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Stress Classification using Deep Learning with 1D Convolutional Neural Networks

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ABSTRACT

Stress has been a major problem impacting people in various ways, and it gets serious every day. Identifying whether someone is suffering from stress is crucial before it becomes a severe illness. Artificial Intelligence (AI) interprets external data, learns from such data, and uses the learning to achieve specific goals and tasks. Deep Learning (DL) has created an impact in the field of Artificial Intelligence as it can perform tasks with high accuracy. Therefore, the primary purpose of this paper is to evaluate the performance of 1D Convolutional Neural Networks (1D CNNs) for stress classification. A Psychophysiological stress (PS) dataset is utilized in this paper. The PS dataset consists of twelve features obtained from the expert. The 1D CNNs are trained and tested using 10-fold cross-validation using the PS dataset. The algorithm performance is evaluated based on accuracy and loss matrices. The 1D CNNs outputs 99.7% in stress classification, which outperforms the Backpropagation (BP), only 65.57% in stress classification. Therefore, the findings yield a promising outcome that the 1D CNNs effectively classify stress compared to BP. Further explanation is provided in this paper to prove the efficiency of 1D CNN for the classification of stress.

I. Introduction

The new COVID-19 has contributed to psychological disorders among people, leading to a higher risk of suicide. Stress endurance varies between individuals; some people can handle it, and others cannot [1]. Some research has been conducted to analyze COVID19 impact on an individual's stress [2][3][4][5][6]. In the new era, stress has been extended related to finances, work, and relationships; it is now a familiar feeling people face each day in their lives. People facing stress are increasing at a fast rate. WillisTowersWatson [7] reported that "75% of the U.S. employers ranked stress as their top health and productivity concern, but employers and employees disagreed on its causes". These findings are based on responses from 487 U.S. employers in Willis Towers Watson's 2015/2016 Global Staying@Work Survey and more than 5000 U.S. employees in Willis Towers Watson's 2015/2016 Global Benefits Attitudes Survey. American Psychological Association [8] reported that the percentage of Americans who experienced at least one symptom of stress over the past month rose from 71 percent in August 2016 to 80 percent in January 2017.

According to Cacioppo, Tassinary, and Berntson [9], chronic psychological stress carries many pathophysiological risks, such as cerebrovascular disease, cardiovascular disease, immune deficiencies, and diabetes. Francis [10] said that young adults spend more than six hours a day "stressed out." It is essential to classify whether someone is stressed before becoming a serious illness [11]. This problem called for a solution where stress can be recognized before it worsens.

Machine Learning is a branch of artificial intelligence that focuses on machines' ability to learn from experience [12]. A computer with the ability has rules put into it to allow it to resolve problems

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without human intervention [13]. Machine learning provides the ability for machines to train on and accordingly adapt when there is new data input, enables the prediction from known data, and learns from the new unknown data.

One of the machine learning methods that can be used to recognize stress is Artificial Neural Networks (ANNs). ANNs are a non-linear data-driven self-adaptive approach instead of the traditional model-based methods" by Solomatine & Ostfeld [14]. "ANNs can determine and study correlated patterns between input data and corresponding target values. It can use to predict the outcome of new independent input data after training. Neural networks (NNs) "have been used in a wide variety of applications where statistical methods are traditionally employed like classifying problems or predicting outcomes as said by Solomatine & Ostfeld [14].

For a very long period, ANNs had to be limited in size due to difficulties in training. However, Hinton, Osindero, and Teh [15] suggested a procedure that could be used with much larger networks known as Deep Learning (DL). LeCun, Bengio, and Hinton [16] said Deep learning allows computational models composed of multiple processing layers to learn the representation of data with multiple levels of abstraction. Convolutional Neural Networks (CNNs), one of the most well-known DL models, have become the de facto standard for many Computer Vision and Machine Learning operations over the last decade. CNNs are feed-forward Artificial Neural Networks (ANNs) with convolutional and subsampling layers that alternate. When trained on a large visual database with ground-truth labels, deep 2D CNNs with many hidden layers and millions of parameters can learn complex objects and patterns. With proper training, this one-of-a-kind ability transforms them into the primary tool for various engineering applications involving 2D signals such as images and video frames. As an alternative, 1D Convolutional Neural Networks (1D CNNs) have recently been developed as modified 2D CNNs. 1D CNNs have been utilized in several classification problems like heart sound and Soil Texture [17][18][19]. It is believed that the classification between stress and non-stress will be more accurate with multiple processing layers compared to the ANNs that only consist of a single processing layer. Smets *et al*. [20] said the previous approach to measure stress does not allow for continuous monitoring and often suffers from biases such as demand effects, response, and memory biases; therefore, the focus has been shifted towards measuring bodily responses as indicators of stress.

