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**RESEARCH**

Health Information Science and Systems

Modeling and classifcation of voluntary and imagery movements for brain–

computer interface from fNIR and EEG signals through convolutional neural network

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**Abstract**

Practical brain–computer interface (BCI) demands the learning-based adaptive model that can handle diverse problems. To implement a BCI, usually functional near-infrared spectroscopy (fNIR) is used for measuring functional changes in brain oxygenation and electroencephalography (EEG) for evaluating the neuronal electric potential regarding the psychophysiological activity. Since the fNIR modality has an issue of temporal resolution, fNIR alone is not enough to achieve satisfactory classifcation accuracy as multiple neural stimuli are produced by voluntary and imagery movements. This leads us to make a combination of fNIR and EEG with a view to developing a BCI model for the classifcation of the brain signals of the voluntary and imagery movements. This work proposes a novel approach to prepare functional neuroimages from the fNIR and EEG using eight diferent movement-related stimuli. The neu roimages are used to train a convolutional neural network (CNN) to formulate a predictive model for classifying the combined fNIR–EEG data. The results reveal that the combined fNIR–EEG modality approach along with a CNN pro vides improved classifcation accuracy compared to a single modality and conventional classifers. So, the outcomes of the proposed research work will be very helpful in the implementation of the fner BCI system. **Keywords:** Voluntary and imagery movements, Functional near-infrared spectroscopy (fNIR), Electroencephalography (EEG), Modeling and classifcation, Convolutional neural network (CNN), Brain–computer interface (BCI)

**Introduction**

Te brain controls all human activities such as move ments, mental workload, emotion, vision, thinking, atten tion, cognitive skills, senses, etc. Te brain-functions are related to the variation of oxygen saturation of the blood, which is called hemodynamics [1, 2]. During the func tioning of the brain, neurons (the unit of brain tissue) communicate with each other through the low potential electric signal. Terefore, changes in the concentration of oxygenated (HbO2) and deoxygenated (dHb) hemoglobin, as well as electrical potential measurement provide

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information about brain functioning. Electroencephalo gram (EEG) and functional near-infrared spectroscopy (fNIR) are two non-invasive methods to measure electric potential and hemoglobin concentrations, respectively, from our brain [3–5].

Functional brain imaging has added a new dimen sion in biomedical engineering and explored the path way to reach the brain–computer interface (BCI). BCI contributes to diverse felds of research in biomedical applications like prevention, detection, diagnosis, reha bilitation, and restoration [6]. In the feld of BCI, EEG and MEG are two non-invasive modalities based on scalp electric potential. EEG has a very high temporal resolution (~1 ms) with a poor spatial resolution (EEG: 5 to 9  cm) [7]. Tough MEG has both high temporal

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(~1  ms) and spatial resolution (<1  cm), it is not suit able for BCI because of its noise sensitivity and weight [8]. Based on the hemodynamics, functional magnetic resonance imaging (fMRI) provides an excellent spatial resolution (3–6 mm), but its temporal resolution is poor (1–3  s). Nevertheless, due to its very high cost, motion sensitivity, and, being bulky, it is also not suitable for BCI [9–11]. To cope with the aforementioned limitations and requirements, it is a high demand for a new modal

ity. fNIR is such a neuroimaging modality discovered in 1977 by Jöbsis [12]. Te researchers in [13–15] reported that near-infrared (NIR) range enables real-time non invasive detection of hemoglobin oxygenation using fNIR. Te fNIR modality provides a very good spatial resolution (~1–1.5  cm), moderate temporal resolution (up to 100 Hz), portability to use, cost-efectiveness, the high value of the signal to noise ratio (SNR), less motion artifact compared to fMRI, MEG, EEG, and PET [9]. Fur

thermore, fNIR is not physically confning the patient as fMRI and it allows movement during imaging. Recent works of literature [16, 17] demonstrated that the results of fNIR are comparable to fMRI and reliable for cortical activations measurement. Since fNIR provides fner spa

tial resolution and EEG provides fner temporal resolu tion, the combined information of both fNIR and EEG is getting much attention in the recent researches [18–23] on neuroimaging and BCI.

Millions of people in the world are sufering from dif ferent kinds of disabilities [24], whereas their brain works partially or fully. In this situation, a fner BCI system is a hope to provide them easier life by operating diferent devices through brain command. Tere are various pro posals for BCI using single modality either EEG or fNIR. One of the main limitations of the single modality based BCI is that it gives lower accuracy (less than 40% for fNIR [25, 26] and less than 70% for EEG [27–31]) for multiple motor imagery tasks’ classifcations. Among the works described [27–31], the research work proposed in [31] claimed to achieve the highest classifcation accuracy for up to 8-class problem which is around 57% in aver age, although the proposed method applied a number of composite methods for feature extraction. Such complex algorithms are required for the feature extraction of the EEG signals due to its poorer spatial resolution. Both the temporal and spatial resolutions should be satisfac tory to achieve higher classifcation accuracy for the BCI implementation.

Terefore, to implement suitable BCI, multimodal neu roimaging methods are proposed. Some recent research works [18, 19, 23] on the classifcation of imagery move ment-related tasks have been proposed by combining fNIR and EEG signals for BCI implementation. It has been revealed in [18–23] that the classifcation efciency of

combining fNIR and EEG is better than that of the indi vidual modality. Tese multimodal proposals used some shallow machine learning algorithms to classify the mul tiple class problems where manual feature extraction was deployed. As a result, the classifcation accuracies are still lower than the expectations. Current researches regarding multi-class motor events show two signifcant limitations:

•Most of the existing BCI’s are designed based on sin gle modality which limits classifcation accuracies for multiple classes due to spatiotemporal resolution.

