ElectroEncephaloGram-Based Stress Prediction Using

Neural Networks

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Context & Motivation

The importance of stress monitoring in neuroscience and BCI research.
Role of ElectroEncephaloGram (EEG) in assessing cognitive and emotional states

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Objective of the Dataset

To capture short-term stress responses via EEG during specific cognitive challenges

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SAM40 Dataset

- **Dataset:** SAM40 (Stress Assessment via Mental tasks, 40 subjects)
- **Population:**
  - 40 participants (14 females, 26 males)
  - Age: 1825 (mean = 21.5 years)
- **Recording Device:** Emotiv Epoc Flex 32-channel gel-based EEG system
- **Sampling Rate:** 128 Hz (14-bit resolution, ś4.12 mV range)

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[1] Informed consent was obtained from all the subjects participating in the study

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- Arithmetic problem solving task

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Description of the Different Mental Tasks

The dataset is created to primarily monitor the stress induced in an individual while performing different cognitive tasks. The different cognitive tasks considered for the experiment are:

- **The Stroop Color Word Test**,
- **Arithmetic Problem Solving**
- **Recognition of Symmetric Images**.

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Stroop Color- Word Test

The Stroop Color- Word Test (SCWT) is a neuropsychological test used to assess the cognitive inference ability while processing multiple stimuli [1].

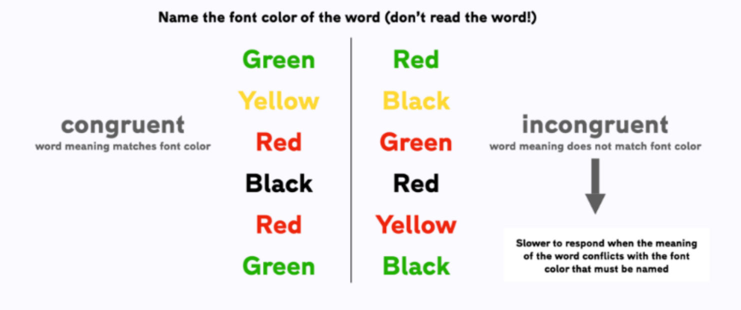

Figure 1: The Stroop Color- Word Test example.

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Mirror image recognition task

Images have also been used in the literature to induce various types of emotions [2] and thus have been adopted in the present work to induce stress in the subjects. In the proposed work, mirror images are presented to the subject and is asked to identify whether the displayed images are symmetric or asymmetric to each other.

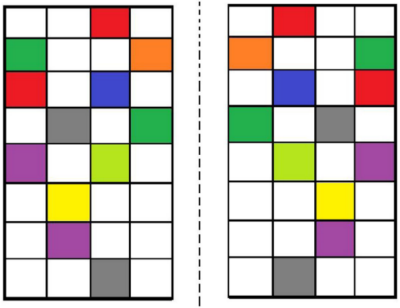

Figure 2: Mirror image recognition task example.

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Arithmetic problem solving task

Arithmetic problem solving task is known to elicit stress in individuals [3]. In the proposed work, the subject is asked to mentally solve the problem and respond with a thumbs up or thumbs down gesture depending on whether the answer displayed on the screen is a correct solution for the arithmetic problem or not.

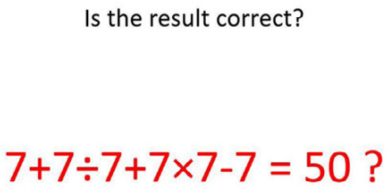

Figure 3: Arithmetic problem solving task example.

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Data recording methodology

The EEG device is mounted over the subject and instructions are given to the subject regarding the experiment. Then the experimenter starts to record the EEG data and the subject is asked to perform the various tasks. The subject is initially asked to relax for 25 s where relaxing music is played to ease the subject. After which, the instructions for the Stroop color-word test is shown to the subjects. The subject is asked to perform the Stroop color-word test for 25 s. The subject then relaxes for 5 s and then the instructions for the next task are displayed for 10 s.

Start of the Trial

End of the Trial

Initial Relaxation	Instructions for Stroop Color-Word Test	Stroop Color-Word Test	Relaxation	Instructions for mirror image symmetry task	Mirror image recognition task	Relaxation	Instructions for arithmetic task	Arithmetic task
25 Seconds	10 Seconds	25 Seconds	5 Seconds	10 Seconds	25 Seconds	5 Seconds	10 Seconds	25 Seconds

Figure 4: Trial recording paradigm.

