Current Trends in Technology and Science
www.ctts.in, ISSN: 2279-0535, January 2022, Volume: 11, Issue: 1

LSTM Based Mental Stress Level Detection using Wearable Sensor Devices

Yashvant Dev, Mayank Namdev, Dr Ritu Shrivastava, Dr Rajiv Srivastava
Department of Computer Science and Engineering
Sagar Institute of Research and Technology, Bhopal
yashvantdev.d@gmail.com

Abstract- Nowadays, mental stress is a severe problem, particularly among teenagers. The age group that was previously thought to be the most carefree is now under much strain. Nowadays, increased stress causes many new issues, including depression, suicide, heart attack, and stroke. Many physical health issues related to stress can be avoided if mental stress is detected beforehand. When a person is stressed, there are noticeable changes in several bio-signals such as thermal, electrical, impedance, acoustic, optical, and others, and stress levels may be determined using these bio-signals. The paper proposes various machine learning and deep learning algorithms for stress detection on persons using wearable sensing devices, which can help people avoid various stress-related health problems. The data are taken from the WESAD dataset. The paper uses classification algorithms, SVM, DT, kNN and deep learning models; Long Short-Term Memory (LSTM) is applied, and confusion metrics parameters are used to measure performance in terms of accuracy, precision, recall, f1-score.

Keywords- Mental Stress, WESAD, Machine Learning, Deep Learning, LSTM

Introduction

Mental stress is one of the significant contributors to various health issues. Scientists and medics have created various measures to determine the intensity of mental stress in its early phases. Many neuroimaging methods for assessing mental stress in the workplace have been presented in the literature. One key candidate is the electroencephalogram (EEG) signal, which offers a wealth of mental states and circumstances. It is described as the human body's response to mental, physical, and emotional stimuli, as governed by the sympathetic nervous system (SNS) and the hypothalamus-pituitary–adrenocortical axis (HPA axis) [1]. This expression may be applied to both internal (personality structure) and external (problem-solving) issues, resulting in a variety of physiological and negative emotional alterations [2]. The three forms of stress are identified in the literature [3]. Acute stress is caused by a brief exposure period and is not damaging. When a stimulus is more frequent for a short period, it is called episodic stress [4].

On the other hand, chronic stress is the most harmful, caused by long-term stressors [5]. According to various studies, mental stress has been linked to various disorders, including stroke, cardiovascular disease, cognitive issues, speech abnormalities, and depression [6, 7]. Furthermore, stress indirectly affects the human body at several levels, including skin diseases, food habits, insufficient sleep, and decision-making [8–10]. As a result, researchers have devised several ways to assess stress levels early on to avert harmful health and performance repercussions. Subjective measures have traditionally been used to assess stress. Self-report questionnaires [12], such as the perceived stress scale [13, 14], are the most often used technique. The questionnaire score and self-report rating or interview have been established as ground truth in many research to evaluate mental stress levels.

On the other hand, questionnaires are subjective and need the user's undivided attention. As a result, people are often unaware of their actual stress levels. In the technological era, several physiological measurements have been discovered as stress indicators, including heart rate variability (HRV), electro-dermal activity (EDA), electroencephalogram (EEG) [11], electromyogram (EMG), blood pressure, pupil diameter, salivary cortisol, and salivary alpha-amylase [2]. It is necessary that the stress level detected by any indicators be accurate so that the proper measures to overcome the effect on the human lifestyle.

Related Work

This section describes literature related to the study about stress detection by various authors on employing various machine learning models. Ciabattoni et al. [15] proposed a real-time mental stress detection during cognitive tasks performed by an individual. The dataset contains features such as body temperature, GSR, RR intervals, gathered using a smartwatch, applied kNN classification approach and acquired accuracy of 89.8%. Yekta et al. [16] acquired data from Smartphones and wearable sensors, conducted a study on the daily life routine of the subjects and detected stress. The authors studied SVM and kNN machine learning models and PCA feature selection algorithm. Anderson et al. [17] collected data in EEG, ECG, GSR, PPG, EOG questionnaires, collecting data from physiological signals collected across three stimulus types – music, videos, and games. The authors applied kNN and SVM classification techniques and categorized Stimulus Classification and Arousal Classification with 80.6% and 88.9% accuracy, respectively. Sun et al. [18]

