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STRESS DETECTION IN IT PROFESSIONAL BY IMAGE PROCESSING AND MACHINE LEARNING

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ABSTRACT: - The main motive of our project is to detect stress in the IT professionals using vivid Machine learning and Image processing techniques. Our system is an upgraded version of the old stress detection systems which excluded the live detection and the personal counseling but this system comprises of live detection and periodic analysis of employees and detecting physical as well as mental stress levels in his/her by providing them with proper remedies for managing stress by providing survey form periodically. Our system mainly focuses on managing stress and making the working environment healthy and spontaneous for the employees and to get the best out of them during working hours.

Index Terms—Stress detection, micro-blog, social media, social interaction , factor graph model.

I. INTRODUCTION Stress management systems play a significant role to detect the stress levels which disrupts our socio economic lifestyle. As World Health Organization (WHO) says, Stress is a mental health problem affecting the life of one in four citizens. Human stress leads to mental as well as socio-fiscal problems, lack of clarity in work, poor working relationship, depression and finally commitment of suicide in severe cases. This demands counselling to be provided for the stressed individuals cope up against stress. Stress avoidance is impossible but preventive actions helps to overcome the stress. Currently, only medical and physiological experts can determine whether one is under depressed state (stressed) or not. One of the traditional method to detect stress is based on questionnaire. This method completely depends on the answers given by the individuals, people will be tremulous to say whether they are stressed or normal. Automatic detection of stress minimizes the risk of health issues and improves the welfare of the society. This paves the way for the necessity of a scientific tool, which uses physiological signals thereby automating the detection of stress levels in individuals. Stress detection is discussed in various literatures as it is a significant societal contribution that enhances the lifestyle of individuals. Ghaderi et al. analysed stress using Respiration, Heart rate (HR), facial electromyography (EMG), Galvanic skin response (GSR) foot and GSR hand data with a conclusion that, features pertaining to respiration process are substantial in stress detection. Maria Viqueira et al. describes mental stress prediction using a standalone stress sensing hardware by interfacing GSR as the only physiological sensor . David Liu et al. proposed a research to predict stress levels solely from Electrocardiogram (ECG). Multimodal sensor efficacy to detect stress of working people is experimentally discussed in . This employs the sensor data from sensors such as pressure distribution, HR,Blood Volume Pulse (BVP) and Electrodermal activity (EDA). An eye tracker sensor is also used which systematically analyses the eye movements with the stressors like Stroop word test and information related to pickup tasks.The authors of performed perceived stress detection by a set of non-invasive sensors which

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collects the physiological signals such as ECG , GSR, Electroencephalography (EEG), EMG, and Saturation of peripheral oxygen (SpO2). Continuous stress levels are estimated using the physiological sensor data such as GSR, EMG, HR, Respiration in. The stress detection is carried out effectively using Skin conductance level (SCL), HR, Facial EMG sensors by creating ICT related Stressors. Automated stress detection is made possible by several pattern recognition algorithms. Every sensor data is compared with a stress index which is a threshold value used for detecting the stress level. The authors of collected data from 16 individuals under four stressor conditions which were tested with Bayesian Network, J48 algorithm and Sequential Minimal Optimization (SMO) algorithm for predicting stress. Statistical features of heart rate, GSR , frequency domain features of heart rate and its variability (HRV), and the power spectral components of ECG were used to govern the stress levels. Various features are extracted from the commonly used physiological signals such as ECG, EMG, GSR, BVP etc., measured using appropriate sensors and selected features are grouped into clusters for further detection of anxiety levels . In, it is concluded that smaller clusters result in better balance in stress detection using the selected General Regression Neural Network (GRNN) model. This results in the fact that different combinations of the extracted features from the sensor signals provide better solutions to predict the continuous anxiety level. Frequency domain features like LF power (low frequency power from 0.04 Hz to0.15Hz), HF power (High frequency power from 0.15Hz to 0.4 Hz) , LF/HF (ratio of LF to the HF). and time domain features like Mean , Median, standard deviation of heart signal are considered for continuous real time stress detection in . Classification using decision tree such as PLDA is performed using two stressors namely pickup task and stroop based word test wherein the authors concluded that the stressor based classification proves unsatisfactory. In 2016, Gjoreski et al. created laboratory based stress detection classifiers from ECG signal and HRV features. Features of ECG are analysed using GRNN model to measure the stress level. Heart rate variability (HRV) features and RR (cycle length variability interval length between two successive Rs) interval features are used to classify the stress level. It is noticed that Support Vector Machine (SVM) was used as the classification algorithm predominantly due to its generalization ability and sound mathematical background Various kernels were used to develop models using SVM and it is concluded in that a linear SVM on both ECG frequency features and HRV features performed best, outperforming other model choices. Nowadays as IT industries are setting a new peek in the market by bringing new technologies and products in the market. In this study, the stress levels in employees are also noticed to raise the bar high. Though there are many organizations who provide mental health related schemes for their employees but the issue is far from control. In this paper we try to go in the depth of this problem by trying to detect the stress patterns in the working employee in the companies we would like to apply image processing and machine learning techniques to analyze stress patterns and to narrow down the factors that strongly determine the stress levels. Machine Learning algorithms like KNN classifiers are applied to classify stress. Image Processing is used at the initial stage for detection, the employee‟s image is clicked by the camera which serves as input. In order to get an enhanced image or to extract some useful information from it image processing is used by converting image into digital form and performing some operations on it. By taking input as an image from video frames and output may be image or characteristics associated with that image. Image processing basically includes the following three steps: that is based on image analysis. System gets the ability to automatically learn and improve from self-experiences without being explicitly programmed using Machine learning which is an application of artificial intelligence (AI). Computer programs are developed by Machine