This study aims to use stress datasets to anticipate an accurate output; society will use the outcomes. The remaining parts of this paper are organized as follows: methodology and empirical studies are presented in section 2; Findings and the analysis of the results are presented in sections 3 and 4, and finally, section 5 concludes the paper's future works.

II. Methods

This section introduces the research methodology that had been used in this research. The components in this section include Dataset Preparation, Data pre-processing, Research Design, Research Implementation, and Instruments, as in Figure 1. DL has become a growing research interest, and the method has shown certain advantages of learning performance. DL can learn from the past data to solve complex problems and has been widely used in classification. It allows the computational models with various processing layers to learn the data representation with various levels of abstraction. The result of the DL method is compared to one of the neural network standards, the Backpropagation (BP) algorithm, which was used in previous studies related to stress classification [21][22]. This comparison is to analyze the effectiveness of the DL algorithms in this study. The research focuses on psychophysiological stress, which looks at heart rate variability (HRV), galvanic skin response (GSR), skin temperature (Temp), and respiration.

A. 1D Convolutional Neural Networks (1D CNNs)

1D CNNs is very similar to CNNs where the input of 1D CNNs is dimensional, whereas an ordinary CNNs is two-dimensional. A Convolutional Neural Network (CNN) is very similar to ordinary neural networks as they are made up of neurons that have learnable weight and biases. Each neuron receives some inputs, performs a dot product, and optionally follows it with a non-linearity. Loss function still can be found in the last layer or fully connected layer, and all the tips developed for learning regular neural networks still apply. Figure 1 shows the schematic representation of 1D CNNs. The first hidden layer is always a convolutional layer, followed by a pooling layer. The convolutional and pooling layers can be present multiple times in the network until the final hidden

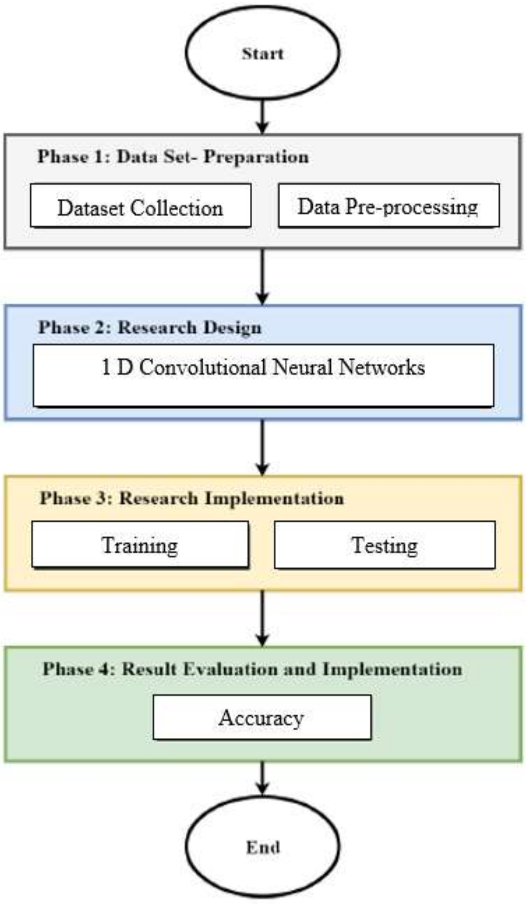

Fig. 1. An overview flow of the research methodology

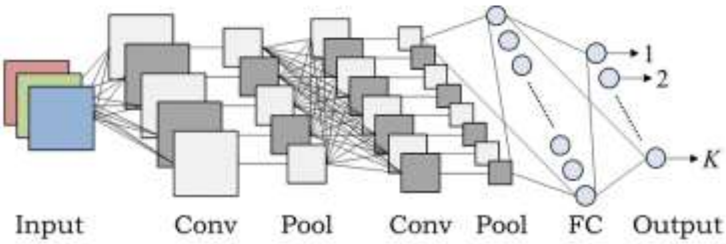

Fig. 2. Schematic representation of 1D convolutional neural networks

layer is the full-connected layer. The Schematic Representation of 1D Convolutional Neural Networks is as shown in Figure 2.