•No signifcant research work has been accomplished utilizing deep neural network on a combination of fNIR and EEG signals.

To overcome these challenges, the proposed work attempts to develop an efective BCI model in classify ing the brain signals (fNIR and EEG) of the voluntary and imagery movements. For achieving the high classifca tion accuracy, a convolutional neural network (CNN) has been used to construct the predictive model as a classi fer. In this work, eight diferent movement-related stim uli (four voluntary and four imagery movements of hands and feet) have been considered. Te multiple channel fNIR and EEG signals are used to prepare functional neu roimages to train and test the performance of the pro posed BCI system. In addition, the proposed procedure is applied to prepare neuroimages from the individual modality (fNIR and EEG separately) to train and test the performance of the BCI system. Te results reveal that the combined-modality approach of fNIR and EEG provides improved classifcation accuracy than the indi vidual one. Besides, the combined fNIR and EEG signals are utilized for manual feature extraction and classifca tion by support vector machine (SVM) and linear discri minant analysis (LDA) so that the performance diference between CNN and conventional classifers i.e., SVM and LDA could be well judged.

Te main contributions of this paper are as follows:

(a) Combining the fNIR and EEG signal to produce CNN compatible functional neuroimages.

(b) Implementation of bimodal BCI using fNIR and EEG signals for classifcation of voluntary and imagery movements utilizing the CNN.

(c) Experimentation with multi-class brain signals using the implemented BCI.

(d) Te classifcation accuracy comparison between CNN, SVM, and LDA.

Te remaining contents of the paper are organized as follows: Te materials and the applied mathematical methodology are presented in “Materials and methods”

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section. Experimental results along with necessary dis cussions are given in “Results and discussion” section. Finally, the paper is concluded in “Conclusion” section.

**Materials and methods**

**Data acquisition protocol**

In this research eight diferent tasks (four voluntary and four imagery) were considered for neural stimulation. Te participants were asked to perform movements by hands and feet by means of voluntary and imagery man

ners. Te data acquisition protocol was checked and approved by the “Data Acquiring Ethics Evaluation Com mittee (DAEEC)” of Khulna University of Engineering & Technology (KUET). Te subjects were verbally informed and practiced the protocol of the data acquisition before actual data acquisition. Te subjects lifted their left hand, right hand, left foot, and right foot, sequentially. For proper neural stimulation, each task was performed for 10  s with 20  s resting period. Terefore, the scheduling of the proposed data acquisition protocol can be pre

sented in Fig.  1. In one session, this unit protocol was performed four times by a participant. After every ses sion, each participant took rest at least fve minutes. Eventually, every participant performed 40 trials for each movement-related task. A graphical protocol aiding soft ware designed by Matlab (given in Fig.  2) was used for this research work that instructed graphically to perform

the tasks according to the schedule. Te Matlab code of this software is freely available in [32]. In this program, there are fve diferent tasks, those are movements of the hands, feet (left and right), and the rest. Eventually, eight diferent tasks have been considered for analysis: volun

tary left hand (LH), right hand (RH), left foot (LF), right foot (RF) and imagery left hand (iLH), right hand (iRH), left foot (iLF), and right foot (iRF).

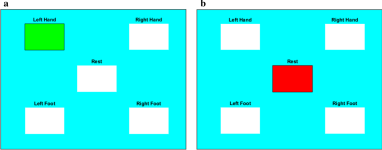
**Data acquisition**

Fifteen right-handed male subjects (age range=22 to 26) participated in this bimodal (fNIR and EEG) data acquisition protocol. No participant had a history of the psychiatric, neurological, or visual disorder. In addition, no participant was reported to have any pain in their both hands and feet. Te verbal consents of the participants were taken prior to the data acquisition as the rule of the university. All data acquisition procedures were completed in the Neuroimag ing Laboratory of the Biomedical Engineering Department of KUET following the declaration of Helsinki [33].

For this work, a 16 channel continuous-wave fNIR system (model: Biopac 1200 fNIR imager) and 9-chan nel EEG device (model: B-Alert X-100) were used. Utilizing both fNIR and EEG devices, the prefrontal, frontal, and central parts of the brain were covered. Te hemodynamic signals from the prefrontal cortex were acquired by the fNIR device and the EEG signals of the



**Fig. 1** Time schedule of data acquisition protocol for each participant regarding both the voluntary and imagery movements. This is a unit task performing schedule that was repeated four times in each session to complete 40 individual trials of every task

**Fig. 2** Schematic illustration of MATLAB based protocol instruction aiding application for the experiment. Regarding the instruction of this applica tion, the participant is asked to move the left hand (voluntary or imagery) by Fig. 3a and after that, Fig. 3b instructs to take rest

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frontal and central part of the brain were captured by the 9 channel EEG device. Te optodes of fNIR devices and the electrode of the B-Alert system were placed at the positions indicated in Fig. 3. Te Cognitive Optical Brain Imaging (COBI) studio and AcqKnowledge soft

ware were used to log the combined fNIR–EEG signal. Although there is a time gap between the starting of the EEG and fNIR signal acquisition software, it has been corrected by a reverse counting approach. Te real

time data acquisition utilizing fNIR devices and B-Alert X-100 from the scalp of a participant is given in Fig. 4.

**Preprocessing**

Since the research work deals with two diferent types of signals, two diferent preprocessing were applied. Te signal preprocessing methods regarding fNIR and EEG signals are separately presented as follows.

