International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-4, November 2019

Detection of Stress Level in Social Media users using Cnn-Fg Model

Tanzila Nargis Nikitha Saurabh

Abstract: ***Psychological stress has become a common condition in today's world owing to the busy life style and competitive environment. This has led to increase of suicidal rates in the recent years. Lately, there has been a tremendous increase in interactions in the social networking sites. As people are spending long hours in the virtual world it is easier to detect and analyze the stress levels of the social media users. In this paper, we have proposed a hybrid approach which is a combination of Factor Graph (FG) model and Convolutional Neural Network (CNN) to analyze the textual contents in social media users' tweets and posts to detect the level of stress of a user. The tweets of an individual user are gathered from Twitter platform which is preprocessed and passed to the cross autoencoder embedded CNN Model which outputs user level attributes. These are then input to the Factor Graph model that detects the stressed tweets. A mechanism has been proposed to inform the friends or relatives of the concerned stressed user if the detected stress level is above the given threshold.***

Keywords **:** ***Stress detection, Factor Graph model, CNN, Social Media.***

I. INTRODUCTION

The psychological stress has become a common reason for many diseases in today's world. The increase in suicidal rates in recent years is directly linked to the psychological stress that people suffer from. Hence detection of stress levels in individuals and prevention of suicidal rates has become a major concern. This has attracted many researchers in this area. With the rapid growth of social media, expressing views, emotions and feelings in the virtual world is an ongoing trend. As people are spending long hours in the virtual world it is easier to detect and analyze the stress levels of the social media users [1]. In social media, the new words created are widely spread. And this imposes greater influence on analysis of sentiments and emotions.[2] Artificial Intelligence has been vital in connecting the gap between the capacity of machines and humans. Applying Deep Learning algorithms to the detection and analyzing tasks aid in providing faster and better results.

Manuscript published on November 30, 2019.
* Correspondence Author

Tanzila Nargis*, Currently working as an Assistant Professor in the Department of Information Science and Engineering at NMAMIT, Nitte, Karkala, Karnataka.

Nikitha Saurabh Currently working as an Assistant Professor in the Department of Information Science and Engineering at NMAMIT, Nitte, Karkala

Convolutional neural network, a Deep Learning approach with embedded cross autoencoders takes performs classification based on learnable biases and weights from input data. CNN's have the capability to learn filters and features automatically in compared to traditional learning algorithms which requires manual selection of attributes [16]. Probabilistic graphical model (PGM) uses a graph to depict the various states of random variables based on probability. Representation of gained knowledge in the form of graph and inferring information from them is considered an easier and effective task. Factor graph, a PG model, that uses variable and factor nodes to portray knowledge gained. It is a two-part graph which can disintegrate a global procedure into several local procedures.

II. RELATED WORKS

Huijie Lin et.al. [1] proposes stress detection model to detect social media user's stress levels by improving the performance by 6-9 percent in F1 score. They highlighted that social structure of stressed users is around 14% higher than that of non-stressed users. ChiyuCai et. al.[2] proposed two novel new words based sentiment analysis namely NWLB(using lexicon) and NWSA(using machine learning) to use the new words in enhancing the process of sentiment analysis. Firoj Fathul Shahare [3] proposed a method using Naïve Bayes and Levenshtein algorithm to classify social media news data into the emotions of various categories. PietroDucange et al. [4] proposed two frameworks, one general and the other specific framework for social media data sentiment analysis.In the general framework data from on line social networks is used for analysis.In the specific framework, data from specific social networks are used for detecting positive ,neutral and negative polarity linked with the textual content. Santhoshi Kumari et al [5] proposed a sentiment analysis model to identify people's emotions like happy, sad and neutral based on their tweets in Twitter platform. They used lexical based text mining and unsupervised classification method for the analysis process. This analysis can prove to be helpful in finding people's likings towards nationalist parties of a country which helps the political parties to improve their party propaganda and work towards betterment of the society. S. Rajalaxmi et al [6] discussed about various tools and techniques used in sentiment analysis of social media data. They highlighted that machine learning algorithms performed better in emotion mining process. Zhi-Oriang et.al.[7] analyzed Chinese micro blogs using vector space model.

