



A Novel Deep Learning Classifier and Genetic Algorithm based Feature Selection for Hybrid EEG-fNIRS Brain-Computer Interface

T.V. Padmavathy^{1*}, M. Pravin Kumar², M. Shakunthala³, M.N. Vimal Kumar⁴, S. Saravanan⁵

Abstract

Brain-Computer Interface (BCI) approaches exhibit remarkable potential in neuro prosthetic applications. Good BCI system must be compact, decreasingly intrusive, have superior accuracy in classification accuracy as well as effective one. In the form of two popularly employed non-intrusive brain imaging techniques, namely, functional near-infrared spectroscopy (fNIRS) and Electroencephalography (EEG), BCI system is included frequently into hybrid BCI system design, based on their complementing characteristics. In this work, the objective is to examine if early temporal information obtained from channels of fNIRS and singular EEG on every hemisphere is utilized for improving hybrid EEG-fNIRS BCI system's efficacy and accuracy. With the expectation of noteworthy BCI performances on an overall, the abilities of integrating EEG and fNIRS recordings with benchmarked Deep Learning processes have been investigated. In this research work, a fine-tuned genetic algorithm's variant is used for selecting few features and deciding optimum feature mix to classify fNIRS signals in BCI system. In multi-modal recording technique, DNN's accuracy in classification is evaluated and compared with standalone EEG, fNIRS and other classifiers like LDA and SVM. The performances of BCI can be substantially enhanced by using multi-modal recordings, which yield hemodynamic and electrical information of brain activity, along with modern non-linear Deep Learning classification processes.

125

Key Words: Functional Near-Infrared Spectroscopy, Electroencephalography, Linear Component Analysis, Support Vector Machine, Brain-Computer Interface, Deep Neural Network, Genetic Algorithm.

DOI Number: 10.14704/nq.2020.18.9.NQ20224

NeuroQuantology 2020; 18(9):125-134

Introduction

Due to its several benefits, which include compactness, easy usage, and scalability, in comparison with functional magnetic resonance imaging, the hemodynamic reactions could be acquired with commendable ease compared with functional near-infrared spectroscopy usage (abbreviated as fNIRS) [1]. The fNIRS demonstrates much lesser vulnerability towards electrical noises and least sensitivity to artifacts of motion compared to EEG. Particularly, fNIRS is found to be

highly resilient to ocular disturbances; therefore, electrooculogram cannot contaminate the frontal and prefrontal hemodynamic responses. These aspects have made those working in the BCI domain turn their attention towards fNIRS-BCIs in the form of an alternate of EEG-BCIs. In case of fNIRS-BCIs, several mental operations such as mental computation, 3D rotation, motor imagery, and word relation are used for task-associated hemodynamic reactions inducement [2].

Corresponding author: T.V. Padmavathy

Address: ^{1*}Professor, Department of ECE, R.M.K. Engineering College, Kavaraipettai, Chennai; ²Associate Professor, Department of Medical Electronics, Velalar College of Engineering and Technology (Autonomous), Thindal; ^{3&4}Assistant Professor, Department of ECE, R.M.D. Engineering College, Kavaraipettai, Chennai; ⁵Professor & Head, Department of CSE, Agni College of Technology, Chennai.

E-mail: ^{1*}tp.ece@rmkec.ac.in, ²pravinkumarmm@gmail.com, ³ms.ece@rmd.ac.in, ⁴mnv.ece@rmd.ac.in, ⁵csehod@act.edu.in

Relevant conflicts of interest/financial disclosures: The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Received: 30 July 2020 **Accepted:** 08 September 2020



But, the hemodynamic responses that are invoked by the visual stimulus generally are quite slow compared to the steady-state optically induced responses, and they do not yield distinct benefits. Hence, these hemodynamic reactions have not been utilized for fNIRS research predominantly [3].

As hemodynamic reactions are usually corrupted by noises physiologically like respiration and cardiac pulses, it is necessary to isolate task-related hemodynamic reactions and unrelated elements. For this, research experts have till now carried out intriguing research on low-pass and band-pass [4], adaptive [5], wavelet [6], short channel separation [7], and principal component analysis filters [8]. Various kinds of machine learning techniques, like linear discriminant analysis, support vector machine (SVM), neural networks, hidden Markov model are used for differentiating the task-associated hemodynamic responses excited by a variety of mental tasks. In addition, feature selection approaches like the Fisher score [9], sequential forward selection [10], and genetic algorithm [11] are used for improving performance achieved in fNIRS-BCI systems. Even though fNIRS-BCIs have primarily been aimed at binary BCI systems implementation, multi-set fNIRS-BCI systems is introduced recently [12]. Along with BCIs, fNIRS has found extensive application in clinical and neuroscience fields [13].

In this research work, the objective is to find the various motion activities employing the fNIRS data, which has recorded from 10 healthy subjects. Traditional classifiers generally require some amount of pre-processing and feature extraction techniques to be carried out for attaining considerable classification accuracy. The progress made in machine learning and usage of deep learning algorithms of Deep Neural Network (DNN) have reduced the necessity for pre-processing or manual extraction of features and selection of the best features. In addition, end-to end NN has been utilized for differentiating the various activities. In this technical work, a new approach for optimum feature selection from fNIRS signals has been proposed with the help of an improved GA [10] to reduce the time taken for the classification process and boost the accuracy rate. In the current work, a new approach, which uses genetic algorithm (GA) for optimum selection of feature from fNIRS signals is derived and, thus, decreases time taken, expense and boosts the classification performance. Also, the primary benefit provided by GA compared to the other optimization methods is that it is not

susceptible to get caught into the local minima.

