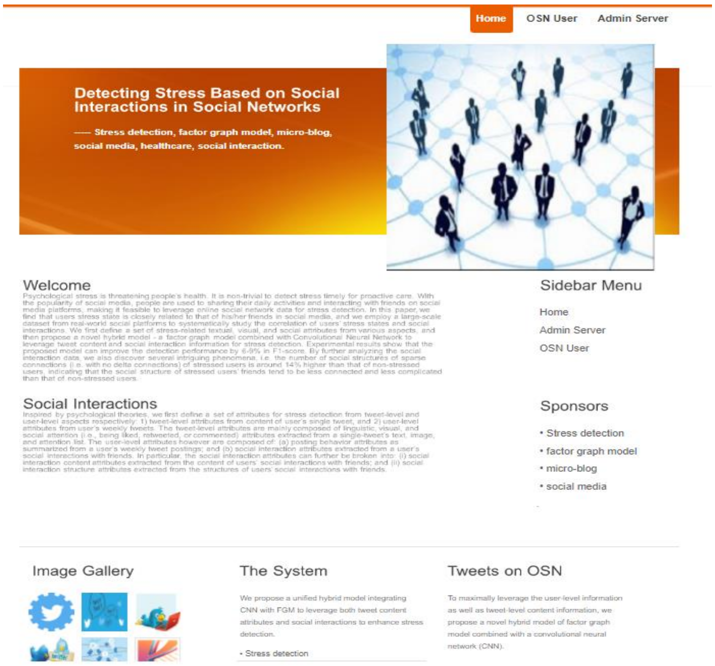
In this, the user can view all the Micro Blogs details, Emotions and user can comment on them by entering their own Emotions. Each time the rank will be incremented for particular Micro Blogs once the review is posted.

VI. ARCHITECTURE OF THE SYSTEM

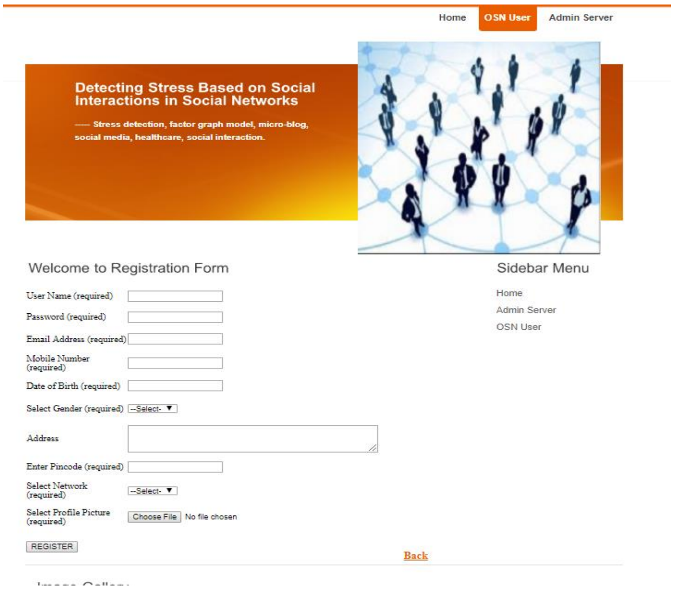


VII. RESULTS

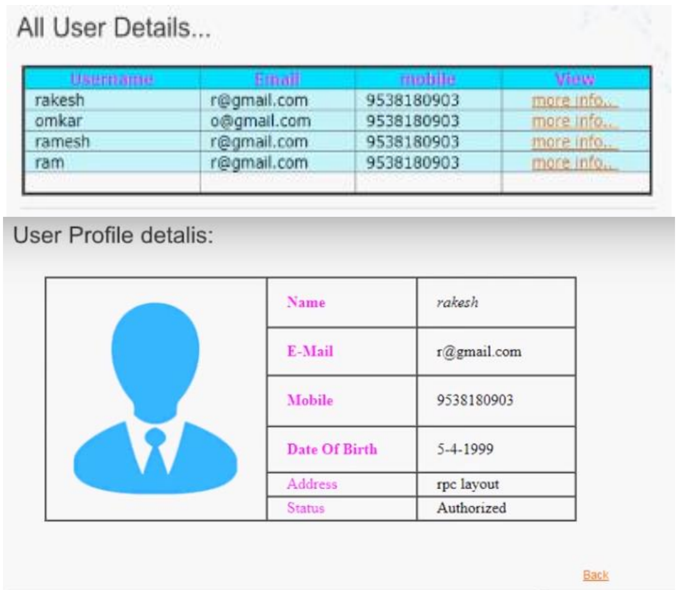
A. Home Screen:



B. User Registration:



C. User Details:



D. User Tweets:

E. Tweet Details:

F. Analysis Reports:

CONCLUSION

In this paper, we presented a framework for detecting users' psychological stress states from users' weekly social media data, leveraging tweets' content as well as users' social interactions. Employing real-world social media data as the basis, we studied the correlation between user' psychological stress states and their social interaction behaviors. To fully leverage both content and social interaction information of users' tweets, we proposed a hybrid model which combines the factor graph model (FGM) with a convolutional neural network (CNN). In this work, we also discovered several intriguing phenomena of stress. We found that the number of social structures of sparse connection (i.e. with no delta connections) of stressed users is around 14% higher than that of non-stressed users, indicating that the social structure of stressed users' friends tend to be less connected and less complicated than that of non-stressed users. These phenomena could be useful references for future related studies.

