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ENHANCING CLASSIFICATION ACCURACY OF EXO-ANKLE USING HYBRID FNIRS-EMG BCI

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ABSTRACT

Brain-computer interfaces (BCIs) have grown as novel technologies that utilize brain activity for communication and control, typically via non-invasive techniques like electroencephalogram (EEG). Although significant advancements have been made, dependence on single-modality systems frequently impacts classification accuracy, limiting their practical use. This study addresses the challenge by utilizing electromyography (EMG) and functional near-infrared spectroscopy (fNIRS) features to improve classification accuracy for motor cortex activity. The aim was to integrate data obtained from several modalities to enhance performance compared to single-modality techniques. EMG and fNIRS data have been acquired during the same motor tasks for four separate classes. To determine the optimal features combination, the Particle Swarm Optimization (PSO) technique has been applied with linear discriminant analysis (LDA), achieving a classification accuracy of 98%. The findings indicated considerable enhancements in classification accuracy by integrating EMG and fNIRS features. This research advances the non-invasive brain-computer technique by presenting a new method for combining features of hybrid modality, allowing the development of more reliable and precise systems for motor rehabilitation and assistive technologies.

INTRODUCTION

Walking is one of the most fundamental and essential part of human motor functions, and it serves as the basic need for people's mobility. Discussing walking, it is important to note that its proper implementation requires stability, the capacity to adapt changes in the surface, and the force created to be sufficient for the body's successful progress. An essential component of this process is the ability to evaluate the lower limb joints and recognize the stability that ankle joint provides to the body during standing, the role of the joint as a shock absorber during heel strike, or the use of the joint during the push-off phase of gait. Most of the ailments resulting from an interference with the normal biomechanics of the ankle joint present a threat to an individual's ability to ambulate or walk, as this affects mobility, quality of life and personal independence.

Active Exoskeletons

On the other hand, active systems enhance the limitations of passive systems since they use actuators, sensors, and controllers to offer real-time support. These powered devices are made up of actuators that can create force to drive such movements as walking, standing or climbing stairs and can modify force and speed according to the feedback from the sensors. In recent studies, active exoskeletons use biological feedback like electromyography (EMG) signals or force sensors to capture the user intention and adapt the real-time support level [3]. These devices are designed to provide personalized and active forms of rehabilitation in motor training to enhance motor recovery and functional independence for individuals with severe motor disability. However, it has been identified that active exoskeletons are heavier, more costly, and require more energy than passive exoskeletons.

Figure 1: Neuromuscular Controller Embedded in a Powered Ankle Exoskeleton [4].

Brain-Computer Interfaces (BCI)

Exoskeletons give physical support, and controlling these devices naturally remains problematic, especially where the user has motor disabilities. BCI offer a way of establishing an interface between the brain and other gadgets. BCIs detect brain signals produced by the individual and convert them into robotic commands that help to operate assistive devices such as exoskeletons. The process of controlling the movement of a device directly through the brain without the need for conventional manual controls makes BCI most suitable for persons with severe motor disabilities who may not be able to uptake the initial form of input devices.

Non-Invasive BCIs

Non-invasive BCIs, on the other hand, in which sensors are placed on the cap, which acquire the brain's electrical activity without surgery. EEG or fNIRS techniques can use brain signals without risking harm to the patient and are helpful as patients can control devices in the external environment [6]. Non-invasive BCIs are much more convenient than invasive BCIs. Furthermore, the risks are lower, but since these interfaces are based on surface sensors mounted on the scalp, they still do not have as high an SD resolution and are also vulnerable to noise, which impacts performance. Nevertheless, noninvasive BCIs are used actively in both basic science research and clinical trials and continue to be the focus of efforts in creating assistive technology for people with motor disabilities [7].

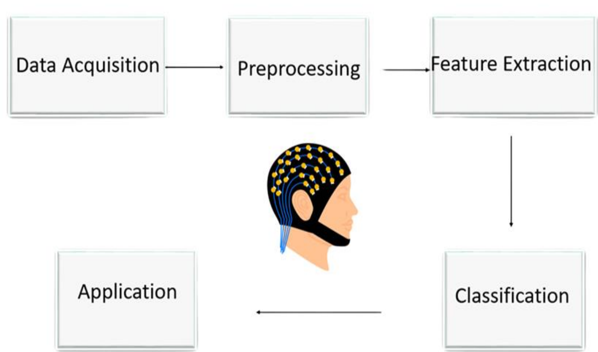

Figure 2: Biomechanical effects of stiffness in parallel with the knee joint during walking.

Functional Near-Infrared Spectroscopy (fNIRS)

fNIRS is a non-invasive functional neuroimaging that measures variation in motor-related oxygenation during motor activity. Compared to oxyhemoglobin (HbO) and deoxyhemoglobin (HbR), fNIRS is an excellent method to acquire information regarding cortical activation. While EEG records electrical activity, fNIRS monitors the hemodynamic responses, providing a view of the brain function complementary to EEG[6], [8]. This makes fNIRS remarkably better for investigating of motor control during dynamic movements such as walking since any movement interference is usually devastating to other imaging methods. In motor control studies, the following limitations of fNIRS have also been identified: limited spatial resolution and sensitivity to skin perfusion; these issues have to be resolved to enhance the credibility of fNIRS[9], [10], [11], [12], [13].

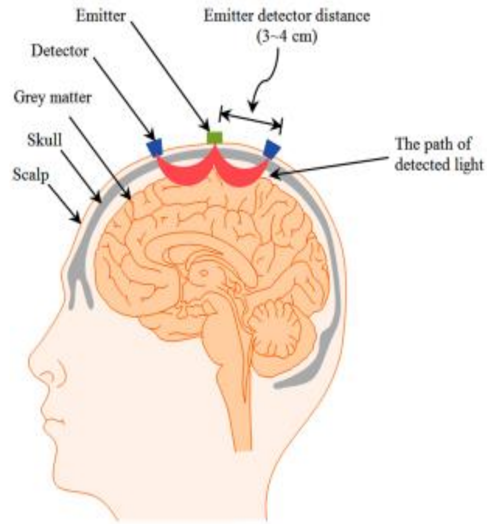

Figure 3: a) fNIRS CAP b) Motor Cortex c) Optodes[9].

LITERATURE REVIEW

fNIRS is recognized as a valuable technique for investigating motor processes, especially in rehabilitation and BCI. fNIRS assesses cortical hemodynamic response using near-infrared light wave changes in oxygenated and deoxygenated haemoglobin in the brain activity during certain motor functions. Compared to other methods, such as fMRI, fNIRS is more portable, user-friendly, and comparatively inexpensive, especially for real-time monitoring, clinical use, and home-based rehabilitation. However, fNIRS has some drawbacks, including motion artifacts and relatively low spatial resolution, which could be eliminated in subsequent studies for precise decoding of motor intention[9], [10], [18].

The use of fNIRS in motor rehabilitation has expanded substantially, especially for studying cortical dynamics for gait and walking motions. The studies have found that fNIRS efficiently identifies the brain activity related to gait initiation, adjustment, and motor control. However, the effectiveness of its application is hampered by motion artifacts due to head and body movements. Over the last couple of years, attempts to improve the functional near-infrared spectroscopy signal processing algorithms have been directed at minimizing these artifacts and increasing the space resolution. Such refinements are required for the adaptive use of fNIRS, for example, in geared-up activities such as walking, where cortical activity is quantitative and stochastic in nature.

For motor control applications, electromyography (EMG), which consists of the electrical signals associated with muscle fibers contractions, has been commonly applied. EMG has an excellent temporal resolution, enabling clinicians and researchers to get real-time readouts of muscle activation patterns suitable for prosthetic control, rehabilitation and assistive devices. However, noise affects EMG signals, and crosstalk between muscles and signals causes variability because of different areas of physiology. Therefore, the strategies for EMG signal processing and feature extraction significantly affect the applicability of control systems. Some works have directed efforts in increasing feature extraction techniques for better classification of EMG signals for increased performance of control mechanisms in prosthetics and exoskeletons[19], [20], [21], [22], [23].

