International Journal of Future Generation Communication and Networking
Vol. 14, No. 1, (2021), pp. 5000-5015

A CALIBRATION-FREE PATTERN-BASED BRAIN MACHINE INTERFACES USING ARTIFICAL NEURAL NETWORKS

Shreyas J[+] ,Shabreen N , Dharamendra Chouhan , Udayaprasad P K, Dilip Kumar S M

[+]Sofware Engineer, Creencia Technology Private Limited, Bangalore, India
Dept. of Computer Science and Engineering, University Visvesvaraya College of Engineering, Bangalore, India

Abstract

A Calibration technique is a method used brain computer interface (BCI) system, which requires a time period of 20-30 minutes. The procedure of calibration is problematic and unfeasible for building the reliable decoder. To overcome the drawback of existing system, a spectral- spatial algorithm is proposed. The data set of motor imagery (MI) which consists of 14 subjects and 15 electroencephalography (EEG) signals is taken into considerations. The two modules are constructed for data preprocessing and feature extraction. The proposed spectral-spatial algorithm is independently trained and test through artificial neural network (ANN). Based on that classification is done using several machine learning approaches like random forest (RF), neural network (NN), XGboost and given as incoming to hidden layer (Lth layer). The obtained results indicates 2% of improvement in comparison with existing methodology.

Keywords: Artificial neural networks (ANN), Brain Computer Interface (BCI), Common Spatial Pattern (CSP), Electroencephalography (EEG) signals.

1. INTRODUCTION

Brain machine interfaces (BCI) acts mediator between human brain and external devices. BCIs have showed considerable promise in a number of therapeutic interaction, management, and rehabilitation purposes. With systems and applications, brain computer interface technology is a fast emerging topic of research. Its contributions in the medical field span from preventing injuries to neural recovery. The functioning of BCI applications is based mostly on monitoring the user's condition or allows the users to provide insights. The brain-computer interface (BCI) system records brain waves and delivers them to a computer system to accomplish the work [1] [2]. A machine could learn on its own utilizing machine learning approaches. As a result, there is no need for human interference. The training set is used in these methods. The training set consists of selected features acquired after manually analyzing the data. This study uses a variety of machine learning techniques to discover subject-independent enhanced stability [3]. A subject liberated context based on spectral–spatial feature representation with ANN is proposed here.

BCI technology has become more widely available, and a rising number of businesses are offering low-cost BCI devices to customers, with some even launching App stores to boost more inventors to create BCI apps. BCIs are becoming increasingly popular in non-medical fields such amusement, individual safety, and business. The majority of traditional MI-based BCI devices are based on subject-dependent approaches that take time to calibrate. Because of

ISSN: 2233 -7857 IJFGCN

the physiological qualities of every human at any given time, a user's brain signals in BCI systems could alter over seconds, moments, or days. Furthermore, subject-specific features can be seen in the spatial origin, intensity variation, and diversity of brain signals. In the broad use of BCIs, a decryption approach to adjust for variations in brain signals is required if the brain signals are only expected to improve intermittently.

Current BCI research has precipitate a lot of interest as a potential future innovation for the subsequent generation. Over the progression of multiple BCI investigations, more and more emphasis has been placed on the evaluation of electroencephalography (EEG) signals, particularly by mobility visualization, also known as motor imagery (MI). Motor imagery capacity to enable both healthy and impaired persons to self-regulate brain activity without an external stimulation has piqued their curiosity. To learn the EEG signal properties for successful output categorization, an Artificial Neural Network (ANN) machine learning technique is used in this work as a classifier. In this proposed work, brain computer interfacing is studied using different machine learning algorithms. The algorithms used under Common Spatial Pattern (CSP) model implementation are Random Forest, K-Nearest Neighbour (KNN), Logistic regression and XGBoost. The algorithms used under Filter Bank Common Spatial Pattern (FBCSP) model implementation are Naive Bayes, Random Forest, K-Nearest Neighbour (KNN), Logistic regression, XGBoost along with Neural networks.

2. LITERATURE SURVEY

Sarah N. Abdulkader et. al., [4] demonstrates the application areas where brain waves can help in enabling or completing tasks. Authors also go over some of the biggest operational and technical issues that come with using brain signals in several BCI components. Various strategies aimed at limiting and reducing their impacts was also examined. They are in charge of exchanging messages from human minds, as well as deciphering their silent concepts. Brain-computer connections have aided study in a variety of domains. They work in the medical, neuro ergonomics, and smart environment disciplines, as well as e - commerce and advertising, education and self-regulation, gaming and entertaining, and encryption and privacy.

Hassan Takabi Joshi et. al., [5] perform the first complete investigation of BCI App stores in points of privacy considerations, encompassing software development kits (SDKs), application programming interfaces (APIs), and BCI programs. The purpose is to learn how BCI applications manage brainwave signals and what concerns to users' security. Frequent programmes, according to research, have free access to users' brainwave signals and could easily collect confidential data about users without their knowledge.

O-Yeon Kwon et. al., [6] showed that subject-independent model surpasses subject-dependent approaches in prediction performance using various approaches such as [common spatial pattern (CSP), common spatiospectral pattern (CSSP), filter bank CSP (FBCSP), and Bayesian spatio spectral filter optimization (BSSFO)]. The experimental data show that the suggested method outperforms both earlier subject-independent and traditional subject-dependent approaches significantly. The suggested feature representation in combination with a deep neural network technique displays superior performance and intriguing prospects.

