Advancement of technology and the desire to cater more to human emotional needs have fostered the conceptualization of numerous humanized systems. This conceptualization is targeted at bringing about radical changes to the way Man interacts with Machine. Apart from emotions there is another aspect that is of interest that how people cope with problems in their surroundings and how it affects the psychology of a subject or the amount of stress induced on the person. Stress identification can be a key factor towards reduction of stress related mishaps. It can also make human computer interaction more pleasing by adjusting the way of interaction according to a person’s stress levels. Identifying stress levels of a person is best done by medical procedures and trained psychologists, but there needs to be a system to recommend when these procedures need to be initiated. Also, research in this domain suggests that both stress and emotions affect facial muscle movements. Accordingly a relationship seems to exist between stress and emotions as depicted on the face.

We proposed an emotion based method to detect and evaluate stress levels from facial expressions of a subject. This method eradicates the cumbersomeness of current research techniques of attaching electrodes, collecting biological samples or the self-reporting bias in questionnaire methods and is very well applicable to real scenarios. The stress we evaluate is not a medical evaluation of psychological stress but just an indicator that can be used to recommend medical attention or consultation. To relate emotions discernible from facial expressions and visually perceptible psychological stress we first performed emotion detection from facial expression and then correlated the findings from emotion detection with facial expression based stress survey responses.

We accurately predicted emotions individually and as a mixture from coded facial expressions using Hidden Markov Models. We used images from a renowned dataset, where the images were accompanied with facial muscle movement data and the emotion they represent. We used muscle movement data of the entire face in predicting emotions rather than using only significant muscle movement information and we achieved a more accurate model than that of current researches. The seven basic emotions that we considered were Anger, Contempt, Disgust, Fear, Happy, Sad and Surprise. To predict basic emotions individually the dataset were partitioned into training and testing segments. The facial muscle movement data served as inputs to our system and the emotion information was used as ground truth for training our model for individual emotion detection. After completion of training the testing partition data was fed into the model and the outputs were tallied with the ground truth emotion information. We achieved a
maximum identification success rate of around 95 percent. An almost similar method was followed for predicting emotion mixture except for the final process where the probabilities of each emotion being predicted was normalized and assumed to be representative of their respective degrees that the facial expression was comprised of. During prediction of emotion mixture we also investigated gender differences in emotion representation on the face by implementing two structurally identical parallel pathways for emotion mixture prediction. The difference between the parallel pathways lies in the data they are trained and tested with. We further segmented the training and testing data into male and female data segments and trained and tested our model selectively. We achieved an emotion prediction accuracy of 97 percent, which is higher than similar researches. Also, we found that although gender differences do not exist for representation of emotion on the face but making different models for males and females we achieved a better model for emotion prediction.

Following the emotion prediction phase we conducted two surveys to relate stress with facial expressions and percentages of individual emotions and stress. The first survey contained facial images which were labeled by respondents with stress levels ranging for 0 to 9, where 0 means no stress and 9 means peak stress. The images used in the survey were also used in our emotion experiment. We considered different models that might best fit as a relational model with the reported stress as dependent variable and emotions as independent variables. The second survey did not contain any images but respondents were asked to relate varying percentages of the seven basic emotions and stress levels. Using the second survey we correlated basic emotions individually with stress values obtained from respondents. In case of correlation between stress and emotion mixture as well as the case of correlation between stress and individual emotions, we found the relationship to be logarithmic. This is in accordance with the famous Weber-Fechner law of stimuli. Summary of our key findings are as follows:

1. Accuracy of Emotion prediction is enhanced when we consider all facial muscle movements together rather than considering only the prominent muscle movements.
2. There is no gender difference in terms of emotion response among different genders but accuracy of overall emotion prediction is improved by gender segmentation during training and testing.
3. Visually Perceptible Psychological Stress can be quantitatively expressed as a function of seven basic emotions (Anger, Contempt, Disgust, Fear, Happy, Sad and Surprise).
4. When stress is considered as the response of occurring emotions on the face of a subject the relationship between stress and emotion is found to be logarithmic, this is in accordance to the famous Weber-Fechner law of stimuli.
5. Accuracy of Stress evaluation is enhanced when we consider all the insignificant emotions as well along with the lead emotion rather than only considering the most prominent emotion.