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Motor Imagery Classification Using Rough Neural Network

J. Anila Maily [1]
Dr. C. Velayutham[2]
Dr. M. Mohamed Sathik[3]

Abstract

Brain Computer Interface is a system which provides a communication channel between the user and a computer without using the normal neuromuscular pathways. With BCI a user will be able to communicate with the mind. In a BCI system the brain activities are measured using EEG acquisition system. The acquired brain signals are analyzed and classified to identify the user's intention. Motor imagery BCI works by making the user imagine their body parts without actually moving it. Prominent features are extracted from the acquired brain signals and the extracted features are classified to find the motor imagery performed by the user. This study uses datasets are provided by the Dr. Cichocki's Lab (Lab for Advanced Brain Signal Processing). We propose the Rough Neural Network (RNN) for Motor imagery classification. The experimental results show that RNN classifier gives higher accuracy than Backpropagation Classifier.

Keywords: BCI, EEG, Motor Imagery, RNN

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[1] Research Scholar, (Part-time internal) (Register Number: 12336), Dept of Computer Science, Sadakathullah Appa College, Rahmath Nagar, Tirunelveli. Affiliated to Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli-627012, Tamil Nadu, India
Associate Professor, St. Mary‟s College (Autonomous), Thoothukudi. Email: anilamaily@gmail.com

[2] Head and Associate Professor, Department of Computer Science, Aditanar College of Arts and Science Tiruchendur Affiliated to Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli-627012, TamilNadu, India. Email:cvsir22@gmail.com

[3] Principal, Sadakathullah Appa College, Rahmath Nagar, Tirunelveli -627011, Affiliated to Manonmaniam Sundaranar University, Abishekapatti, Tirunelveli-627012, Tamil Nadu, India. Email: mmadsadiq@gmail.com

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1. Introduction

Brain Computer Interfacing (BCI) is to provide a communication channel between man, and machine, BCI users brain signals are captured, analyzed into commands for communication and control (Birbaumer et. al., 2003, Wolpow et. al.,2002) [1, 2]. BCI is a boon for people with severe motor disorders like Amyotrophic Lateral Sclerosis (ALS), brain stem stroke, cerebral palsy and spinal cord injury. A user's intent, as reflected by brain signals, is translated by the BCI system into a desired output: computer-based communication or control of an external device (Joseph et. al., 2009) [3]. Motor Imagery works by making the people imagine the moving their body parts without actually doing it. The brain signals during the imagination are recorded and analyzed to identify the intent of the person.

In BCI systems the brain signals are recorded from multiple channels to preserve high spatial accuracy. The Rough Set Theory (RST) enables the discovery of data dependencies and the reduction of the number of attributes contained in the data set using the data alone requiring no additional information. Given a dataset with discretized attribute values, it is possible to find a subset (of the original attributes using Rough Set Theory that are the most informative. All other attributes can be removed from the dataset with minimal information loss. (Velayutham, C., et. Al., 2011) [4].

2. Classification by BPN and RNN

Neural networks are the classifier used mostly in BCI. Neural network integrated with Rough Set Theory (RST) is known as Rough Set Neural network (RNN). The rough set theory and neural network are the two important methods of intelligent information processing. Optimizing the net for correct responses to the training input data set is done by Backpropogation. More than one hidden layer may be beneficial for some applications, but one hidden layer is sufficient if enough hidden neurons are used ((R. Jensen, and Q. Shen, 2008, C. Velayutham, and K. Thangavel, 2011, Simon Haykin, 2005) [5 - 7].

Rough set and neural networks can solve complex and high-dimensional problems, which are called Rough Neural Networks (RNNs) (Weidong Zhao, and Guohua Chen. 2002) [8]. This paper investigates the Motor Imagery classification accuracy using Backpropagation network classifier and propose Rough neural network classifier. The rest of the paper is organized as follows. Section II briefly describes classification technique used with EEG. Section III presents the methodology adopted, Section IV is about results and discussion. Section V concludes the paper.

3. Literature Review

Hong K-S et al., (2018), [9] presented a brain-computer interface (BCI) framework for hybrid functional near-infrared spectroscopy (fNIRS) and electroencephalography (EEG) for locked-in syndrome (LIS) patients. For classification, linear discriminant analysis has been most widely used.

