Abstract—Stress is known as one of the major factors threatening human health. A large number of studies have been performed in order to either assess or relieve stress by analyzing the brain and heart-related signals. In this study, signals produced by functional Near-Infrared Spectroscopy (fNIRS) of the brain recorded from 10 healthy volunteers are employed to assess the stress induced by the Montreal Imaging Stress Task by means of a deep learning system. The proposed deep learning system consists of two main parts: First, the one-dimensional convolutional neural network is employed to build informative feature maps. Then, a stack of deep fully connected layers is used to predict the stress existence probability. Experiment results showed that the trained fNIRS model performs stress classification by achieving 88.52 ± 0.77% accuracy. Employment of the proposed deep learning system trained on the fNIRS measurements leads to higher stress classification accuracy than the existing methods proposed in fNIRS studies in which the same experimental procedure has been employed. The proposed method suggests better stability with lower variation in prediction. Furthermore, its low computational cost opens up the possibility to be applied in real-time stress assessment.

Keywords—functional near infrared spectroscopy; stress assessment; deep learning; convolutional neural network; independent component analysis.

I. INTRODUCTION

Stress is one of the major factors leading to chronic disorders [1], [2]. It is a common physical response to the environment making people feel uncomfortable, challenged or threatened [3]. Stress disturbs imagination, problem-solving, decision making, working memory and other related prefrontal cortex (PFC) activities [4], [5]. Therefore, precautionary measures to assess and then relieve stress are vitally important for both individual health and the welfare of society at a broader level.

Appropriate standardized protocols for studies of stress are required to induce stress in a reliable and credible way. Montreal Imaging Stress Task (MIST) is one of the popular psychological stressor protocols employed in the stress assessment studies [6]. In the MIST, mental arithmetic calculations are performed during a stressful condition (in a limited time) while the participants' response is assessed [7].

To study the development of stress, continuous measurements are required to study the mental state throughout consecutive and stressful tasks over a long period [8], [9]. It has been shown that stress can be assessed by brain-related physiological variables including EEG (Electroencephalography) and functional near-infrared spectroscopy (fNIRS) [10]–[15]. In the past decade, mental stress and workload assessments [16], [17] have been addressed by employing the fNIRS as a measure for quantification, showing an increased concentration of oxyhemoglobin (HbO2) and decreased concentration of deoxyhemoglobin (HbHb) in the prefrontal.

For stress detection utilizing physiological signals, an intelligent system based on machine learning approach is needed. Several studies have shown the superiority of deep learning as the main sub-fields of machine learning in data analysis tasks [18], [19]. The advantage of deep learning is caused by its ability to automatically learn high-level, layered,
hierarchical abstractions from data and mapping the extracted features to desired labels by end-to-end training [20]. For automatic feature extraction, a type of deep artificial neural networks named convolutional neural networks (CNN) is widely used in the field of computer vision [21]. CNNs have been applied to many tasks, including image classification [22], object detection [23], and semantic segmentation [24]. Although CNNs was introduced for images, several studies have shown the CNN’s ability in extracting deep features from one-dimensional data such as speech signals [25] and vector of raw input data [26].

Motivated by promising results of deep networks in various fields [27]–[31], in this study we investigated its applicability in stress prediction by means of fNIRS which to the best our knowledge has not been done. The stress protocol conducted in this study is a modified version of the MIST [7], designed and used to induce a higher level of mental stress. An fNIRS dataset is made by extracting features from both time and frequency domains of fNIRS signals. This study proposes a deep learning based algorithm that can figure out specific abstract patterns in each data to determine the distinctiveness of each case and is able to map the input data directly to their corresponding label, determining whether it is stress related or not.

