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Research Paper

STRESS DETECTION IN IT PROFESSIONALS BY 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.

Keywords: Analyze, Live Detection, Kaggle, Determine, Accuracy

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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 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:

- Importing the image via image acquisition tools.
- Analyzing and manipulating the image.
- Output in which result is altered image or report 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 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 stress include feelings of guilt, shame, anxiety, aggression or frustration. Individuals also feel tired, tense, nervous, irritable, moody, or lonely.
- Visible changes in a person's 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.
- Some symptoms of cognitive stress include diminished mental capacity, poor judgment, making snap decisions, forgetfulness, and/or intolerance to criticism.

II. LITERATURE REVIEW

1) Stress and anxiety detection using facial cues from Videos

This study develops a framework for the detection and analysis of stress/anxiety emotional states through video-recorded facial cues. A thorough experimental protocol was established to induce systematic variability in affective states (neutral, relaxed and stressed/anxious) through a variety of external and internal stressors. The analysis was focused mainly on non-voluntary and semi-voluntary facial cues in order to estimate the emotion representation more objectively. Features under investigation included eye-related events, mouth activity, head motion parameters and heart rate estimated through camera-based photoplethysmography. A feature selection procedure was employed to

select the most robust features followed by classification schemes discriminating between stress/anxiety and neutral states with reference to a relaxed state in each experimental phase. In addition, a ranking transformation was proposed utilizing self reports in order to investigate the correlation of facial parameters with a participant perceived amount of stress/anxiety. The results indicated that, specific facial cues, derived from eye activity, mouth activity, head movements and camera based heart activity achieve good accuracy and are suitable as discriminative indicators of stress and anxiety.

2) Detection of Stress Using Image Processing and Machine Learning Techniques

Stress is a part of life it is an unpleasant state of emotional arousal that people experience in situations like working for long hours in front of computer. Computers have become a way of life, much life is spent on the computers and hence we are therefore more affected by the ups and downs that they cause us. One cannot just completely avoid their work on computers but one can at least control his/her usage when being alarmed about him being stressed at certain point of time. It is vital for an individual's safety to keep an eye on their mental state when they are spending extended amounts of time in front of a computer. This technique uses real-time, non-intrusive video recording to analyze a subject's facial expressions to determine their emotional state.. We detect an individual emotion in each video frame and the decision on the stress level is made in sequential hours of the video captured. We employ a technique that allows us to train a model and analyze differences in predicting the features. Theano is a python framework which aims at improving both the execution time and development time of the linear regression model which is used here as a deep learning algorithm. The experimental results show that the developed system is well on data with the generic model of all ages.

3) Machine Learning Techniques for Stress Prediction in Working Employees

Stress disorders are a common issue among working IT professionals in the industry today. With changing lifestyle and work cultures, there is an increase in the risk of stress among the employees. Though many industries and corporates provide mental health related schemes and try to ease the workplace atmosphere, the issue is far from control. In this paper, we would like to apply machine learning techniques to analyze stress patterns in working adults and to narrow down the factors that strongly determine the stress levels. Towards this, data from the OSMI mental health survey 2017 responses of working professionals within the tech-industry was considered. Various Machine Learning techniques were applied to train our model after due data cleaning and preprocessing. The accuracy of the above models was obtained and studied comparatively. Boosting had the highest accuracy among the models implemented. By using Decision Trees, prominent features that influence stress were identified as gender, family history and availability of health benefits in the workplace. With these results, industries can now narrow down their approach to reduce stress and create a much comfortable workplace for their employees.

4) Classification of acute stress using linear and non-linear heart rate variability analysis derived from sternal ECG

Chronic stress detection is an important factor in predicting and reducing the risk of cardiovascular disease. This work is a pilot study with a focus on developing a method for detecting short-term psychophysiological changes through heart rate variability (HRV) features. The purpose of this pilot study is to establish and to gain insight on a set of features that could be used to detect psychophysiological changes that occur during chronic stress. This study elicited four different types of arousal by images, sounds, mental tasks and rest, and classified them using linear and non-linear HRV features from electrocardiograms (ECG) acquired by the wireless wearable ePatch® recorder. The highest recognition rates were acquired for the neutral stage (90%), the acute stress stage (80%) and the baseline stage (80%) by sample entropy, detrended fluctuation analysis and normalized high frequency features. Standardizing non-linear HRV features for each subject was found to be an important factor for the improvement of the classification results.

