Journal of Advanced Engineering Research
ISSN: 2393-8447
Volume 10, Issue 1, 2023, pp.75-78

Deep Learning Algorithms To Identify Stress In Humans By Monitoring Physiological Data

Poonam Juneja[1] , Almaas Zafar[1], Vyom Dev Chhabra[1], Ayush Kumar[1]

[1]Department of Electrical and Electronics Engineering, Maharaja Agrasen Institute of Technology, Delhi-110086, India

Corresponding author email: almaaszafar@gmail.com, Tel. : 8800618584

ABSTRACT

Stress is a typical human reaction that everyone experiences. In truth, the human body is built to experience and respond to stress. When we face changes or challenges, our body responds physically and mentally. That is the result of stress. Humans have been subjected to much stress in the last ten years, which is why stress measurement is becoming increasingly crucial in our daily lives. It is critical to recognize stress since it is a big worry, and it also helps to raise awareness. The physiological data plays a significant part in detecting human stress since alterations in the data make it extremely easy to learn about stress levels as well as anxiety, which appears first and is followed by stress. When the data is combined with machine learning and deep learning algorithms, detection becomes more accurate after training on the training data. The major goal of this research is to find a unique accuracy of stress detection using physiological data and to compare models using the acquired accuracies.

Keywords -Stress Detection, Deep Learning, Neural Networks, Artificial Neural Networks, Data Science, Convolutional Neural Network

1. INTRODUCTION

There are several causes for experiencing so much stress in today's environment. Stress is quite frequent in today's society. It was not normal in any timeframe, but previous generations managed to live with it. However, increased competitiveness, population, and poor lifestyle choices are producing stress at the next level. BP (blood pressure) issues were once uncommon, but nowadays even teenagers have high BP. The degree of stress must be identified at an early stage in order to avoid having a BP problem. So, using multi-layered perceptrons, our study seeks to determine stress levels based on the amount of sleep people get. Many detection techniques are still being developed by scientists. This approach is being tested on 20 different persons. Stress may be produced in different situations, therefore we tested these individuals under three distinct conditions: listening to music, exercising, and doing the Stroop Color-word test, which is a reference to Relaxation, Physical, and Psychological stress. And the findings appear to be rather good, as psychological stress varies from physical and relaxing stress. The Kinect sensors utilized in this are light in weight, tiny in size, and inexpensive, making it a viable alternative for stress detection. This ECG signal is mostly used to diagnose psychological stress. The Heart Rate Variability is determined using ECC (Error Correction Code) signals (HRV). Following the reception of signals, they are categorized into two sections: Stress Level 1 and Stress Level 2, which are further subdivided into low (for Stress Level 1), medium, and severe stress (for Stress Level 2).