The convolution layer is where the previous layer's feature maps are folded with learnable kernels and execute the activation function to form the output feature map. Each output map may combine convolutions with multiple input maps. The mathematical formula for constructing the convolution layer is used (1).

$$x_j^\ell = f\left(\sum_{i\in M_j} x_i^{\ell-1} * k_{ij}^\ell + b_j^\ell\right) \tag{1}$$

where M_j is the selection of input maps, each output map is given an additive bias b, for an output map, the input maps will be folded with different kernels. So, if output map j and map k both sums over input map i, the kernels applied to map i are different for output maps j and k.

The pooling layer produces downsampled versions of the input maps. If there are N input maps, there will be exactly N output maps, although the output map is smaller (2).

$$x_j^\ell = f(\beta_j^\ell down(x_j^{\ell-1}) + b_j^\ell \quad (2)$$

where $down(x_j^{\ell-1})$ represents a sub-sampling function. This function will sum over each distinct n-by-n block in the input so that the output is n-times smaller along both spatial dimensions. Each output map is given its multiplicative bias β and an additive bias b.

The fully connected layer will combine features learned by different convolution kernels so that the network can build a global representation of the holistic input. Let α_{ij} Denote the weight given to input map i when forming the output map j. The output map j is (3).

$$x_j^\ell = f(\sum_{i=1}^{N_{in}} \alpha_{ij} \left(x_i^{\ell-1} * k_i^\ell\right) + b_j^\ell \quad (3)$$

Subject to the constraints (4).

$$\sum_i \alpha_{ij} = 1, \text{ and } 0 \leq \alpha_{ij} \leq 1 \quad (4)$$

These constraints can be enforced by setting the α_{ij} variables equal to the softmax over a set of unconstrained, underlying weight c_{ij} use (5).

$$a_{ij} = \frac{exp(c_{ij})}{\sum_k exp(c_{kj})} \quad (5)$$

Each set of weights c_{ij} for fixed j are independent of all other such sets for any other j, the single map is updated, and the subscript j. Each map is updated in the same way except with different j indices.

B. Empirical Studies

Several experiments are conducted on the psychophysiological stress dataset. The implementation is multivariate analysis to evaluate 1D CNNs deep learning model. There is a total of twelve features in the raw data given by Dr. Elena Smets [20], which include Skin Conductance / Galvanic Skin Response (SC/GSR), Skin Temperature (Temp), Blood Volume Pulse (BVP), Respiration Changes (RSP), Heart Rate (HR), Electromyography amplitude (EMG amp), Blood Volume Pulse amplitude (BVP amplitude), Respiration Changes rate (RSP-Rate), Respiration Changes amplitude (RSP-amplitude), Heart Rate Variability amplitude (HRV amplitude), Respiration Changes + Heart Rate Coherence (RSP+HR Coherence), and Segments. The segments will display the state of the respondents at that moment. For each sensing modality, features have been calculated on a sliding window of 30 s with 29 s overlap. The illustration of the datasets is shown in Figure 3.

The dataset had been separated into two parts: a training set and a testing set. The training set usually consists of input vectors and corresponding output vectors that fit into the model to produce a result compared with the target for each input vector in the training dataset. The testing set is utilized

