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Stress Level Assessment of an Individual using Neural Networks based on Tweets

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Abstract
Stress in workplace is deteriorating both physical and mental health of an individual. It also makes the individual less productive and less efficient in work. It is necessary to assess the stress level before coping with it. There are so many methodologies that are used to detect stress. Inspired by psychological research stating that people feel more comfortable to express feelings on social media than through verbal communication, we are proposing a simple model to assess the stress level of an individual which can prevent psychological complications. In this paper, we propose a system similar to twitter that analyzes the stress level of an individual which can be viewed by the admin. Main emphasis is laid on stress level detection using Neural Networks and Semantic Similarity. Dataset, consisting of the stressed words is trained. Then, we find the similarity between tweet content and the trained dataset using Leacock and Chodorow's (LCH) semantic similarity between words. Results show the stress level of each individual based on his/her tweet/s.

Keywords: *Workplace Stress, Stress Level Assessment, Neural Networks, Semantic Similarity.*

INTRODUCTION

Stress is deteriorating Human health, both physical and mental. According to a survey report by Economic Times, 46% of Employees in India have one or the other form of stress. Workplace stress plays a crucial role in this. Enduring stress increases the risk of many health problems like anxiety, depression, headache, heart disease and insomnia. An individual with stress cannot be productive and efficient. Also, stress may lead to situations like suicidal tendency. So, it is the need of the hour to detect the stress in the early stages and cope with it. The traditional method of stress analysis like face to face interviews involves two people where one will ask question to stressed person and try to analyze their stress levels and impart confidence to face situations. There is a type of psychometric test which contains set of questions which have predefined answer found by survey based on which analysis is made, but this is done by an individual. As we can see all this requires some involvement of human intervention and cost.

According to psychological research, stressed people tend to be less active. So, it is difficult to know whether he is stressed or not. Some people prefer to share their feelings more on Social Media than verbal communication. Hence, user's content on social media can be analyzed to identify stress based on words and their similarity with stress based words with less human intervention.

OUR WORK

In this paper, we are proposing a methodology to identify the stress level of a user based on his/her tweets or social interactions. A social networking platform

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similar to twitter is developed where users can tweet, retweet, and follow other users. An admin has the permission to view the stress levels of the users in the network. Admin can also add stress related words to the database. Users share their feelings in the form of tweets which conveys their state of mind. Tweet content can be either textual or visual. Textual content may convey positive, negative or neutral feelings. The negative words are the stressed words that are trained as dataset. We find the semantic similarity between the tweet content and the trained dataset to detect the stress level of the user.

RELATED WORK

The quality of life decreases due to stress in our day to day activities. It can also lead to various diseases. Thus, researchers have designed various ways of detecting the stress which can be further analyzed. Many of these methods include the social interactions and the data collected from it which can provide us with a lot of useful information. Some methods detect the stress based on certain psychological characters but it needs the use of sensors which reduces the efficiency of the system[1],[2],[3],[11]. We can draw a very close relationship between psychological traits and the stress. [4]The user's phone activities can be tracked along with other parameters such as the weather conditions and other environmental conditions. But, the implementation is restricted only to multimedia applications. [5]The training data cost can be reduced significantly by using the available Twitter data. Text based features are used in many social media based stress analysis methods. An emotional analysis is performed on a Chinese social networking platform by classifying the emotions into four categories i.e., angry, disgusting, joyful and sad[8]. [6] studied the social media interactions and found that negative emotions such as stress spread more quickly compared to positive emotions. This result lets us make use of the social interactions of the users to detect and analyze stress. [7] designed a deep sparse neural network for learning the categories of stress for consolidating cross-media attributes. The method detects the psychological stress from a micro blogging site.

PROCESS FLOW

Figure 1 gives the description of the process flow that has been followed for analyzing stress level of a user.