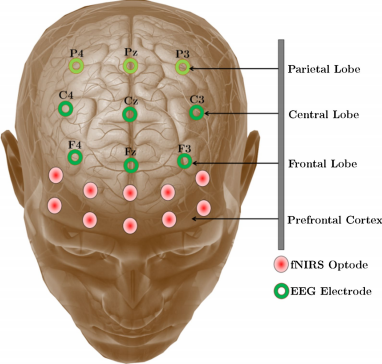
***fNIR signal preprocessing***

Te following steps showing in Fig. 5 were used for the fNIR signal processing. Te fNIR signals were smoothed by using the 3rd  order Savitsky–Golay flter with 21 frame-size as recommended in [34]. Ten  the  signals were divided according to the time schedule to separate each trial fNIR signal regarding applied stimuli. Te base

lines of all trials were corrected by subtracting baseline from the fltered signals. Baseline was calculated from the average of the frst 3 s of the signals. Tis consideration [35, 36] ensures that the initial signal points regarding each trial remain at zero or close to zero levels.

***EEG signal preprocessing***

In this preprocessing, the EEG signals are fltered in sev eral steps because EEG signals are too much noise sensi tive and complex in nature. Diferent types of noises are incorporated in EEG signals like power line noise, eye

**Fig. 3** The combined fNIRS-EEG sensor positions on the scalp and prefrontal cortex. The data of parietal lobe are acquired through the main data acquisition period but excluded for proposed ofine processing

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blink, electrooculogram (EOG), etc. Te fow diagram of this preprocessing is presented in Fig. 6.

All raw EEG signals are fltered by a 50 Hz notch flter to remove power line noise [37]. After that, a bandpass elliptical flter is used to separate the strong band power from 1 to 40 Hz. Te elliptic flter provides sharp cut-of frequency and low flter order than the other IIR flters like Chebyshev, Butterworth, Bessel, etc. It is also known

relation (1) is difcult, however, the order calculation procedure is compact at all [39–41] and is given by,

1 − k21 )

N = (2) ψ(k)ψ(ψ(k1)ψ(~~√~~1 − k~~2~~)

In (2), k = ωp

~~ω~~sand k1 = √δA~~2~~−1, where,ωs is stopband fre quency and A is stopband attenuation. Besides,

as Zolotarev or Cauer flters. Tis flter shows equi-rip ple characteristics both in the pass-band and stop-band. Since the elliptic flter achieves the minimum order value

ψ(k) =  π 0

√dθ

1−k~~2~~ sin θ, which is an elliptical integral. A 5th

for a given specifcation, it is considered as an optimal flter [38]. Eventually, it is slightly complex to design and it often needs several complex algorithms to implement. Te response of an elliptical flter in the magnitude

square aspect in the frequency domain can be presented as [38],

(1) |H(iω)| = 1 1 + δ2J 2N ω~~ω~~c

Here, ω and ωc are for the frequency and cut-of fre quency, respectively. In addition, the passband ripples are presented by δ. Here, JN (•) is the *N*th order Jacobian elliptical function. Tough the solution analysis of the

order elliptical flter was used in this work to flter the EEG signals. In addition, the eye blink and EOG efects in the EEG signals were removed by the enhanced auto matic wavelet independent component analysis (EAWICA) toolbox [42]. Finally, the EEG signals were separated according to the time schedule of the tasks.

**Combining fNIR and EEG signal to produce neuroimages** A two-dimensional data arrangement of the combined fNIR–EEG has been proposed in this work. Since the sampling rate of fNIR (2 Hz) and EEG (256 Hz) are not similar, the data of EEG signal has been transformed into the frequency domain to represent it into the similar sampling rate of the fNIR signal.

**Fig. 4** Data acquisition of voluntary and imagery movements using fNIR and EEG modality

Raw fNIR

signals Filtering **Fig. 5** Preprocessing steps of the fNIR signals

Data separation according to the task

Baseline correction

Preprocessed fNIR signal

Raw EEG signals

Notch

Filtering

Bandpass Filtering

Eye Blink Removal

Data separation according to the task

Preprocessed EEG signal

**Fig. 6** The steps applied in EEG signal preprocessing

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According to this proposal, the fNIR signal length is 30  s (10-s stimuli+20-s activation). Tere are 16 chan nels (60 samples per channel) of both HbO2 and dHb data. Te 16 channel data of HbO2 and dHb are arranged as the procedure shown in Fig. 7.

Since neural activities of imagery and voluntary move ments are connected with the frontal and central parts of the brain, only frontal three channels, and central three channels were taken for further processing. Te most dominant features of imagery and voluntary movements are included in the alpha, beta, and total band power of the EEG signal [15, 30]). As a result, the relative PSD of the alpha and beta band from the six channels (F3, Fz,

where ‘⊗’ denotes convolution of two signals [43, 44]. Window-based PSD calculation is very important for an EEG signal. In this case, the Welch method is the most renowned method. Suppose, the successive sequences are ofset by *D* points, where each sequence is *L* points long, then the *i*th sequence is,

xi(n) = x(n + iD) (5) Tus L–D points are overlapped. If entire *U* data points are covered by *K* sequences then,

N = L + D(K − 1) (6) According to the conditions (7), the PSD calculation method was given in [45].