The remaining section of the research work is structured as given: Section II provides an overview on the relevant works. In section III, the details on the collection of data and the technique for the activity identification/classification is provided. Section IV provides the results and the performance of the recognition, and Section V concludes the work.

Related Work

One research work explored these brain changes employing multi-channel fNIRS incorporated with several sessions of visual feedback EEG-BCI training [12]. An experimental concept, which comprises of alternative fNIRS and EEG training sessions, is designed. The entire data were gathered in sensor motor cortex and then 15 subject controls were requested to carry out motor imagery during every session. It has been noticed that training combined with visual feedback BCI helps increase HbO of low BCI performers (less than 70%) along with great EEGbeta activity over sessions. This work showed the manner in which visual feedback EEG-BCI training has an effect on brain activations corresponding hemodynamic reactions employing fNIRS.

Influenced by excellent classification involving mental arithmetic employing fNIRS [16], one work tried decoding motor execution and mental arithmetic achieved from EEG and fNIRS [17]. An experimental concept, which included carrying out four diverse tasks of 60 s was designed and accuracies of classification between every baseline and task period, is computed. EEG and fNIRS sensors were then positioned on sensor motor and prefrontal sites. Much better classification accuracies (greater than 80%) for each of the four tasks were achieved and it is used in BCI systems.

Important fNIRS BCI drawback involves intrinsic delay incurred in hemodynamic reactions, which renders it hard to develop applications in BCI that can be used in real-time. In an earlier study [18], peak accuracy of classification in fNIRS was less by 7s in comparison with that in achieved EEG. Hence, to get over and make adjustments for this intrinsic delay, a study conducted recently designed a novel feature known as slope indicator, which, measures difference between current time unit mean and that which is computed from an earlier time unit [19]. HbO/HbR and Band-power are employed in inputs form for LDA classifiers and 15 control subjects were made for doing four motor moves. In each of



the four tasks, EEG-fNIRS attained much superior accuracy during classification in comparison with single modality and slope indicator in novel feature form used in fNIRS decreased delay incurred during peak performance up to 2 s from start time. Along with sensor motor tasks, optical and auditory perception can be categorized with better accuracy (greater than 90%) employing EEG and fNIRS simultaneously [20]. This research work recommended that passive BCI utilized for detecting the perceptual action is also possible for much normal BCI from the human-machine interaction point of view. [21] was carried out with a dual objective: to examine the practicability of employing an integrated electroencephalogram/functional near-infrared spectroscopy (EEG-fNIRS) SMR-based brain switch in persons affected with tetraplegia, and for investigating variation performance between motor imaging and efforts for this set of users. In [22] designed novel mechanisms to extract signal and signal processing to boost BCI system performance with few channels. During signal acquisition phase, source analysis is used in EEG and fNIRS signals to choose optimum channels of bimodal signals collection. In [23] examined association between hand clenching speed and EEG activity and it was observed that activities happening in alpha and beta frequency bands exhibited linear correlation with hand

clenching speed. But, it is not known whether any differentiation is made between hand clenching force and motor imaging speed. As a result, this work examines motor parameter images corresponding to both force and hand clenching speed. This concept is found to be a practical scheme for substantial BCI commands generation.

Proposed Work

Fig.1.shows a general BCI approach, which includes acquisition of signal, filtering, extraction of feature, classification, and extrinsic devices interfacing. Once classification step is done, management interface forms system’s last part. In this work, with the expectation of mentionable BCI performances on an overall, the abilities of integrating multi-modal EEG-fNIRS brain recordings with benchmarked Deep Learning classification processes are investigated. In the form of a first step of investigation, a guided Left and Right Hand Motor Imagery step is performed and using 1 second typical time frame between techniques, estimation of Left against Right classification accuracy achieved using a DNN in multimodal recording modality is done and then its comparison is done with independent EEG, fNIRS and few other kinds of classification algorithms.

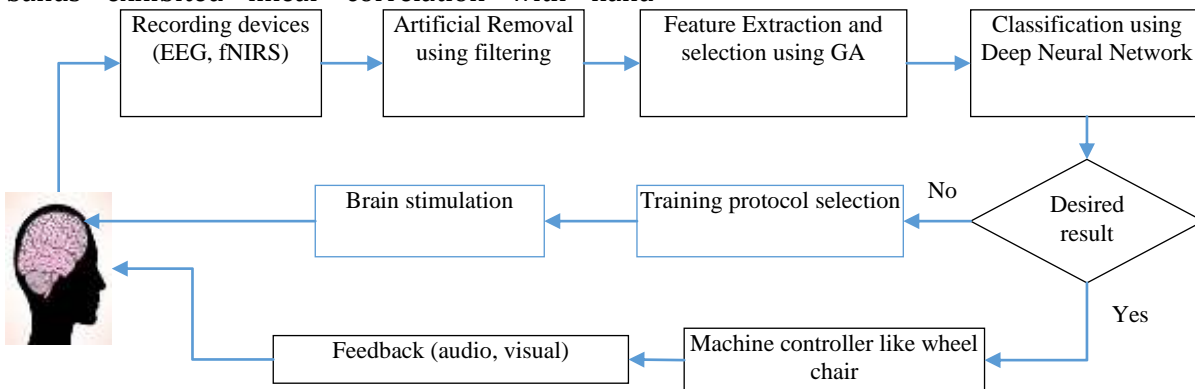


Fig.1. Deep Learning based BCI approach for Control Applications with Brain Function Recovery Signal acquisition