II. MATERIALS AND METHODS

A. Experiment Procedure

Ten healthy, right-handed, male adults (aged 25.3 ± 2.6) participated in this experiment. It should be mentioned that none of them had psychological and neurological diseases and did not take any special medication. Before experimenting, they were informed about the experiment and gave written consent. Signals were registered at the Iranian National Brain Mapping Lab. The laboratory had an environment with a good air-condition without any environmental stress and noises. Participants were seated in a comfortable chair, located approximately 1.5 meters away from the monitor while they were asked to avoid shaking during the experiment as much as possible (Figure 1). The experiment has an ethics code of IR.IUMS.REC.1396.810194120 from the Iranian University of Medical Sciences.

Figure 1. The Experiment Procedure for participant conducting the task. The experiment was performed at the Iranian National Brain Mapping Lab.
signals are computed and compared with the simulated heart wave. Finally, 20% of components have the lowest correlation with the simulated wave are reconstructed. The optimum percentage of the selected components has been obtained by doing try and error.

In addition to ICA denoising, a band-pass filter of [0.001-0.14] Hz is applied to the fNIRS signal before classification and comparison processes in order to eliminate the unrelated frequency components to brain hemodynamic response [37], [38].

2) Stress Classification

To describe the feature extraction process, in addition to four features in the time domain including mt, sdt, Skt, and Kut, four features in the frequency domain including mf, sdf, Skf, and Kuf have also been extracted from fNIRS signals. All in all, eight different features are considered for fNIRS signals. The selected features have been described in studies [33], [39].

As mentioned in Task Sequence section, Control and Stress levels have five two-part periods including 20 seconds Rest, and 30 seconds mathematical questions. In this study, a classification procedure is conducted which is based on the study [32]. In this procedure, a classification of the 30-second parts between Control and Stress levels is pursued.

To form an fNIRS dataset, ten 30-second parts are separated from each recorded fNIRS signal. Then each part is divided into three 10-second sections, and the considered eight features for fNIRS representation are extracted from each of these three sections. This process is applied to both oxyhemoglobin and total hemoglobin signals of fNIRS channels, which is the best combination based on our results. The constructed fNIRS datasets are fed into a deep neural network architecture which is explicitly explained in the following and illustrated in Figure 3.

The network consists of two main blocks: feature extraction and classification blocks which are connected to each other by flattening layer. For automatic extraction of feature maps from raw input samples, a one-dimensional convolutional neural network with ten 3x1 kernel size, Batch Normalization and ELU non-linearity are used. The classification block contains five blocks in which three first blocks are made from a Dense (fully-connected) layer, Batch Normalization, ELU non-linearity, and Dropout layer. In the last block, we used one neuron layer and Sigmoid function. The numbers of activation neurons of Dense layers are 256, 16, 4, and 1 respectively. In order to prevent over-fitting problem due to the relatively large number of trainable parameters, three 60%, 40% and 20% drop-out layers are added after the ELU nonlinearities in three first blocks respectively.

The proposed model is implemented using Tensorflow library [40] and is optimized by minimizing Adam algorithm with 0.0002 learning rate. This task is treated as binary classification problems, where each output neuron decides if a sample belongs to a class or not, so binary cross-entropy is used for loss function which Adam algorithm [41] tries to decrease it through the epochs. At each epoch, a mini-batch size of 200 samples is randomly selected from the training images and is fed into the network. It is notable that for training the network with fNIRS data, the batch size is set to 20. The network will converge in 500 epochs, and neither data augmentation nor pre-train weights is used during training.

In order to show that the results do not depend on the choice of test dataset, the five-fold cross-validation strategy has been employed based on the articles [33], [38], [42] which use cross validation strategy. In five-fold cross-validation, the original sample was randomly partitioned into five equal-sized subsamples. In each experiment, a single subsample was retained for testing the model, and the remaining four subsamples were used for training the networks. The cross-validation process was then repeated five times, with each of the five subsamples used exactly once as the test dataset.

III. RESULT
An example of the filtered fNIRS signals averaged between channels and recorded from the ninth participant is illustrated in Figure 4.

