Faculty of Engineering
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# Medical Instrumentation (1)

## Project 02


**Team 13**

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**Signal Acquisition and BCI**

## Data description

The data used in this project is from Kaggle which is “a data science competition platform and online community of data scientists and machine learning practitioners under Google LLC.”
Data acquisition process involved the use of an EMOTIV EPOC+ ***14 Channel*** electroencephalogram (EEG) device for capturing brain impulses on **four subjects**. This device is designed to record electrical activity from the brain and has specific technical specifications, including a 128 Hz sampling frequency and a 16-bit analog-to-digital converter. It also features 14 electrode channels to collect data from various areas of the scalp.
**Data Collection Protocol:** A structured data collection protocol was created for this study. It lasts for twenty-five minutes and is divided into different cycles. During each acquisition cycle, the participant is exposed to images representing different voluntary motor actions. Specifically, there are three types of images:

- Right Arrow: This image represents a motor action in the right direction. The idea is that the participant's brain activity when observing this image can be associated with a command to move a virtual object to the right.
- Left Arrow: This image represents a motor action in the left direction, and it is likely associated with a command to move a virtual object to the left.
- Circle: The circle image represents no motor action. It serves as a neutral state or a rest condition for the participant's brain.

**Data preprocessing:** The collected data is in the form of a 128x14 matrix at each reading. This means that for each instance of time, we have 14 EEG channel values recorded at a 128 Hz sampling frequency.

The brainwaves of interest are in the range of 0 to 30 Hz. So, to analyze the frequency components of the EEG data, it is passed through the Fast Fourier Transform (FFT) algorithm, which is a mathematical technique used to transform a signal from its time domain representation (as recorded by EEG) to the frequency domain.
The result is a 30x14 matrix representing the data in the frequency domain. Each element in this matrix corresponds to the strength or amplitude of a specific frequency component at each of the 14 EEG channels.

Further processing is done for each moment of data collected by calculating mean and standard deviation of each frequency band in the frequency range from 0 to 30 for each of the 14 EEG channels.
This results a matrix with dimensions 14x4x2, 14 is the number of channels or locations on the scalp where the EEG measurements are taken, and from the data's csv file they are: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. 2 is the mean and standard deviation calculated, and 4 represents the brainwave patterns that are categorized into different frequency bands associated with different mental states and activities:

- Delta (0.5 - 4 Hz):
  Delta waves are the slowest brainwaves and are usually associated with deep sleep or unconsciousness. They are prominent during deep, dreamless sleep and are associated with restorative and regenerative processes.
- Theta (4 - 8 Hz):
  Theta waves are often observed during light sleep, meditation, and states of creativity. They can be associated with relaxed awareness and daydreaming.
- Alpha (8 - 12 Hz):
  Alpha waves are prominent when we are awake but in a relaxed and calm state. They are often seen when we close your eyes and start to unwind, like when you're taking a break or meditating.
- Beta (12 - 30 Hz):
  Beta waves are associated with active, alert, and focused states of consciousness. They are most prominent when we are awake, attentive, and engaged in mental activities like problem-solving or decision-making.

The resulting 14x4x2 matrix is translated to 112 columns in the data's file and an additional column for the 3 different classes (Right, left, no action). Each data collected for each subject has a separate file.

## Machine Learning Model

The primary machine learning algorithm used in this code is a feedforward neural network, also known as a multilayer perceptron. It's a type of artificial neural network where information flows in one direction, from input to output. This neural network is implemented using TensorFlow/Keras and serves as the core algorithm for classifying EEG data.

**Model Structure:**

- **Input Layer:** The input layer of the neural network is the entry point for the EEG data. It consists of neurons equal to the number of features in the EEG data. This setup allows the model to receive and process the EEG data, preparing it for further analysis.

- **Hidden Layers:** The neural network incorporates two hidden layers, each consisting of 128 neurons. These hidden layers play a vital role in capturing complex patterns in the EEG data. To introduce non-linearity into the model and enable it to comprehend intricate relationships in the data, the Rectified Linear Unit (ReLU) activation function is employed. The ReLU function replaces negative values with zero, effectively introducing non-linear behavior and enabling the model to learn and represent complex patterns.

- **Output Layer:** The output layer is specialized for multi-class classification. It leverages the softmax activation function, which is ideal for predicting class probabilities for multiple classes. The softmax function converts the network's raw output into probabilities, ensuring that the predicted class probabilities sum up to 1. Each class is associated with a probability, and the class with the highest probability is the model's prediction for a given input.

- **Loss Function:** During training, the'sparse_categorical_crossentropy' loss function is employed. This loss function is particularly suitable for multi-class classification tasks. It quantifies the dissimilarity between the predicted class probabilities and the actual class labels present in the training data. Minimizing this loss function is the primary objective of the training process, as it guides the model towards accurate classification.

- **Optimizer:** The 'adam' optimizer is chosen for gradient-based parameter optimization. The Adam optimizer is an adaptive optimization technique that dynamically adjusts learning rates for each parameter during training. This adaptability enhances the model's convergence speed and effectiveness.

**Training the Model:**
The model is trained on the training data with 50 epochs. Early stopping is implemented to prevent overfitting.

**Model Evaluation:**
The model's performance is assessed using the testing data, and the accuracy results for each epoch are displayed.
Here is a closer look at how accuracy evolves during the training process:

- **Initial Epochs:** In the early epochs, the model exhibits an accuracy of around 0.52 on the training data and approximately 0.62 on the validation data.

- **Mid-training Epochs:** As the model continues to learn, the accuracy steadily improves. By the middle of the training process, the accuracy reaches around 0.88 on the training data and about 0.80 on the validation data.

- **Later Epochs:** Substantial progress is made in the later training epochs, with the accuracy climbing to approximately 0.99 on the training data and around 0.86 on the validation data

These accuracy changes show the model's ability to learn and adapt as it refines its parameters over time. The increasing accuracy demonstrates its skill in recognizing complex patterns in EEG data, becoming a highly accurate classifier as training advances.

**Conclusion:**

In this project, EEG data was collected using an EMOTIV EPOC+ 14 Channel EEG device, and a feedforward neural network, implemented using TensorFlow/Keras, was employed for classification. Data preprocessing involved converting raw EEG data into the frequency domain using Fast Fourier Transform. The model exhibited increasing accuracy during training, demonstrating its ability to recognize complex patterns in EEG data.