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Framework for analyzing stress using deep learning

Arun Kumar S
arunkumars@sapthagiri.edu.in
Sapthagiri College of Engineering, Bengaluru, Karnataka

Newby Das
newbydas754.457@gmail.com
Sapthagiri College of Engineering, Bengaluru, Karnataka

Nishchitha D S
nishchitha1020@gmail.com
Sapthagiri College of Engineering, Bengaluru, Karnataka

Ranjitha V
ranjithavelayudham@gmail.com
Sapthagiri College of Engineering, Bengaluru, Karnataka

Sahana M R
sahana.jyothi@gmail.com
Sapthagiri College of Engineering, Bengaluru, Karnataka

ABSTRACT

These days most people frequently experience stress and anxiety. Chronic and excessive stress can lead to increase in blood pressure, insomnia, heart attacks or even death. Stress has become a prevailing factor for causing mental illness agencies. The Leacock-Chorodow (LCH) algorithm, an advanced deep learning algorithm along with the WordNet library. If we do not get a control on our stress, it becomes deep-rooted and can seriously interfere with our daily activities. So, it is important to detect stress before it interferes with a person's well-being. Traditional face-to-face psychological diagnosis and treatment cannot meet the demand of peoples' stress completely due to its lack of timeliness and diversity. Nowadays the influence of Facebook, Twitter, YouTube and other social media giants has spread across modern society. People share their daily activities with friends on social media platforms. So, we create a social website where people can interact with their friends and this social media data can be used to analyze user's stress state. Our model will be useful in developing stress detection tools for health is used to detect the stressed words from a user's tweet. We subsume two types of attributes namely tweet-level content attributes where we consider each and every tweet or post made by the user and user-scope statistical attribute where the weekly tweet is taken. We propose a Deep Neural Network (DNN) model to incorporate the two types of user-scope attributes to detect users' psychological stress. Our social website can be used to detect stress based on the user's interactions with his friends and how active the user is on the social website.

Keywords: *Stress detection, Convolutional neural network, Cross autoencoders, Deep learning, Micro-blog, and social media*

1. INTRODUCTION

In today's society, we thrive on performance, competition, and perfection, which leads to an insidious increase in stress. Stress is a problem that infiltrates our society in countless ways. It manifests itself at the office, at home and in our relationships with others, and it can also affect our loved ones. These days society and the workplace put an unparalleled level of pressure on people. Stress causes damage that is often underestimated and it is a social phenomenon that should be closely examined and evaluated. Stress touches all social groups and all age categories; no one can truly escape it. Signs of stress are omnipresent and its consequences are numerous.

The latest research by workspace provider Regus[1] shows that Indian workers are getting more stressed. The survey reveals that work (51%) and personal finances (50%) are the contributing factors for the increased stressed levels of the Indian work-force. The Regus survey, canvassing the opinions of over 16,000 professionals across the globe, found that over half (51%) of Indian respondents say their stress levels have risen over the past year. Stress levels have only multiplied, thanks to a bad economic year.

Therefore, we should all take time to re-evaluate our stress-level for the well-being of ourselves and our society. With the fast development of social networks, people are widely using social-media platforms who share their thoughts and feelings. We make use of these interactions made by the users on the social media platforms to detect stress as early as possible in order to suffice the diagnosis process.

1.1 Motivation

Post-Traumatic Stress is the prime cause of many health-related problems and psychiatric disorders. Chronic stress increases the chances of developing health problems such as insomnia, obesity, heart diseases, etc. Situations that cause stress:

[1]Regus is a multinational company that offers serviced office space, virtual offices, co-working spaces, and meeting rooms in centers across the world.
[2] http://tinyurl.com/htunr9g

failure to meet deadlines, paying bills, increasing family responsibilities and juggling childcare that makes the body react, the body's natural alarm system - the flight response may be stuck in the on-position can have a major effect on peoples' health. This can have serious consequences on health. So, it is necessary to root out stress for intensive care. According to a worldwide survey reported by *New business* in 2010[2] over half of the population has experienced an appreciable rise in stress over the last two years. The Chinese Center for Disease Control and Prevention notifies that suicide has become the chief cause of death among Chinese youths. Unrestrained stress is considered to be a prominent factor for suicides.