F4, C3, Cz, and C4) were extracted considering a window of time period 1 s with 50% overlapping. We know that for a discrete-time signal, *x*(*n*) the PSD can be equated as [43],

Px (3) (ejω) =  ∞

Pˆw(ejω) = 1 KLU

K −1 i=0

L−1 n=0

w(n)x(n + iD)e−jnω

2

(7)

rx(k)e−jkω

k=−∞

If any band relates to specifc neural activities, its relative power also increases with respect to its resting condition. Terefore, relative power plays important roles in fnd

In (3), rx(k) represents the autocorrelation of a periodic signal. But for an Ergodic process, we can write,

ing the specifc electrical activities from the EEG signal. In this work, total power is calculated from 1 to 40 Hz by

rx(k) = Lim N→∞

1

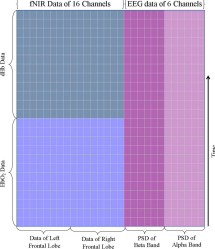
2N + 1

N

n=−N

x(n + k) ⊗ x(n)

(4)



the previously explained Welch method. Eventually, the relative power of a band is the ratio of the power of the band *P* and total power, *Ptotal* that can be presented as, [43, 46],

P(f1, f2)

RP(f1, f2) = (8) Ptotal× 100%

Here, *P* indicates the power, *RP* represents the relative power, and *f*1 and *f*2 are the low- and high-frequency of the specifc band, respectively. Furthermore, before applying the combined fNIR–EEG data to CNN the fea

tures of HbO2, dHb, alpha PSD, and beta PSD are nor malized separately using the following equation: π (9) ′ = π − πmin πmax − πmin

Here, π′ are the feature values that are rescaled between the range 0 and 1. Te maximum and minimum feature values are presented as πmax and πmin, respectively.  Finally, we get a data matrix of size 120×28. Te arrange

ment of fNIR and EEG data are given in Fig. 7. Te data set for every task was used to prepare functional neu roimage. A demo Matlab code is given in the appendix to demonstrate the procedure of making the functional neuroimages from the numerical data of fNIR and EEG.

**CNN‑based modeling**

CNN shows nice performance in signal and image clas

**Fig. 7** Combining the fNIR and EEG data to prepare the spatiotem poral neuroimages for classifcation by CNN

sifcations. To improve accuracy further, deep CNNs (where the number of convolutional layers≥3) are often

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**Table 1 The architecture of the proposed CNN**

**Type Description**

Image input layer 384×384×3

Convolution layer 1 Filter size=[8, 8]; number of channels=3; number of flters=9; padding size=[3, 4, 3, 4]; stride=[1, 1] Batch normalization layer

ReLU layer

Maxpooling layer Pool size=[2, 2]; stride=[2, 2]

Convolution layer 2 Filter size=[4, 4]; number of channels=9; number of flters=16; padding size=[1, 2, 1, 2]; stride=[1, 1] Batch normalization layer

ReLU layer

Maxpooling layer Pool size=[2, 2]; stride=[2, 2]

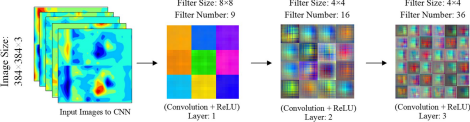
Convolution layer 3 Filter size=[4, 4]; number of channels=16; number of flters=36; padding size=[1, 2, 1, 2]; stride=[1, 1] Batch normalization layer

ReLU layer

Fully connected layer Output size=4/6/8

Softmax layer

Classifcation output layer Output size=4/6/8; loss function=crossentropy

**Fig. 8** The features of the input images with the changes of layers of the CNN based classifers

**Table 2 Parameters considerations in the proposed CNN based model training**

**Parameter Name Consideration Parameter Name Consideration**

Activation function Sigmoid Maximum epoch 20 Momentum 0.90 Mini batch size 128 Initial learning rate 0.01 Verbose frequency 50 L2 regularization 1.00×10−4 Validation frequency 4 Gradient threshold method L2 norm Validation patience 5

used [47]. In this work, a deep CNN is used to construct a predictive model for classifying voluntary and imagery movements. In CNN, each neuron receives some inputs and performs a dot product. CNN represents a speciali

zation of the conventional neural networks where the individual neurons create a mathematical estimation of the biological visual receptive feld [48]. Te basic structure of a CNN consists of a number of layers: con

volutional layer, batch normalization layer, rectifed lin ear unit (ReLU activation layer), max pooling layer, etc.

An inception block extracts the feature maps from the input images, which are concatenated and passed on to a global average pooling layer. Eventually, there is a two unit dense layer with a softmax activation layer, which gives the categorical probability. To prevent the over ftting problem, the weights of the dense layers are L2 regularized.

Te architecture of our applied CNN model is sum marized in Table 1. Te CNN model includes three con volutional, two max pooling, three batch normalization,

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Organize the HbO2 and dHb

signals (120×16)

fNIR Signal

preprocessing

Combine fNIR & EEG

information and create 120 by

Train CNN

CNN based

28 size Neuroimage Load fNIR & EEG

for modeling

predictive model

Signals

***e***

***s***

***a***

***h***

***P***

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Signal

EEG Signal

filtering

Separate the

channel: F3 Fz F4 C3 Cz C4

Prepare 12 column feature vectors with relative band power of frontal and central EEG channel (2×6 channels)

STFT of frontal and central channels to calculate the relative power of alpha and beta band

***Preprocessing for Proposed Model***

***e***

Preprocessing for

***s***

fNIR and

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***h***

proposed model

***P***

EEG signals

compatibility

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Task classification for BCI

Voluntary and imagery movements

**Fig. 9** The main steps of the proposed method of processing of the EEG and fNIR signal, image formation, and classifcation Preprocessed EEG signal

Reduce the dimension of the signal by CAF

Extract features from the signals

Combine them as the proposed method

Separate the training and testing data

Train the model with SVM or LDA algorithm

Preprocessed fNIR signal

Store the testing

*Task prediction by*

*the model* Voluntary &

data

Predictive model

imagery

movements

**Fig. 10** Steps regarding the manual feature extraction and classifcation of the combined fNIR and EEG signals by the conventional classifers

and four/six/eight fully connected layers. Tere are four, six, and eight fully connected layers for 4-, 6-, and 8-class problems, respectively. As explained earlier, the input image size is 384×384×3, which indicates 384×384

image size with three color components. Te flter ker nel was used as 8×8, 4×4, and 4×4 for the 1st, 2nd, and 3rd convolutional layers, respectively. We have used stride [1 1] for the convolutional layers and [2 2] for max

