DETECTING STRESS BASED ON SOCIAL INTERACTIONS IN SOCIAL MEDIA

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ABSTRACT

Psychological stress is threatening people's health. It is non-trivial to detect stress timely for proactive care. With the growing use of social networking platforms like Facebook, Twitter, and Instagram have become central to how people communicate and express themselves such as their posts, comments, and messages. These interactions can reveal much about a person's emotional state, including stress. Here we use computer algorithms to study patterns in their online behavior, like changes in tone or frequency of posts, and interactions with friends. This approach can help in providing early warnings and support for those experiencing stress. We find that users stress state is closely related to that of his/her friends in social media, and 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, and then propose a novel hybrid model - a factor graph model combined with Convolutional Neural Network to leverage tweet content and social interaction information for stress detection.

1 INTRODUCTION

Psychological stress is becoming a threat to people's health nowadays. With the rapid pace of life, more and more people are feeling stressed. According to a worldwide survey reported by new business over half of the population has stress over the last two years. Though stress itself is non-clinical and common in our life, excessive and chronic stress can be rather harmful to people's physical and mental health. According to existing research works, long-term stress has been found to be related to many diseases, e.g., clinical depressions, insomnia etc. All these reveal that the rapid increase of stress has become a great challenge to human health and life quality.

Thus, there is significant importance to detect stress before it turns into severe problems. 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 and time-costing. Are there any timely and proactive methods for stress detection? more and more people are willing to share their daily events and moods, and interact with friends through the social networks.

Daily stress recognition from mobile phone data, weather conditions and individual traits:

Research has proven that stress reduces quality of life and causes many diseases. For this reason, several researchers devised stress detection systems based on physiological parameters. However, these systems require that obtrusive sensors are continuously carried by the user. In our paper, we propose an alternative approach providing evidence that daily stress can be reliably recognized based on behavioral metrics, derived from the user's mobile phone activity and from additional indicators, such as the weather conditions (data pertaining to transitory properties of the environment) and the personality traits (data concerning permanent dispositions of individuals). Our multifactorial statistical model, which is person-independent, obtains the accuracy score of 72.28% for a 2-class daily stress recognition problem. The model is efficient to implement for most of multimedia applications due to highly reduced low-dimensional feature space (32d). Moreover, we identify and discuss the indicators which have strong predictive Power.

3 IMPLEMENTATION STUDY

3.1 Existing System:

- Rapid increase of stress has become a great challenge to human health and life quality. Thus, there is significant importance to detect stress before it turns into severe problem.
- Traditional psychological Stress detection is mainly based on face-to face interviews, self-report questionnaires
- There are also some research works, using user tweeting contents on social media platforms to detect users psychological stress.
- Users social interactions on social networks contain useful cues for stress detection.

Disadvantages of Existing System:

- There are no timely and proactive methods for stress detection.
- Firstly, tweets are limited to a maximum of 140 characters on social platforms like Twitter and users do not always express their stressful states directly in tweets.
- Users with high psychological stress may exhibit low activeness on social networks, as reported by a recent study.

3.2 Proposed System:

- Inspired by 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, and 2) **user-level attributes** from user's weekly tweets.
- Here, we define user-level attributes from two aspects to measure the differences between stressed and non-stressed states based on users' weekly tweet postings: 1) user-level posting behavior attributes from the user's weekly tweet postings; and 2) user-level social interaction attributes from the user's social interactions his/her weekly tweet postings.

Advantages of Proposed System:

- We presented a framework for detecting users psychological stress states from users weekly social media data, leveraging tweets content as well as users social interactions.
- Employing real-world social media data as the basis, we studied the correlation between user psychological stress states and their social interaction behaviors.
- we proposed a hybrid model which combines the factor graph model (FGM) with a convolutional neural network (CNN).

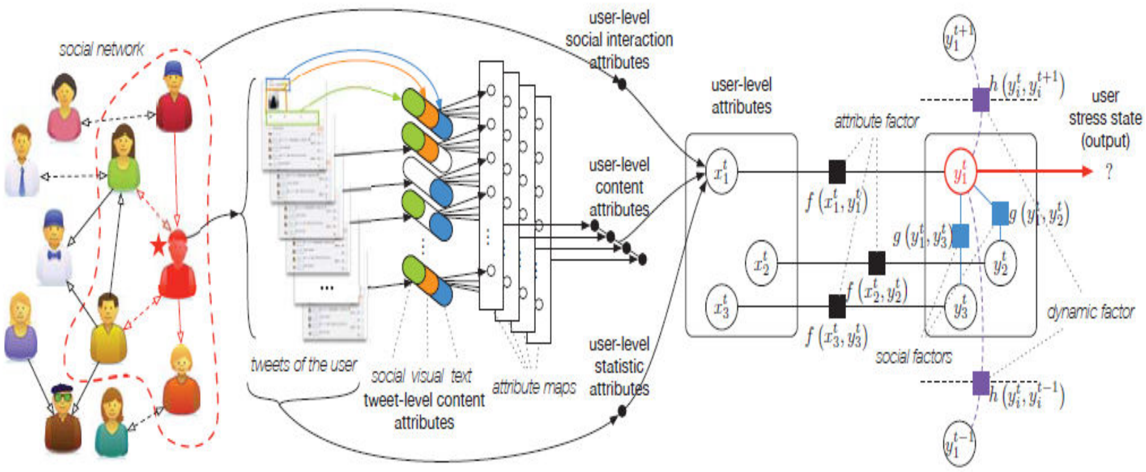

Fig1: SYSTEM ARCHITECTURE

. IMPLEMENTATION

4.1 Modules:

- Social Interactions

- Attributes categorization
- Tweet-level Attributes
- User-Level Attributes

Modules Description:

Social Interactions:

The Social interaction module helps to detect stress by looking at how people interact on social media.

Module description:

Data Collector: It collects the data like posts, comments, likes and messages from social media.

Features Extracted: It looks at

- Frequency: How often someone posts or comments.
- Engagement: How many likes and comments their posts get
- Sentiment: Whether their posts and comments are positive or negative
- Interaction patterns: Changes in how they interact in over time

Analysis and Detection:

- Indicators: It looks for signs of stress like frequent negative posts or less interaction with others.
- Pattern Recognition: It notices changes in behavior that might indicate stress.
- Real-time Monitoring: It can keep an eye on social interactions in real-time and update stress levels.

Attributes categorization

We first define two sets of attributes to measure the differences 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.