A1 | *fx* | RAW Data export file (tab separated)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
10														
11	hh:mm:ss	32 SPS	32 SPS	128 SPS	32 SPS	32 SPS	32 SPS	32 SPS	32 SPS	32 SPS	32 SPS	32 SPS		
12	TIME	Sensor-E:S	Sensor-F:T	Sensor-G:[	Sensor-H:f	HR (BVP)	EMG1 amp	BVP amplit	RSP- Rate	RSP Amplit	HRV Ampli	RSP+HR Cc	Events	Segments
13														
14														
15	0:00:00	3.029	28.397	-25.307	631.106	70	0	6.184	10	3.093	35.626	-0.147		
16	0:00:00	3.029	28.397	-34.423	631.106	70	0	6.184	10	3.093	35.626	-0.147		
17	0:00:00	3.029	28.397	-34.536	631.106	70	0	6.184	10	3.093	35.626	-0.147		
18	0:00:00	3.029	28.397	-34.36	631.106	70	0	6.184	10	3.093	35.626	-0.147		
19	0:00:00	2.525	21.258	-34.159	608.15	70	0	6.139	10	1.556	35.59	-0.147		
20	0:00:00	2.525	21.258	-34.152	608.15	70	0	6.139	10	1.556	35.59	-0.147		
21	0:00:00	2.525	21.258	-34.344	608.15	70	0	6.139	10	1.556	35.59	-0.147		
22	0:00:00	2.525	21.258	-34.578	608.15	70	0	6.139	10	1.556	35.59	-0.147		
23	0:00:00	2.525	21.258	-34.832	608.097	70	0	6.19	10	1.556	35.553	-0.147		
24	0:00:00	2.525	21.258	-35.342	608.097	70	0	6.19	10	1.556	35.553	-0.147		
25	0:00:00	2.525	21.258	-35.867	608.097	70	0	6.19	10	1.556	35.553	-0.147		
26	0:00:00	2.525	21.258	-36.24	608.097	70	0	6.19	10	1.556	35.553	-0.147		
27	0:00:00	2.525	21.258	-36.695	608.055	70	0	6.237	10	1.556	35.517	-0.147		
28	0:00:00	2.525	21.258	-36.677	608.055	70	0	6.237	10	1.556	35.517	-0.147		
29	0:00:00	2.525	21.258	-36.444	608.055	70	0	6.237	10	1.556	35.517	-0.147		
30	0:00:00	2.525	21.258	-35.894	608.055	70	0	6.237	10	1.556	35.517	-0.147		
31	0:00:00	2.525	21.258	-34.844	608.032	70	0	6.211	10	1.556	35.48	-0.147		
32	0:00:00	2.525	21.258	-33.945	608.032	70	0	6.211	10	1.556	35.48	-0.147		
33	0:00:00	2.525	21.258	-32.451	608.032	70	0	6.211	10	1.556	35.48	-0.147		
34	0:00:00	2.525	21.258	-31.21	608.032	70	0	6.211	10	1.556	35.48	-0.147		
35	0:00:00	2.525	21.258	-30.064	608.011	70	0	6.204	10	1.555	35.443	-0.147		
36	0:00:00	2.525	21.258	-29.03	608.011	70	0	6.204	10	1.555	35.443	-0.147		

Fig. 3. Psychophysiological stress dataset

to provide an unbiased evaluation of a final model fit on the training dataset. The dataset had been normalized using the Z-Score normalization technique to scale the dataset value from 0 to 1. The normalized data then fits into the proposed deep learning model for classification. The classification performance of the deep learning model will be evaluated by utilizing the k-fold cross-validation. Brownlee [23] said that Cross-validation is a resampling procedure used to evaluate a limited data sample of machine learning models. In k-fold cross-validation, the dataset is divided into k subsets of equal size. The model is built fork times, leaving one of the subsets from training and using it as the test set.

Python is a hugely popular general-purpose programming language, so it is beneficial to apply solidly to AI and profound learning principles. Keras is a high-level neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, or Theano. TensorFlow serves as the backend engine for the Keras API to handle the low-level operations such as tensor products and convolutions. The machine used is Intel® Core™ i7-4720HQ CPU @ 2.60GHz 2.59GHz with 8.00GB RAM. The proposed method uses the 1D CNNs deep learning model to classify. 1D CNNs works precisely like normal CNNs but with different input dimension. The input for normal CNNs usually be two-dimensional or image datasets, but the input for 1D CNNs is one-dimensional or signal datasets. Table 1 shows the dataset, batch size, epochs, activation function, and optimizer used in this study.

