Abstract

The integration of machine learning techniques with brain-computer interface (BCI) technology has ushered in a new era of assistive robotics. This research explores our development and implementation of a novel Machine Learning-Driven Brain-Controlled Robotic One-Hand Exoskeleton. The primary objective is to enhance mobility and autonomy for individuals with upper-limb disabilities by enabling real-time control of exoskeleton movements through neural signals. Our system comprises three main components: the brain-computer interface for signal acquisition, machine learning algorithms for signal processing and classification, and the robotic exoskeleton for physical assistance. Advanced machine learning models, including deep neural networks and adaptive algorithms, are employed to interpret electroencephalography (EEG) signals in real time, allowing users to intuitively control the exoskeleton's movements with minimal cognitive load.

Through rigorous experimentation and evaluation, including user trials and performance metrics, this research demonstrates the feasibility and effectiveness of the system in enhancing user mobility, improving hand movement patterns, and promoting natural interaction between the wearer and the robotic device. The findings underscore the potential of integrating cutting-edge machine learning with BCI technology to create robust, adaptive assistive technologies for individuals with mobility impairments, paving the way for future advancements in neurorehabilitation and human-machine interfaces.

Introduction

EEG

What Happens in Your Brain When You Think, Dream, or Even Sleep? Electroencephalography (EEG) offers a window into this mysterious world, allowing us to measure the brain's electrical activity.

Every machine requires a system that controls its functions and operations. Similarly, humans have a complex computing system within the body—the brain. The human brain is the most intricate organ ever created by nature. With 100 billion neurons and numerous contact points between them, our brain has capabilities that no supercomputer can match to date. [2],[5]

Advances in medical science and inventions have improved our understanding of how the brain functions. One such invention is electroencephalography, a method and device used to record and analyze the electrical activity occurring within the brain. [5]

Electroencephalography, or EEG, is a non-invasive neuroimaging technique used to measure and record the brain's electrical activity in the form of waves.
The neurophysiological function of the brain can be monitored while the subject

performs various tasks. Additionally, it can accurately detect different types of electrical abnormalities.

Our brain consists of billions of interconnected neurons. These neurons operate by generating electrical signals that reflect cognitive processes, emotions, and motor commands. The brain is divided into different regions, each with a specific function. [2]

An EEG machine detects and measures tiny electrical charges resulting from the activity of brain cells by recording voltage differences between different points using pairs of electrodes. The recorded data is then sent to an amplifier. The amplified data is eventually digitized and displayed on the EEG device's screen as a sequence of voltage values varying over time. The resulting EEG waveforms are interpreted to identify signs of abnormalities within the brain.

An EEG device consists of the following main components:

Electrodes that are attached to the scalp with a special paste and capture small brain waves produced by neurons, amplifiers responsible for amplifying the incoming signal enough to be displayed on the screen, a computer control module that processes the amplified signals, and a display device so that the processed signals can be shown on the screen as a graph or recording for analysis by the operator. [5]

An EEG test may be conducted as an outpatient study or as part of a hospital stay. The patient is asked to relax while lying on a bed or sitting in a chair. Various electrodes are attached to the scalp. [4] The device measures electrical frequencies, with frequency being the number of times a wave repeats itself within a second. Fast Fourier Transform (FFT) and other signal processing techniques convert the incoming signals measured by the EEG into information that can help diagnose various types of brain disorders through brief bursts of energy and can be used to determine the overall electrical activity of the brain by responses to stimuli.

FFT is a mathematical algorithm that efficiently implements the Fourier Transform. The Fourier Transform is a method for transitioning between the representation of a signal in time and its representation in the frequency domain. With the efficient tool FFT, the frequency range can be extracted to identify which wave is present, as each wave is defined within different ranges.

The FFT takes the signal, which is a function of time, and converts it into a signal represented by different sinusoidal frequencies. In other words, the FFT decomposes the signal into its frequency components and displays which frequencies are present in the signal and at what intensity each frequency appears. The result of the FFT is a series of frequencies, along with the intensity of each frequency. This way, it is possible to determine the frequencies at which different brain activities occur.

EEG waveforms can be characterized based on their location, amplitude, frequency, morphology, continuity (intermittent or continuous), synchronization, symmetry, and reactivity. However, the most common method for classifying EEG waveforms is by frequency, to the extent that EEG waves are named based on their frequency range using Greek letters. Each brain wave is associated with specific brain functions. The most studied waveforms include delta, theta, alpha, sigma, and beta. [6]

Main Waves in EEG Measurement: [5], [6], [7]

- **Delta Waves** (0.5 Hz to 3 Hz): Slow but strong brain waves generated during dreamless sleep. When Delta waves synchronize between distant cortical areas, they often trigger sharp waves considered relevant for memory formation.

- **Theta Waves** (3 Hz to 7 Hz): Primarily occur during REM sleep. They originate from deep subcortical sources, making them often undetectable by EEG. Normal Theta waves are involved in learning and memory, while pathological Theta waves indicate brain dysfunction. In the Theta state, we experience dreams with vivid imagery and intuitions.

- **Alpha Waves** (7 Hz to 13 Hz): Occur when the person is relaxed, clear, or calm. These are mainly found in the occipital and posterior regions of the brain. Whenever someone is asked to close their eyes and relax, the brain disengages from complex cognitive tasks or thinking, causing Alpha waves.

- **Beta Waves** (14 Hz to approximately 38 Hz): Related to an alert, attentive, and conscious state of mind. These have a low amplitude and are also associated with motor decisions. Beta waves are divided into low Beta (Beta1, 12-15 Hz) during reflection, mid-Beta (Beta2, 15-22 Hz) during intense engagement or active understanding, and high Beta (Beta3, 22-38 Hz) during complex thoughts and integration of new experiences. They are also linked to anxiety or intense excitement.

- **Gamma Waves** (38 Hz to 120 Hz): The fastest of all brain waves with the highest frequency and the smallest amplitude. Due to their small amplitude and high frequency, they are often contaminated by electrical noise or muscle artifacts. If Gamma waves are captured and measured by EEG, they inform us about information processing in the brain. These are also divided into low Gamma (38-60 Hz) during attentive behavior and cognitive tasks, and high Gamma (60-120 Hz) whose exact role is not completely clear but is considered significant in diagnosing epilepsy.

EEG is the most powerful and preferred diagnostic procedure for epilepsy. Additionally, it is very helpful in diagnosing sleep disorders such as insomnia, parasomnia, etc. The device also has valuable diagnostic potential for other neurological conditions such as stroke, autism, depression, ADHD, and more. [5]

Machine Learning
Machine learning is a field within artificial intelligence focused on developing algorithms that learn and improve their performance automatically, without explicit programming. Its main advantage is the ability to tackle complex problems that are difficult to solve with traditional programming. It is used in areas such as image processing, speech recognition, text analysis, recommendations, prediction, robotics, and medicine.