gathered data from 20 subjects across various basic activities such as sitting, standing, walking using various sensors. The authors collected data in the form of ECG, GSR, applied decision tree, SVM, naive Bayes classification algorithm and obtained an accuracy of 92.4%. Castaldo et al. [19] proposed a method to explore the extent to which HRV excerpts can be shortened without losing their ability to automatically detect mental stress employing the SVM classification data-driven approach and obtained an accuracy of 88%. Schmidt et al. [22] aimed to improve human-computer interaction (HCI) by detecting a person's affective state based on observables. The authors introduced a new publicly available dataset, WESAD, for wearable stress and affected detection. A multimodal dataset features physiological and motion data, recorded from both a wrist- and a chest-worn device, of 15 subjects during a lab study. Bajpai et al. [20] evaluated the performance of the WESAD dataset by employing the kNN model. The authors' evaluation is based on changing the K-fold cross-validation parameter and the total number of nearest neighbours while classifying data. Hence, the tradeoff between optimum performance and computational cost is achieved by limiting the number of neighbours and controlling the model's complexity. Lai et al. [21] proposed a prototype of intelligent Stress Monitoring Assistant (SMA) for first responders and professionals coping with exposure to extreme physical and psychological stressors such as firefighters, emergency medical technicians and many more; it is the next generation stress detector. SMA is designed using a residual-temporal convolution network to learn data from sensors and detect stress features. In both modes, stress recognition and stress detection, the SMA achieves 86% and 98% accuracy for the WESAD dataset.

Algorithm 1: Proposed algorithm for Mental Stress prediction

Results: *Mental Stress Recognition using Precision, F1-score, Recall, Sensitivity, Specificity, classification accuracy and Conversion curve;*

Input: *WESAD Dataset*

Output: *Classify Stress level*

Procedure:

Step 1: Extract the features from input data:
- *1.1 Clean unnecessary data;*
- *1.2 Missing Values;*
- *1.3 Scaling the data(if required)*

Step 2: Apply Feature selection method;

Step 3: Apply Machine Learning and LSTM Model and compare with the existing model;

Step 4: Generate and store obtained classification accuracy, precision, recall, f1-score, Sensitivity, Specificity and classification accuracy and ROC curve;

Step 5: Repeat Step 3 and Step 4.

The WESAD

WESAD (Wearable Stress and Affect Detection) dataset [22] is collected from 15 subjects, consisting of 13 male and two female participants. Each subject participates in two hours of data collection protocol with four types of conditions: baseline, amusement, stress, and meditation condition. We used these four conditions data as the classes for the classification task. WESAD provides data from two kinds of sensors: chest-worn (RespiBAN) and wrist-worn device (Empatica E4). In this research work, we use only wrist-worn device data because it is not as intrusive as a chest-worn device, and they state that wrist-worn device data is quite promising to use for the classification process [22].

Proposed Work

The paper proposed Long short-term memory (LSTM), an artificial recurrent neural network (RNN) architecture used in deep learning. Unlike standard feedforward neural networks, LSTM has feedback connections. It can process single data points (images) and entire data sequences (such as speech or video). It is capable of learning long term dependencies in data. This is achieved because the recurring module of the model has a combination of four layers interacting with each other. Algorithm 1 proposes the procedure to predict the individual's stress using the WESAD dataset.