The Batch Size used is 256. Batch Size is the number of training examples utilized in one iteration. The data was run for 15 epochs to see the model's performance. Epoch is one forward pass and one backward pass of all the training examples. The activation functions are ReLU and Softmax. ReLU or Rectified-Linear Unit Layer will provide a threshold at zero. Softmax function or normalized exponential function is used to represent categorical distribution. The optimizer function is SGD. SGD or Stochastic Gradient Descent is a simple yet efficient approach to discriminative learning of linear classifiers under convex loss functions such as Support Vector Machine or Linear Regression. Figure 4 shows the schematic representation of the 1D CNNs model.

The classification accuracy of the output is calculated according to the use of equation (6).

$$Accuracy = \frac{Number\ of\ correct\ prediction}{Total\ Number\ of\ predictions} \tag{6}$$

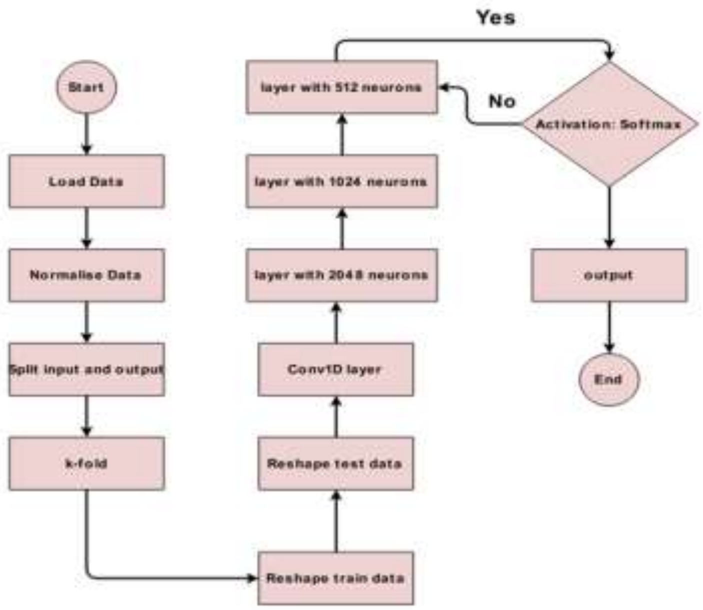

Fig. 4. Schematic representation of 1D CNNs

Table 1. Hyper parameter of 1D CNNs

Dataset	Batch Size	Epochs	Activation	Optimizer
Psychophysiological Stress Dataset	256	15	ReLU Softmax	SGD

III. Results and Discussions

Table 2 shows the results of the 1D CNNs deep learning model with 10-fold cross-validation. In each fold, the data had been divided into ten groups. The first group will be used as testing in the first fold, and the other groups will be used as training. In the second fold, the second group will be used as testing, and the other groups will be used as training, followed by the third group for testing in the third fold. This will recursively continue until the 10^{th} fold is completed. Besides that, the plotting of accuracy and loss function for each training process and testing process also can be seen in Table 2. The Final accuracy for 1D CNNs is 99.97%.

The dataset is tested in a second experiment with The Backpropagation (BP) algorithm for further proof. BP is fit into the same data to compare the performance of both models. In Table 2, it is clearly stated that the training classification performance of 1D CNNs is 100% and the testing classification performance of 1D CNNs is 99.97%. However, the training classification performance of BP is 65.85%, and the testing classification performance of BP is 65.57%. Figure 5 clearly shows that the 1D CNNs deep learning model outperforms the BP algorithms. Moreover, our algorithm achieved higher accuracy than the methods mentioned in [24].

Table 3 compares the implementation of the CNN and other recent works based on different machine and deep learning algorithms. As shown in Table 3, our work achieves better accuracy than most of the other recent works (which have been reported in this paper) except that of [20], which achieved 99.8% using the physiological signals dataset. However, our work's accuracy gains better results than the same dataset.

The datasets must be structured appropriately to fit perfectly into the model and provide a good analysis of the results. Every step, from loading the dataset from a text file or CSV file to evaluating the trained model's performance, is critical because simple errors can cause errors when the code is run. The parameters used to build the model must be tested repeatedly to find the best parameter. For example, a sigmoid may be better when ReLU is a terrible choice and vice versa. Building the best model requires a lot of trial and error. The deep learning model is well-known for its high accuracy, regardless of whether it can solve a classification problem or a regression problem.

