A DEEP LEARNING APPROACH FOR HUMAN STRESS DETECTION

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ABSTRACT:

Human psychological stress and human emotion are very much interconnected. In computational psychology study, the relationship between stress and emotions is the key to understanding the human behavior [1]. Research has been done for detecting facial emotions from images using deep learning but has not been explicitly taken up yet to find psychological stress [2]. In this paper, a hybrid system is presented in which a convolutional neural network (CNN) and a regression classifier are combined. A CNN is trained to detect and recognize facial expressions and classify human faces into discrete emotion categories (Anger, Disgust, Neutral, Fear, Sad, Happy and Surprise). Further logarithmic regression is applied to evaluate stress as a function of the deciphered emotions. We performed experiments on Facial Expression Recognition (FER2013) dataset to evaluate our architecture. Our method achieved the result, 67.76% accuracy, for 5 layer CNN and 65 iterations.

Keywords: Deep Learning, Convolutional Neural Network (CNN), Facial Expression Recognition (FER2013), Human emotions, regression classifier, logarithmic regression.

[1] INTRODUCTION

In recent times, psychological stress has grown to be an extreme risk to public fitness. Immoderate pressure might also motive many mental and bodily health issues such as insomnia, cancer, depressions etc., or even suicide. Existing stress detection techniques are mainly face-to-face interviews, self-file mental questionnaires and wearable physiological sensors. However, these methods are commonly exertions-ingesting, time-costing and hysteretic.

The knowledge of psychological stress and human emotions is well related but has not been explicitly taken up for research yet. They're always dealt in researches as two specific fields of study to look at. In this research, we present a quantitative indicator for stress from the human facial emotions which we term as facial expressions. Facial musculature is substantially varied amongst humans and to set up an ordinary or generalized technique to assess facially found stress could be not possible if we have been to use most effective the muscle movement data. So we express the muscle movement data to an intermediate form before we develop a model to evaluate facially observed stress. According to the Facial Action Coding System developed by Ekman and Friesen [6, 7] seven basic emotions anger, disgust, neutral, fear, happy, sad and surprise are innate and universal to humans. These emotions can be used as an intermediate form to evaluate our stress indicator.

We used the Kaggle FER2013 dataset for the training and testing of our model. Our model was divided in two phases: the emotion detection phase and the stress detection phase. Once the emotion detection phase was completed, we conducted surveys that related stress and emotions. From these surveys and our emotion detection results we analyzed the relationship between emotions and visually perceptible psychological stress as reported by psychologists in the survey responses using regression analysis.

In psychiatry and medical science there are plenty of solutions like consultation or medication to cope with stress specifically that originate from the workplace. But all these methods will only be effective when there is a way to indicatively predict the stress level of a person without making the subject aware of it. So, a stress monitoring system needs to be developed that will indicate the stress levels without asking the subject, answers to questions , biological samples or sport electrodes all the time as this would help not to intervene in a person's work schedule. This kind of system is not intended as a replacement for the scientific medical procedures to identify stress levels completely and accurately but it would act as an aid to determine when such procedures need to be initiated. This is highly desirable as bio-medical or psychiatric procedures cannot be performed continuously and hence needs some indicators for considering assessment and treatment.

In this dissertation we intend to propose and implement a more accurate method to identify emotions from facial muscle movement using Convolutional Neural Network and use these identified emotions to evaluate facially observable stress levels by finding the best emotion stress relational model from stress survey data.

[2] RELATED WORK

There have been several facial expression and emotion recognition approaches evolved in the ultimate decade and lots of development has been made on this research region recently. A full survey can be found in [5], [6]. In [1], the authors propose a simple solution for facial expression recognition on Extended Cohn-Kanade (CK+) dataset, that uses a combination of standard methods, like Convolutional Network and specific image pre-processing steps with 97.81% of accuracy, and takes less time to train than state-of-the-art methods. But it was seen that the accuracy of some expressions, like fear and sad, was less than 80%, As described in [2], 5-layer CNN and deeper CNN was applied on Kaggle FER dataset to achieve an accuracy of 48%. Also as seen in [3], the authors presents the model with 4 convolutional layers and 2 fully connected layers on Kaggle FER2013 dataset and also comparison between shallow and deep models where the deep network enabled us to increase the validation accuracy by 18.46%. In [4], a cascade network with 6 CNN including 3 CNNs for face vs. non-face binary classification and 3 CNNs for bounding box calibration, which is formulated as multi-class classification of discretized displacement pattern is proposed on the FDDB dataset with an accuracy of 85.1%.