5) Healthy Office: Mood recognition at work using smartphones and wearable sensors

Stress, anxiety and depression in the workplace are detrimental to human health and productivity with significant financial implications. Recent research in this area has focused on the use of sensor technologies, including smartphones and wearables embedded with physiological and movement sensors. In this work, we explore the possibility of using such devices for mood recognition, focusing on work environments. We propose a novel mood recognition framework that is able to identify five intensity levels for eight different types of moods every two hours. We further present a smartphone app ('HealthyOffice'), designed to facilitate self-reporting in a structured manner and provide our model with the ground truth. We evaluate our system in a small-scale user study where wearable sensing data is collected in an office environment. Our experiments exhibit promising results allowing us to reliably recognize various classes of perceived moods.

III. METHODOLOGY

Image Pre-processing : $G(i, j) = \alpha . F(i, j) + \beta$, $\alpha > 0$ and β are called as gain and bias parameters, these are used to bright and contrast the image. Here $G(i, j)$ is output image pixel and $F(i, j)$ is input image pixel.

Pixel transformation: Pixel transformation is a technique used in image processing to obtain pixel values. This transformation is used to make image generic and diverse. The image is converted into Gray scale image that is a color image is converted into black and white or in shades of grey. Threshold of the image is found which is used to convert gray scale image into binary form, If the pixel value is greater than threshold pixel value is set to 1 otherwise 0.

One hot encoding: All the textual responses were given numerical weights according to their significance. 'Yes' is taken to be 1, 'no' to be 0. The categorical data was converted into numeric using label encoder. A decoder is used to decode into binary code. Though a one-hot state machine, does not need a decoder as machine is in the nth state if and only if the nth bit is high.

Logistic Regression: Like all regression methods, the logistic regression is a predictive analysis. It is used in scenarios where one binary variable is dependent on one or more independent variables. A logistic regression can be called as a statistical model that uses a binary dependent variable. In regression analysis, logistic regression is estimating the parameters of a logistic model. Mathematically, a binary logistic model has a dependent variable with two possible value, which is represented by an indicator variable, where the two values are labeled "0" and "1".

Mini-Batch Gradient Descent: A subset of training is considered; it can make quick updates in the model parameters and can also exploit the speed associated with vectorizing the code. Depending upon the batch size, the updates can be made. Mini Batching is used to set the threshold value updated by gradient which makes it a robust algorithm

KNN Classifier: K-Nearest Neighbor (KNN) is used for classification as well as regression analysis. It is a supervised learning algorithm which is used for predicting if a person needs treatment or not. KNN classifies the dependent variable based on how similar it is; independent variables are to a similar instance from the already known data.

Dataset: Dataset contains grid view of already stored dataset consisting numerous properties[8], by Property Extraction newly designed dataset appears which contains only numerical input variables as a result of Principal Component Analysis feature selection transforming to 6 principal components which are Condition (No stress, Time pressure, Interruption), Stress, Physical Demand, Performance and Frustration. dataset contains numerous unusable properties like Temporal Demand, Heart Rate, Effort, Mental Effort, Nasa TLX, Mental Demand etc.

Essential properties namely Condition (No stress, Time pressure, Interruption), Stress, Physical Demand, Performance and Frustration from raw dataset are extracted to build a new property extracted dataset.

The system is divided into three modules the first module registers the employee, sends alerts and later provides survey forms. Second module works on image capturing, conversion of image into coordinates and then mapping the image and getting a prediction about stress and the third module converts data into binary values, based on which stress level is detected and based on the level solution is provided for overcoming stress.