The field relies on mathematical and statistical techniques including neural networks, decision trees, support vector machines, and genetic algorithms. It is rapidly evolving, with growing demand for skilled developers and numerous career opportunities. Machine learning offers innovative solutions to complex problems and has the potential to transform how we live and work.

Machine Learning & EEG
In our research, we used machine learning in conjunction with EEG signals. This combination allows for more advanced and accurate analysis of brain activity and enhances the ability to diagnose and investigate neurological and pathological conditions.

Machine learning can extract significant features from EEG signals, including identifying patterns or features that may not be easily discernible by human eyes alone. Using machine learning algorithms, different types of EEG signals can be classified into categories such as epileptic activity, psychological states, or types of movements. Machine learning can also provide insights into brain activity that can aid in diagnosing neurological diseases such as epilepsy, autism, and others. Over time, machine learning algorithms can improve their accuracy by learning from new data, leading to more precise diagnostic results.

Signal Processing
Signal processing is a scientific and engineering field that involves the analysis, modification, and extraction of information from signals. These signals can be analog, such as sound waves or electrical currents, or digital, such as sequences of numbers or bytes. Signal processing is used in a wide range of fields.

Acquisition of signals and imaging from the human body has become essential for early diagnosis of various diseases. Such data can take the form of electro-biological signals. Electroencephalography (EEG) measures the activities of neurons in the form of electrical currents generated by synchronized activity of a group of specialized pyramidal cells within the brain.

Hans Berger (1873–1941), a German physician, coined the term "electroencephalogram" to define the electrical potentials occurring in the human brain. He took the first EEG recordings from patients using metal strips and a galvanometer, and succeeded in characterizing the α ("slow and large") and β ("fast and smaller") rhythms, focusing on changes occurring in EEG patterns. His findings opened the door for most applications based on EEG signals today, as he observed that these brain signals were neither irregular nor inconsistent. Any subtle change in the frequency patterns of these waves aids in diagnosing certain neurological disorders or inferring neuronal activity in response to specific external stimuli.

Signal processing and analysis are carried out in four stages:[15] acquisition of brain activity, preprocessing, feature extraction, and result analysis/classification. This field is evolving at a rapid pace, with new discoveries and advanced technologies continually being developed in machine learning, artificial intelligence, advanced sensors, and EEG-based BCI systems.

Signal Processing in EEG

Application of EEG Signal Processing in Brain-Computer Interfaces (BCIs)

In the ever-changing landscape of technological advancement, EEG is emerging as a tool for the next generation of brain-computer interfaces (BCIs) and neural prosthetics. BCI systems are groundbreaking, providing direct communication between the human brain and external devices using only thoughts. Signal processing plays a crucial role in the development of BCIs, as it enables the translation of the brain's complex electrical activity into understandable commands. These systems offer a glimpse into a future where thoughts and actions seamlessly integrate with digital technology. The convergence of electroencephalography (EEG) and robotics could enable individuals with severe motor impairments to control external devices using their brain signals. This has opened new possibilities for people with conditions such as spinal cord injuries or amyotrophic lateral sclerosis (ALS) to perform daily tasks independently, significantly improving their quality of life. Tasks like eating, dressing, and even driving could become accessible to those who previously relied on others for assistance. [8]

EEG has the potential to revolutionize the way we interact with robots and computers. The ability to control robots with our thoughts opens up endless possibilities, from assisting people with disabilities to enhancing automation in industries. Imagine a world where paralyzed individuals can regain mobility by controlling a robotic exoskeleton with their brain signals. This incredible achievement is becoming increasingly possible thanks to the integration of EEG and robotics. [3],[8]

This is done by capturing and interpreting signals of brain activity that are translated into computer commands. Researchers are developing sophisticated algorithms that can interpret EEG signals and translate them into commands for robots. [8] These algorithms analyze patterns in brain waves and map them to specific actions, allowing users to control robots with their thoughts.

The journey toward brain-controlled robotics has been an evolution of ideas, technological advancements, and sheer determination. Initially, researchers focused on decoding basic brain signals, such as motor imagery, to enable simple commands for robotic movements. By asking participants to imagine specific movements, such as moving a hand or leg, researchers were able to correlate these imagined actions with corresponding brain activity.

However, challenges can arise in the development of BCIs. The accuracy and reliability of EEG signals can be affected by various factors such as EEG signal noise, individual differences, making the development of universal BCIs problematic, [8] and the need for precision and speed to allow for effective communication and control. Moreover, with any revolutionary technology, ethical considerations are of utmost importance. Brain-controlled robotics is no exception. Since brain-controlled robotics involves accessing and analyzing intimate neural signals, privacy and data security become critical concerns.

This field is rapidly evolving, and today BCIs are tangible tools with the potential to revolutionize many aspects of our lives, from healthcare and communication to gaming and education. [1]

Related Work:

Literature Review: EEG & Machine Learning

Recently, the availability of large EEG databases and advancements in machine learning have led to the deployment of deep learning architectures in EEG signal analysis. Strong automatic classification of these signals is crucial for practical EEG applications, reducing reliance on skilled experts. A systematic review of the literature on deep learning applications for EEG classification tasks was conducted.

Many EEG analysis tools use machine learning to reveal relevant information for classification and neural imaging. This review presents four studies on different EEG classification tasks and a comparative study analyzing these tasks based on task type, input type, and machine learning architecture.

In the study of deep learning applications for EEG classification tasks, the task groups using machine learning were divided into general categories: emotion recognition, motor imagery, seizure detection, and sleep assessment. Each task type included a description of specific input formulations, key features, and classification recommendations found in the review. The studies identified three categories of input formulations: computed features, images, and signal power.

In emotion recognition studies, participants watched video clips pre-rated for specific emotions by experts. EEG was measured during viewing, followed by self-assessment of emotions.[12] In motor imagery studies, participants were required to imagine specific muscle movements. These applications are related to brain-machine interfaces (BMI), which require precise classification of intended movements. Motor imagery-based BMI aims to decode brain signals to control external devices.[13]

A comparative study of EEG classification tasks found that computed features were commonly used in emotion recognition and motor imagery tasks. Effective architectures for emotion recognition tasks varied by dataset: CNN for image input, RNN for signal values, and DBN for computed features. The four studies achieved accuracy between 87% and 89%. In motor imagery tasks, CNN significantly outperformed RNN.[11]

Seizure detection studies analyzed EEG signals from epilepsy patients during and between seizures, including control signals from non-epileptic patients. These studies aimed to detect impending seizures.[14] Sleep assessment studies recorded nocturnal EEG signals, which were classified by experts into sleep stages and rapid eye movement (REM) stages. Visual inspection of neurophysiological signals forms the basis for standard sleep assessment.
In this study, Artificial Neural Networks (ANNs) and statistical classifiers such as SVM, LDA, and HMM were used. Due to the limited amount of research on sleep scoring tasks, no specific recommendation regarding architecture was provided.[15]

Seizure detection and sleep assessment tasks often used signal values as input. Seizure detection studies showed the highest rate of signal value input usage, with two studies achieving classification performance of 99% with CNN and 100% with RNN.[11]
A comparative study of EEG classification tasks found that in CNN studies using image input, the average accuracy matched CNN studies using computed features. Both input strategies achieved an average accuracy of 84%, compared to 87% in CNN studies using signal power as input. Studies using computed features achieved an accuracy of 85%, while signal power input studies achieved an accuracy of 86%. RNN studies with signal value input achieved an accuracy of 85%, lower than computed features (89%) and images (100%).

