21 Mobile EEG-Based Workers' Stress Recognition by Applying Deep Neural Network

Houtan Jebelli, Mohammad Mahdi Khalili, and SangHyun Lee

Abstract

A large number of construction workers are struggling with high stress associated with their perilous job sites. Excessive occupational stress can cause serious job difficulties by negatively impacting workers' productivity, safety, and health. The first step to decrease the adverse outcomes of this work-related stress is to measure workers' stress and detect the factors causing stress among workers. Various self-assessment instruments (e.g., a stress assessment questionnaire) have been used to assess workers' perceived stress. However, these methods are compromised by several drawbacks that limit their use in the field. Firstly, these methods interrupt workers ongoing tasks. Secondly, these methods are subject to a high degree of bias, which can lead to inconsistent results. The authors' earlier work attempted to address the limitations of these subjective methods by applying different machine learning methods (e.g., Supervised Learning algorithms) to identify the pattern of workers' brain waves that is acquired from a wearable Electroencephalography (EEG) device, while exposed to different stressors. This research thus attempts to improve the stress recognition accuracy of the previous algorithms by developing an EEG-based stress recognition framework by applying two Deep Learning Neural Networks (DNN) structures: a convolutional deep learning neural network (deep CNN) and a Fully Connected Deep Neural Network. Results of the optimum DNN configuration yielded a maximum of 86.62% accuracy using EEG signals in recognizing workers' stress, which is at least six percent more accurate when compared with previous handcraft feature-based stress recognition methods. Detecting workers' stress with a high accuracy in the field will lead to enhancing workers' safety, productivity, and health by early detection and mitigation of stressors at construction sites.

Keywords

Brain waves • Workers' stress • Wearable electroencephalography (EEG) • Convolutional deep neural network • Fully connected deep neural network • Occupational stress • Workers' productivity • Health • Safety

21.1 Introduction

With 68% of construction workers suffering from high mental stress as a result of working in the industry, construction work is one of the most stressful occupations [1]. Workplace stress is strongly associated with workers' productivity, health, and safety behavior [2]. Therefore, it is critical to measure and characterize construction workers' stress levels in the field, which can not only reduce their injuries, accidents, and errors but also improve their productivity and job satisfaction.

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Various instruments to measure workers' stress have been used, but they either rely on imprecise memory and reconstruction of feelings in the past (e.g., stress assessment questionnaires) [3] or interfere with workers' ongoing work (e.g., biochemical measurement), which limits their use in the field. One of the most reliable ways to assess stress is to examine the reflection of various stressors on brain activity [4, 5]. To measure this reflection, an Electroencephalogram (EEG) has frequently been used in clinical diagnosis and biomedical research [4–7]. In spite of the fact that EEG holds promise as a means to assess individuals' stress in the clinical domain, using traditional EEG devices to assess construction workers' EEG signals while working on a construction site is impractical due to the wired connections and complicated settings of these devices.

Due to recent technological advancements, wearable and wireless biosensors are readily available and have demonstrated a great potential to be used at construction sites to improve workers' safety, well-being, and health [8–21]. Wearable technology offers a less invasive method for assessing construction workers' stress using their EEG signals, which remain independent of workers' imprecise memories. Quite recently, the authors' applied different signal processing and machine-learning techniques (e.g., Supervised Learning algorithms) to recognize construction workers' stress by extracting a handcraft feature from EEG [19]. This research seeks to improve the stress recognition accuracy of the current frameworks by proposing a Deep Learning based stress recognition. In this research, the authors examine two classes of Deep Neural Network (DNN) architectures models. First, a convolutional neural network (CNN) was trained to recognize workers stress based on their EEG signals. CNN was selected due to its high performance in Deep Learning based classification task. Then, the authors developed a Fully Connected Deep Neural Network, based on the EEG signals that were collected at real construction sites.

To examine the performance of the proposed Deep Learning based stress recognition framework, the authors collected EEG signals from 10 construction workers while performing different tasks in the field. Workers' stress-related hormone (cortisol), which is a reliable method to assess human stress [22], was measured using a saliva sample. Workers' cortisol level was used to label different construction tasks as low or high stress. Recognizing workers' stress with high accuracy is expected to improve the conditions of construction sites and workers' well-being through the detection and mitigation of the stressors at construction sites.