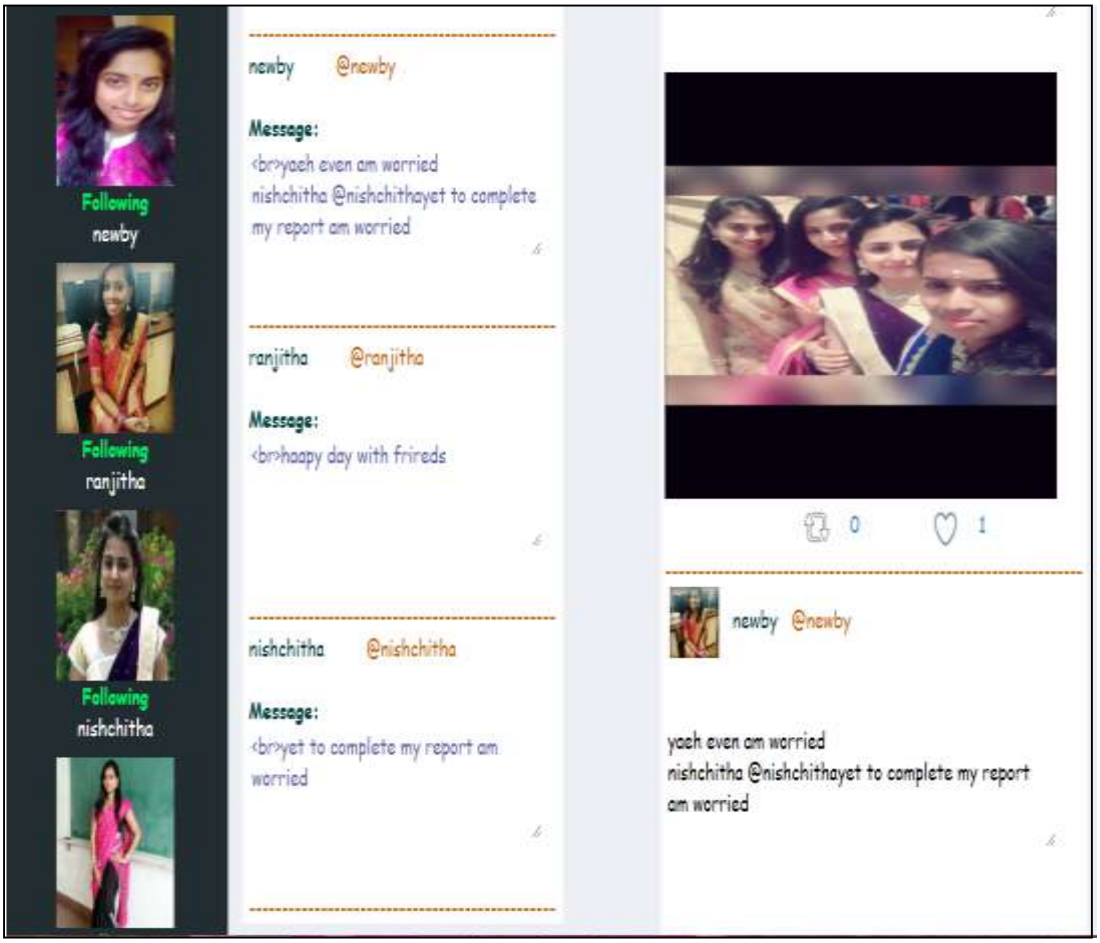

Fig. 1: Sample tweets from the website that is created. We can observe in the figure the stressed words such as "worried", "low", "sad" have been used which are indicators of stress. The words such as "bre*k" will be automatically encoded to the correct word i.e. "break".

Recent developments in technologies for social networks that help to leverage the process of stress detection. With the popularity of social networks, people are extensively using the social media platforms to express their feelings and thoughts. A statistic report from statisticbrain.com (http://www.statisticbrain.com/twitter-statistics/) shows that by 2014.1.1, the total number of active registered users on Twitter has reached more than 645 million, with an average of 58 million tweets posted per day. As per Sina Weibo, the number of web users has reached more than 600 million (http://www.comsoc.org/blog?page=3). Linguistic and visual contents that may indicate stress-related symptoms can be obtained, which makes the detection of users' psychological stress through their tweets and posting patterns from micro-blog feasible.

