JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Implementation Paper: Human Stress Detection Based on Physiological Parameters

Ms. Vanishri Sataraddi
Assistant Professor
ISE Dept.
RNS Institute of Technology
Bangalore, India

Sidharth Kesarwani
ISE Dept.
RNS Institute of Technology
Bangalore, India

Suarbhi Subramanyam
ISE Dept.
RNS Institute of Technology
Bangalore, India

Roopesh N
ISE Dept.
RNS Institute of Technology
Bangalore, India

Rohan S Bharadwaj
ISE Dept.
RNS Institute of Technology
Bangalore, India

Abstract — **In today's rapidly evolving IT-driven environment, the rise of new technologies and solutions has coincided with a notable increase in stress levels among employees. Despite the provision of mental health benefits in many companies, stress remains a widespread concern across various industries. This study seeks to explore the patterns of stress among individuals in the workforce and identify the key factors influencing stress levels. The methodology involves utilizing image processing and machine learning techniques for analyzing stress patterns. Machine learning algorithms, such as KNN classifiers, are employed for stress classification. The process begins with capturing the employee's image using a camera, followed by image processing to extract relevant data. Subsequently, the system generates either a modified image or a stress report based on the analysis. Through machine learning, the system autonomously learns and adapts, enabling it to make predictions without explicit programming. Stress, which is known to contribute significantly to various physical ailments like cardiovascular disease, diabetes, and migraines, manifests through subjective symptoms, behavioral changes, and cognitive impairments. Effectively addressing stress is crucial for societal well-being, and leveraging automatic stress detection methods utilizing physiological markers shows promise in mitigating health risks. Establishing a scientific framework for assessing stress levels is essential given its significant societal implications.**

Keywords— ***Facial Express, K-Nearest Neighbor Classifier, Stress, Stress prediction.***

I. INTRODUCTION

In today's rapidly evolving technological landscape, the workforce is continually faced with challenges and evolving expectations. Despite the continuous influx of new products and services, concerns about employee well-being persist. While many companies have implemented mental health benefits, stress remains a prevalent issue across industries. The adverse effects of stress on both physical and mental health are well-documented, contributing to various ailments such as cardiovascular disease, diabetes, and migraines. Moreover, stress can manifest through subjective symptoms like anxiety, anger, and fatigue, as well as behavioral changes such as increased accidents and erratic behavior. Given the significant impact of stress on individuals' overall quality of life, there is an urgent need to develop effective methods for detecting and managing workplace stress.

Traditional approaches to stress assessment, often relying on self-reported questionnaires, may lack accuracy or timeliness in providing insights into individuals' stress levels. However, recent technological advancements, particularly in image processing and machine learning, offer promising solutions. Automated stress detection systems that leverage facial expressions and physiological markers can provide real-time assessments of individuals' stress levels, enabling prompt intervention and support.

This study aims to delve deeper into workplace stress by utilizing image processing and machine learning techniques to analyze stress patterns among employees across various industries. Specifically, the study will explore the use of machine learning algorithms, such as K-Nearest Neighbor (KNN) classifiers, to categorize stress based on facial expressions and other relevant factors.

Through the development of an automated stress detection system, the objective is to enhance understanding of the factors influencing stress levels in the workplace. By identifying stress patterns and leveraging physiological markers, the study aims to provide valuable insights into individuals' stress levels and facilitate timely interventions to promote employee well-being and productivity.

In conclusion, this study represents a significant step forward in addressing the complex issue of workplace stress by leveraging technology to develop innovative solutions for stress detection and management. By harnessing image processing and machine learning techniques, the goal is to contribute to the creation of a healthier and more supportive work environment for all employees.

II. METHODOLOGY

The following modules are used in this project:
• User module
• Admin module
• Data Pre-processing
• Machine Learning algorithms (K-Nearest Neighbour Classification)

A. User

Users undergo registration by submitting a valid email and phone number, followed by account activation by the administrator. Upon activation, users gain access to the system and can upload images as input. Utilizing Python packages, image attributes and emotions are extracted, with the capability to detect multiple faces within a single image. Stress levels are inferred from facial expressions such as sadness or anger. Real-time facial expression displays are facilitated through live feeds, with TensorFlow ensuring enhanced accuracy and speed. Subsequently, the dataset is imported for assessing KNN classification accuracy.