The process flow begins with our input which will be the email id and the password. When the correct mail id and the password is entered the flow continues and encounters the decision making, here we are checking if the entered information is of a user or of the admin. If the email id turns out to be that of the user then the flow goes to where the flow encounters another decision whether the entered user exists or not. If the entered mail id does not exist, the user is given an option to create a new account of his own. If the user already has an account then the functions that the user can perform are, follow new friends to keep updated with the tweets they post or post tweets of their own or like and comment on the tweets. When, all the possible activities are done by the user then the user logs out of the account where the flow comes to an end. If the mail id belonged to the admin then the admin can perform different activities such as view all the users who have an account and the admin can also view the stress level of all the users and generate report based on the stress level. The admin can train the data set as and when it is required. When the admin is done with all the different processes then the admin logs out of the account where the flow comes to an end.

TRAINING DATASET

We are training the model with a dataset

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that consists of stress related words. This dataset has the features of stress. In general they can be termed as Negative words that convey negative feelings.

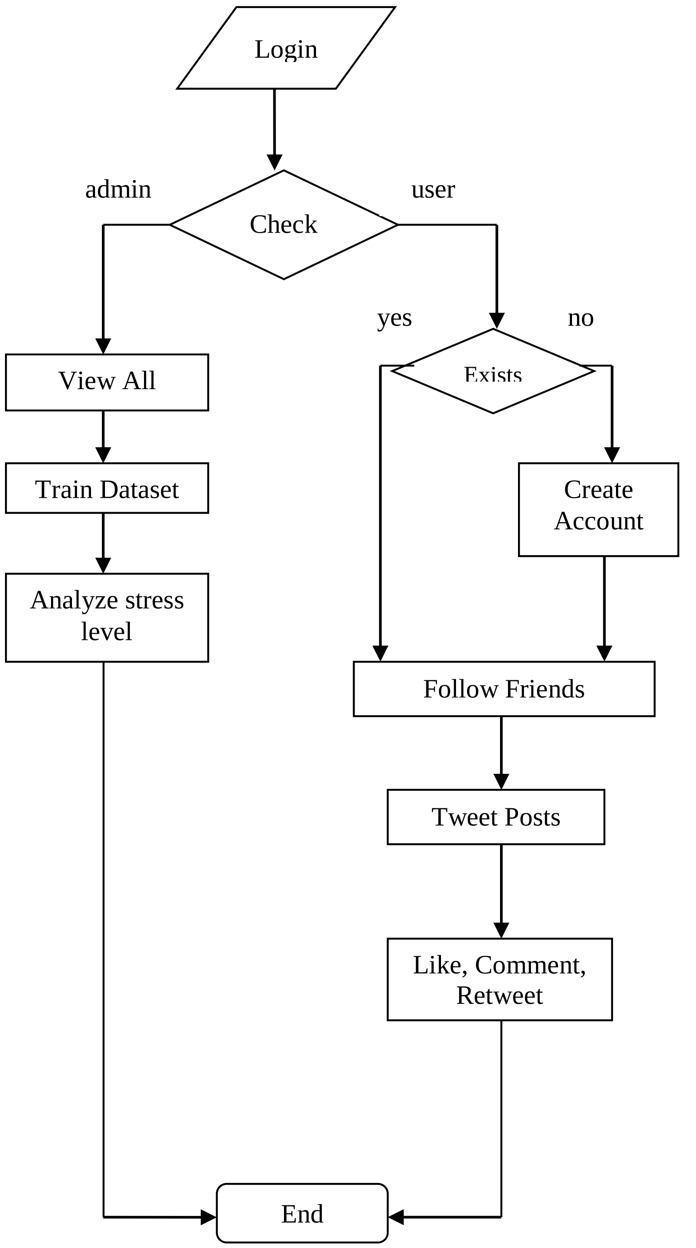

Fig: 1. *Process Flow*

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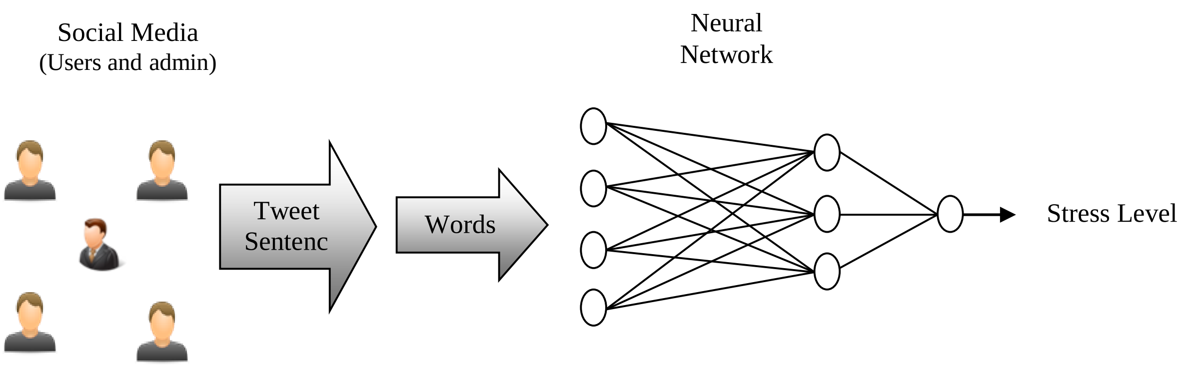

***Fig: 2.** Architecture of the Proposed System*

METHODOLOGY

A Social Media is developed similar to that of twitter. Figure 2 depicts the architecture of the proposed system. Here, a new user can sign up with his details and existing users can login with credentials. User can tweet, Retweet and follow other users. User's tweets may contain stress based words which is helpful in detecting stress. Firstly, the user's tweet sentences are split into words. Then, the semantic similarity between each word and the trained dataset word is calculated. Here, we use Leacock and Chodorow's (LCH) method to calculate the semantic similarity based on the WordNet[19]. It gives the correlation between the user's tweet and the stress based words. It is calculated by using the formula given below.

$$sim_{LC}(W1,W2) = -\ln(length(W1,W2)/2D)$$

Where, W1 is the tweet word and W2 is the dataset word. D is the taxonomy Depth. Length is the number of nodes from word W1 to W2 in the WordNet including the source and destination word. If the similarity is high, then it is classified as a stressed tweet.