Inferring Social Ties in Large Networks. As many large-scale online social networks are successful such as Facebook, MySpace and Twitter and the quick rise for mobile social networks such as FourSquare (which has 6 million registered users by the end of 2010), the online social network have connected our real daily life with the virtual web space. In social media, people don't spend the time to label their relationships (example: friends, siblings, colleagues, etc.). The major goal is to determine the factors that are needed to know the type of the social relationships. Detecting the relationship semantics makes online social networks colorful and closer to our real physical networks. It represents a new research direction in social network analysis.

1.2 Our Work

Micro-blogs are one of the most publicly accessible popular social media. In this paper, we investigate the possibility of using the social media to detect the user's psychological stress. We first define the set of attributes for stress detection from the tweet-level and the user-level perspectives. On the website that is created, users can post text no more than 144 words, re-tweet, and comment on the already existing post and have social interactions. Accessing the real world data from the social media platform we first explore the correlations between users' stress and their social interactions. Two types of stress-related attributes are defined: a) user-level attributes summarized from a user's weekly tweets and b) tweet-level attributes from a user's single tweet. We address our 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 structural differences in terms of structural diversity, social influence, and strong/weak tie. In this paper we propose a novel hybrid model using LCH algorithm from deep learning concept to leverage tweet content and social interaction information for stress detection.

The contributions of this paper are as follows.

- We propose a novel model using the LCH algorithm in the Deep learning concept to leverage both the tweet content attributes and the social interactions to enhance stress detection.
- We build several stressed posting datasets as well as non-stressed datasets in order to thoroughly evaluate our proposed model with respect to various aspects.
- We can also conduct a survey using the graphs and pie charts based on individual user and multiple user aspects provided by our model.

It is found that the number of social structures of sparse connection of stressed users is higher than that of non-stressed users, indicating that the social structure of stressed users' friends tends to be less connected and less complicated than that of non-stressed users. Therefore, there is a high probability that users tend to become less active when the stress level is high.

2. RELATED WORK

2.1. Research on Deep learning approaches for cross-media data modeling.

Immense researches on deep learning show that there is a surpassing ability of Deep Neural Network (DNN) in learning features from a large set of unlabeled data [5-7]. [8-9] further extends the deep models for multimodal learning. Micro-blog data is a typical cross-media data. The objects may come from a variety of sources and sensations. It is very strenuous to handle the heterogeneous cross-media data. [10] Models a cross-media learning method, which is based on DNN and helps the model for detecting psychological states and corresponding categories from a single tweet. Anyways, stress is a continuous state compared to prompt emotions notifying that the stress stated can last for several days in psychology.

2.2. Research on detection of user's personality/behavior using social networks.

"Personality Profiling" is the process of using the writing styles of authors in order to detect their personality traits. Myers Briggs Type Indicator (MBTI) is a personality topology which is used by many people to analyze their own personalities and to talk about the results online. [11] a novel corpus tweets annotated with MBTI personality type and gender of their author for six Western European languages is presented. It contains personality and gender annotations for a total of 18,168 authors spanning six languages (Dutch, German, French, Italian, Portuguese and Spanish). It is freely available at http://www.clipsuantwerpen.be/datasets.

Social media is a place where users express themselves to the world, disclosing personal details and insights into their lives. Personality is relevant to many types of user-to-user interactions, it is also useful in anticipating job satisfaction, professional and romantic relationship success, etc. [12] attempts to bridge the vocabulary gap between social media and personality research by utilizing the information people reveal in their online profiles. [2] Uses an inductive, theory building methodology to develop propositions regarding how effectuation processes are impacted when entrepreneurs adopt Twitter. Twitter-based interaction can trigger effectual cognitions.

2.3. Research on existing methods for stress detection.

In recent years many attempts have been devoted for developing convenient tools for individual stress detection. Widespread devices such as personal computers and mobile phones have been used by researchers for routinely detecting stress. [13] Enquired the initial lab evidence of the use of a computer mouse in the detection of stress. [14] Proposed Stress Sense to unassumingly identify stress from human voice using smartphones.