ISSN: 2233 -7857 IJFGCN

Natasha Padfield et. al., [7] examines up-to-date signal processing approaches. It also highlights the most common EEG-based BCI applications, notably those relying on MI data and a full review of the most common roadblocks to the marketing of EEG-based BCIs is presented. The goal of this study is to examine a wide range of signal processing techniques utilized in MI-based EEG systems, with a special emphasis on the up-to-date in feature extraction and classification. The study also goes through some of the difficulties and constraints that have been found while developing and implementing associated methods. In addition, the study outlines the key uses of EEG-based BCIs as well as the present problems in developing and commercialising such BCI systems.

Murat Kaya et. al., [8] acquittance a big group of EEG BCI data gathered until the creation of an EEG BCI based on slow cortical potentials. The absence of big, homogenous, and accessible datasets has hampered the development of more efficient statistical data analysis tools for EEG BCI. Using EEG signals, this BCI interaction exemplary was designed to investigate the differentiation of voluntary motor actions prior to their physical manifestation. This field of research was not explored substantially in this work, and only a few recording sessions for this model are accessible.

Andrea Bonci et. al., [9] purposes to evaluate main features and complexities of BCI with a focus on methodological framework and automation industrial uses. BCI is designed to provide for constant communication between among the brain and controlled devices, allowing for data assets and control. The interface allows for direct interaction between the brain and the managed object. A BCI could enable a person with paralysis to write a novel or manage a motorised wheelchair by sensing neural oscillations from an array of neurons and translating the signals into motions utilizing computer chips and programming. Existing BCIs necessitate conscious cognition, however future uses, including such prosthetic control, are likely to function without difficulty. One of the most difficult aspects of creating BCI techniques has been the development of minimally invasive sensors and surgical techniques.

Ulrich Hoffmann, et. al., [10] gives an overview of some of the above-mentioned features of BCI research, represent a specific interpretation of a Brain computer interface system, and discuss current growths and unresolved issues. Authors have endeavoured to provide an overview. BCI enables people to interact with their surroundings solely through brain activity, rather than peripheral nerves and muscles. The main goal of BCI research is to create systems that enable impaired people to interact with others, control artificial limbs, and regulate their surroundings. The topic of communication systems is an alternate application field for brain-computer interfaces. Several features of BCI systems are constantly being explored in order to build systems for use in the field of assistive devices.

Sonam et. al., [11] examined historical and modern research efforts on BCI, along with their effectiveness in the ground of BCI, and critical debates around potential research methodologies for future advances is provided. BCIs have progressed past test results systems, with some currently being sold as commercial items. BCIs have become a practical and successful solution for assistive devices and a variety of commercial uses, and they are no more the stuff of science fiction. New communication models expand BCI's capabilities and bring up new research areas, including such neural imaging for computational customer experience.

Ms. Parija S. Shaikh et. al., [12] suggested an interactive multimedia BCI that can analyse bio signals in real time. A four-channel physiological acquisition along with amplifying unit, a

ISSN: 2233 -7857 IJFGCN

wireless connectivity unit, a dual-core signal-processing unit, a detecting real-signal projection surveillance unit, warning device comprise system. A brain-machine interface is a interaction network that is independent of the brain's usual external nerve and muscle output routes. It is a novel way for a functioning human mind to communicate with the rest of the globe. These are electronic connections with the brain that allow the brain to transmit signals. Through brain interface with external systems and devices, BMI employs brain function to command, control, operate, and connect with the world directly. Without any direct brain interaction, the impulses from the brain are sent to the computer through the implants for entering data.

D Angelakis et. al., [13] demonstrate the development and operation of a BCI system for robotic claw operation. In recent times, Human-Computer Interaction has shown promise and is continuously developing. The majority of practical uses are centred on the recovery of intellectual or neurological impairments, as well as assisting people with cosmetic issues. To overcome, the concept that could handle a simple robotic claw was shown this work. This work shows a working model of a basic Brain computer interface system. It makes use of an inexpensive microcontroller board and a commercially accessible EEG headset. The obtained EEG signals are translated into appropriate commands for manipulating the claw using specialized technology.

3. BACKGROUND WORK

3.1 Problem Statement

Brain signals keep on fluctuating over a period of time. The procedure of calibration is problematic and unfeasible for building the decoder, using of convolutional neural network (CNN) has some limitation which should be addressed. In brain compute interface system calibration techniques is one stoppage that discourages the discovery to implementation in BCI system.

3.2 Objectives:

1. To increase the efficiency in term of mean.
2. Accuracy is been improved for predicting whether left or right hand of motor imagery.
3. Time consumption is less compared to existing system for decoding the electroencephalography (EEG).
4. Prediction of median and range has effectively progressed.
5. To increase of epochs on classification of performance.

3.3 Contributions:

The key commitments can be summed up as follows.

1. Chebyshev bandpass filter used to improve the performance of filtering the raw electroencephalography signals.
1. Spectral- spatial algorithm is independently trained, tested and feature extraction is done using artificial neural network (ANN) which is given to Lth layer of hidden layer.
2. Due which overall outcome of proposed work has increased is efficiency by 2% when compared to existing methodology.

4. PROPOSED WORK

ISSN: 2233 -7857 IJFGCN

A BCI system is proposed, which incorporates various modules that assist in feature extraction, classification, and model training using various machine learning methods. The data is normalized to its original state. Finally, BCI is created in collaboration with the subject to artificial intelligence, an independent architecture using spectral-spatial feature representation using ANN. Figure 4.1 displays the block diagram of proposed system. The project is implemented basically two modules with datasets available in .mat format in separate folder named EEG_Dataset. The dataset are publicly collected with different subjects and sessions of left and right hand. Module 1 is proposed with the CSP algorithm as the spatial feature representation, followed by FBCSP used in module 2 for representation of spatial feature both the modules under training and testing for all the datasets.

