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MULTI-CLASS STRESS DETECTION THROUGH HEART RATE VARIABILITY USING DEEP NEURAL NETWORKS

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ABSTRACT

Stress is a natural human reaction to demands or pressure, usually when perceived as harmful or/and toxic. When stress becomes constantly overwhelmed and prolonged, it increases the risk of mental health and physiological uneasiness. Furthermore, chronic stress raises the likelihood of mental health plagues such as anxiety, depression, and sleep disorder. Although measuring stress using physiological parameters such as heart rate variability (HRV) is a common approach, how to achieve ultra-high accuracy based on HRV measurements remains as a challenging task. HRV is not equivalent to heart rate. While heart rate is the average value of heart beats per minute, HRV represents the variation of the time interval between successive heartbeats. The HRV measurements are related to the variance of RR intervals which stand for the time between successive R peaks. In this study, we investigate the role of HRV features as stress detection bio-markers and develop a machine learning-based model for multi-class stress detection. More specifically, a convolution neural network (CNN) based model is developed to detect multi-class stress, namely, *no stress, interruption stress, and time pressure stress*, based on both time- and frequency-domain features of HRV. Validated through a publicly available dataset, SWELL−KW, the achieved accuracy score of our model has reached 99.9% (*Precision=1*, *Recall=1*, *F1−score=1*, and *MCC=0.99*), thus outperforming the existing methods in the literature. In addition, this study demonstrates the

effectiveness of essential HRV features for stress detection using a feature extraction technique, i.e., analysis of variance.

1. INTRODUCTION

Physical or mental imbalances caused by noxious stimuli trigger stress to maintain homeostasis. Under chronic stress, the sympathetic nervous system becomes overactive, leading to physical, psychological, and behavioral abnormalities [1]. Stress levels are often measured using subjective methods to extract perceptions of stress. Stress level measurement based on collected heart rate viability (HRV) data can help to remove the presence of stress by observing its effects on the autonomic nervous system (ANS) [2].

Typically, people with anxiety disorders have chronically lower resting HRV compared with healthy people. As revealed in [2] and [3], HRV increases with relaxation and decreases with stress. Indeed, HRV is usually higher when a heart is beating slowly and vice versa. Therefore, heart rate and HRV generally have an inverse relationship [2], [3]. HRV varies over time based on activity levels and the amount of work-related stress.

Furthermore, stress is usually associated with a negative notion of a person and is considered to be a subjective feeling of human beings that might affect emotional and physical well-being. It is described as a psychological and biological reaction to internal or external stressors [4], including a biological or chemical agent and environmental stimulation that induce stress in an organism [5]. On a molecular scale, stress impacts the ANS [6], which uses sympathetic and parasympathetic components to regulate the cardiovascular system. The sympathetic component in a human body [7] works analogously to a car's gas pedal. It activates the fight-or-flight response, giving the body a boost of energy to respond to negative influences. In contrast, the parasympathetic component is the brake for a body. It stimulates the body's *rest and digests* reaction by relaxing the body when a threat has passed. Given the fact that the ANS regulates the mental stress level of a human being, physiological measurements such as electrocardiogram (ECG), electromyogram (EMG), galvanic skin response (GSR), HRV, heart rate, blood pressure, breath frequency, and respiration rate can be used to assess mental stress [8].

ECG signals are commonly adopted to extract HRV [9]. HRV is defined as the variation across intervals between consecutive regular RR intervals,1 and it is measured by determining the length between two successive heartbeat peaks from an ECG reading.

Conventionally, HRV has been accepted as a term to describe variations of both instantaneous heart rate and RR intervals [12].

Obtaining HRV from ECG readings requires clinical settings and specialized technical knowledge for data interpretation. Thanks to the recent technological advances on the Internet of medical things (IOMT) [17], it is possible to deploy a commercially available wearable or non-wearable IOMT devices to monitor and record heart rate measurements.