Rahman *et al. Health Inf Sci Syst (2019) 7:22* Page 9 of 22 **a**

r

a

lo

m

o

r

c

iM

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m

o

r

c

iM

20

|  |  |  |  |  |  |  | Raw fNIR data Filtered fNIR data |
| --- | --- | --- | --- | --- | --- | --- | --- |
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|  |  |  |  |  |  |  |  |

15

10

5

0

-5

-10

-15

0 10 20 30 40 50 60 70 80 Times [s]

**b**

20

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
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|  |  |  |  |  |  | Raw fNIR data after baseline correction |  |
|  |  |  |  |  |  | Filtered fNIR data after baseline correction |  |

15

10

5

0

-5

-10

-15

0 10 20 30 40 50 60 70 80 Times [s]

**Fig. 11 a** Raw and fltered fNIR signal without baseline correction and **b** fltered fNIR signal after baseline correction that starts from the baseline or zero levels

pooling layers. Te convolution layers and its kernel and flter numbers of this proposed CNN model are given in Fig. 8 along with the feature maps for the 4-class problem of a typical subject.

**Training and testing the model**

Te proposed CNN model was trained based on some initial considerations about diferent parameters, which are defned in Table 2. Te loss function was calculated from the cross-entropy in the softmax layer. On the other hand, the training and testing data ratio is considered 4:1. Te classifcation accuracy, we used fvefold cross

validation technique. Here, 25% of the training data was used for validation. Te training and testing of the pro posed model were conducted at the subject-dependent approach. Eventually, the data of 15 participants were separately used for training and testing. Te classifcation

accuracy was conducted for 4-, 6-, and 8-class problems, where the class level was set as 4-class: [LH, RH, iLH, and iRH], 6-class: [LH, RH, iLH, iRH, iLF, and iRF], and 8-class [LH, RH, LF, RF, iLH, iRH, iLF, and iRF]. Further

more, the training process was conducted by two types of data set: (i) only fNIR data and (ii) combined fNIR and EEG data. Te methodology of the proposed work including preprocessing, image construction by com

bined fNIR and EEG along with CNN based model is presented in Fig. 9.

**Manual feature extraction and classifcation by SVM and LDA**

Unlike CNN, for the classifcation of the multiple class signals their manual feature extraction is necessary. An excellent review work has been done in [5] where the signal’s feature extraction procedure of the combined

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50

0

-50

500 1000 1500 2000 2500 3000 3500 4000 4500 5000

**b**

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50

0

-50

500 1000 1500 2000 2500 3000 3500 4000 4500 5000

**c**

50

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |  |  |  |

0

-50

500 1000 1500 2000 2500 3000 3500 4000 4500 5000

**d**

50

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |  |  |  |

0

-50

500 1000 1500 2000 2500 3000 3500 4000 4500 5000

**Fig. 12** Step by step EEG signal pre-processing: **a** raw EEG signal of a single channel, **b** EEG signal after removing 50 Hz power line noise, **c** fltered EEG signal up to 45 Hz by third-order elliptical flter, and **d** eye-blink and EOG artifact-free EEG signal which is fltered by the EAWICA toolbox

fNIR and EEG system is recommended. According to the recommendations of the work [5], the signal dimen sions of both fNIR and EEG signals were reduced in this work. In the case of the fNIR signal, common averaging fltering (CAF) was used to reduce the dimension of the signal from 16 to 4 as recommended in [44]. In the case of the EEG signals, the required six channels (F3, F4, Fz, C3, C4, and Cz) were reduced to 4 signals by excluding the Fz and Cz. Terefore, for manual feature extraction in case of both fNIR and EEG signals, four channels were considered.

From fNIR signals, two signifcant features were extracted those are signal mean and slope. Te calcula tion procedures of the signal mean and slope are given in [5, 49]. On the other hand, the following features were extracted from the EEG signals: PSD [43], logarithmic power [5], L2 norm [50], and spectral entropy [51]. As a result, each fNIR signal depicts 4×2 = 8 (signal dimen sion×number of features) features and each EEG signal depicts 4×4  =  16 features. Terefore, the dimensions of the features of the combined fNIR and EEG signals

would be (16+8)×4=96×1, (16+8)×6=144×1, and (16+8)×8=192×1 for 4-, 6-, and 8- class, respectively. According to the recommendations of the review work [5], SVM and LDA were chosen for modeling and clas sifcation. Since the operating mechanism of the SVM and LDA classifer is well known, the detail explanation is unnecessary (worth reading [52]). In case of modeling by the SVM structure, polynomial kernel function was used considering order value 3 and performances were meas ured utilizing fvefold cross-validation. Te cost function was considered as 75%. Furthermore, the classifcation performances of the LDA model was also measured uti lizing fvefold cross-validation. Te predictive model preparation using SVM and LDA by the features extrac tion and their classifcation accuracy calculating steps are shortly presented by the fow diagram given in Fig. 10.