21.2 EEG-Based Stress Recognition by Applying Deep Learning

Figure 21.1 illustrates the overview of the proposed framework to recognize workers' stress using their brain waves. As the first step, the workers' brain waves were collected from 14 different locations of their scalp using a wearable EEG headset, which was fit into their safety hard hat. As mentioned earlier, workers' cortisol level was measured as a ground truth to be used to label workers' stress. Then, as the second step, a signal processing framework that was proposed by authors' previous work [23] was applied to enhance the quality of the EEG signal by reducing signal noises and artifacts. As the last step, two DNN structures (a Fully Connected Deep Neural Network and a Convolutional Neural Network) were applied to recognize workers' stress.

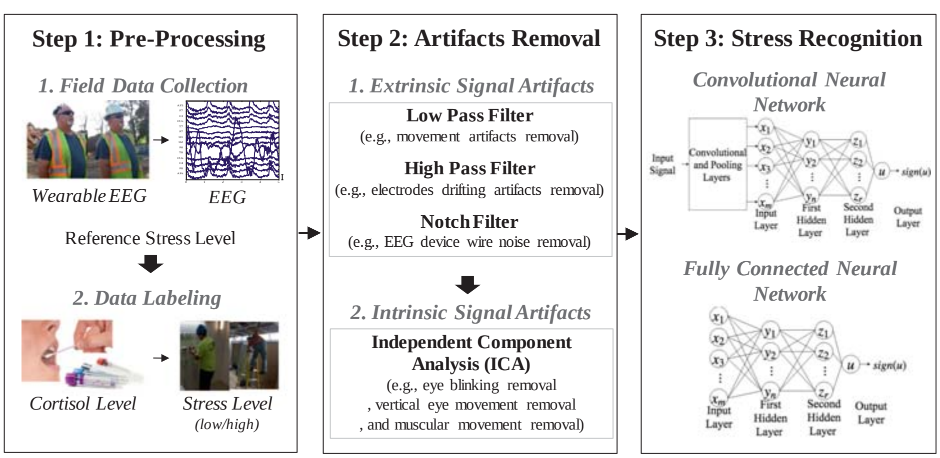

Fig. 21.1 The overview of a Deep Neural Network (DNN)-based stress recognition framework using the EEG signals collected in the field

21.2.1 EEG Signal Pre-processing: Artifacts Removal

A large number of external and internal sources can contaminate the quality of EEG signals [24]. In this regard, EEG signal artifacts can be divided into two groups: intrinsic signals artifacts, that come from the body itself (e.g., vertical eye movement, eye blinking) [24], and extrinsic signal artifacts, that come from external factors (e.g., movement, respiration, and use of muscles) [25–27]. EEG signal artifacts are more significant while collecting data at construction sites, due to the noisy sites environment and frequent body movement of the workers. Therefore, it is essential to reduce EEG signal artifacts before analyzing data. To reduce EEG signal artifacts, the authors previously developed an EEG signal processing framework, which acquires high-quality EEG signals by removing the most common EEG signal artifacts from the EEG recorded using a wearable EEG device at the construction site [23]. The proposed framework in the authors' former work, reduces both extrinsic and intrinsic artifacts in EEG signals. To reduce extrinsic artifacts from the EEG signals recorded in the real construction sites a 60 Hz low-pass filter, a 0.5 Hz high-pass filter, and a notch filter with the cutoff frequency of 60 Hz were applied. To reduce intrinsic artifacts, the authors applied an independent component analysis (ICA). ICA is a computational method that has been commonly used in EEG research to remove intrinsic signal artifacts [28–30]. ICA detects and removes the artifactual components from the EEG signal [31] by separating the original signal into multiple components [25].

