# DETECTION OF STRESS RELATED POSTS IN TWITTER DATA STREAMS

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*Abstract*: Psychological wellness conditions influence anoteworthy level of the world's population every year. Thestress investigation of emotional wellness phenomena inopenly accessible social networking sites like twitter, sinaweibo and facebook. A set of stress-related textual, visual, and social attributes from various aspects are first defined andthen propose a novel hybrid model. The 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. It is a ccess the user posts on their facebook page. Inorder to obtain the user data from facebook, system have toget the access token from facebook developer page. The APIact as an intermediate system that will help the system toanalysis the user information from the facebook page. Thesystem will also help to Recommending users with different links for psychological counseling centers, soft music orarticles to help release their stress according to users' stresslevel.

### IndexTerms - Stress detection, social media, micro-blog, access tokens, and face book.

# **1. INTRODUCTION**

Mental stress is turning into a risk to individuals these days. With the fast pace of life, progressively more and more individuals are feeling stressed. Though stress itself is non-clinical and common in our life, excessive and chronicstress can be rather harmful to people's physical and mental health. User's social interactions on social networkscontain useful cues for stress detection. Social psychological studies have made two interesting observations. The firstis mood contagion: a bad mood can be transferred from one person to another during social interaction. The second isSocial Interaction: people are known to social interaction of user in social media. The advancement of social networkslike Twitter, Facebook and Sina Weibo2, an ever increasing number of people will share their every day events and moods, and interact with friends through the social networks. We can classify using support vector machine whether the user is stressed or not. After getting stress level, system can recommended user hospital for further treatment, we can show that hospital on map and system also recommends to take precaution to avoid stress. More and more teenagers today are overloaded withadolescent stress from different aspects: academic future, self cognition, inter-personal, and affection. Long-lastingstress may lead to anxiety, withdrawal, aggression, or poorcoping skills such as drug and alcohol use, threateningteenagers' health and development. Hence, it is important forboth teenagers and their guardians/teachers to be aware of the stress in advance, and manage the stress before itbecomes severe and starts causing health problems. Thecurrent social media micro-blog offers an open channel forus to timely and unobtrusively sense teenager's stress basedon his/her tweeting contents and behaviors. This studydescribes a framework to further predict teenager's futureadolescent stress level from micro-blog, and discusses howwe address the challenges (data incompleteness and multifaceted prediction) using machine learning and multi-variant time series prediction techniques. For the comparison of the series prediction techniques are series prediction techniques are series prediction techniques. influence teenager's stress levels are also incorporated into our prediction method. Our experimental results demonstrate the effectiveness of considering correlated features and event influence in prediction. To thebest of our knowledge, this is the first work on predictingteenager's future stress level via micro-blog.College can be stressful for many freshmen as they cope with variety of academic, personal, and social pressures .Although not all stress is negative, a certain level of stresscan be beneficial to help improve performance. However, toomuch stress can adversely affect health in the annual surveyof the American Freshman; the number of students reportedfeeling overwhelmed and stressed has increased steadily in he last decade. Over 50% of college students suffersignificant levels of stress during a typical college semester .Consequently, there is a need to find innovative and costeffectivestrategies to help identify those students experiencing high levels of stress and negative emotions early on so that they can receive the appropriate treatmentin order to prevent future mental illnesses. Social media use, such as Twitter and Facebook, has been rapidly growing, and research has already shown that data from these technologies can be used for novel approaches to publichealth surveillance. Twitter usage among young adults hasincreased 16% from 2012 to 2014. Currently, 32% of adultsof the ages 18-29 years use Twitter, and the usage is expected to increase steadily in the future. People often havethe need to share their emotions and experiences .Researchers have theorized that emotional sharing mayfulfill a socio-affective need by eliciting attention, affection, and social support. Consequently, this may help individualscope with their emotions and provide an immediate relief .Users often share their thoughts, feelings, and opinions on these social media platforms, and as a result, social mediadata may be used to provide real-time monitoring of stressand emotional state among college students . Previousstudies have shown that Twitter data can be used to monitora wide range of health outcomes, such as detecting humanimmunodeficiency virus infection outbreaks and predictingan individual's risk of depression . For example, DeChoudhury et al conducted one of the first studies that usedan individual's tweets to predict the risk of depression . Theauthors found that certain features extracted from a person'stweets collected over a 1-year period were highly associated with the risk

of depression in adults, such as raised negativesentiment in the tweets, frequent mentions of antidepressant medication, and greater expression of religious involvement. Currently, no studies have examined whether Twitter data can be used to monitor stress level and emotional state among college students. Studying this topic is important because the large amount of social media datafrom college students' frequent use of social media can be used to help university officials and researchers monitor and reduce stress among college students.