This study uses a simultaneous EEG and fNIRS measurement configuration. EEG signals recording is done at 500 Hz frequency employing a Brain Amp DC EEG recording system. 16 EEG electrodes are attached on scalp over left and right motor cortices (which include FFT7h, FFC5h, FFC3h, FFT8h, FFC6h, FFC4h, FTT7h, FCC5h, FCC3h, FTT8h, FCC6h, FCC4h, CCP5h, CCP3h, CCP4h, and CCP6h). Two EEG electrodes are placed on mastoids, and mean of these signals is utilized in form of re-referencing signal in raw EEG data reprocessing. fNIRS signals are concurrently recorded employing

a NIRS cout system using twelve sources, twelve detectors. Inter-optode distance is about 3 cm and overall thirty four fNIRS channels are distributed at equal distance in entire motor cortex regions. Wavelengths of oxy- and deoxy- haemoglobin detection is about 760 and 850 nm. fNIRS signals are obtained at 7.81 Hz sampling frequency rate.

Signal Processing

In first step, Raw EEG signals of all channels are re-referenced by subtracting two EEG channels mean



of on both mastoids. As useful EEG data associated with motor activity is generally associated with frequencies much lesser than 40 Hz, first down-samples raw EEG signals into 250 Hz and then filtered from 1 to 45 Hz employing a 3rd order Butterworth band-pass filter. Then Single-trial EEG data segmentation is done from 2 seconds before instruction start for movement to 5 seconds just after e start, leading to 25 segmented trials made for every hand move. After this, baseline correction was carried out through subtraction of every baseline interval's average value from its respective segmented trial.

For processing fNIRS signal, concentration variations of haemoglobin (HbO and HbR) are measured with Modified Beer-Lambert Law (differential path length factors greater than 850 nm and lower than 760 nm) wavelengths are about 6.38 and 7.15) [24]. Then, a 4th order Butterworth band-pass filter was used in 0.01 to 0.2 Hz for eliminating noises, inclusive of cardiac disturbances and respiration. Also, spline interpolation was carried out to eliminate any movement artifact corruption in fNIRS signal. Single trial fNIRS data is segmented from time of 5 second earlier to instruction start for movement to 20 s just after start, generating fNIRS trials, which relate directly to those acquired using EEG segmentation process. Every baseline signals average value is then subtracted from respective task of execution.

EEG Feature Extraction

For the extraction of the features related to prior temporal data, EEG information between 0 to 1 second (0 second represents stimuli beginning) is then separated from chosen channels, leading to a 1 s-long-time EEG window in for with 250 points in each trial. Then discrete wavelet transform (DWT) is used to segment single trial EEG data decomposition, DWT is an approach, which divides time series data of every chosen EEG channel into several layers. In every layer, signal filtration is carried out using quadrature mirror filter (combination of low-pass and high-pass filter). Resultant output of every layer is actually detail coefficients sequence (derived from high-pass filter) and approximation coefficients (derived from low-pass filter). In this work, it is presumed that wavelet approximation coefficients resulting from final DWT layer output has event-associated oscillation's primary power in brain activity, which is used to discriminate right and left hand

movement. In this, chosen EEG channel's segmented signals are divided using a 4-layer "Symlet" wavelet, leading to 22 coefficients of approximation obtained for every trial. After this, all coefficients of approximation of chosen EEG channels are integrated into a EEG feature set with 44-dimension (22-dimensional \times 2 channels) for a single trial classification of left and right hand movements.

fNIRS Feature Extraction

Peak information obtained from HbO and HbR signals are extensively employed in several fNIRS-specific BCI researches. But, the intrinsic delay incurred in the hemodynamic reaction decreases the efficacy of real-time fNIRS-specific BCI application. Hemodynamic feature considered in research work is called as initial dip, typically a metabolically-linked process in which HbO concentration mildly reduces or concentration of HbR mildly improves 0–2 s once the stimuli is presented. This change is regarded as blood-borne oxygen's pre-mature and quick metabolism by reacting population with neurons, happening prior to primary activity-integrated vascular response. Even though initial dip has a comparatively less amplitude. Zafar et al. revealed that detection and classification of the initial dips is practical using fNIRS [26]. Due to their quick development in stimuli walk, extraction of initial dip information was done for classification purposes in this research work.

Principal Component Analysis (PCA) is done. before extracting information on initial dip for further eliminating any interferences left in pre-processed fNIRS signal. In this way, N-trial fNIRS data set obtained from chosen channel is modified into N linearly unrelated entities called as principal components, governed by variance amount in actual data for which every component is accountable. Use of PCA in filtering multi-trial fNIRS data in channel presumes that event-initiated hemodynamic reaction forms primary component across every trial. This implies that hemodynamic reaction yields prominent contribution made to fNIRS variance information and indicates that first different principal components will also in same way be connected to anticipated event-initiated hemodynamic reaction.

