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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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Mental stress is recognized as a significant contributing factor to numerous health problems. Different measures have been created by scientists and medical professionals to gauge the severity of mental stress in its early phases. As described in related research, a number of neuroimaging instruments have been suggested for evaluating workplace mental stress. One significant contender is the EEG signal, which offers rich details regarding mental conditions and states [Sharma & Sharma, 2021]. Different neuroimaging methods have been employed to directly or indirectly measure brain activity in order to evaluate mental stress. A few benefits of the EEG modality include its simplicity of use, low cost, and great temporal resolution. As a result, it is the method most frequently employed to examine mental states, such as stress [Katmah et al., 2021]. EEG, a recording of the oscillations in the human brain made electronically, can be used to detect this. Multiple electrodes are attached to the scalp to record the EEG, which records the oscillations. In addition to analyzing the neutral activity taking place in the brain, EEG employs sensors to record the time-varying amplitude of electric fields coming from the brain [Gedam & Paul, 2021].

The frequency ranges of these brain waves [Dave et al., 2022] shown in Table 1.

Table 1. For monitoring brain activities, frequency band categorization.

Bands	Frequency
Delta	0.5–4 Hz
Theta	4-8 Hz
Alpha	8-12Hz
Beta	12-35Hz
Gamma	Above 35Hz

In the modern era, mental stress is a serious health issue in the majority of industrialized nations. Even though there isn't a clear definition of stress, the idea is widely employed in day-to-day living [Khosrowabadi et al., 2011]. Anxiety is a mental illness that affects people all over the world and negatively impacts their ability to think. The brain uses its electrical system in order to function, which involves producing a little electrical signal that is organized into a pattern and sent across a network of nerve cells called neurons. The membrane potential, which is caused by the ionic composition differences between intracellular and external fluids, is an electric voltage gradient across the membrane. EEG was used to capture this potential [Dimas, 2022].

The format of this article is as follows: The review of literature is shown in Section 2, the proposed methodology for this study is presented in Section 3, the experiment's findings are demonstrated in Section 4, and the conclusion and future perspective are illustrated in Section 5.

2. Review of Literature

A deeper understanding of the issue and its main components can be attained through the examination of related literature, which also helps to prevent duplication. The results of many studies and experiments motivate the researcher to priorities worthwhile projects in their field of research and enable them to avoid past mistakes or flaws in the process. Realizing the significance of related studies, the researchers will make every effort to review the prior literature, which will be briefly discussed below.

In a research investigation on the classification of mental states using EEG signals, three separate states—neutral, relaxed, and concentrated—were identified. The study offered a set of features utilizing a short-term windowing retrieved from five signals from an EEG sensor. Data from five participants collected across one-minute sessions for each state were used to construct a dataset [Bird et al., 2018].

Researchers [Arsalan et al., 2019] conducted an experimental investigation with the goal of identifying an EEG recording phase that would be appropriate for classifying experienced mental stress into different categories. During an open eye condition, five types of characteristics were extracted from EEG data in the delta, theta, alpha, beta, and gamma frequency bands, both before and after the activity. These characteristics include correlation, differential asymmetry, rational asymmetry, and power spectrum. Researchers proposed in their work to create a methodology to track student progress in flipped learning by passively recording each student's brain waves as they watch lectures on video.

The siamese neural network is used to analyze recorded brain waves in order to categorize the pupils into three groups based on their degree of attention, such as Weak, Good, and Outstanding [Shaw & Patra, 2022].

One proposed approach for accurately detecting and evaluating stress levels during mental arithmetic exercises is the development of a portable, real-time EEG-based neuro-feedback system, as recommended by a study [Attallah, 2020]. This strategy utilizes a hybrid feature set and five classification models to achieve high detection and classification rates. Stimulating the frontal area of the brain is also noted to have a significant impact on stress level detection and assessment. The utilization of alpha asymmetry as a feature proved to be optimal for categorizing long-term human stress using support vector machines [Gaurav & Kumar, 2018]. A study demonstrated that by utilizing the expert evaluation-based labelling method, the classification accuracy improved by as much as 85.20% [Saeed et al., 2020]. The utilization of alpha asymmetry as a potential biomarker for stress identification may be possible when assigning labels based on professional evaluation.