Sample Data Captured

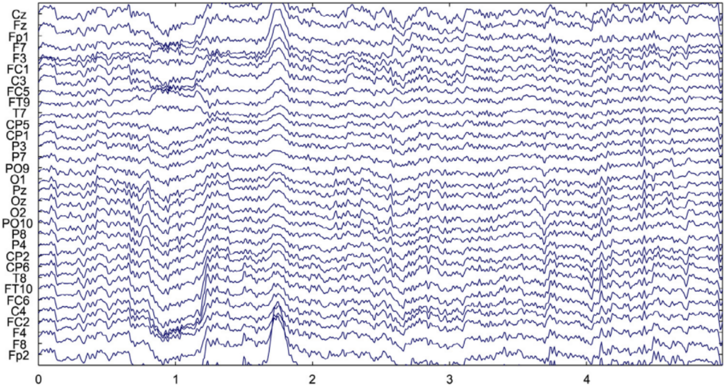

Figure 5: Raw EEG Data of Subject 10.

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Raw EEG Data Structure

```
/
├── Data
│   ├── Arithmetic
│   │   ├── Arithmetic_sub_1
│   │   ├── Arithmetic_sub_2
│   │   └── ...
│   ├── Stroop
│   │   ├── Stroop_sub_1
│   │   ├── Stroop_sub_2
│   │   └── ...
│   ├── Mirror_image
│   │   ├── mirror_image_sub_1
│   │   ├── mirror_image_sub_2
│   │   └── ...
│   └── Relax
│       ├── relax_sub_1
│       ├── relax_sub_2
│       └── ...
├── Organized_data
│   ├── Relax
│   └── Stress
├── Corrupted_EEG.mat
├── EEG_Stress_Prediction_Project.ipynb
├── EEG_model.h5
└── S0001E01.edf
```

Figure 6: EEG Data Folder Structure.

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Data Preprocessing Pipeline

1. Initial Processing: Band-pass filtering (0.545 Hz)

Band-pass filtering a filter that allows frequencies within a certain range to pass through while attenuating (reducing) frequencies outside that range. Filtering from 0.5 Hz to 45 Hz helps Remove very low-frequency noise. Remove high-frequency noise (like muscle artifacts, electrical interference).

Frequency (Hz)	**Brain Wave Type**	**Description**
0.5–4	Delta	Deep sleep
4–8	Theta	Drowsiness, meditation
8–13	Alpha	Relaxed wakefulness
13–30	Beta	Active thinking, focus
30–45	Gamma	High-level information processing

Table 1: EEG Brain Wave Types by Frequency Band

Data Preprocessing Pipeline

Discrete-Time Band-Pass Filter (Digital)

In EEG signal processing, a digital band-pass filter is implemented using the following difference equation:

$$y[n] = \sum_{k=0}^{M} b_k \cdot x[n-k] - \sum_{k=1}^{N} a_k \cdot y[n-k] \tag{1}$$

- $x[n]$ input signal (raw EEG)
- $y[n]$ filtered output signal
- b_k numerator coefficients (FIR part)
- a_k denominator coefficients (IIR part)
- M, N filter orders

Note: The coefficients a_k and b_k are calculated using standard filter design techniques such as Butterworth, Chebyshev, or FIR window methods.

Data Preprocessing Pipeline

2. Artifact Removal:

1. **(1) Savitzky-Golay Filter:** Trend removal The Savitzky-Golay filter is a digital smoothing filter used primarily to preserve important features of a signal (like peaks and edges) while reducing random noise. Given a discrete signal $x[n]$, the Savitzky-Golay filter computes a smoothed signal $\hat{x}[n]$ using a polynomial fit within a moving window:

$$\hat{x}[n] = \sum_{k=-M}^{M} c_k \cdot x[n+k] \quad (2)$$

- $\hat{x}[n]$: Smoothed value at time index n
- c_k: Convolution coefficients (precomputed from polynomial least-squares fitting)
- $2M+1$: Window length (must be odd)

Data Preprocessing Pipeline

2. Artifact Removal:

- **(2) Wavelet Thresholding:** is a denoising technique that works by transforming a signal into the wavelet domain, suppressing small (noise-related) coefficients, and then reconstructing the signal. Its especially useful for non-stationary signals like EEG, where noise and features vary over time. In EEG signal denoising, soft thresholding is typically used because it provides a better trade-off between noise removal and signal integrity.
  Given wavelet coefficients w_i and a threshold λ, the soft thresholding operation is defined as:

$$\tilde{w}_i = \begin{cases} \text{sign}(w_i)\left(|w_i| - \lambda\right), & \text{if } |w_i| \geq \lambda \\ 0, & \text{if } |w_i| < \lambda \end{cases} \tag{3}$$