Filtration of PCA is expressed by:

$$Y = E * X$$

Where, X refers to $N \times M$ data matrix (N represents data points of every trial and M represents number



of trials), E indicates eigenvector matrix with $N \times N$ dimensions, and Y refers to $N \times M$ matrix with N unrelated principal components. With first R components having highest variances saved and eliminating rest of components, reconstruction of data X shall be given by:

$$X_{recon} = Y_{new} * E_{new}^T$$

where, X_{recon} refers to $N \times M$ filtered data, E_{new} indicates new eigenvector matrix with $N \times R$ dimension, Y_{new} indicates $N \times R$ matrix with R unrelated principal components.

In this work, each of the trials on every movement of the hand were filtered with the help of PCA having the first component making up for nearly 70% of the data set variance. After this, HbO and HbR's average value changes within 0–2 s interval, then computed to all trials, leading to afNIRS feature set with 4-dimension (2 mean \times 2 channels) for a single trial classification process on left and right hand motion.

Feature Selection Using Modified Genetic Algorithm

A less number of features is always desirable, since it takes up much lesser computational expense for implementing a BCI in real-time. GA is one among the feature-selection techniques of feature-selection used often within the BCI field[27]. The primary disadvantage of the conventional GA is that in case a probability distribution of uniform nature is used while choosing the initial generation, a maximum number of features is added to every individual. Since selection's growth directly depends on the classifier, the objective of GA is to increase the precision of the classifier by having a greater features count. Ultimate feature set's real size obtained using GA is same as initial feature set. By theory, selection process is need not to be governed by just accuracy of classification. It is feasible to present a penalty term to the GA fitness function, which will stop the individuals from having more number of features added. It is also feasible to design specific genetic operators that convert these unnecessary features as individuals inclusive of a lesser features count. But, practically, scale associated with necessary minimization of feature set is very big which is highly cumbersome for designing a function such as this that penalizes individuals that have extremely more genes or functions or features. A solution that is easier is found to specified for encoding genetic operators and individuals, which will allow GA to get just feature subsets having certain size to be processed. The technique, which has been utilized for selecting

the features relevant out of the entire features pool involves genetic algorithm with aggressive mutation (GAAM) [28] as illustrated in fig.2. Its population comprises of individuals having a constant genes count.

Integer coding approach is brought into use, where every gene is associated with a feature index related to an individual, which arbitrarily uses a value in set $\{1, \dots, R\}$, where, R represents entire feature set's dimensions. Integer coding approach forms primary aspect that differentiates GAAM and conventional GA. Since genes proportion to entire features is a very less value, mutation is quite strong here. GAAM not just performs mutation of every individual but also all individual genes. Consequently, a massive number of newer individuals are brought into individuals population. In case of GAAM, reproduction occurs prior to selection. In reproduction is performed on parent population having a probability of one. In reproduction stage, parent population is extended through addition of new-born individuals. Every individuals quality is assessed by considering accuracy of classification in form of a fitness function. In selection stage, population is decreased to its actual size by choosing individuals with greatest fitness function value. Reproduction and selection steps are repeated in a predefined number of iterations.

1. Decide the parameters of the algorithm: T refers generations count, M indicates individuals count present in a population (features), and N indicates genes count present in an individual.
2. Form initial population with M individuals, population EEG-fNIRS features is generated in random by selecting successive genes values out of set $\{0, 1, \dots, R\}$.
3. Carry out strong mutation on individuals taken from earlier population. Due to this operation, one mother individual has N off-springs group, with every one generated through the mutation of another gene of that individual.
4. Carry out the conventional Holland crossover on individuals taken from earlier population here as EEG-fNIRS features (with a probability equivalent to 1).
5. Generate a parent population EEG-fNIRS features, with M individuals from the earlier population, which includes EEG-fNIRS features, $N \times M$ individuals generated in strong mutation operation and MM



individuals generated in crossover operation.

6. Assess individuals quality generated from parent population with fitness function corresponds to classification accuracy.
7. Eliminate $M+N \times M$ individuals having least accuracy in classification. After that, just M individuals having greatest accuracy in classification exist in population. As each one of best individuals generated from earlier population participate in procedure of selection, best individual in present population can hold at least fitness value same as in earlier one.
8. Move to step 3.

Deep Neural Network and Classification

DNNs permits computational models, which has several processing layers made by non-linear units, known as neurons, with capability of learning the data representations having several abstraction stages. DNNs discover complicated arrangement in data-sets employing back propagation algorithm, which directs the variations in the parameters of the Networks, which are updated in sequence in every layer from the previous layer's representation. When the data is used for learning the network parameters, the DNN structure must be heuristically chosen a priori or decided using computationally extreme hyper-parameters optimization algorithms. As an initial step, performance comparison analysis between DNN and other classifiers was performed, and it was determined to set the DNN structure without examining several structures of DNN. Full connected feed-forward DNN network is used and figure 3 shows its architecture. The data set has 123 neurons for independent EEG classification, 16 neurons for independent fNIRS classification, 139 neurons for both EEG and fNIRS classification. Input neurons features are 1 second mean ERD/ERS, ΔO_2Hb and ΔHHb . It is to be observed that the mean value of the features had the magnitude of one and all the feature' values were under a degree of magnitude. In reality, the order of magnitude of the input values is a significant fact to be considered during the DNNs training. Every neuron belonging to the hidden layers non-linearly transforms every output's linear combination obtained from earlier layer. Rectified Linear Unit (ReLU) function is used non-linear processing function for reducing vanishing gradient problem yielding improved performance compared with

other non-linear functions. Hidden neurons outputs, while using ReLU function is expressed as:

$$y = \begin{cases} 0 & \text{if } wx + b \leq 0 \\ wx + b & \text{if } wx + b > 0 \end{cases}$$

