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# Mental Stress Classification from Brain Signals using MLP Classifier

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## Abstract

INTRODUCTION: The most common and widespread mental condition that unavoidably affects people's mood and conduct is stress. The physiological reaction to powerful emotional, intellectual, and physical obstacles might be viewed as stress. As a result, early stress detection can result in solutions for potential improvements and ultimate event suppression.
OBJECTIVES: To classify mental stress from the EEG signals of humans using an MLP classifier.
METHODS: We examine the EEG signal analysis techniques currently in use for detecting mental stress using Multi-layer Perceptron (MLP).
RESULTS: The suggested technique has a 95% classification accuracy performance.
CONCLUSION: In our study, the use of MLP classifiers for stress detection from EEG signals has shown promising results. The high accuracy and precision of the classifiers, as well as the informative nature of certain EEG frequency bands, suggest that this approach could be a valuable tool for stress detection and management.

**Keywords:** Mental stress, Electroencephalogram (EEG), Healthcare, Classification, Multi-layer Perceptron (MLP), Brain Signal

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## 1. Introduction

The human brain is considered to be one of the most intricate systems in the universe. It is composed of numerous billions of neurons, which serve as the primary gateway of communication for the body. A pressure that is not desired has a stressful effect on the body and mind. This alters the neurons' excitatory as well as inhibitory activity. In the healthcare field and in biomedical research, the EEG signal is the first and one of the most popular signals for detecting various neurological problems. The EEG signal is used to examine any brain activity, and its measurement is crucial. As a first line of treatment, EEG signal recording has enormous promise for both diagnosing and treating any brain-related illnesses and disorders [Shakya et al., 2021]. In healthcare research field, predominantly EEG data are employed for categorization purposes of different neural illnesses. By utilizing machine learning, healthcare providers can improve their ability to make informed decisions regarding patient diagnoses and treatment options, ultimately leading to an overall enhancement of healthcare services. [Samarpita & Satpathy, 2022].

EEG signals are used to track conscious brain electrical activity, and digital signal processing algorithms that the user creates are used to identify features of EEG patterns. The majority of Brain-Computer-Interface (BCI) systems are constructed using spontaneous EEG signal analysis [Suryawanshi, R., & Vanjale, S., 2023]. Lots of neurons in the human brain produce tiny electrical signals for every psychological task. The electrodes can be used to measure these electrical signals collectively. Each area of the brain has a clearly defined function, which is documented in a variety of sources [Manjunatha 2020].

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Forward Pass: For each training data point, a forward pass is performed through the network. The input vector is multiplied by the weights of the input layer, the bias term is added, and an activation function is applied to generate the output of the current layer. This process is repeated for each layer, passing the output to the next layer until the final output layer is reached.

Loss Calculation: Once the forward pass is completed, the loss between the predicted output and the actual target output is calculated using a loss function. The choice of the specific loss function depends on the problem at hand, such as mean squared error (MSE) or cross-entropy loss.

Backward Pass: After calculating the loss, a backward pass is performed to compute the gradients of the loss with respect to the weights and biases of the net-work. The chain rule of calculus is applied to efficiently propagate the gradients from the output layer to the input layer.

Weight and Bias Update: The gradients obtained from the backward pass are then used to update the weights and biases of the network. This update is typically performed using an optimization algorithm such as stochastic gradient descent (SGD) or Adam, which adjusts the weights and biases in the direction that minimizes the loss function.
The weight and bias updates are applied for each training data point, and once the loop over all training data points is completed, the algorithm proceeds to the next epoch. After completing the specified number of epochs, the training process is considered complete.

Prediction: Once the network is trained, it can be used to make predictions on new data. A forward pass is performed through the network, and the predicted output is obtained.

By following this classification algorithm based on MLP, the weights and biases of the MLP are updated iteratively to minimize the loss, improving the model's ability to classify and predict mental stress levels.

