International Journal of Recent Technology and Engineering (IJRTE)
ISSN: 2277-3878 (Online), Volume-8 Issue-4, November 2019

Brain Computing Interface using Deep Learning for Blind People

V. J. Chakravarthy, M. Seenivasan,

Abstract: ***The developing area of research in Brain Computer Interface (BCI) is used to enhance the quality of human computer applications. It can be decoding individuals by the computer device signals converted into commands between human's neural world and outer physical world. The brain use bodies under some circumstances to interact with the external world and also brain can be depressed of their sensing abilities namely blindness or deafness. In this study, analyze of brain's behavior using BCI for blind people in spatial activity. The common beliefs in blind people using other senses by compensate their lack of vision. In case of BCI system can able to understand the brain's activity even in very difficult challenge. Therefore we propose the data mining technique. In this research work, deep learning approach based on the framework of Convolution Neural Networks (CNN) with Long Short-Term Memory (LSTM) can help us to discover their brain's activity for blind people.***

Keywords: Brain-computer interface (BCI), blind people, Convolution Neural Networks (CNN), deep learning, Long Short-Term Memory (LSTM)

I. INTRODUCTION

Brain-Computer Interface (BCI) is a system [1] which can able to translates activity patterns of the human brain into messages or commands to communicate with the outer world [2]. BCI underpins many novel applications that are important to people's daily life, especially to people with psychological/physical diseases or disabilities. Blindness is a rigorous or entire modification of basic function which influences the capability for identifying size, color, shape, distance and action or positions with an available space. The phrase "Visual impairment" has been referred for the spectrum which ranges from low vision to blindness. There are two kind of blind person's namely

- Acquired blind
- Congenitally blind

The acquired blind is said to be person's who required for adapting cognitive system to their new conditions whereas in the case of congenitally blind person's have cognitive system which entirely depend upon only four kind of sense from birth without an any kind of reference to the visual components. However, the nervous system is an essential to response, store and release of information or activity which is a composite system contains several structures and specific organs with various functions. This get separated into three types of system namely sensor, motor system and associative system. Moreover, the sensor system is one of an important system to gather information about an organism and environment. Similarly, the motor system as associative system has organized and executes or performs actions. BCIs system consists of both devices like hardware and software which permits path of communication among the computer and the brain [3]. The BCI basic principle has been considered from neural signal as inputs that are essential components of any kind of BCI system and then progress the signal, extraction of features, classifying the features and subsequently converted those recognized signal into the command of device control and even commands of the preferred operations. The basic structure of BCI system is shown in Fig. 1.

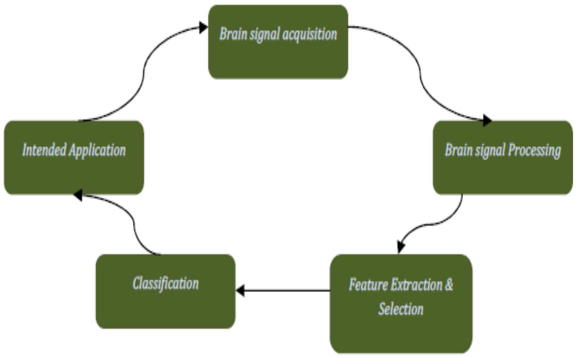

Fig.1. Basic structure of BCI System

BCI has been classified into two type namely invasive and non-invasive whereas the BCIs of invasive are fixed straight away to the grey matter of brain by neurosurgery and thus the devices have produces the high signal quality in BCI devices but in the case of non-invasive does not involved any kind of surgery comparatively the signals are obtained from the brain surface itself [4]. In this study we use deep learning technique as a classification component of BCI system in order to analyze the blind people brain's behavior. The method of deep learning is illustrated to provide better accuracy of classification in the literature. However, the deep network has the ability for detecting the latent features or structure from the unprocessed data which assist in reducing the dependency over feature extraction position of the BCI system.

