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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.

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.
 Diminishing mental ability, impaired judgment, rash decisions, forgetfulness and/or hypersensitivity to criticism are some of the effects of Cognitive stress

II. **LITERATURE SURVEY**

1) Stress and anxiety detection using facial cues from videos
AUTHORS: G. Giannakakis, D. Manousos, F. Chiarugi

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
AUTHORS: Nisha Raichur, Nidhi Lonakadi, Priyanka Mural

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. Monitoring the emotional status of a person who is working in front of a computer for longer duration is crucial for the safety of a person. In this work a real-time non-intrusive videos are captured, which detects the emotional status of a person by analysing the facial expression. 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
AUTHORS : U. S. Reddy, A. V. Thota and A. Dharun

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

AUTHORS : Tanev, G., Saadi, D.B., Hoppe, K., Sorensen, H.B

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) HealthyOffice: Mood recognition at work using smartphones and wearable sensors

AUTHORS: Zenonos, A., Khan, A., Kalogridis, G., Vatsikas, S., Lewis, T., Sooriyabandara

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. 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 Non-stationary 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

IV.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

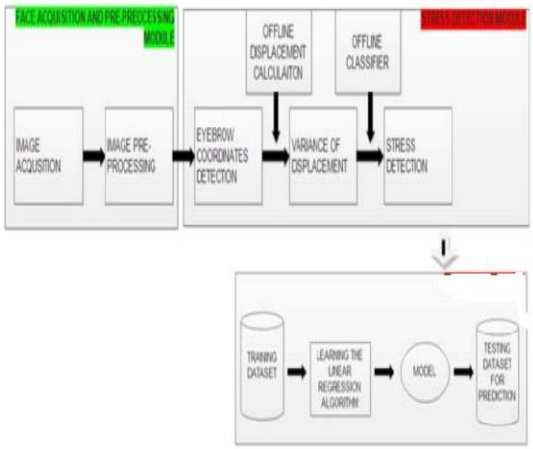
it. By taking input as an image and output may be image or characteristics associated with that images. The emotion are displayed on the rounder box. The stress level indicating by Angry, Disgusted, Fearful, Sad.

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 and then the tradition survey forms will be given to the employees

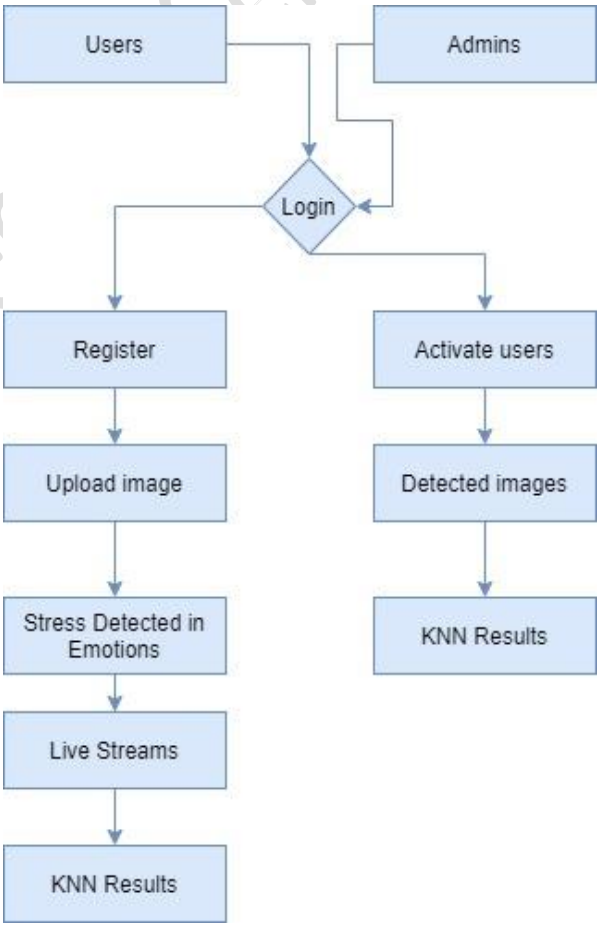
Algorithm: K-Nearest Neighbor (KNN)

V. SYSTEM ARCHITECTURE:



DATA FLOW DIAGRAM:

1. The DFD is also called as bubble chart. It is a simple graphical formalism that can be used to represent a system in terms of input data to the system, various processing carried out on this data, and the output data is generated by this system.
2. The data flow diagram (DFD) is one of the most important modeling tools. It is used to model the system components. These components are the system process, the data used by the process, an external entity that interacts with the system and the information flows in the system.
3. DFD shows how the information moves through the system and how it is modified by a series of transformations. It is a graphical technique that depicts information flow and the transformations that are applied as data moves from input to output.
4. DFD is also known as bubble chart. A DFD may be used to represent a system at any level of abstraction. DFD may be partitioned into levels that represent increasing information flow and functional detail.



UML DIAGRAMS

UML stands for Unified Modeling Language. UML is a standardized general-purpose modeling language in the field of object-oriented

software engineering. The standard is managed, and was created by, the Object Management Group.

The goal is for UML to become a common language for creating models of object oriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modeling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modeling and other non-software systems.

The UML represents a collection of best engineering practices that have proven successful in the modeling of large and complex systems.

The UML is a very important part of developing objects oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

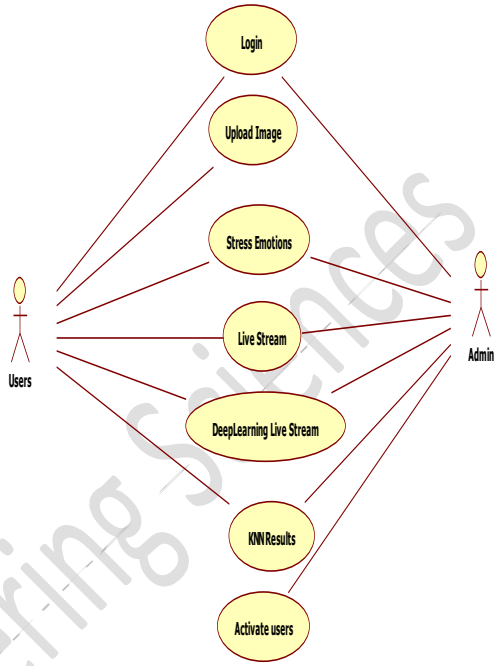
GOALS:

The Primary goals in the design of the UML are as follows:

1. Provide users a ready-to-use, expressive visual modeling Language so that they can develop and exchange meaningful models.
2. Provide extendibility and specialization mechanisms to extend the core concepts.
3. Be independent of particular programming languages and development process.
4. Provide a formal basis for understanding the modeling language.
5. Encourage the growth of OO tools market.
6. Support higher level development concepts such as collaborations, frameworks, patterns and components.
7. Integrate best practices.

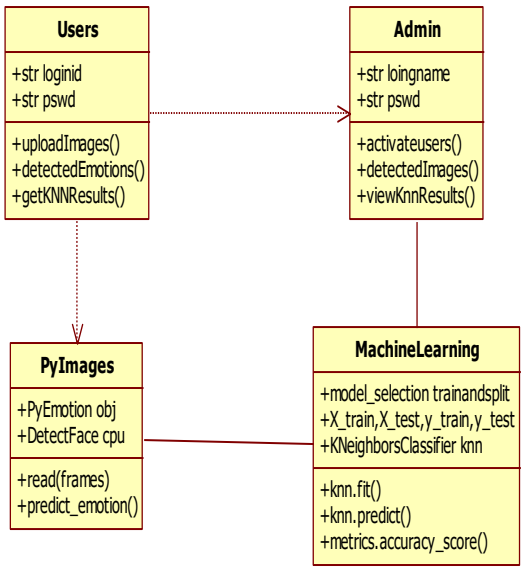
USE CASE DIAGRAM:

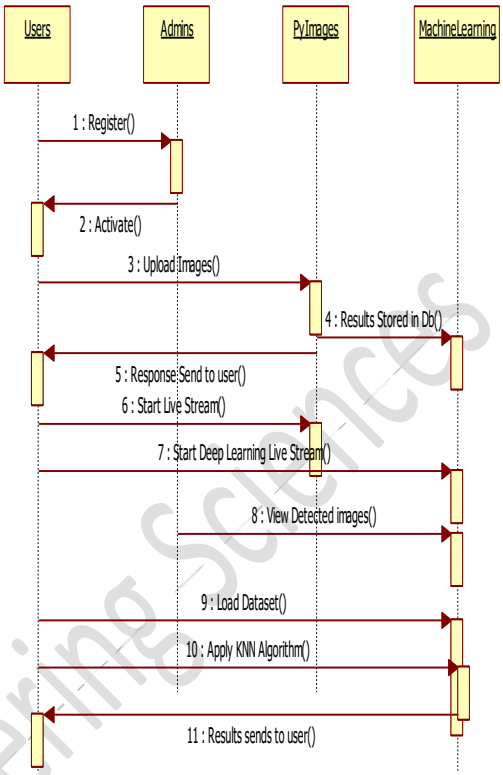
A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies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



CLASS DIAGRAM:

In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that 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.



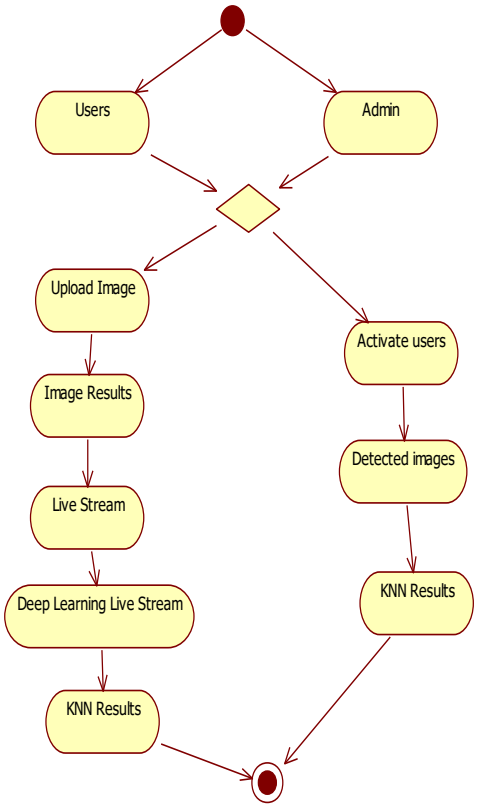


SEQUENCE DIAGRAM:

A sequence diagram in Unified Modeling Language (UML) is a kind of 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.

ACTIVITY DIAGRAM:

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.



VI. MODULES:

- **User**
- **Admin**
- **Data Preprocess**
- **Machine Learning**

MODULES DESCRIPTION:

User:

The User can register the first. While registering he required a valid user email and mobile for further communications. Once the user register then admin can activate the customer. Once admin activated the customer then user can login into our system. First user has to give the input as image to the system. The python library will extract the features and appropriate emotion of the image. If given image contain more than one faces also possible to detect. The stress level we are going to indicate by facial expression like sad, angry etc.. The image processing completed the we are going to start the live stream. In the live stream also we can get the facial expression more that one persons also. Compare to tensorlflow live stream the tesnorflow live stream will fast and better results. Once done the we are loading the dataset to perform the knn classification accuracy precession scores.

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Admin:

Admin can login with his credentials. Once he login he can activate the users. The activated user only login in our applications. The admin can set the training and testing data for the project dynamically to the code. The admin can view all users detected results in hid frame. By clicking an hyperlink in the screen he can detect the emotions of the images. The admin can also view the knn classification detected results. The dataset in the excel format. By authorized persons we can increase the dataset size according the imaginary values.

Data Preprocess:

Dataset contains grid view of already stored dataset consisting numerous properties, 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.

Machine Learning:

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. the Knn Classification can be called as a statistical model that uses a binary dependent variable. In classification analysis, KNN is estimating the parameters of a KNN model. Mathematically, a binary KNN 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".

VII. SYSTEM SPECIFICATION:

HARDWARE REQUIREMENTS:

- **System** : Intel i3
- **Hard Disk** : 1 TB.

- **Monitor** : 14' Colour Monitor.
- **Mouse** : Optical Mouse.
- **Ram** : 4GB.

SOFTWARE REQUIREMENTS:

- **Operating system** : Windows 10.
- **Coding Language** : Python.
- **Front-End** : Html. CSS
- **Designing** : Html,css,javascript.

Data Base : SQLite.

VIII.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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