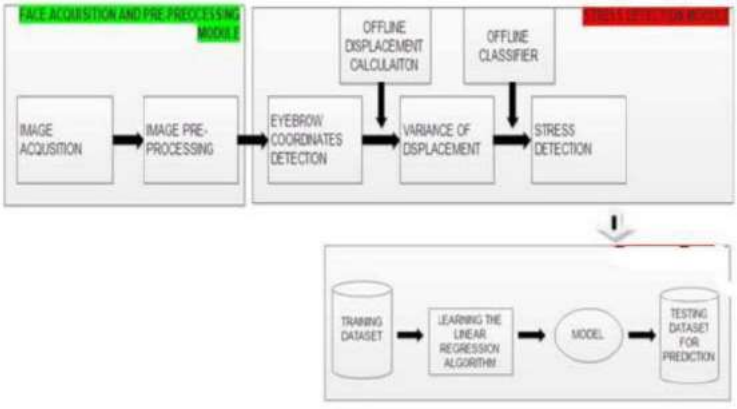


Figure 1: Architecture

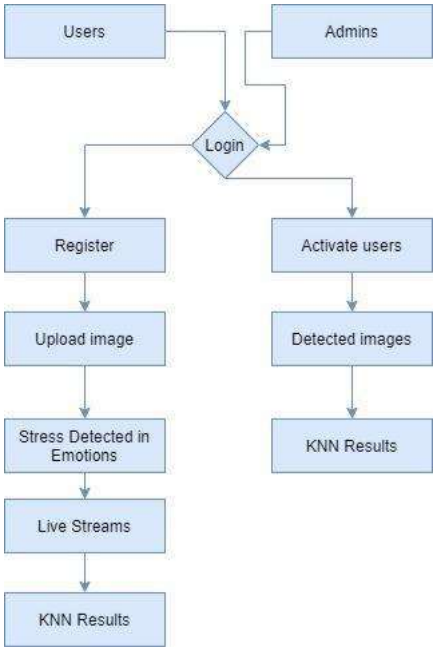


Figure 2: Data Flow Diagram

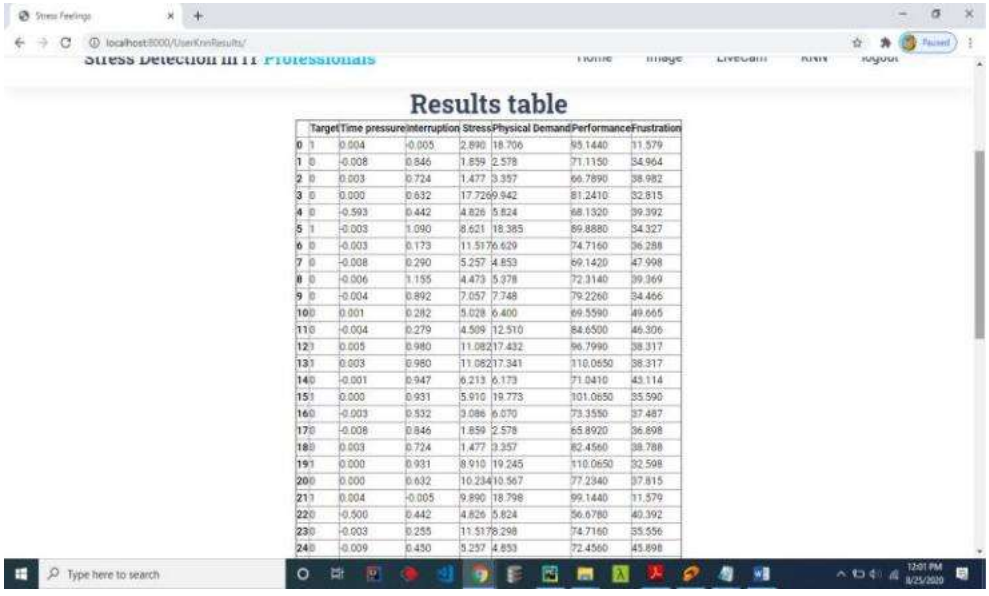
IV.RESULTS AND ANALYSIS

Fig 1: User login page

Fig 2: Giving Image as Input

	Target	Time pressure	Interruption	Stress	Physical Demand	Performance	Frustration
0	1	0.004	-0.005	2.890	18.706	95.1440	11.579
1	0	-0.008	0.846	1.859	2.578	71.1150	34.964
2	0	0.003	0.724	1.477	3.357	66.7890	38.982
3	0	0.000	0.632	17.726	9.942	81.2410	32.815
4	0	-0.593	0.442	4.826	5.824	68.1320	39.392
5	1	-0.003	1.090	8.621	18.385	89.8880	34.327
6	0	-0.003	0.173	11.517	6.629	74.7160	36.288
7	0	-0.008	0.290	5.257	4.853	69.1420	47.998
8	0	-0.006	1.155	4.473	5.378	72.3140	39.369
9	0	-0.004	0.892	7.057	7.748	79.2260	34.466
10	0	0.001	0.282	5.028	6.400	69.5590	49.665
11	0	-0.004	0.279	4.509	12.510	84.6500	46.306

Fig 3: KNN Algorithm Results



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10	0	0.001	0.282	5.028	6.400	69.5590	49.665
11	0	-0.004	0.279	4.509	12.510	84.6500	46.306
12	1	0.005	0.980	11.082	17.432	96.7990	38.317
13	1	0.003	0.980	11.082	17.341	110.0650	38.317
14	0	-0.001	0.947	6.213	6.173	71.0410	43.114
15	1	0.000	0.931	5.910	19.773	101.0650	35.590
16	0	-0.003	0.532	3.086	6.070	73.3550	37.487
17	0	-0.008	0.846	1.859	2.578	65.8920	36.898
18	0	0.003	0.724	1.477	3.357	82.4560	38.788
19	1	0.000	0.931	8.910	19.245	110.0650	32.598
20	0	0.000	0.632	10.234	10.567	77.2340	37.815
21	1	0.004	-0.005	9.890	18.798	99.1440	11.579
22	0	-0.500	0.442	4.826	5.824	56.6780	40.392
23	0	-0.003	0.255	11.517	8.298	74.7160	35.556
24	0	-0.009	0.430	5.257	4.853	72.4560	45.898

Fig 4: Results Table

V. 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.

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