Manuscript published on November 30, 2019.
*Correspondence Author
V. J. Chakravarthy*, P.G. Department of ComputerScience, The New College, Chennai. Email: chakku_vjc@yahoo.co.in
M. Seenivasan, Department of mathematics, Annamalai university, Annamalai Nagar, Tamilnadu, India. Email: emseeni@yahoo.com

Therefore, the traditional classification algorithms have been analyzed with novel technique whereas the technique of deep learning as CNN is associated with LSTM.

II. DEEP LEARNING

The key challenge of BCI is to recognize human intents accurately given the meager Signal-to-Noise Ratio (SNR) of brain signals. Both low classification accuracy and poor generalization ability limit the real-world application of BCI. To overcome the above challenges, deep learning techniques, i.e., deep neural networks, have been investigated to deal with the brain information in the past few years whereas the ML subfield is deep learning gets stimulated by the function and structure of brain. It has shown excellent representation learning ability since 2006 [5] and therefore been impacting a wide range of information-processing domains such as computer version, natural language processing, activity recognition, and logic reasoning [6].

Although traditional BCI systems have made tremendous progress [7, 8] in the past decades, there search in BCI still faces significant challenges. First, brain signals are easily corrupted by various biological (e.g., eye blinks, muscle artifacts, fatigue and concentration level) and environmental artifacts (e.g., environmental noise) [7]. Therefore, it is crucial to distill informative data from corrupted brain signals and build a robust BCI system that works under different situations. Second, BCI has a low SNR due to the non-stationary nature of electrophysiological brain signals [9]. Although several preprocessing and feature engineering methods have been developed to decrease the noise level, such methods (e.g., feature selection and extraction both in the time domain and frequency domain) are time-consuming and may cause information loss in the extracted features [10].

Third, feature engineering highly depends on human expertise in the specific domain. For

Example, it requires basic knowledge of biology to investigate the sleep state through EEG signals. Human experience may help capture features on some particular aspects but prove insufficient in more general conditions. Therefore, an algorithm is required to extract representative features automatically. Moreover, most existing machine learning research focuses on static data and therefore cannot classify rapidly changing brain signals accurately. For example, the state-of-the-art classification accuracy for motor imagery EEG is merely 60% to 80% [11], which is unfeasible for practical uses. It generally requires novel learning methods to deal with dynamical data streams in BCI systems. Deep learning possesses two advantages. First, it avoids the time-consuming preprocessing and feature engineering steps by working directly on raw brain signals to learn distinguishable information through back-propagation. Second, deep neural networks can capture both representative high-level features and latent dependencies through deep structures [12][13].

III. PROPOSED METHOD

The mining and extraction process of information or knowledge from the huge volume of data is said to be data and there are several algorithms that can be used to discover patterns in a dataset. This research has been mainly focused the utilization of decision tree to discover the knowledge over brain signal datasets for blind person during an activity concerning spatial capability for identifying their brain activity. In this research, deep learning approach based on involving CNN-LSTM framework may assist for understanding the behavior of brain to the blind people.

A.Convolution Neural Networks (CNN)

The most familiar model of deep learning is CNN which gets specialized in spatial information exploration [14]. This session has been illustrated the CNN working mechanism briefly whereas it is frequently utilized for identifying the inherent spatial data in application namely image recognition, ubiquitous, and object searching because of its salient features presented are invariance of translation, good local spatial and regulation of structure. Especially in BCI, the presumption of CNN is to seize the dependencies of distinctive between the patterns gets related with various brain signals to blind persons. Therefore, this study has been presented with traditional architecture of CNN that is shown in Fig.2.

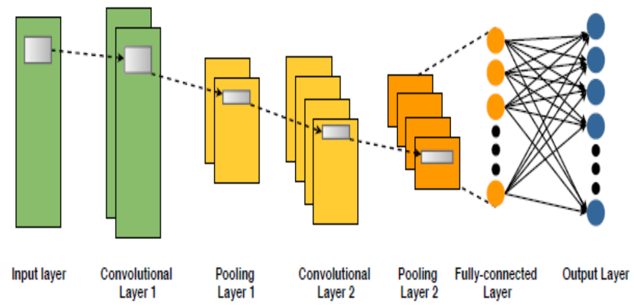

Fig.2. Architecture of CNN

The CNN is most familiar method with difference of Multilayer Perceptron (MLP) has constructed for reducing an essential step as pre-processing which are generally required for the task of BCI for blind people. However, the each input brain signal presents in the CNN gets progressed using a single neuron that may perform as a filter and this filter is learned from its input. In addition, the filter is made to share its entire data that reduces size of the network and also reduces the amount of weight present in the network. This network consists of different layer types namely convolution layer, ReLU layer, input layer, FC layer and pooling layer with its loss functions.

