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STRESS DETECTION USING FACIAL RECOGNITION

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Abstract:* Stress is the body's natural reaction to external and internal stimuli. Despite being something natural, prolonged exposure to stressors can contribute to serious health problems. These reactions are reflected not only physiologically, but also psychologically, translating into emotions and facial expressions. Based on this, we developed a proof of concept for a stress detector. With a convolutional neural network. We also designed a deep neural network that receives facial landmarks as input to take advantage of the fact that eye moments, lips moment, and head movements are different from normal situations when a person is stressed. These results show that the proposed algorithm recognizes stress more effectively. We are using convolutional neural network (CNN) for classification and training purpose capable of classifying facial expressions, and an application that uses this model to classify real-time images of the user's face and thereby assess the presence of signs of stress. The results obtained are very promising and the proposed stress- detection system is noninvasive, only requiring a webcam to monitor the user facial expressions.

Keywords: Face recognition, Stress detection, Convolutional Neural Network(CNN)

1. INTRODUCTION

Demanding jobs are a major source of stress for people. Situations such as frequent exposure to danger, tight deadlines, demanding tasks, or repetitive tasks are stress triggers. It is important to identify people's stress conditions early and prevent the negative effects of stress on people. A psychological assessment of stress can be used to identify a person's stress state. Stress

is assessed by filling out questionnaires or talking to a psychologist. Because psychological assessments are immediate and subjective, they often lead to false or even false positives of stress, failing to meet the requirements of real-time detection. On the other hand, in the case of stress detection research using general images, most of the studies used relatively simple features. In this project, we propose a method to detect stress by extracting high-dimensional

features from facial images taken with a general camera. We then use the positions of facial features that show large changes under stress to learn more efficient functions.

2. LITERATURE SURVEY

Philipp Schmid et al. introduced the WESAD dataset for portable emotion and stress detection and made it available to the public. To collect these data, they selected his 15 subjects and collected physiological data such as triaxial acceleration, electrocardiogram, blood volume pulse, body temperature, respiration, electromyogram, and electrodermal activity on wearable devices. (RespiBAN Professional and Empatica E4) and recorded. Subjects were exposed to different stress conditions, including baseline, entertainment, stress, and meditation. They used and compared the performance of five machine learning algorithms (K Nearest Neighbors (KNN), Linear Discriminant Analysis (LDA)) in detecting stress conditions.), Random Forest (RF), Decision Trees (DT), Adaboost (AB). They used common features and conventional machine learning methods to achieve up to 80.34% and 93.12% accuracy, respectively, considering three- class (entertainment vs. baseline vs. stress) and binary (stress vs. non-stress) classification problems. achieved classification accuracy.
Jacqueline Wisman et al. also measured physiological signals with wearable sensors to detect psychological stress. We recorded participants' electrocardiograms, skin conductances, respirations, and EMGs, from which a total of 19 physiological features were calculated. A subset of 9 features were selected from these 19 features, examined for correlation and normalized feature

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values, then subjected to further analysis and reduced to 7 features after using principal component analysis. By using these functions and various classifiers such as Linear Bayes Normal Classifier, Quadratic Bayes Normal Classifier, K-Nearest Neighbors Classifier, and Fisher's Least Squares Linear Classifier, we can determine the stress state and non-stress state of an individual. An accuracy of 80% was achieved between states. . This experiment is almost identical to the one conducted, except for the number of participants and extracted features. They used three different stressors in his study and compared the results with other studies on stress classification in which he used only one type of stressor.Biopac's BioNomadix model BN- PPGED was a portable device used to measure physiological responses. The participant wore her BN-PPGED on her non-dominant hand like a bracelet and attached her two electrodes to two fingers to measure pulse plethysmograph (PPG) and cutaneous electrode activity (EDA) signals. bottom. Additionally, PPG autocorrelation signals and heart rate variability (HRV) were extracted using AcqKnowledge software. A support vector machine (SVM) was used to classify individuals as stressed or not with an accuracy of 82%.
Regarding employee reports of stress at work, Saskia Koldijk et al. Using sensor data such as posture, facial expressions, computer logging, and physiology (ECG and skin conductance), she I developed an automatic classifier that examines the relationship between When we divided similar users into subgroups, we found that the specialized model performed as well or better than the general model in almost all cases when the model was trained on specific subgroups. I was. Posture was found

to provide the most important information among the most useful modalities for distinguishing between stressor and non- stressor working conditions.Adding data on facial expressions further improved performance. You can. We achieved 90% accuracy with the SVM classifier.Facial features are another important factor that can define a person's stress level. Furthermore,
G. Giannakakisa et al. A framework for detecting and analyzing emotional stress/anxiety states via video-recorded facial expressions. Features examined were mouth activity, eye-related events, camera- based photoplethysmographic estimation of heart rate, and head movement parameters. Participants had to sit at a distance of 50 cm from him in front of a computer monitor with a built-in camera. Methods such as Generalized Likelihood Ratio, Naive Bayes Classifier, Support Vector Machines, K- Nearest Neighbors, and AdaBoost Classifier were used and tested. For the social exposure process, the best classification performance was achieved with the Adaboost classifier, which achieved an accuracy of 91.68%.