They have also found that EMG signals can be suitably employed for the operation of lower-limb exoskeleton for persons with motor disabilities, especially stroke survivors. Nonetheless, much like has been summarized here, we see that non-stationarity, fundamental to EMG, and variability between people can potentially depress the operation of EMG-based control systems. These problems demonstrate the importance of using reliable signal processing algorithms and adaptive system solutions to overcome different possible real-world disturbances. Furthermore, integrating fNIRS with other signal sources, including EMG, may extend the drawbacks of every modality signal and improve the overall functionality of assistive technology.

Problem Statement

In the Brain-Computer Interface (BCI) domain, single-modality approaches utilizing fNIRS or EMG for exo-ankle demonstrate limited accuracy.

Objectives

To address this challenge, we aim to integrate a hybrid system incorporating fNIRS and EMG modalities. This hybrid configuration seeks to enhance the reliability and accuracy of BCI systems beyond the capabilities achievable through single-modality methods.

- Designing and implementing a hybrid fNIRS-EMG BCI system to analyse neural and muscular activity.
- Investigating the feasibility and efficacy of combining fNIRS and EMG modalities to enhance the reliability and accuracy of BCI systems.

Scope

- Develop a hybrid BCI system that integrates fNIRS and EMG modalities.
- Aim to overcome limitations of single-modality approaches in ankle movement assessment.
- Potential for more reliable and accurate ankle movement analysis.
- Significance for rehabilitation and assistive technology applications.
- Implications for improving the quality of life for individuals with mobility problems.

RESEARCH METHODOLOGY

This work examines the combination of EMG and fNIRS signals for quantitatively evaluating motor cortex activity with a unique concentration on the lower limb. Several subjects EMG signals were obtained to analyze a muscle’s electric activity during different movements that would reflect its neuromuscular activation[34]. At the same time, fNIRS was used to evaluate cerebral hemodynamic responses to expand the understanding of cortical activation. The modality goals seek to exploit the benefits offered by these methods; EMG, for instance, has a high temporal density while fNIRS is designed to measure brain activity, such that if employed in parallel, the constructs are provocative and would ideally result in a hybrid system with stronger signals and accuracy. The work also uses feature extraction and selection methods to select the best feature sets for classification problems to enhance motor control study.

The research was grounded on systematic when it came to data collection and preprocessing. For EMG measurement, portable electrodes were placed on lower limb muscles, and fNIRS sensors were fixed in the motor cortex to obtain precise signals. Daily movement tasks used to obtain similar muscle and brain activation patterns were used as standardized tasks where participants were encouraged to minimize interference. Acquired data was filtered: band-pass filtering for the EMG signal and motion artifact correction for the fNIRS signal. This step was considered mandatory because noise and artefacts often corrupt raw signals[35].

Materials and Methods

This cross-sectional study employed the fNIRS-EMG hybrid protocol methodology to assess cortical and muscular responses of the lower limbs during motor tasks. The hybrid modality approach was chosen to leverage the strengths of each technique: fNIRS offered information about cortical hemodynamic changes, whereas EMG recorded the electrical activity resulting from muscle contractions. All these modalities allowed the creation of a partially invasive hybrid BCI system intended for decoding motor plans. Thus, the recent study attempted to fill the gap concerning high-level cortical control mapping and muscular signals specifically for neurorehabilitation and assistive technology applications[37], [38].

fNIRS data acquisition was concerned with quantifying oxygenation changes in the motor cortex, which is part of the brain and consists of neurons that generate commands for voluntary movement. The associated hemodynamic activity was averaged for specific motor tasks, including changes in ΔO (2) Hb and ΔdO (2) Hb. EMG recorded the electrical signals from electrodes placed onto lower limb muscles, offering a definitive picture of motor unit signal wave. Combining these signals imparted a broad view of motor task execution, explicitly showing how movement's cortical and muscular aspects interact.

Subjects

The participants for the study were 20, 10 males and 10 females, aged between 20 and 35 years and were healthy. Specific inclusion criteria wanted participants to have no history of neurological disease, musculoskeletal injury, or other conditions that might affect motor performance. To control variation due to Lifestyle factors, participants were advised not to smoke, take caffeinated products like tea or coffee or indulge in rigorous vehicular activities for at least 12 hours before the experiment as instructed in 7. This precaution minimizes interferences in cortical and muscular activities as smoking and caffeine affect physiological data such as blood flow, oxygenation level and muscular co-activation [15]-[16].

Data Acquisitions

The data acquisition process was implemented so that the EMG and fNIRS signals could be recorded faithfully and simultaneously during coordinated and controlled lower-limb movements. Experimental motor tasks were executed according to the script for participants in a noise-reduced environment. Both surface EMG electrodes and fNIRS sensors were placed as strategically as possible to record the muscle contraction and the cortical oxygenation, respectively. The coordination between the two modalities was achieved in parallel to allow for the quantitative and qualitative analysis of the neuromuscular and cortical activity. The data thus obtained were stored and used offline for further feature extraction and classification. This systematic approach to data acquisition was crucial to arriving at the intended objectives of the study, as well as the generation of valid results[9].

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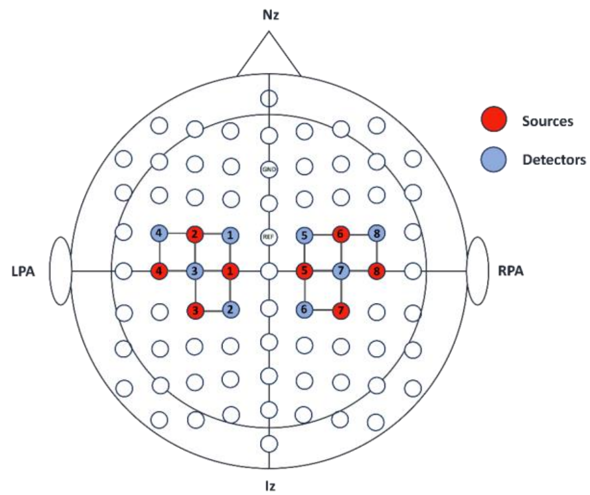

Figure 4: Optodes placement on the motor cortex

Figure 5: Experimental Setup for fNIRS.

EMG Setup

Surface EMG data were recorded for 12 muscles positioned on the subject's legs. Six electrodes were assigned per leg, four targeting major muscles essential for ankle functionality. Therefore, the electrodes were placed on the tibialis anterior and gastrocnemius muscles. The exact location of electrodes was used following the international 10–20 system, which allows for reliable signal acquisition despite inter-group variability. Skin preparation was performed by using cleaning electrode sites with alcohol wipes to minimize the impedance to obtain better signal quality. The electrodes were cemented with adhesive pads to reduce movement interference while performing tasks. The raw EMG signals were recorded at a sampling frequency of 1000 Hz so as to acquire the entire bandwidth of the muscle signals. Any of these signals were later analyzed to extract stimuli pertinent to the execution of motor tasks, including the timing and intensity of muscle activation[39].

[a] [b]

Figure 6: [a]EMG Electrodes [b]EMG Placement.

Experimental Paradigm

The exact nature of the different motor tasks was to be investigated during the experimental procedure to enable the assessment of cortical and muscular metabolic activity in relation to lower limb motor tasks. One session took 860 seconds and was done with switching between work and break times. Four different strains of lower-limb movements were conducted by the participants to activate both cortical and muscle areas. These were activities such as dorsiflexion of right ankle joint, plantarflexion of right ankle joint and lateral movements in relation to the ankle joint resembling gait patterns[40].

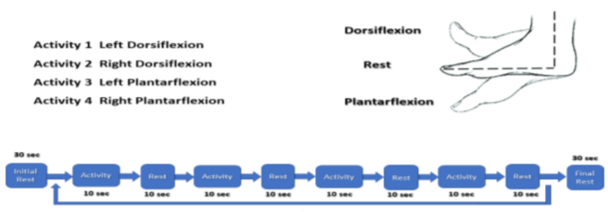

Figure 7: Sequence of experimental protocol.

Data Pre-processing

In this study, pre-processing of raw fNIRS and EMG data was done to eliminate noise and unwanted feature extraction from signals necessary for the completion of the task.

fNIRS Pre-processing

The fNIRS data recorded during the experiment were preprocessed with the aid of the MNE toolbox. Thereby, motion artefacts were detected and subsequently removed by applying precautionary artifact removal algorithms to identify adequate hemodynamic signals corresponding to cortical activity. The bandpass filter was used to limit the range of frequency to 0.01- 0.2 Hz which was chosen to capture slow hemodynamic response related to brain activity. To increase the computational speed, the data was down-sampled from the original sampling rate of 30Hz to 10 Hz while maintaining enough temporal resolution required for decoding of motor intentions. The collected data were then divided into task-related epochs corresponding to the activity and the break time of the experimental schedule.