A1. Convolution layer

The relationship among the input brain signal of blind people assist to learn CNN with representation of extracting features by both pooling and convolution operations whereas detected features at every layer from learnt kernels get varies about their complexness in the first layer extraction with ease features namely edges and the subsequent layer has extracted more complexity in high features level. In this CNN, the convolution operation consists of three major metrics are

1. The arrangement of high dimensional data is assisted based on mechanism of weight sharing whereas the data may be either 2D signal or 3D signal.

2. The input topology present in the local connectivity can be used by either 2D kernels or 3D kernels.

3. The proportional of slight shift can be accomplished by pooling layer.

Given a set of filters w_1, w_2, ….,w_k…………,w_K

Where, K = Neurons layer number

$f_k = w_k * x$ (1)

Where, x = input or output BCI data from the earlier layer

And (*) is Convolution operation

A2. Non-linearity layer

In general, the operation of non-linearity has been followed from convolution layer whereas the non-linearity gets accomplished by particular functional family is said to be activation functions. Hence, this activation functions has ensured the illustration present in the input space gets mapped to inadequate and can be accomplished using two major cases are

- The data variability with certain level
- The representation of effective calculations

The earlier condition referred for fact which gets inadequate representations are highly flexible for minor modifications than intense and the precedent function of both sigmoid and hyperbolic tangent are generally utilized to the purpose. The layer of ReLU has computed based on element wise activation function for increasing non-linearity:

$f(x) = \max(0, x)$ ……(2)

However, the comparisons of other general functions of activations are hyperbolic tangent or sigmoid and ReLU whereas the ReLU is more rapidly activation function which performs without affecting the dimensional sizes (n x n x k).

A3. Pooling layer and sub-sampling layer

There are three steps need to be followed for an usual convolution layers are

- Step 1: In order to produce feature maps, the several convolutions have performed by layers.
- Step 2: In this step, the resulting gets mapped using the function of non-linear activations.
- Step 3: In this step, the pooling layer has used for modifying output before subsequent convolution layer gets reached.

The pooling features fundamental is for extracting a summary of non-overlapped neighborhoods statistics which is generally used for reducing the parameters number in the given layer, controlling the over fitting and invariance of small translation gets accomplished. There are several pooling methods are available but the most commonly used methods are mean pooling and max pooling whereas the operations of both pooling method are same but earlier maximum is used as activation. Therefore, max pooling is the most frequently used for its empirical performance.

A4. Fully Connected Layer

The FC layer has computed the score of final class after analyzing various layers namely ReLU layer, convolution layer and pooling layers whereas the FC layer is as similar as MLP which is completely depend upon weights (W) and biases (b). However, the network is basically trained along back propagation and few loss functions namely the cross-entropy function with soft max function. This layer has modified the earlier layer of 2D structural features into predetermined 1D feature vector. Basically, the major task of FC layer is to extract the incoming features for extracting the data about the brain signal for blind people. In this proposed research, the LSTM layer has been used instead of fully connected layer which has utilized for solving this problem using explicitly that introduces a memory unit is said to be cell present in the network [15].

A4.1. LSTM layers

One of the RNN models is LSTM which has general LSTM units composed of cell and 3 gates whereas the three gates are input gate, forgot gate and output gate. However, the value of cell members in arbitrary time intervals and the 3 gates have regulated information flow inwards and outwards of the cells. The interactive operation between these 3 gates have created LSTM which provide an adequate capability for solving the long term dependencies issue that cannot be learn in traditional RNNs. Moreover, the general issues in deep neural network is said to be gradient vanishing whereas the learning speed present in earlier hidden layer is lower than deeper hidden layers. Hence, this event has leaded to minimize the accuracy rate while the hidden layer gets increased. Thus the BCI system understand the brains work for blind people of cell memory present in LSTM has efficiently resolve the gradient vanishing issue in back propagation and may able to learn the input arrangement with time steps as longer. Thus, LSTM is mainly utilized to solve an application associated with the brain's behavior of blind people in a spatial activity of time serials.