3. INPUT AND OUTPUT DESIGN SPECIFICATIONS

3.1 Input Design

The input design is the link between the information system and the user. Input Design considered the following things:

- What data should be given as input?
- How should the data be arranged or coded?
- The dialog to guide the operating personnel in providing input.
- Methods for preparing input validations and steps to follow when error occurs.

3.2 Objective

1. Input Design is the process of converting a user-oriented description of the input into a computer-based system. This design is important to avoid errors in the data input process and show the correct direction to the management for getting correct information from the computerized system.
2. It is achieved by creating user-friendly screens for the data entry to handle a large volume of data. The goal of designing input is to make data entry easier and to be free from errors. The data entry screen is designed in such a way that all the data manipulates can be performed. It also provides record viewing facilities.
3. When the data is entered it will check for its validity. Data can be entered with the help of screens. Appropriate messages are provided as for when needed so that the user will not be in maize of instant. Thus the objective of input design is to create an input layout that is easy to follow

3.3 Output Design

A quality output is one, which meets the requirements of the end user and presents the information clearly. Efficient and intelligent output design improves the system's relationship to help user decision-making.

1. Designing computer output should proceed in an organized, well thought out manner; the right output must be developed while ensuring that each output element is designed so that people will find the system can use easily and effectively. When analysis design computer output, they should Identify the specific output that is needed to meet the requirements.
2. Select methods for presenting information.
3. Create document, report, or other formats that contain information produced by the system.

The output form of an information system should accomplish one or more of the following objectives.

- Convey information about past activities, current status or projections of the future.
- Signal important events, opportunities, problems, or warnings.
- Trigger an action.
- Confirm an action.

4. MODULES CATEGORIZATION

In this paper to address the problem of stress detection three modules have been mainly defined in order to measure the differences of stressed and non-stressed users on social media platforms: System Framework, Social Interactions and Attributes categorization.

4.1 System Framework:

In this framework we propose a novel hybrid model - a factor graph model combined with Convolution 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.

4.2 Social Interactions:

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. Our investigation unveils some intriguing social phenomena. For example, we find that the number of social structures of sparse connection (i.e. with no delta connections4) of stressed users is around 14% higher than that of non-stressed users, indicating that the social structure of stressed users' friends tends to be less connected and complicated, compared to that of non-stressed users.

4.3 Attributes categorization

We first define two sets of attributes to measure the differences of the stressed and non-stressed users on social media platforms: namely tweet-level attributes from a user's single tweet and user level attributes summarized from a user's weekly tweets.

ATTRIBUTES

- **Tweet-level Attributes**
    - **(a)Linguistic**
    - **(b)Social**
    - **(c)Visual**
- **User-level Attributes**
    - **(a)Posting-behavior Attributes**
    - **(b)Social-interaction Attributes**
        - **i. Social-interaction content**
        - **ii. Social-interaction structure**

4.3.1 Tweet-level Attributes

Tweet-level attributes describe the linguistic and visual content, as well as social attention factors (being liked, commented, and re-tweeted) of a single tweet. We can classify words into different categories, e.g. positive/negative emotion words, degree adverbs. Furthermore, we extract linguistic attributes of emoticons, so we can map the keyword in square brackets to find the emoticons. Twitter adopts Unicode as the representation for all emojis, which can be extracted directly.

4.3.2 User-Level Attributes

Compared to tweet-level attributes extracted from a single tweet, user-level attributes are extracted from a list of user's tweets in a specific sampling period. We use one week as the sampling period in this paper. On one hand, psychological stress often results from cumulative events or mental states. On the other hand, users may express their chronic stress in a series of tweets rather than one. Besides, the aforementioned social interaction patterns of users over a period of time also contain useful information for stress detection. Moreover, as aforementioned, the information in tweets is limited and sparse. We need to integrate more complementary information around tweets, e.g., users' social interactions with friends.

5. ARCHITECTURE

According to existing research works, long-term stress has been found to be related to many diseases, e.g., High Blood Pressure, aging, clinical depressions, insomnia etc. Moreover, according to Disease Control and Prevention, suicide is the main cause of death among youths. All these reveal that the rapid increase of stress has become a great challenge to human health and life quality.

Psychological stress detection, two challenges always exist. One is how to use the user-level attributes in order to extract the user's tweeting series and also how to deal with the problem of the absence of modality in the tweets. The other is how to leverage social interactions, inclusive of the interactive content and the structure patterns, to aid in the stress detection process. In order to handle these problems, we introduce a novel model using the LCH Algorithm from the Deep Learning concept.