Choosing the machine learning architecture and input is critical and can improve learning outcomes.[11]

Building on these studies, a recent research that examined schizophrenia developed a channel selection method based on the performance analysis of a Convolutional Neural Network (CNN).[21], [22] The study examined 14 paranoid patients and 14 normal controls. Each subject was recorded for 15 minutes at a sampling rate of 250 Hz while resting with closed eyes. The data were processed using a Butterworth band-pass filter to remove noise and then normalized.

The study was conducted using two testing strategies: 10-fold cross-validation for non-subject-based tests and 14-fold cross-validation for subject-based tests. A Convolutional Neural Network (CNN) was used for feature extraction and EEG signal classification. Channel selection was then performed, and it was found that the temporal and central areas (channels T4, Cz, T3, and C4) were the most relevant for schizophrenia detection, achieving classification accuracy of up to 98%.[18]

The study presented experiments showing that combining three channels (T4, T3, Cz) achieves 90% and 98% accuracy in subject-based and non-subject-based tests, respectively, using a hybrid of CNN and Logistic Regression (LR). The use of selected channels significantly reduced data dimensions and computation time, facilitating data transfer on mobile devices.

T4 (Temporal Right): Located on the right side of the head, above the ear, in the temporal region, which is associated with auditory processing, memory, and language.
T3 (Temporal Left): Located on the left side of the head, above the ear, also in the temporal region, and involved in auditory processing and language.
Cz (Central): Located at the center of the scalp, along the midline, and is important for motor control and movement planning.

Most earlier studies used all 19 EEG channels or relied on advanced algorithms for feature extraction. This study used only a subset of selected channels, reducing the number of channels, computational complexity, and facilitating data transfer to the cloud. Future research directions may include the use of additional neural networks, such as LSTM and RNN, and testing the methodology on additional EEG datasets and different applications.

Literature Review: EEG & Signal processing

In a study examining signal processing for the diagnosis of epilepsy and autism spectrum disorder, 46 participants were evaluated, some diagnosed with epilepsy or autism spectrum disorder and some undiagnosed. EEG signals were acquired from the participants and filtered to limit the signals to a frequency range between 0.5 and 60 Hz. Then, DWT and cross-correlation were used to extract features from the EEG segment. For the classification of the patient's diagnosis, machine learning algorithms SVM, KNN, ANN, and LDA were used.
DTW is capable of capturing small changes in the EEG signal by representing the signal in multi-dimensional time-frequency domains in terms of approximations and coefficients. In this study, decomposition with 6 levels based on the Db4 wavelet, commonly used for EEG analysis, was employed.
Another method used by the researchers for feature extraction was based on synchronization within and between different brain regions (frontal, central, and posterior) for each EEG sub-band. Abnormal connectivity and synchronization between brain regions may reveal certain brain disorders and pathologies, including epilepsy and autism. The study presented techniques for feature extraction and classification of EEG for diagnosing epilepsy and autism spectrum disorder (ASD).
An electrode map was shown for three different frequencies: 6 Hz (within the theta band), 10 Hz (alpha), and 22 Hz (beta). The study found that, compared to the three types of participants, features extracted using DWT combined with the functions SD, SE, BP, and LLD showed that SE had the best ability to differentiate between types of EEG data, followed by LLD. Additionally, SD showed the poorest performance. The

findings also indicated that epileptic EEG exhibited higher SE values than all other data types, including autistic and normal EEG. In the synchronization technique, it was found that it is more challenging to distinguish between autistic and normal EEG compared to epileptic EEG. The combination of DWT, SE, and KNN achieved the best results with an accuracy of 94.6% in classifying the three classes (normal, epilepsy, autism).[19]

In a separate study that investigated 122 alcoholic and non-alcoholic individuals, flexible analytical models of the analytical wavelet transform (FAWT) based on machine learning were proposed for automatic detection of alcoholism. In this study, the EEG signals of the participants were recorded according to the international 10/20 system, with 61 of the 64 electrodes used for obtaining 32-second time series data, and the remaining electrodes served as reference electrodes. In the proposed methodology, EEG signals were decomposed into approximated and detailed wavelet coefficients using FAWT, a mathematical tool used to analyze non-stationary signals by decomposing them into components at different scales and frequencies. The EEG signals were decomposed into five levels of approximated and detailed coefficients for normal and alcoholic classes. Statistical features such as mean, standard deviation, kurtosis, skewness, and Shannon entropy were extracted from the selected wavelet coefficients. These features were fed into various machine learning models, including SVM, LS SVM, and Naive Bayes. Training and testing were conducted using 10-fold cross-validation to ensure there was no statistical bias in the classification results. The performance of the models was evaluated using all essential metrics such as accuracy, sensitivity, specificity, F-measure, precision, Matthews correlation coefficient (MCC), and ROC. The results of this study indicate that LS SVM with a polynomial kernel demonstrated the best performance with an accuracy of 99.17%, sensitivity of 99.17%, and specificity of 99.44%. In contrast, the performance of LS SVM with a linear kernel was the poorest. Similarly, SVM with an RBF kernel showed close performance with an accuracy of 97.92%. Naive Bayes classifier achieved an accuracy of 91.25%, which was lower compared to others. The study found that only polynomial and RBF kernels of third order and above are capable of representing the non-linear and non-stationary information contained in EEG signals. [20]

In another study aimed at improving classification accuracy for left/right hand movements, EEG signals were recorded from a group of 103 participants who were asked to move their hands according to an EEG movement dataset. Initially, the negative effects of noise in the EEG signals were reduced to improve data quality. Then, features were extracted from the signals in the time and frequency domains and used as input for an LSTM network with attention. [23]

To find the optimal time segment for classification, the researchers tested different time segments (between 0.25 and 2.0 seconds). It was found that a 2-second segment provided the highest accuracy with the lowest standard deviation. The method was tested using intra-subject and cross-subject validation, with both methods employing 10-fold cross-validation without overlap between training and testing segments. The study compared the proposed method with existing solutions from the literature, including PLV, ANN, SVM, Naive Bayes, decision tree, logistic regression, random forest, CNN, and without attention mechanism. In one comparison using random forest, it was identified that the FT7-FT8 sensor pair was the most dominant.

These sensor pair located in the forehead area, on both sides of the head (left and right) near the temples. These channels are positioned between the frontal (Frontal) and temporal (Temporal) regions. They are used to detect brain activity related to visual and auditory information processing.