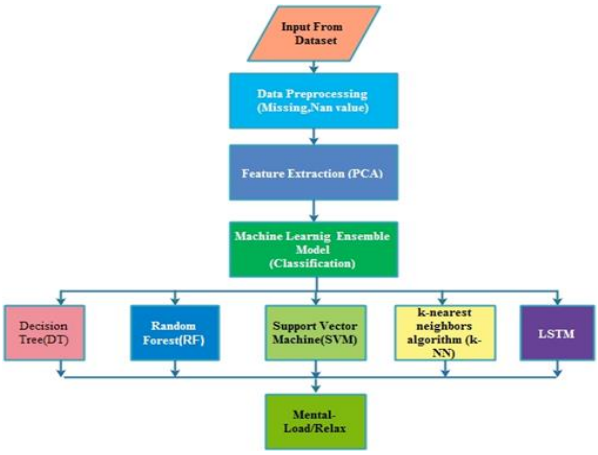

Figure 1: Flow Chart of the Proposed Model

Empirical Results

Different metrics have been used to evaluate the performance of proposed deep learning models on test sets, such as precision, recall, f1-score, and accuracy. The comparison of different models concerning performance metrics by all the applied machine learning algorithms and deep learning model LSTM is depicted in Table 1. Compared to other models, our proposed deep learning model LSTM achieved better accuracy than other machine learning algorithms such as DT, SVM and kNN. The accuracy obtained by LSTM models is 98%.

Table 1: Comparison of different ML models and Proposed Model

Model	Precision	Recall	F1-Score	Accuracy
DT	96	96	96	96
SVM	81	75	77	79
KNN	88	92	90	90.49
PLSTM	97	97	97	98
DT-> Decision tree, **SVM**->Support Vector Machine				
kNN-> k-nearest neighbors, **PLSTM->** Proposed LSTM				
All measurements are in %				

Figure 2 shows the graphical comparison of accuracy after generating confusion matrix on applying Decision Tree (DT), k Nearest Neighbors (KNN), Support Vector Machine (SVM) and LSTM models on the WESAD dataset.

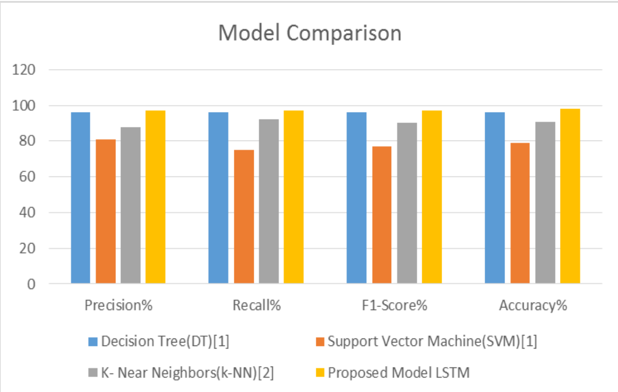

Figure 2: Model Comparison

Conclusion and Future work

Stress is a significant problem in today's society, with social and economic consequences. It is one of the variables that contribute to health issues. It is described as the human body's response to mental, physical, and emotional stimuli, governed by the sympathetic nervous system (SNS) and hypothalamic-pituitary-adrenocortical axis (HPA axis). The research began in a controlled laboratory setting, and the results show a high degree of accuracy in recognizing stress. Our suggested LSTM model attained a 98% accuracy compared to other models. There are still open research difficulties for detecting stress in everyday life, and there is space for development in this field. We will continue to work on the Internet of Things employing high-quality sensing devices and more precise data categorization approaches in the future.

References

[1]. Selye, H. The stress syndrome. Am. J. Nurs. 1965, 65, 97–99.

[2]. Giannakakis, G.; Grigoriadis, D.; Giannakaki, K.; Simantiraki, O.; Roniotis, A.; Tsiknakis, M. Review on psychological stress detection using biosignals. IEEE Trans. Affect. Comput. 2019, 1–16. [CrossRef]

[3]. Lazarus, J. Stress Relief & Relaxation Techniques; McGraw Hill Professional: New York, NY, USA, 2000.

[4]. Bakker, J.; Pechenizkiy, M.; Sidorova, N. What's your current stress level? Detection of stress patterns from GSR sensor data. In Proceedings of the 2011 IEEE 11th International Conference on Data Mining Workshops, Vancouver, BC, Canada, 11 December 2011; pp. 573–580.