**Results and discussion**

For raw data logging of EEG and fNIR, Acqknowledge 4.0 and COBI studio were used, respectively. Te ana lytical outcomes regarding this research work are solely

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**Table 3 The average neural activation regarding diferent stimuli**

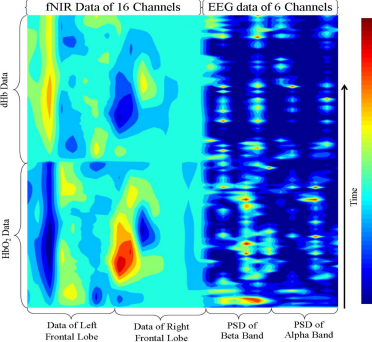
| RH | LH | iRH | iLH |
| --- | --- | --- | --- |
|  |  |  |  |
| RF | LF | iRF | iLF |
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The activation was calculated based on the relative power spectral density of the channels

accomplished by Matlab 2018a programming software in a computer having a Core-i7 processor with 8 GB RAM. In the processing steps, we frst executed the data fl tering part. Te fltering efect on the raw fNIR signal has been shown in Fig.  11 and that of the EEG signal has been given in Fig.  12. Here we considered the cen tral and frontal EEG channels. Tis is because the func tional changes occur in the central lobe mostly, but the frontal lobes become also activated due to voluntary and imagery movement-related tasks. For the justifcation, we have added the activation level of diferent positions of the brain concerning frontal, central, and parietal lobe of the brain as topoplot. Te topoplots are presented in Table 3. Te totoplots are prepared from the average acti vations of fve randomly chosen subjects. A Matlab based free toolbox [53] has been utilized to prepare the graphi cal topoplots, which is solely designed for the 9-channel EEG data of B-Alert wireless devices. From the topoplots, we get that the voluntary movements of hands and feet create signifcant activations in the central lobe. On the other hand, due to imagery movements, both the frontal and central lobes become activated. One thing is noticea ble for the imagery feet movements that the impact of the

activation is slightly lower than that of the imagery hand movements. In addition, the patterns are also irregular compared to the movements of the voluntary feet move ments. In most of the cases, the parietal lobe was inac tive and that is why the information of the parietal lobe is excluded in the functional neuroimage construction. For the same reason, during the manual feature extraction from the EEG signal, the three channels of parietal lobe were excluded. Since there is a tradeof relation between the feature dimension and the classifcation accuracy, this excluding process helps to reduce the feature dimension and indirectly helps to increase the possibility of higher classifcation accuracy.

According to our proposal of the fNIR–EEG com bined spatiotemporal data, a typical fNIR and EEG data of a particular stimulus has been considered to make the functional neuroimage and the resulting image is given in Fig. 13. Te color bar is given on the right side of the fg ure. Terefore, using the proposed method the combined fNIR–EEG data can be transformed into images that can be applied to the input of the CNN. Te Matlab code of the image generation has been given in the “Appendix”. Tis is our original approach of presenting the combined

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**Fig. 13** Combining the fNIR and EEG data to prepare the spatiotemporal neuroimages for classifcation by CNN

fNIR–EEG time series data because, so far our knowl edge, no research work has not proposed in such a form of fNIR and EEG data combination process.

It should be mentioned that along with the combined fNIR–EEG based image, we also used only the fNIR data (HbO2 and dHb) to produce the neuroimages for the training of the CNN. It was performed to show the dif

ference in the classifcation accuracy between the single fNIR modality and the combined modality approach. Te neuroimages regarding the single and bimodal data of eight diferent class stimuli have been presented by Tables 4 and 5, respectively. Te images are prepared on the basis of their normalized value. Furthermore, these

images are RGB color image those are prepared to feed to the CNN.

Tese images are sequentially fed to the CNN for auto matic feature extraction and to train the predictive model for further classifcation. Te trained model was con structed for 4-, 6-, and 8-classes. Te training and valida tion accuracy with respect to the iteration of 4-, 6-, and 8-class problems are given in Figs. 14, 15, and 16, respec tively. Te loss reduction during training and validation of the proposed CNN models is also given in the fgures. Te training and validation accuracy of the proposed CNN model are found best in case of a 4-class problem.

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**Table 4 Neuroimages from the temporal HbO2 and dHb fNIR data of 10-s task plus 20-s activation**

| Tasks | Trial # 1 | Trial # 2 | Trial # 3 | Trial # 4 | Trial # 5 | Trial # 6 | Color bar |
| --- | --- | --- | --- | --- | --- | --- | --- |
| iLH |  |  |  |  |  |  |  |
| iRH |  |  |  |  |  |  |
| iLF |  |  |  |  |  |  |
| iRF |  |  |  |  |  |  |
| LH |  |  |  |  |  |  |
| RH |  |  |  |  |  |  |
| LF |  |  |  |  |  |  |
| RF |  |  |  |  |  |  |

Here, there are images of eight types of tasks with 6 trials of each task

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**Table 5 Neuroimages from the combined fNIR and EEG data of 10-s task plus 20-s activation**

| Tasks | Trial # 1 | Trial # 2 | Trial # 3 | Trial # 4 | Trial # 5 | Trial # 6 | Color bar |
| --- | --- | --- | --- | --- | --- | --- | --- |
| iLH |  |  |  |  |  |  |  |
| iRH |  |  |  |  |  |  |
| iLF |  |  |  |  |  |  |
| iRF |  |  |  |  |  |  |
| LH |  |  |  |  |  |  |
| RH |  |  |  |  |  |  |
| LF |  |  |  |  |  |  |
| RF |  |  |  |  |  |  |

On the other hand, the validation accuracy was slightly inferior in the case of 6- and 8-classes.