21.2.2 Fully Connected Deep Neural Network

A Fully Connected Deep Neural networks can be interpreted as a complex function which gets an input data, $x = [x_1, x_2, \ldots, x_m]$ (e.g., EEG signals across different channels) and predicts the label of the data as an output (e.g., different stress levels). Network layers and neurons make the structure of a Fully Connected Deep Neural networks. The first hidden layer comprises of n neurons and n hidden variables $(y_1, y_2, \ldots, y_n)$. Each edge between neuron x_i and y_j is associated with a weight value represented by α_{ij}. The hidden variables $(y_1, y_2, \ldots, y_n)$ are calculated based on Eq. 21.1.

$$y_j = f\left(\sum_{i=1}^{m} \alpha_{ij} x_i\right) j = 1, 2, \ldots, n, i = 1, 2, \ldots, m \tag{21.1}$$

where $f(.)$ is an arbitrary function and usually is taken to be the sigmoid function. Similarly, the second hidden layer has r neurons and r hidden variables $(z_1, z_2, \ldots, z_r)$. Let β_{ij} denote the weight value between neuron y_i and z_j. Then, hidden variables of the second hidden layer are calculated using Eq. 21.2.

$$z_j = f\left(\sum_{i=1}^{n} \beta_{ij} y_i\right) j = 1, 2, \ldots, r \tag{21.2}$$

Finally, the output u, which represents the predicted label (low or high stress) is calculated using Eq. 21.4.

$$u = f\left(\sum_{i=1}^{r} \gamma_i z_i\right) \tag{21.3}$$

where, γ_i is the weight value of neuron z_i and output u. After observing output u, if $u \geq 0$, we predict the label of the input data as 1 (high stress), otherwise the predicted label is -1 (low stress). In other words, the predicted label is $sign(u)$. For training a neural network, the authors applied a backpropagation algorithm [32] to find optimal weight values α_{ij} and β_{ij} and γ_i based on the training data. Fully Connected Deep Neural Network in this research was modeled off-line using a custom developed software based on the Neural Network Toolbox provided by MATLAB. A MATLAB version 8.1.0.604 program was used for all of the computations.

21.2.3 Deep Convolutional Neural Network

In addition to a Fully Connected Deep Neural Network, the authors explored the capability of a Deep Convolutional Neural Networks (CNN) to recognize workers' stress using their EEG signals. Convolutional and pooling layers are two essential

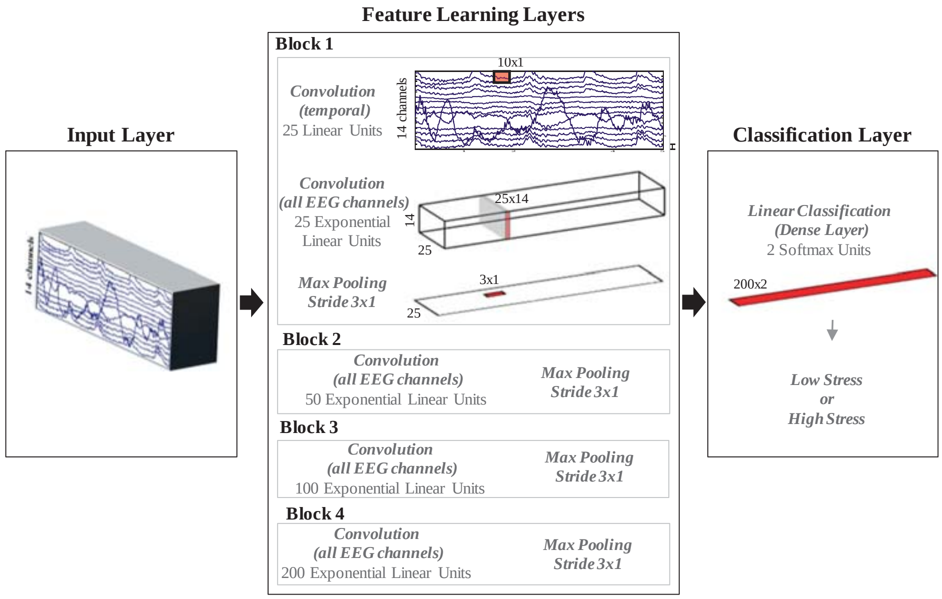

Fig. 21.2 Deep Convolutional Neural Network architecture to recognize construction workers' stress level based on their EEG signals

types of layers that create the structure of a CNN. Convolutional layers extract the patterns of different blocks of the data around each window of the input signal. Then, pooling layers aim to reduce the risk of model overfitting and the computational cost and time of the model by decreasing the spatial size of the output of convolutional layers. Each convolution layer calculates the convolution of its input with a bunch of filters. Each filter defined as a $p \times q$ matrix. The convolution between input signal I and filter F is calculated using Eq. 21.4.

$$O[m,n] = (I * F)[m,n] = \sum_{i=1}^{p} \sum_{j=1}^{q} I[m-i, n-j] \cdot F[i,j] \tag{21.4}$$

where, O is the convolution of I and F. I is the input signals (different EEG channels) and F is a filter. Notice that if $m - i \leq 0$ or $n - j \leq 0$, then $I[m-i, n-j] = 0$.

