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A Deep Learning Approach for Human Stress Detection

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ABSTRACT: *S*tress and emotions are interdependent. The relationship between stress and emotions is a key to one person's behavior [1]. Detecting emotions from images using deep learning techniques is not discovered still to find psychological stress [2]. A hybrid system with a combination of convolutional neural network (CNN) and a regression classifier is introduced. A convolutional neural network (CNN) is trained to determine facial expressions and categorize human faces. A logarithmic regression is applied further to estimate stress. The research was conducted on Facial Expression Recognition (FER2013) dataset to evaluate the architecture. It reached 67.76% accuracy for 5 layer CNN with 65 iterations**.**

KEYWORDS: Deep Learning, Human Emotions, Facial Expression Recognition (FER2013), Convolutional Neural Network (CNN), Regression Classifier, Logarithmic Regression.

I. INTRODUCTION

Emotions are an essential part of human communication that affects our consciousness dramatically. It can be expressed in terms of affective states which represent feelings or emotions such as joy, fear, stress, etc. within a specific period. Stress, which is an affective state, is a psychological response to the challenges humans may face. Stress plays a fundamental role in controlling one's decision-making capability, attention span, learning, and problem-solving capacity. Stress detection and modeling is a progressive area of research in the fields of psychology and computer science in recent times. Detection, characterization, and treatment of human stress are active research gaining a lot of attention due to their importance in our daily lives. Some of the stress sources are due to financial, economical, political, chemical, biological, physical as well as social factors. Several stress sources lead to lots of human disorders, diseases, depression, and more. Several research papers have presented several methods to detect and analyze such facts to indicate that the person identified with stress needs some sort of treatment. The knowledge of stress and emotions is closely related but not directly researched so far. They're always handled as two specific fields of study in research activities. In this research, A quantitative indicator for stress from human facial emotions is termed facial expressions. Facial muscle structure is significantly varied amongst humans and to theorize a technique assessing facially found stress could be possible only if we use effective muscle movement data. The muscle movement data is extracted to an intermediate form before developing a model to evaluate facially detected stress. There are some basic emotions as anger, disgust, normal, fear, happiness, sad, and surprise are inborn and ubiquitous to humans. These emotions can be used as a sample format to evaluate the sign of stress. The prototype is divided into two stages: emotion recognition and a stress detection phase. Once the emotion recognition phase is completed, Surveys had been held related to stress and emotions. These surveys and results convey the relationship between emotions and prominently noticeable stress as detailed by psychologists in the survey responses. According to medical science, there are plenty of solutions like a consultation with a doctor and medication that could manage. But all these will only be constructive when there is a way to typically envision the stress level of a person without making the particular person aware of it. So, a stress monitoring system needs to be developed that will indicate the stress levels without asking that particular person questions, biological samples or wearing something all the time as that would meddle with that person's work schedule. It is not a replacement for the scientific medical procedures completely but it would act as a supporting system to determine when such procedures need to be started. This is highly convenient as medical procedures cannot be performed continuously and hence needs some indicator to indicate whether the medical procedures are required. The disquisition is intended to propose and implement a more explicit method to identify emotions from facial muscle movement using Convolutional Neural Network and use these recognized emotions to evaluate stress levels by finding the finest emotion stress relational model from stress survey data.

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II. RELATED WORK

Several facial expression and emotion recognition approaches developed through research practices. A full survey can be found in [5], [6]. In [1], the authors propose a simple solution for facial expression recognition on the Extended Cohn-Kanade (CK+) dataset, which uses a combination of standard methods, like Convolutional Network and specific image pre-processing steps with 97.81% of accuracy, and takes less amount of time to train than state-of-the-art methods. But it was seen that the accuracy of some expressions, like fear and sadness, was less than 80%, As described in [2], 5-layer CNN and deeper CNN were applied on the Kaggle FER dataset to achieve an accuracy of 48%. Also as seen in [3], the authors present the model with 4 convolutional layers and 2 fully connected layers on the Kaggle FER2013 dataset and also a comparison between shallow and deep models where the deep network qualified us to increase the validation accuracy by 18.46%. In [4], a cascade network with 6 CNN which comprises 3 CNN's for face vs. non-face binary classification and 3 CNNs for bounding box calibration, which is formulated as multi-class classification of various displacement patterns is proposed on the FDDB dataset with an accuracy of 85.1%.