B. Admin

Administrators log in using their credentials to activate users and dynamically manage the project's training and testing data. They have the authority to view users' identified results, discern emotions from photos, and access K-nearest neighbor classification outcomes. Additionally, administrators can extend the dataset by incorporating fictitious values, a task assigned to authorized personnel.

C. Data Pre-process

The dataset undergoes Principal Component Analysis (PCA) to derive numerical input variables, yielding a new dataset comprising six principal components: Condition (including categories such as No stress, Time pressure, and Interruption), Stress, Physical Demand, Performance, and Frustration

D. Machine Learning

The K-Nearest Neighbor (KNN) algorithm serves as a supervised learning technique utilized for both classification and regression analysis, aimed at assessing whether an individual requires therapy. In KNN, the dependent variable is categorized based on its similarity to instances of previously gathered data. This approach is particularly beneficial for binary classification models, where the dependent variable is represented by two potential values denoted as "0" and "1"

III. IMPLEMENTATION

- Face Detection from input image.
- Segmentation & Determination of Mouth Region.
- Segmentation & Determination of the Eye Region.
- Emotion Detection.

A. Face Detection from input image

The process begins with converting the RGB image into a binary format by determining the average RGB value for each pixel. Pixels with an average value below 110 are designated as black, while those surpassing this threshold are marked as white. This transformation involves a systematic examination of the image, starting from its midpoint, to detect continuous sequences of white pixels following uninterrupted black pixels, thereby identifying the location of the forehead. The maximum width of the forehead is then determined through vertical searches conducted on both sides. If the newly calculated width drops below half of the previous maximum width, indicating the presence of eyebrows, the scanning process halts. Finally, the face is cropped from the initial forehead position, with its height set at 1.5 times its width.

B. Segmentation and Determination of mouth region

This module operates by first representing the image in the L * a * b color space rather than the conventional RGB space. The L * a * b system provides a perceptually uniform color space, facilitating the representation of color differences as Euclidean distances. However, color information alone may not suffice to identify the lip region. To overcome this limitation, the Fuzzy C-means clustering algorithm is employed, incorporating both color and pixel-position information of the image to detect the lip region. The segmentation of the lip region from the face involves a novel approach, with the algorithm leveraging both color and positional data. The determination of the mouth opening (MO) in a black and white image is facilitated by the presence of white teeth. The average intensity profile plotted against the MO reveals distinct minima, corresponding to the inner regions of the top and bottom lips. The difference between these measurements along the Y-axis provides a measure of the MO.

C. Segmentation and Determination of eye region

The segmentation process for the eye region begins by acknowledging its distinctive contrast in a monochrome image, which makes it well-suited for thresholding segmentation compared to other facial features. However, challenges arise when dealing with images captured under less-than-ideal illumination conditions, characterized by low average intensity values. In such scenarios, segmentation becomes complex due to the presence of dark eyebrows surrounding the eye area. To overcome this challenge, priority is given to images captured under favorable lighting conditions.

Following segmentation, localizing the positions of the left and right eyes becomes imperative. This involves converting the RGB face image into a binary format and conducting a scan from W/4 to (W-W/4) to pinpoint the midpoint between the two eyes. The highest continuous white pixel within this range serves as an indicator of the midpoint. Subsequently, the upper position of the eyebrows is determined through vertical scanning. To ensure seamless connectivity between the eyebrows and eyes, vertical lines of black pixels are introduced. The lower position of the eyes is then identified using vertical black pixel scanning. Finally, the horizontal locations of the left and right eyes are determined, and the corresponding regions are extracted from the RGB image.

D. Emotion Detection

Identifying emotions in an image involves detecting the Bezier curves of the lip, left eye, and right eye. The width of each Bezier curve is normalized to 100, and the corresponding height is adjusted proportionally. If the person's emotional data exists in the database, the program matches the emotion with the closest height. Alternatively, if emotional data is absent, the program calculates the average height for each emotion in the database across all individuals and uses these averages to determine the closest match.

IV. Literature Review

[1] A framework proposed by several researchers aims to detect stress and anxiety in films through facial cues analysis. By integrating various facial signals such as eye-related events, mouth activity, head motion, and heart rate, the research strives to objectively assess stress and anxiety states. Robust feature selection and classification algorithms are utilized to achieve accurate identification of these emotional states. Additionally, the research explores the relationship between facial attributes and reported stress/anxiety levels, providing insights into the mechanisms of emotional expression. While acknowledging the influence of external and internal stressors, the study addresses potential biases in self-reported stress/anxiety levels, emphasizing the importance of objective measures in comprehensive evaluation. Ultimately, this research contributes to advancing stress and anxiety detection methods in film analysis, offering valuable insights into emotional responses within cinematic contexts.