They used support vector machine to classify the sentiments into positive and negative category and achieved an accuracy of 80-86%. Zhang Xiangyul et.al. [8] proposed a context-based regularization classification method to analyze short text sentiments. They used TextRank algorithm to rank the words in a sentence for analysis. The model was tested on both English and Chinese dataset. Shuozeng et.al.[9] proposes a message level text-based classification model to detect and categorize user emotion. This model incorporates user dynamic behavior and time dimensions for better analysis. The model was applied on dark web forum. Sonia Xylina Mashal and Kavita Asnani [10] built a model to recognize emotion intensity in short texts and in turn detecting the sentence level emotion category to classify the emotions. Viviana Patti et.al. [11] highlights the perils of analyzing human emotions in interactions and sheds light on ethical practices to be followed in creation of automated human emotion detection tools. Andrey Bogomolov et. al. [12] proposed a model to analyze individual happiness based on the machine learning model using random forest classifier and indicators such as mobile phone usage data and noise in the background as the feature set for analysis. This model achieved an accuracy of 80.81 percent. Chaiyong Ragkhitwetsagul [13] highlights certain techniques to measures the similarity of code and are applied to the clone detection and plagiarism detection. Jingen Lie et.al.[14] proposes a concept-based event representation model to classify video events using TRECVID multimedia event detection open source event definition and dataset comprising of 1400 hours of videos. Salas, A. and Georgakis, P. [15] proposes a framework for traffic management by analyzing and classifying twitter tweets related to traffic. This paper user used text mining approaches to recognize traffic related tweets. The tweets are classified as positive, negative ad neutral tweets.

III. METHODOLOGY

A. System Design

In the initial stage, the data from social media platform like Twitter is collected. Preprocessing of this raw data involves data tokenization, stop word removal and stemming which translates raw data into required format essential to represent a training set. The Convolutional Neural Network- Factor Graph Model is then trained with this data to construct the stress detection model. After this stage the prepossessed test data of a particular user is sent to the stress detection model to detect the stress level of that individual. This outputs if tweet is Stressed tweet or Not. For a particular user if the stressed tweets are above a given threshold then it indicates that the concerned individual is under extreme stress. Hence the system sends an email to his/her friends or relatives to intimate them about the user's condition. All the stages are depicted in the Fig. 1 shown below

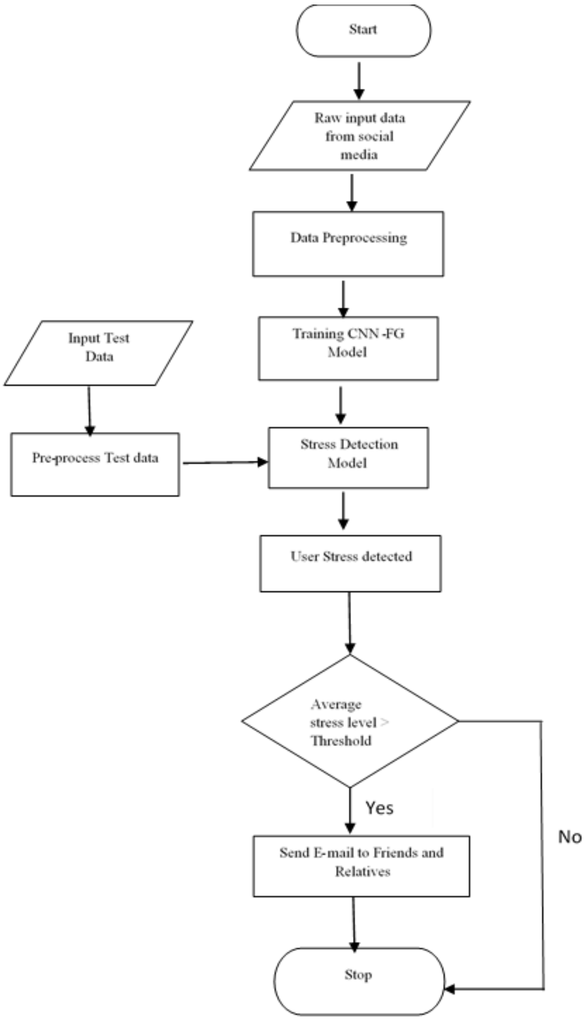

Fig. 1 System Design

B. CNN-FG Model

The Convolution neural network is used to extract user level attributes from users' tweets. The cross-auto encoders embedded in CNN are used to map tweets to user level attributes. The user level attributes which comprises of user's social interaction, posting behavior and content attributes are then passed to Factor Graph Model that connect the user level attributes to stressed states. The outcome of this hybrid model is the stressed state of the user. All the stages are shown in the Fig. 2 shown below.