Where x refers to input vector, w refer weight vector and b indicate bias, y stands for resultant output vector. As classifier needs to differentiate two states, namely Left or Right Motor Imagery state, there is a need of two neurons in output layer for performing Softmax Transformation (ST):

$$\begin{bmatrix} P_{Right} \\ P_{Left} \end{bmatrix} = \begin{bmatrix} STRight \\ STLeft \end{bmatrix}$$

Where $STRight = \frac{e^{w_1x}}{\sum_{k=1}^2 e^{w_kx}}$ and $STLeft = \frac{e^{w_2x}}{\sum_{k=1}^2 e^{w_kx}}$.

The softmax function output of two neurons is estimated as a probability of being in right (P_{Right}) or left (P_{Left}) imagery state and x refers to softmax layer's input vector and w_1 and w_2 indicates neurons weight vectors. Hidden layers count (4) and neurons as illustrated in fig.2, were chosen to nearly reduce the number of processing units (therefore performing the information compression) by a factor of 2 between every subsequent layer. Weights initialization is done in a pseudo-random manner using a truncated normal distribution having zero mean, 0.1 standard deviation and, 2 standard deviation truncation), with Zero value of biases.

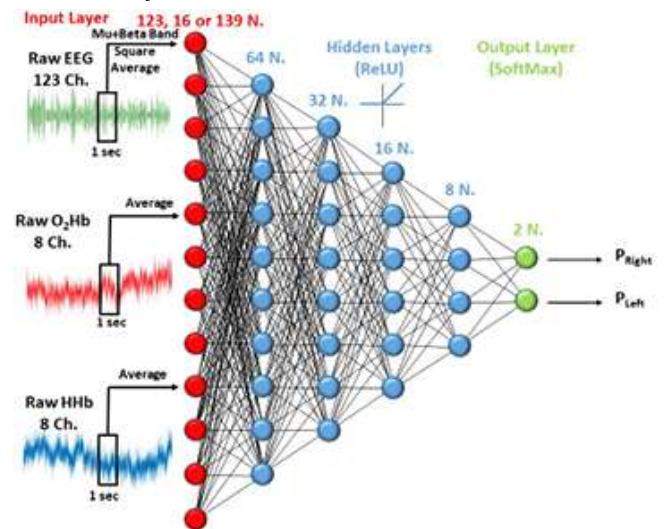


Fig.2. DNN Model for EEG-fNIRS and BCI

In the supervised learning, the parameters of the DNN, like weights w_s , biases b_s , are varied according to an objective function reduction process. This objective function provides an error measure or distance between output and required scores. Cross-entropy error is employed as objective function. Hence, the Cross-entropy (CE) is expressed as:



$$\text{Cross entropy} = - \sum_i y'_i \ln y_i$$

Where, y refers to DNN's resultant output vector, y' indicates known state ([1 0] for Right Hand, [0 1] for Left Hand Image). Cross entropy metric considers proximity of a prediction made. DNN accuracy was assessed using number of DNN predictions done correctly once an argmax assessment of DNN output vector probabilities is performed.

Linear Discriminant Analysis

Linear discriminant analysis (LDA) is popularly employed classification technique used in fNIRS and hybrid EEG-fNIRS analysis. It uses discriminant hyper-plane(s) for differentiating data that represents two or multiple classes. Due to its simple function and lesser computational demands, it is perfectly apt for online BCI systems. In case of LDA, differentiating hyperplane is got by looking for a data projection, which increases distance between average of two or multiple classes and reduces interclass variances.

Support Vector Machines

Support vector machine (SVM) is a highly common pattern identification approach used to classify brain signal. It is employed in different studies involving fNIRS [29] and is a supervised classifier, which helps in defining two or multiple classes by deciding maximum class isolation, called as "maximum margin hyperplane." Algorithm performs this through feature space mapping of input data, which can be partitioned with help of linear or non-linear decision boundaries, which is kernel-based. SVM classifier attempts maximizing distance between isolating hyperplane and closest training point(s).

Results and Discussion

To analyse EEG-fNIRS combined feature performance, four normalized EEG and fNIRS concentration features are integrated as one feature vector, and it is optimized using improved GA feature selection algorithm. Accuracy achieved in EEG-fNIRS combined feature and its results are compared with those attained in classifiers including LDA, SVM and DNN. Accuracies obtained in all investigated fusions of recordings and classifiers are illustrated in Fig.3.