EMG Pre-processing

The same preprocessing pipeline was applied to EMG data set in order to compare and align with the fNIRS data set. Before analysis of the signals, the raw EMG signals were filtered using band pass filters to include frequency range of 10Hz-

1000Hz to capture muscle activity while excluding other noise and baseline drifts. Windowing was used to divide data into evenly overlapping time frames so that features could be extracted for each of the motor tasks. These datasets were then down sampled to 10Hz, which was equivalent to preprocessing of fNIRS signals and sequential fusion during hybrid BCI examination.

RESULTS ANALYSIS

Preprocessing is very important in preparing the signals from EMG and fNIRS for use in classification processes. For the EMG signals, several time-domain features such as root mean square (RMS) and wavelet transform has been calculated in order to evaluate muscle activity. These features give an account of the amplitude and frequency characteristics of the muscle's electrical activity. In the case of fNIRS, only the amplitude of the hemodynamic response, signal slope and time domain parameters like peak and mean are extracted to describe the pattern and flow of cortical oxygenation. The integration of both modalities was beneficial in capturing more features on the motor imagery task, and the features extracted were fine-tuned using Particle Swarm Optimization (PSO) aims at selecting the best attributes among the features extracted. This provides a richer classification and offsets the inherent dangers of just getting better channels of the same feature since the feature set improves on the classification accuracy and gives a proper representation of the neural muscular signals during executing of motor tasks[5].

Wavelet Transform applied to features of fNIRS

Wavelet transform is one of the powerful techniques in analyzing time series data such as fNIRS Signals as the method can show both frequency and temporal nature of the data. The CWT is used routinely for feature extraction from fNIRS signals for classification or grouping analysis. The Continuous Wavelet Transform (CWT) is defined as:

$$W\psi(s,t) = \int -\infty\infty x(\tau) \cdot \psi \times (s\tau - t) d\tau \qquad (1)$$

Where:

- $W\psi(s,t)$ is the wavelet transform at scale sss and time t,
- $x(\tau)$ is the fNIRS signal,
- ψ is the mother wavelet,
- s is the scale (related to frequency),
- t is the time.

Variance

Variance is a basic tool for quantizing the dispersion of signal amplitude with respect to the time domain. However, to eliminate variability in the types of signals being compared, variance might prove useful in the case of fNIRS signals since they bear information about changes in the brain functions. Mathematically defined as:

$$Variance = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2 \qquad (2)$$

Where:

- N: Number of samples in the signal.
- x_i: Signal amplitude at sample iii.
- μ: Mean of the signal

Variance expresses the ability or occupancy of other activities or volatility, that is, a deviation from the mean level of oxygenation in a given region of the brain.

Standard Deviation

Another statistical features most commonly used is a standard deviation (SD) that characterizes signal amplitudes spread or dispersion around mean value. Standard deviation is better than variance since it is in the same unit as the data set hence it is more understandable in some circumstances. In the case of the fNIRS signals, standard deviation will be beneficial to determine the change in the oxygen level during different tasks or circumstances.

The formula is:

$$Standard\ Deviation\ (SD) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \quad (3)$$

Where:

- x_i: Signal amplitude at sample i,
- μ: Mean of the signal
- N: Number of samples.

When calculating standard deviation of fNIRS signals, evaluating variability and further employing the obtained result in exploratory analysis or classification studies.

Skewness

Skewness is another measure of the degree of departure of a distribution from symmetry which is standardized by the standard deviation of the sample. In the case of fNIRS signals, which measure dynamic changes in oxygenated and deoxygenated hemoglobin concentration in the brain, skewness helps to understand the nature of the signal's amplitude distribution. While measures such as mean and variance essentially tell the reader a signal's central tendency and spread, skewness tries to answer the question of whether values are skewed towards being more extreme or less extreme, adding another dimension to the reader's understanding of the signal.

$$Skewness(S) = E_x\left(\frac{S - \delta}{\sigma}\right)^3 \quad (4)$$

The symbols with specific notation are Where is the expected value of S, and is the standard deviation of δ.

Signal Energy

Signal energy is among the basic features considered in fNIRS; it is a measure of the accumulated power of the signal over time. It is calculated as the sum over the squared amplitudes of the signal, thus periodic fluctuations which are positive in sign and negative in sign are treated equally. In fNIRS, the signal energy characterized the magnitude of fluctuations of oxygenated and deoxygenated hemoglobin levels, which are tightly connected with neuronal activity. Signal energy might best be described as high if the energetic indices correspond to high cognitive or motor loads and low if the energy levels correspond to rest. When fNIRS data is divided into task-specific epochs and energy is computed for each segment, it is easier for researchers to view how the neural activity changes from one segment to another, or from one brain region or experimental condition to the other. Signal energy is also helpful in detecting deviations like motion that appear as high energy while other signal look like they are flat lined and hence low energy will be determined. Furthermore, the signal energy is another useful input for the machine learning algorithm to classify the brain states or cognitive task. Because of its relative ease of interpretation, signal energy forms a central parameter when qualitatively or quantitatively analyzing the fNIRS data.

The formula is:

$$Energy = \sum_{i=1}^{N}|x[n]|^2 \quad (5)$$

Where:

- x[n]: The amplitude of the signal at sample n,
- N: Total number of samples.

The square of each amplitude guarantees that negative and positive signal values contribute equally to the amount of energy.

Root Mean Square (RMS)

The signal range is just a simple measure of the extent to which the values are spread out; this is obtained by subtracting the lower signal's general amplitude from the higher signal's general amplitude. In an fNIRS analysis, a broad range may reflect high activity or include artifacts, whereas a narrow range can reflect very low activity or bad sensor position. In this way, the range enables the researchers to instantly get the overall impression of the signal's variability and strength.

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2} \tag{6}$$

Range

The range of a signal is one of the simplest statistical measures that quantitatively describe the variability in a set of values, determined by the difference between the maximum and minimum amplitudes. In fNIRS analysis a large range may represent high neural activity or may contain artifacts while a small range may correspond to steady state or bad positioning of the probe. With range, the variability as well as the strength of a signal can be assessed almost instantly by the researchers.

$$\text{Range} = V_{\max} - V_{\min} \tag{7}$$

Mode

The mode indicates a value that can recur most often within the signal. As for fNIRS, the mode tends to represent the primary state of the oxygenation specifically in the state of rest. It offers hints as to the signal distribution's center point, and one can use these results to recognize regularity that is consistent across different tasks or between different experiment conditions.

Minimum and Maximum

The minimum value of the signal points to the time in the Observation window when the signal strength was at the lowest value. In fNIRS analysis, this metric is important for finding some low oxygenation points that can be related to changes in tasks or between tasks rest. The monitoring of the minimum assists in determining the primary levels of neural activity, as well as assessing sensor problems.

The maximum value is the value that defines the greatest frequency amplitude in the certain signal. This is the main reason why peaks in fNIRS data are frequently used to indicate that there are many neural activities or quickly changing oxygenation. Examining the maximum values may allow for understanding of qualitatively different movie-specified activations as well as quantifying remaining abnormally high spikes resulting from motion artifacts or physiological noise.

Median

The magnitude of the median is the middle of the signal levels if all signal levels are arranged in increasing order. It is a strong index and numbers average specifically helpful for fNIRS that eliminates the impact of outliers or noises. The median also gives a clear measure of the most representative signal level especially in cases where the data presents much noise or the channel shows once in a while exception level.