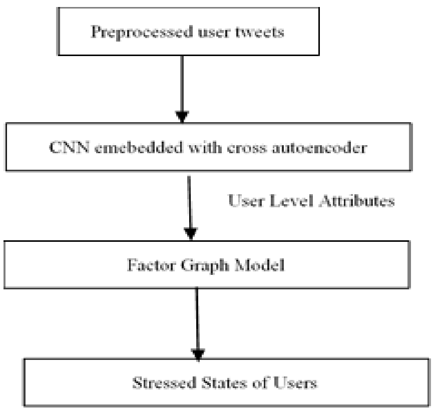

Fig. 2 CNN-FG Model

International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-4, November 2019

C. Algorithm: Stress Detection

Input: user tweets t = {t_1, t_2, t_3,…};
Output: each users stress level S_l;
Step1: Raw data collection of user tweets from Twitter, t
Step2: Preprocessing is applied to tweets t, consisting of data tokenization, stop word removal and stemming to obtain preprocessed data, t_p
Step 3: CNN-FG model is trained with preprocessed data t_p, to produce stress detection model
Step 4: Apply test user data t_d,to stress detection model and perform the following substeps
a) collect test data tweets, td
b) compare tweets t_d and
Dataset keywords, k
Where k = {abnormal, stressed, abort…}
to check whether they match.
c) If Yes then the taken tweets are
stressed tweets $S_{t.}$
d) If No then the taken tweets are
normal tweets $N_{t.}$
e) calculate the average stress level, S_l
$S_l = \sum S_{t.}$ / no. of tweets, t
Step5: Detecting the stress level in each user
if Average of stress level,
$S_l >$ threshold, t_h
then
Email is sent to the stressed user's friends and relatives.
else
Do nothing

IV. RESULTS AND ANALYSIS

Results are shown using the factor graph model based on the user inputs. A pie-chart is generated and distinguishes the tweets as stressed and normal tweets and also the value is depicted in percentage. The green color represents the normal tweets and the red color represents the stressed tweets.

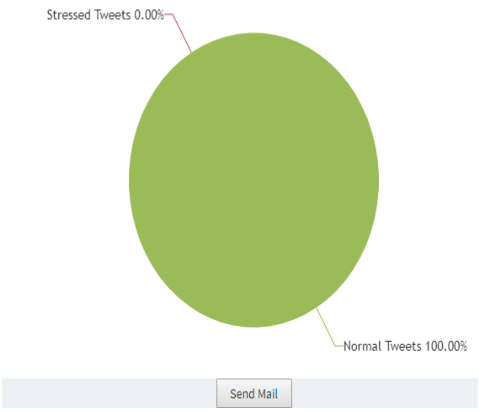

Fig. 3 Normal Tweets

As shown in Fig. 3 all the tweets are 100% normal and the user is stress free.

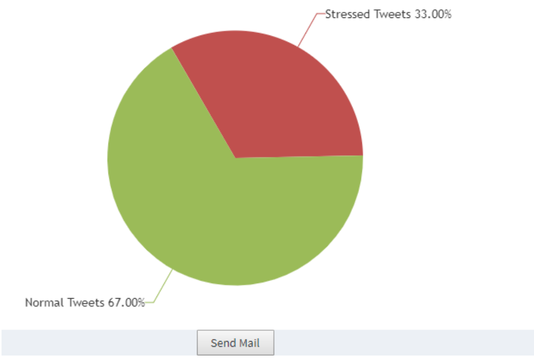

Fig. 4 Both stress and normal tweet level of user

The Fig 4 gives 33% stressed tweets and 67% normal tweets. The threshold is set to 50%. If the stressed tweets go above 50% then the user is referred as stressed.

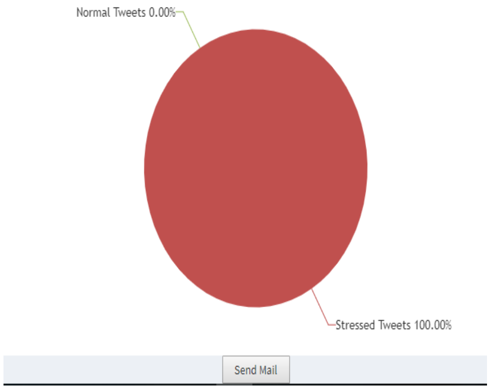

Fig. 5 Stressed Tweets.

In this Fig. 5, it represents the user is 100% stressed and it sends an e-mail to his/her friends or relatives.

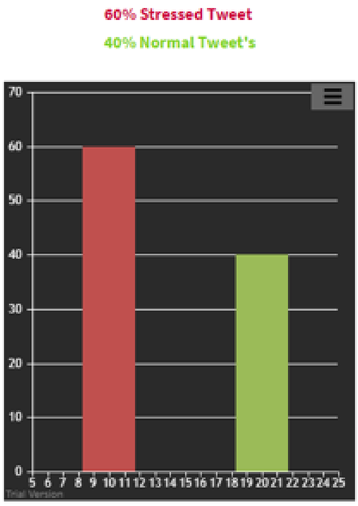

Fig. 6 Overall stress level of a user

The Fig. 6 represents the overall stress level of a user using the bar graph. Here red represents stressed tweets and it is 60% and green represents normal tweet and it is 40%.