Based on ECG data analysis (or HRV features, various machine learning (ML) and deep learning (DL) algorithms have been developed in recent years for stress prediction [20], [21], [22], [23], [24], [25], [26], [27] (see more details in Sec. II). Among the publicly available datasets for stress detection, SWELL−KW developed in [13] and [14] one of the two most popular ones. However, none of the existing ML and DL studies based on the SWELL−KW dataset for multi-class stress classification have achieved ultra-high accuracy, especially for multi-class stress level classification [15], [16]. Therefore, there exists a research gap on developing novel ML models which are able to achieve ultra-high accurate prediction.

Motivated by various existing applied ML and DL based studies on HRV feature processing for stress level classifications, we have designed and developed a one-dimensional convolutional neural network (1D CNN) model for multi-class stress classification and demonstrate its superiority over the state-of-the-art models based on the SWELL-KW dataset in term of prediction accuracy. More specifically, we have performed studies on stress detection using both traditional machine learning algorithms and/or multi-layer perceptron (MLP) algorithms which are inspired from the fully connected neural network (FCNN) architecture. In our work, we have developed a 1D CNN model which is based on the convolution operation. CNN reduces number of training parameters as MLP takes vector as input and CNN takes tensor as input so that CNN can understand spatial relation.

While the accuracy achieved with full features is nearly 100%, we have also introduced a feature reduction algorithm based on *analysis of variance (ANOVA)* F-test and demonstrate that it is possible to achieve an accuracy score of 96.5% with less than half of the features that are available in the SWELL−KW dataset. Such a feature extraction reduces the computational load during the model training phase.

In a nutshell, the novelty and the main contributions of this study are summarized as follows:

• We have developed a novel 1D CNN model to detect multi-class stress status with outstanding performance, achieving 99.9% accuracy with a *Precision*, *F1-score*, and *Recall* score of 1.0 respectively and a *Matthews correlation coefficient (MCC)* score of 99.9%. We believe this is the first study that achieves such a high score of accuracy for multi-class stress classification.

• Furthermore, we reveal that not all 34 HRV features are necessary to accurately classify multi-class stress. We have performed feature optimization to select an optimized feature set to train a 1D CNN classifier, achieving a performance score that beats the existing classification models based on the SWELL-KW dataset.

• Our model with selected top-ranked HRV features does not require resource-intensive computation and it achieves also excellent accuracy without sacrificing critical information.

The remainder of the paper is organized as follows. After summarizing related work and pointing out the distinction between our work and the existing work in Sec. II, we introduce briefly the framework for stress status classification, dataset, and data preprocessing in Sec. III. Then the developed CNN model is presented in Sec. IV. Afterwards, Sec. V defines the performance metrics to evaluate the proposed classifier and Sec. VI presents the numerical results. Further discussions are provided in Sec. VII. Finally, the paper is concluded in Sec. VIII

2. LITERATURE SURVEY

Stress detection is a critical area of research due to its significant impact on physical and mental health. Heart Rate Variability (HRV), which measures the variation in time intervals between consecutive heartbeats, is a key physiological indicator of stress. Recent advances in deep learning have shown promise in enhancing the accuracy and reliability of stress detection systems. This literature survey reviews various studies that employ deep neural networks (DNNs) for multi-class stress detection using HRV data.

To detect the stress through heart rate variability the following dataset values are used:

FID, Median_RR, RMSSD,

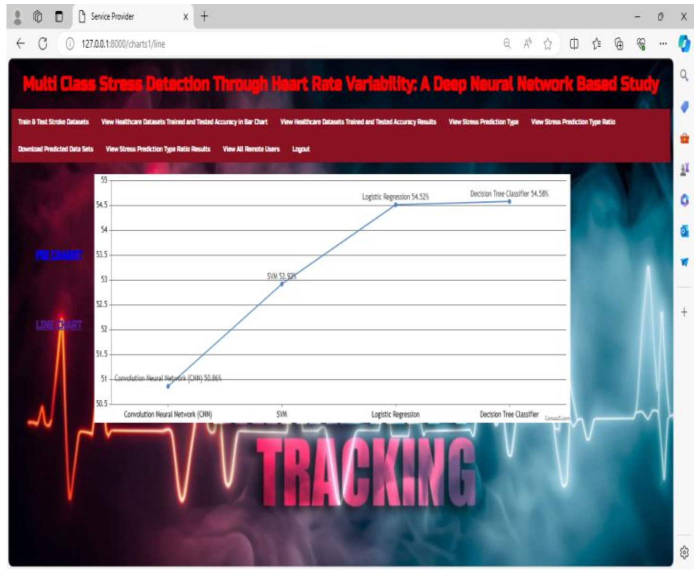
SDRR_RMSSD, VLF, LF, LF_NU,

HF_PCT, TP, HF_LF, higuct, Mean_RR, SDRR, SDSD, HR, VLF_PCT, LF_PCT, HF, HF_NU, LF_HF, sampen. These are the input values to predict stress detection through heart rate variability. In my project we use four algorithms. They are:

- Convolution Neural Network(CNN)
- SVM
- Logistic Regression
- Decision Tree Classifier

Out of the above four algorithms Decision Tree Classifier algorithm get the best accuracy. So it is good for detect the stress through heart rate

3. OUTPUTSCREENS



4. CONCLUSION

In this study, we have developed novel a 1D CNN model for stress level classification using HRV signals and validated the proposed model based on

a publicly available dataset, SWELL−KW. In our model, we also applied an ANOVA feature selection technique for dimension reduction. Through extensive training and validation, we demonstrate that our model outperforms the state-of-the-art models in terms of major performance metrics, i.e., *Accuracy*, *Precision*, *Recall*, *F1-score*, and *MCC* when all features are employed. Furthermore, our approach with ANOVA feature reduction also achieves excellent performance. For future work, we plan to further investigate the feasibility of optimizing the model to fit it into edge devices so that real-time stress detection can become a reality.

5. REFERENCE

[1] H.-G. Kim, E.-J. Cheon, D.-S. Bai, Y. H. Lee, and B.-H. Koo, ''Stress and heart rate variability: A meta-analysis and review of the literature,'' *Psychiatry Invest.*, vol. 15, no. 3, pp. 235–245, Mar. 2018.

[2] D. Muhajir, F. Mahananto, and N. A. Sani, ''Stress level measurements using heart rate variability analysis on Android based application,'' *Proc. Comput. Sci.*, vol. 197, pp. 189–197, Jan. 2022.

[3] J. Held, A. Vîslă, C. Wolfer, N. Messerli-Bürgy, and C. Flückiger, ''Heart rate variability change during a stressful cognitive task in individuals with anxiety and control participants,'' *BMC Psychol.*, vol. 9, no. 1, p. 44, Mar. 2021.

[4] K. M. Dalmeida and G. L. Masala, ''HRV features as viable physiological markers for stress detection using wearable devices,'' *Sensors*, vol. 21, no. 8, p. 2873, Apr. 2021.

[5] J. A. Miranda-Correa, M. K. Abadi, N. Sebe, and I. Patras, ''AMIGOS: A dataset for affect, personality and mood research on individuals and groups,'' *IEEE Trans. Affect. Comput.*, vol. 12, no. 2, pp. 479–493, Apr./Jun. 2021.

[6] E. Won and Y.-K. Kim, ''Stress, the autonomic nervous system, and the immune-kynurenine pathway in the etiology of depression,'' *Current Neuropharmacol.*, vol. 14, no. 7, pp. 665–673, Aug. 2016.

[7] B. Olshansky, H. N. Sabbah, P. J. Hauptman, andW. S. Colucci, ''Parasympathetic nervous system and heart failure: Pathophysiology and potential implications for therapy,'' *Circulation*, vol. 118, no. 8, pp. 863–871, Aug. 2008.

[8] S. Goel, P. Tomar, and G. Kaur, ''ECG feature extraction for stress recognition in automobile drivers,'' *Electron. J. Biol.*, vol. 12, no. 2, pp. 156–165, Mar. 2016.