Kurtosis

Kurtosis is a method used to evaluate how acute the peak of the distribution of fNIRS signals is. It helps know the dispersion of the data points in the tails, which can provide a clue about the shape and more particularly the concentration of this distribution. It also facilitates in judging the shape of the hemodynamic response and also whether the values of the signals follow a standard normal distribution or not.

$$Kurtosis(S) = E_x\left(\frac{S-\delta}{\sigma}\right)^4 \quad (8)$$

Entropy

Entropy quantifies the level of chaos in a signal or in other words how much disorder there is in the signal. In fNIRS entropy refers to how random and stochastic the changes in oxygenation are over time. High entropy is said to represent diverse neural responses in what may be a high demand function, whereas low entropy represents perhaps more consistent or repetitive responses linked with resting. Entropy is an expressive measure for differentiating between cognition state or tasks because it describes the detailed measures of brain flow.

$$H(X) = -\sum_{i=1}^{n} P(x_i)\log_2 P(x_i) \quad (9)$$

Classification

The simplest and most common form of supervised learning includes tasks in which learning set data must be grouped into previously planned classes[5], [41]. In classification issues, the model learns from trained data where every input is linked with a particular class. Once trained, the model can predict the class of new unseen data for certain; Different classification algorithms which can be used include but not limited to; Linear Discriminant Analysis (LDA), k-Nearest Neighbor (kNN), and Support Vector Machine (SVM). Each of them has its own way of splitting the data space and making the resulting predictions.

Support Vector Machine (SVM):

Supervised Learning begins with Support Vector Machine (SVM), that is a powerful and a general classification technique based on the identification of the hyperplane that define the best separation of classes of feature space. SVM is designed to find a hyperplane that classification by providing the maximum margin between the two classes with the maximum distance of the closest points to the hyperplane known as the support vectors[21], [34].

SVM operates as follows:

1. **Linear SVM**: In the case of linearly separable data the goal of SVM is to find a hyperplane that provides the maximum margin between the classes. The hyperplane is determined by the Support vectors that are those of the data space which is nearest to the Decision line[44], [45].
2. **Non-linear SVM:** When the data distribution is not linearly separable then SVM uses the phenomenon known as the kernel trick to transform the data in to a higher dimensional space where it can be separated by a line. Examples of kernel functions include; the Radial Basis Function (RBF) Kernel, polynomial kernel, and sigmoid kernel.
3. **Soft Margin SVM:** The SVM includes a degree of misclassification within the data, which will be extensive in noisy data to the fact that it has a soft margin. This implies that for the algorithm, it is okay for some points to lie on the wrong side of the margin with others on the correct side; thus improving the general separation between the classes.

A kernel function is effective in capturing complicated decision boundary, SVM is capable of working in high dimensional space[46], [47]. It is a method good for linear and non-linear classification problems and is very useful when the number of features is larger than the number of samples. However, the computation of SVM may be quite slow, especially when working with large numbers of records and the kernel selection and the parameters tuning in the regularized formulation of the model are critical aspects.

$$f(x) = wx + b$$

k-nearest Neighbors (kNN):

K Nearest Neighbors (KNN) is a basic classification technique that is also non-parametric in nature and for classification it provides a hypothesis based on distance. The process is performed by comparing a given data point to the nearest ones in the feature space and attributing the class which is most often met in the nearest neighbors[48].

KNN operates as follows:

1. Said test data point, the algorithm computes the measure of similarity or dissimilarity between this point and all other points in the training data set with 'distance'.
2. Upon calculating each distance, k kk control the size of the neighborhood of chosen nearest neighbors, where k it could be greater than the vectors' dimension. Here the parameter «kkk» is an integer which is specified by user and it shows the number of neighbors for which we are taking into consideration[49].
3. The class is then determined as the majority class among kkk nearest neighbors out of test point.

These assignments of weights demonstrate that the value of kkk is a key to the functioning of kNN[50], [51]. A small kkk increases the amount by which the algorithm reacts to noise in the data, while a big kkk makes the model overly smooth, and could potentially 'miss' patterns in the data. KNN is very suitable to problems that have very complex decision boundaries or decision boundaries that are non linear since KNN doesn't make any assumption about its decision boundaries[52], [53].

A major drawback of KNN is that it can be quite computationally costly, particularly when working with large datasets since we have to use distance measure between the test sample and each of the training data sample. Further, KNN is sensitive to noise in data and excessive values may affect the distance of two points in higher dimensions because of the curse of dimensionality. Value of 'k' can be given as:

$$k = \sqrt{\frac{N}{2}} \tag{11}$$

where 'N' represent the number of sample in the training set.

Optimal Feature combination

Feature selection is the action of choosing from a pool of larger feature set which of them has the most useful in improving a model performance. In machine learning and signal processing context features are derived from input data to model its inherent behavior characteristics. However, not all features are useful and including a large number of features will lead to an overfit model while having few an underfit model. The purpose of feature subsets selection is, therefore, to make an optimal combination of the features to achieve the best output, as measured by accuracy or any other performance standards. This process is essential in the reduction of necessary computations, the enhancement of generalization of the model as well as diminishing the redundancy of features[54], [55].

How PSO Works for Optimal Feature Combination

Specifically, when it comes to feature selection, it is possible to use PSO in order to determine the best set of features given a larger set of features[59]. Here's how PSO works for optimal feature combination:

Initialization of Particles

In fact each particle of the swarm is a candidate to be a feature combination, in which each dimension of the particle is corresponding to a certain feature. For instance, if you're dealing with an example with 10 features, each particle could be of depth ten, where a single depth might lie in the bin of 0 = feature not chosen, 1 = feature chosen. The positions of the particles at the start of the optimization process are arbitrary and denote various feature characteristics.

Fitness Evaluation

Each particle's fitness is calculated by training a model with the feature set specified by the particle and then determining the performance of the model with a performance measure, such as accuracy. Thus, the fitness score higher means that feature combination provides better performance in the model.

Velocity and Position Update

After the fitness function of all particles has been assessed, the particles recalculates their position and velocity[60]. The position update is guided by two factors:

- **Personal Best**: Every particle maintains the best feature combination indicating fitness that it comes across.
- Global Best: The particle is also attracted to the global best feature combination identified by all the swarms.

The velocity update contributes to the directions of particles towards the best solution through the successful combination of exploitation to focus on the best solution found and exploration to search more area.

Convergence

The swarm goes on to hone, with particles of the swarm making movements at different times. In the course of the successive iterations, the particles get nearer and nearer to the optimal or at least close to it value of feature combination that provides the best performance of the classification model.

1. As applicable for feature selection, PSO performs well to navigate through the feature space despite not needing to search intensively. It is particularly useful when the type of the functions relating features is unspecified, or when it is logarithmic, exponential, or some other function. PSO gets to increase the accuracy and generality of feature subset in machine learning models, making it guarantee only the best features[61].

Table 1:Optimal feature combination of 18 Subjects from Hybrid Modality

	fNIRS_Wavelet Transform	fNIRS_Variance	fNIRS_Standard Deviation	fNIRS_Skewness	fNIRS_Signal Energy	fNIRS_Root Mean Square	fNIRS_Range	fNIRS_Mode	fNIRS_Minimum	fNIRS_Median	fNIRS_Mean	fNIRS_Maximum	fNIRS_Kurtosis	fNIRS_Entropy	EMG_Wavelet Transform	EMG_Variance	EMG_Standard Deviation	EMG_Signal Energy	EMG_Root Mean Square	EMG_Mode	EMG_Median	EMG_Mean	Total Selected Features
S1		√	√	√	√	√				√			√	√					√		√		10
S2	√		√						√						√				√	√	√	√	8
S3	√		√	√	√	√		√	√		√		√	√	√	√	√			√	√		15
S4	√	√	√	√		√	√	√		√	√	√	√	√	√	√	√	√	√	√	√		19
S5	√	√	√	√	√	√			√				√	√	√		√	√	√		√	√	15
S6	√	√		√	√	√	√			√	√		√	√	√	√	√			√	√	√	16
S7		√	√					√			√		√	√	√		√	√		√	√	√	12
S8	√	√	√		√	√			√			√			√	√	√	√	√	√			13
S9	√		√			√		√	√		√	√						√	√	√		√	11
S10					√				√					√		√		√	√		√		7
S11					√			√				√	√	√		√	√	√		√			9
S12	√	√				√				√	√	√	√		√		√	√	√		√		12
S13	√	√	√		√		√		√				√	√				√	√		√		11
S14	√		√	√		√	√	√			√	√		√	√		√		√	√			13