III. PROPOSED ALGORITHM

A. *Design Considerations:*

- Capturing the video and converting the video into frames
- Performing background separation and image segmentation and ROI
- The processed image is compared with deep learning model file
- The level of stress is obtained and accuracy is plotted

B. *Description of the Proposed Algorithm:*

The prototype comprises two steps: Emotion recognition and Stress detection from the decoded set of emotions. Convolutional Neural Network (CNN) is used to find the probabilities that facial expression represents a particular emotion for all emotions (As shown in figure 1).

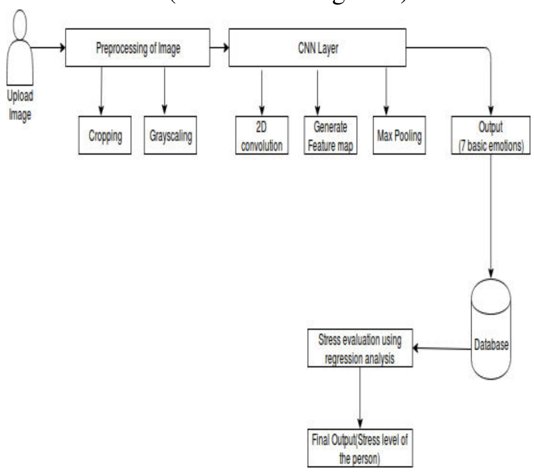

Figure: 1. Architectural diagram of our model

Step 1: Emotion recognition

As a part of emotion recognition, in the input layer, we did preprocess on the acquired image. Preprocessing comprises 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 a NumPy array. The NumPy array is then passed to the convolutional layer which consisted of 3 convolution layers and the set of filters to generate the feature maps. The combination of depth-

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wise separable convolutions and residual modules is included in place of fully connected layers. The prototype is trained with an ADAM optimizer. Global Average Pooling is used to completely remove any fully connected layers. This was accomplished by having in the last convolutional layer the same number of feature maps as several classes and applying a softmax activation function to each reduced feature map. Lastly, in the output layer, the softmax function presented the output as a possibility for each emotion class.