A confusion matrix is typically a table, which is

frequently employed for describing classification model performance on a test data set for which true values are actually known values. It permits predicting algorithm performance. In case of predictive analytics, a confusion matrix (Table 2), has a Table with two rows and columns with respect to number of false positives, false negatives, true positives, and true negatives.

Table 2. Confusion Matrix

		Predicted	
		Positive	Negative
Actual	Positive	tp	fp
	Negative	fn	tn

- True Positive (tp) is called as predicting a label right (predicted "yes", and it's "yes"),
- True Negative (tn) is called as predicting the other label right (predicted "no", and it's "no"),
- False Positive (fp) is called as falsely Predicting a label (predicted to be "yes", but it's "no"),
- False Negative (fn) is called as missing and inward label (predicted to be "no", but it's "yes").

Accuracy is defined as the ratio of overall number of correct predictions that were right. Its definition is given as

$$\text{Accuracy} = \frac{(tp + tn)}{(tp + tn + fp + fn)}$$

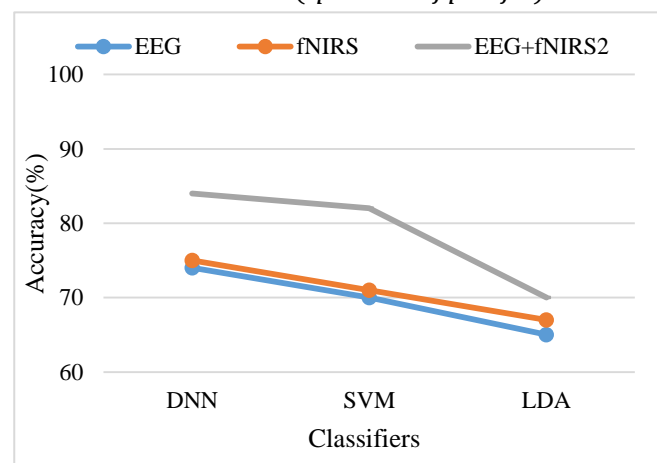


Fig. 3. Accuracy of standalone EEG, standalone fNIRS, and combined EEG-fNIRS as a function of classifying techniques-LDA, SVM, DNN

Fig.6 illustrated above describes that the comparison of accuracy between the independent EEG, independent fNIRS, and integrated EEG-fNIRS. The techniques used include LDA, SVM and DNN. The classifiers are plotted along the x-axis and the accuracy value is plotted along the y-axis. It is evident from this graph that the novel DNN yields much better accuracy rate of 74%, 75% and 84%



for independent EEG, independent fNIRS, and integrated EEG-fNIRS correspondingly. Simultaneously, the accuracy rate of SVM technique is achieved at 70%, 71% and 82% for independent EEG, independent fNIRS, and integrated EEG-fNIRS correspondingly. At last, the accuracy rate of LDA technique is achieved at 65%, 67% and 70% for independent EEG, independent fNIRS, and integrated EEG-fNIRS correspondingly. It is evident from the results that the DNN based classification system yields much better accuracy rate compared to the LDA and SVM. The reason behind this is that the available mechanism yields a very less success rate with a greater probability to result in the misdetection of the developing variations. The novel system uses the GA based feature selection which improves the classification rate of the proposed DNN technique.

Conclusion and Future Work

With synergistic effects combined multi-modal EEG-fNIRS recording and deep learning classifiers exhibit a superior performance as shown demonstrated in results. Superior performances achieved in multi-modal acquisition with regard to independent EEG and fNIRS shows remarkable data of integration of electrical and hemodynamic brain activity recordings. Superior performances of DNN based on linear SVM, indicates non-linearity of BCI classification process and, in comparison with inefficient results acquired through the implementation of non-linear SVM, the abilities of benchmarked DNN learning processes to prevent generalization performance becoming reduced. The setting back aspect of EEG technologies low spatial resolution and less data points attainable in-vivo is not permitting effective extraction of feature by CNN enforcing few pre-processing before DNN. Multi-modal hemodynamic and electrical brain imaging, integrated with few feature extraction process and DNN may result in BCI research to improve. But, CNN performances were not much noticeable in comparison with the DNN provided in signals. These output results can be based on less training information of BCI, an inherent setback aspect when obtaining the data on brain activity. Factually, this factor can probably restrict the CNN's automated selection of signal feature abilities, enforcing some amount of feature extraction carried out before the classification process. Also, it has to be noticed that the RNN architectures' testing were not done on data set. In self-paced motor imagery BCI, RNNs can be utilized

and imagery classification is based on sequential temporal information.