The introduced ICA denoising and band-pass filter in fNIRS Signal Preprocessing section have been used to remove artifacts and noises irrelevant to the brain hemodynamic response. The first five green parts and the second five orange parts are related to the Control and Stress levels, respectively. After entering to the Stress level, a significant difference in the signal variation is visually observable.

Based on the 5-fold cross-validation strategy defined in the Stress Classification section, Table I reports the accuracy of network prediction in each fold in addition to the mean and standard deviation (STD) of the accuracy over five-fold strategy. In particular, the prediction accuracy obtained using fNIRS is 88.52 ± 0.77%.

In the Stress Classification section, it was mentioned that each 30-second desired part of the signal is divided into three 10-second sections to form the dataset, and the considered features were extracted from each of these three sections. To identify the information richness level of these three time frames, stress classification was separately performed by using each of these time frames. The related results of the classification are reported in Table II. It is observed that the second and third time frames of fNIRS signals respectively contain much more levels of information richness than other corresponding time frames, where 85.14% of mean accuracy was obtained by using features extracted from the mentioned best time frames of fNIRS signals.

In this study, in addition to features from the time domain of the signals, some features in the frequency domain of the signals were also extracted to represent the variations of the signals as better and efficient as possible. To show the effectiveness of these time and frequency domain features, stress classification was separately performed by using each of the time and frequency feature sets. The related results of classification are reported in Table II, indicating that the time domain features (First Feature Set) can better modulate the stress related variations rather than the frequency domain feature set (Second Feature Set), or in other words, the stress-related alterations are significantly made in the time domain of the signal. For example, utilizing the time domain features of the fNIRS signal could provide the mean stress classification accuracy of 86.10% compared with 80.74% of accuracy by the employment of the frequency domain features.

However, incorporation of time domain features with the frequency ones could provide a better stress classification accuracy. So that by using both time and frequency domain features of fNIRS signals, a mean stress classification accuracy of 88.52% was obtained.

The size of the training data is one of the determinant factors in the results obtained from the deep networks. Naturally, with increasing the number of training samples, the network performance is expected to be improved. On the other hand, a model is better which could discover the patterns needed for decision making using minimum possible data. In this experiment, the number of training data has gradually decreased, while the test data size has been kept constant to see the reaction of three models. The mean accuracy of the trained model by fNIRS over five folds is reported in Table III.

By comparing the performance of the models trained on different data sizes, we conclude that fNIRS model has high stability against a reduction in input samples. For example, with 20% drop from the whole dataset, the accuracy of fNIRS contains much more levels of information richness than other corresponding time frames, where 85.14% of mean accuracy was obtained by using features extracted from the mentioned best time frames of fNIRS signals.

In this study, in addition to features from the time domain of the signals, some features in the frequency domain of the signals were also extracted to represent the variations of the signals as better and efficient as possible. To show the effectiveness of these time and frequency domain features, stress classification was separately performed by using each of the time and frequency feature sets. The related results of classification are reported in Table II, indicating that the time domain features (First Feature Set) can better modulate the stress related variations rather than the frequency domain feature set (Second Feature Set), or in other words, the stress-related alterations are significantly made in the time domain of the signal. For example, utilizing the time domain features of the fNIRS signal could provide the mean stress classification accuracy of 86.10% compared with 80.74% of accuracy by the employment of the frequency domain features.

However, incorporation of time domain features with the frequency ones could provide a better stress classification accuracy. So that by using both time and frequency domain features of fNIRS signals, a mean stress classification accuracy of 88.52% was obtained.

The size of the training data is one of the determinant factors in the results obtained from the deep networks. Naturally, with increasing the number of training samples, the network performance is expected to be improved. On the other hand, a model is better which could discover the patterns needed for decision making using minimum possible data. In this experiment, the number of training data has gradually decreased, while the test data size has been kept constant to see the reaction of three models. The mean accuracy of the trained model by fNIRS over five folds is reported in Table III.