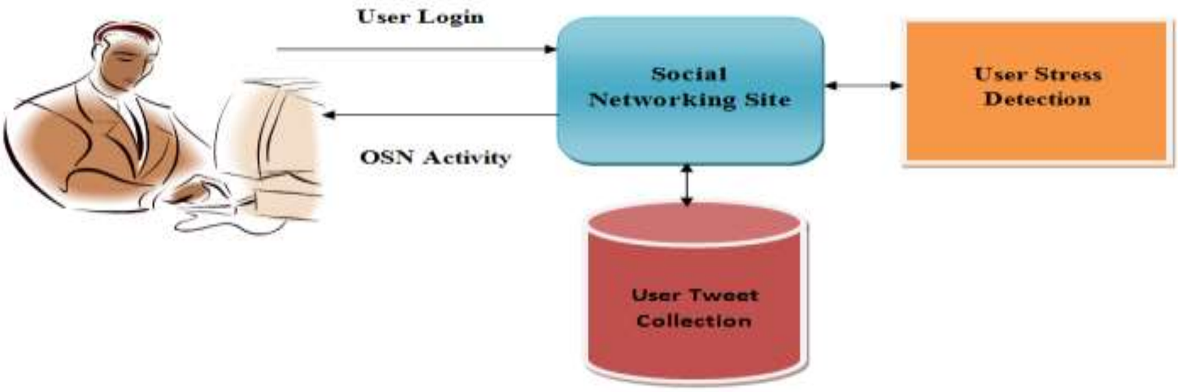

Fig. 2: Design of the Stress-detection System Architecture

The system architecture shown above summarizes the following steps:

- The user first logs into the social networking site that has been developed. If the user doesn't have an account, then he must first create an account by providing the necessary information.
- Once the user logs in he can view all the posts that have been made by him as well as the post made by the other users.
- He can like as well as comment on the posts made by other users.
- The tweets/posts made by these users are stored in the database.
- In turn, this collection can be used to leverage the Stress detection process (where the LCH algorithm is used internally and comparisons are made between the user tweet contents and the trained stressed words).

Contributions to the field:

- Our proposed scheme improves the accuracy of stress detection rate.
- Our scheme improves the speed of detection of stress compared to any of the existing solutions
- This can be applied in the field of any organization human resource department, social media, etc.
- It can also be used in social media profiles.

CROSS AUTO ENCODERS (CAE)

CAE's are used to generate user-level content attributes from tweet-level attributes. It is also used to reduce the noise from the tweets for example: if the tweet consists of the word bre*k, it is automatically encoded to break. Rather than summarizing the user's state alone, we further incorporate the detail attributes with multiple modalities of every tweet by utilizing a recently proposed cross-media model, namely the Cross Auto-Encoders (CAE).

6. SYSTEM DESIGN

6.1 Data-flow diagram

If the user logs into the system then he can make posts, re-post, comment and like on the posts made by other users, whereas if the admin logs into the system then he can make comparisons of the user's interactions and contents with the dataset that he has already trained into the system. The admin can view individual user stress states and overall users stress states.