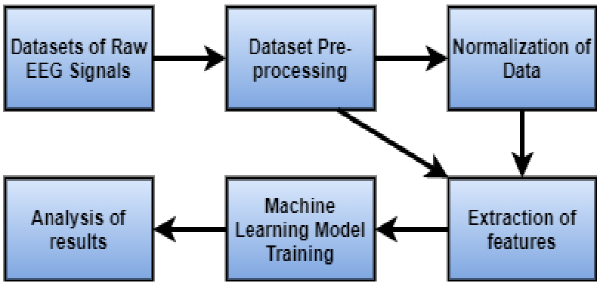

Figure 4.1: Architectural diagram for proposed system

4.1 Dataset:

There are 15-channel EEG recordings from nine people in the data set. The signals are sampled with rate of 250 Hz. Information is gathered with help of two different MI tasks, involving the left and right hands. The first session's MI data were utilized for training, whereas the second session's data were used for testing. In our experiments, the temporal segment of a second is taken into account.

4.2 Data preprocessing:

Preprocessing is a technique for removing superfluous components from an EEG signal in order to maintain important brain information. Preprocessing is thus an important foundation in the BCI process, and when done properly, it results in cleaner EEG data; otherwise, it may bias the EEG analysis and result in inaccurate conclusions. Preprocessing effectively reduces the computing load on the remaining BCI components while simultaneously improving classification outcomes.

Body moment generated visual artifacts, which we were able to remove. The notch is an extremely selective filter that rejects all frequencies save a tiny band around the desired frequency. It will not deal with the EEG signal's other frequencies.

4.3 Feature Extraction:

The feature extraction phase follows, which entails evaluating the signal and extracting data. Because the EEG signal is so complex, extracting valuable information from it just by looking at it is difficult. Various scholars have offered several features and extraction methods for investigating EEG frequency bands in the research. Because signals is variable and keep on changing, extracting important features EEG bands is essential. As a response, the preprocessed EEG signals should be turned into a collection of vectors, each containing a set of features.

ISSN: 2233 -7857 IJFGCN

The core idea behind the CSP approach is to utilize appropriate levels to shift a multichannel EEG dataset to a lower dimensional domain using a matrix for each row containing each channel's weights. With this change, the distinction between the two classes can be amplified. The CSP technology utilizes the diagonalization of the covariance matrix for both classes at the same time. Commonly utilized for MI tasks are supervised techniques for discovering spatial filters, like common spatial patterns (CSPs). Employing EEG frequency sub-band data, the FBCSP method provides the weighted combination of filtered channels. The FBCSP method comprises a filter bank that uses a bandpass filter with a frequency spacing of 4 Hz to divide the EEG signal into nine bands ranging from 4 to 40 Hz. Each sub-CSP band's filter is then determined. To distinguish among two groups, the CSP method is extensively employed. CSP is being used to generate new time series by creating spatial filters. Filter construction is based on diagonalizing two covariance matrices for two groups at the same time. Figure 3.2 shows the block diagram for Feature extraction.

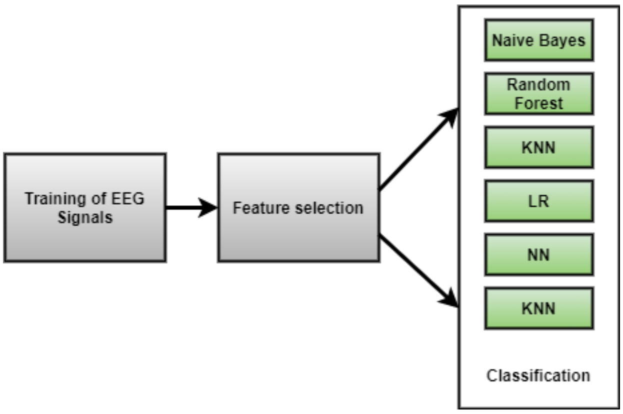

Figure 4.2: Architectural diagram for Feature extraction

5. IMPLEMENTATION

Software tools along with algorithms proposed in this work are described here as a part of implementation.

5.1 Anaconda:

Anaconda is a free program that gives you access to a toolbox designed for study and science. Anaconda provides access to a variety of environments that allow you to code in Python or R. Integrated development environments (IDEs) are platforms or program that allow developing software. The development of code is substantially facilitated. The Anaconda website has links to download the free software in Windows, Mac OS X, and Linux. There are also instructional videos, documents, courses, and support available. This tutorial offers step-by-step installation guidance as well as a review of the many alternatives may discover to make this procedure easier.

5.2 Jupyter Notebook:

Jupyter notebooks are interactive documents that run in a web browser. Human-authored contextual components, computer code, and computer-generated results from operating the computer are all included in the notebook elements. Tables and graphs are examples of such outputs. The notebook elements can be interacted with, and the whole thing can be done in real

ISSN: 2233 -7857 IJFGCN

time. The notebook can be saved, loaded, and run again, or converted to read-only forms like HTML, LaTeX, and PDF. Jupyter notebooks could be used to enhance the performance of computational and data investigation, documenting, communication, reproducibility, and re-usability of scientific research findings by leveraging these qualities. They also serve as the foundation for remote data access and analysis, which is necessary for facilities that handle huge data sets and activities.