Table 2: Optimal feature combination of 18 Subjects from fNIRS Modality

	fNIRS_Wavelet Transform	fNIRS_Variance	fNIRS_Standard Deviation	fNIRS_Skewness	fNIRS_Signal Energy	fNIRS_Root Mean Square	fNIRS_Range	fNIRS_Mode	fNIRS_Minimum	fNIRS_Median	fNIRS_Mean	fNIRS_Maximum	fNIRS_Kurtosis	fNIRS_Entropy	Total Selected Features
S1	√	√	√	√	√	√		√		√	√	√	√	√	12
S2	√	√	√		√	√	√	√	√				√		9
S3	√	√	√	√	√	√					√	√	√		9
S4	√	√		√		√	√	√		√			√	√	9
S5	√		√		√	√		√		√	√			√	8
S6	√	√	√	√	√					√	√	√		√	9
S7	√	√	√	√						√	√	√	√		8
S8		√	√	√			√			√	√	√	√		8
S9	√	√	√	√	√	√		√	√	√	√	√	√	√	13
S10	√	√	√	√	√			√		√		√	√		9
S11	√	√	√				√		√	√			√		7
S12	√	√	√	√	√		√	√	√	√	√		√		11
S13	√				√	√			√			√	√		6
S14	√		√	√	√	√		√	√		√	√	√	√	11
S15					√		√	√		√	√	√	√		7
S16		√	√	√	√	√	√	√			√			√	9
S17	√	√	√		√	√	√				√	√	√	√	10
S18	√		√	√		√	√		√	√	√	√	√		10

Table 3: Optimal feature combination of 18 Subjects from EMG Modality

	EMG_Wavelet Transform	EMG_Variance	EMG_Standard Deviation	EMG_Signal Energy	EMG_Root Mean Square	EMG_Mode	EMG_Median	EMG_Mean	Total Selected Features
S1	√	√	√				√		4
S2	√				√		√	√	4
S3	√	√	√			√	√		5
S4	√	√	√	√	√	√	√	√	8
S5	√	√	√	√	√				5
S6	√	√	√	√		√			5
S7	√		√	√	√	√	√	√	7
S8			√	√		√		√	4
S9			√			√	√		3

S10			√	√	√		√		4
S11				√		√	√	√	4
S12		√		√	√				3
S13		√			√	√			3
S14			√			√		√	3
S15		√	√		√				3
S16	√			√	√	√	√		5
S17	√	√				√	√	√	5
S18	√	√			√	√	√	√	6

Optimal Feature Combinations Using LDA-Based Fitness Evaluation

Based on PSO with LDA as the fitness evaluation model, this section reports the features which have the highest performances in the different experiments. First, there are results for the combined EMG and fNIRS features, as well as results for the individual modalities for all 18 subjects[62].

Feature Selection of fNIRS Only (From All the Subjects)

The fNIRS features alone obtained across the 19 subjects are depicted in Table 2 along refined feature combinations. By applying LDA to perform the feature selection, the present analysis identifies the fNIRS features responsible for the highest classification accuracy irrespective of EMG signals.

EMG only Features for all subjects (Selected Features)

Table 3 presents the best feature then selected for EMG data from the nineteen subjects as discussed above. In this study, the combined EMG features are examined to find the best features in classification tasks associated with lower limb motor activity by using LDA as an evaluation model.

Comparison of Average Classification Accuracy with Reference to Modalities and Models

Figure 9 presents the average classification accuracy achieved using three different machine learning classifiers: In this research, Linear Discriminant Analysis (LDA), k-Nearest Neighbors (KNN), and Support Vector Machines (SVM) are used. The analysis was performed across three modalities: of EMG + fNIRS, fNIRS only and EMG only. The results are summarized as follows:

Hybrid Modality Outperforms Individual Modalities

The average accuracy of the classifier was highest in case of the proposed hybrid modality throughout the experiments exhibited the importance of the blended feature of EMG and fNIRS. This superior performance demonstrates the benefits of the union of the two modalities since more significant and diverse details of the lower limb motor tasks were acquired by both systems.

LDA: The Most Effective Classifier

KNN and SVM: AS competitive as it was, it was outperformed by LDA.

KNN and SVM were compared with LDA and they were found to be close in accuracy to that achieved by LDA but never accomplished it. The findings imply that, although, these classifiers would be able to manage these pieces of data, they may not optimally employ the feature set in the way LDA does in this case.

Modality Comparison

- **Hybrid Modality:** Had the best performance of all classifiers with LDA recording the highest accuracy.
- **fNIRS Modality:** Combined technique also demonstrated decent results with LDA being the highest among all classifiers.
- **EMG Modality:** Got the lowest average accuracy and hence it shows that using EMG

alone discriminates lesser information than that of fNIRS or hybrid.

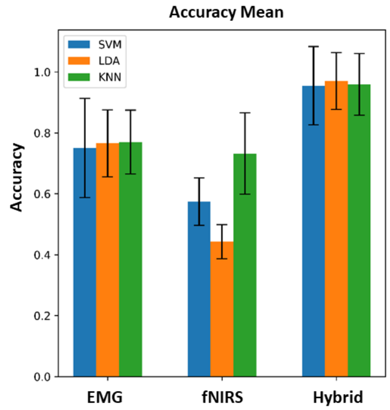

Figure 9: compares the mean classification accuracies of using different classifiers (kNN, SVM, LDA) for overlapping combined all modality

Computational Cost Analysis

Figure 10 presents the computational cost for training and testing across the three modalities: and the three configurations which include fNIRS-only, hybrid (EMG + fNIRS) and EMG-only. Due to the complexity in processing of the hemodynamic signals, the fNIRS modality took more time compared with the hybrid modality that combines the features of both EMG and fNIRS signals. Consistent with the signal processing requirements involved in the estimation of the respective modalities, the EMG-only modality incurred the lowest computational cost. In this analysis, the compromise between computational speed and the richness of the signal being extracted for each modality is explained.

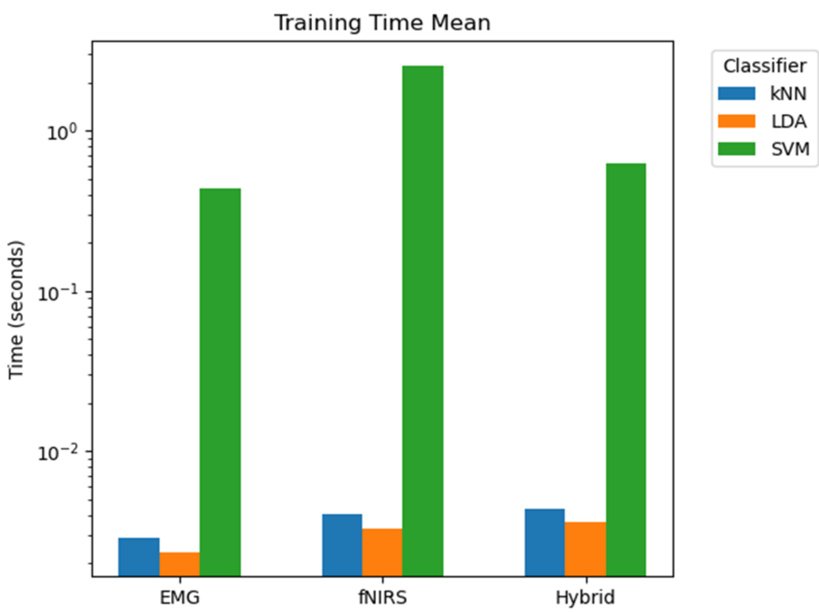

Figure 8: Computational time of training and testing

Number of Features Selected for Optimal Combinations

Figure 11 illustrates the minimum and maximum number of features selected for the optimal combinations across the three modalities: EMG, fNIRS and a combination of both systems (EMG and fNIRS). The chosen EMG modality had between 3 and 8 features, which was fewer than in the other modalities. The fNIRS modality, we selected a wider range, starting with at least 6 and at most of 13 features to show the level of difficulty of working with hemodynamic data. The hybrid modality that had the widest range of selectivity operated between 7 and 19 features in order to achieve maximum classification benefits as given by the integration of both EMG and fNIRS data.

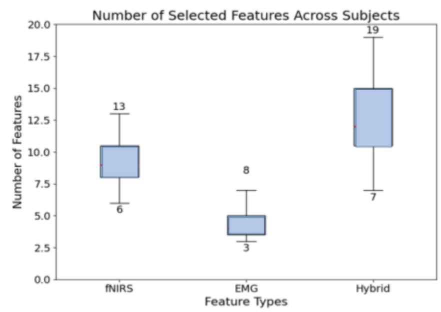

Figure 9: Minimum and maximum feature selected with the view of achieving the best combination

Final Classification Results Across All Subjects

Figures 12, 13, and 14 present the final classification results for all 19 subjects across the three modalities: as EMG/fNIRS or EMG only and fNIRS only). It could be observed that the hybrid modality always provided the highest classification performance for every subject thus confirm the usefulness of a fusion of EMG and fNIRS features. The results obtained with the EMG-only modality were superior to those achieved with fNIRS only, underlining efficiency of the former in obtaining the data on motor task implementation. Yet, fNIRS offered additional useful information when applied alongside the main measurement techniques, primarily EMG in this study's hybrid approach, presented the best outcomes.