LSTM-RNN model is created for predicting the brain state of every time points depending upon its functional profile and temporal dependency in its points of preceding time whereas the LSTM-RNN architecture is utilized in this study involved with two LSTM hidden layer and one fully connected layer. However, the two LSTM hidden layer are utilized for encoding the functional data with temporal dependency to each time point and fully connected layer is utilized for learning a map among the learned representation of features and the brain states. Thus, the representation of function encoded present in every layer of LSTM get calculated as

$$f_t^l = \sigma\left(w_f^l\left[h_{t-1}^l, x_t^l\right] + b_f^l\right) \quad (3)$$

$$i_t^l = \sigma\left(w_i^l\left[h_{t-1}^l, x_t^l\right] + b_i^l\right) \quad (4)$$

$$\breve{C}_t^l = \tanh(w_c^l\left[h_{t-1}^l, x_t^l\right] + b_c^l) \quad (5)$$

$$C_t^l = f_t^l * C_{t-1}^l + i_t^l * \breve{C}_t^l \quad (6)$$

$$o_t^l = \sigma\left(w_o^l\left[h_{t-1}^l, x_t^l\right] + b_0^l\right) \quad (7)$$

$$h_t^l = o_t^l * \tanh(C_t^l) \quad (8)$$

$f_t^l, i_t^l, C_t^l, o_t^l, h_t^l$ and x_t^l mentioned as forget gate output, input gate output, cell state output, hidden state output and the input of feature vector present in 1st LSTM layer (l=1,2) at the tth time point respectively and the σis represented as sigmoid function. The features of first LSTM layer inputs are functional signatures gets derived from FNs and the subsequent LSTM layer input is a vector of hidden state accomplished using the first LSTM layer. The output node (s) with respect to fully connected layer can be adopt to predict the brain state as

$$S_t = soft\max(w_s.h_t^2 + b_s) \qquad (9)$$

Where,

S= brain states number for decoded

h_t^2 = Hidden state output for second LSTM layer

This layer has encoded the functional signature input at the tth time point and the encoded data of temporal dependency present in the cell state from its earlier time points.

IV. CONCLUSION

In this research, the study of CNN has illustrated about the superiorities present in the deep learning technique for BCI system placed on the physical of blind person's which involves in discovery of analysis of words, emotions or feeling using brain signals. However, this is simple for detecting decision making and also justifies them whether they are telling the truth. Therefore, this deep learning technique has been completely minimized the dependency on feature extraction components present in the BCI systems. In the future work, the study may proposed in term of evaluating the various dataset for validating the deep learning performance to analyze several general features for specific BCI dataset to the blind persons and also planning for feature extraction using the technique of deep learning.