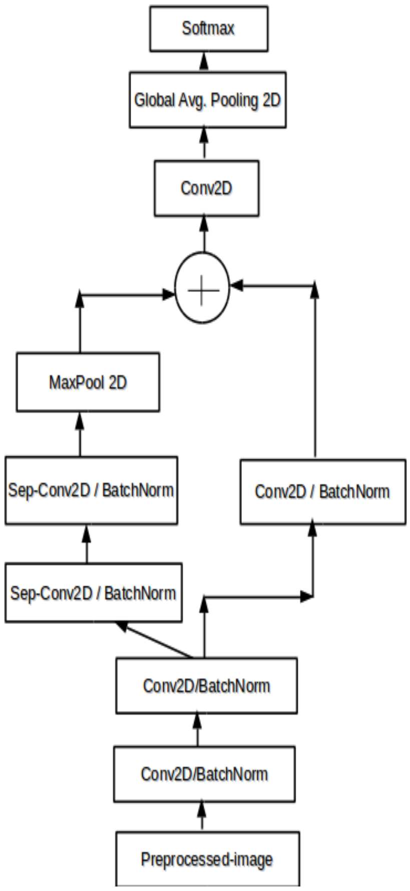

Figure: 2. CNN Implementation

Step 2: Stress detection

After deciphered emotion information is collected from the facial expression the stress levels are being evaluated and to that effect, a survey is conducted among people that relates emotion degrees to stress levels. The survey was conducted without examining any images. Respondents were given emotion intensity percentages in steps of 20 in a range of 0 to 100 and they were requested to map each level of the basic human emotion with a stress level between 0 to 9 and a total of 108 responses were received. After this survey, the results of the survey and the deciphered emotion information data are used to predict a regression model that describes the stress and emotion data. Five different linear and non-linear regression models were analyzed for the prediction of stress levels from emotion degrees or percentages and the best model is chosen based on parameters like the goodness of fit and root mean square errors. The logarithmic fit was the best model among all the models and it was also following the Weber-Fechner law. Then the logarithmic model equations were presented determining the coefficients of unknown variables using regression analysis. This approach can finally be used to evaluate visually perceptible stress levels 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.

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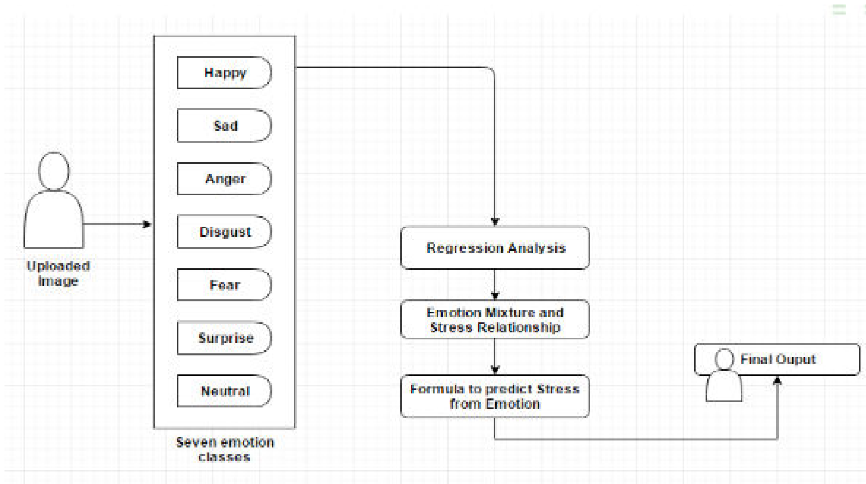

Figure: 3. Stress Evaluation Model

IV. DATASET

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

Figure: 4. Sample from FER2013 dataset with their corresponding emotions

V. SIMULATION RESULTS

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

Figure 5 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 angry outburst of a person which of course will keep on increasing with the continued presence of the cause of Anger but not at such a high rate as it was initially. This outburst in real scenarios sometimes is visible but many times suppressed at will as well due to environmental restriction or personal habits.

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

Figure 7 shows the logarithmic curve for Stress vs. Fear which exhibits similar traits as anger but higher in magnitude than that in anger. From the 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 instill fear. After 20 percent with the persistence of the causal element, the stress level for fear raises slowly reaching a peak stress level of around 8.5.

Figure 8 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 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 is much lower than any other basic emotion.

Figure 9 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 10 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 the severity of stress response following Fear and Anger.

Figure 11 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.