Siavash Sakhavi et al., (2018) [10] proposed a classification framework for Motor Imagery (MI) data by introducing a new temporal representation of the data and utilized a convolutional neural network (CNN) architecture for classification. The framework classified BCI competition IV-2a 4-class MI data set by 7% increase in average subject accuracy.

Vladimir A. Maksimenko et al., (2018) [11] applied Artificial Neural Network (ANN) for recognition and classification of EEG patterns associated with motor imagery in untrained subjects. ANN optimization is proposed by pre-processing the EEG signals with a low pass filter and it is shown filtration of high frequency spectral components enhances the classification performance up to 90±5%.

Han, C., Kim, Y., Kim, D.Y. et al., (2019) [12] investigated the possibility of using an EEG-based endogenous BCI paradigm for online binary communication by a patient in Complete Locked in Syndrome (CLIS). An online classification accuracy of 87.5% was achieved when Riemannian geometry-based classification was applied to real-time EEG data recorded while the patient was performing one of two mental-imagery tasks for 5 s.

Shiu Kumar et al., (2019) [13] introduced a novel scheme for classifying motor imagery (MI) tasks using electroencephalography (EEG) signal that can be implemented in real-time having high classification accuracy between different MI tasks. They proposed a new predictor, OPTICAL, that uses a combination of common spatial pattern (CSP) and long short-term memory (LSTM) network for obtaining improved MI EEG signal classification.

4. Methodology

The methodology followed for Motor Imagery classification is shown in figure 1.

Data sets of motor imagery EEG

The Datasets provided by the Dr. Cichocki's Lab (Lab. for Advanced Brain Signal Processing), is used for this study.

Data files and format

All data sets are stored in the MATLAB format (*.mat). The file name consists of subject ID, channel number, imagery tasks and session number. For example, *'SubC_6chan_3LRF_s1':* Subject C, 6 channels, 3-class imagery tasks of left hand, right hand and feet and session 1. Each file contains one session which consists of several runs separated by short breaks. Some subjects have many sessions conducted on different days. The detailed information of the dataset is given in table 1.

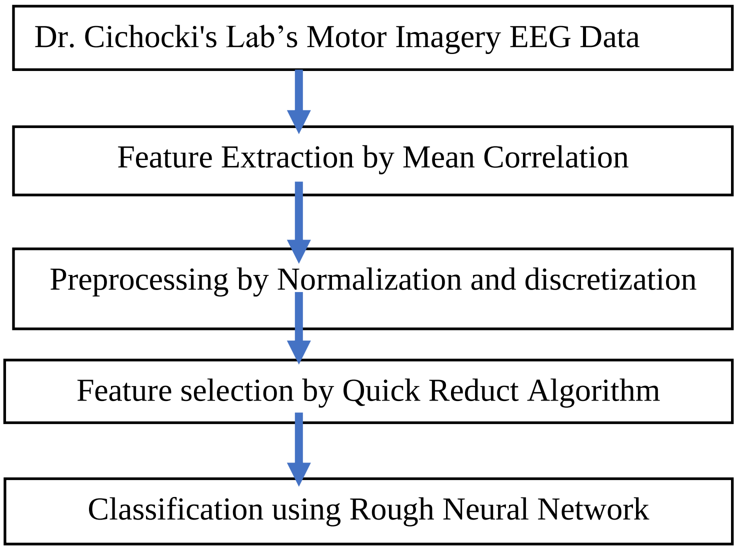


Figure 1: Methodology

Feature Extraction and Feature selection

Prominent features are extracted from the signals using statistical parameter mean correlation. The extracted features are preprocessed by applying minmax normalization and discretized with k-means algorithm. The preprocessed datasets are further reduced by using supervised feature selection algorithm Quick Reduct based on Rough Set Theory.