[3] DATASET

We have used FER2013 dataset from the Kaggle Facial Expression Recognition Challenge to train our model. The dataset consists of 35,887 grayscale images, each image of 48-by-48 pixel labeled with one of the 7 emotion categories : Angry, Disgust, Fear, Happy, Sad, Surprise and Neutral. We used 80% of the dataset for training and remaining 20% for testing.

Figure: 1. A sample of images from FER2013 dataset with their corresponding emotions

[4] PROPOSED METHODOLOGY

Our model comprises of two main steps : Facial emotion recognition and stress detection from the deciphered emotions. We used Convolutional Neural Network (CNN) to find the probabilities that facial expression represent a particular emotion for all emotions (As shown in figure 2).

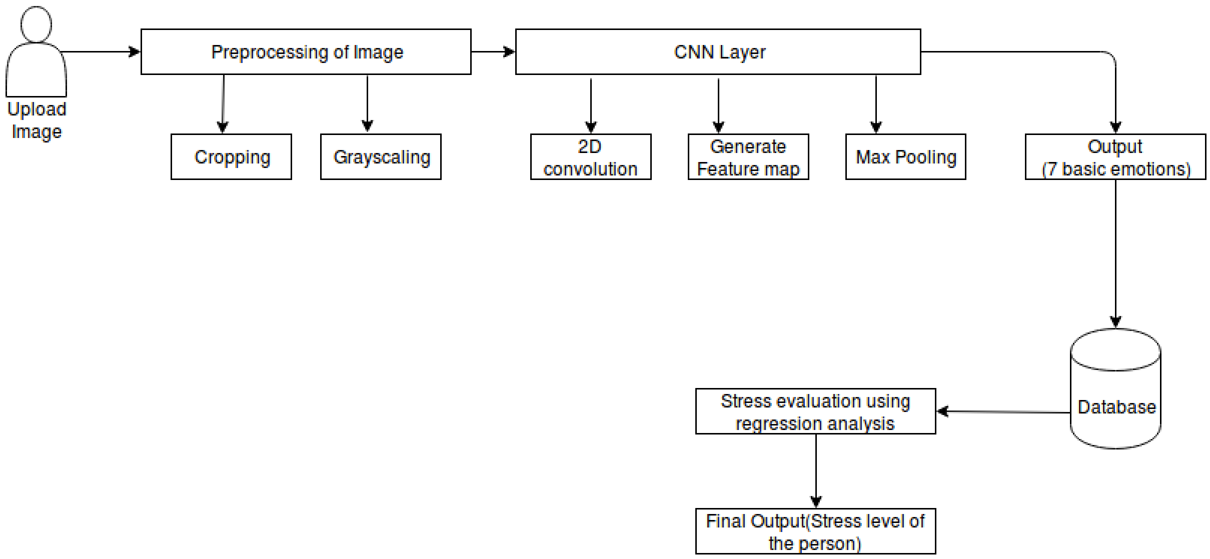

Figure: 2. Architectural diagram of our model

[4.1] STEP 1

As a part of emotion recognition, in input layer, we did preprocessing on the acquired image. Preprocessing included activities like cropping and gray scaling of the images to obtain the images that have a normalized size or intensity. Then this preprocessed image was fed into numpy array.

The numpy array was then passed to convolutional layer which consisted of 3 convolution layers and the set of filters to generate the feature maps. We included the combination of depth-wise separable convolutions and residual modules in place of fully connected layers. The model was trained using the ADAM optimizer. We used Global Average Pooling to completely remove any fully connected layers. This was achieved by having in the last convolutional layer the same number of feature maps as number of classes, and applying a softmax activation function to each reduced feature map.