Similarity of each word is summed up and divided by the number of words in the tweet. If it is above 1.5, it is considered as a stressed tweet. Else, it is considered as a normal tweet. In this way, neural networks are involved in the system.

RESULTS

For numerous tweets, Stress level was observed. Here are few examples. For the tweet "Have a nice day", similarity between these words and stress related words is found to be less. Hence, it is a normal tweet. For the tweet "sad and frustrated", similarity is found to be more and this came out to be a stressed tweet. Results for the tweets of some users are shown in Table 1.

***Table: 1.** Stress Level for Various Tweets*

User No.	***Tweet/s***	***Stress Level (%)***
1.	Have a nice day	0
2.	Sad and Frustrated	100
3.	Good Morning Have a nice day I am sad	33.33
4.	Busy schedule Worried of dull performance	50

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DISCUSSIONS

We can observe the stress level for various tweets given in the table. For users with corresponding user id, his /her tweet/s is analyzed to find the stress level. For users who have tweeted multiple times, all of their tweets are considered and stress level is calculated based on all the tweets.

CONCLUSION

Judging behavior based on online posts alone is challenging, but there are potential warning signs or indicators for self-harm or suicide. So, in our work we are analyzing peoples' stress based on social media interaction. Here we created an online Social networking site where people can create their account and post tweets on daily basis. We have maintained a dataset of negative words which helps to analyze tweets and retweets and this analysis can be viewed by the admin only. The admin can also add stressed words to the dataset. Using those results we are trying to help people with such mentality either by taking help of experts or by contacting his friends or relative who can help him out of such situation or convince him to seek some help.

FUTURE WORK

In this paper, we are just analyzing the tweet content. Further advancement can be done by adding an image processing module. According to psychological reports, even colors reflect person's mood. For example, pictures of low brightness, low saturation contrast or cool color indicate sadness and low saturation, cool color, dull color, low color difference between figure and ground, cluttered composition indicate fear and emoticon can also be analyzed [12]. As we all know, face is the mirror of our expression, we can also involve a camera module which will capture our facial expression and detect stress on timely basis. A combined model can be developed so that it can detect stress based on both social interactions and facial expressions using neural networks and Image processing algorithms respectively.

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