Classification by BPN and RNN

The reduced feature set selected from the feature selection algorithms are assigned to the input neurons. The number of hidden neurons is greater than or equal to the number of input neurons, and there is only one output neuron. Initial weights are assigned randomly. The output from each hidden neuron is calculated using the sigmoid function

$$S_1 = \frac{1}{1+e^{-\lambda x}} \text{ where } \lambda = 1 \text{ and } \quad x = \sum_i w_{ih}\, k_i \qquad (1)$$

where w_{ih} is the weight assigned between input and hidden layer and k is the input value. The output from the output layer is calculated using the sigmoid function.

$$S_2 = \frac{1}{1+e^{-\lambda x}}, \text{ where } \lambda = 1 \text{ and } \quad x = \sum_i w_{ho}\, S_i \qquad (2)$$

where w_{ho} is the weight assigned between hidden and output layer and S_i is the output value from hidden neurons. S_2 is subtracted from the desired output. Using this error (e) value, the updating of weight is performed as:

$$\delta = eS_2(1 - S_2) \qquad (3)$$

The weights assigned between the input and the hidden layer and the hidden and output layer are updated as:

Sl. No.	Dataset	Subject	Class	Channel	Duration (sec)	Trial	10x10 CV (Acc.±std.)	Sample rate	Device
1	SubA_5chan_3LRF	A	LH/RH/F	5	4s	270	0.92±0.004	256Hz	G. tec
2	SubB_5chan_3LRF	B	LH/RH/F	5	4s	174	0.86±0.01	250Hz	Neuroscan
3	SubB_6chan_3LRF			6		150	0.80±0.03		
4	SubC_5chan_3LRF	C	LH/RH/F	5	4s	180	0.86±0.01	256Hz	g.tec
5	SubC_6chan_3LRF_s1			6	3s	300	0.89±0.01		
6	SubC_6chan_3LRF_s2					300	0.84±0.01		
7	SubC_6chan_3LRF_s3					204	0.89±0.01		
8	SubC_5chan_3LRF _Day1	C	LH/RH/F	5	4s	210	0.72±0.02	256Hz	g.tec
9	SubC_5chan_3LRF _Day2					210	0.81±0.01		
10	SubC_5chan_3LRF _Day3					180	0.81±0.01		
11	SubC_5chan_3LRF _Day4					180	0.83±0.02		
12	SubC_5chan_3LRF _Day5					234	0.87±0.01)		
13	SubC_5chan_3LRF _Day6					150	0.88±0.01		
14	SubC_5chan_3LRF _Day7					180	0.88±0.01		
15	SubC_14chan_3LRR	C	LH/RH/R	14	4s	350	0.78±0.01	250Hz	Neuroscan

Table 1: The detailed information of three class dataset

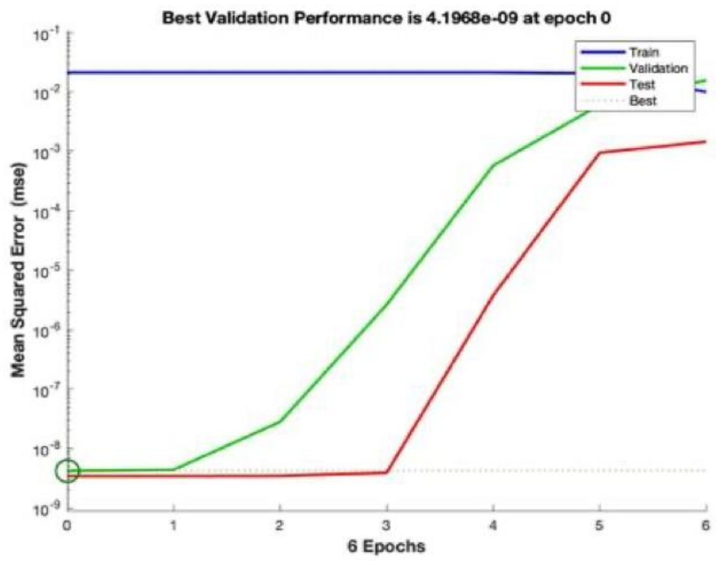
5.Results

The classification accuracy of three class datasets using Backpropagation classifier and Rough Neural Network classifier is tabulated in table 2. Figure 2 and figure 3 depicts the classification accuracy of SubA_5chan_3LRF. Classification accuracy of SubB_6chan_3LRF using BPN and RNN classifier is shown in Figure 4 and Figure 5. Figure 6 and figure 7 depicts the Regression plot of SubA_5chan_3LRF using BPN and RNN. It is observed that the performance of RNN classifier shows higher performance than the BPN classifier for all the datasets. Figure 8 shows the accuracy of all three class datasets using BPN and RNN classifier.