Finally in the output layer, the softmax function presented the output as a probability for each emotion class.

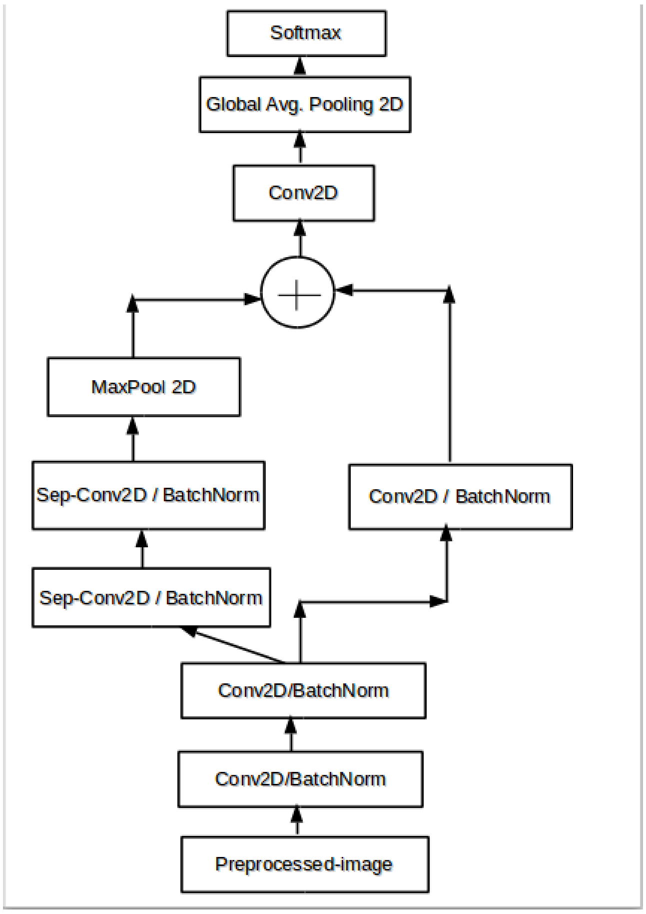

Figure: 3. CNN Implementation

[4.2] STEP 2

After we have deciphered emotion information from the facial expression we evaluated the stress levels and to that effect we conducted a survey among people that relates emotion degrees to stress levels. The survey was conducted without considering any images. Respondents were given emotion intensity percentages in steps of 20 varying from 0 to 100 and they were asked to map each level of the basic emotion with a stress level ranging from 0 to 9. We received a total of 108 responses.

After this survey was conducted, we used the results of the survey and the deciphered emotion information data to predict a regression model that best describes the stress and emotion data. We proposed five different linear and non-linear regression models for prediction of stress levels from emotion degrees or percentages and we chose the best model based on parameters like goodness of fit and root mean square errors. We found out that logarithmic fit was the best model among all the models and it was also in accordance with the Weber-Fechner law. Then we presented the logarithmic model equations by determining the coefficients of unknown variables using regression analysis.

The above mentioned approach can finally be used to evaluate visually perceptible stress levels (in terms of probability) as observable from the face of a subject in terms of seven basic emotions and the emotions can be deciphered using facial muscle movement information.