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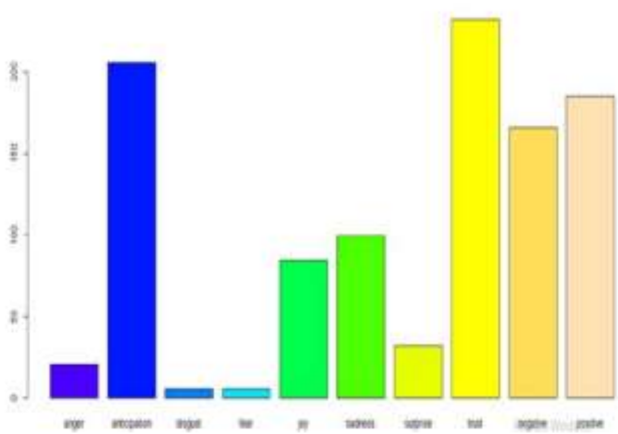
Learning that can access data and use it to learn for themselves. Explicit programming to perform the task based on predictions or decisions builds a mathematical model based on "training data" by using Machine Learning. The extraction of hidden data, association of image data and additional pattern which are unclearly visible in image is done using Image Mining. It"s an interrelated field that involves, Image Processing, Data Mining, Machine Learning and Datasets. According to conservative estimates in medical books, 50- 80% of all physical diseases are caused by stress. Stress is believed to be the principal cause in cardiovascular diseases. Stress can place one at higher risk for diabetes, ulcers, asthma, migraine headaches, skin disorders, epilepsy, and sexual dysfunction. Each of these diseases, and host of others, is psychosomatic (i.e., either caused or exaggerated by mental conditions such as stress) in nature. Stress has three prong effects: subjective effects of include feeling of guilt, shame, anxiety, aggression or frustration. Individuals also feel tired, tense, nervous, irritable, moody, or lonely. visible changes in the behavior ARE represented by Behavioral effects of stress. Effects of behavioral stress are seen such as increased accidents, use of drugs or alcohol, laughter out of context, outlandish or argumentative behavior, very excitable moods, and/or eating or drinking to excess.diminishing mental ability, impaired judgment, rash decisions, forgetfulness and/or hypersensitivity to criticism are some of the effects of Cognitive stress



Limitations in existing system is that stress analysis is a crucial tool for designing structurally sound shapes. However, the expensive computational cost has hampered its use in interactive shape editing tasks.We augment the existing

example-based shape editing tools, and propose a fast subspace stress analysis method to enable stress-aware shape editing. In particular it is constructed by a reduced stress basis from a small set of shape exemplars and possible external forces. This stress basis is automatically adapted to the current user edited shape on the fly, and thereby offers reliable stress estimation. We then introduce a new finite element discretization scheme to use the reduced basis for fast stress analysis. Some Limitations exist in tweeting content based 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. Secondly, users with high psychological stress may exhibit low activeness on social networks. These phenomena incur the inherent data sparsity and ambiguity problem, which may hurt the performance of tweeting content based stress detection performance

PROPOSED SYSTEM Sentiment analysis is to define automatic tools able to extract subjective information from texts in natural language, such as opinions and sentiments, in order to create structured and actionable knowledge to be used by either a decision support system or a decision maker.In Social Networks begins with an overview of the latest research trends in the field. Sentiment analysis has gained even more value with the advent and growth of social networking. It explores both semantic and machine learning models and methods that address context-dependent and dynamic text in online social networks, showing how social network streams pose numerous challenges due to their large-scale, short, noisy, context- dependent and dynamic nature. The contributions of this paper are as following:

• We propose a unified factor graph model in R studio to leverage both tweet content attributes and social interactions to enhance stress detection.

• We build several stressed-twitter-posting datasets by different ground-truth labeling methods from several popular social media platforms and thoroughly evaluate our proposed method on multiple aspects.