5.3 Python:

Python is a good language for learning as well as real-world programming. Python is a strong object-oriented programming language with a high level of abstraction. Python is a multi-paradigm programming language that provisions both object-oriented and organized programming .

Algorithms:

5.4 Naive Bayes:

Naive Bayesian decision theory has a subset called Bayes. Because the approach contains some naive assumptions, it is labelled naive. Python's text-processing capabilities are utilised to break a document into a vector. Text can be classified using this method. It is possible to convert the classifications into a human-readable format. Along with conditional independence, over fitting, and Bayesian approaches, it is a common classification technique. Despite its simplicity, Naive Bayes has a remarkable ability to classify documents. An intuitive reason for the conditional assumption of independence is that if the document is about politics, this is solid proof of the types of other words found in the document. In this sense, Naive Bayes is an acceptable classifier with low storage and quick training. It's used in time-sensitive applications like automatically identifying web pages into kinds and spam detection [14].

5.5 Random Forest:

Random forest is one of kinds of ensemble learning approaches. The data always has an impact on the ability and efficiency of traditional procedures. The capacity to adapt to problematic space settings and liberation from the data domain is the most demanding concerns with various types of classifiers. In the homogeneity supervised learning subgroup, random forest is one of the ways of ensemble learning [15].

5.6 K-Nearest Neighbour (KNN):

KNN is a case-based learning method for classification that retains all of the training data. Its status as a slow learning method precludes from being used in a variety of applications, like dynamic web mining with a big repository. Numerous current techniques like decision trees and neural networks, were built specifically to build such a model. The performance of various algorithms is one of the criteria used to evaluate them. Because KNN is a modest but successful classification approach that has been exposed to be one of the most operational ways in classification [16].

5.7 Logistic regression:

Quantitative methods of machine learning include logistic regression. In logistic regression, the likelihood that the output variable's realisation falls into the correct category is calculated. The employment of a set of separately trained Logistic regression transforms an under-completed

ISSN: 2233 -7857 IJFGCN

problem into an over-completed problem, greatly improving the possibilities of improved reconstruction quality [17].

5.8 XG Boost:

Tree boosting is a popular and successful machine learning technique. Data scientists utilise XGBoost to produce cutting-edge outcomes on a variety of machine learning problems. The most significant component in XGBoost's success is its scalability across all scenarios. On a physical console, the system is more than ten times faster than current popular methods. Using out-of-core processing, XGBoost allows data scientists to examine hundreds of millions of instances on a single computer .

5.9 Neural networks:

A neural network (ANN) is a computer simulation of the human brain. A normal brain can adapt to new and changing environments and discover new things. The brain has the incredible ability to comprehend partial, ambiguous, and fuzzy information in order to make its own decisions based on it. Neurons are the processing units that make up an artificial neural network. A neuron has one yield and set of inputs. The stimulation of the neuron is influenced by the function of the neuron [18].

To make things easier, a neural network's structure and functioning can be summarized as follows: To begin, a neural network's abstract model is made up of neurons, also known as units or nodes. They can collect data from the environment or from other neurons and send it on to other neurons or produce it as a final conclusion. In general, input neurons, hidden neurons, and output neurons can be distinguished. The input neurons take information from the outside world in the form of graphs or signals [19]. The hidden neurons reflect internal data patterns and are placed between the input and output neurons. As an outcome, the output neurons send information and signals to the outside world. The so-called edges link many neurons to one another. As a result, one neuron's outcome could become the input of the next neuron. The edge has a certain weighting based on the strength and relevance of the link. The stronger the weighting, the more impact a neuron can have on another neuron's connectivity [20]. Figure 5.1 shows the architecture of Artificial neural network.

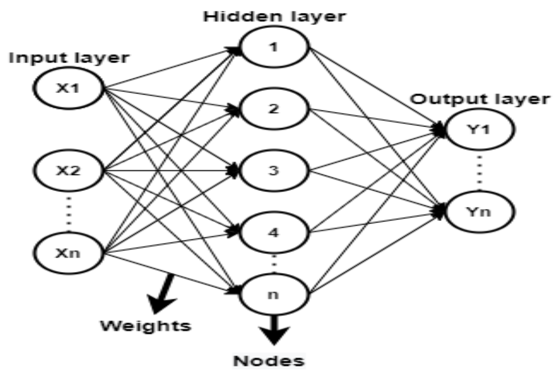

Figure 5.1: ANN Architecture

The ANN algorithm with CSP filter is detailed in below steps with input and output:

Input: A set of training information is begin collected from motor imagery database (M, N).

ISSN: 2233 -7857 IJFGCN

M= $\{m_i\}_{i=1}^{s}$, m□$\mathbb{R}^{axb}$ single set of EEG signals
Where s is complete number of trial, a is sample point, b is frequency of channels
N= $\{n_i\}_{i=1}^{s}$, y_i □ {Left, Right} class labels

Output: Spectral spatial dimensional feature representation L^{th} layer

Procedure:

M_{concat} = Concat $\{(m_1, m_1^1), (m_2, m_2^1)\ldots\ldots\ldots\ldots (m_k, m_k^1)\}$
N_{concat} = Concat $\{(n_1, n_1^1), (n_2, n_2^1)\ldots\ldots\ldots\ldots (n_k, n_k^1)\}$
Concatation of training datapoint, k number of training sample
for i= 1 to k do,
E_k= cheby [n, R_p, W_p] M_{concat}
N is order Lowpass digital Chebyshev type 1 filter with Passband edge frequency W_p & R_p o peak to peak passband ripple
Solve W_K^T $(\sum^{(Left)} + \sum^{(Right)})W_k = 1$
for i=1 to j do,
f_K^i = Log [var ($W_K^T . e_K^i$)]
end
$I(f_k , N_{concat}) = H(f_k) – H(f_k \mid N_{concat})$
end
Ⅲ$_i$ P= 1 to p do
Remap spectical filter with spatial filter
For i=1 to j do
A_p^i= cov ($W_p^T . e_p^i$)
end
$L_p = f(A_p)$

6. RESULTS

This sector shows the outputs of the projected work. The web page is designed to predict the left, right hand and others by selecting eeg_signal.csv file. Based on inputs provide by the user, output is displayed according whether it is left hand or right, if any dataset is inputted then others will be printed. Figure 6.1 shows webpage outlook.