By comparing the performance of the models trained on different data sizes, we conclude that fNIRS model has high stability against a reduction in input samples. For example, with 20% drop from the whole dataset, the accuracy of fNIRS contains much more levels of information richness than other corresponding time frames, where 85.14% of mean accuracy was obtained by using features extracted from the mentioned best time frames of fNIRS signals.

In this study, in addition to features from the time domain of the signals, some features in the frequency domain of the signals were also extracted to represent the variations of the signals as better and efficient as possible. To show the
model only was decreased by 3%. The results of the table indicate that the trained model on fNIRS dataset is robust, in which the trained model with only 20% fraction of the data achieved 78.58% accuracy.

IV. DISCUSSION

This study investigated the applicability of deep learning in stress prediction by using fNIRS signal, a novel idea presented for the first time. In this regard, we assessed mental states of 10 healthy right-handed male subjects under the induction of a stressful condition by MIST. Before performing the stress assessment, fNIRS signals were preprocessed. Next, extracting efficient features from both time and frequency domains of fNIRS signals, a deep learning based algorithm was applied to determine the distinctiveness of each case and able to map the input data directly to their corresponding label. This algorithm was applied in order to propose a reasonably comprehensive, feature set, and deeply learned system to be sufficiently successful in this regard.

Our results show that the fNIRS provides an effective means for prediction of the stress during the MIST in the sense of providing higher classification accuracy. Using the features extracted from fNIRS signal, stress was classified employing intelligence model based on deep neural network architecture with the mean accuracy of 88.52%. When it comes to STD, it can be observed that the fNIRS model could provide an STD accuracy of 0.77%. Therefore, the proposed model trained on fNIRS not only provides a viable system for stress detection but also suggests better stability in terms of accuracy of the network’s prediction which ensures us the system’s performance is not related to the choice of train and test dataset.

In this study, a highly sufficient stress predictor is proposed by employing fNIRS signal which is real-time and non-invasively recorded. By broadcasting the artificial neural networks as an exclusive method for classification, a new deep learning model is introduced in this study in order to bring accurate and reliable prediction beside to low computational cost, making it totally suitable for wearable and real-time applications [43]. Employment of the proposed deeply learned system with the extraction of efficient features from the fNIRS signals lead to a mean classification accuracy of 88.52% which is higher than the accuracies reported in [32], [33], [38], [42], in which the same stress protocol and the same signal were employed. However, one of the limitations of our study is that a less number of subjects were investigated compared with their study. It will be interesting to investigate the applications of the proposed system in such similar research fields of attention, mental workload, mental diseases, and sleep [43]–[50].

In this study, to determine the information richness level of the three 10-second time frames considered for feature extraction, stress classification was separately performed by using the extracted features from each of these time frames. It was observed that the third time frame of fNIRS signals is informative than other corresponding time frames. It confirms the natural delay of the hemodynamic response in representing the brain related changes induced by mental stress in the fNIRS signal.

As two types of features have been extracted to convey the stress-related information as efficient as possible; frequency and time domain features, to show the effectiveness of these features, stress classification was separately performed by using each of the time and frequency feature sets. The results indicate that the time domain features can better modulate the stress-related information compared with the frequency domain feature set so that by employing four features from the time domain of the fNIRS signal, we could predict the stress induced by MIST with a remarkable accuracy of 86.10%, which is applicable for real-time applications where calculation time is restricted. However, incorporation of frequency domain features into the time domain ones could provide a better stress classification accuracy.

Regarding the model’s mean accuracy in a different fraction of dataset, it is concluded that the fNIRS model performs robust. In particular, when 80% of the training data were excluded, the mean accuracy of fNIRS models was only decreased almost by 10% to 78.58%. In other words, fNIRS could provide an effective representation of stress-related patterns and performance.