V. CONCLUSION

The increase in suicidal rates in recent times have encouraged researchers to find out mechanisms to detect stress levels in individuals at an early stage to take necessary steps to curb the suicide attempt. As people spend a lot of time in the virtual space, social media platforms have become an important place of research.

Analysis of user's posts and tweets can aid in detecting the stress levels in individuals faster. This paper focuses on detection of stress levels in social media users in Twitter platform. This paper proposes a hybrid model which combines the factor graph model (FGM) with a convolutional neural network (CNN) to detect the stress of the users. Based on the experimental outcome user's stress state can be analyzed and his/her stress level can be detected and immediate action can be taken by informing his/her close ones through an e-mail. This initiative can help in early detection of psychological stress and prevent suicidal rates which has become an alarming condition in today's world.

REFERENCES

1. Huijie Lin, JiaJia, "Detecting Stress Based on Social Interactions in Social Networks", Tsinghua University, ISSN:1041-4347, Vol.29, September-2017.
2. ChiyuCai, Linjing Li, Daniel Zeng, "New Words Enlightened Sentiment Analysis in Social Media", University of Arizona, Tucson, 2016 IEEE.
3. Firoj Fattulal Shahare,"Sentiment Analysis for the News Data Based on the social Media", International Conference on Intelligent Computing and Control Systems, 2017 IEEE.
4. Pietro Ducange, Michela Fazzolari, "Social Sensing and Sentiment Analysis: Using Social Media as Useful Information Source", Smartest Research Centre, Institute of Informatics and Telematics(IIT), Vol.24, November-2017.
5. SanthoshiKumari, Narendrababu C, "Real Time Analysis of Social Media to Understand People Emotions Toward s National Parties", 8th ICCCNT 2017, Vol.20, July 3-5, 2017.
6. S.Rajalakshmi, S. Asha, N. Pazhaniraja, "Comprehensive Survey on Sentiment Analysis", Communications and Networking (ICSCN-2017), March 16-18, 2017.
7. Zhi-Qiang Xiang1, Y. X. Zou ," Sentiment Analysis of Chinese Micro-blog Using Vector Space Model", ADSPLAB/ELIP, School of Electronic Computer Engineering, Peking University, Shenzhen, China, 2014.
8. Zhang Xiangyu1, Li Hong," A Context-Based Regularization Method for Short-Text Sentiment Analysis", School of Economics and Management, Beihang University, Beijing, China.
9. ShuoZeng, Mingfeng Lin, Hsinchun Chen," Dynamic User-level Affect Analysis in Social Media: Modeling Violence in the Dark Web", Department of Management Information Systems,2011.
10. Sonia Xylina Mashal,Kavita Asnani,"Emotion Intensity Detection for Social Media Data ", Department of Computer Engineering, Goa,IEEE International Conference on Computing Methodologies and Communication, (ICCMC),2017.
11. Viviana Patti and Rossana Damiano and Cristina Bosco, "Ethical Implications of Analyzing Opinions, Emotions and Interactions in Social Media ", Seventh International Conference on Affective Computing and Intelligent Interaction Workshops and Demos (ACIIW),2017.
12. Andrey Bogomolov, Bruno Lepri," Happiness Recognition from Mobile Phone Data", IEEE,2013.
13. Chaiyong Ragkhitwetsagul," Measuring Code Similarity in Large-scaled Code Corpora", IEEE International Conference on Software Maintenance and Evolution,2016 .
14. Jingen Liu, Qian Yu," Video Event Recognition Using Concept Attributes",IEEE ,2013.
15. Salas, A., Georgakis, P," Traffic Event Detection Framework Using Social Media",IEEE International Conference on Smart Grid and Smart Cities,2017.
16. Yao Guangle, Lei, Tao, Zhong, jiandian, "A review of Convolutional-Neural-Network-based action recognition", science direct Elseveir, volume118, February 2019, pages-14-22.
17. Li Hongmei, Hao Wenning, Gan Wenyan, Chen Gang "Survey of probabilistic graphical models" 10th Web Information System and Application Conference, 2013

AUTHORS PROFILE

Tanzila Nargis Currently working as an Assistant Professor in the Department of Information Science and Engineering at NMAMIT, Nitte, Karkala, Karnataka ,India. She has 2.5 years of teaching experience. Her research interests include Cyber Security, Wireless Sensor Networks and Machine Learning.

Nikitha Saurabh Currently working as an Assistant Professor in the Department of Information Science and Engineering at NMAMIT, Nitte, Karkala, Karnataka ,India. She has 9.5 years of teaching and 1 year of industry experience. Her research interests include Cyber Security, Machine Learning and Artificial Intelligence.