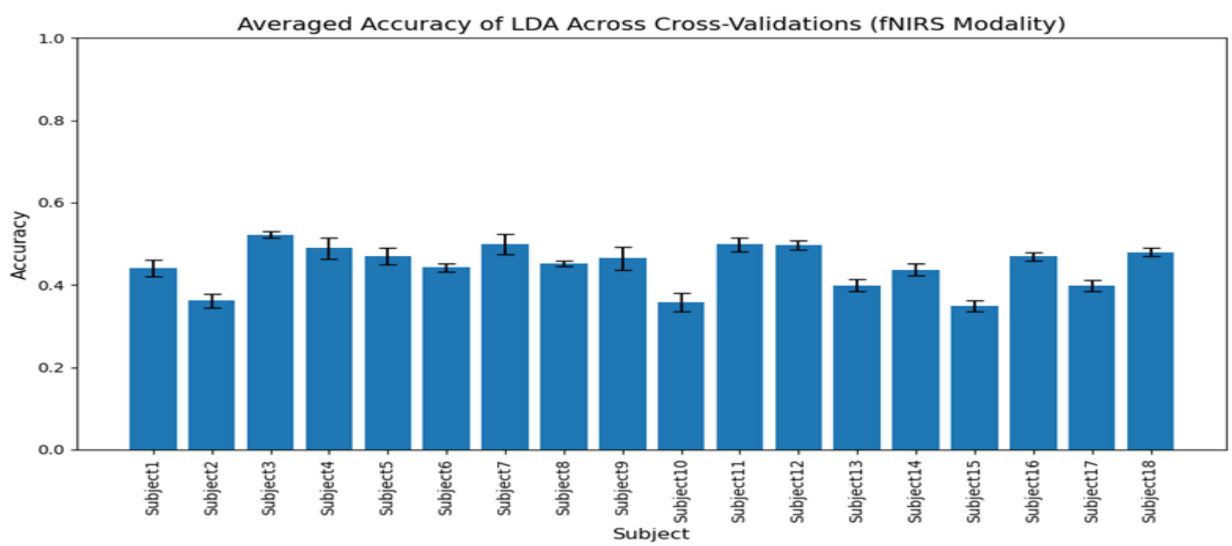

Figure 10: Accuracy chart of 18 subject using fNIRS modality

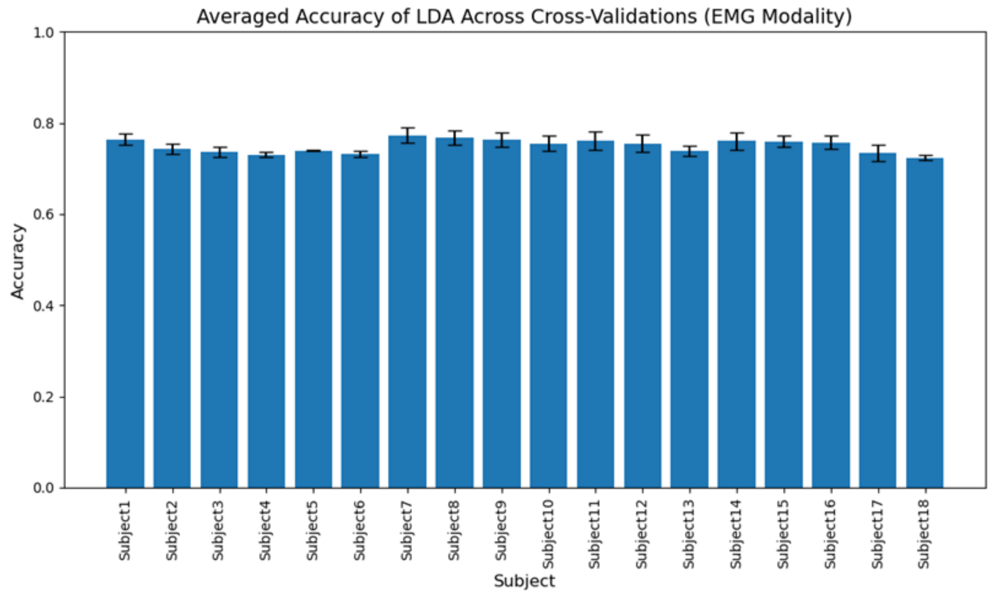

Figure 11: Accuracy chart of 18 subjects using EMG

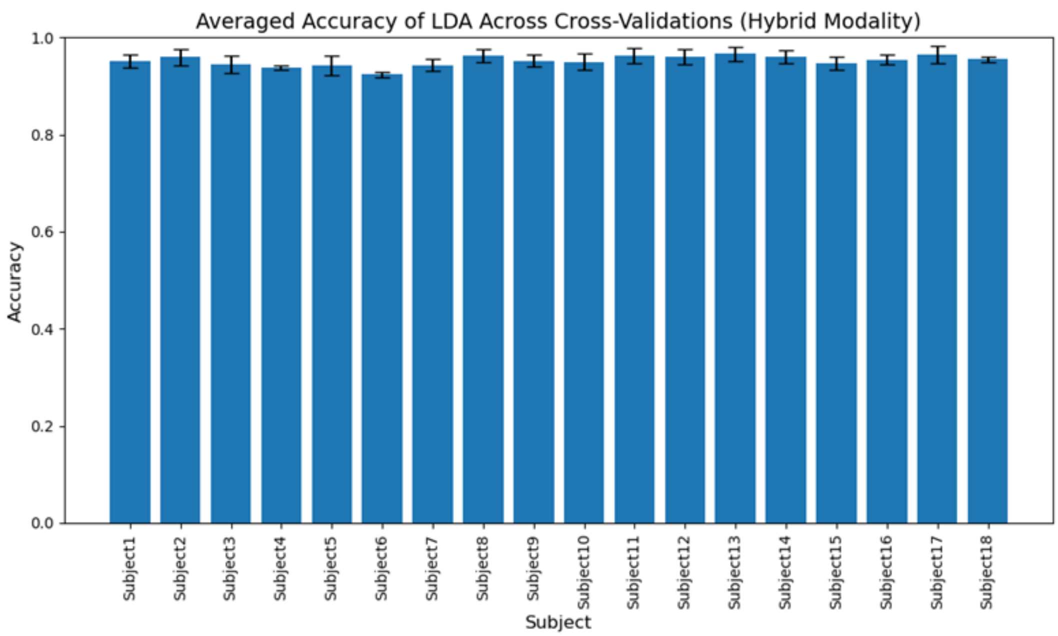

Figure 12: Accuracy chart of 18 subjects using EMG

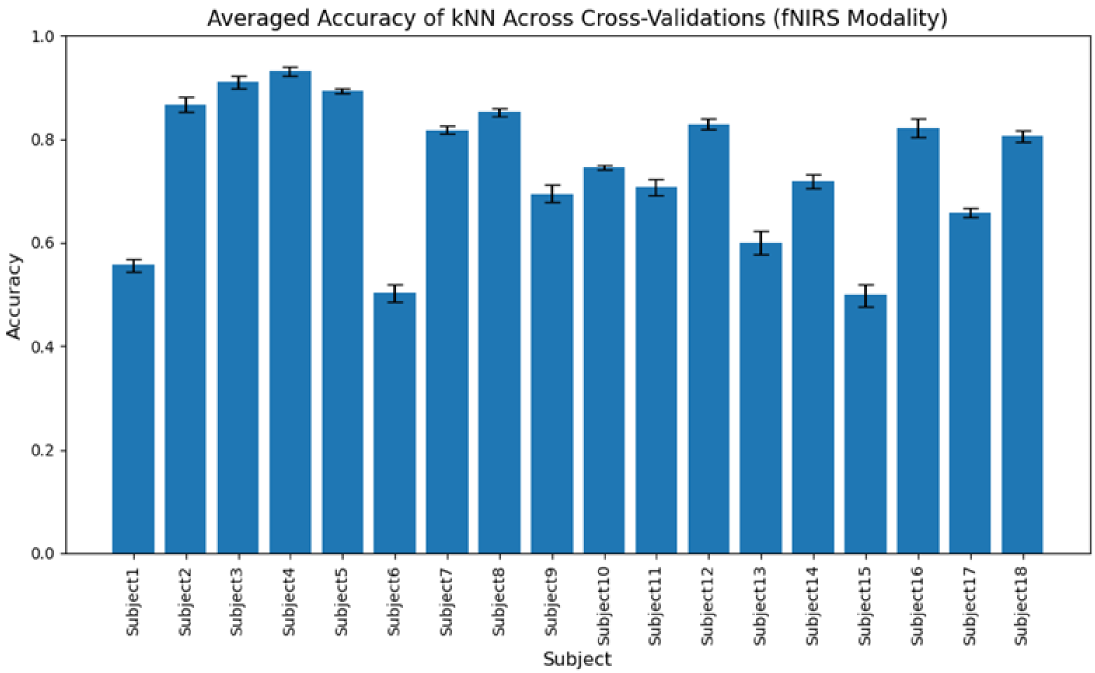