Sl No.	Dataset	Accuracy	
		BPN	RNN
	SubA_5chan_3LRF	98.80	99.70
	SubB_6chan_3LRF	97.20	99.00
	SubB_5chan_3LRF.	96.00	99.10
	SubC_5chan_3LRF.	98.00	99.50
	SubC_6chan_3LRF_s1	95.30	98.70
	SubC_6chan_3LRF_s2	99.40	99.70
	SubC_6chan_3LRF_s3	98.40	99.60
	SubC_5chan_3LRF_day1	99.60	100.0
	SubC_5chan_3LRF_day2	98.30	99.60
	SubC_5chan_3LRF_day3.	93.70	97.90
	SubC_5chan_3LRF_day4	97.80	99.50
	SubC_5chan_3LRF_day5	96.80	99.30
	SubC_5chan_3LRF_day6	97.50	99.90
	SubC_5chan_3LRF_day7	98.70	99.90
	SubC_14chan_3LRR	98.90	99.10

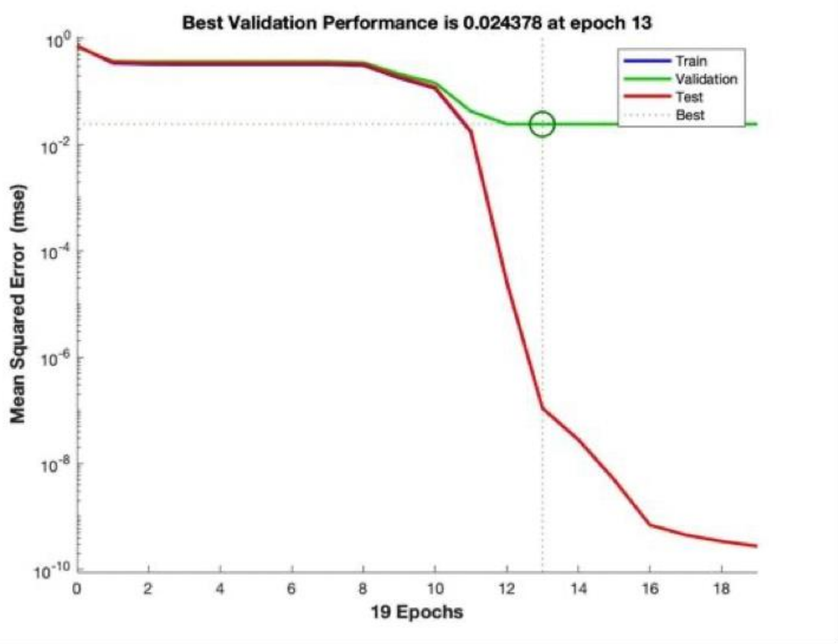
Table 2: Classification accuracy of three class data sets by BPN and RNN

Figure2:



Classification Performance of SubA_5chan_3LRF by BPN Classifier

Figure 3 :