Figure 6.1: Outlook of webpage

ISSN: 2233 -7857 IJFGCN

The output obtained after selecting different types of eeg-signals.csv to predict the best accuracy after training and testing the modules. Figure 6.2 shows the left hand output. Figure 6.3 shows right hand output. Figure 6.4 shows the other output.

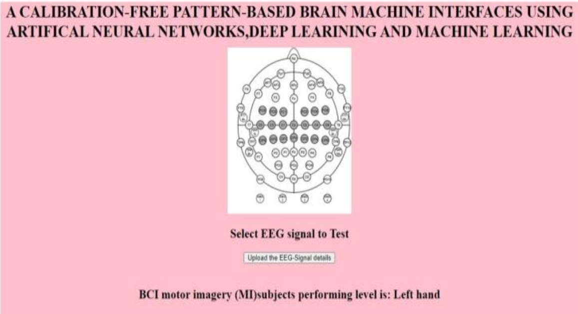

Figure 6.2: Predicting the left hand output

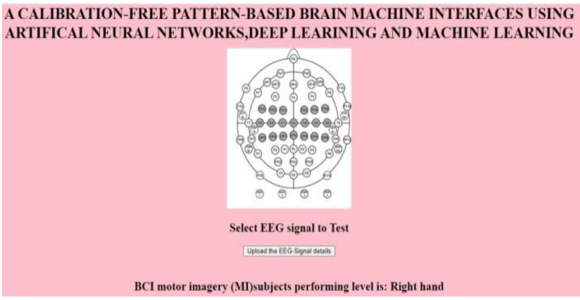

Figure 6.3: Predicting the right hand output

Figure 6.4: Predicting the other output

Individual graphs of all the machine learning algorithms implemented under CSP model with respect to training and testing are shown. Figure 6.5 shows graph of Random Forest, Figure 6.6 shows graph of K-Nearest Neighbour (KNN), Figure 6.7 shows graph of Logistic regression and Figure 6.8 shows graph of XGBoost.