## 4. Result Analysis

To evaluate the performance of the stress detection system, the classification accuracy metric was employed, which is determined by the ratio of accurate predictions. The dataset in our experiment is divided into two sets, namely the training set (2231, 988) and the testing set (248, 988). The training set is utilized to train the MLP model, while the testing set is used to gauge the model's performance.

Using the chosen features, the MLP model is trained on the training set to recognize patterns and correlations between input features and corresponding mental stress labels. We evaluated the performance of the MLP classifier using a test dataset and commonly used evaluation metrics such as accuracy, precision, recall, and F1-score.

According to the confusion matrix below, the model performs flawlessly when evaluated on the EEG signals that were previously familiar or used for training. The confusion matrix of our experiment is shown in Fig. 3.

```
[[77  4  0]
 [ 6 81  2]
 [ 0  1 77]]
```

**Figure 3.** Confusion Matrix

The results showed that the MLP classifiers were able to accurately detect stress with an overall accuracy of 95%. Further analysis revealed that certain EEG frequency bands were particularly informative for stress detection, as they exhibited significant differences between the EEG signals of participants under different stress levels.

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0.0 | 0.93 | 0.95 | 0.94 | 81 |
| 1.0 | 0.94 | 0.91 | 0.93 | 89 |
| 2.0 | 0.97 | 0.99 | 0.98 | 78 |
| accuracy | | | 0.95 | 248 |
| macro avg | 0.95 | 0.95 | 0.95 | 248 |
| weighted avg | 0.95 | 0.95 | 0.95 | 248 |

**Figure 4.** Classification Report

The Fig. 4 demonstrates that MLP performs well in terms of accuracy, precision, recall and f1-score.

## 5. Conclusion

In our study, the use of MLP classifiers for stress detection from EEG signals has shown promising results. The high accuracy of 95% was achieved by MLP classifiers. The high accuracy and precision of the classifiers, as well as the informative nature of certain EEG frequency bands, suggest that this approach could be a valuable tool for stress detection and management. Further research is needed to validate these findings and explore the potential applications of MLP classifiers in real-world settings. Moreover, in the future, researchers could explore the potential of employing alternative machine learning algorithms and feature extraction techniques for identifying stress from EEG signals. Overall, the development of accurate and efficient methods for stress detection and management could have significant implications for improving mental health and well-being. The use of EEG signals and machine learning techniques, such as MLP classifiers, could provide valuable insights into the physiological mechanisms underlying stress and aid in the development of personalized stress management strategies

Future research can focus on collecting a larger and more diverse dataset, including individuals from different age groups, cultural backgrounds, and with varying stress levels. Additionally, collecting longitudinal data to study the temporal dynamics of mental stress can provide valuable insights for developing more robust classifiers. Real-time stress monitoring can be a valuable application of the classifier algorithm. Future work can explore techniques to implement the proposed algorithm in real-time scenarios using portable EEG devices or wearable sensors. This can enable continuous monitoring of mental stress levels and facilitate timely interventions and feedback for individuals.

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## References

[1] Arsalan, A., Majid, M., Butt, A. R., & Anwar, S. M. (2019). Classification of perceived mental stress using a commercially available EEG headband. IEEE journal of biomedical and health informatics, 23(6), 2257-2264.

[2] Asif, A., Majid, M., & Anwar, S. M. (2019). Human stress classification using EEG signals in response to music tracks. Computers in biology and medicine, 107, 182-196.

[3] Attallah, O. (2020). An effective mental stress state detection and evaluation system using minimum number of frontal brain electrodes. Diagnostics, 10(5), 292.

[4] Bird, J. J., Manso, L. J., Ribeiro, E. P., Ekart, A., & Faria, D. R. (2018, September). A study on mental state classification using eeg-based brain-machine interface. In *2018 international conference on intelligent systems (IS)* (pp. 795-800). IEEE.