2. RELATED WORK

Stress has become a part of our everyday lives in the modern period. We as humans worry about our relationships, financial situation, and jobs, among other things. Excessive stress or concern leads to sickness, whether physical or mental. There have been previous studies conducted on stress, its varied degrees, and how to deal with it. Many approaches are used to give dependable output, such as Heart Rate Variability (HRV), which is frequently assessed via ECG readings. The HRV output is then entered into the two-stage classifier to identify the four degrees of stress, which are no-stress, low-stress, medium-stress, and high-stress. The categorization is separated into two stages: stress level 1 (no-stress and low-stress), stress level 2 (medium-stress and high-stress), and stress level 3 (high-stress).[1]It has long been understood that stress is the body's reaction to a change that necessitates both physical and mental responses. Because stress causes numerous illnesses and disorders, as well as long-term chemical changes in our bodies, it is critical to recognize and categorizes stress at an early stage. At an early stage when stressful circumstance develops the body opposes the change so as to preserve the hormonal balance in our body, this stage is known as 'Eustress'.When the stressful circumstance remains for a long-time the body enters into the tiredness stage known as 'Distress'. The determination of stress level is critical since it defines numerous health-related concerns. The HRV and ECG are reliable measurements for classifying and identifying stress. The accuracy of stress categorization remains around 91 percent[2]. With the expansion in the number of organizations and the complexity of work, there has also been an increase in occupational stress. With the proliferation of smartphones, even the most remote communities now have access to them. Smartphones are or can be used to track our various stress-related behaviors. To measure stress levels, we have access to data generated by the built-in accelerometer. We employ accelerometers because they are less intrusive to privacy and can be used in smaller devices such as smartphones and fitness trackers[3]. Today's world is so competitive that the competitive character of the international economy and workplace leads to a rise in workload. This condition has become a prevalent problem in many firms, resulting in employees experiencing psychological difficulties and occupational stress. Many illnesses are caused by work-related stress. Many studies have shown that stress is a key role in anxiety and depressive disorders. It has also been noticed that there has been a reduction in the mental health of workers and employees, which eventually leads to a decline in individual performance and hence a decline in the total productivity of the organization. Although job-related stress is frequent and low-level stress often leads to increased productivity, high-level stress that pushes people to work overtime results in a decrease in output. Considering the long-term repercussions of chronic stress leads to mental health breakdowns or significant bodily breakdowns. With these considerations in mind, the study concluded that cell phones may be used to detect stress and, based on the results, provide a better solution for the mental health of employees in competitive environments[6]. Smartphones have significantly more potential than we previously imagined; they may be utilized as personal stress monitors in the workplace. The use of an accelerometer to classify people's behavior and stress. This model outperforms the usual techniques in terms of overall performance, but it does not necessitate such a time-consuming input data set[9].

3. METHODOLOGY

3.1 Data Preparation

The dataset is acquired from an organization that is currently working on a product called Smart-Yoga Pillow (SaYoPillow), which aids in understanding the link between sleep and stress, and the entire dataset is developed based on that.The dataset has 630 rows of data and 9 columns of characteristics.The dataset includes the following features: snoring rate, respiration rate, body temperature, limb movement, blood oxygen, eye movement, sleeping hours, heart rate, and stress level. Figure 1 displays a preview of the dataset, which includes the data as well as the characteristics in a tabular format.

	A	B	C	D	E	F	G	H	I
1	sr	rr	t	lm	bo	rem	sr	hr	sl
2	93.8	25.68	91.84	16.6	89.84	99.6	1.84	74.2	3
3	91.64	25.104	91.552	15.88	89.552	98.88	1.552	72.76	3
4	60	20	96	10	95	85	7	60	1
5	85.76	23.536	90.768	13.92	88.768	96.92	0.768	68.84	3
6	48.12	17.248	97.872	6.496	96.248	72.48	8.248	53.12	0

Figure 1. Dataset Overview

3.2 Data Preprocessing

The dataset contains no null values, indicating that the data collecting process was carried out properly with the utmost precision, and every attribute of this dataset is relevant for training our model. We utilized One Hot Encoding on our target feature, stress level because it includes categorical values ranging from 0 to 4 (0-low/normal,1-medium-low,2-medium,3-medium-high, 4-high).

3.3 Feature Visualisation

Since the number of features is more than the average features considered traditionally, we continued to investigate the correlation between the features, with the main goal of knowing what features link to each other and how the model can process it in producing the output. Figure 2 depicts a correlation heat map of all the characteristics that are related to one another.