[5]. Colligan, T.W.; Higgins, E.M. Workplace stress: Etiology and consequences. J. Workplace Behav. Health 2006, 21, 89–97. [CrossRef]

[6]. Crowley, O.V.; McKinley, P.S.; Burg, M.M.; Schwartz, J.E.; Ryff, C.D.; Weinstein, M.; Seeman, T.E.; Sloan, R.P. The interactive effect of change in perceived stress and trait anxiety on vagal recovery from the cognitive challenge. Int. J. Psychophysiol. 2011, 82, 225–232. [CrossRef] [PubMed]

[7]. O'Connor, D.B.; Thayer, J.F.; Vedhara, K. Stress and health: A review of psychobiological processes. Annu. Rev. Psychol. 2021, 72, 663–688. [CrossRef] [PubMed]

[8]. Thoits, P.A. Stress and health: Major findings and policy implications. J. Health Soc. Behav. 2010, 51, S41–S53. [CrossRef] [PubMed]

[9]. Garg, A.; Chren, M.-M.; Sands, L.P.; Matsui, M.S.; Marenus, K.D.; Feingold, K.R.; Elias, P.M. Psychological stress perturbs epidermal permeability barrier homeostasis: Implications for the pathogenesis of stress-associated skin disorders. JAMA Dermatol. 2001, 137, 53–59. [CrossRef] [PubMed]

[10]. C.Adam, T.; S.Epel, E. Stress, eating and the reward system. Physiol. Behav. 2007, 91, 449–458. [CrossRef] [PubMed]

[11]. Hou, X.; Liu, Y.; Sourina, O.; Tan, Y.R.E.; Wang, L.; Mueller-Wittig, W. EEG based stress monitoring. In Proceedings of the 2015 IEEE International Conference on Systems, Man, and Cybernetics, Hong Kong, China, 9–12 October 2015; pp. 3110–3115.

[12]. Holmes, T.H.; Rahe, R.H. The social readjustment rating scale. J. Psychosom. Res. 1967, 11, 213–218. [CrossRef]

[13]. Monroe, S.M. Modern approaches to conceptualizing and measuring human life stress. Annu. Rev. Clin. Psychol. 2008, 4, 33–52. [CrossRef]

[14]. Weiner, I.B.; Craighead, W.E. State-Trait anxiety inventory. Corsini Encycl. Psychol. 2010, 4, 2002.

[15]. L Ciabattoni, F Ferracuti, S Longhi, L Pepa, L Romeo, F Verdini, Real-time mental stress detection based on smartwatch,, 2017 IEEE International Conference on Consumer Electronics (ICCE), 110-111

[16]. YS Can, A Bert, C Ersoy, Stress Detection in Daily Life Scenarios Using Smartphones and Wearable Sensors: A Survey, Journal of Biomedical

Informatics 92, 103-139

[17]. Anderson, Adam, Thomas Hsiao, and Vangelis Metsis. "Classification of emotional arousal during multimedia exposure." Proceedings of the 10th International Conference on Pervasive Technologies Related to Assistive Environments. 2017.

[18]. Sun, Feng-Tso, et al. "Activity-aware mental stress detection using physiological sensors." International Conference on Mobile computing, applications, and services. Springer, Berlin, Heidelberg, 2010.

[19]. Castaldo, Rossana, et al. "Acute mental stress assessment via short term HRV analysis in healthy adults: A systematic review with meta-analysis." Biomedical Signal Processing and Control 18 (2015): 370-377.

[20]. D. Bajpai and L. He, "Evaluating KNN Performance on WESAD Dataset," 2020 12th International Conference on Computational Intelligence and Communication Networks (CICN), 2020, pp. 60-62, DOI: 10.1109/CICN49253.2020.9242568.

[21]. KENNETH LAI, (Student Member, IEEE), SVETLANA N. YANUSHKEVICH, (Senior Member, IEEE), AND VLAD P. SHMERKO, Intelligent Stress Monitoring Assistant for First Responders, 2021, VOLUME 9, pp. 25314-25329, DOI: 10.1109/ACCESS.2021.3057578

[22]. P. Schmidt, A. Reiss, R. Duerichen, and K. Van Laerhoven, "Introducing WeSAD, a multimodal dataset for wearable stress and affect detection," in ICMI 2018 - Proceedings of the 2018 International Conference on Multimodal Interaction, 2018, pp. 400–40