This study proposes an approach to measure a signal arising from brain which can be employed for other applications besides stress assessment in which brain function is altered including biofeedback [51], BCI [52]–[55], infant studies [56]–[59]. The present study was limited to the PFC region while such applications might also require recording the brain activities of other brain regions. So investigating the neuronal activities of those regions can be pursued as a future study.

V. CONCLUSION

In this study, fNIRS signals were employed to assess the stress induced by the Montreal Imaging Stress Task using a deep learning system. On purpose, mental states of 10 healthy volunteers were assessed by recording and then preprocessing the fNIRS signals. In our proposed method, feature maps were automatically extracted utilizing the convolutional network, and then a stack of fully connected layers classified the feature maps to determine the probability of stress in input data. With several experiments, we showed the high performance of our proposed method trained on fNIRS dataset in terms of prediction accuracy, model stability and fast performance applicable for real-time stress assessment.

ACKNOWLEDGMENT

This project was partially supported by NBIC council (Nano-technology, Biotechnology, Information Technology & Cognitive Sciences), NBML (National Brain Mapping Lab), and CSTC (Cognitive Sciences and Technologies Council) of Iran. The authors would like to thank all the people who participated in the study, including subjects and students that collaborated.

REFERENCES

[1] D. Desker, M. Schönendorf, F. Bidlingmaier, A. Hirner, and A. A. von Ruecker, “Surgical stress induces a shift in the type-1/type-2 T-helper cell balance, suggesting down-regulation of cell-mediated and up-regulation of antibody-mediated immunity commensurate to
the trauma," Surgery, vol. 119, no. 3, pp. 316–325, Mar. 1996.

[2] D. A. Lawrence and D. Kim, "Central/peripheral nervous system and immune responses," Toxicology, vol. 142, no. 3, pp. 189–201, Jan. 2000.

[3] B. Engdahl et al., "Post-traumatic stress disorder: a right temporal lobe syndrome?" J. Neural Eng., vol. 7, no. 6, p. 066005, Dec. 2010.

[4] A. F. T. Arnsten, "Stress weakens prefrontal networks: molecular insults to higher cognition," Nat. Neurosci., vol. 18, no. 10, pp. 1376–1385, Oct. 2015.

[5] K. Starcke and M. Brand, "Decision making under stress: A selective review," Neurosci. Biobehav. Rev., vol. 36, no. 4, pp. 1228–1248, Apr. 2012.

[6] K. Dedovic, C. D'Aguiar, and J. C. Pruessner, "What Stress Does to Your Brain: A Review of Neuroimaging Studies," Can. J. Psychiatry, vol. 54, no. 1, pp. 6–15, Jan. 2009.

[7] K. Dedovic, R. Renwick, N. K. Mahani, V. Engel, S. J. Lupien, and J. C. Pruessner, "The Montreal Imaging Stress Task: using functional imaging to investigate the effects of perceiving and processing psychosocial stress in the human brain.," J. Psychiatry Neurosc., vol. 30, no. 5, p. 319–25, Sep. 2005.

[8] J. Wang et al., "Perfusion functional MRI reveals cerebral blood flow pattern under psychological stress.," Proc. Natl. Acad. Sci. U. S. A., vol. 102, no. 49, pp. 17864–9, Dec. 2005.

[9] J. C. Pruessner et al., "Deactivation of the Limbic System During Acute Psychosocial Stress: Evidence from Positron Emission Tomography and Functional Magnetic Resonance Imaging Studies," Biol. Psychiatry, vol. 63, no. 2, pp. 234–240, Jan. 2008.

[10] B. Czéh et al., "Stress-induced changes in cerebral metabolites, hippocampal volume, and cell proliferation are prevented by antidepressant treatment with tianeptine.," Proc. Natl. Acad. Sci. U. S. A., vol. 98, no. 22, pp. 12796–801, Oct. 2001.

[11] C. M. Vander Weele, C. Scozzi, J. Yao, S. S. Correia, and K. A. Goosens, "Restoration of hippocampal growth hormone reverses stress-induced hippocampal impairment," Front. Behav. Neurosci., vol. 7, p. 66, Jun. 2013.