In this study, the visual regions of the brain were the most active, and after receiving the visual stimulus, the information was transmitted to the temporal and parietal regions. At the end of the experiment, the frontal and temporal regions were the most active and continued to be active until the end of the movement.

This study found that the LSTM method achieved 5% higher accuracy than the PLV model, which had previously shown the best results,[24] and demonstrated impressive performance in both intra-subject and cross-subject validation. The FT7-FT8 sensors were the most dominant with 5 significant features, and other sensors with significant contributions included T9-T10, F7-F8, and T7-T8. The study offers an innovative and significant approach to improving the classification of hand movements based on EEG. The study presents a promising research tool for use in a range of future classification tasks in this field and offers new and significant solutions for enhancing performance and generalizing classifications across different subjects.

The purposes of the research

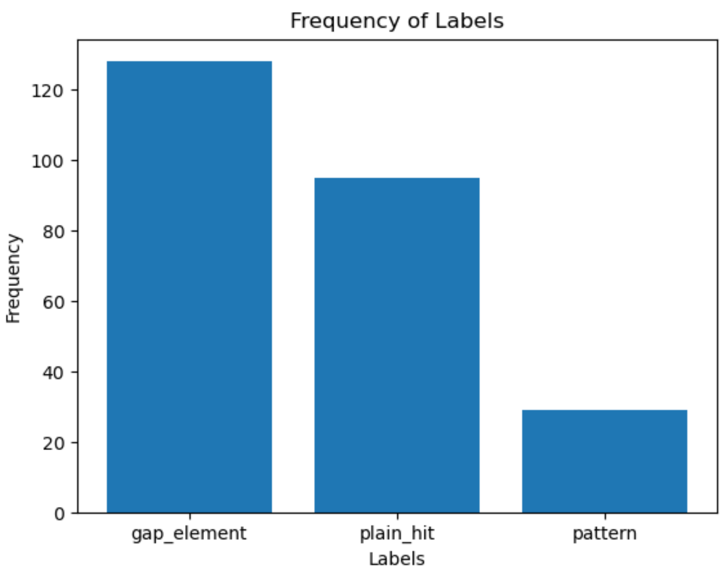
The main goal of this research is to control prostheses with the mind as a means of replacing a missing limb using a robotic exoskeleton that will attach to a patient's legs and hips and be controlled by electrical pulses in the brain, which will be detected using the Emotiv helmet with the addition of AI. By that, through this, to innovate in the field of mind-controlled exoskeleton. This goal is being pursued through the use of a new headset that can transmit meaningful brainwave data wirelessly to a computer in high spatial resolution.
The primary objective is to enhance mobility and autonomy for individuals with lower-limb disabilities by enabling real-time control of exoskeleton movements through neural signals.

Methods and Methodology

Our system, which we refer to as the Machine Learning-Driven Brain-Controlled Robotic One-Hand Exoskeleton, comprises three main components: a brain-computer interface for signal acquisition, machine learning algorithms for signal processing and classification, and a robotic exoskeleton for physical assistance. We employ advanced machine learning models, including deep neural networks and adaptive algorithms, to interpret EEG signals in real time, enabling users to control the exoskeleton's movements intuitively with minimal cognitive effort.

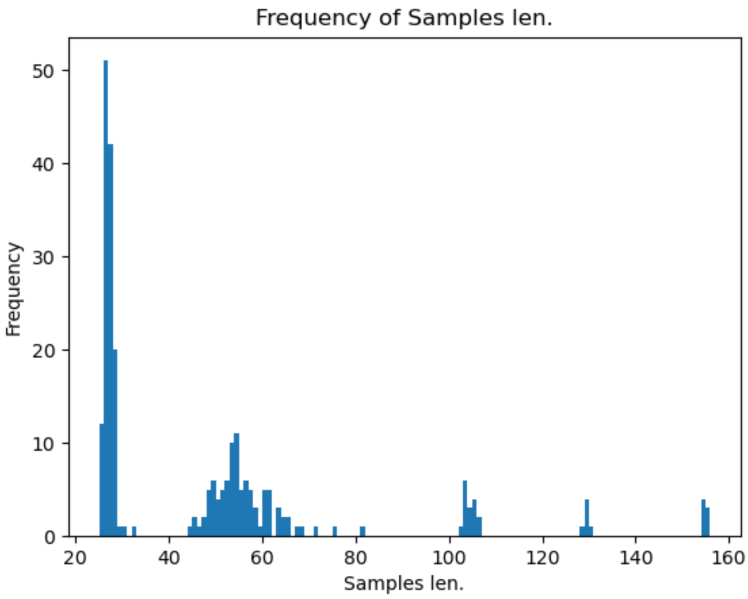
For reach our data we use the Emotiv EPOC
The Emotiv EPOC is an EEG headset that provides a cost-effective option for recording brain activity data compared to professional EEG equipment. It is wireless, user-friendly, and does not require conductive gel. It features 14 active electrodes and offers EEG signal measurement capabilities around the head (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4), with a sampling rate of 128Hz. The data undergoes Bandpass filtering in the range of 2-30Hz to separate into different frequency bands (delta, theta, alpha, beta). Fast Fourier Transform (FFT) is then used to calculate the signal power at each frequency. [26]
Compared to traditional medical equipment, the Emotiv EPOC is somewhat limited due to the absence of electrodes at the center of the skull [25] and a lower signal-to-noise ratio, which results in less accuracy compared to professional systems. However, advanced processing techniques have enabled achieving high accuracy despite these limitations.

Step 0.5 - How we created our samples. We got the two csv files: Marker data, and EEG data. The Marker data indicating each experiment event and EEG data indicating the pulses measurements from each of 14 different channels. We've needed to connect between each event in Marker file to his corresponding measurements in EEG raw data. In order to do that we take the duration of each event which has been reported in Marker file, and the beginning of the event in terms of EEG internal clock ("Time Stamp" in our csv's) and extract with a loop the relevant rows from EEG raw data file. We saved it in a dictionary dataset in the following format: { sample idx : {eeg_data: [[.....], [....],...[...]]
Label: "gap_element/ plain_hit",
Set: "train/val/test"}.
In the original dataset, we got 3 events: hitting keyboard while seeing plain circle, "gap_element" which means that the user doesn't see any shape and "pattern" which means seeing patterned circle.
In order to properly training our data, we need to check whether our data is well balanced. We've build an histogram checking the amount of samples for each label/event and got the following result:

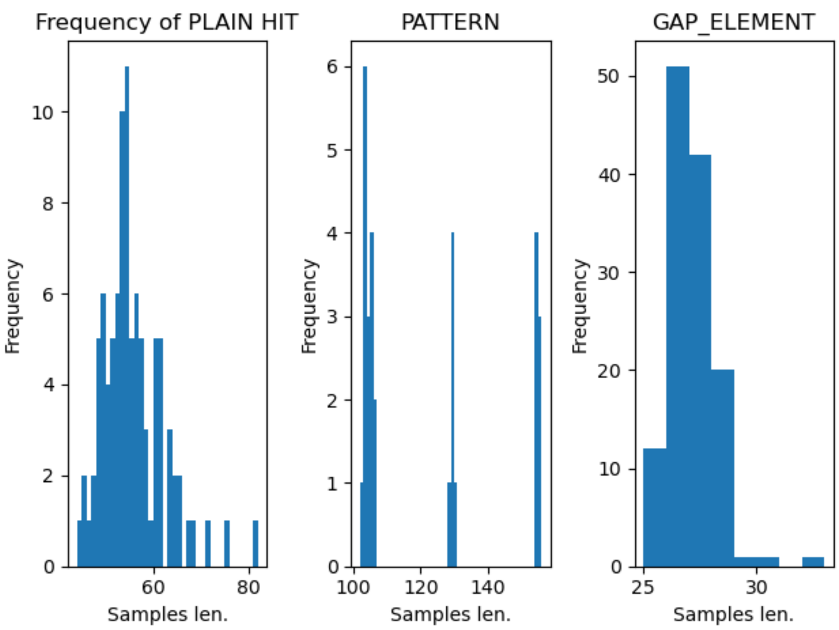


We see clearly the we, relatively, have few samples of pattern label and the data will be much more balanced if we would stay with only "gap_elememt" and "plain_hit" labels, so we'll further proceed with those two labels.

In addition, We need constant dimensions for our samples. Namely in the current mentioned process of building our data dictionary, each sample have different time duration. We've needed to decide about constant dimension. Then cutting too large sample and zero padding to short sample accordingly. In order to decide about the proper time dimension, we did histogram of each sample duration:



We see that most of the samples are below 80 rows(~0.6 secs because our EEG sample frequency is 128Hz).
More over, we did histogram which further categorize each sample duration the her label and got:



We decided on 62 rows for each sample, because it still covers the majority of our samples lengths and in order to be compatible for our model.
The results are further support our action to delete “pattern” samples because we see that all of them are much longer than 80 so they would all be cutted and damaged.

Step 1- pre processing: input X goes to STFT processing with 64 freq_bins and about 60 time frames. We got a complex number and we compute the power of that values for each frequency bin.
We have 14 channels from the EEG so we saved STFT plots from the dominant channel (FC3, FC5, T7, T8, FC6, F4). We inserted the averaged STFT on channels to our model. To see the STFT result, go to /exp/stft_plot directory.

Step 2 :
Before we explain about our model and forward process, we want to describe the Attention module mechanism which will be used as one of our major parts in our model. [27]
The main idea is to look on a sequence of vectors concurrently(assume each member in the sequence has dimension of dmodel) which are gotten from a process called “embedding”, and Then we want to learn “Attention”, i.e. adequate weight for each member depending on the required mission(classification, representation, data compression, etc.). Namely, by learning the relations between sequence members, we can give better representation for our data for the purpose of optimizing our final prediction accuracy.

The potential of using Attention is prominently better especially for sequential data, like: texts, sentence completion and signals (which is our case). In order to better classifying this information, we need to know the relations between the different chronological parts of the sample. Sometimes it’s needed to make a connections between early part and lately part of the same sample even though the length of the sample can be relatively long. Before Self Attention design, Recurrent Neural Networks(RNN) was traditionally used. [29] In RNN, each output of a layer was dependent on the same output of one unit time earlier. Building of such a model demanded a lot of computational and memory resources and even caused training problems such exploding/vanishing gradients of the learnt weights in contrast to the Self Attention module which is more economized and better trained.
Self Attention is also more useful than CNN’s. In CNN’s the typically dimensions of the kernel are small and we need numerous CNN’s layers in order to make kernel with receptive field which semantically connects between distant parts of the same sample/image. In contrast, Self Attention can achieve all the connections between different parts of the sample in quite a few layers and without recurrence.

Now we'll further explain of Self Attention process. As we've explained, the input is a matrix of a sequence of some embedded vectors of our signal. Embedding can be done in various ways like: output of dense NN or output of CNN network. Our embedding process will be in signal processing methods which will further be explained.
In order to ease the explanation, we'll treat embedded vectors as words in a lingual sentence. It's easy to make the analogous to our case, thinking the EEG different chronological transmission as words coming one after another in a sentence.

The mechanism is working with three main components: 1 - query. 2 - keys. 3 - values.
The query is a certain word from which wants to know how other words are related to her, namely what is the amount of attention it get from the other words. The other words are the keys. The values will be the output of the mechanism and will deliver us the same sentence but with addition of adequate weights/attention values for each word.

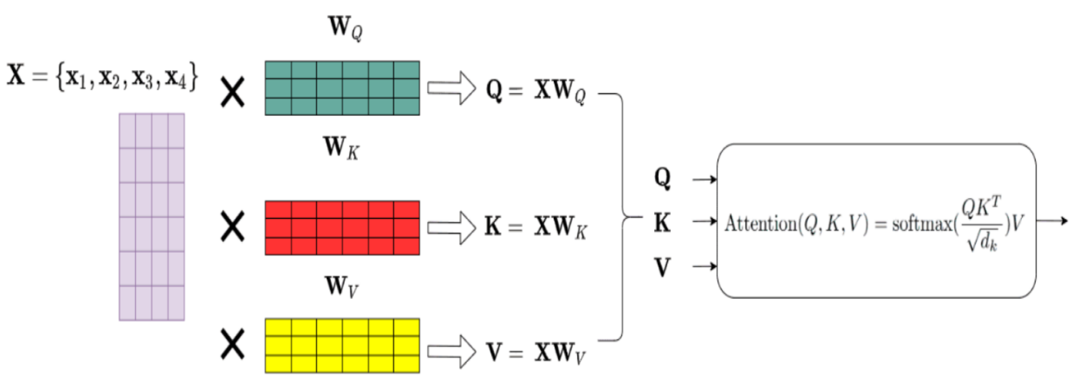
Mathematically, given a sequence of N embedded vectors, each of them with dmodel dimension. Notify $X \in \mathbb{R}^{N \times d_{model}}$ as input for the attention module. In order to get q,k and v with optimal representation we'll multiply each of them with learnable matrices: $W_q, W_k, W_v \in \mathbb{R}^{d_{model} \times d_k}$:

$$q = x\,W_q\,, \qquad k = xW_k\,, \qquad v = xW_v$$

When: xR1Xdmodel is a single vector from the N existing vectors.
For efficient computation we'll stack each trio of q,k and v from each vector to a matrix:
$Q, K, V \in \mathbb{R}^{N \times d_k}$, $Q = XW_q$, $K = XW_k$,$V = XW_v$