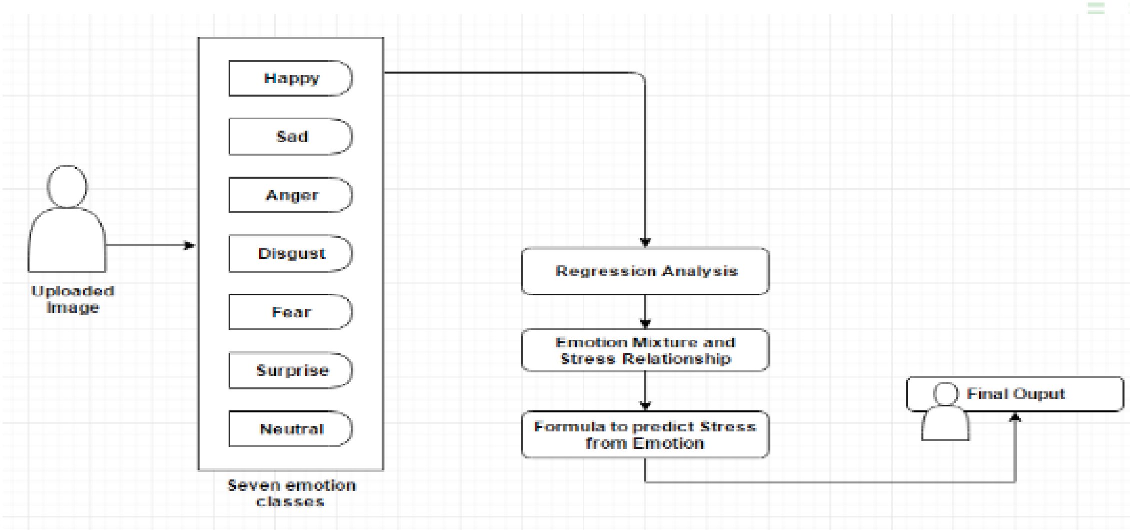

Figure: 4. Stress Evaluation Model

[5] RESULTS

Results of the emotion classification task and stress level detection can be observed in Figure5 and Figure 6. The corresponding image and its detected emotion label and probability and stress probability is shown in these figures.

Figure: 4. Group Image

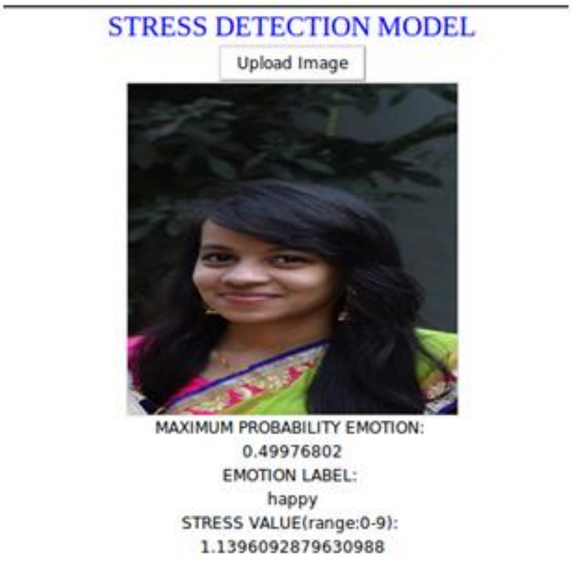

Figure: 5. Individual Image

The final curve fitting and parameter estimation of the logarithmic model for all emotion were done using all 108 observations per emotion using MATLAB.

Figure 7 shows the logarithmic curve for Stress vs. Anger where we can see that from 0 to 20 percent the increase in stress level is steep but from 20 percent onwards the slope is very moderate and positive. The initial steepness can be visualized as an anger outburst of a person which of course will keep on increasing with continued presence of the cause of Anger but not at such high rate as it was initially. This outburst in real scenarios sometimes is visible but many a times suppressed at will as well due to environmental restriction or personal habits.