#### **II LITERATURE SURVEY**

Huijie Lin, JiaJia, QuanGuo, YuanyuanXue, Qi Li, Jie Huang, LianhongCai, Ling Feng et al. [1] the study of "User-LevelPsychological Stress Detection From Social Media UsingDeep Neural Network" .The paper employs real onlinemicroblog data to investigate the correlations betweenusers' stress and their tweeting content. It also defines twotypes of stress related attributes: - Low-level contentattributes from a single tweet, including text, images and social interactions; and Userscope statistical attributes through their weekly micro-blog postings, mappinginformation of tweeting time, tweeting types and linguisticstyles. Li-fang Zhang et al. [7] proposed the study on titledOccupationalstress and teaching approaches among Chineseacademics (2009). Researcher suggested that, controlling theself-rating abilities of the participants, the favorableconceptual changes in teaching approach and their roleinsufficiency predicated that the conceptual change inteaching strategy is negative. Another approach for stress analysis is Kavitha et al. [4] inher research titled -Role of stress among women employeesforming majority workforce at IT sector in Chennai andCoimbatore (2012), she has focuses on the organizationalrole stress for the employees in the IT sector. She found inher research that, women face more stress than men in theorganization and she viewed to be more specific marriedwomen faces more stress than the unmarried women. Another approach is Amir Shani and Abraham Pizam(2009)et al. [6] -Work-Related Depression among Hotel Employeeshave conducted a study on the depression of work amonghotel employees in Central Florida. They have found that, incidence of depression among workers in the hospitalityindustry by evaluating the relationship between theoccupational stress and work characteristics. Another approach is Kayoko Urakawa and KazuhitoYokoyam et al. [] in their work on Sense of Coherence (SOC)may Reduce the Effects of Occupational Stress on MentalHealth Status among Japanese Factory Workers (2009) hasfound the result i.e. adverse effects on mental health due tothe job demand and job stress was positively associated withSOC, the mental health status of males in managerial workwas adversely negative, where as it was positive among thefemale co-workers. Finally they found that, SOC is animportant factor determining the coping ability over the jobstress for both the genders.3. PROPOSED WORKIn this proposed work, we build a practical application todetect and release user's psychological stress by leveraginguser's social media data in online social networks, andprovide an interactive user interface to present users and friends psychological stress states. With the given usersonline social media data as input, our proposed systemintelligently and automatically detects users stress states. Moreover, it will recommend users with different links tohelp release their stress. The main technology of this projectis a clustering model, which can leverage social mediacontent and social interaction information for stressdetection.

#### III. PROBLEM FORMULATION

To formulate our problem, we declare some notations in advance. In particular, we use bold capital letters (e.g., X) and bold lowercase letters (e.g., x) to denote matrices and vectors, respectively. We employ non-bold letters (e.g., x) to represent scalars, and Greek letters (e.g., ) as parameters. If not clarified, all vectors are in column form. Suppose that we have K stressor events and M stressor subjects. Let us denote ei 2 RK as the event label vector, and si 2 RM as the subject label vector, for the i-th tweet. Given a set of tweets  $T = \{t1, t2, \dots, tN\}$ , it consists of N distinct training samples. Let xi 2 RD be the feature vector of the i-th tweet. Each training sample ti = (xi, ei, si) consists of a feature vector denoted by xi, with the corresponding stressor event label ei and the stressor subject label si. Let  $X = [x1, x2, \dots, xN] T 2 RN \rightarrow D$  be the feature matrix,  $E = [e1, e2, \dots, eN] T 2 RN \rightarrow K$  be the stressor event label matrix, and  $S = [s1, s2, \dots, sN] T 2 RN \rightarrow M$  be the stressor subject label matrix, respectively. 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 treeInput: an attribute valued dataset DTree={}If D is "Pure" OR other stopping criteria met thenTerminateEnd if

For all attribute  $a \in D$  do Compute information thereotic criteria if we split on a End for abest = Best attriubuteaccording to above computed criteria Tree= Create a decision node that tests abest in the root Dv= Induced sub-Datasets from D based on abest For all Dv do Treev=C4.5(Dv) Attach Treev to the corresponding branch of Tree End for Return Tree

## IV. METHODOLOGY

1.Registration: The user who are all wants to know their stress levels they first have to register in to the stress analysissystem.In the registration phase the user will have to fill the details consisting in the registration phase. After registration the user can access the stress analysisapplication.