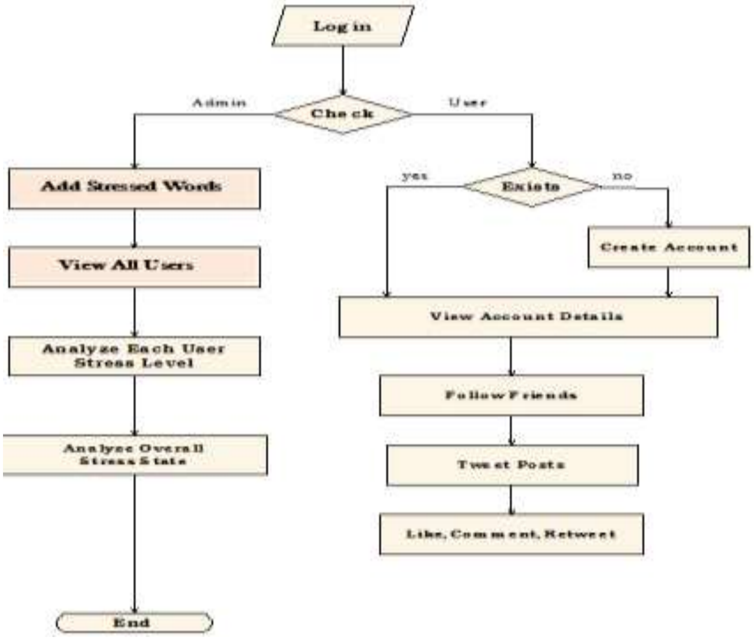

Fig. 3: The data-flow diagram representing the sequence of actions that are happening when the user first logs into the system until the stress states of the user have been detected.

6.2 UML diagrams
UML stands for Unified Modeling Language. The Primary goals in the design of the UML are as follows:
- It provides an expressive visual modeling language so that meaning full model can be developed and exchanged.
- Provide extendibility and specialization mechanisms to extend the core concepts.
- Be independent of particular programming languages and development process.
- Provide a formal basis for understanding the modeling language.
- Encourage the growth of OO tools market.
- Support higher level development concepts such as collaborations, frameworks, patterns, and components.
- It integrates the best practices.

6.3 Use Case Diagram
A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals, and any dependencies between those use cases. It tells what system functions are performed for which actor. Roles of the actors in the system can be illustrated.

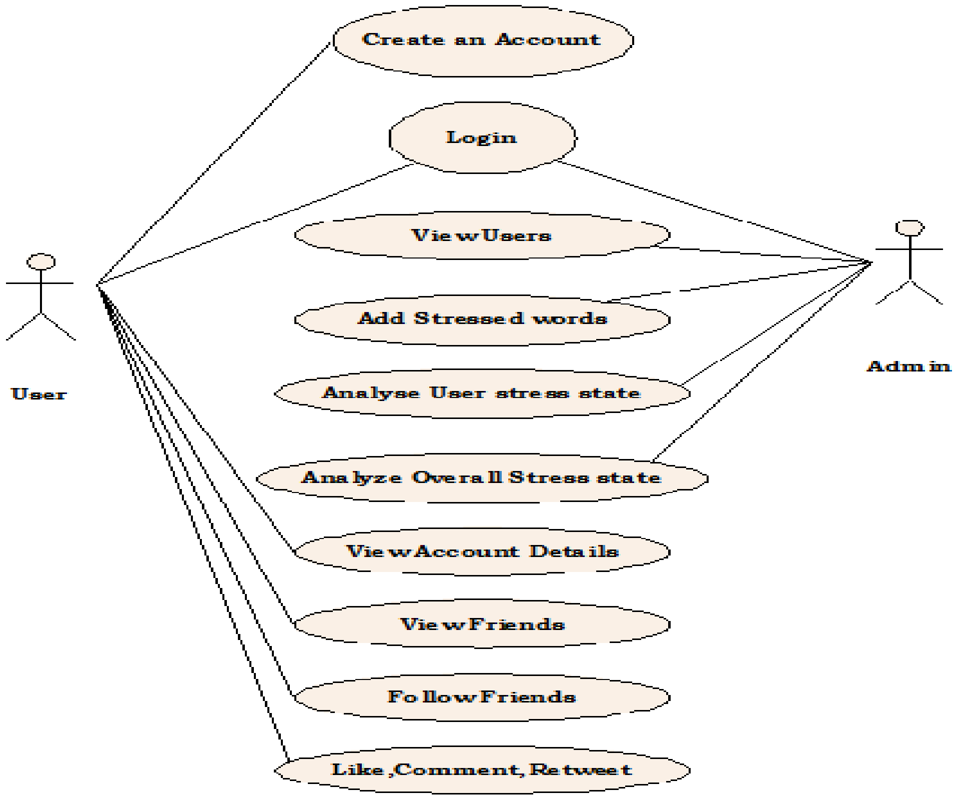

Fig. 4: A use case diagram depicting the functions that are performed by the corresponding actors (user and admin).

6.4 Class Diagram
In software engineering, a class diagram in the Unified Modeling Language (UML) describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information. Admin functions are View User Details(), View User Stress State(), Overall Stress State(), Add Stressed words(). User functions are View Account Details(), View Friends(), Follow Friends(), Tweet, Retweet, Like, Comment, Post().