5 RESULTS AND DISCUSSION

Screenshorts

5.3.1 Home Page:

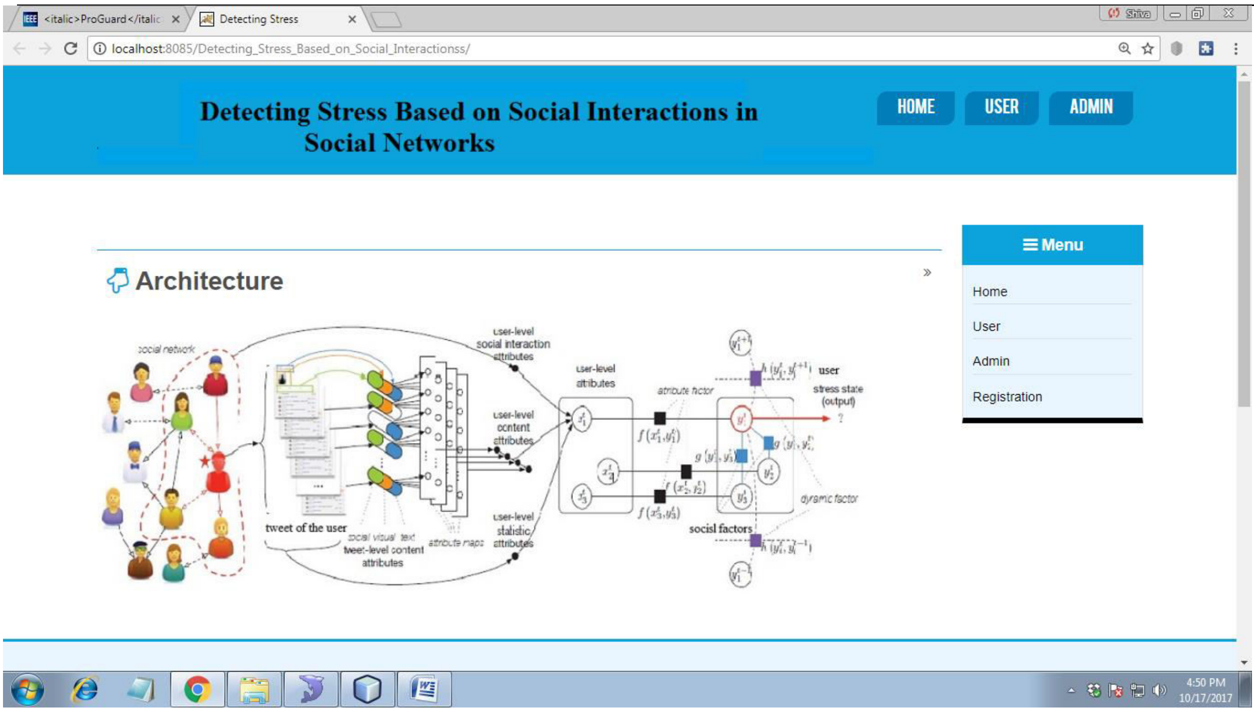

Fig: 5.1 Home Page- Screenshot

5.3.2 Admin login:

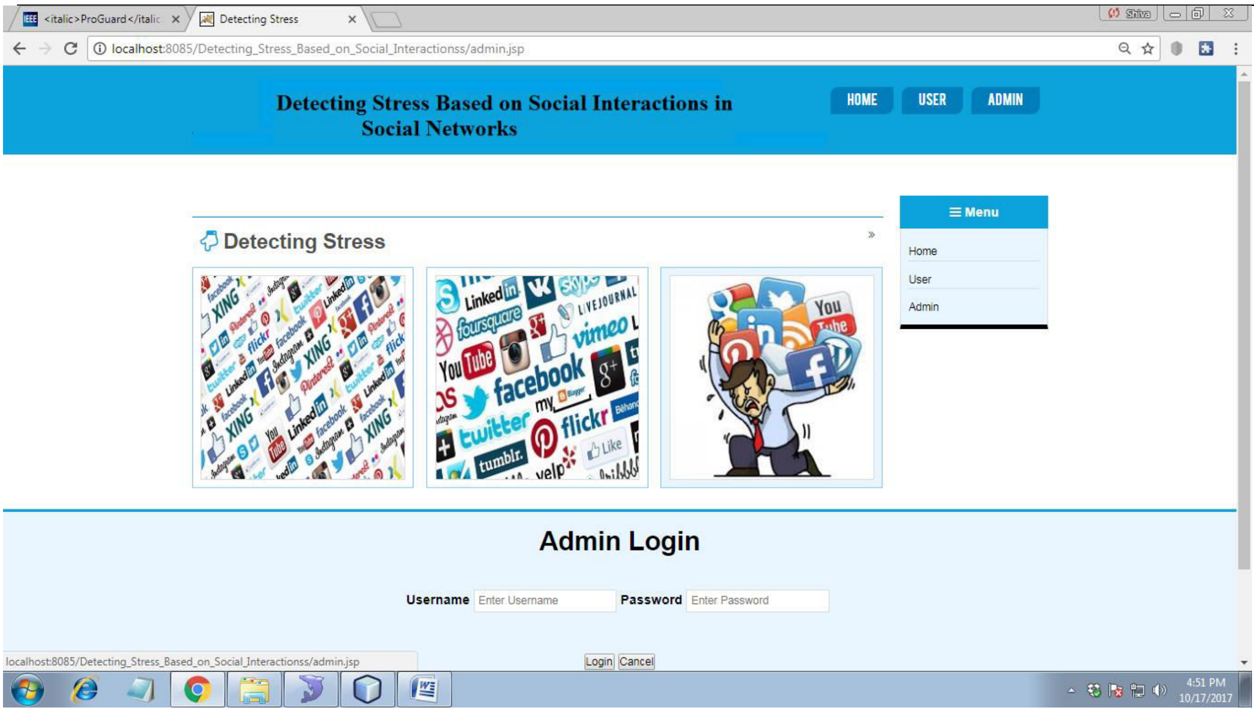

Fig: 5.2 Admin Login- Screenshot

5.3.3 Admin home:

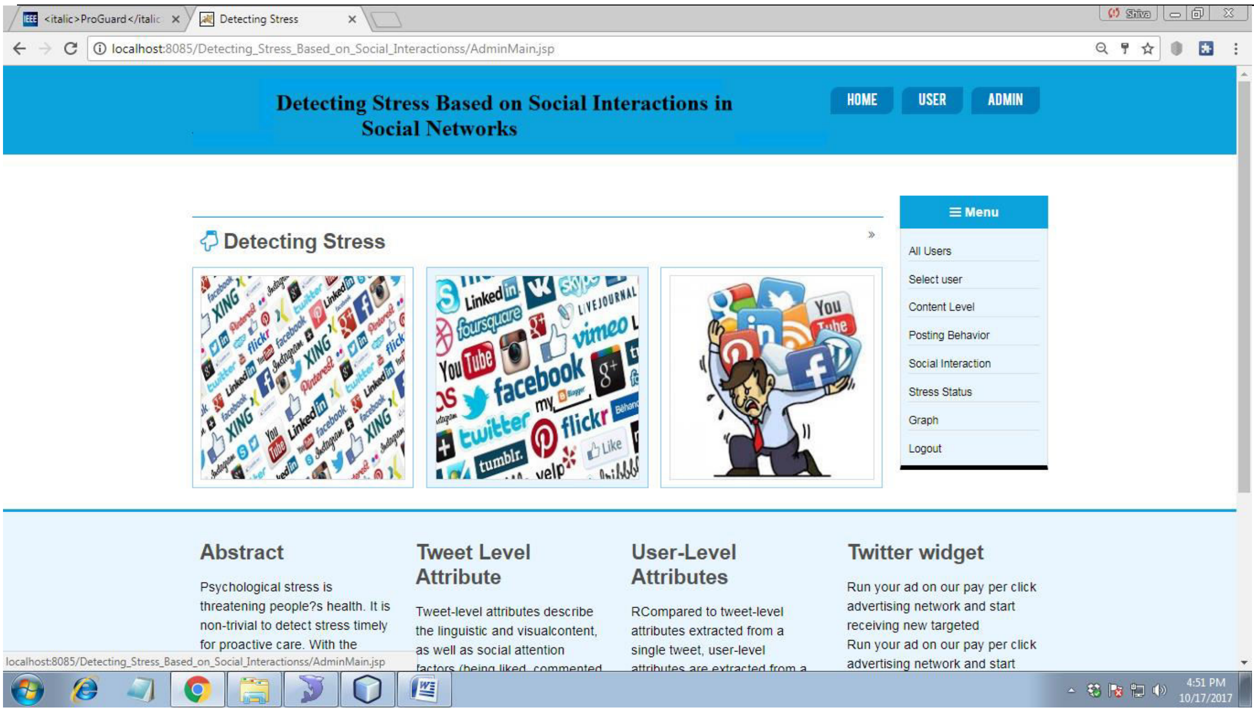

Fig: 5.3 Admin Home- Screenshot

5.3.4 Select user:

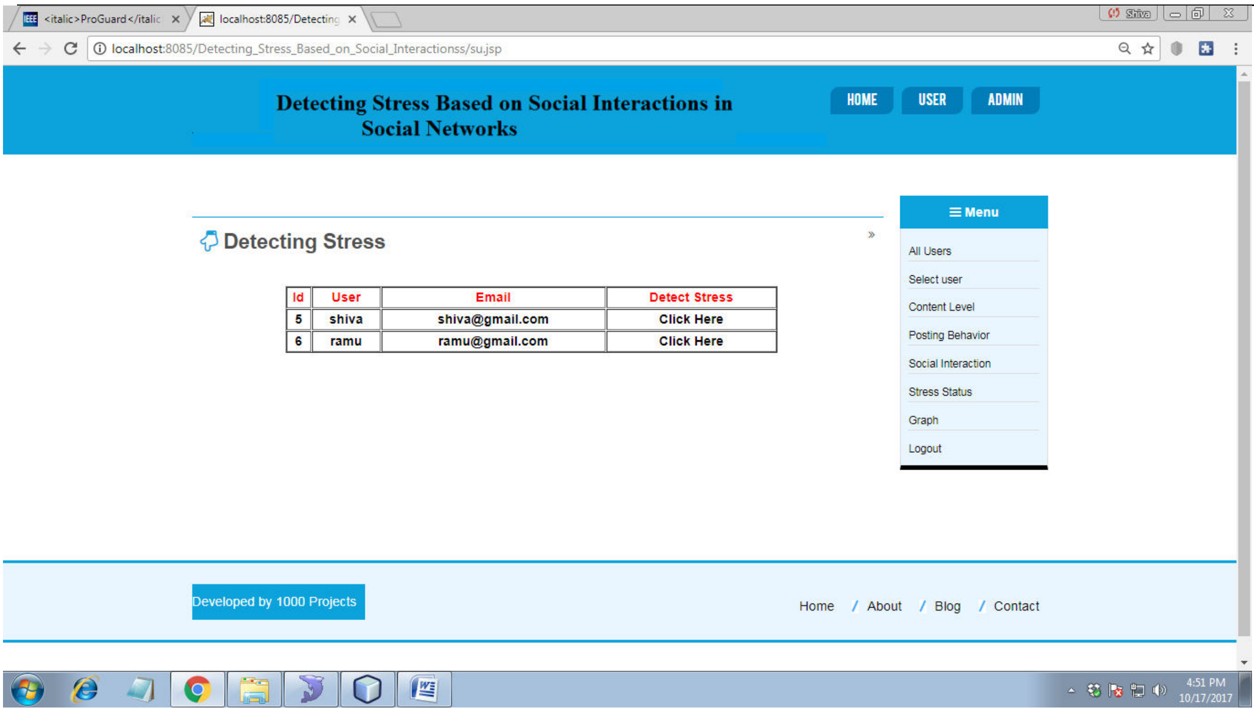