Classification Performance of SubA_5chan_3LRF by RNN Classifier

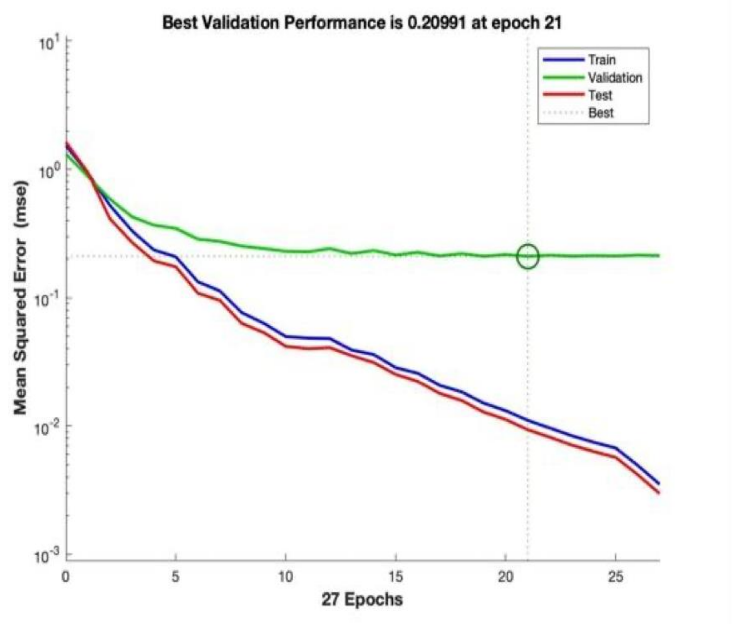


Figure 4: Classification Performance of SubB_6chan_3LRF BPN Classifier

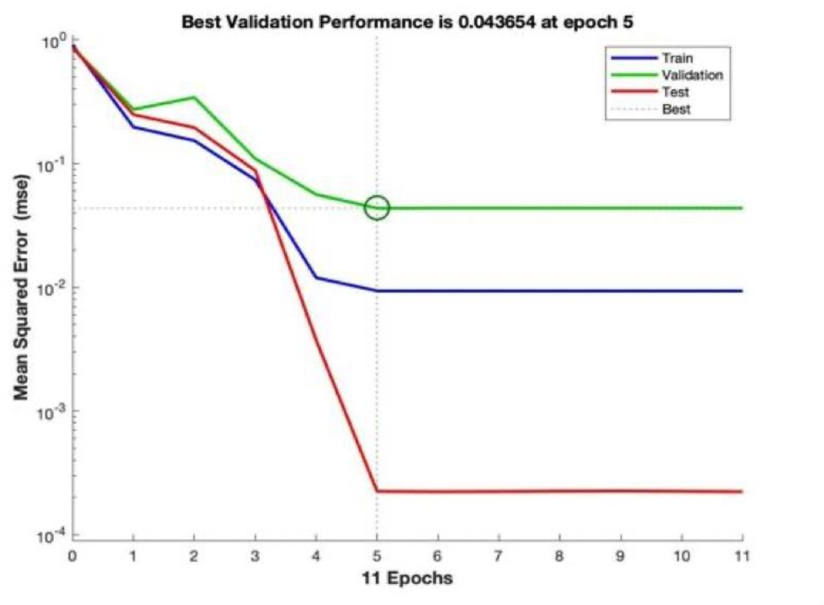


Figure 5: Classification Performance of SubB_6chan_3LRF RNN Classifier

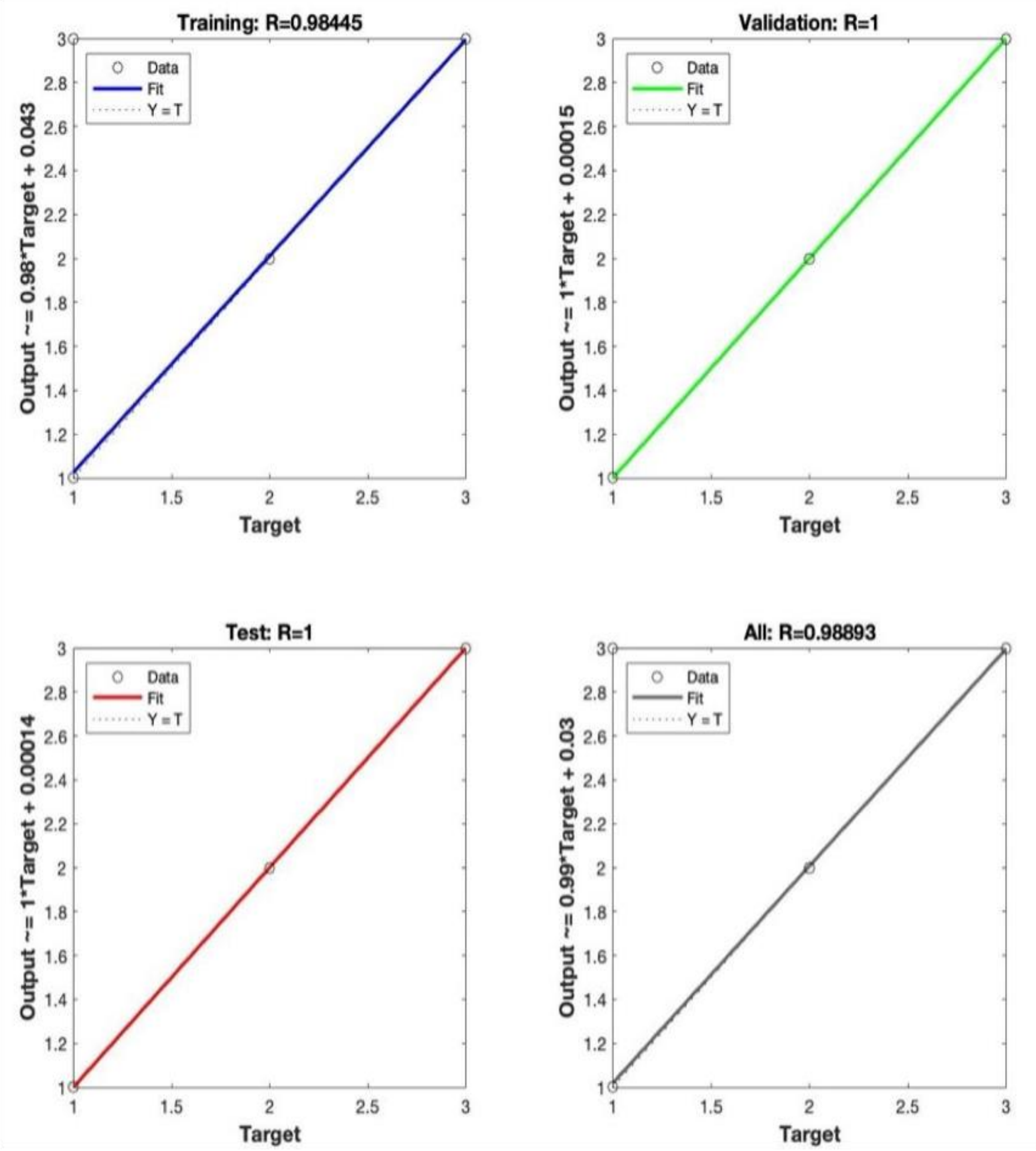


Figure 6: Regression plot of SubA_5chan_3LRF by BPN Classifier

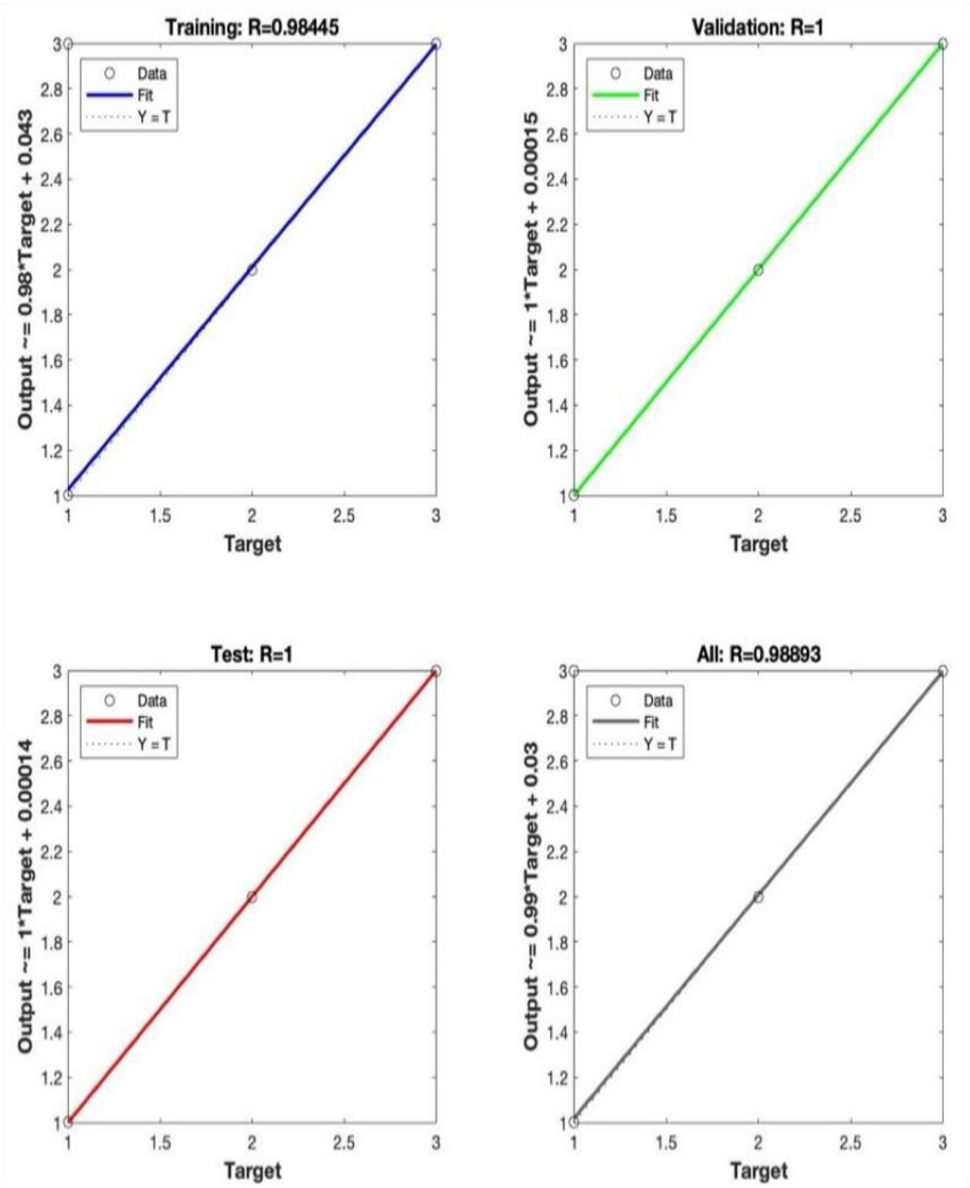