[12] S. A. Hosseini, M. A. Khalilzadeh, M. B. Naghibi-Sistani, and V. Niazmard, "Higher Order Spectral Analysis of EEG Signals in Emotional Stress States," in 2010 Second International Conference on Information Technology and Computer Science, 2010, pp. 60–63.

[13] N. Sulaiman et al., "Development of EEG-based stress index," in 2012 International Conference on Biomedical Engineering (ICoBE), 2012, pp. 461–466.

[14] S. Moghimi, A. Kuski, S. Power, A. M. Ogerguerian, and T. Chau, "Automatic detection of a prefrontal cortical response to emotionally rated music using multi-channel near-infrared spectroscopy," J. Neural Eng., vol. 9, no. 2, p. 026022, Apr. 2012.

[15] R. N. Roy, S. Charbonnier, A. Campagne, and S. Bonnet, "Efficient mental workload estimation using task-independent EEG features," J. Neural Eng., vol. 13, no. 2, p. 026019, Apr. 2016.

[16] M. Tanida, M. Katsuyana, and K. Sakatani, "Relation between mental stress-induced prefrontal cortex activity and skin conditions: A near-infrared spectroscopy study," Brain Res., vol. 1184, pp. 210–216, Dec. 2007.

[17] M. Causse, Z. Chua, V. Peyssakhovich, N. Del Campo, and N. Matton, "Mental workload and neural efficiency quantified in the prefrontal cortex using fNIRS," Sci. Rep., vol. 7, no. 1, p. 5222, Dec. 2017.

[18] A. Oliver, A. Odena, C. A. Rafiol, E. D. Cubuk, and I. Goodfellow, "Realistic Evaluation of Deep Semi-Supervised Learning Algorithms.," pp. 3235–3246, 2018.

[19] S. Boulis et al., "Optimal Deep Learning LSTM Model for Electric Load Forecasting using Feature Selection and Genetic Algorithm: Comparison with Machine Learning Approaches," Energies, vol. 11, no. 7, p. 1636, Jan. 2018.

[20] Y. Chen, H. Jiang, C. Li, X. Jia, and P. Ghamisi, "Deep Feature Extraction and Classification of Hyperspectral Images Based on Convolutional Neural Networks.," IEEE Trans. Geosci. Remote Sens., vol. 54, no. 10, pp. 6232–6251, Oct. 2016.

[21] H.-C. Shin et al., "Deep Convolutional Neural Networks for Computer-Aided Detection: CNN Architectures, Dataset Characteristics and Transfer Learning," IEEE Trans. Med. Imaging, vol. 35, no. 5, pp. 1285–1298, May 2016.

[22] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks.," pp. 1097–1105, 2012.

[23] C. Szegedy, A. Toshev, and D. Erhan, "Deep Neural Networks for Object Dtection.," pp. 2553–2561, 2013.

[24] K. He, G. Gkioxari, P. Dollar, and R. Girshick, "Mask R-CNN.," pp. 2961–2969, 2017.

[25] T. N. Sainath et al., "Deep Convolutional Neural Networks for Large-scale Speech Tasks.," Neural Networks, vol. 64, pp. 39–48, Apr. 2015.

[26] N. Kalchbrenner, E. Gregorsteite, and P. Blunsom, "A Convolutional Neural Network for Modelling Sentences.," Apr. 2014.

[27] A. Jodeiri et al., "Estimation of Pelvic Sagittal Inclination from Anteroposterior Radiograph Using Convolutional Neural Networks: Proof-of-Concept Study.," pp. 114–108. A. Jodeiri et al., "Region-based Convolutional Neural Network Approach for Accurate Segmentation of Pelvic Radiograph.," Oct. 2019.