Fig: 5.4 Select User- Screenshot

5.3.5 Content level:

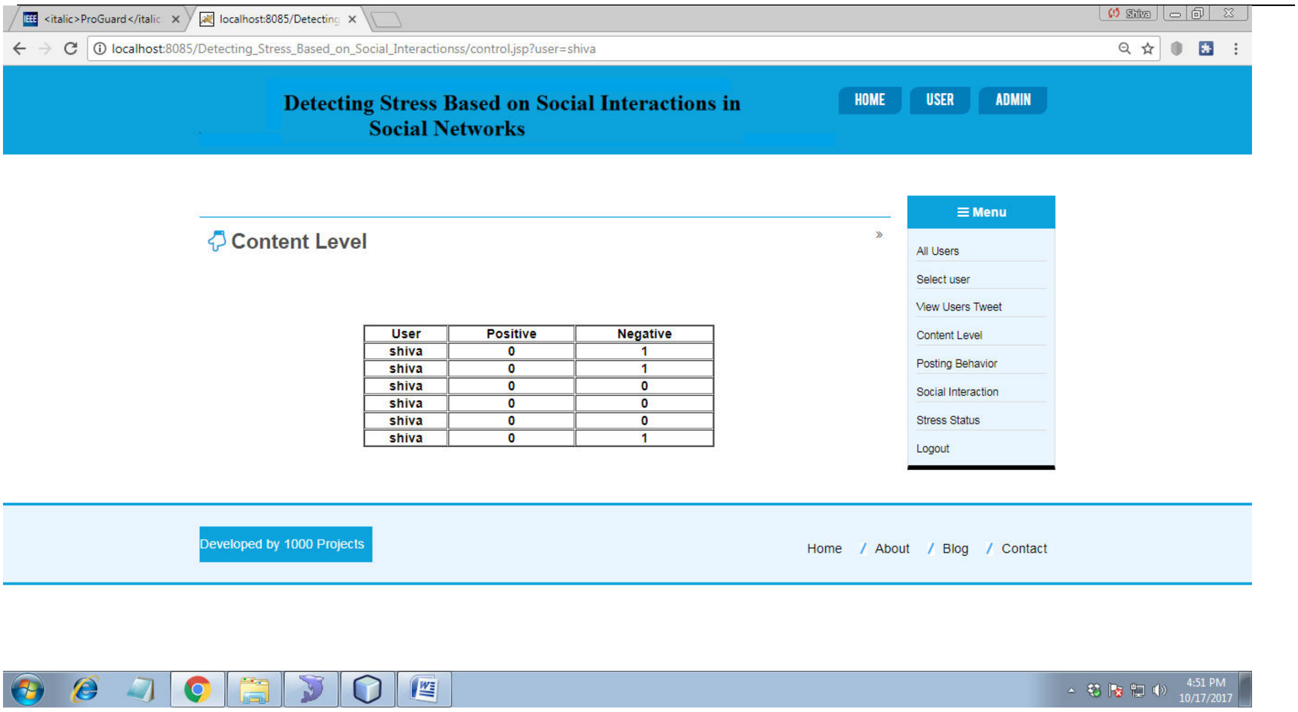

Fig: 5.5 Content Level- Screenshot

5.3.6 Posting behavior:

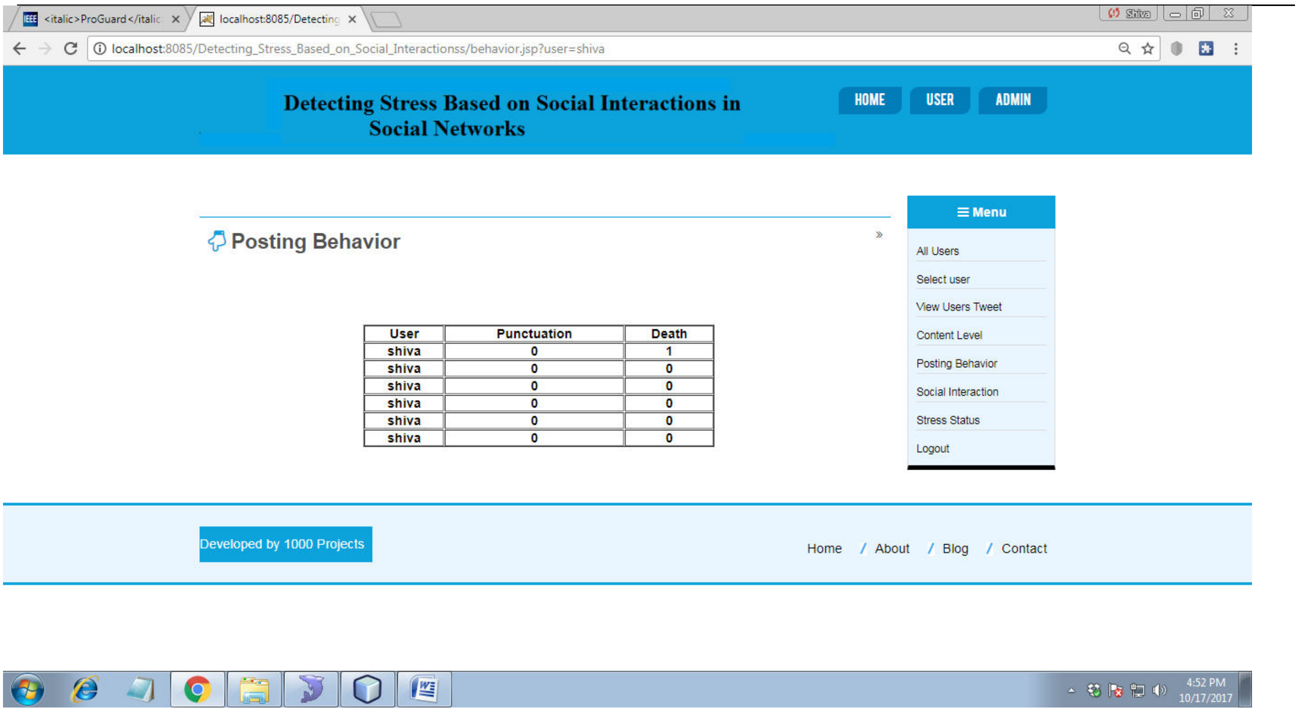

Fig: 5.6 Posting Behavior- Screenshot

5.3.7 Social interactions:

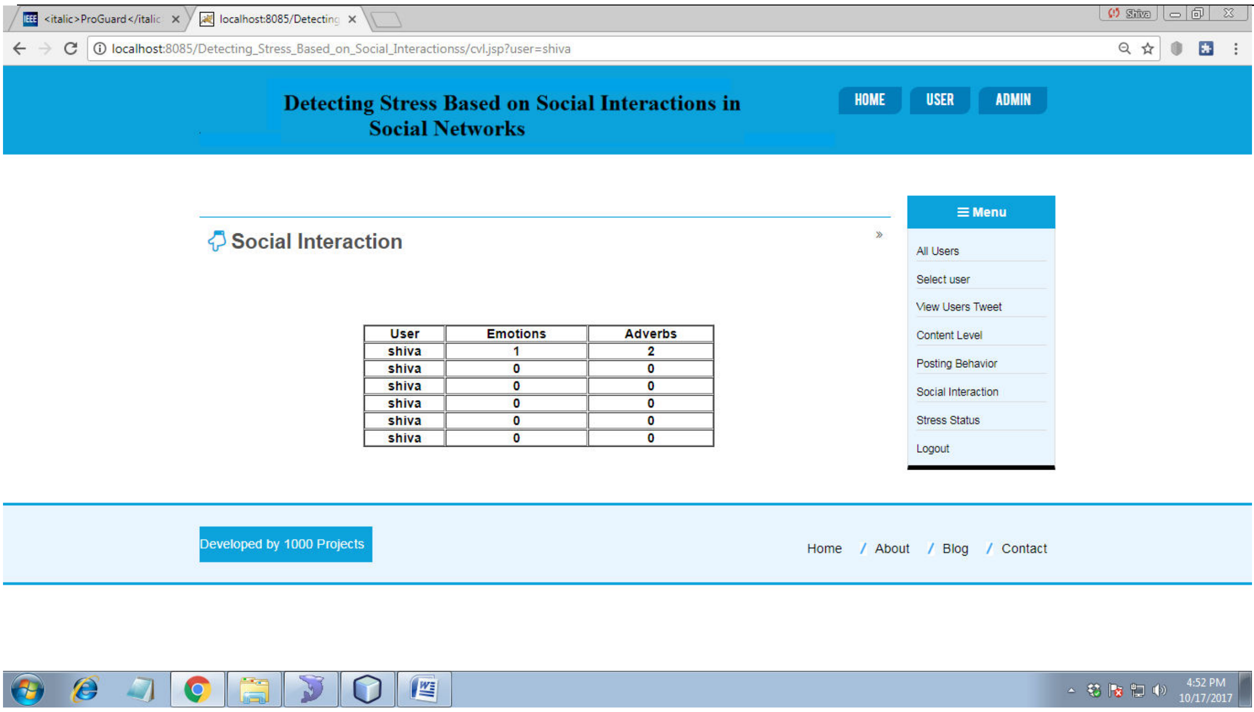

Fig: 5.7 social Interaction- Screenshot

5.3.8 Stress status:

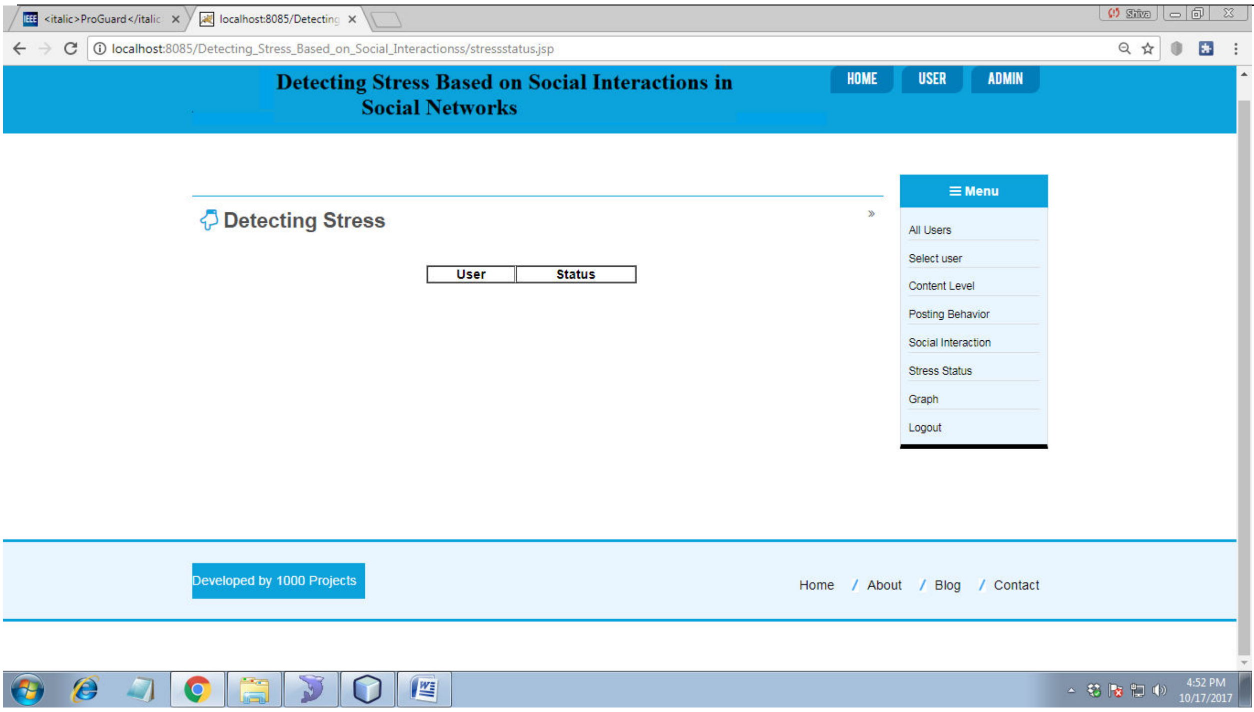

Fig: 5.8 Stress Status- Screenshot

5.3.9 User registration:

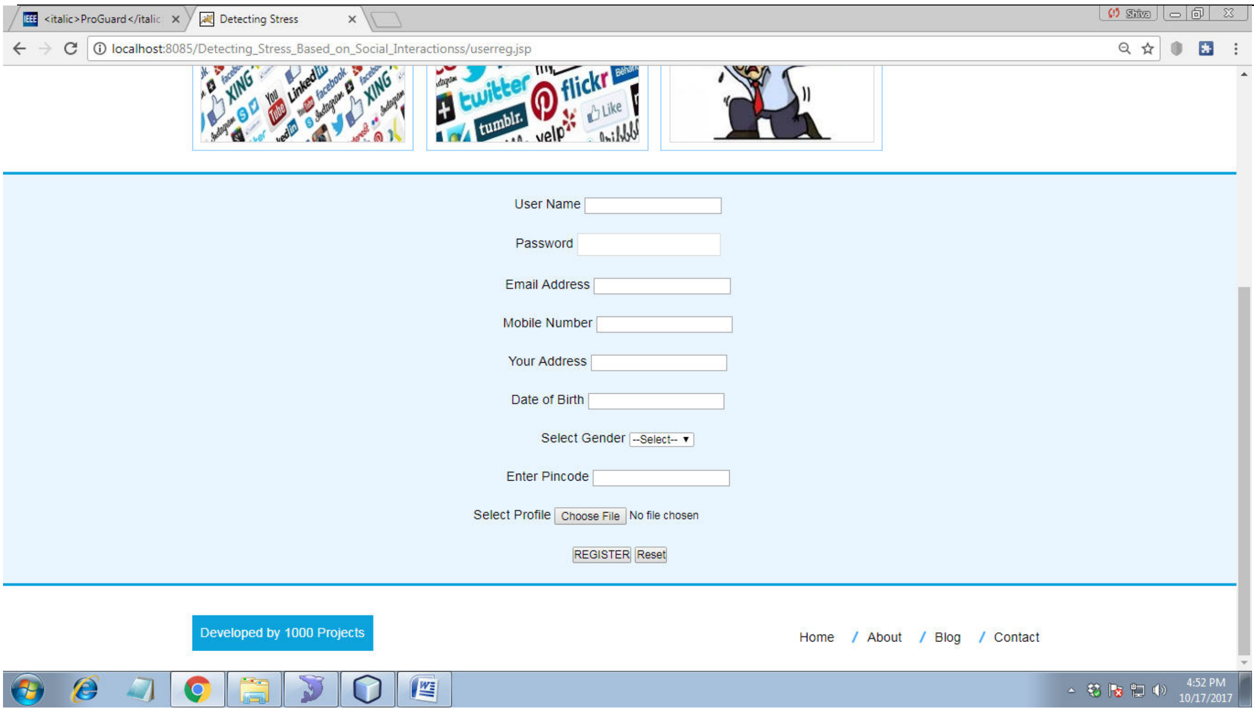

Fig: 5.9 User Registration- Screenshot

5.3.10 User login:

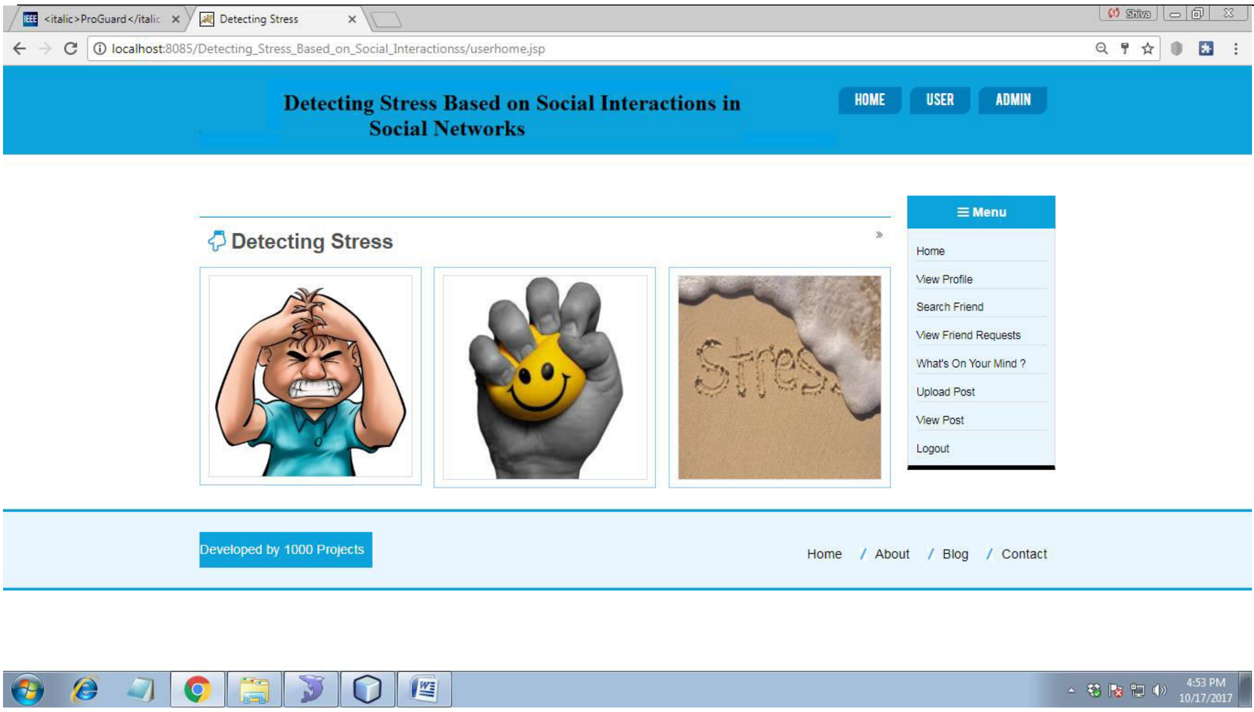

Fig: 5.10 User Login- Screenshot

5.3.11 User home:

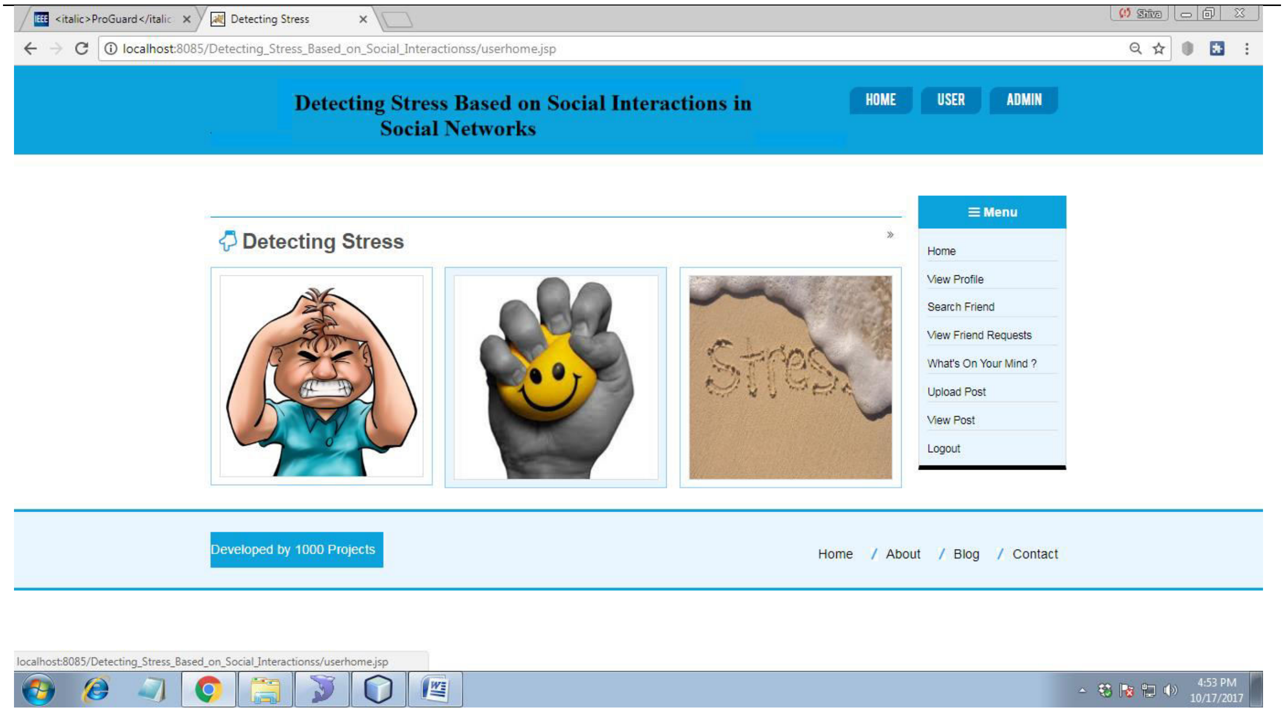

Fig: 5.11 User Home- Screenshot

5.3.12 View profile:

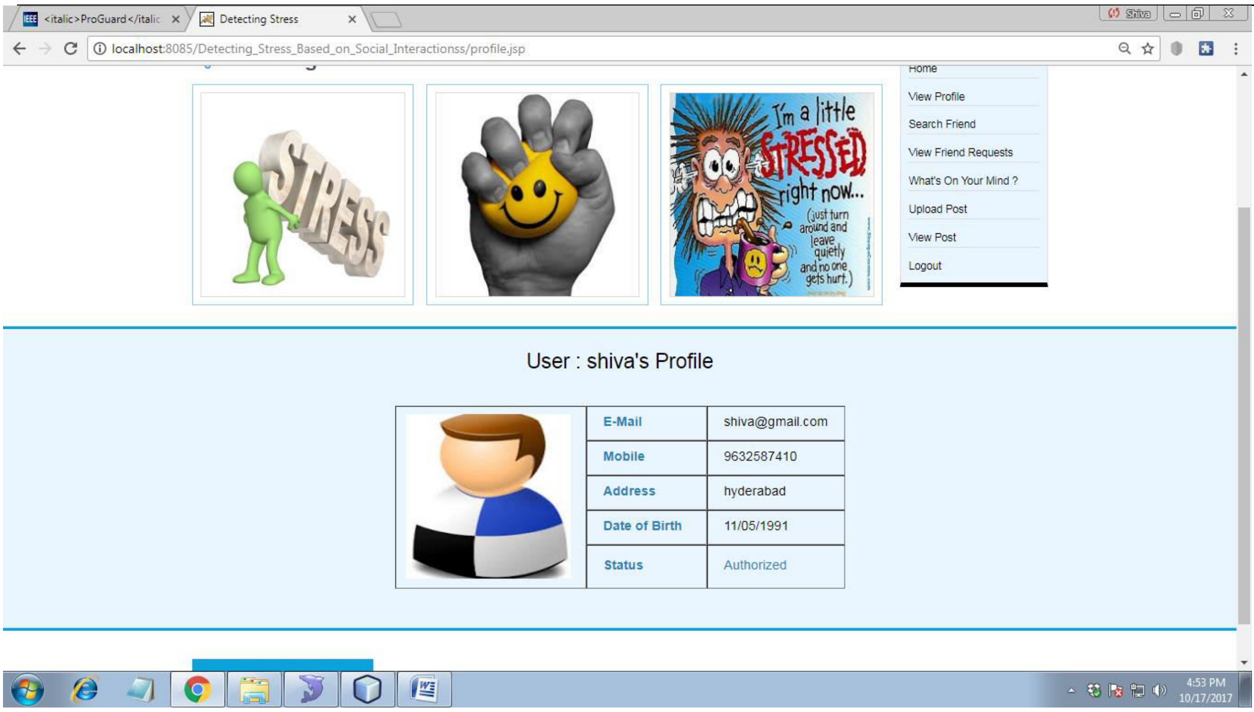

Fig: 5.12 View Profile- Screenshot

5.3.13 Search friend:

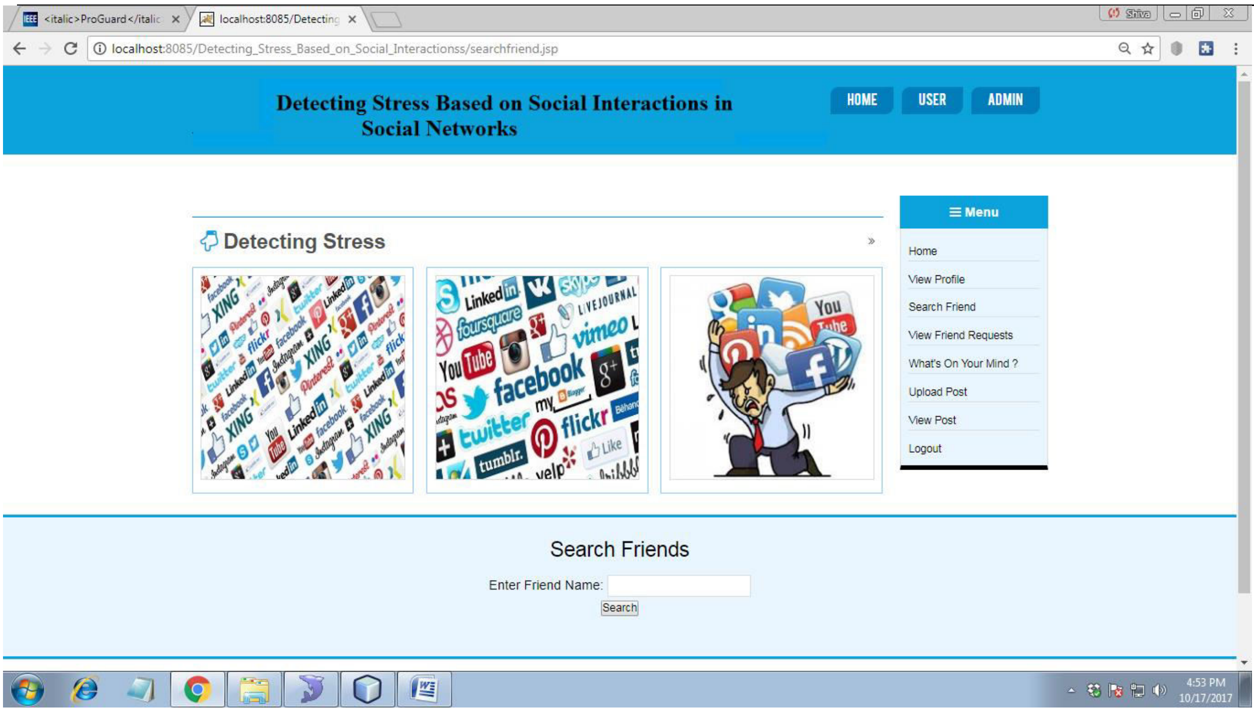

Fig: 5.13 Search Friend- Screenshot

5.3.14 View friend request:

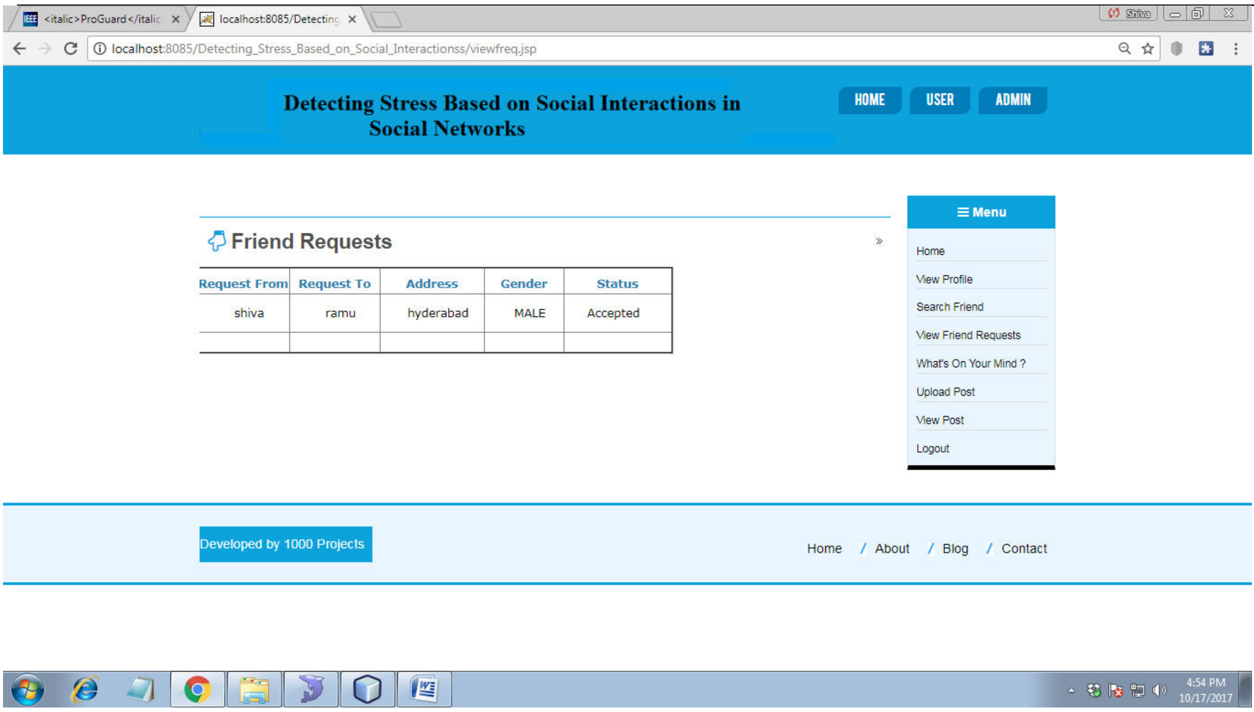

Fig: 5.14 View Friend Request- Screenshot

5.3.15 What's on your mind:

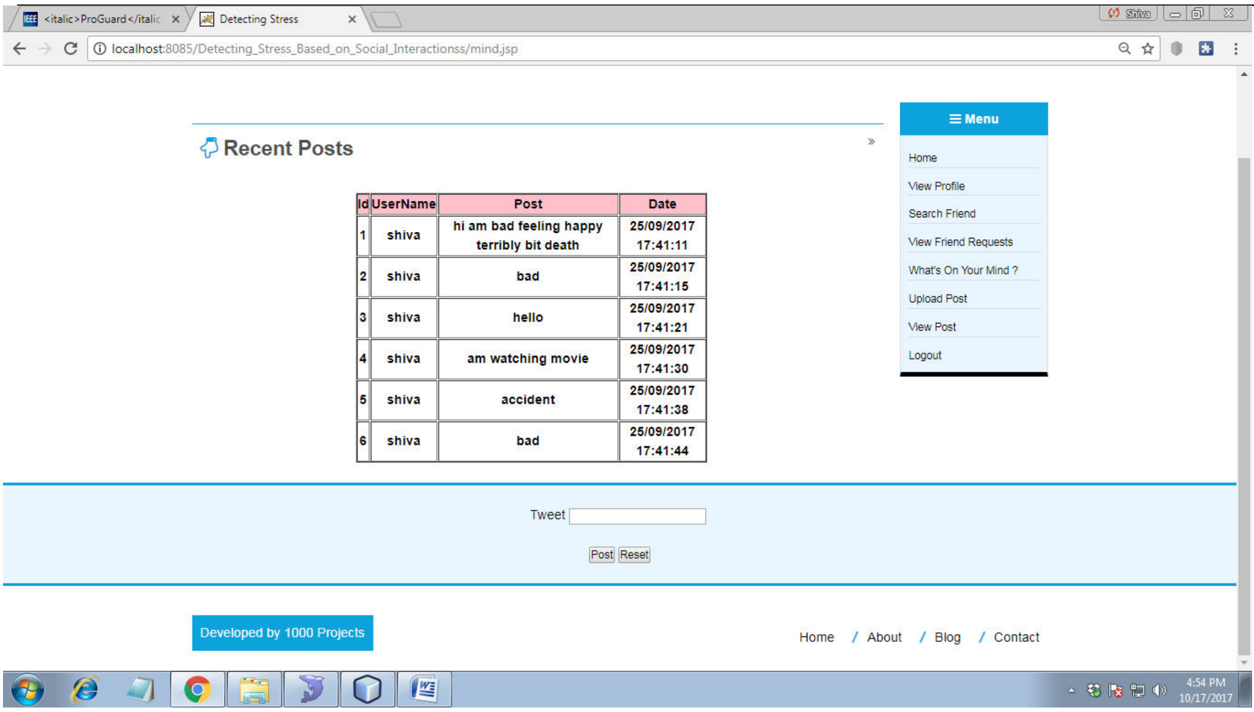

