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STRESS IDENTIFICATION IN SOCIAL NETWORKS BASED ON SOCIAL INTERACTIONS

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Abstract: **Psychological stress is becoming a threat to people's health now-a-days. With the rapid advancement of life, more and more people are feeling stressed. Stress Detection among individual is not an easy task, and if no proper care is taken it make cause harm to individuals. With the rapid growth of web-based social networking, individuals are sharing their daily routines and are interacting with friends via social media. Studies shows that individual's stress state is potentially dependent on their friend across social platform. This information available via social network can be used for user's stress detection. 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. We have proposed system using Convolutional Neural Network (CNN). We can do analysis of social media post after formation of topic using Support Vector Machine (SVM) and we can classify user is in stress or not.**

Keywords: Stress detection, factor graph model, micro-blog, social media, social interaction.

I INTRODUCTION

Mental stress is turning into a risk to individuals these days. With the fastest growing life more and more individuals are feeling stressed. Though stress itself is non-clinical and common in daily life, excessive and chronic stress can become harmful to people's physical and mental health. Studies shows that long term stress can lead to multiple diseases like depression insomnia etc. Another study shows that depression is very common in youth which in turn is responsible for high suicide rate. Traditional psychological stress detection is mainly based on face-to face interviews, self-report questionnaires or wearable sensors. However, traditional methods are actually reactive, which are usually labor consuming, time-costing and hysteretic. Are there any timely and proactive methods for stress detection? Yes, we do have an option of utilizing user's social interactions on social networks to identify users' level of stress. The advancement of social networks like Twitter, Facebook and Sina Weibo, large population of people will share their every day events and moods, and interact with friends through the social networks. As these data from social media platform shows real time data in terms of users mental and emotional state and mood we can use this information and using data mining concept we can identify user's behavior pattern and by using support vector machine we can conclude whether the user is stressed or not.

For example, [1] found that stressed users are more likely to be socially less active, and more recently, there have been research efforts on harnessing social media data for developing mental and physical healthcare tools. For example, [2] proposed to leverage Twitter data for real-time disease surveillance; while [4] tried to bridge the vocabulary gaps between health seekers and providers using the community generated health data. There are also some research works [3], [5] using user tweeting contents on social media platforms to detect users' psychological stress.

II LITERATURE SURVEY

1. Daily stress recognition from mobile phone data, weather conditions and individual traits[6]:In the paper of Daily stress recognition from mobile phone data, weather conditions and individual traits. Analysis is done stating stress can be dependably perceived in the form of behavioral measurements, we get information from the clients cell phone, for example, the climate conditions (information relating to short lived properties of the condition) and the identity attributes. In work environments, where stress has become a serious problem affecting the productivity, leading to occupational issues and causing health diseases. Our proposed system could be extended and employed for early detection of stress-related conflicts.
2. Flexible, high performance convolutional neural networks for image classification [7]:In this paper, they present the new deep CNN architecture, MaxMin-CNN, to better encode both positive and negative filter detections in the net. The system 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[8]: In this Paper they are interested in the identity of clients. 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 relationship achievement, and even inclination for various interfaces. And begin to answer more sophisticated questions about how to present trusted, socially-relevant, and well-presented information to users.

4. Learning robust uniform features for cross-media social data by using cross auto encoders [9]: In paper Learning robust uniform features for cross-media social data by using cross auto encoders. To solve learning models 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 data samples and train the CAE. Learning robust uniform features for cross-media social data by using cross auto encoders take a more time.

5. We feel fine and searching the emotional web[10]: This paper is about the user feel fine and searching the emotional web. On the usage of We Feel Fine to suggest a class of visualizations called Experiential Data Visualization, which focus on item-level interaction with data. The implications of such visualizations for crowd sourcing qualitative research in the social sciences. Repeated information in relevant answers requires the user to browse through a huge number of answers in order to actually obtain information .

III EXISTING SYSTEM APPROACH

Existing works demonstrated that leverage social media for healthcare, and in particular stress detection, is feasible. However, limitations exist in tweeting content-based stress detection, as tweets are limited to a maximum of 140 characters on social platforms like Twitter and Sina Weibo, and users do not always express their stressful states directly in tweets.

Secondly, users with high psychological stress are less active on social networks, as reported by a recent study in Pew Research Center3. These phenomena incur the inherent data sparsity and ambiguity problem, which may hurt the performance of tweeting content-based stress detection performance.

IV PROPOSED SYSTEM APPROACH

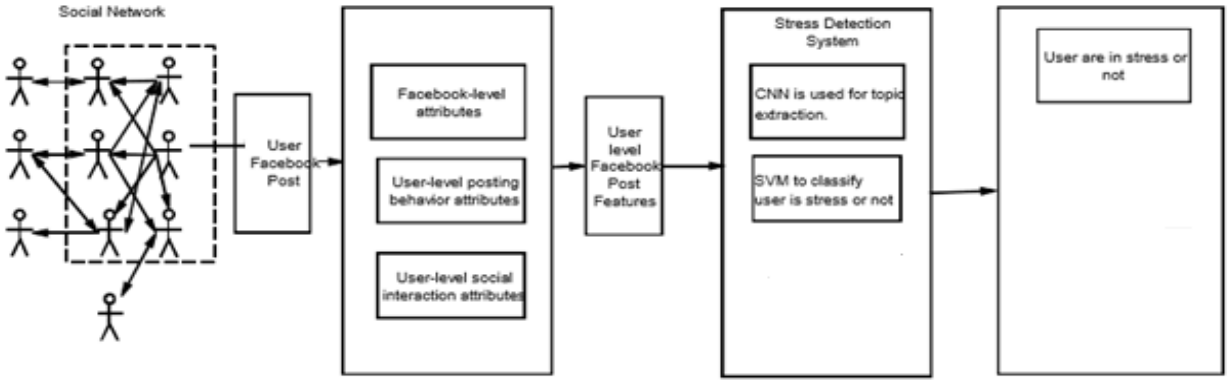

Figure 1 Block Diagram of Proposed System

In a proposed system architecture, we can detect if user is in stress or not due to interaction on social network. A social network contains Facebook, twitter. On a Facebook user interact with other people. User can post on a Facebook. Based on existing 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.
2) user-level attributes from user's weekly tweets.

The tweet-level attributes are mainly composed of linguistic like positive and negative words, visual like brightness, cool color, dull color and social attention attributes like (being liked, commented) which are extracted from a users' single-tweet/post

The user-level/Social interaction attributes however are composed of: (a) posting behavior attributes summarized from a user's weekly tweet postings like social interaction content attributes extracted from the content of user's social interactions with friends like words and emotions and (b) social interaction attributes extracted from a user's social interactions with friends. social interaction structure attributes extracted from the structures of user's social interactions with friends.

Convolutional Neural Network (CNN) is used for topic extraction because CNN is capable of identifying unified latent features from multiple modalities, and factor graph model is good at modeling the correlations.. Using CNN we can do analysis of Facebook post after Formation of topic. Using Support Vector Machine (SVM) we can classify whether user is in stress or not.

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 analyze the correlation of users' stress states and their social interactions on the networks, and address the problem from the standpoints of: (1) social interaction content, by investigating the content differences between stressed and non-stressed users' social interactions; and (2) social interaction structure, by investigating the structure differences in terms of structural diversity, social influence, and strong/ weak tie.

VI CONCLUSION

Psychological stress is threatening people's health. It is non-trivial to detect stress timely for proactive care. Therefore, we 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 the basis, we studied the correlation between user's psychological stress states and their social interaction behaviors.

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