2.Data collection: Collection of user data from the facebook.It is not directly access the user posts on their facebookpage.In order to obtain the user data from facebook, we have to get the access token from facebook developerpage.The API act as an intermediate system that will help us to collect the user information from the facebookpage.All the information posted are stored in the analysisdatabase.

3.Clustering: The posts from different users arevr2collected together and separated by clusteringtechniques. The cluster comprises of sentiment basedseparation and classification k-mean algorithm have to used in this module.

4.Stress level prediction: Finding stress level of the user in

different states. Recommending users with different links forpsychological counseling centers, soft music or articles tohelp release their stress according to users' stress levels.

1. Daily stress recognition from mobile phone data, weather conditions and individual traits: In the paper of Daily stress recognition from mobile phone data, weather conditions and individual traits. That day byday stress can be dependably perceived in the form of behavioural measurements, get information from the clients cellphone, for example, the climate conditions (information relating to short lived properties of the condition) and theidentityattributes .In work environments, where stress has become a serious problem affecting the productivity, leadingto occupational issues and causing health diseases. Our proposed system could be extended and employed for earlydetection of stress-related conflicts and stress contagion, and for supporting balanced workloads.

2. Flexible, high performance convolutional neural networks for image classification:

In this paper, they present the new deep CNN architecture, MaxMin-CNN, to better encode both positive and negative filter detections in the net.Thesystem to adjust the standard convolutional square of CNN keeping in mind the end goal to exchange more data layer after layer while keeping some invariance inside the system. Fundamental thought is to abuse both positive and negative high scores got in the convolution maps. This conduct is acquired by altering the customary enactment work venture before pooling. Time required for this is more. It is time consuming process.

3. Predicting personality from twitter:

In this Paper theyare interested in the identity of clients. Identity has been appeared to be applicable to many sorts of cooperation; it has been appeared to be helpful in anticipating work fulfilment ,relationship achievement, and eveninclination .They are intrigued in the identity of clients. Identity has been appeared to be applicable to many sorts of communications; it has been appeared to be valuable in foreseeing work fulfilment, expert and sentimental relationshipachievement, and even inclination for various interfaces. And begin to answer more sophisticated questions about howto present trusted, socially-relevant, and well-presented information to users.

4. Learning robust uniform features for cross-media social data by using cross autoen coders: In paper Learning robust uniform features for cross-media social data by using cross auto encoders. To solve learningmodels to address problem handle the cross-modality correlations in cross-media social elements. They propose CAE to learn uniform modality-invariant features, and they propose AT and PT phases to leverage massive cross media datasamples and train the CAE. Learning robust uniform features for cross-media social data by using cross auto encoderstake a more time.

5. We feel fine and searching the emotional web:

This paper is about the user feel fine and searching the emotional web. On the usage of We Feel Fine to suggest a classof visualizations called Experiential Data Visualization, which focus on immersive item-level interaction with data. Theimplications of such visualizations for crowd sourcing qualitative research in the social sciences. Repeated informationin relevant answers

requires the user to browse through a huge number of answers in order to actually obtaininformation Existing works demonstrated that leverage social media for healthcare, and in particular stress detection, is feasible. There are some limitations exist in facebook content based stress detection. Users do not always express their stressful states directly in facebook post. Although no stress is revealed from the post itself, from the follow-up interactive comments made by the user and his/her friends, we can find that the user is actually stressed from work. Thus, simplyrelying on a user's facebook post content for stress detection is insufficient. Users with high psychological stress may exhibit low activeness on social networks. Stress detection performance is low.

#### V. CONCLUSION

We made use of k-mean clustering techniques in order to cluster the user data and provide an accuracy for the user stresslevels.that are gathered and provided by graph internetexplorer. In this system, we displayed a system for distinguishing users psychological stress states from clients Psychological stress is threatening people's health. It is non-trivial to detect stress timely for proactive care. Thereforewe have presented a framework for detecting user's psychological stress states from user's monthly social media data, leveraging facebook post content as well as user's social interactions. Employing real-world social media data as thebasis, we studied the correlation between user's psychological stress states and their social interaction behaviours. We recommend the user for health consultant or doctor. We show the hospitals for further treatment on a graph whichlocate shortest path from current location of user to that hospital. We recommended the user for health precaution andsend mail for user interaction purpose.

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