Now we'll want to measure the amount of similarity between q_i $\{1,2, \ldots . N\}$to each of the keys.
We'll do it with dot production $K^T q_i$which we'll deliver us high grades for highly correlative k_i , q_i pair. We'll stack each result dot product of each one of the N queries by matrix multiplication: QK^T.
In addition, we'll use softmax for normalized weights for. Then we'll multiply with V matrix in order to get the final weighted sentence:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right) V \in \mathbb{R}^{N \times d_k}$$

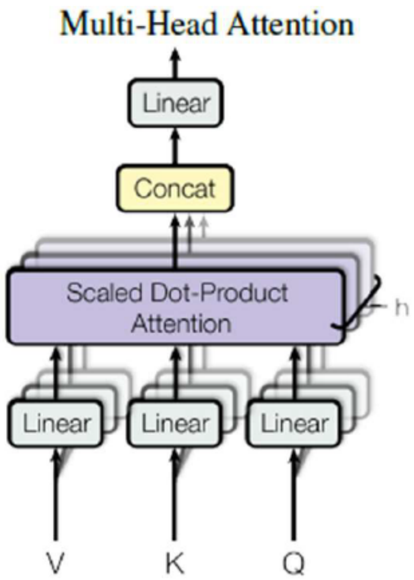


It can be seen that there is another normalization of d_k because a high dimension of d_k can lead to high values of dot products and we've learned that the derivative of softmax function is:

$$\frac{\partial softmax(out_k)}{\partial out_j} = \begin{cases} softmax(out_k) \cdot \left(1 - softmax(out_k)\right), & k = j \\ -softmax\left(out_j\right) \cdot softmax(out_k), & k \neq j \end{cases}$$
$$= softmax(out_k) \cdot \left(\delta_{kj} - softmax(out_k)\right)$$

Therefore as long as the dot product is higher, the softmax gradient is lower and weights learning update can be damaged.
The output is depended in d_k because given i.i.d keys and queries with zero mean and unitary variance, as we've seen in probability course, we'll get dot product of $q \cdot k$ is: $q \cdot k = \sum_{i=1}^{d_k} q_i k_i$ distributed normal with mean 0 and variance d_k so indeed we should normalize it with d_k.

For better and fast implementation, we'll stack all the different W matrices and we'll get: $\begin{bmatrix} q \\ k \\ v \end{bmatrix} = \begin{bmatrix} W_q \\ W_k \\ W_v \end{bmatrix} x \in \mathbb{R}^{3d_k}$. Following it, we're creating a dictionary which contains some queries, keys and values which is called "Multi-Head Attention".[28] Namely, we concatenate some matrices of queries, some matrices of keys and some matrices of values and each such trio is called "Head".



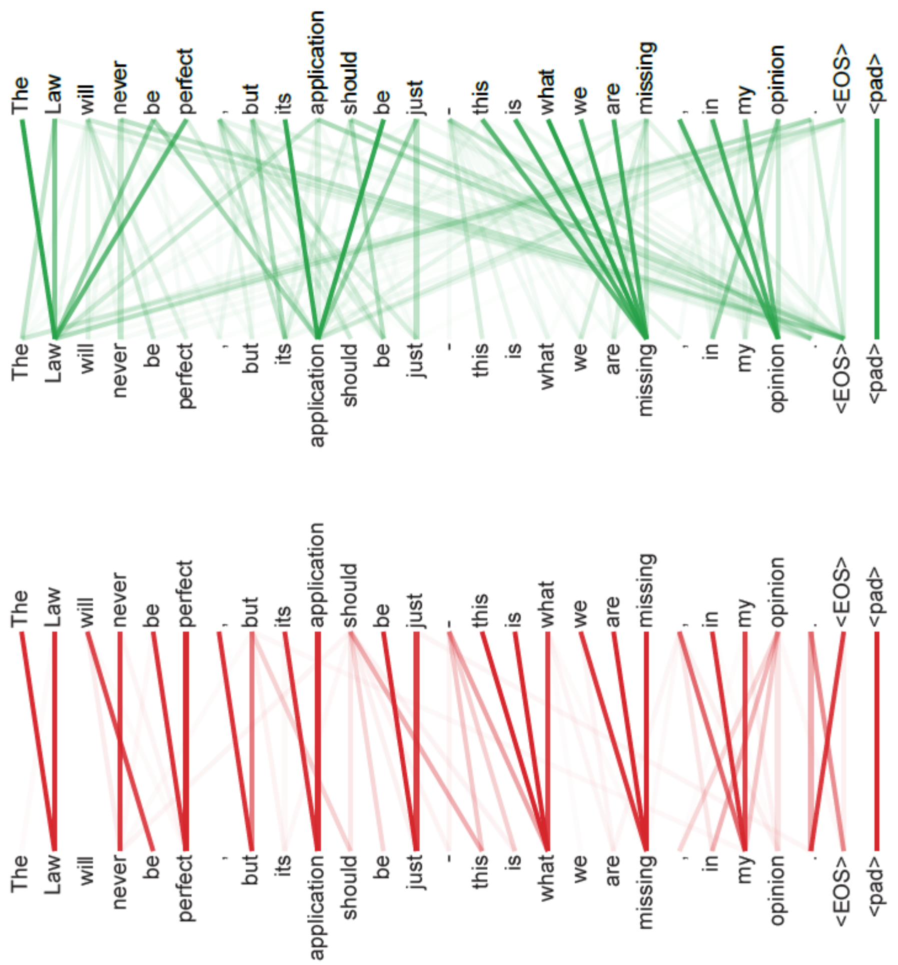
Mathmatically, we do:

$$Concat(h_1, h_2 \dots h_h) = \begin{bmatrix} W_q^1 \\ \vdots \\ W_q^h \\ W_k^1 \\ \vdots \\ W_k^h \\ W_v^1 \\ \vdots \\ W_v^h \end{bmatrix} x \in \mathbb{R}^{3h \times d_k}$$

$$MultiHeadAttenetion(Q, K, V) = \; Concat(h_1, h_2 \dots h_h)W_o, \quad W_o \in \mathbb{R}^{d_k \times hd_k}$$