[9] V. N. Hegde, R. Deekshit, and P. S. Satyanarayana, ''A review on ECG signal processing and HRV analysis,'' *J. Med. Imag. Health Informat.*,

vol. 3, no. 2, pp. 270–279, Jun. 2013.
[10] M. Vollmer, ''A robust, simple and reliable measure of heart rate variability using relative RR intervals,'' in *Proc. Comput. Cardiol. Conf. (CinC)*, Sep. 2015, pp. 609–612.
[11] M. H. Kryger, T. Roth, andW. C. Dement, *Principles and Practice of Sleep Medicine*, 5th ed. Amsterdam, The Netherlands: Elsevier, 2011.
[12] M. Malik, J. T. Bigger, A. J. Camm, R. E. Kleiger, A. Malliani, A. J. Moss, and P. J. Schwartz, ''Heart rate variability: Standards of measurement, physiological interpretation, and clinical use,'' *Eur. Heart J.*, vol. 17, no. 3, pp. 354–381, Mar. 1996.
[13] S. Koldijk, M. Sappelli, S. Verberne, M. A. Neerincx, and W. Kraaij, ''The SWELL knowledge work dataset for stress and user modeling research,'' in *Proc. 16th Int. Conf. Multimodal Interact.*, Nov. 2014, pp. 291–298.
[14] S. Koldijk, M. A. Neerincx, and W. Kraaij, ''Detecting work stress in offices by combining unobtrusive sensors,'' *IEEE Trans. Affect. Comput.*, vol. 9, no. 2, pp. 227–239, Apr. 2018.
[15] M. Albaladejo-González, J. A. Ruipérez-Valiente, and F. G. Mármol, ''Evaluating different configurations of machine learning models and their transfer learning capabilities for stress detection using heart rate,'' *J. Ambient Intell. Human. Comput.*, pp. 1–11, Aug. 2022, doi: 10.1007/s12652-022-04365-z.
[16] R. Walambe, P. Nayak, A. Bhardwaj, and K. Kotecha, ''Employing multimodal machine learning for stress detection,'' *J. Healthcare Eng.*, vol. 2021, Oct. 2021, Art. no. 9356452.
[17] A. Ibaida, A. Abuadbba, and N. Chilamkurti, ''Privacy-preserving compression model for efficient IoMT ECG sharing,'' *Comput. Commun.*, vol. 166, pp. 1–8, Jan. 2021.
[18] W. C. Dobbs, M. V. Fedewa, H. V. MacDonald, C. J. Holmes, Z. S. Cicone, D. J. Plews, and M. R. Esco, ''The accuracy of acquiring heart rate variability from portable devices: A systematic review and meta-analysis,'' *Sports Med.*, vol. 49, no. 3, pp. 417–435, Mar. 2019.
[19] C.-M. Chen, S. Anastasova, K. Zhang, B. G. Rosa, B. P. L. Lo,

H. E. Assender, and G.-Z. Yang, ''Towards wearable and flexible sensors and circuits integration for stress monitoring,'' *IEEE J. Biomed. Health Informat.*, vol. 24, no. 8, pp. 2208–2215, Aug. 2020.

[20] R. A. Rahman, K. Omar, S. A. M. Noah, M. S. N. M. Danuri, and M. A. Al-Garadi, ''Application of machine learning methods in mental health detection: A systematic review,'' *IEEE Access*, vol. 8, pp. 183952–183964, 2020.

[21] S. H. Jambukia, V. K. Dabhi, and H. B. Prajapati, ''Application of machine learning methods in mental health detection:Asystematic review,'' in *Proc. Int. Conf. Adv. Comput. Eng. Appl.*, 2015, pp. 714–721.

[22] S. Celin and K. Vasanth, ''ECG signal classification using various machine learning techniques,'' *J. Med. Syst.*, vol. 42, no. 12, p. 241, Oct. 2018.

[23] A. Padha and A. Sahoo, ''A parametrized quantum LSTM model for continuous stress monitoring,'' in *Proc. 9th Int. Conf. Comput. Sustain. Global Develop. (INDIACom)*, Mar. 2022, pp. 261–266.

[24] S. Sriramprakash, V. D. Prasanna, and O. V. R. Murthy, ''Stress detection in working people,'' *Proc. Comput. Sci.*, vol. 115, pp. 359–366, Dec. 2017.

[25] P. Sarkar and A. Etemad, ''Self-supervised learning for ECG-based emotion recognition,'' in *Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP)*, May 2020, pp. 3217–3221.