To learn complex EEG signal patterns, four blocks of the consecutive convolutional and pooling layers were used. Then, to classify the learned patterns, a softmax layer was added after convolutional and pooling layers. A fully connected network was used as the classification layer. The fully connected neural network tries to find the best classifier using extracted features by convolutional and pooling layers. In other words, convolutional and pooling layers helps classifier to extract features from neighboring pixels. On the contrary, the softmax layer considers input data (all EGG channels) without emphasis on the patterns existing among neighbor pixels and data points. Figure 21.2 shows the architecture of the developed Deep CNN in this research. The network was modeled off-line using a custom developed software based on an open source library (Keras-toolbox) provided by Python. A Python version 2.7.11 program was used for all of the computations.

21.3 Experimental Setting

To examine the performance of the proposed Deep Learning-based stress recognition framework to recognize workers' stress while exposed to different stressors at actual construction sites, the authors' visited four different construction sites and recorded 10 construction workers' brain waves using a wearable EEG headset. Subjects reported no mental disorders or history of epilepsy that could affect their brain waves. Subjects' were asked to perform same tasks under low stress conditions (e.g., working on the ground level and working right after taking a break) (Fig. 21.3a) and high stress conditions (e.g., working at the top of a ladder, working in confined space, and continuous work without taking a break) (Fig. 21.3b). Before starting the data collection, all the subjects were informed of the purpose and procedure of the data collection.

Fig. 21.3 EEG data collection in field: **a** Low stress experimental tasks (e.g., working on the ground level and working right after break); **b** High stress experimental tasks (e.g., working at top of a ladder, working in a confined space, and working in dangerous environment); **c** Wearable EEG headset fit into worker's safety hardhat; **d** Salivary cortisol samples kit

Workers' brain waves were collected across 14 different channels using a wearable EEG headset (Fig. 21.3c). The data collection rate was set at 128 data per second, with the recording resolution of 14 bits with the connectivity at a 2.4 GHz band a dynamic range of 8400 μV (peak to peak). Subjects' actual stress was determined by measuring their cortisol level. Cortisol is known as stress hormone and is highly associated with subjects' stress. In this study subjects' cortisol level was measured using the saliva sample (Fig. 21.3d). Subjects' cortisol level was used as a baseline to label their stress level as low or high while working in different conditions.

21.4 Results and Findings

The authors applied two proposed deep learning neural network on the data collected at actual construction sites. The result of this study shows that the proposed Fully Connected Deep Neural Network led to an overall prediction accuracy of 86.62%. On the other hand, the Convolutional Deep Neural Network model led to an overall prediction accuracy of 64.20%.

Figure 21.4 shows the stress recognition accuracy of the model under different network structures (different number of layers and neuron in the model). According to Fig. 21.4a, a network with two hidden layers is preferable and will lead to the highest prediction accuracy and lowest computation cost as well. The result of optimizing the number of neurons in each layer show that selection of 83 neurons in the first layer and 23 neurons in the second layer will lead to the optimum network structure (Fig. 21.4b).

The present finding is promising, considering that highest EEG-based stress recognition prediction accuracy using supervised learning algorithms is around 80.00% by applying Gaussian Kernel Support Vector Machine (SVM) [19]. Also, the proposed deep learning-based stress recognition does not have the limitation of supervised learning algorithms (e.g., SVM and logistic regression), which are fundamentally a binary classifier and have not been standardized for dealing with multi-class problems, to identify multiclass classification (identifying different stress levels).