[28] M. Mirbagheri, N. Hakimi, E. Ebrahimzadeh, K. Pourrezaei, and S. K. Setarehdan, "Enhancement of optical penetration depth of LED-based NIRS systems by comparing different beam profiles.," Biomed. Phys. Eng. Express, Sep. 2019.

[29] M. Mirbagheri, N. Hakimi, E. Ebrahimzadeh, and S. K. Setarehdan, "Simulation and in vivo investigation of LED-NIR Gaussian beam profile.," J. Near Infrared Spectrosc., p. 09670351988420, Nov. 2019.

[30] E. Ebrahimzadeh et al., "Quantitative determination of concordance in localizing epileptic focus by component-based EEG-FMRI.," Comput. Methods Programs Biomed., vol. 177, pp. 231–241, Aug. 2019.

[31] F. Al-Shargie, M. Kiguchi, N. Badruddin, S. C. Dass, A. F. M.
Hani, and T. B. Tang, “Mental stress assessment using simultaneous measurement of EEG and fNIRS,” *BioMed. Opt. Express*, vol. 7, no. 10, p. 3882, Oct. 2016.

N. Hakami and S. K. K. Setarehdan, “Stress assessment by means of heart rate derived from functional near-infrared spectroscopy,” *J. Biomed. Opt.*, vol. 23, no. 11, p. 1, Nov. 2018.

H. Santosa, M. Jiyoon Hong, S.-P. Kim, and K.-S. Hong, “Noise reduction in functional near-infrared spectroscopy signals by independent component analysis,” *Rev. Sci. Instrum.*, vol. 84, no. 7, p. 073106, Jul. 2013.

G. Baumertfeld, S. C. Wriesnegg, I. Daly, and G. R. Müller-Putz, “Separating heart and brain: on the reduction of physiological noise from multichannel functional near-infrared spectroscopy (fNIRS) signals,” *J. Neural Eng.*, vol. 11, no. 5, p. 65010, Oct. 2014.

F. Scarpa et al., “A methodology to improve estimation of stimulus-evoked hemodynamic response from fNIRS measurements,” in *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 2011, pp. 785–788.

A. Janani and M. Sasikala, “Investigation of different approaches for noise reduction in functional near-infrared spectroscopy signals for brain-computer interface applications,” *Neural Comput. Appl.*, vol. 28, no. 10, pp. 2889–2903, Oct. 2017.

F. Al-Shargie, T. B. Tang, and M. Kiguchi, “Assessment of mental stress effects on prefrontal cortical activities using canonical correlation analysis: an fNIRS-EEG study,” *BioMed. Opt. Express*, vol. 8, no. 5, p. 2583, May 2017.

M. Choi and B. Sweetman, “Efficient Calculation of Statistical Moments for Structural Health Monitoring,” *Struct. Heal. Monit. An Int. J.*, vol. 9, no. 1, pp. 13–24, Jan. 2010.

M. Abadi et al., “TensorFlow: A System for Large-Scale Machine Learning,” pp. 265–283, 2016.

D. P. Kingma and J. Ba, “Adam: A Method for Stochastic Optimization,” Dec. 2014.

F. Al-Shargie, T. B. Tang, and M. Kiguchi, “Stress Assessment Based on Decision Fusion of EEG and fNIRS Signals,” *IEEE Access*, vol. 5, pp. 19889–19896, 2017.

P. Pinti et al., “A Review on the Use of Wearable Functional Near-Infrared Spectroscopy in Naturalistic Environments,” *Jpn. Psychol. Res.*, vol. 60, no. 4, pp. 347–373, Oct. 2018.

G. Duranti, J.-F. Gagnon, S. Tremblay, and F. Dehais, “Using near infrared spectroscopy and heart rate variability to detect mental overload,” *Behav Brain Res.*, vol. 259, pp. 16–23, Feb. 2014.