Data Preprocessing Pipeline

Results

Cleaned EEG signals with preserved temporal and spectral characteristics

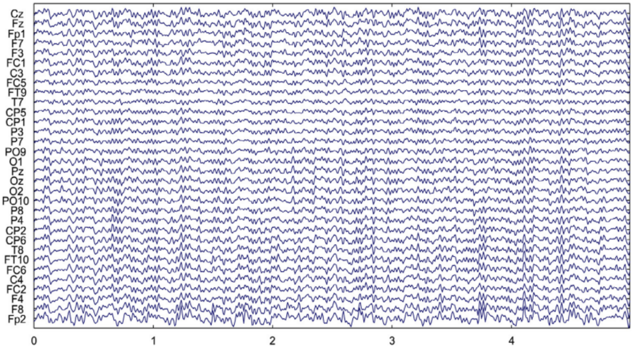

Figure 7: EEG Data of Subject 10 after preprocessing artifact removal.

EEG Signal Comparison Before and After Artifact Removal

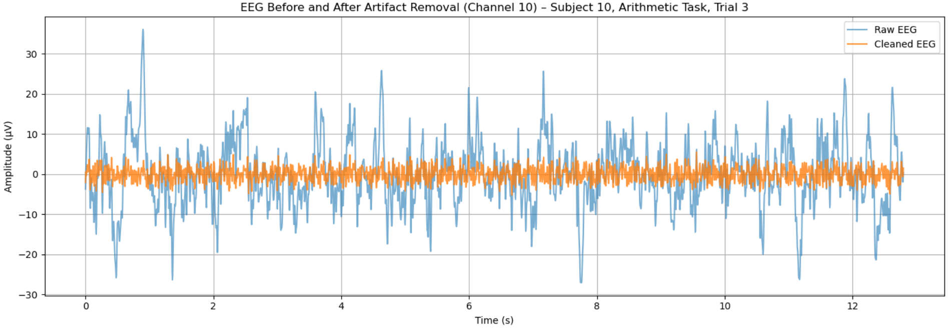

Figure 8: EEG Signal Comparison Before and After Artifact Removal.

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Model Developpement

1. **Data Source:**
    - EEG recordings labeled as **calm** and **stress**.
    - Organized in separate directories.
2. **Loading Strategy**
    - Up to 16 `.mat` files per class are loaded.
    - EEG data is transposed to shape `(time_steps, features)` for sequence modeling.
3. **Labeling**
    - Calm samples labeled as **0**.
    - Stress samples labeled as **1**.

1. **Concatenation**
    - Calm and stress data samples are combined into a single dataset.
2. **Shuffling**
    - Random permutation is applied to mix class labels.
    - Helps improve training robustness.
3. **Normalization**
    - Input features are normalized using `StandardScaler`.
    - Ensures consistency across all samples.

LSTM Model Architecture

Long-Short Term Memory Model

- **Model Layers:**
  - *LSTM Layer 1:* 64 units, returns sequences
  - *Dropout:* 0.2
  - *LSTM Layer 2:* 64 units
  - *Dropout:* 0.2
  - *Dense Output:* 1 unit, sigmoid activation (for binary classification)

LSTM Model Architecture

Training Process

Loss Function: Binary crossentropy
Optimizer: Adam
Metrics: Accuracy
Epochs: 20
Batch Size: 32

LSTM Model Evaluation

Accuracy: 96%
Loss: 8%

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Thank You For Your Attention!

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[2] K. S. Rahnuma, A. Wahab, N. Kamaruddin, and H. Majid, “Eeg analysis for understanding stress based on affective model basis function,” pp. 592–597, 2011.

[3] C. Kirschbaum, K.-M. Pirke, and D. H. Hellhammer, “The trier social stress test a tool for investigating psychobiological stress responses in a laboratory setting,” *Neuropsychobiology*, vol. 28, pp. 76–81, 02 2008.

[4] R. Ghosh, N. Deb, K. Sengupta, A. Phukan, N. Choudhury, S. Kashyap, S. Phadikar, R. Saha, P. Das, N. Sinha, and P. Dutta, “Sam 40: Dataset of 40 subject eeg recordings to monitor the induced-stress while performing stroop color-word test, arithmetic task, and mirror image recognition task,” *Data in Brief*, vol. 40, p. 107772, 02 2022.

[5] A. Albasri, “EEG dataset of Fusion relaxation and concentration moods,” 2019.