Tese results are found for subject 1 while the mod els were trained by combined fNIR and EEG data. We have applied two diferent approaches to fnd the clas sifcation accuracy: one is based on fNIR data only and

the other is based on the combined information of fNIR and EEG data. Te results of 15 participants are given in Tables 6 and 7, respectively. In addition, according to the proposition and scope of this work, the conventional classifcation methods such as LDA and SVM were also

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0 2 4 6 8 10 12 14 16 18 20 Iteration

|  |  |  |  |  |  |  | Training | Training(Smoothed) |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
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0 2 4 6 8 10 12 14 16 18 20 Iteration

**Fig. 14** The training and validation accuracy with loss performances with respect to the epoch iterations for 4-class problem

applied to check their performances. Te extracted fea tures of the fNIR data and the combined fNIR and EEG data were classifed utilizing the SVM and LDA method and the regarding results are also given in Tables 6 and 7, respectively.

From the result, we get that the combined informa tion provides us greater classifcation accuracy. For 4-, 6-, and 8-class problems, the classifcation accuracies are signifcantly improved by 9%, 11%, and 17% on average by the combined fNIR–EEG information in case of the CNN. On the other hand, the improvement in the clas sifcation accuracy occurred 10%, 8%, and 8% for SVM and 7%, 4%, and 5% for LDA. In the case of the conven tional classifers, the performances for the 6- and 8-class are not convincing at all and that is why the choice of CNN is inevitable. Te average classifcation perfor mances of SVM, LDA, and the proposed CNN model

for single and bimodal data are presented in Figs. 17 and 18, respectively to refect the importance of utilizing the combined information of fNIR and EEG signal as well as choosing CNN as a classifer. Te results claim that for 8-class problem classifcation, CNN exceptionally plays a signifcant role to achieve the expected BCI goal. In addition, the combination of the EEG information with the fNIR signal provides an excellent increment in the classifcation performances. Te result proves that com bined information of fNIR and EEG outperforms the information regarding the fNIR signal alone. In addition, the classifcation accuracy has been achieved 90±4.54%, 82±5.12%, and 72±4.34% for 4-, 6-, and 8-class prob

lems, respectively, which is too convincing for the BCI implementation.

Although there is numerous research work on motor imagery signal classifcation, their data acquisition

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**Fig. 15** The training and validation accuracy with loss performances with respect to the epoch iterations for 6-class problem

protocols, devices, participants, and modalities are dif ferent from each other. Terefore, to compare them directly are difcult in the scientifc aspect. Although some research works have existed that deploys 4-class motor imagery EEG or fNIR signal classifcation, there is only one work [31] that presents both 4-class and 8-class BCI for robot hand control. Since the main objective of all these research works is to implement BCI, a general comparison regarding their protocols, methods, and per

formances could be a nice presentation to observe the overall concept about the trends of the multiple-class BCI implementation through fNIR, EEG or combined fNIR and EEG. Such a comparison of 4-class and 8-class BCI

of the proposed method with the others has been pre sented in Table 8. From the performance of the proposed method, it is clear that in the process of improvement trending in the research of BCI, our proposed bimodal approach outperforms the existing previous works.

**Conclusion**

Tis paper is the frst research paper based on the com bined fNIR and EEG signals that deals with up to 8-class problems classifcation by CNN—an artifcial intelli gence tool. Besides, this is the frst proposal to decode voluntary and imagery movements combining prefron tal hemodynamic signals (fNIR) along with the frontal

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**Fig. 16** The training and validation accuracy with loss performances with respect to the epoch iterations for 8-class problem

**Table 6 The classifcation accuracy of the SVM, LDA, and the proposed model with the fNIR data only Participant # 4-class 6-class 8-class**

**SVM LDA Proposed CNN**

**SVM LDA Proposed CNN**

**SVM LDA Proposed CNN**

1 60% 76% 82% 52% 61% 74% 48% 45% 55% 2 63% 66% 78% 53% 59% 71% 45% 48% 50% 3 68% 66% 80% 57% 53% 77% 52% 43% 50% 4 70% 74% 84% 60% 63% 77% 58% 54% 55% 5 65% 70% 85% 53% 54% 67% 37% 39% 65% 6 68% 69% 76% 61% 58% 71% 54% 47% 60% 7 64% 72% 81% 56% 67% 75% 41% 50% 60% 8 69% 67% 78% 64% 58% 61% 52% 56% 55% 9 66% 70% 89% 54% 53% 78% 43% 35% 50% 10 65% 68% 78% 59% 62% 65% 48% 48% 55% 11 72% 66% 78% 59% 60% 62% 48% 58% 45% 12 68% 64% 82% 56% 59% 71% 37% 48% 50% 13 73% 75% 84% 65% 66% 71% 56% 52% 60% 14 70% 74% 90% 62% 62% 74% 58% 51% 65% 15 74% 72% 75% 65% 64% 64% 43% 50% 50% Average±(SD) 68%±(3.88) 70%±(3.76) 81%±(4.45) 58%±(4.42) 60%±(4.33) 71%±(5.56) 48%±(6.98) 48%±(6.07) 55%±(5.97)

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**Table 7 The classifcation accuracy of the SVM, LDA, and the proposed model with the combined fNIR and EEG data Participant # 4-class 6-class 8-class**

**SVM LDA Proposed CNN**

**SVM LDA Proposed CNN**

**SVM LDA Proposed CNN**

1 77% 80% 92% 70% 65% 90% 54% 50% 74% 2 82% 76% 88% 61% 68% 82% 52% 58% 72% 3 81% 80% 88% 69% 57% 84% 58% 60% 75% 4 86% 82% 90% 65% 64% 90% 61% 52% 76% 5 77% 78% 94% 73% 70% 88% 48% 54% 70% 6 75% 80% 92% 58% 57% 86% 60% 50% 80% 7 80% 77% 94% 62% 69% 82% 55% 48% 78% 8 72% 66% 86% 70% 61% 75% 61% 56% 69% 9 78% 74% 98% 65% 65% 85% 58% 55% 71% 10 71% 76% 84% 65% 53% 75% 55% 50% 70% 11 81% 79% 83% 66% 69% 78% 58% 58% 68% 12 77% 68% 91% 71% 68% 82% 48% 52% 65% 13 78% 80% 90% 65% 68% 80% 60% 54% 65% 14 76% 82% 96% 61% 58% 78% 62% 55% 72% 15 84% 78% 87% 64% 70% 75% 54% 50% 70%