V. Kumar, V. Shivakumar, H. Chhabra, A. Bose, G. Venkatasubramanian, and B. N. Gungadhar, “Functional near infrared spectroscopy (fNIRS) in schizophrenia: An review,” *Asian J. Psychiart.*, vol. 27, pp. 18–31, Jun. 2017.

I. Maidan, H. Bernad-Elazari, E. Gazit, N. Giladi, J. M. Hausdorff, and A. Mirelman, “Changes in oxygenated hemoglobin link freezing of gait to frontal activation in patients with Parkinson disease: an fNIRS study of transient motor-cognitive failures,” *J. Neurol.*, vol. 282, no. 4, pp. 899–908, Apr. 2015.

S. Ahn, T. Nguyen, H. Jang, J. G. Kim, and S. C. Jun, “Exploring Neuro-Physiological Correlates of Drivers’ Mental Fatigue Caused by Sleep Deprivation Using Simultaneous EEG, ECG, and fNIRS Data,” *Front. Hum. Neurosci.*, vol. 10, p. 219, May 2016.

T. Soshi et al., “Sleep Deprivation Influences Diurnal Variation of Human Time Perception with Prefrontal Activity Change: A Functional Near-Infrared Spectroscopy Study,” *PLoS One*, vol. 5, no. 1, p. e3895, Jan. 2010.

K. Pillay, A. Derymacker, K. Jansen, G. Naulaers, S. Van Huffel, and M. De Vos, “Automated EEG sleep staging in the term-age baby using a generative modelling approach,” *J. Neural Eng.*, vol. 15, no. 3, p. 036004, Jun. 2018.

A. H. Ansari et al., “Quiet sleep detection in preterm infants using deep convolutional neural networks,” *J. Neural Eng.*, vol. 15, no. 6, p. 066006, Dec. 2018.

E. Solovey, P. Schemerhorn, M. Schuetz, A. Sassaroli, S. Fantini, and R. Jacob, “Brainput,” in *Proceedings of the 2012 ACM annual conference on Human Factors in Computing Systems - CHI ’12*, 2012, p. 2193.

M. J. Khan and K.-S. Hong, “Hybrid EEG-fNIRS-Based Eight-Command Decoding for BCI: Application to Quadcopter Control,” *Front. Neurorobot.*, vol. 11, p. 6, Feb. 2017.

X. Yin et al., “A hybrid BCI based on EEG and fNIRS signals improves the performance of decoding motor imagery of both force and speed of hand clenching,” *J. Neural Eng.*, vol. 12, no. 3, p. 036004, Jun. 2015.

A. M. Chiarello, P. Croce, A. Morla, and F. Zappasodi, “Deep learning for hybrid EEG-fNIRS brain-computer interface: application to motor imagery classification,” *J. Neural Eng.*, vol. 15, no. 3, p. 036028, Jun. 2018.

S. B. Erdogan, E. Ozsarifat, B. Dilek, K. S. Kadak, L. Hanoglu, and A. Akun, “Classification of motor imagery and execution signals with population-level feature sets: implications for probe design in fNIRS based BCI,” *J. Neural Eng.*, vol. 16, no. 2, p. 026029, Apr. 2019.

M. Ferrari and V. Quaresima, “A brief review on the history of human functional near-infrared spectroscopy (fNIRS) development and fields of application,” *NeuroImage*, vol. 63, no. 2, pp. 921–935, Nov. 2012.

S. Lloyd-Fox et al., “Functional near infrared spectroscopy (fNIRS) to assess cognitive function in infants in rural Africa,” *Sci. Rep.*, vol. 4, no. 1, p. 4740, May 2015.

Y. On et al., “Identifying ADHD children using hemodynamic responses during a working memory task measured by functional near-infrared spectroscopy,” *J. Neural Eng.*, vol. 15, no. 3, p. 035005, Jun. 2018.

Z. Liang et al., “Symbolic time series analysis of fNIRS signals in brain development assessment,” *J. Neural Eng.*, vol. 15, no. 6, p. 066013, Dec. 2018.