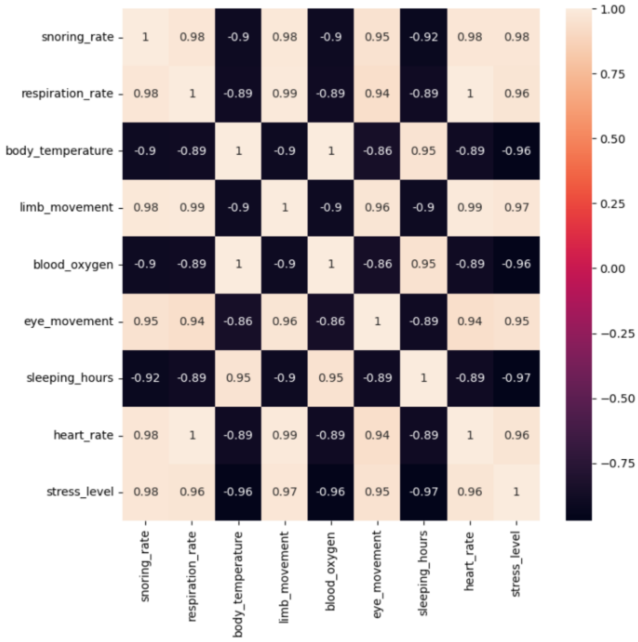

Figure 2. Correlation Heat Map

3.4 Model Architecture

Beginning with neural networks, which are human brains, and progressing to models that predict or categorize problem statements. We employed artificial neural networks, convolution neural networks, and deep neural networks in the issue statement below. The primary architecture of an artificial neural network is connected to or may be seen as being comparable to logistic regression. It has a number of perceptrons that may be located at different levels and layers. It is extensively used because it can quickly solve nonlinear equations and since its inputs are only handled forward.While the convolutional neural network is most recognized for its automation in filtering out what has been explicitly taught, it is also quite good at obtaining spatial information from the dataset's image, which is what we have in this case, and in aiding in the arrangement and identification of the pixels. Finally, because it is a type of neural network and an artificial neural network, using the recurrent neural network is important to the comparison's effectiveness. The algorithm's principal application is for time-sensitive scenarios requiring a quick answer, such as Siri and Alexa.

4. EXPERIMENTAL RESULTS

Since the entire model is based on data and cannot be done without good data management, data pretreatment and visualization are required only to obtain a clear concept. The models used were artificial neural networks, convolutional neural networks, and recurrent neural networks. The accuracies are shown in table 1 of the accuracy table.

Model Name	Author's Accuracy
Artificial Neural Network	98%
Convolution Neural Network	93%
Recurrent Neural Network	90%

5. CONCLUSION

The amount of stress and worry that individuals experience during their lives is growing dramatically, and this is affecting their psychological traits. In answer to this challenge, psychological data were collected, and deep learning models were done, yielding varying accuracies such as 98 percent for the artificial neural network, 93 percent for the convolution neural network, and 90 percent for the recurrent neural network. As a result, we find that the artificial neural network outperforms and has the maximum accuracy.

FUTURE WORK

The identification of stress is a significant big issue, and data is the most important component in recognizing it. New psychological data may be acquired from a variety of additional sources and correctly preprocessed before being tested with the various ensemble models.

REFERENCE

[1] Z. Yu, C. Scherjon, Y. Mahsereci and J. N. Burghartz, "A new CMOS stress sensor ratiometric readout for in-plane stress magnitude and angle detection," *2017 IEEE SENSORS*, Glasgow, UK, 2017, pp. 1-3, doi:10.1109/ICSENS.2017.8234135.

[2] T. Lin and W. Zi, "Stress detection and tension control technique of pre-stressed reinforcement," 2011 International Conference on Consumer Electronics, Communications and Networks (CECNet), Xianning, China, 2011, pp.1676-1678, doi: 10.1109/CECNET.2011.5769247.

[3] S. Elzeiny and M. Qaraqe, "Blueprint to Workplace Stress Detection Approaches," 2018 International Conference on Computer and Applications (ICCA), Beirut, Lebanon, 2018, pp. 407-412, doi: 10.1109/COMAPP.2018.8460293.

[4] J. Bakker, M. Pechenizkiy and N. Sidorova, "What's Your Current Stress Level? Detection of Stress Patterns from GSR Sensor Data," 2011 IEEE 11th International Conference on Data Mining Workshops, Vancouver, BC, Canada, 2011, pp. 573-580, doi: 10.1109/ICDMW.2011.178.