3. METHODOLOGIES

The proposed network uses a hair cascade classifier to detect facial land markers from real-time recorded video data to detect the subject's facial emotion. Once the facial expression recognition using the deep neural network is complete, this data is used to predict the subject's stress level. When collecting training photos, group them into categories such as anger, happiness, sadness, surprise, neutral, and fear. Additionally, the dataset should be sorted by sentiment class, and any photos with

uncertain sentiment should be removed. We use a CNN algorithm to train the dataset and classify emotions until we reach maximum accuracy (the more we track, the better). and 200 epochs and achieved 89% accuracy. We also used the AdBoost activation feature to reduce training loss, as seen in our Loss vs. Epoch results.
Face landmark detection (64) points using haarcascadefrontalface.xml and Shape Predictor.dat files. These files are published by Open CV and are useful for detecting frontal landmarks on faces and human bodies. Use OpenCV to recognize facial expressions and predict stress levels based on specific classes of emotions. All phases come together to create the final product of the project. Repeatedly test your project for errors and ensure that the results meet your project criteria.

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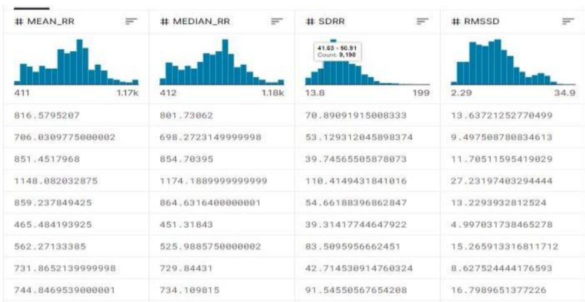
4. DATASETS



# MEAN_RR	# MEDIAN_RR	# SDRR	# RMSSD
411 – 1.17k	412 – 1.18k	13.8 – 199	2.29 – 34.9
816.5795207	801.73062	70.89091915008333	13.63721252770499
706.0309775000002	698.2723149999998	53.129312045898374	9.497508780834613
851.4517968	854.70395	39.74565505878073	11.70511595419029
1148.082032875	1174.1889999999999	110.4149431841016	27.23197403294444
859.237849425	864.6316400000001	54.66188396862847	13.2293932812524
465.484193925	451.31843	39.31417744647922	4.997031738465278
562.27133385	525.9885750000002	83.5095956662451	15.265913316811712
731.8652139999998	729.84431	42.714530914760324	8.627524444176593
744.8469539000001	734.109815	91.54550567654208	16.7989651377226

5. SYSTEM ARCHITECTURE AND WORKFLOW

In the proposed network, previously detected face photos and face tags are input to the proposed network, and stress detection results are output. Stress detection provides a scale from 0 to 100. Shortcut mapping and bottleneck architecture are used in the network proposal to optimize the neural network structure. Different hierarchies can simplify the learning process and determine the direction of learning when the links are mapped to a deeper neural network structure. With improved depth, deep neural networks can now be easily tuned to improve accuracy. Also, the number of internal parameters can be reduced, and the number of feature maps can also be reduced. The result is improved performance and reduced computation time.

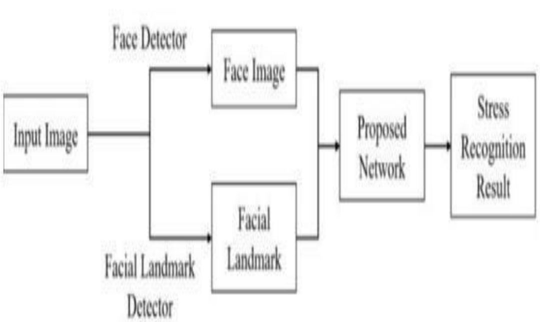


FIG- The architecture of stress detection

1. The datasets are imported.
2. Capturing the live image using web cam.
3. Using the CNN algorithm the captured image is visualize.
4. Parameters like eyebrows, eye moments, lip moments, head position and datasets are used to analyze the image.
5. then stress level is shown on 0 to 100 scale.

6. RESULT

This result indicates that the person is stressed, with a stress score of 79 and a high stress level.

7. CONCLUSION

The stress detection system monitors photos collected from authorized users to predict worker stress and keep the system safe. When an authenticated user logs in, image capture is automatically performed according to the time of day. The captured image is used to determine the user's exposure based on certain common conversion and image processing processes. The system then uses machine learning algorithms to analyze your stress levels and derive more efficient results. Stress detection accuracy is 97%.

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