Figure 13: Accuracy chart of 18 subject using fNIRS modality

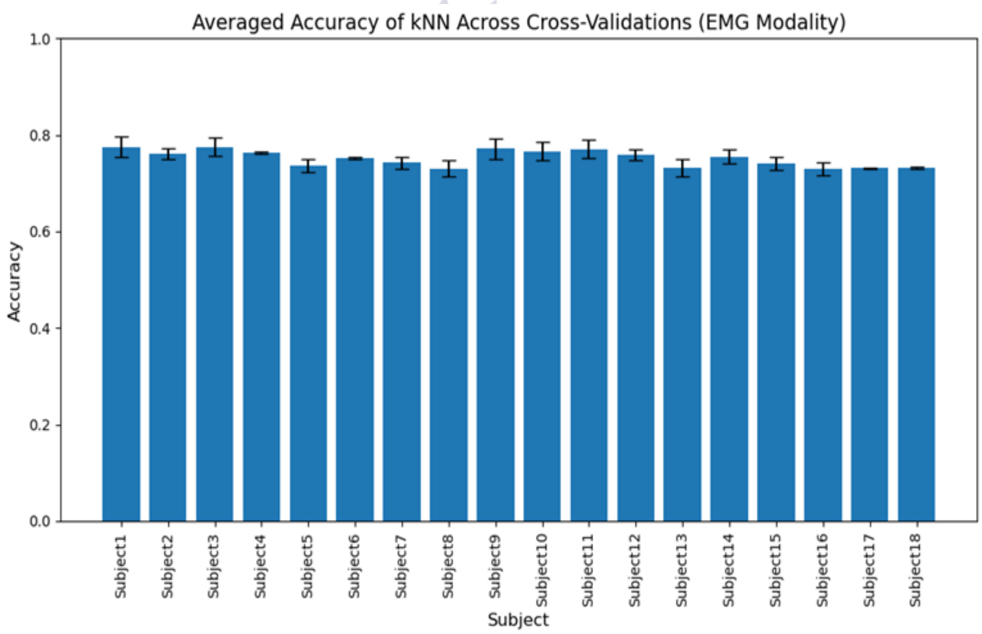

Figure 14: Accuracy chart of 18 subject using EMG modality

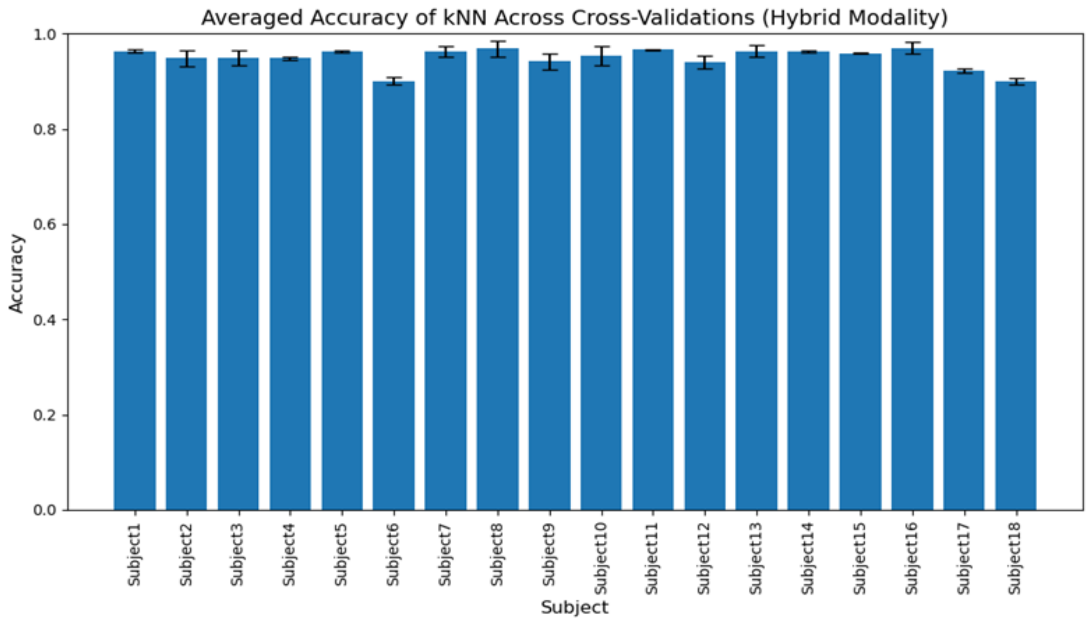

Figure 15: Accuracy chart of 18 subject using Hybrid modality

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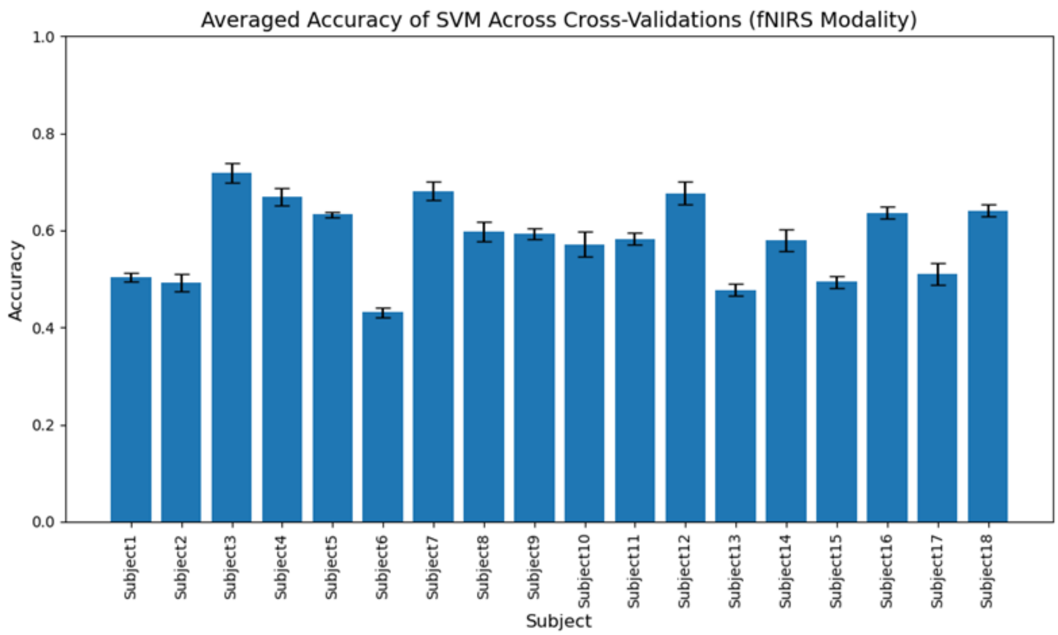