Another study used two experimental conditions—before and after the exam—to analyze how stressed out the students were during the exam period. According to the results of their study, students' theta energy bands were high before exams, indicating that they were under a great deal of stress, and their memory retrieval was higher than it was after exams [Rajendran et al., 2022]. Numerous health problems are produced as a result of the stress concerns. EEG is an effective method for identifying stress. To extract the pertinent data from EEG, authors [Sharma & Chopra, 2020] employed time frequency analysis. When participants are under stress, the alpha wave accuracy achieved is 90.32%. The outcomes show that employing EEG for stress detection is feasible. In another investigation [Asif et al., 2019], the brain signals are used to classify human stress in reaction to music. Using the brain sensing MUSE headband, which is available commercially, EEG readings of 27 subjects were collected. Prior to and during the presentation of musical stimuli, the signals were recorded. Five characteristics—absolute and relative power, coherence, phase lag, and amplitude asymmetry—were used to analyze the collected data.

In a study [Lekshmi et al., 2014], the wavelet transform is utilized to extract the statistical features. Discretized wavelet transform performs better and requires less computing time than continuous wavelet transform and other conventional approaches. For their five datasets, an artificial neural network is used as the classifier. To get the findings, the wavelet transforms and PCA feature extractors are used to the classifier. According to their study, compared to wavelet transforms with artificial neural networks (ANN), PCA with ANNs is a more precise method.

According to literature review, it is necessary to address issues like the practicality of employing EEG equipment for stress detection in real-world situations and potential difficulties in implementing the proposed classifier algorithm.

3. Proposed Methodology

A novel multi-layer perceptron is used in this work for classification. The following steps make up the framework.

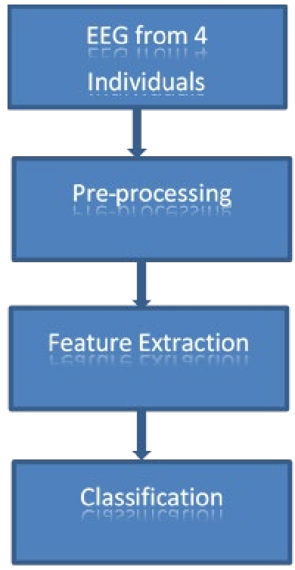

Figure 1. Proposed Methodology

3.1 Description of the Dataset

We obtained the dataset [Bird et al., 2018] for this study by downloading it from the Kaggle website, which is an online platform. Data was gathered from four individuals—two men and two women—for 60 seconds in each of the following states: relaxed, focused, and neutral. The TP9, AF7, AF8, and TP10 EEG locations were recorded using dry electrodes on a Muse EEG headband.

3.2 Pre-processing

When the EEG signal is obtained from the headset, it often contains noise due to a variety of reasons associated with the headset. The noise typically arises when there is movement in the body while collecting the EEG signal. Eliminating this noise from the signal can be a challenging task because the amplitude of the EEG signal is very low [Hayashi & Tsuji, 2022]. The headsets contain electrodes that capture signals from the brain. Noise is eliminated using band pass and notch filters.