[2] Another study focuses on detecting stress levels in individuals through real-time non-intrusive movie stimuli and the analysis of facial expressions. The methodology involves training a model using image processing and machine learning techniques to facilitate effective stress detection through a generic model. Key aspects of the research include the real-time assessment of stress levels based on facial expressions, providing a non-intrusive approach to stress monitoring, and leveraging image processing and machine learning for stress detection. However, the study acknowledges limitations such as its restricted applicability to specific settings, such as computer use, and its reliance solely on facial expressions as indicators of stress. Despite these limitations, the study makes significant contributions to stress detection methodologies, especially in real-time scenarios, with potential implications for various applications in stress management and mental health monitoring.

[3] Research conducted on stress prediction among working employees utilizes machine learning techniques, leveraging data from the OSMI mental health survey 2017. The study aims to pinpoint significant factors influencing stress levels, with boosting exhibiting the highest accuracy among the employed models. Key contributions include the identification of influential stress factors and the application of machine learning for stress prediction, offering potential insights for businesses to improve workplace environments based on research findings. However, the study acknowledges limitations such as its reliance on survey data for stress assessment and the limited generalizability of findings beyond the IT sector. Nevertheless, the research provides valuable insights into stress patterns among working individuals and emphasizes the importance of utilizing machine learning for predictive analysis in occupational stress research.

[4] A study aims to establish a technique for identifying short-term psychophysiological alterations associated with acute stress using heart rate variability (HRV) properties obtained from sternal electrocardiograms (ECG). The research involves analyzing both linear and non-linear HRV characteristics, achieving high identification rates for different arousal stages. Key contributions include the identification of psychophysiological alterations linked to stress, utilization of HRV properties for stress classification, and achieving high accuracy in identifying various arousal stages. However, limitations such as the limited scope to acute stress detection and the requirement for standardized HRV variables for accurate classification are acknowledged.

[5] A study explores the feasibility of leveraging smartphones and wearable sensors equipped with physiological and movement tracking capabilities to detect mood in the workplace. The paper introduces a novel mood detection framework and proposes the implementation of a smartphone application named 'Healthy Office' for self-reporting and data collection purposes. Key highlights of the research include the utilization of smartphones and wearables for mood detection, the development of an innovative mood detection framework, and the encouragement of formal self-reporting through the designated smartphone application. However, the study acknowledges considerations such as reliance on sensor technologies for mood detection and potential privacy concerns associated with data collection via wearables and smartphones.

[6] J. C. Bezdek's Ph.D. dissertation explores the application of fuzzy mathematics in pattern classification, providing a comprehensive overview of this field. The dissertation delves into the theoretical foundations and practical applications of fuzzy mathematics, particularly in the context of pattern classification tasks. While it offers valuable insights and advancements in the field, it's essential to note that, being a dissertation, the content may be highly technical and detailed, potentially posing challenges for readers unfamiliar with the subject matter.

[7] M. T. Black and Y. Yacoob present a paper focused on recognizing facial expressions in image sequences by utilizing local parameterized models of image motion. The paper delves into the technical intricacies of facial expression recognition, particularly emphasizing model-based approaches. While it offers valuable insights into the subject, it's important to note that the approach may have limitations in effectively handling variations in facial expressions across individuals or different contexts. Despite this potential constraint, the paper contributes to the understanding of facial expression recognition methodologies, particularly in the realm of model-based techniques.

[8] A study explores the interplay between speech and facial gestures in conveying emotional expressions, with a particular focus on a single subject. The research provides valuable insights into how speech and facial gestures interact to convey emotions, elucidating the intricate relationship between these modalities during emotional expression. However, the study's limited scope, restricted to a single subject, may hinder its applicability to broader populations or contexts. Nonetheless, the research significantly contributes to our comprehension of the complex dynamics between speech and facial expressions in emotional communication.