Figure 16: Accuracy chart of 18 subject using fNIRS modality

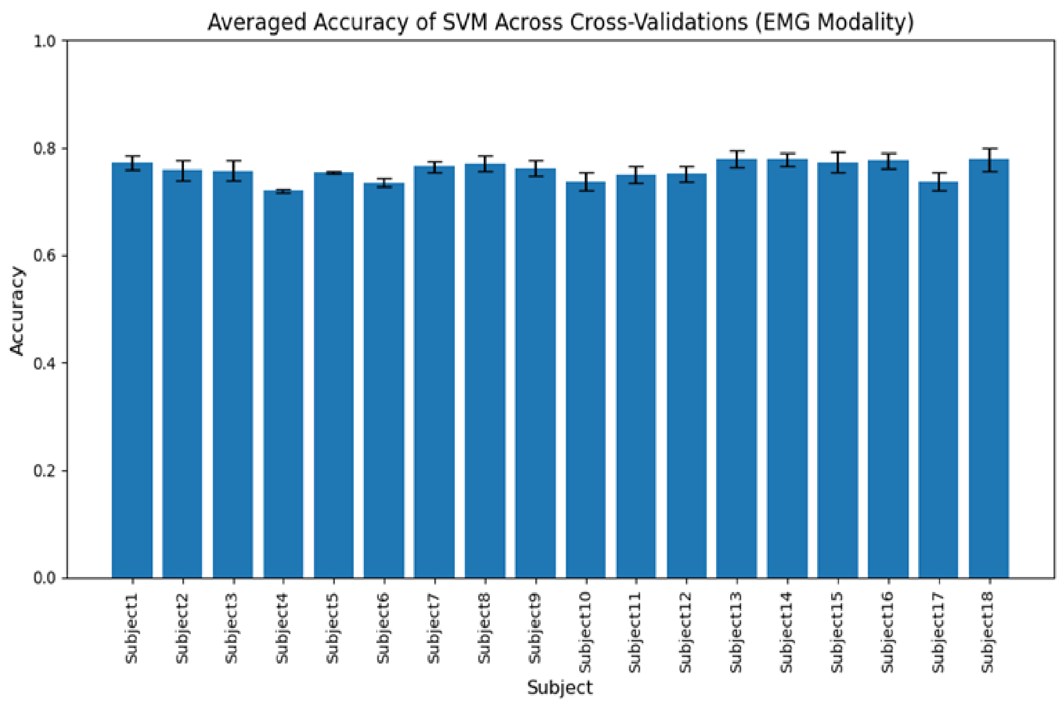

Figure 17: Accuracy chart of 18 subject using EMG modality

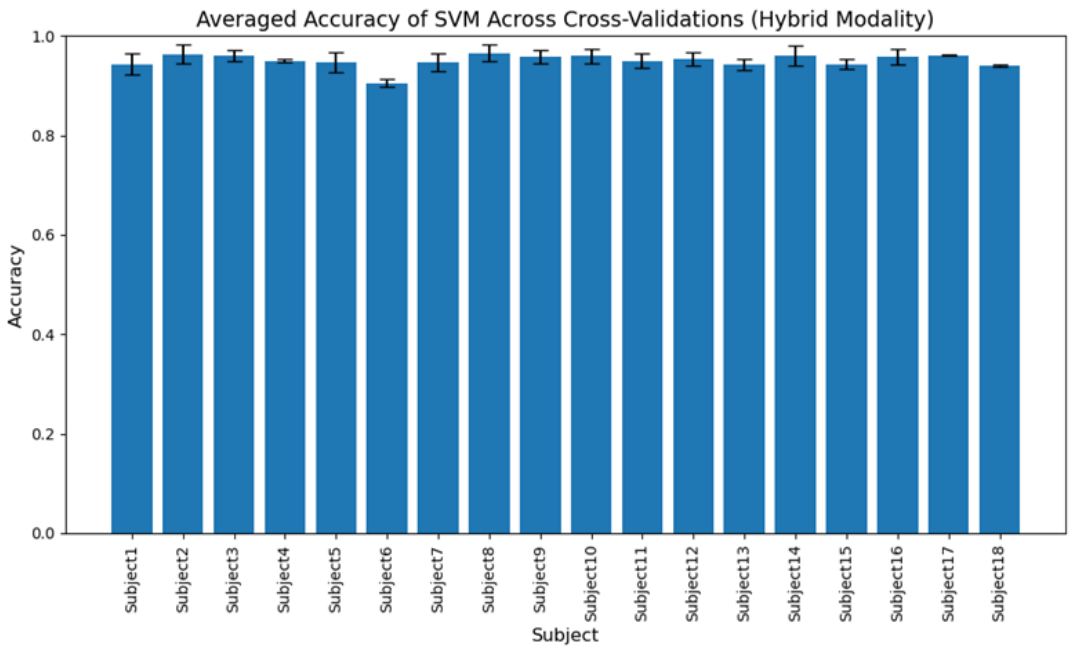

Figure 18: Accuracy chart of 18 subject using Hybrid modality

DISCUSSION

The combination of EMG and fNIRS has been used sequentially as single modalities to study either motor control and cortical activity. EMG outperforms others in the ability to record electrical signals produced during muscle contractions while providing time density that facilitates the investigation of fast neuromuscular processes. EMG is useful in evaluating muscle activities, fatigue, and rehabilitation of motor tasks. Nevertheless, the implementation of EMG-based analysis has certain drawbacks when used independently. Possible signal noise coming from motion artifacts, cross-talk between muscles and variations in position of electrodes affect the quality of the produced signals. Therefore, the greater problem of feature extraction arises, not to mention situation where fine demarcation between various motor activities is needed[63].

As well, fNIRS has been found as a sensitive and potent modality for evaluating cortical hematocrit, including both oxyhemoglobin and deoxygenated hemoglobin. This allows an understanding of brain function with the help of oximetry, which compares the concentration of oxygen-rich and poor blood in response to motor tasks. The advantages of using fNIRS for neurorehabilitation and development of brain-computer interface were underlined by Johnson et al. since the underlying cortical activity in these fields is vital. Nonetheless, fNIRS has a relatively slow time resolution compared to EMG making it difficult to detect fast neural activities. Moreover, fNIRS is known to be more susceptible to motion artifacts than other neuroimaging techniques, such that the data collected contains motion artifacts and needs much preprocessing. The present study pointed out the inherent limitations of both modalities; therefore, it is crucial to design hybrid models based on the synergism between them[3].

In recent years, research has been done on combining EMG with fNIRS into a single system with encouraging findings. Together with muscle activity obtained by EMG, the classification accuracy was enhanced using fNIRS's cortical hemodynamic data in upper-limb movements. This was a more informative approach to probing the relationship between cortical and neuromuscular functions for the patient. Moreover, the role of hybrid systems in neurorehabilitation is that the integration of multiple data sources produced more accurate predictions regarding patients' prognosis than single-modality methods. But these assessments are mainly concerned with the discrimination of upper limb and: especially hand grasping and reach; targets that are relatively simple compared to the tasks seen in lower limb rehabilitation. Gait and balance are complex movements of the lower limbs therefore their analysis requires unique protocols owing to the interaction of muscles and motor cortex[8].

CONCLUSIONS AND RECOMMENDATIONS

Conclusions

The result of this research offers a definite protocol for classifying and applying fNIRS and EMG data.

- This study explored the merging of EMG and fNIRS data to analyze the motor cortex, focusing specifically on lower limb movements associated with the ankle sensors.
- In contrast to conventional methods that analyze these signals independently, a hybrid classification framework has been implemented to enhance accuracy.
- Three classifiers—K-nearest neighbors (KNN), Linear Discriminant Analysis (LDA), and Support Vector Machines (SVM)—were evaluated, indicating that the integration of multimodal data enhances classification accuracy performance.
- Particle Swarm Optimization (PSO) was applied to refine feature selection, further optimizing the models.
- The results indicate that various classifiers respond distinctly to feature selection, underscoring the necessity for customized preprocessing techniques.

These findings contribute to advancements in motor rehabilitation and brain-computer interface (BCI) research, showcasing the potential of multimodal signal processing. Future research could explore deep learning models, real-time implementation, and larger subject groups to validate and expand on these results.

Recommendations for Further Work

The following recommendations and suggestions aim to advance this research towards the development of a cutting-edge fNIRS-BCI system:

- Future investigations should explore integrating multimodal data using techniques like fMRI or EEG for a comprehensive understanding of brain activation patterns across tasks. Combining these modalities allows researchers to gain deeper insights into neural processes and improve brain-computer interface accuracy. Implementing deep learning algorithms can enhance fNIRS-BCI system efficiency. Access to improved datasets and varied subjects enables deep learning models to effectively learn complex fNIRS data patterns.

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