Figure 7: Regression plot of SubA_5chan_3LRF by RNN Classifier

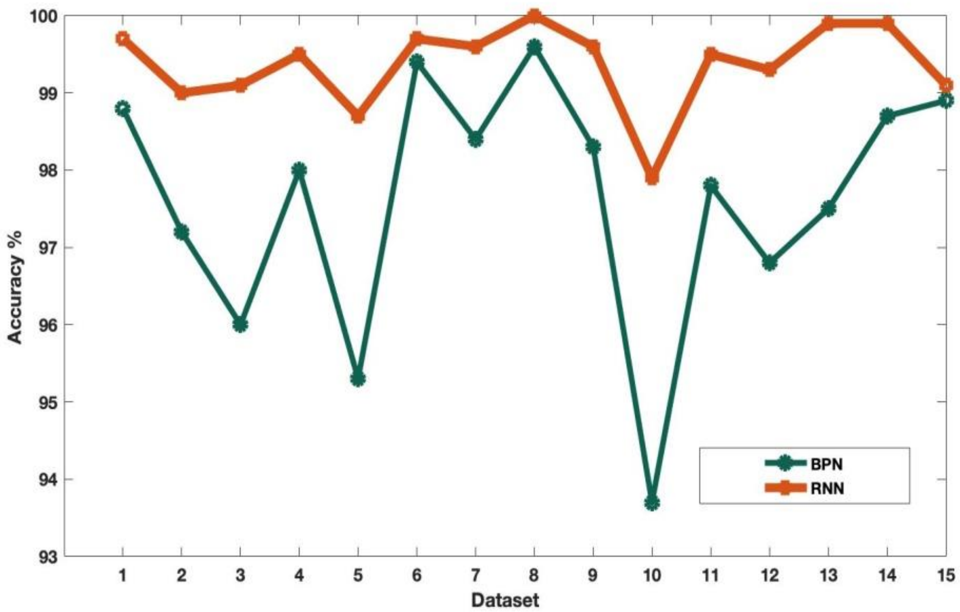


Figure 8: Classification Accuracy by BPN and RNN

5. Conclusion

The main aim of BCI is to identify the user's intention through the brain signals. Once the prominent features are extracted and selected, they have to be classified using the classification algorithm. The performance of BCI depends on the classification accuracy. Rough Neural Network (RNN) is proposed for Motor imagery classification. It is tested on three class datasets with feature extraction using mean correlation and supervised feature selection method using Quick Reduct algorithm. The RNN classifier gives higher accuracy for the three class datasets than the neural network back-propagation (BPN) classifier.

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