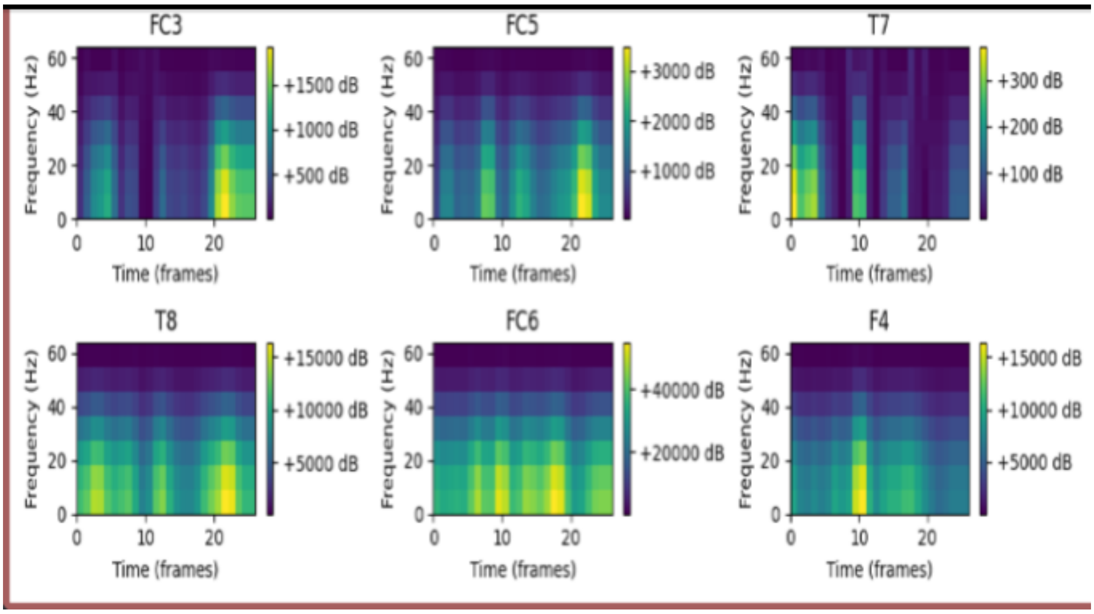
When W_o is another learnable matrix which is doing reprojection to the trio query-key-value with the original embedding dimension.

In addition to the advantage of this fast, efficient parallel solution of $MultiHeadAttenetion$, the NLP(Natural Language Processing) area reveals that for each Attention module, every head is separately succeeding to learn unique aspects of regarding the structure of sentence, as show in the below figure.
For the purpose of extracting considered and informative information on the structure of the EEG samples, we'll use this $MultiHeadAttenetion$ instead of "classic" Attention.



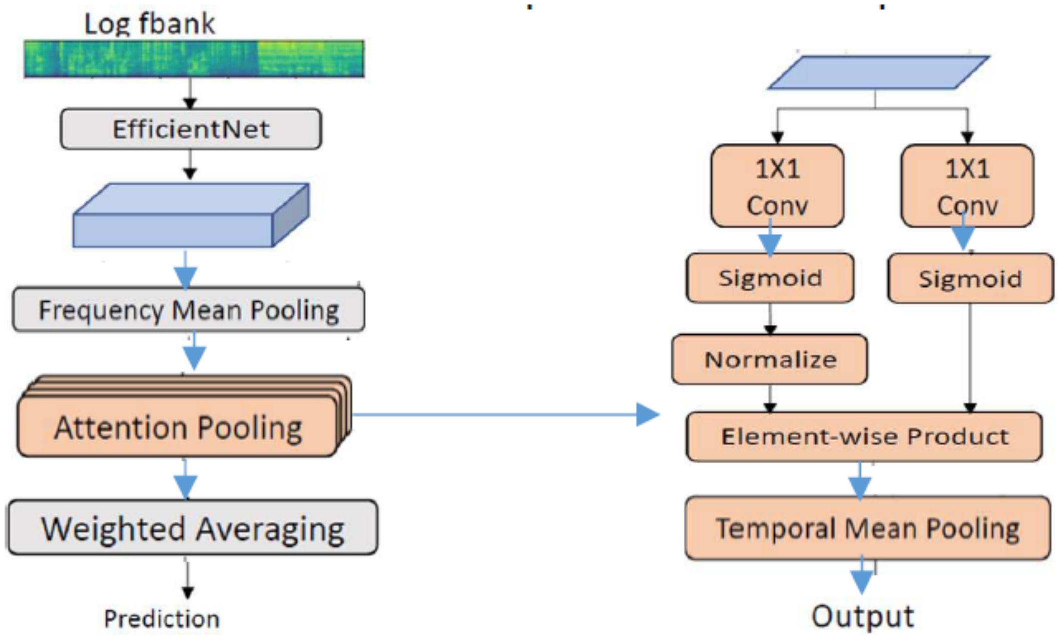
We insert [62X64] input to model consisting: a. EfficentNet CNN. B. Multi Head Attention. We have seen that 4 head attention got the best results in accuracy and mAP. We averaged the result on our head dimension(4).
For each sample we make signal pre-processing of STFT filter banks. For each sample, we zero-padding if necessary to constant time of 62 row (~0.6 secs).
The key innovation behind EfficientNet is the compound scaling method, which uniformly scales all dimensions of depth, width, and resolution using a set of fixed scaling coefficients. EfficientNet models achieve high accuracy with fewer parameters and lower computational costs compared to other state-of-the-art models like ResNet, Inception, and DenseNet. EfficientNet models are commonly used in tasks like image classification, object detection, and semantic segmentation due to their high accuracy and efficiency.

It can be wrongly deduced that this backbone will not be useful for our purposes because it was designed for missions of image classification which is different than signals classification. However, after STFT pre-processing we're getting a 2D time-frequency matrices which can be reconsidered as images. Thus the layers of Efficient can recognize patterns of: edges, corners and various contours in various positions in the STFT image. Such capabilities can give better, well represented features to input of our next modules.



To further enhance Efficient functionality, we use pre-trained weights for this module which were trained on Image-Net dataset in a process called "Transfer Learning". In general, Transfer Learning is taking a pre-trained model on different large dataset with different mission, then taking part of this model weights values for our module for our mission. The assumption is that those pre-trained weights have already learnt relevant feature extraction skills which can be useful also for our model and mission (as we've mentioned above: detection of edges, corners and various contours in various positions in the STFT image).

After forwarding our efficientNet model, we got extra channel dimension and downsamping in factor of 32 for both time and frequency dimensions, so overall we stay with 1X2X1280 input before Frequency Mean Pooling module. After it we stay with 1X1280 signal. Now our signal is inserted to our 4-head Multi-Head-Attention which is 4 concatenated Self Attentions. The learnable weight is got from two convolutions with 1x1 kennel such that we got two outputs of 2X2 dimension. The left output is representing the dot product between query and keys and the right output is representing the values. We make the mentioned formula at “Element-Wise Product” block, and then we do average on time dimension in order to get 2X1 softmax output for our predictions.
This process is done for each of the 4 heads and then make an average on heads to get the final output. [30]



CNN+Self Attention: 23איור

Step 3 - Training: Our chosen hyperparameters: Loss - Cross Entropy, Optimized - Adam, Learning Rate - 0.0005, Batch Size-16 and 40 epochs.

On results.csv we further reporting the measurements of [mAP, mAUC, average_precision, average_recall, loss_meter.avg, valid_loss, Learning Rate].