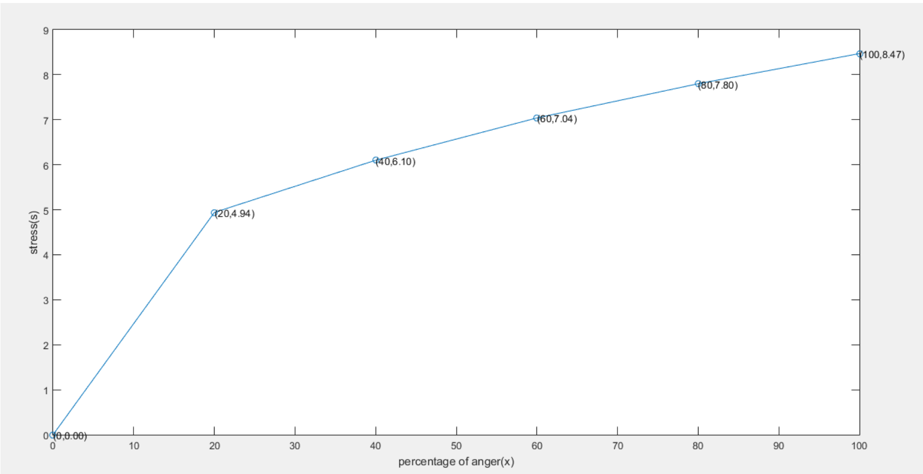

Figure: 7. Stress vs. Anger logarithmic curve

Figure 8 shows the logarithmic curve for Stress vs. Disgust which is close to linear without and sharp uprisings or spikes. The stress levels rises for Disgust smoothly but with continued presence of the causal factors it can reach a moderately high peak value of around 6.

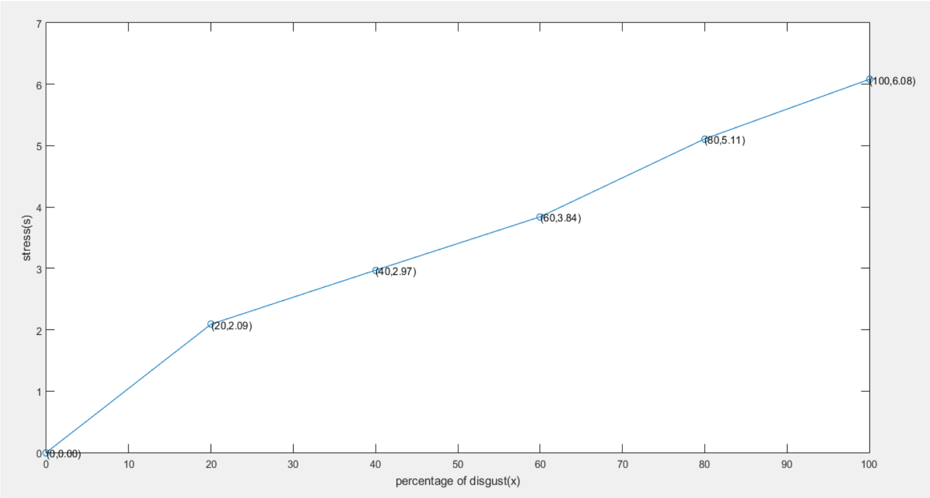

Figure: 8. Stress vs. Disgust logarithmic curve

Figure 9 shows the logarithmic curve for Stress vs. Fear which exhibits similar traits as anger but higher in magnitude than that in anger. From figure we can observe that in the initial 20 percent interval the stress level jumps steeply from 0 to 6. This can be explained as a sudden appearance of a causal element in the surroundings or in thoughts that instills fear. After 20 percent with persistence of the causal element the stress level for fear raises slowly reaching peak stress level of around 8.5.