ISSN: 2233 -7857 IJFGCN

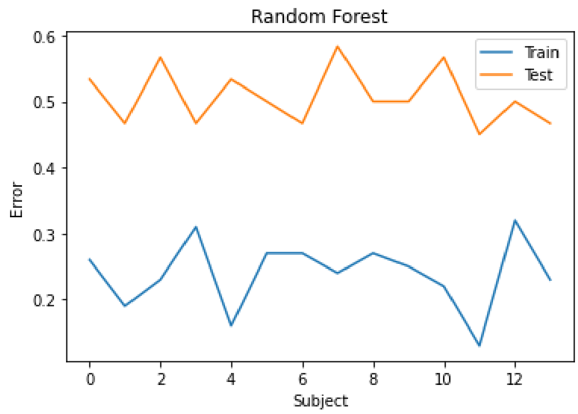

Figure 6.5: CSP Random Forest

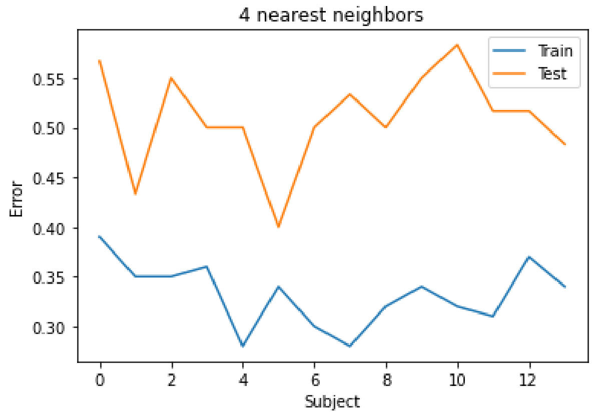

Figure 6.6: CSP K-Nearest Neighbour

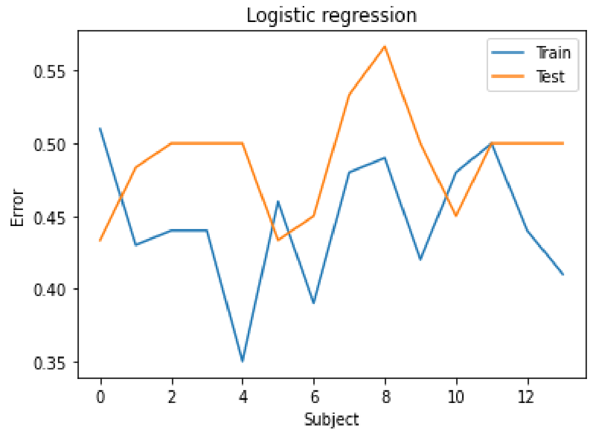

Figure 6.7: CSP Logistic regression

ISSN: 2233 -7857 IJFGCN

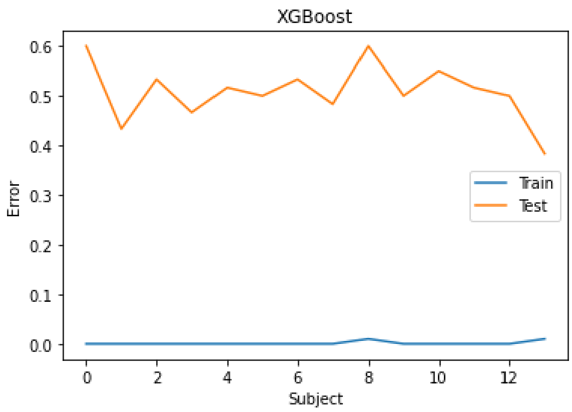

Figure 6.8: CSP XGBoost

All the algorithms of CSP model are compared to training and testing. Figure 6.9 depicts bar graph with Training mean comparison. Figure 6.10 predicts the bar graph of Testing mean comparison.

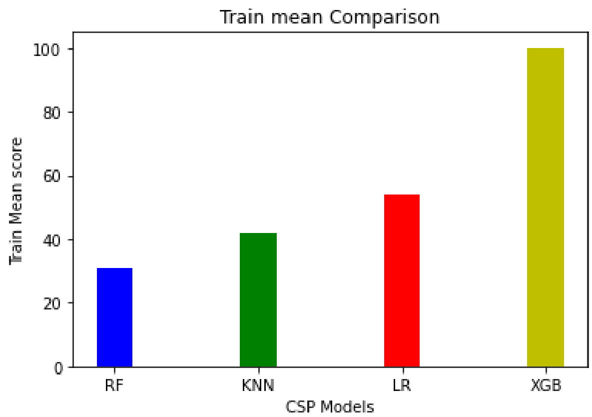

Figure 6.9: Training mean comparison of CSP Modules

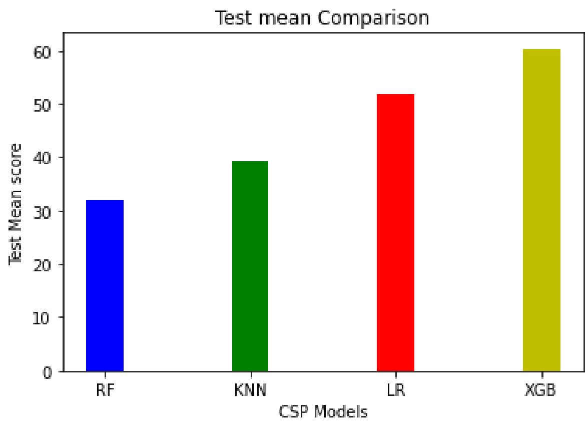

Figure 6.10: Testing mean comparison of CSP Modules

Individual graphs of all the machine learning algorithms implemented under FBCSP model with respect to training and testing are shown. Figure 6.11 shows graph of Naive Bayes, Figure 6.12 shows graph of Random Forest, Figure 6.13 shows graph of K-Nearest Neighbour (KNN),

ISSN: 2233 -7857 IJFGCN

Figure 6.14 shows graph of Logistic regression, Figure 6.15 shows graph of XGBoost and Figure 6.16 shows graph of Neural networks.