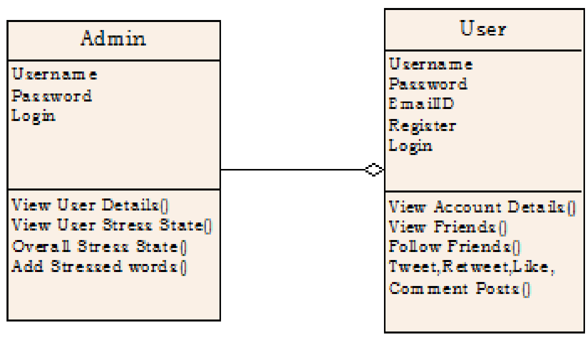

Fig. 5: A Class Diagram representing the various classes, attributes, and operations with respect to our model.

6.5 Sequence Diagram
A sequence diagram in Unified Modeling Language (UML) is an interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and timing diagrams.

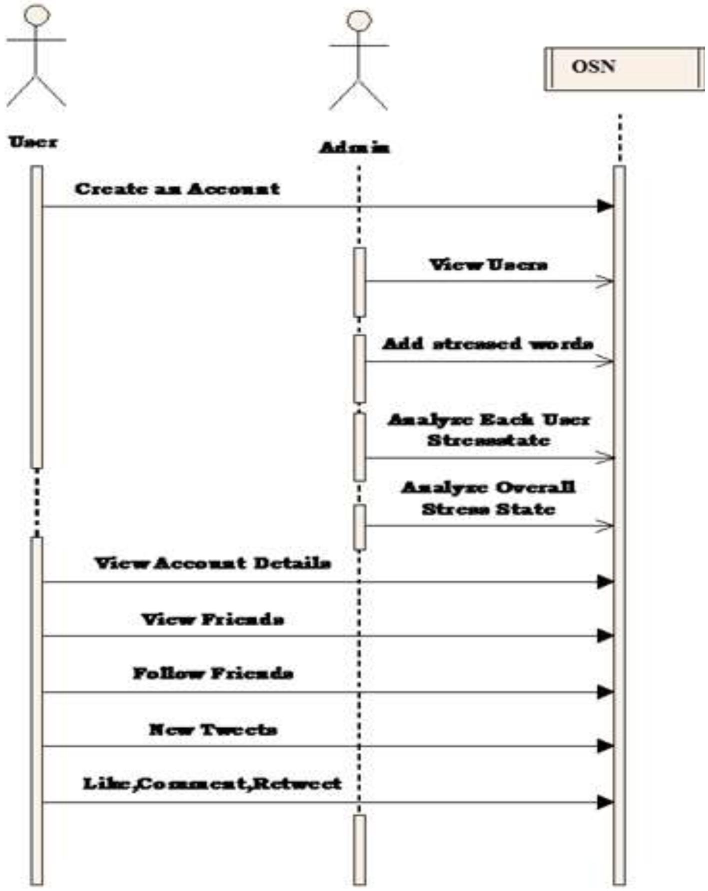

Fig. 6: A Sequence Diagram depicting how the control flows through the various sections of our system when the actor performs certain executions.

6.6 Activity Diagram

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration, and concurrency. An activity diagram shows the overall flow of control. Here when a person logins it is checked whether a person is an admin or a user. If he is an admin then he can view all users, he can train the machine, analyze each users' stress state and analyze the overall stress state. If he is a user software checks whether he has already registered or not, if not he needs to register by entering his personal details. After registering the user can view his profile and he can interact with his friends and post the pictures.