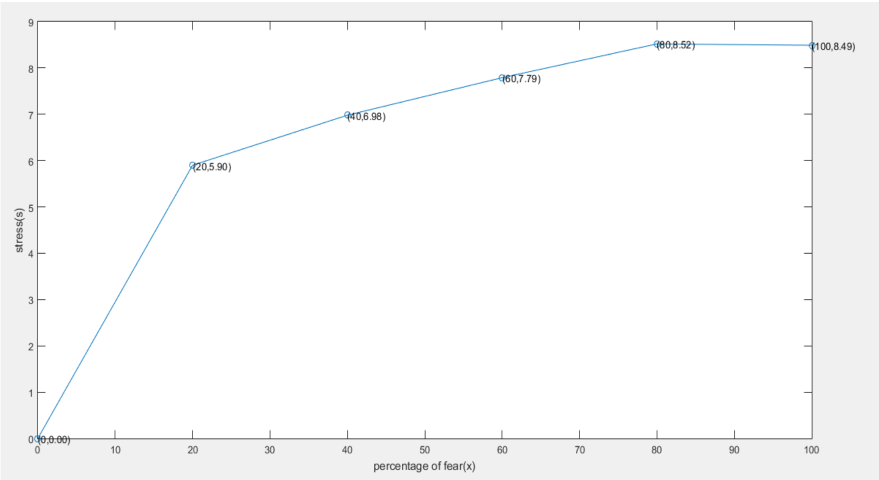

Figure: 9. Stress vs. Fear logarithmic curve

Figure 10 shows the logarithmic curve for Stress vs. Happy is the most unique among all the stress curves relating individual basic emotions to stress. In the interval of 0 to 40 percent it is at a stress level of 0 and in beyond 40 percent it almost resembles a straight line with a very moderate positive slope. For Happiness the peak value reached is just over 2.5 which are much lower than any other basic emotion.

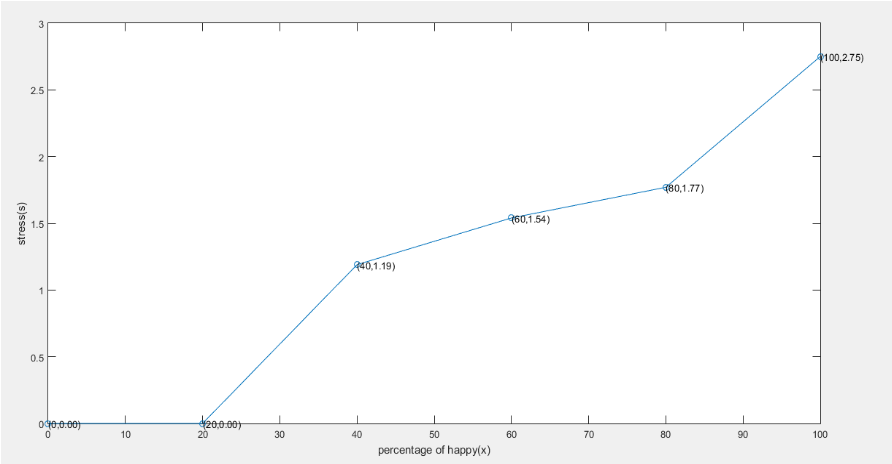

Figure: 10. Stress vs. Happy logarithmic curve

Figure 11 shows the logarithmic curve for Stress vs. Sad and it is easily observable that the peak stress level for sadness reaches near 8. In the initial 20 percent interval it steeply raises 4 units and from there onwards climbs steadily to the peak. An example situation for the initial steep climb can be given. Suppose a person suddenly comes to know that a close relative died, he experiences the initial shock of sadness, hence the steep climb of stress level.

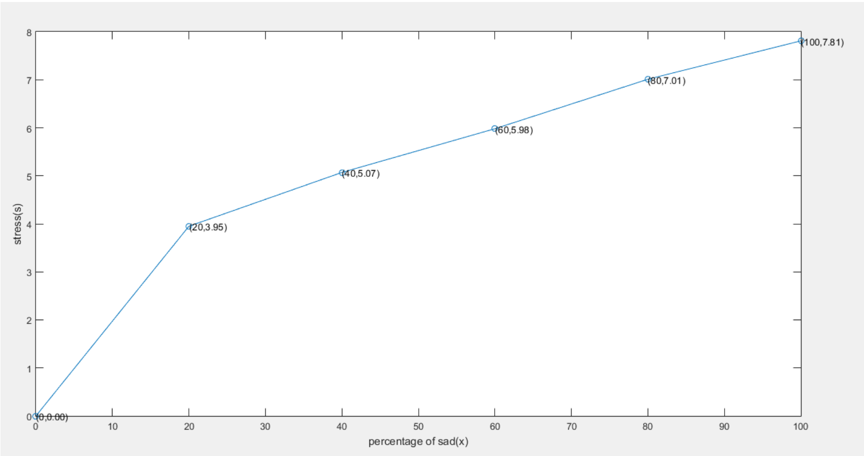

Figure: 11. Stress vs. Sad logarithmic curve

Figure 12 shows the logarithmic model curve for Stress vs. Surprise appears similar to that of Anger but for Surprise the peak stress is marginally lower. Surprise is the emotion that ranks third in severity of stress response following fear and Anger.