Fig: 5.15 what's on your mind-Screenshot

5.3.16 Upload post:

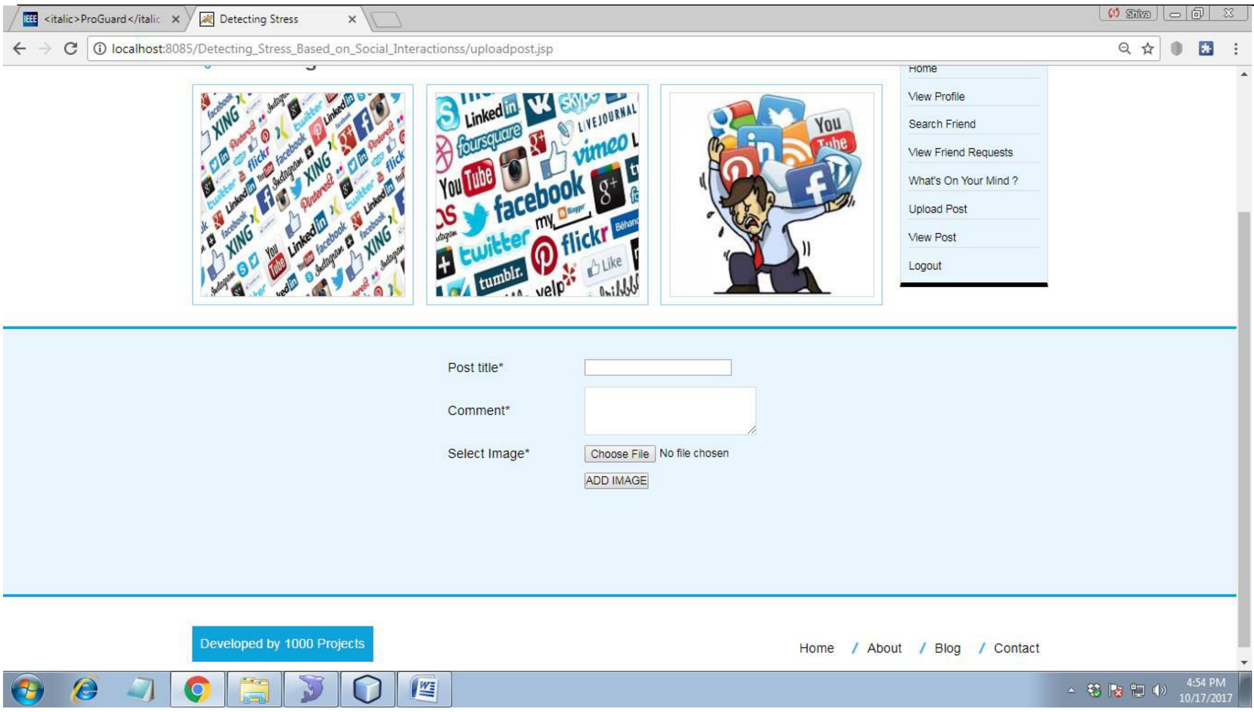

Fig: 5.16 upload Post- Screenshot

5.3.17 View post:

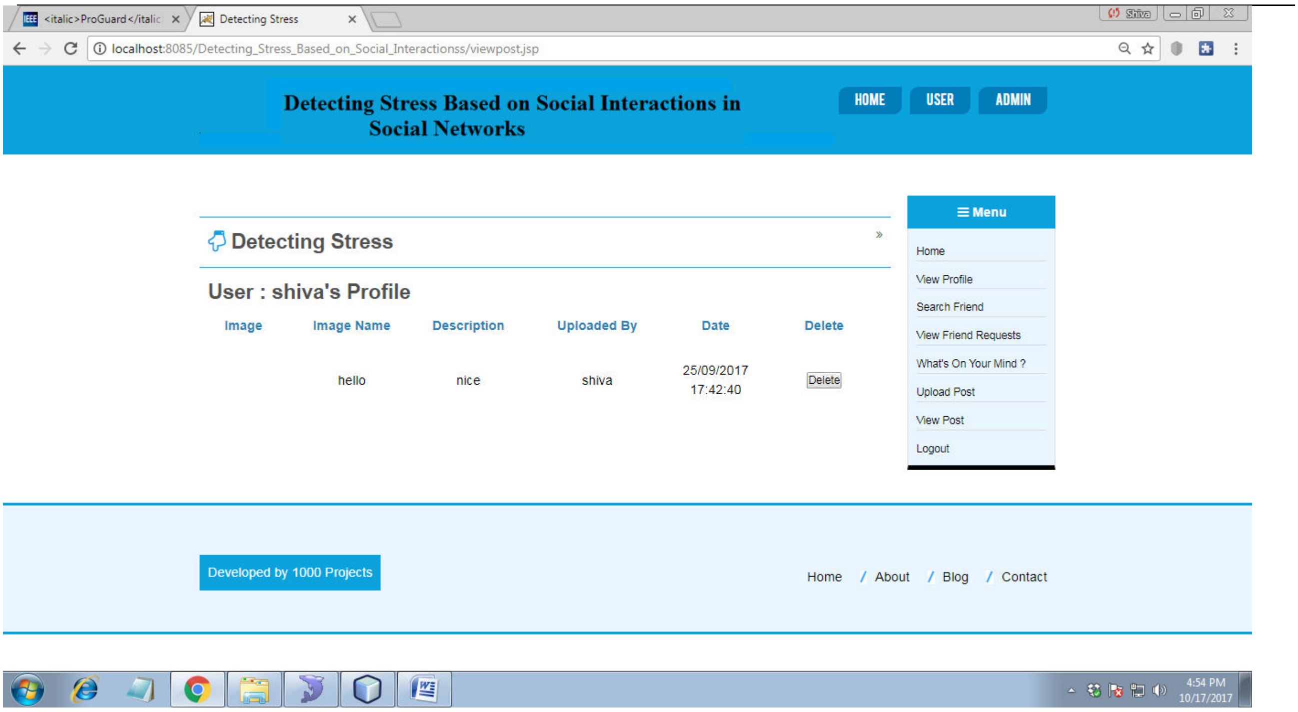

Fig: 5.17 View Post- Screenshot

6. CONCLUSION AND FUTURE WORK

In this paper, we presented a framework for detecting users ‘psychological stress states from users’ weekly social media data, leveraging tweets’ content as well as users’ social interactions. Employing real-world social media data as the basis, we studied the correlation between user’ psychological stress states and their social interaction behaviors. To fully leverage both content and social interaction information of users’ tweets, we proposed a hybrid model which combines the factor graph model (FGM) with a convolution neural Network (CNN).

In this work, we also discovered several intriguing phenomena of stress. We found that the number of social structures of sparse connection (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. These phenomena could be useful references for future related studies.

7. REFRENCES

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