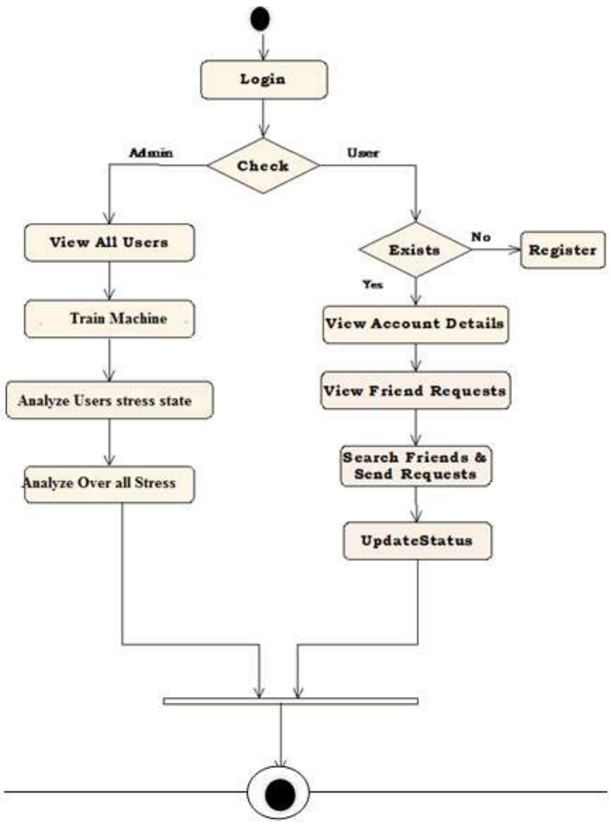

Fig. 7: An activity diagram representing the workflow of the components in our system.

7. RESULTS

The result is evaluated using datasets from the MySQL database. We make use of three attributes namely: user-level social interaction attributes, user-level posting behavior attributes and user-level content-attributes generated from the tweet-level attributes by DNN + CAE. The results for the various datasets are as shown in the figures depicted below.

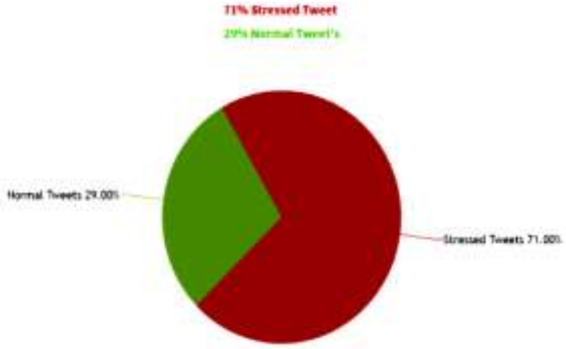

Fig. 8: A sample test result of individual user that indicates the stress-level which is predicted from the user's tweet contents.

In the pie chart, it can be implied that there are 29% of normal tweets (as indicated in green) and 71% of stressed tweets (as indicated in red) that have been made by the user.

Fig. 9: A sample test result of overall stress levels of all the users who interact using the created website.

In the bar, graph red indicates the percentage of the stressed-tweets and green indicates the percentage of the normal tweets made by the user. This clearly indicates that the percentage of stressed tweets is high which in turn implies that the stress level of users is increasing with the current lifestyle of people.

8. CONCLUSION

In this paper, we make use of micro-blog data to detect user-level psychological stress. We make use of negative tweets such as “feeling low” to detect the stress-level of the user. Firstly we define two sets of attributes to measure the ratio of the stressed and non-stressed users on social media platforms: 1) tweet-level attributes from a user’s single tweet; 2) user level attributes summarized from a user’s weekly tweets. Then a Deep Neural Network, LCH Algorithm with cross-auto encoders is designed to encapsulate weekly low-level content attributes and generate user-scope attributes.

We test the model on the datasets from the micro-blog that has been designed. In this work, we also discovered several intriguing phenomena of stress. We found that the number of social structures of sparse connection of stressed users is higher than that of non-stressed users, which means that stressed users tend to interact less with their friends than that of non-stressed users.

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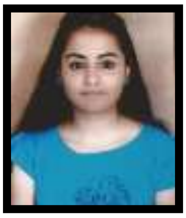
BIOGRAPHY

Arun Kumar S
Assistant Professor
Computer Science & Engineering
Sapthagiri College of Engineering
Bengaluru

Newby Das
Student (B. E.)
Computer Science & Engineering
Sapthagiri College of Engineering
Bengaluru

Nishchitha D S
Student (B. E.)
Computer Science & Engineering
Sapthagiri College of Engineering
Bengaluru



Ranjitha V
Student (B. E.)
Computer Science & Engineering
Sapthagiri College of Engineering
Bengaluru

Sahana M R
Student (B. E.)
Computer Science & Engineering
Sapthagiri College of Engineering
Bengaluru