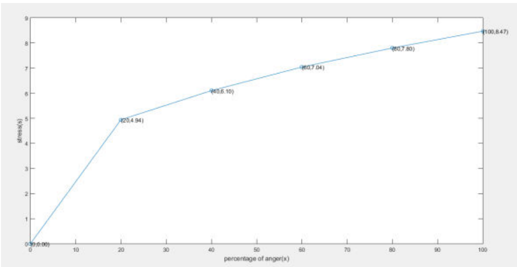

Figure: 5. Stress vs. Anger logarithmic curve

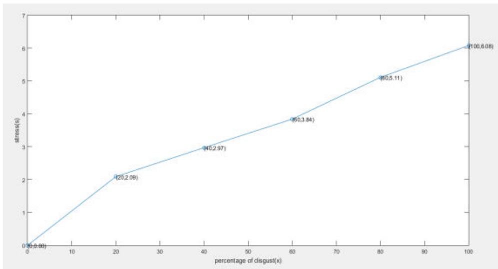

Figure: 6. Stress vs. Disgust logarithmic curve

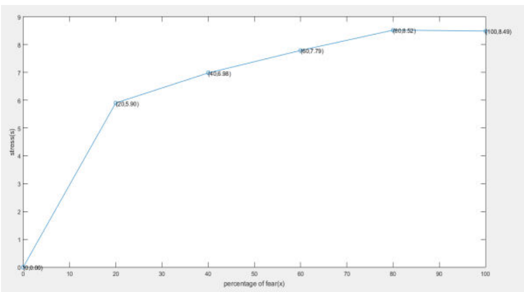

Figure: 7. Stress vs. Fear logarithmic curve

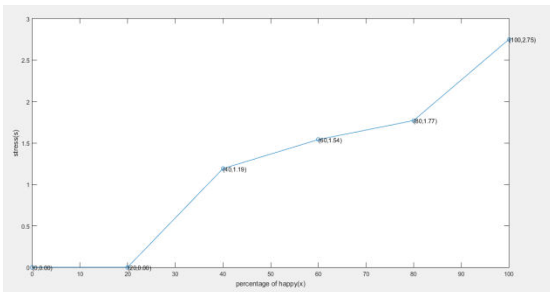

Figure: 8. Stress vs. Happy logarithmic curve

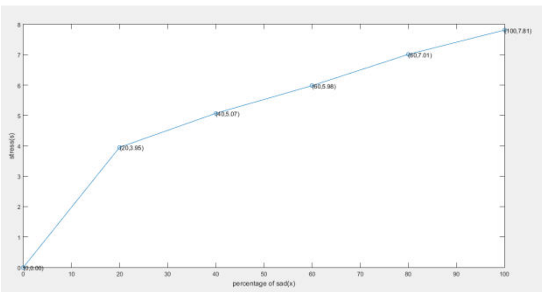

Figure: 9. Stress vs. Sad logarithmic curve

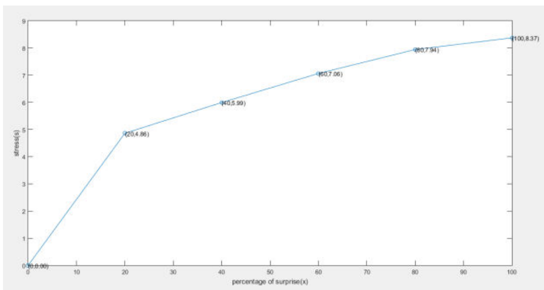

Figure: 10. Stress vs. Surprise logarithmic curve

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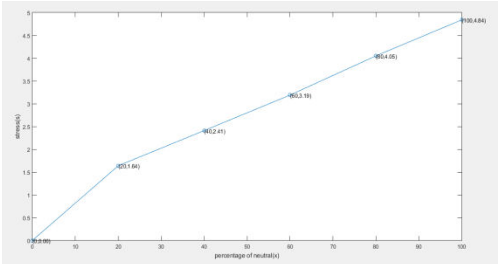

Figure: 11. Stress vs. Neutral logarithmic curve

VI. DISCUSSION

If anyone tries to give fake expressions or if there is a beard or glasses are used in the image, this model may give the wrong output. Also as the training done on the images is minimal, the expressions like fear, sad or disgust may not be identified correctly. The stress results depend only on that one survey which may rarely give incorrect stress probability.

VII. CONCLUSION AND FUTURE WORK

This paper ascertained a working solution for stress detection from facial recognition of emotion using CNN. As shown in the results, in comparison with the other methods that use the same facial expression database, the method uses CNN that works better for images and presents a simpler solution. As future work, the approach will be tested in other databases, and perform a cross-database validation. Also, the accuracy of our model can be improved by using GPU or cloud for training. Further, this will be extended to real-time stress monitoring of personnel in organizations

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