References

- Boas DA, Elwell CE, Ferrari M, Taga G. Twenty years of functional near-infrared spectroscopy: Introduction for the special issue. *Neuroimage* 2014; 85: 1–5.
- Shin J, Klaus RM, Han JH. Near-infrared spectroscopy (NIRS)-based eyes-closed brain-computer interface (BCI) using prefrontal cortex activation due to mental arithmetic. *Scientific reports* 2016; 6: 36203.
- Tomita Y, Vialatte FB, Dreyfus G, Mitsukura Y, Bakardjian H, Cichocki A. Bimodal BCI using simultaneously NIRS and EEG. *IEEE Transactions on Biomedical Engineering* 2014; 61(4): 1274-1284.
- Shin J, Von Lühmann A, Blankertz B, Kim DW, Jeong J, Hwang HJ, Müller KR. Open access dataset for EEG+ NIRS single-trial classification. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 2016; 25(10): 1735-1745.
- Dong S, Jeong J. Improvement in recovery of hemodynamic responses by extended Kalman filter with non-linear state-space model and short separation measurement. *IEEE Transactions on Biomedical Engineering* 2018; 66(8): 2152-2162.
- Abibullaev B, An J. Classification of frontal cortex haemodynamic responses during cognitive tasks using wavelet transforms and machine learning algorithms. *Medical Engineering & Physics* 2012; 34(10): 1394-1410.
- Gagnon L, Cooper RJ, Yücel MA, Perdue KL, Greve DN, Boas DA. Short separation channel location impacts the performance of short channel regression in NIRS. *Neuroimage* 2012; 59(3): 2518-2528.
- Abibullaev B, An J, Lee SH, Moon JI. Design and evaluation of action observation and motor imagery based BCIs using Near-Infrared Spectroscopy. *Measurement* 2017; 98: 250-261.
- Hwang HJ, Choi H, Kim JY, Chang WD, Kim DW, Kim K, Im CH. Toward more intuitive brain-computer interfacing: classification of binary covert intentions using functional near-infrared spectroscopy. *Journal of biomedical optics* 2016; 21(9): 091303.
- Schudlo LC, Chau T. Dynamic topographical pattern classification of multichannel prefrontal NIRS signals: II. Online differentiation of mental arithmetic and rest. *Journal of neural engineering* 2013; 11(1): 016003.
- Noori FM, Naseer N, Qureshi NK, Nazeer H, Khan RA. Optimal feature selection from fNIRS signals using genetic algorithms for BCI. *Neuroscience letters* 2017; 647: 61-66.
- Kaiser V, Bauernfeind G, Kreiling A, Kaufmann T, Kübler A, Neuper C, Müller-Putz GR. Cortical effects of user training in a motor imagery based brain-computer interface measured by fNIRS and EEG. *Neuroimage* 2014; 85: 432-444.
- Schudlo LC, Chau T. Towards a ternary NIRS-BCI: single-trial classification of verbal fluency task, Stroop task and unconstrained rest. *Journal of neural engineering* 2015; 12(6): 066008.
- Wallois F, Mahmoudzadeh M, Patil A, Grebe R. Usefulness of simultaneous EEG-NIRS recording in language studies. *Brain and language* 2012; 121(2): 110-123.



Rejer I. Genetic algorithms in EEG feature selection for the classification of movements of the left and right hand. *In Proceedings of the 8th International Conference on Computer Recognition Systems CORES, Springer, Heidelberg, 2013, 579-589.*

Verner M, Herrmann MJ, Troche SJ, Roebbers CM, Rammsayer TH. Cortical oxygen consumption in mental arithmetic as a function of task difficulty: a near-infrared spectroscopy approach. *Frontiers in human neuroscience, 2013; 7: 217.*

Khan MJ, Hong MJ, Hong KS. Decoding of four movement directions using hybrid NIRS-EEG brain-computer interface. *Frontiers in human neuroscience 2014; 8: 244.*

Fazli S, Mehnert J, Steinbrink J, Curio G, Villringer A, Müller KR, Blankertz B. Enhanced performance by a hybrid NIRS-EEG brain computer interface. *Neuroimage 2012; 59(1): 519-529.*

Buccino AP, Keles HO, Omurtag A. Hybrid EEG-fNIRS asynchronous brain-computer interface for multiple motor tasks. *PLoS one 2016; 11(1): e0146610.*

Putze F, Hesslinger S, Tse CY, Huang Y, Herff C, Guan C, Schultz T. Hybrid fNIRS-EEG based classification of auditory and visual perception processes. *Frontiers in neuroscience 2014; 8: 373.*

Blokland Y, Spyrou L, Thijssen D, Eijsvogels T, Colier W, Floor-Westerdijk M, Farquhar J. Combined EEG-fNIRS decoding of motor attempt and imagery for brain switch control: an offline study in patients with tetraplegia. *IEEE transactions on neural systems and rehabilitation engineering 2013; 22(2): 222-229.*

Ge S, Yang Q, Wang R, Lin P, Gao J, Leng Y, Wang H. A brain-computer interface based on a few-channel EEG-fNIRS bimodal system. *IEEE Access 2017; 5: 208-218.*

Yuan H, Perdoni C, He B. Relationship between speed and EEG activity during imagined and executed hand movements. *Journal of neural engineering 2010; 7(2): 026001.*

Scholkmann F, Spichtig S, Muehleemann T, Wolf M. How to detect and reduce movement artifacts in near-infrared imaging using moving standard deviation and spline interpolation. *Physiological measurement 2010; 31(5): 649-662.*

Naseer N, Hong KS. fNIRS-based brain-computer interfaces: a review. *Frontiers in human neuroscience 2015; 9: 3.*

Zafar A, Hong KS, Khan MJ. Initial dip detection based on both HbO and HbR vector-based phase analysis. *In IEEE 55th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE) 2016: 543-548.*

Rejer I. Classic genetic algorithm vs. genetic algorithm with aggressive mutation for feature selection for a brain-computer interface. *Przegląd Elektrotechniczny 2015; 1: 100-104.*