Results and discussion

Step 4 - Result Explanation: we save our results in exp directory. Each directory name is the date and hour of the running. In each of them, directory notifying the model name and the important hyper parameters of the experiment. In this directory, we save the checkpoints of our model, pickle documents which are saving the results of each epoch, we are notifying the best results and se are saving in two directories the plot results based on mAP and Cross Entropy Loss. In the second directory ("predictions"), we are saving the softmax vector value in each epoch.
Before showing the results, we'll explain about our tool of estimating the model results – mAP.
mAP(mean Average Precision) is widely used in estimating models in missions of representing/restoring information and object classification. It delivers widely estimation of the quality and accuracy of the model. mAP takes into account both precision and recall by computing the averaged accuracy for each category and making mean on all of the previous results. This metric is useful when we want equal importance to different categories without considerate their relative weight in the whole dataset. Thus it's a way to examine the efficiency of the model even in classifying rare samples in the dataset - In our case, it be sample of too short or too long recording.

The algorithm of mAP is:

1. Run on all number of classes - $k \in \{1,2 \dots n\}, n - number\ of\ classes.$
   a. For each class: run on different thresholds $TH \in \{0.0, 0.1, 0.2 \dots 1\}$.
      i. Calculate Precision: $P_{k,TH} = \frac{TP_k}{TP_k+FP_k}$
   b. After calculating a-i for each threshold, calculate Average Precision:

$$AP(k) = \frac{1}{|num\ of\ TH|} \sum_{TH=0.0}^{1.0} \{P_{k,TH}\}$$

2. After running on all the classes, make an average on all Average Precisions from 1-b phase:

$$mAP = \frac{1}{n} \sum_{k=1}^{n} \{(AP)_k\}$$

We ran our model with the following set of hyper-parametrs: batch_size=16, optimizer='adam', learning rate=0.0005, number of epochs=40, number of attention heads=4, loss='BCE'.
The Binary Cross Entropy loss is :

$$-\sum_{i=1}^{2} 1 \cdot \log(p_i)$$

, when

$$p_i = softmax(MultiHeadAttention)$$

This loss is convex and as long as it decreases in out learning process, it strives to the representation of out Ground Truth vector : $\begin{bmatrix}0\\1\end{bmatrix}\ or\ \begin{bmatrix}1\\0\end{bmatrix}$.

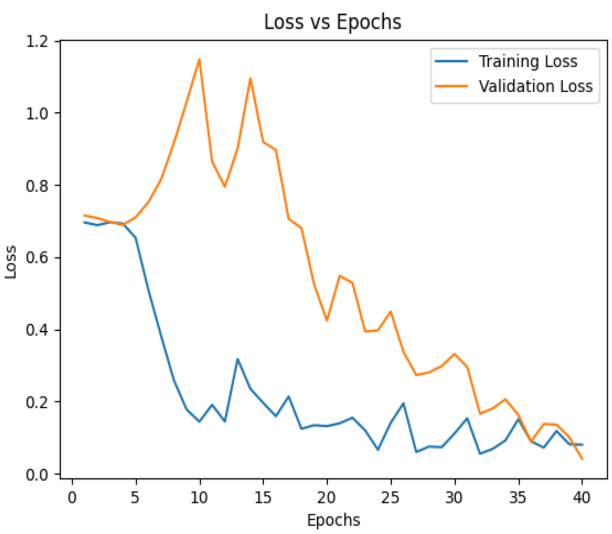
We use Learning rate decay scheduler for our learning process in order to improve convergence and avoid overfitting as our learning rate become smaller and prevent oscillation around the minimum of the loss. We empirically chose the parameters of: lrscheduler_start=10, lrscheduler_decay=0.5.

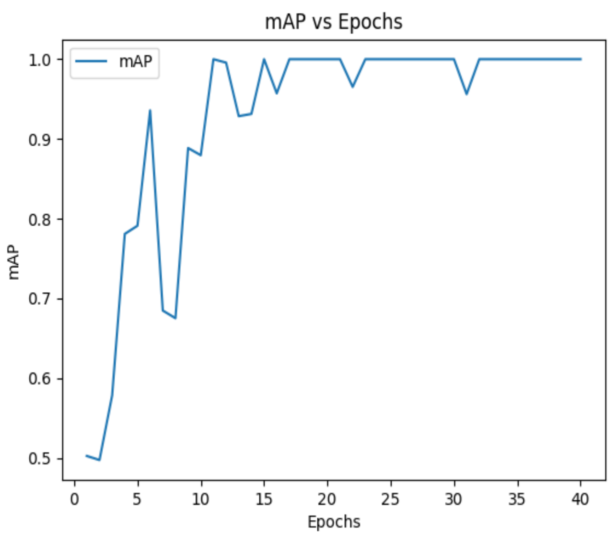
Additionally, we use warming process which is refers to gradually increasing the learning rate from a very small value to the initial set learning rate over a few initial update iterations. This practice helps stabilize the training process and can lead to better convergence and improved model performance. At the beginning of training, the model's weights are typically randomly initialized, which can cause large gradients. A high learning rate at this stage can lead to unstable updates and divergence.
Starting with a low learning rate and gradually increasing it allows the model to stabilize and find a reasonable set of weights before making larger updates and potentially avoiding poor local minima.
The formula learning rate for warmup we've chosen is:

$$lr_{warm} = \frac{1}{i} * lr_{init}$$

$$when\ lr_{init} - 0.0005, i - number\ of\ gradients\ update\ iteration$$
$$we\ chose\ 1\ to\ 100\ first\ update\ as\ warming\ process\ \ 1 \le i \le 100.$$

We got the following results:





On the left, we have we have the plot of loss on train and validation set vs epochs. We see clearly how the model started on first 15 epochs in doing overfitting on train set because the there is considerable gap between training and validation losses when↔ training performance is much better loss is lower. As we know, overfitting may not represent well the data because high loss on validation set can testify on poor performance on test set. However as long as we adapt our learning rate by scheduler and as we doing more and more updates on our weights, we can clearly see that the gap is closed and both validation and test set stabilizing on about 0.1 BCE loss.

On the right, we examine the mAP grade on our validation set every epoch. As we see the performance increases with the epochs and we go a saturation of 1.00 mAP score which is the best as we can do with that metric measure.

On test set, we got 0.9045 mAP score which is relatively high and consistent with the performance on validation set on last train-epochs.

Conclusions and recommendations

Based on the available data from the Emotive Epoch device, we were able to design our project according to hand movements and create a BCI intended for an exoskeleton model for the hand. Lower limb disability is a common phenomenon compared to other disabilities, so as a continuation of our work, we can expand our research to develop an exoskeleton intended for the lower limbs.

To achieve this, a new experiment can be conducted that is tailored to leg movement. This experiment would require the collection of real-time EEG data, and it is preferable to have as many participants as possible. Additionally, updates related to the device itself would be necessary, such as adjusting the number of channels and identifying which channels are dominant and relevant for lower limb movements. To maintain balanced data, it is essential to conduct an equal number of trials for each classification category. Furthermore, measurement times should be approximately equal and synchronized with the timing of the leg movement, ensuring that the participant does not hold their leg in the air for too long, as this might affect the EEG signals and record a specific movement incorrectly.

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