[5] L. Xue, C. Hu, S. Luo, J. Li and J. Li, "Study on the relationship between the shape of stress crack and its detection signal," 2020 3rd International Conference on Electron Device and Mechanical Engineering (ICEDME), Suzhou, China, 2020, pp. 233-235, doi: 10.1109/ICEDME50972.2020.00060.

[6] M. Kuczynska et al., "The role of stress state and stress triaxiality in lifetime prediction of solder joints in different packages utilized in automotive electronics," 2016 17th International Conference on Thermal, Mechanical and Multi-Physics Simulation and Experiments in Microelectronics and Microsystems (EuroSimE), Montpellier, France, 2016, pp. 1-10, doi: 10.1109/EuroSimE.2016.7463328.

[7] A. O. Akmandor and N. K. Jha, "Keep the Stress Away with SoDA: Stress Detection and Alleviation System," in IEEE Transactions on Multi-Scale Computing Systems, vol. 3, no. 4, pp. 269-282, 1 Oct.-Dec. 2017, doi: 10.1109/TMSCS.2017.2703613.

[8] L. Rachakonda, S. P. Mohanty and E. Kougianos, "Stress-Lysis: An IoMT-Enabled Device for Automatic Stress Level Detection from Physical Activities," 2020 IEEE International Symposium on Smart Electronic Systems (iSES) (Formerly iNiS), Chennai, India, 2020, pp. 204-205, doi: 10.1109/iSES50453.2020.00052.

[9] S. Aristizabal et al., "The Feasibility of Wearable and Self-Report Stress Detection Measures in a Semi-Controlled Lab Environment," in IEEE Access, vol. 9, pp. 102053-102068, 2021, doi: 10.1109/ACCESS.2021.3097038.

[10] H. Chengliang and X. Wubin, "Monitoring and Diagnosis of Health State of Converter Tilting Trunnion Bearing Based on Stress Wave Analysis Technology," 2021 CAA Symposium on Fault Detection, Supervision, and Safety for Technical Processes (SAFEPROCESS), Chengdu, China, 2021, pp. 1-4, doi: 10.1109/SAFEPROCESS52771.2021.9693697.
[11] I. Samarasekara, C. Udayangani, G. Jayaweera, D. Jayawardhana and P. K. W. Abeygunawardhana, "Non Invasive Continuous Detection of Mental Stress via Readily Available Mobile-Based Help Parameters," 2020 IEEE REGION 10 CONFERENCE (TENCON), Osaka, Japan, 2020, pp. 579-584, doi: 10.1109/TENCON50793.2020.9293878.
[12] A. Fernandes, R. Helawar, R. Lokesh, T. Tari, and A. V. Shahapurkar, "Determination of stress using Blood Pressure and Galvanic Skin Response," 2014 International Conference on Communication and Network Technologies, Sivakasi, India, 2014, pp. 165-168, doi: 10.1109/CNT.2014.7062747.
[13] L. Czap and J. M. Pintér, "Intensity feature for speech stress detection," Proceedings of the 2015 16th International Carpathian Control Conference (ICCC), Szilvasvarad, Hungary, 2015, pp. 91-94, doi: 10.1109/CarpathianCC.2015.7145052.
[14] H. -b. Tian, C. -g. Xu, J. -f. Wang and J. -f. Song, "A study of the residual stress of rail detection and regulation technology," 2016 IEEE Far East NDT New Technology & Application Forum (FENDT), Nanchang, China, 2016, pp. 80-84, doi: 10.1109/FENDT.2016.7992000.
[15] Q. -w. Li, C. -g. Xu and Z. -x. Li, "A Research on Stress Gradient for HIP in Ultrasonic Nondestructive Testing Technology," 2018 IEEE Far East NDT New Technology & Application Forum (FENDT), Xiamen, China, 2018, pp. 175-179, doi: 10.1109/FENDT.2018.8681987.