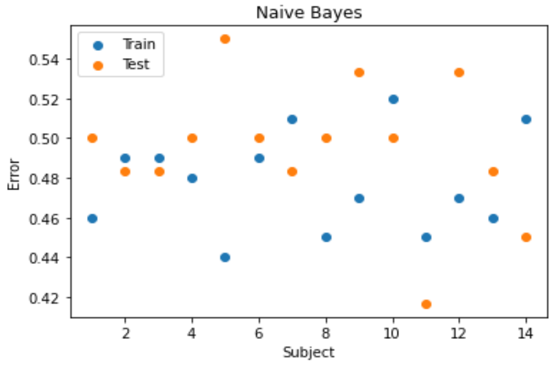

Figure 6.11: FBCSP Naive Bayes

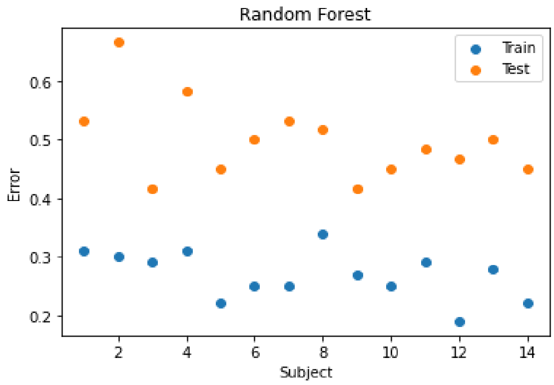

Figure 6.12: FBCSP Random Forest

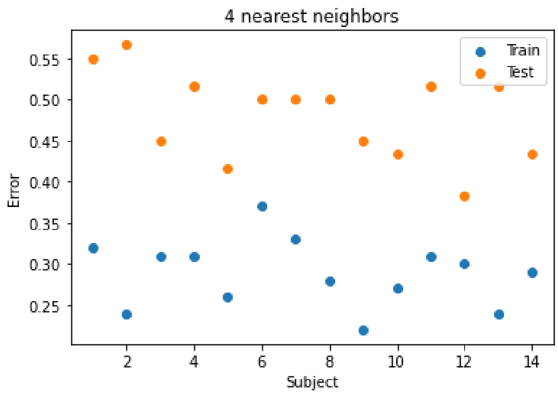

Figure 6.13: FBCSP K-Nearest Neighbour

ISSN: 2233 -7857 IJFGCN

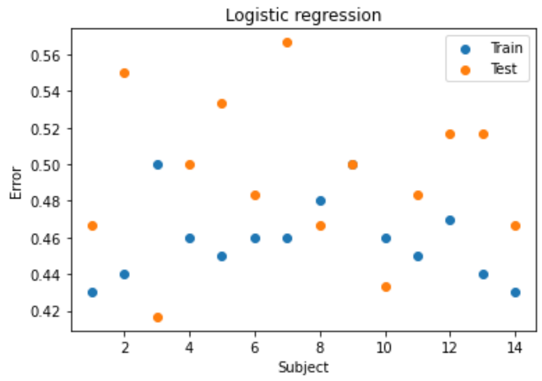

Figure 6.14: FBCSP Logistic regression

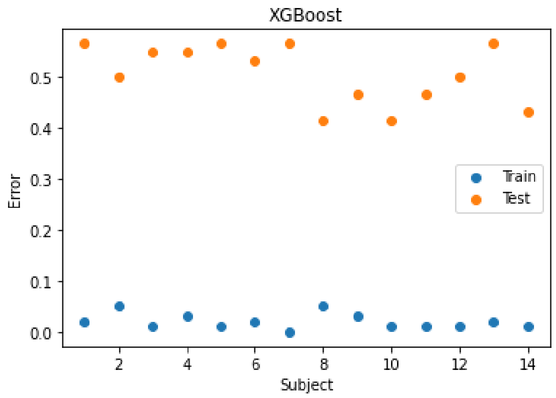

Figure 6.15: FBCSP XGBoost

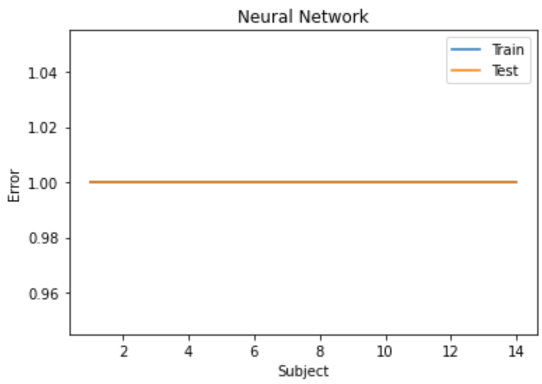

Figure 6.16: FBCSP Neural networks

All the algorithms of CSP model are compared to training and testing. Figure 6.17 predicts bar graph of Training mean comparison. Figure 6.18 predicts bar graph of Testing mean comparison.

ISSN: 2233 -7857 IJFGCN

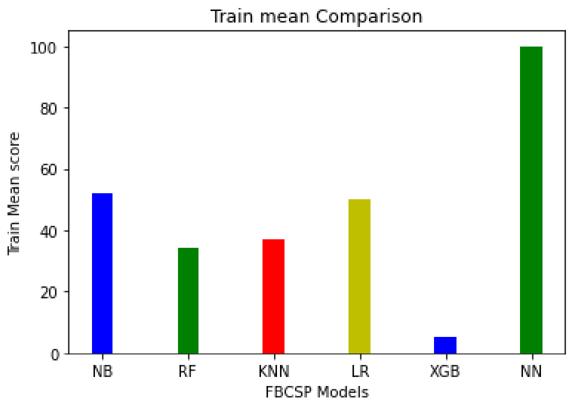

Figure 6.17: Training mean comparison of FBCSP Modules

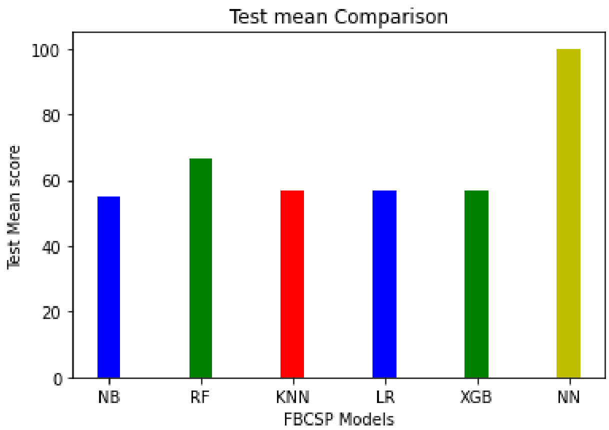

Figure 6.18: Testing mean comparison of FBCSP Modules

The graph plotted for epoch average of left and right hand is shown in figure 6.19.

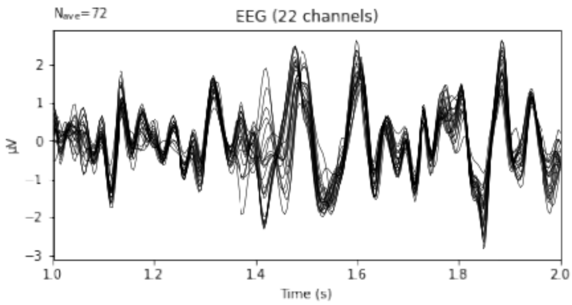

Figure 6.19: Left and right hand Epoch average

7. CONCLUSION

The proposed methodology is based on the Artificial Neural Network (ANN) architecture and uses two models namely Common Spatial Pattern (CSP) and Filter Bank Common Spatial Pattern (FBCSP) under which different machine learning algorithms are implemented with respect to training and testing. The proposed approach for a MI-based brain computer interface is subject-independent. Machine learning approaches are used to combine outstanding performance and promising potential feature representation. The utilization of a larger number

ISSN: 2233 -7857 IJFGCN

of subjects for training has resulted in an improvement in performance in terms of high mean accuracy. The findings appear to show that narrow frequency bands can retrieve discriminating features and thus provide classification accuracy, as well as minimize subject-wise signal variability.