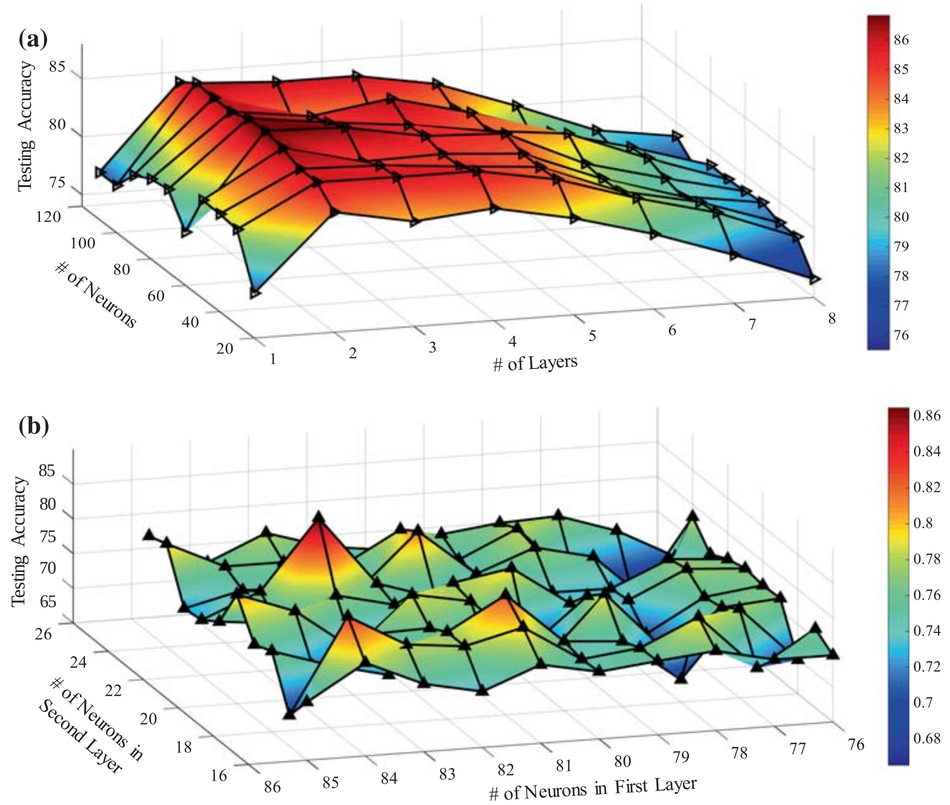

Fig. 21.4 Optimizing the architecture of Fully Connected Deep Neural Network: **a** optimizing the number of layers in the network; **b** optimizing the number of neurons in each layer

Table 21.1 Confusion matrices of training and testing steps

Training	Low stress	High stress	Recall
Low stress	2670	320	0.893
High stress	270	2740	0.91
Precision	0.90	0.89	Accuracy: 0.90
Testing	*Low stress*	*High stress*	*Recall*
Low stress	580	70	0.89
High stress	100	540	0.84
Precision	0.85	0.88	Accuracy: 0.87

To further investigate the classification performance, the confusion matrices for training and testing steps of the proposed network are shown in Table 21.1. In this table, each row represents actual labels (stress level) while each column corresponds to predicted labels. In addition to classifier accuracy, Table 21.1 shows two critical parameters to further examine the performance of the classifier; accuracy and recall. Precision is defined as the ratio of the number of correct prediction to the total number of instances classified as positive (high stress) or negative (low stress). The recall represents the ratio of the number of correct predictions (correct high or low stress) to the total number of instances (total high stress or low stress). Both “high stress” and “low stress” labels achieved relatively high recall and precision, which shows the high performance of the performance in detecting both low stress and high stress conditions.

21.5 Conclusion

This study was undertaken to develop an EEG-based stress recognition framework by applying deep learning algorithms to recognize construction workers' stress while performing different tasks at actual construction sites. This study showed the capability of a Fully Connected Deep Neural Network to recognize workers stress with high accuracy. According to the results, the optimum network configuration to recognize construction workers' stress requires two hidden layers, 83 neurons in the first hidden layer and 23 neurons in the second hidden layer. Also, the proposed DNN based stress recognition eased the need for feature extraction and feature engineering, one the most time-consuming steps in the Supervised Learning algorithms. Besides, multi DNN based stress recognition is expected to be the ultimate classifier to recognize workers' stress with high accuracy, particularly while dealing with different levels of stress, where most of the supervised learning algorithms are limited to a binary classification setting. This study will serve as a basis for future studies to accurately identify different workers' stress levels using their brain waves in the field.

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