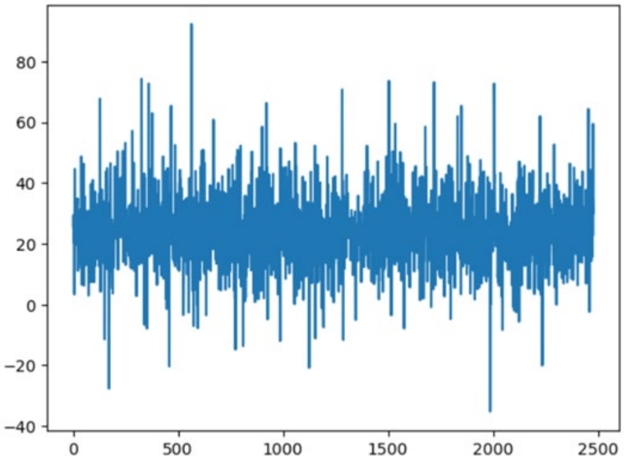

Figure 2. Pre-processed EEG Signals

3.3 Feature Extraction

It is a technique used to extract relevant features from the pre-processed EEG signals. There are various feature extraction techniques used for EEG signals [Zhang et al., 2020]. Here are some commonly used ones:

a. Time-domain features: In the time domain, these characteristics are obtained by directly analysing the EEG signal. Examples include mean, variance, standard deviation, skewness, and kurtosis.
b. Frequency-domain features: By utilizing methods like the Fast Fourier Transform (FFT) or the Wavelet Transform (WT), these attributes are de-rived from examining the EEG signal in the frequency domain. Examples include power spectral density, band power, peak frequency, and coherence.
c. Time-frequency features: These features combine information from both the time and frequency domains. Methods like the Short-Time Fourier Transform (STFT) or Continuous Wavelet Transform (CWT) are employed to obtain them. Examples include spectral entropy, wavelet coefficients, and relative wavelet energy.

The choice of feature extraction technique depends on the specific application and the research question being addressed. Often, a combination of techniques is used to obtain a comprehensive set of features that can capture different aspects of the EEG signal.

3.4 Classification

The MLP (Multi-Layer Perceptron) Classifier is a type of ANN that is commonly used for supervised learning tasks such as classification and regression. It is a feedforward neural network whose architecture comprises an input layer, one or more hidden layers, and an output layer. Each layer consists of multiple nodes, also known as neurons, which are connected to nodes in the adjacent layers by weighted connections [Arsalan et al., 2019]. The MLP classifier is trained using a backpropagation algorithm with an appropriate loss function. The performance of the trained model is evaluated using the testing set. The performance metrics are accuracy, precision, and F1 score. During training, the MLP learns to adjust its weights and biases to minimize the loss function and improve the accuracy of the predictions. Once training is complete, the MLP can be used to make predictions on new data by performing a forward pass through the network.

Overall, this methodology is provided an effective and reliable approach to detect stress from brain signals using MLP classifiers. However, it is important to note that the performance of the classifier is dependent on the quality of the data, the choice of features, the selection of the classifier, and the evaluation metrics used. Therefore, it is necessary to carefully design and validate the methodology to ensure its reliability and effectiveness.

Here is a flowchart representation of the MLP classifier algorithm of our pro-posed methodology.

```
Start
Initialize weights and biases randomly or with a specific initialization scheme
For each epoch:
  For each training data point:
    Perform a forward pass through the network:
      - Multiply input vector with weights of input layer
      - Add bias term
      - Apply activation function
      - Pass output to next layer
 Calculate the loss between predicted output and actual target output using a loss function
 Perform a backward pass through the network:
      - Compute gradients of loss with respect to weights and biases
      - Use chain rule of calculus
 Update the weights and biases of the network using an optimization algorithm:
      - Stochastic gradient descent (SGD) or Adam
  End of training data loop
End of epoch loop
Use the trained network to make predictions on new data:
  - Perform a forward pass through the network
  - Obtain predicted output
End
```

Here's an explanation of how the classification algorithm is used based on the provided pseudocode:

Epoch Loop: The training process begins with an outer loop iterating over multiple epochs. Each epoch represents a complete pass through the entire training dataset.

Training Data Loop: Within each epoch, the algorithm iterates over each training data point. The purpose of this loop is to update the weights and biases of the network based on the forward and backward pass through the network.

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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