Table 2. Summary of the accuracy 1D CNNs

Fold	**Accuracy**
1^{st}	99.98
2^{nd}	100.00
3^{rd}	99.99
4^{th}	99.98
5^{th}	99.97
6^{th}	99.93
7^{th}	99.99
8^{th}	99.97
9^{th}	99.94
10^{th}	99.98
Final Accuracy	99.97

Table 3. Comparison with other published works

Published Work	**Dataset**	**Accuracy**
Deep neural networks [25]	Physiological signals	99.80%
ANN [26]	WESAD dataset	95.21%
SVM [20]	Psychophysiological Stress	93.4 ± 3.2%
Convolutional Neural Network (CNN) [27]	The heart rate signal	98.69 ± 0.45%
Machine learning [28]	The mind-brain-body dataset	81.33%
Machine learning [29]	Questionnaire (DASS 21)	Between 0.628 - 0.798
Hybrid deep learning technique [30]	Employee Data	96.2 %
This work	Psychophysiological Stress	99.7%

Fig. 5. Comparison in training and testing accuracy of 1D CNNs

IV. Conclusion

In this study, the 1D CNNs model was utilized to classify stress and compared with BP and various techniques from the Literature review. A psychophysiological stress dataset was used in this study. The performance of the developed model is evaluated by comparing it with the BP model and other works. The result obtained in this study shows that the 1D CNNs model is reliable in classifying stress with low lost function, which is 0.001, and high accuracy of 99.97%. More datasets are required to enhance the result of stress classification in the future. Skill and experience are essential in assisting the person in selecting and checking the best method in the modeling process. Spiking Neural Network as the latest generation of neural network and other areas of study will be applied to do stress classification.

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Declarations

Author contribution

All authors contributed equally as the main contributor of this paper. All authors read and approved the final paper.

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Conflict of interest

The authors declare no known conflict of financial interest or personal relationships that could have appeared to influence the work reported in this paper.

Additional information

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References

[1] P. Priya, "How to Overcome Stress during COVID19 Pandemic," *International Journal of Entrepreneurship and Economic Issues*, vol. 4, no. 1, pp. 75-78, 2020.

[2] M. Fawaz and A. Samaha, "COVID-19 quarantine: Post-traumatic stress symptomatology among Lebanese citizens," *International Journal of Social Psychiatry*, vol. 66, no. 7, pp. 666-674, 2020.

[3] L. Liang, T. Gao, H. Ren, R. Cao, Z. Qin, Y. Hu, C. Li, and S. Mei, "Post-traumatic stress disorder and psychological distress in Chinese youths following the COVID-19 emergency," *Journal of Health Psychology*, vol. 25, no. 9, pp. 1164–1175, Jul. 2020.

[4] R. N. Kumar Anil, S. C. Karumaran, D. Kattula, R. Thavarajah, and A. M. Anusa,, "Perceived stress and psychological (dis) stress among Indian endodontists during COVID19 pandemic lock down," *MedRxiv*, 2020.

[5] D. Choudhury, S. Bhowmick, S. Parolia, S. Jana, D. Kundu, N. Das, K. Ray, and S. KarPurkaysatha, "A study on the anxiety level and stress during Covid19 lockdown among the general population of West Bengal, India- A must know for primary care physicians," *Journal of Family Medicine and Primary Care*, vol. 10, no. 2, p. 978, 2021.

[6] E. Esterwood and S. A. Saeed, "Past epidemics, natural disasters, COVID19, and mental health: learning from history as we deal with the present and prepare for the future," *Psychiatric quarterly*, pp. 1-13, 2020.

[7] Willis Towers Watson Public Limited Company, "Seventy-five percent of U.S. employers say stress is their number one workplace health concern," *GLOBE NEWSWIRE*, June 29, 2016. [Online]. Available: https://www.globenewswire.com/news-release/2016/06/29/852338/0/en/Seventy-five-percent-of-U-S-employers-say-stress-is-their-number-one-workplace-health-concern.html.

[8] American Psychological Association, "Stress in America: Coping with change," *Stress in America Survey*, PsycEXTRA Dataset, 2017.

[9] J. T. Cacioppo, L. G. Tassinary, and G. Berntson, *Handbook of psychophysiology*. Cambridge university press, 2007.