• We carry out in-depth studies on a real-world large scale dataset and gain insights on correlations between social interactions and stress, as well as social structures of stressed users

RELATED WORK Psychological stress detection is related to the topics of sentiment analysis and emotion detection. Research on tweet-level emotion detection in social networks. Computer-aided detection, analysis, and application of emotion, especially in social networks, have drawn much attention in recent years [8], [9], [28], [41], [52], [53]. Relationships between psychological stress and personality traits can be an interesting issue to consider [11], [16], [43]. For example, [1] providing evidence that daily stress can be reliably recognized based on behavioral metrics from users mobile phone activity. Many studies on social media based emotion analysis are at the tweet level, using text-based linguistic features and classic classification approaches. [53] proposed a system called MoodLens to perform emotion analysis on the Chinese micro-blog platform Weibo, classifying the emotion categories into four types, i.e., angry, disgusting, joyful, and sad. [9] studied the emotion propagation problem in social networks, and found that anger has a stronger correlation among different users than joy, indicating that negative emotions could spread more quickly and broadly in the network. As stress is mostly considered as a negative emotion, this conclusion can help us in combining the social influence of users for stress detection. However, these work mainly leverage the textual contents in social networks. In reality, data in social networks is usually composed of sequential and inter-connected items from diverse sources and modalities, making it be actually crossmedia data. Research on user-level emotion detection in social networks. While tweet-level emotion detection reflects the instant emotion expressed in a single tweet, people's emotion or psychological stress states are usually more enduring, changing over different time periods. In recent years, extensive research starts to focus on user-level emotion detection in social networks [29], [36], [38], [50]. Our recent work [29] proposed to detect users psychological stress states from social media by learning user-level presentation via a deep convolution network on sequential tweet series in a certain time period. Motivated by the principle of homophily, [38] incorporated social relationships to improve user-level sentiment analysis in Twitter. Though some userlevel emotion detection studies have been done, the role that social relationships plays in one's psychological stress states, and how we can incorporate such information into stress detection have not been examined yet. Research on leveraging social interactions for social

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media analysis. Social interaction is one of the most important features of social media platforms. Now many researchers are focusing on leveraging social interaction information to help improve the effectiveness of social media analysis. [12] analyzed the relationships between social interactions and users' thinking and behaviors, and found out that Twitter-based interaction can trigger effectual cognitions. [49] leveraged comments on Flickr to help predict emotions expressed by images posted on Flickr. However, these work mainly focused on the content of social interactions, e.g., textual comment content, while ignoring the inherent structural information like how users are connected.

EXISTING SYSTEM In the existing system work on stress detection is based on the digital signal processing, taking into consideration Galvanic skin response, blood volume, pupil dilation and skin temperature. And the other work on this issue is based on several physiological signals and visual features (eye closure, head movement) to monitor the stress in a person while he is working. However these measurements are intrusive and are less comfortable in real application. Every sensor data is compared with a stress index which is a threshold value used for detecting the stress level.

DISADVANTAGES OF EXISTING SYSTEM: Physiological signals used for analysis are often pigeonholed by a Nonstationary time performance.

- The extracted features explicitly gives the stress index of the physiological signals. The ECG signal is directly assessed by using commonly used peak j48 algorithm
- Different people may behave or express differently under stress and it is hard to find a universal pattern to define the stress emotion. Algorithm: Bayesian Network, J48

PROPOSED SYSTEM The proposed System Machine Learning algorithms like KNN classifiers are applied to classify stress. Image Processing is used at the initial stage for detection, the employee‟s image is given by the browser which serves as input. In order to get an enhanced image or to extract some useful information from it image processing is used by converting image into digital form and performing some operations on it. By taking input as an image and output may be image or characteristics associated with that images. The emotion are displayed on the rounder box. The stress level indicating by Angry, Disgusted, Fearful, Sad.

ADVANTAGES OF PROPOSED SYSTEM:

- Output in which result is altered image or report that is based on image analysis.
- Stress Detection System enables employees with coping up with their issues leading to stress by preventative stress management solutions.
- We will capture images of the employee based on the regular intervals

CONCLUSION Stress Detection System is designed to predict stress in the employees by monitoring captured images of authenticated users which makes the system secure. The image capturing is done automatically when the authenticate user is logged in based on some time interval. The captured images are used to detect the stress of the user based on some standard conversion and image processing mechanisms. Then the system will analyze the stress levels by using Machine Learning algorithms which generates the results that are more efficient.

FUTURE WORK The future scope of the project is to develop a system that not only detecting the stress and also able to analyze people mind means that it will play as a survey system. So that

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it may provide a better solution on behalf of people of the society for every debatable concepts and also it will indirectly play an important role in political, government and also social media. So we may efficiently analyze stress and also find solution to every social issue by means of polling and analyzing comments.

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