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78%±(4.11) 77%±(4.66) 90%±(4.54) 66%±(4.23) 64%±(5.57) 82%±(5.12) 56%±(4.49) 53%±(3.56) 72%±(4.34)

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**Fig. 17** Overall performances (mean±SD) of the classifcation accuracy through SVM, LDA, and the proposed CNN method while only the fNIR data were considered

and central neuroelectric signal (EEG). Tis proposal on the bimodal approach for CNN-based BCI implementa tion found excellent results in classifcation accuracy of the voluntary and imagery movement-related tasks. It has been also shown that the classifcation accuracies are

increased in the combined fNIR–EEG signal rather than the unimodal information (fNIR only). In addition, this proposal extends the pathway to implement up to 8-class problem utilizing fNIR and EEG data where most of the current literature discussed 2- or 4-class. Te proposed

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**Fig. 18** Overall performances (mean±SD) of the classifcation accuracy through SVM, LDA, and the proposed CNN method while combined fNIR and EEG data were considered

**Table 8 Comparison of the proposals of the multiple class BCI system**

**Research work Work objectives Methodology Modality Resulting accuracy**

**(%)**

4-*class database classifcation*

Leon et al. [31] Combined motor imagery classifcation *Feature extraction*: modifed CSP *classifer*: multistep SVM EEG 71.67 Rahman et al. [54] Moto imagery classifcation *Feature extraction*: PCA and wavelet *classifer:* two-step ANN EEG 74.60 Ge et al. [30] Moto imagery classifcation *Feature extraction*: STFT and CSP *classifer:* SVM EEG 88.1

Batula et al. [26] Moto imagery classifcation *Feature extraction*: mean value *Classifer:* SVM

Shin et al. [55] Moto imagery classifcation *Feature extraction*: statistical features *Classifer:* Naive Bayes classifer

fNIR 54 fNIR 83.15

Proposed method Moto imagery classifcation Feature extraction and classifcation by CNN fNIR+EEG 90 8-*class database classifcation*

Leon et al. [31] Combined motor imagery classifcation Feature extraction: modifed CSP classifer: multistep SVM EEG 51.67%

Proposed method Voluntary and imagery motor move ment classifcation

Feature extraction and classifcation by CNN fNIR+EEG 77%

*CSP* common spatial pattern, *PCA* principal component analysis, *STFT* short time Fourier transform

method is robust, intelligent, and efcient for the move ment classifcation problems, which makes hope in establishing an efective BCI for the motor impaired or paralyzed persons.

Tis work also added the performances of the conven tional classifcation methods where the feature extraction was done manually. During feature extraction, recommen dations of some scholarly article were obeyed although the performance of the conventional classifer solely depends on the discriminative features. Terefore, further improved

feature extraction method could change the performances of the conventional methods, slightly, but not be able to exceed the proposed method.

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**Compliance with ethical standards**

**Conflict of interest**

This research work has no confict of interest to anyone.

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**Appendix**

*Pseudocode for preparing the functional neuroimages combining fNIR and EEG signal*

% loading the fNIR and EEG data

load('fNIR\_data.mat');

load('EEG\_data.mat');

% locating the fNIR and EEG data in variables

HBO=fNIR\_HbO2;

HBR=fNIR\_dHb;

EEG=EEG\_data; % Here the EEG data is the PSD of alpha and beta bands

sub=1;

for i=1:40

req\_data\_1(:,:,i)=vertcat(HBO(1:60,:,i,sub), HBR(1:60,:,i,sub));

req\_data\_2(:,:,i)=horzcat(EEG(1:120,1:4,i),EEG(1:120,5:8,i))

end

for k=1:40

x1=req\_data\_1(:,:,k);

[M1 N1]=size(x1);

x1\_min=min(min(x1));

x1\_max=max(max(x1));

x2=req\_data\_2(:,:,k);

[M2 N2]=size(x2);

x2\_min=min(min(min(req\_data\_2(:,:,k))));

x2\_max=max(max(max(req\_data\_2(:,:,k))));

for i=1:1:M1

for j=1:1:N1

y1(i,j)=(x1(i,j)-x1\_min)/(x1\_max-x1\_min);

end

end

for i=1:1:M2

for j=1:1:N2

y2(i,j)=(x2(i,j)-x2\_min)/(x2\_max-x2\_min);

end

end

data\_1=horzcat(y1,y2(:,1:4),y2(:,5:8));

x\_data=1:1:24;

y\_data=1:1:120;

z\_data=(data\_1(1:120,1:24));

xx = x\_data; % Horizontal axis coordinates

yy = y\_data; % Vertical axis coordinates

z = z\_data; % Feature values of the corresponding electrodes

nx = linspace(min(xx), max(xx),24);

ny = linspace(min(yy), max(yy),120);

[xxx,yyy] = meshgrid(nx,ny);

zz = griddata(xx,yy,z,xxx,yyy,'cubic');

contourf(xxx,yyy,zz,'linestyle','none','LineWidth',0.5);

colormap('JET');

axis off;

set(gcf,'PaperUnits','inches','PaperPosition',[0 0 4 4]); % Set the image size and position print(1,'-dpng', [['' num2str(k) '.png'],'-r0'); % save it as an image

%colorbar

end

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