REFERENCES

1. Sherif M Abdelfa.ah, Ghodai M Abdelrahman, and Min Wang. 2018. Augmenting .e Size of EEG datasets Using Generative Adversarial Networks. In 2018 International Joint Conference on Neural Networks (IJCNN). IEEE, pp.1–6.
2. Fabien Lo.e, Laurent Bougrain, Andrzej Cichocki, Maureen Clerc, Marco Congedo, Alain Rakotomamonjy, and FlorianYger. 2018. A review of classification algorithms for EEG-based brain–computer interfaces: a 10 year update. Journal of neural engineering 15, 3 (2018), 031005.
3. Narusci S. Bastos, Diana F. Adamatti, and Cleo Z. Billa , "Discovering Patterns in Brain Signals Using Decision Trees" , Hindawi Publishing Corporation Computational Intelligence and Neuroscience Volume 2016, Article ID 6391807, 10 pages http://dx.doi.org/10.1155/2016/6391807
4. Vasudha Vashisht, Dr. T. V. Prasadand Dr. S.V.A.V. Prasad, "Technology Boon: EEG Based Brain Computer Interface - A Survey", IJCSMC, Vol. 2, Issue. 4, April 2013, pg.447 – 454.
5. Li Deng. 2014. A tutorial survey of architectures, algorithms, and applications for deep learning. APSIPA Transactions on Signal and Information Processing 3 (2014).
6. Jindong Wang, Yiqiang Chen, ShujiHao, Xiaohui Peng, and Lisha Hu. 2018. Deep learning for sensor-based activity recognition: A survey. Pa.ern Recognition Le.ers (2018).
7. Sarah N Abdulkader, AymanAtia, and Mostafa-Sami M Mostafa. 2015. Brain computer interfacing: Applications and challenges. Egyptian Informatics Journal 16, 2 (2015), pp. 213–230.
8. Ali Bashashati, MehrdadFatourechi, Rabab K Ward, and Gary E Birch. 2007. A survey of signal processing algorithms in brain–computer interfaces based on electrical brain signals. Journal of Neural engineering 4, 2 (2007), R32.
9. WojciechSamek, Klaus-Robert M¨uller, Motoaki Kawanabe, and Carmen Vidaurre. 2012. Brain-computer interfacing in discriminative and stationary subspaces. In Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE. IEEE, pp.2873–2876
10. Xiang Zhang, Lina Yao, .an Z Sheng, Salil S Kanhere, Tao Gu, and Dalin Zhang. 2018. Converting your thoughtsto texts: Enabling brain typing via deep feature learning of EEG signals. In 2018 IEEE International Conference onPervasive Computing and Communications (PerCom). IEEE,pp. 1–10.
11. Fabien Lo.e, Marco Congedo, Anatole L´ecuyer, FabriceLamarche, and Bruno Arnaldi. 2007. A review of classification algorithms for EEG-based brain–computer interfaces. Journal of neural engineering 4, 2 (2007), R1.
12. Hubert Ceco.i, Miguel P Eckstein, and Barry Giesbrecht. 2014. Single-trial classification of event-related potentials in rapid serial visual presentation tasks using supervised spatial filtering. IEEE transactions on neural networks and learning systems 25, 11 (2014), pp.2030–2042
13. Mu.i Mahmud, Mohammed Shamim Kaiser, Amir Hussain, and Stefano Vassanelli. 2018. Applications of deep learning and reinforcement learning to biological data. IEEE transactions on neural networks and learning systems 29, 6(2018), pp.2063–2079.
14. Mohamed Attia, ImaliHettiarachchi, Mohammed Hossny, and Saeid Nahavandi.2018." A time domain classification of steady-state visual evoked potential susing deep recurrent-convolution neural networks", In Biomedical Imaging (ISBI 2018), 2018 IEEE 15th International Symposium on.IEEE,pp.766–769.
15. Xiang Zhang, Lina Yao, Xianzhi Wang, Jessica Monaghan, David Mcalpine, Yu Zhang, "A Survey on Deep Learning based Brain Computer Interface: Recent Advances and New Frontiers",arXiv:1905.04149v3 [cs.HC] 15 Jun 2019.

AUTHORS PROFILE

Dr. V. J. Chakravarthy was born in India in 1979. He received the MCA degree in 2003 from Bharathidasan University, M.Phil degree from Periyar University in 2005 and Ph.D in from University of Madras 2015. He is currently working as an Assistant Professor in New College, Chennai. He has published 25 papers in reputed journals both national & international levels. His main areas of research interest are Computer Networks, Data Mining, Artificial Intelligence, Machine Learning, Big Data Analytics& Data Sciences. Dr. V. J. Chakravarthy is a member of the Indian Science Congress, ICT Academy.

Dr. M. Seenivasan is working as Associate Professor in Department of Mathematics, Annamalai University. He was awarded Ph.D degree by Annamalai University in the year 2012. He was 17 years of teaching and 15 years of research experience. His area of research is Stochastic Processes, Graph theory and Computer Networks. He has published more than 20 research articles in reputed indexed international journals. He has guided 20 M.Phil scholars. At present, he is guiding three Ph.D scholars. He acted as editorial members of more than 13 international journals. He organized four international conferences in abroad. He visited Thailand , Malaysia, Singapore and USA.