8. REFERENCES

[1] Shreyas, J., Singh, H., Bhutani, J., Pandit, S., Srinidhi, N. N., & SM, D. K. (2019, December). Congestion aware algorithm using fuzzy logic to find an optimal routing path for IoT networks. In *2019 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE)* (pp. 141-145). IEEE.

[2] Shreyas, J., Chouhan, D., Akshatha, A. R., Udayaprasad, P. K., & SM, D. K. (2020, March). Selection of Optimal Path for the Communication of Multimedia Data in Internet of Things. In *2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS)* (pp. 477-481). IEEE.

[3] Shreyas, J., Chouhan, D., Rao, S. T., Udayaprasad, P. K., Srinidhi, N. N., & Kumar, S. D. (2021). An energy efficient optimal path selection technique for IoT using genetic algorithm. *International Journal of Intelligent Internet of Things Computing*, *1*(3), 230-248.

[4] Sarah N. Abdulkader, Ayman Atia and Mostafa-Sami M. Mostafa, “Brain computer interfacing: Applications and challenges,” *Video Egyptian Informatics Journal*, pp. 213-230, 2015.

[5] Hassan Takabi, Anuj Bhalotiya and Manar Alohaly, “Brain Computer Interface (BCI) Applications: Privacy Threats and Countermeasures,” *International Conference on Collaboration and Internet Computing*, pp. 102-111, 2016.

[6] O-Yeon Kwon , Min-Ho Lee , Cuntai Guan and Seong-Whan Lee, “Subject-Independent Brain–Computer Interfaces Based on Deep Convolutional Neural Networks,” *IEEE Transactions on Neural Networks and Learning Systems*, pp. 3839-3852, Vol. 31, 2020.

[7] Natasha Padfield, Jaime Zabalza, Huimin Zhao, Valentin Masero and Jinchang Ren, “EEG-Based Brain-Computer Interfaces Using Motor-Imagery: Techniques and Challenges,” Sensors, pp. 1-34, 2019.

[8] Murat Kaya, Mustafa Kemal Binli, Erkan Ozbay, Hilmi Yanar and Yuriy Mishchenko, “Data Descriptor: A large electroencephalographic motor imagery dataset for electroencephalographic brain computer interfaces,” *Scientific Data*, pp. 1-16, 2018.

[9] Andrea Bonci, Simone Fiori, Hiroshi Higashi, Toshihisa Tanaka and Federica Verdini, “An Introductory Tutorial on Brain–Computer Interfaces and Their Applications,” *Electronics*, pp. 1-42, 2021.

[10] Ulrich Hoffmann, Jean-Marc Vesin and Touradj Ebrahimi, “Recent Advances in Brain-Computer Interfaces,” 2014.

[11] Sonam and Yashpal Singh, “A Review Paper on Brain Computer Interface,” *International Journal of Engineering Research & Technology*, pp. 1-6, Vol. 3, 2015.

[12] Ms.ParijaS.Shaikh, Mr.Abhijit.N.Patil and Ms.Rachana B.Thombare, “Brain Computer Interfacing,” *International Journal of Scientific and Research Publications*, pp. 1-6, Vol. 3, 2013.

[13] D Angelakis, S Zoumis and P Asvestas, “Design and Implementation of a Brain Computer Interface System for Controlling a Robotic Claw,” *Journal of Physics*, pp. 1-4, 2017.

[14] Damien Rolon-Merette, Matt Ross, Thadde Rolon-Merette and Kinsey Church, “Introduction to Anaconda and Python: Installation and setup,” *The Quantitative Methods for Psychology*, pp. 3-11, Vol. 16, 2020.

ISSN: 2233 -7857 IJFGCN

[15] H. Fangohr et. al., “Data exploration and analysis with jupyter notebooks,” *Physics Control Systems*, pp. 799-806, 2020.
[16] K. R. Srinath, “Python – The Fastest Growing Programming Language,” *International Research Journal of Engineering and Technology*, pp. 354-357, Vol. 4, 2017.
[17] Pouria Kaviani and Mrs. Sunita Dhotre, “Short Survey on Naive Bayes Algorithm,” *International Journal of Advance Engineering and Research Development*, pp. 607-611, Vol. 4, 2017.
[18] Mohammad Savargiv, Behrooz Masoumi and Mohammad Reza Keyvanpour, “A New Random Forest Algorithm Based on Learning Automata,” *Computational Intelligence and Neuroscience*, pp. 1-19, 2021.
[19] Gongde Guo, Hui Wang, David Bell, Yaxin Bi and Kieran Greer, “KNN Model-Based Approach in Classification”.
[20] Pouria Tomasz Rymarczyk, Edward Kozłowski, Grzegorz Kłosowski and Konrad Niderla, “Logistic Regression for Machine Learning in Process Tomography,” *Sensors*, pp. 1-19, 2019.
[21] Shreyas.J, Anand Jumnal, S.M Dilip Kumar, K.R Venugopal, “Application of computational intelligence techiques for internet of things: an extensive survey” *Int. J. Computational Intelligence Studies, Vol. 9,* No. 3, 2020.
[22] J Sheryas, SM Kumar “A Survey on Computational Intelligence techinques for internet of things” *International Conference On Communication and Intelligence Systems,* pp-271-282, 2019.

ISSN: 2233 -7857 IJFGCN