REFERENCES

[1] Andrey Bogomolov, Bruno Lepri, Michela Ferron, Fabio Pianesi, and Alex Pentland. Daily stress recognition from mobile phone data, weather conditions and individual traits. In *ACM International Conference on Multimedia*, pages 477–486, 2014.

[2] Chris Buckley and EllenM Voorhees. Retrieval evaluation with incomplete information. In Proceedings of the 27th annual international ACM SIGIR conference on Research and development in information retrieval, 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 Joint Conference on Artificial Intelligence*, pages 2234–2240, 2015.

[4] Wanxiang Che, Zhenghua Li, and Ting Liu. Ltp: A Chinese language technology platform. In *Proceedings of International Conference on Computational Linguistics*, pages 13–16, 2010.

[5] Chih chung Chang and Chih-Jen Lin. Libsvm: a library for support vector machines. *ACM TRANSACTIONS ON INTELLIGENT SYSTEMS AND TECHNOLOGY*, 2(3):389–396, 2001.

[6] Dan C Ciresan, Ueli Meier, Jonathan Masci, Luca Maria Gambardella, and J ¨ urgen Schmidhuber. Flexible, high performance convolutional neural networks for image classification. In *Proceedings of 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 the International Conference on Weblogs and Social Media*, pages 579–582,2014.

[9] Rui Fan, Jichang Zhao, Yan Chen, and Ke Xu. 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 Jarder Luo. Modeling paying behavior in game social networks. In *In Proceedings of the Twenty-Third Conference on Information and Knowledge Management (CIKM'14)*, pages 411–420, 2014.

[11] Golnoosh Farnadi, Geetha Sitaraman, Shanu Sushmita, 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.

[12] Eileen Fischer and A. Rebecca Reuber. Social interaction via new social media: (how) can interactions on twitter affect effectual thinking and behavior? *Journal of Business Venturing*, 26(1):1–18, 2011.

[13] Jerome H. Friedman. Greedy function approximation: A gradient boosting machine. *Annals of Statistics*, 29(5):1189–1232, 1999.

[14] Rui Gao, Bibo Hao, He Li, Yusong Gao, and Tingshao Zhu. Developing simplified chinese psychological linguistic analysis dictionary for microblog. pages 359–368, 2013.

[15] Johannes Gettinger and Sabine T. Koeszegi. More Than Words: The Effect of Emoticons in Electronic Negotiations.

[16] Jennifer Golbeck, Cristina Robles, Michon Edmondson, and Karen Turner. Predicting personality from twitter. In *Passat/socialcom 2011, Privacy, Security, Risk and Trust*, pages 149–156, 2011.

[17] Mark S. Granovetter. The strength of weak ties. *American Journal of Sociology*, 1973.

[18] Quan Guo, Jia Jia, Guangyao Shen, Lei Zhang, Lianhong Cai, and Zhang Yi. Learning robust uniform features for cross-media social data by using cross autoencoders. *Knowledge Based System*, 102:64– 75, 2016.

[19] David W. Hosmer, Stanley Lemeshow, and Rodney X. Sturdivant. Applied logistic regression. *Wiley series in probability and mathematical statistics*, 2013.

[20] Sung Ju Hwang. Discriminative object categorization with external semantic knowledge. 2013.

[21] Sepandar D. Kamvar. We feel fine and searching the emotional web. In *In Proceedings of WSDM*, pages 117–126, 2011.

[22] Herbert C. Kelman. Compliance, identification, and internalization: Three processes of attitude change. *general information*, 1(1):51–60, 1958.

[23] Shigenobu Kobayashi. The aim and method of the color image scale. *Color research & application*, 6(2):93–107, 1981.

[24] Novak P Kralj, J Smailovi, B Sluban, and I Mozeti. Sentiment of emojis. *Plos One*, 10(12), 2015.

[25] Frank R Kschischang, Brendan J Frey, and H-A Loeliger. Factor graphs and the sum-product algorithm. *Information Theory, IEEE Transactions on*, 47(2):498–519, 2001.

[26] Yann LeCun and Yoshua Bengio. Convolutional networks for images, speech, and time series. *The handbook of brain theory and neural networks*, 3361, 1995.

[27] Kathy Lee, Ankit Agrawal, and Alok Choudhary. Real-time disease surveillance using twitter data: demonstration on flu and cancer. In *Proceedings of ACM SIGKDD international conference on Knowledge discovery and data mining*, pages 1474–1477, 2013.

[28] H. Lin, J. Jia, Q. Guo, Y. Xue, J. Huang, L. Cai, and L. Feng. Psychological stress detection from cross-media microblog data using deep sparse neural network. In *proceedings of IEEE International Conference on Multimedia & Expo*, 2014.