Rejer I. Genetic algorithm with aggressive mutation for feature selection in BCI feature space. *Pattern Analysis and Applications 2015; 18(3): 485-492.*

Koo B, Lee HG, Nam Y, Kang H, Koh CS, Shin HC, Choi S. A hybrid NIRS-EEG system for self-paced brain computer interface with online motor imagery. *Journal of neuroscience methods 2015; 244: 26-32.*

Tacconi L, Giordan E. Endoscopic transforaminal discectomy vs. Far lateral discectomy for extraforaminal disc protrusions: Our experience. *NeuroQuantology 2019; 17(7): 18-22.*

Pradhan RK, Tripathy A. On the question of free will in a quantum physics inspired model of consciousness. *NeuroQuantology 2019; 17(8): 14-18.*

Authors Profile



Dr.T.V. Padmavathy, Professor, Department of ECE in R.M.K. Engineering College, has 24 years of teaching and research experience in the in the fields of Wireless sensor networks, Under Water Acoustic Sensor Networks and Antenna Design. She has graduated from Institution of Engineers (India), in Electronics and Communication Engineering. She has obtained her Master degree in Control and Instrumentation from College of Engineering, Guindy, Anna University, Chennai and Ph.D. degree from Anna University, Chennai. She has published more than 50 research papers in International and National Journals and conferences in the area of Mobile Ad hoc Networks, Wireless sensor networks, Under Water Acoustic Sensor Networks and Antenna design and she has four Patents in Wireless Sensor Networks. Her current area of research includes security and architecture issues of Mobile ad hoc networks, Wireless sensor networks and Millimeter Wave Antenna design for Wireless Communications. She is a technical paper reviewer for African Journal of Engineering Research and Journal of Engineering and Technology Management. She is recognized as Fellowship member by The Institution of Engineers (India) also she is a member of various professional bodies such as Institute of Electrical and Electronics Engineers (IEEE), Life member of Institution of Electronics and Telecommunication Engineers (IETE), International Association of Engineers (IAENG), ACM, ISSE and Life member of Indian Society for Technical Education ISTE.



Dr.M. Pravin Kumar, Associate professor, Department of Medical Electronics, Velalar College of Engineering and Technology, Erode, Tamil Nadu, India. He received Ph.D., (Information and Communication Engineering) in the year 2018, M.E., (Applied Electronics) in the year 2009, and B.E., (Electronics and Communication Engineering) in the year 2006 from Anna University, Tamil Nadu, India. He has 11 years of teaching experience. He holds 2 patent publications and more than 50 research papers publications in various journals and conferences. He is a member in IEEE and ISTE. Area of specialization includes process modeling and optimization, computational intelligence, medical electronics, image processing, and Networking.





M. Shakunthala, received her B.E. Degree in Electronics and Communication Engineering from Magna College of Engineering affiliated to Anna University in the year 2007 and M.E Degree in Embedded System Technologies from Anna University of Technology, Tirunelveli in the year 2010. She is First Rank holder in M.E degree. She is Pursuing Ph.D. in the area of Medical Image Processing under Anna University. She is currently working as an Assistant Professor in the Department of Electronics and Communication Engineering at R.M.D Engineering College. She is having more than 10 years of teaching and research experience. She has guided many B.E. projects and participated in many hackathons. She has published more than 10 papers in her credit in National, Inter-National Conferences and International Journals. She has delivered lectures on recent technologies like IoT, Machine Learning as Resource Person in various Engineering Colleges. She has been announced as Second Learner who has taken most number of NPTEL exams so far in January 2018. Her areas of interests are Embedded System, Signal Processing and Image processing. She has published the book on 'Signals and Systems' by June 2013 for the benefit of second year ECE students. She is Life Member of ISTE.



Dr.S. Saravanan has received his Ph.D degree from Anna University in 2018. He is a member of ISTE, IAENG, IAOE, IFERP, CSTA, ICSES, UACEE and SWIDC. He is working as Professor and Head in the department of Computer Science and Engineering in Agni College of Technology, Chennai. He has received Teacher innovation award from Shri Aurobindho Society. His area of expertise includes Artificial intelligence, Network Security and IOT.



Dr.M.N. Vimalkumar, B.E, M.E, Ph.D, is Assistant Professor in the Department of Electronics and Communication Engineering at R.M.D Engineering College since December 2013. He has completed his B.E degree in Electronics & Communication Engineering from GCE, Salem affiliated to Anna University, Chennai in 2007 and M.E degree in Applied Electronics from Kongu Engineering College, Perundurai affiliated to Anna University, Coimbatore in 2009. He has completed Ph.D under Anna University in the area of Medical Image Processing in 2018. He has 12.5 years of teaching experiences and 6 years of industry experiences and has guided many B.E. and M.E projects. He has received First Rank with Gold Medal in M.E from Anna University of Technology, Coimbatore. He has attended many National / International conferences, workshops, seminars and faculty development programs. He has organized one International / National conference and 4 workshops. He published 21 research papers in International / National Journals. He has one patent published. He has several awards received by reputed origination. He has written the book Principles of Digital Signal Processing and Control System Engineering published by Anuradha Publications. He is a Life time member of ISTE. His areas of Interest are Digital Signal Processing, Medical Image Processing, IoT, Wireless Network and Health Care.