[10] G. Francis, "Young adults spend more than six hours per day feeling 'stressed out', finds Mental Health study," *The Independent*, 2018. [Online]. Available: https://www.independent.co.uk/life-style/mental-health-young-adults-stress-depression-anxiety-ocd-study-a8233046.html .

[11] K. G. Kim, "Book review: Deep learning," *Healthcare informatics research*, vol. 22, no. 4, pp. 351-354, 2016.

[12] K. Das and R. N. Behera, "A survey on machine learning: concept, algorithms and applications," *International Journal of Innovative Research in Computer and Communication Engineering*, vol. 5, no. 2, pp. 1301-1309, 2017.

[13] I. Arel, D. C. Rose, and T. P. Karnowski, "Deep machine learning-a new frontier in artificial intelligence research [research frontier]," *IEEE computational intelligence magazine*, vol. 5, no. 4, pp. 13-18, 2010.

[14] D. P. Solomatine and A. Ostfeld, "Data-driven modelling: some past experiences and new approaches," *Journal of hydroinformatics*, vol. 10, no. 1, pp. 3-22, 2008.

[15] G. E. Hinton, S. Osindero, and Y.-W. Teh, "A fast learning algorithm for deep belief nets," *Neural computation*, vol. 18, no. 7, pp. 1527-1554, 2006.

[16] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *nature*, vol. 521, no. 7553, pp. 436-444, 2015.

[17] S. Kiranyaz, O. Avci, O. Abdeljaber, T. Ince, M. Gabbouj, and D. J. Inman, "1D convolutional neural networks and applications: A survey," *Mechanical systems and signal processing*, vol. 151, p. 107398, 2021.

[18] F. Li *et al.*, "Feature extraction and classification of heart sound using 1D convolutional neural networks," *EURASIP Journal on Advances in Signal Processing*, vol. 2019, no. 1, pp. 1-11, 2019.

[19] F. M. Riese and S. Keller, "Soil texture classification with 1D convolutional neural networks based on hyperspectral data," *arXiv preprint arXiv:1901.04846*, 2019.

[20] E. Smets *et al.*, "Comparison of machine learning techniques for psychophysiological stress detection," in *International Symposium on Pervasive Computing Paradigms for Mental Health*, 2015: Springer, pp. 13-22.

[21] Z. Qin, M. Li, L. Huang, and Y. Zhao, "Stress level evaluation using BP neural network based on time-frequency analysis of HRV," in *2017 IEEE International Conference on Mechatronics and Automation (ICMA)*, 2017: IEEE, pp. 1798-1803.

[22] C. Liu, Y. Feng, and Y. Wang, "An innovative evaluation method for undergraduate education: an approach based on BP neural network and stress testing," *Studies in Higher Education*, pp. 1-17, 2020.

[23] J. Brownlee, "A gentle introduction to k-fold cross-validation," *Machine Learning Mastery*, vol. 2019, 2018.

[24] K. Sardeshpande and V. R. Thool, "Psychological Stress Detection Using Deep Convolutional Neural Networks," in *International Conference on Computer Vision and Image Processing*, 2019: Springer, pp. 180-189.

[25] R. Li and Z. Liu, "Stress detection using deep neural networks," *BMC Medical Informatics and Decision Making*, vol. 20, no. 11, pp. 1-10, 2020.

[26] P. Bobade and M. Vani, "Stress detection with machine learning and deep learning using multimodal physiological data," in *2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA)*, 2020: IEEE, pp. 51-57.

[27] N. Hakimi, A. Jodeiri, M. Mirbagheri, and S. K. Setarehdan, "Proposing a convolutional neural network for stress assessment by means of derived heart rate from functional near infrared spectroscopy," *Computers in biology and medicine*, vol. 121, p. 103810, 2020.

[28] H. Baumgartl, E. Fezer, and R. Buettner, "Two-level classification of chronic stress using machine learning on resting-state EEG recordings," 2020.

[29] A. Priya, S. Garg, and N. P. Tigga, "Predicting anxiety, depression and stress in modern life using machine learning algorithms," *Procedia Computer Science*, vol. 167, pp. 1258-1267, 2020.

[30] R. Reshma, "Emotional and Physical Stress Detection and Classification Using Thermal Imaging Technique," *Annals of the Romanian Society for Cell Biology*, pp. 8364-8374, 2021.