[5] Dave, S., Ambudkar, B., & Dave, N. (2022 May). Stress Analysis of Brainwave Using EEG Click.

[6] Dimas, A. (2022). Classification of Electroencephalogram Generated by Brain for Analysis of Brain Wave Signals in Students Depression. *International Journal of Engineering Technology and Natural Sciences*, *4*(2), 95-101.

[7] Gaurav, A. R., & Kumar, V. (2018). EEG-metric based mental stress detection. *Netw Biol*, *8*(1), 25-34.

[8] Gedam, S., & Paul, S. (2021). A review on mental stress detection using wearable sensors and machine learning techniques. *IEEE Access*, *9*, 84045-84066.

[9] Hayashi, H., & Tsuji, T. (2022). Human–Machine Interfaces Based on Bioelectric Signals: A Narrative Review with a Novel System Proposal. *IEEJ Transactions on Electrical and Electronic Engineering*, *17*(11), 1536-1544.

[10] Katmah, R., Al-Shargie, F., Tariq, U., Babiloni, F., Al-Mughairbi, F., & Al-Nashash, H. (2021). A review on mental stress assessment methods using EEG signals. *Sensors*, *21*(15), 5043.

[11] Khosrowabadi, R., Quek, C., Ang, K. K., Tung, S. W., & Heijnen, M. (2011, July). A Brain-Computer Interface for classifying EEG correlates of chronic mental stress. In *The 2011 international joint conference on neural networks* (pp. 757-762). IEEE.

[12] Lekshmi, S. S., Selvam, V., & Rajasekaran, M. P. (2014, April). EEG signal classification using principal component analysis and wavelet transform with neural network. In *2014 International Conference on Communication and Signal Processing* (pp. 687-690). IEEE.

[13] Manjunatha Siddappa, D. K. A Cognitive Approach towards Measuring Effectiveness of Meditation Using Enobio-8 EEG Device. *European Journal of Molecular & Clinical Medicine*, *7*(08), 2020.

[14] Rajendran, V. G., Jayalalitha, S., & Adalarasu, K. (2022). EEG Based Evaluation of Examination Stress and Test Anxiety Among College Students. *Irbm*, *43*(5), 349-361.

[15] Saeed, S. M. U., Anwar, S. M., Khalid, H., Majid, M., & Bagci, U. (2020). EEG based classification of long-term stress using psychological labeling. *Sensors*, *20*(7), 1886.

[16] Samarpita, S., & Satpathy, R. N. (2022, October). Applications of Machine Learning in Healthcare: An Overview. In *2022 1st IEEE International Conference on Industrial Electronics: Developments & Applications (ICIDeA)* (pp. 51-56). IEEE.

[17] Shakya, N., DUBEY, R., & Shrivastava, L. (2021). Stress Detection using EEG Signal Based on Fast Walsh Hadamard transform and Voting Classifier.

[18] Sharma, R., & Chopra, K. (2020). EEG signal analysis and detection of stress using classification techniques. *Journal of Information and Optimization Sciences*, *41*(1), 229-238.

[19] Sharma, S., Singh, G., & Sharma, M. (2021). A comprehensive review and analysis of supervised-learning and soft computing techniques for stress diagnosis in humans. *Computers in Biology and Medicine*, *134*, 104450.

[20] Shaw, R., & Patra, B. K. (2022). Classifying students based on cognitive state in flipped learning pedagogy. *Future Generation Computer Systems*, *126*, 305-317.

[21] Suryawanshi, R., & Vanjale, S. (2023). Brain Activity Monitoring for Stress Analysis through EEG Dataset using Machine Learning. *International Journal of Intelligent Systems and Applications in Engineering*, *11*(1s), 236-240.

[22] Zhang, Y., Wang, Q., Chin, Z. Y., & Ang, K. K. (2020, July). Investigating different stress-relief methods using Electroencephalogram (EEG). In *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)* (pp. 2999-3002). IEEE.