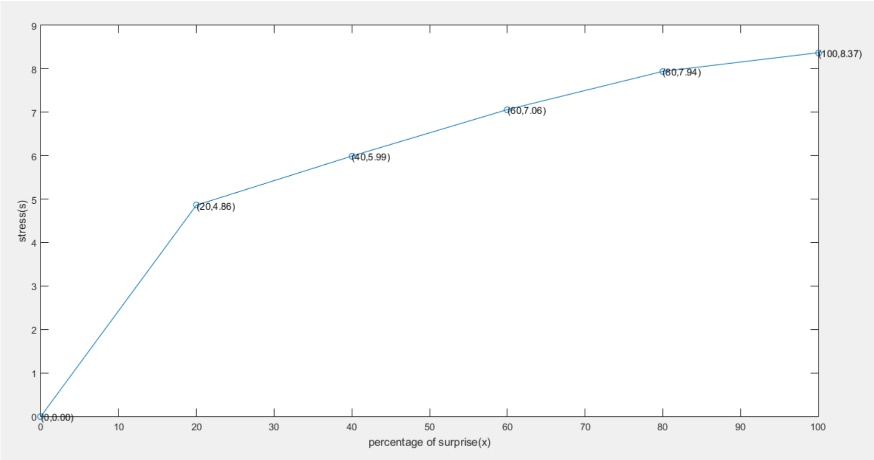

Figure: 12. Stress vs. Surprise logarithmic curve

Figure 13 shows the logarithmic model curve for Stress vs. Neutral appears to be steady and constantly increasing, indicating that the stress levels of a neutral person are in the range of 4-5.

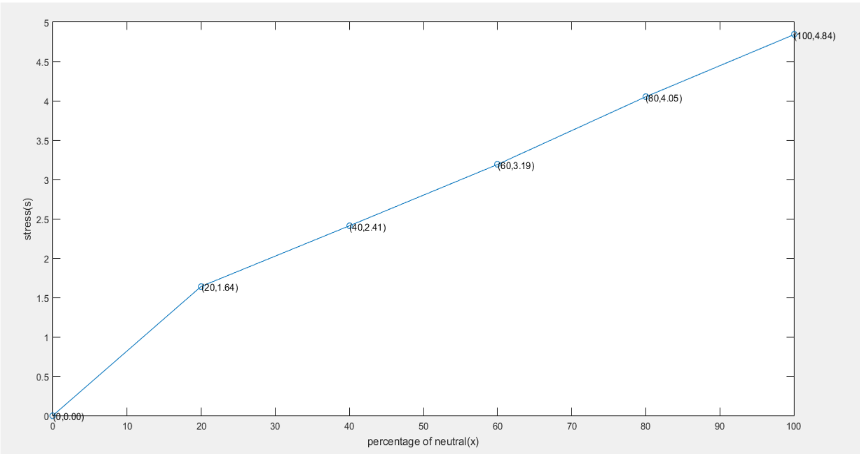

Figure: 13. Stress vs. Neutral logarithmic curve

[6] DISCUSSION

We are aware that our current implementation of the stress detection model may have the following limitations. If anyone tries to give fake expressions or if there is beard or glasses are used in the image, our model may give wrong output.

Also as the training done on the images is less, the expressions like fear, sad or disgust may not be correctly identified. The stress results also depend only on the one survey which may sometimes give incorrect stress probability.

[7] CONCLUSION AND FUTURE SCOPE

This paper presented a novel solution, for stress detection from facial emotion recognition using CNN. As shown in the results, in comparison with the other methods that use the same facial expression database, our method uses CNN that works better for images, and presents a simpler solution.

As future work, we want to test this approach in others databases, and perform a cross database validation. Also, the accuracy of our model can be increased by using GPU or cloud for training. Further, we want to extend our research to real-time stress monitoring of personnel in organizations.

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Author[s] brief Introduction

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