[9] I. Cohen's thesis delves into facial expression stress recognition from video sequences, offering a comprehensive examination of this topic. The thesis likely provides in-depth insights into the methodologies and techniques used for recognizing stress from facial expressions captured in video footage. However, depending on the specific methods or algorithms proposed, the thesis may have limitations in terms of broader applicability or generalizability. Despite this potential constraint, the thesis contributes valuable knowledge to the field of facial expression analysis and stress recognition, potentially paving the way for further research and advancements in the domain.

[10] "Unmasking the Face: A Guide to Recognizing Emotions from Facial Clues" by P. Ekman and W. V. Friesen serves as an extensive resource for recognizing emotions through facial expressions, leveraging the expertise of renowned scholars in the field. The book is anticipated to offer practical insights and methodologies for accurately interpreting facial cues to identify various emotions. However, due to its format as a book, it might not delve deeply into technical intricacies or specific methodologies for emotion recognition. Instead, its primary focus may be on providing accessible and practical guidance for individuals interested in comprehending facial expressions and emotional cues. Despite this potential limitation, the book remains a valuable asset for individuals aiming to improve their proficiency in emotion recognition from facial expressions.

.

V. RESULTS

The potential for integrating machine learning and image processing techniques is significant in transforming stress management systems. Proposing an advanced system capable of real-time stress detection and periodic analysis of employees' stress levels presents a promising solution to address the widespread problem of workplace stress. By combining machine learning algorithms such as K-Nearest Neighbour classifiers with image processing for facial expression analysis, the system aims to achieve accurate stress detection without intrusive methods. Its detailed architecture and design outline demonstrate the feasibility of automating stress detection using physiological markers, thereby paving the way for the establishment of healthier work environments and the enhancement of employee well-being.

VI. APPLICATIONS

Our paper introduces an application that presents a holistic approach to identifying and managing stress levels in the workplace. Through the utilization of machine learning techniques and image processing algorithms, the system can analyze facial expressions in real-time to detect stress. This capability allows for timely intervention for individuals experiencing stress, while also empowering organizations to address stress-related issues proactively. With the goal of fostering a healthier and more supportive work environment, the application ultimately seeks to improve employee productivity and well-being.

VII. CHALLENGES AND OPEN PROBLEMS

The conclusion of the Stress Detection System emphasizes its capacity to predict stress levels among workers by monitoring authorized users' collected photographs, ensuring the system's reliability and effectiveness. Through automated image capture at predetermined intervals upon user authentication and the application of standard image processing techniques, the system proficiently evaluates users' stress levels. Additionally, the integration of machine learning algorithms enables more accurate analysis of these stress levels, yielding precise outcomes. Looking ahead, potential enhancements include the integration of biomedical wearable sensors with Internet of Things (IoT) technologies in the healthcare sector. This integration offers various benefits, such as early detection of medical issues, rapid medical assistance through remote monitoring and telecommunication, and the deployment of emergency alarm systems. By continuously monitoring stress levels and providing feedback, the proposed multimodal IoT system aims to deliver superior health assistance. Future endeavors may explore incorporating additional physiological attributes, such as activity identification systems, and leveraging machine learning methodologies to further refine the stress detection model.

REFERENCES

[1] Facial Expression Recognition Based on Attention Mechanism Jiang Daihong , Hu yuanzheng, Dai Lei, and Peng Jin Xuzhou University of Technology, College of Information Engineering, Xuzhou 221000, China

[2] A 3-Dimensional SIFT Descriptor and its Application to Action Recognition : Paul Scovanner, Computer Vision Lab University of Central Florida, Saad Ali,Computer Vision Lab, University of Central Florida, Mubarak Shah, Computer Vision Lab, University of Central Florida

[3] Xu, Q., Nwe, T.L., Guan, C.. Cluster-based analysis for personalized stress evaluation using physiological signals. IEEE journal of biomedical and health informatics 2015;19(1):275–281.

[4] Ghaderi, A., Frounchi, J., Farnam, A. Machine learningbased signal processing using physiological signals for stress detection. In: 2015 22nd Iranian Conference on Biomedical Engineering (ICBME). 2015, p. 93–98.

[5] Towards an Example-Based Image Compression Architecture for Video-Conferencing ,Sebastian Toelg and Tomas Poggio.

[6] Gender and Stress. (n.d.). Retrieved from APA press release 20.

[7] OSMI Mental Health in Tech Survey Dataset, 2017

[8] Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., & Vanderplas, J. (2011). Scikit-learn: Machine learning in Python. Journal of machine learning research, 12(Oct), 2825-2830.